Empirical Essays on the Economics of Inequality

Marta Golin

Nuffield College

University of Oxford

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Abstract

This dissertation reflects the focus of my research agenda on the determinants of inequality along different dimensions, including, but not limited to, socio-economic status and gender. It consists of two chapters on the determinants of inequality in human capital and three chapters on the unequal impact of Covid-19.

In Chapter 1, co-authored with Teodora Boneva and Christopher Rauh, we examine whether differences in individual perceived returns to a postgraduate degree can explain the socio-economic enrollment gap in postgraduate education. We document that first-generation students have worse life experiences at university and perceive the returns to postgraduate education to be significantly lower than their continuing-generation counterparts do. We also find that differences in beliefs about the returns to postgraduate education can explain around 70% of the socio-economic gap in intentions to enroll in a postgraduate degree. These results shed light on the role that perceived returns to education play in determining socio-economic differences in educational attainment.

In Chapter 2, I explore the role of broadband Internet as a determinant of the gender gap in mental health. I combine restricted-access survey data from the German Socio-Economic Panel with publicly available information on the characteristics of the German telecommunication infrastructure to quantify the causal impact of having access to broadband Internet on mental health. Using an instrumental variable strategy I find that having access to high-speed Internet significantly reduces mental health among women, thus widening the existing gender gap. The results are driven by a worsening of women's socializing behavior and ability to cope with emotional stress, and concentrated among the younger cohorts. These findings contribute to our understanding of gender gaps in mental-health disorders and the ongoing societal debate on how to encourage a healthier use of new technologies.

Finally, the last three Chapters of this dissertation examine inequalities in the impacts of the Covid-19 crisis. In Chapters 3 and 4, co-authored with Abi Adams-Prassl, Teodora Boneva and Christopher Rauh, we use novel survey data to document the unequal impact of Covid-19 on workers in the UK, US and Germany. We show that job losses in the first months of the crisis have been higher in the UK and the US compared to Germany. We additionally highlight large inequalities in the impact of the economic shock *within* countries. More specifically, workers on alternative work arrangements and those who can do less of their tasks from home have been more likely to lose their job in the first months of the pandemic. Crucially, women have also

been more severely affected by the crisis than men. Turning to the role of policies in mitigating the negative economic shock, in Chapter 4 we investigate which workers were furloughed under the UK Coronavirus Job Retention Scheme and examine inequalities in the terms under which they were put on furlough. Among other results, this chapter shows that women have been significantly more likely to be put on furlough, and to have initiated the furloughing decision. This is especially true for mothers, which suggests a large role played by inequalities in care responsibilities. Consistent with this hypothesis, in Chapter 5 I exploit novel survey data from parents of school-aged children in England to study parental time use during the pandemic. I find that mothers have increased the time they spend on childcare activities significantly more than fathers have, thus leading to a widening gender gap in time dedicated to childcare, and to educational activities with children in particular. The rest of the chapter examines the role of different sets of variables in explaining these trends. In particular, I focus on the role of perceived gender roles and perceived returns to maternal (vs paternal) time investment in home-schooling in explaining changes in the way couples allocate time to educational activities with children during the pandemic. I find that changes in the employment status of parents are strong predictors of changes in the home-schooling gender gap. Additionally, parental beliefs about returns to maternal time investment and their attitudes towards gender roles are significantly correlated with changes in the way in which parents shoulder childcare responsibilities, even when controlling for labor market status of parents. The findings from these three chapters contribute to our understanding of the impact of Covid-19 on workers and parents, and point to an alarming widening of existing gender inequalities.

Declaration The work in this thesis is based on research carried out by me at the University of Oxford between September 2018 and February 2021. No part of this thesis has been submitted for a doctoral degree at this, or any other, university.

Supervisors This thesis was supervised by Prof. Hamish Low (University of Oxford), Prof. Teodora Boneva (University of Zurich) and Prof. Climent Quintana-Domeque (University of Exeter).

Total words This thesis contains approximately 95,000 words.

Statement of authorship Chapters 2 and 5 of my thesis ("The Effect of Broadband Internet on the Gender Gap in Mental Health: Evidence from Germany" and "Gender Gaps in Home-Schooling Time") are single-authored and fully my own work.

Chapter 1 ("Can Perceived Returns Explain Enrollment Gaps in Postgraduate Education?") is joint work with Teodora Boneva and Christopher Rauh. Teodora Boneva has supervised my doctoral work and is currently Assistant Professor at the University of Zurich. Christopher Rauh is Lecturer (Assistant Professor) at the University of Cambridge. All three of us contributed to the development of the survey. I was responsible for the data collection and contributed most to the data handling and analysis for the paper (including but not limited to comparing our survey data with existing data from the UK and generating the final result tables and figures for the paper). I drafted large parts of sections 2, 3, 4, 5 and 6 of the paper, and additionally contributed to writing all other sections of the chapter.

Chapters 3 and 4 ("Inequality in the Impact of the Coronavirus Shock: Evidence from Real Time Surveys" and "Furloughing") are joint work with Abi Adams-Prassl, Teodora Boneva and Christopher Rauh. Abi Adams-Prassl is Associate Professor at the Department of Economics, University of Oxford. These chapters are part of a broader research project ("The COVID Inequality Project") which we launched in March 2020 to document the impact of the Covid-19 pandemic on workers across the United States, United Kingdom and Germany. As a co-founder of the project, I contributed to the design of the novel survey modules we used to collect information on the short-term impacts of Covid-19 on workers and was responsible for the collection of three waves of survey data across the three countries. I also contributed to the data analysis for both Chapters and made substative contributions to the narrative building and write up of the papers. Finally, I was involved in the revision stage of both Chapters for publication in peer-reviewed journals.

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Ethical approval For Chapters 1, 3, 4 and 5, ethical approval has been sought and obtained from the University of Oxford CUREC committee. Please refer to the individual Chapters for their reference numbers.

Restricted data access Chapter 2 of this thesis exploits confidential data on the household coordinates of respondents to the German Socio-Economic Panel. The data are only accessible from a secure-access room located at the DIW in Berlin (Germany). Any further data analysis would require me to book a desk in the DIW secure-access room and travel internationally. At the time of writing, both of these activities are limited by the ongoing pandemic.

Marta Golin (June 2021)

Contents

Thesis Introduction

This thesis is the result of my research in the areas of behavioral and labor economics. My research agenda exploits a combination of existing survey data from large longitudinal panel data and novel survey data to investigate the determinants of inequalities, with a particular focus on the socio-economic and gender dimensions. The first two chapters of this thesis examine inequalities in educational attainment and mental health. The last three chapters explore inequalities in labor market outcomes and the division of unpaid work that have been generated or exacerbated by the Covid-19 pandemic.

Chapters on Human Capital

A growing body of evidence shows that individual investments in education can have far-reaching impacts on future life outcomes, from labor market outcomes to crime and health (see for example Heckman et al., 2018). Moreover, inequalities in educational investment decisions are strongly linked with wage inequality, which has increased rapidly over the last decades in many countries around the world, including the US and the UK. This trend has been particularly pronounced in the upper tail of the wage distribution and within the group of college-educated workers, which has drawn attention to the role of postgraduate education in explaining this pattern (Lemieux, 2006). Despite the fact that a significant and increasing share of workers now holds postgraduate qualifications and that workers with a postgraduate degree are over-represented in the upper tail of the earnings distribution, surprisingly litte attention has been devoted to the question of who obtains a postgraduate degree and what drives this investment choice.

In the first chapter of this dissertation, co-authored with Teodora Boneva and Christopher Rauh, we examine the role of students' beliefs about the returns to educational investment decisions in contributing to inequalities in enrollment into postgraduate education across socio-economic groups. The role of the "psychic costs" of education in explaining educational investment decisions has long been highlighted (see e.g. Carneiro et al., 2003; Cunha and Heckman, 2007; Heckman et al., 2006). However, what constitutes these psychic costs is less understood. In a recent paper on socio-economic gaps in university attendance, Boneva and Rauh (2019) explore the role of beliefs about different pecuniary and non-pecuniary aspects of university education in driving differences in students' intentions to obtain a university degree. Chapter 1 of this thesis extends this work to the choice of whether or not to pursue a postgraduate degree, and examines socio-economic differences in beliefs about the benefits and costs of postgraduate education.

To understand how students perceive the returns to postgraduate education, we collect novel survey data from a sample of around 1000 undergraduate university students in the UK. We design novel survey modules to collect information about students' intentions to enroll in a postgraduate degree, and their beliefs about the returns and costs of postgraduate education. We document large differences both in intentions to enroll in postgraduate education and in perceptions about the returns to a postgraduate degree depending on the student's socio-economic status. In particular, we document a 5 percentage points socio-economic gap in intentions to enroll in a postgraduate degree, and that first-generation students perceive the immediate benefits of postgraduate education as significantly lower. We then examine to what extent differences in beliefs about the returns to postgraduate education can account for the socio-economic gap in students' intentions to obtain it in the context of a flexible choice model that allows for differences in preferences and beliefs across socio-economic groups. Our decomposition exercise shows that around 70% of the gap in intentions to enroll across socio-economic status can be explained by differences in beliefs about the returns to postgraduate education, and that beliefs about immediate outcomes play a particularly important role. Finally, we examine whether students' experience of life as undergraduate students influence their perceptions about postgraduate education. We show that first-generation students have significantly worse experiences of life at university compared to their continuing-generation counterpart. In particular, first-generation students are more likely to struggle financially and less likely to enjoy their social life or receive parental support. Further, we find that current experiences are strong determinants of students' beliefs about postgraduate education.

This chapter contributes to the literature on what drives socioeconomic differences in educational attainment. We add to the existing body of work by looking at the decision to enroll in a postgraduate degree, and examine the role of differences in perceived pecuniary and non-pecuniary returns to postgraduate education in explaining the socio-economic gap in intentions to enroll. The results from this chapter point to alarming differences in students' experience of life at university already during their undergraduate years, and stress the importance of policies aimed at supporting disadvantaged students during their university life. In addition, the differences in students' undergraduate experiences suggest that socio-economic differences in beliefs about the immediate, non-pecuniary returns to postgraduate education would correlate highly with actual differences in *postgraduate* students' experience. More research should go into understanding whether realised returns to postgraduate education, including pecuniary returns, are actually lower for first-generation students than they are for continuing-generation students and, if so, what drives these differences in returns by socioeconomic status. A better understanding of socio-economic gaps in experiences of life at university and beyond will be informative for the implementation of policies aimed at reducing inequality.

In the second chapter of this dissertation, I examine gender gaps in mental health and explore the role of one specific driver of mental health differences across gender, namely broadband Internet. The importance of mental health in boosting productivity and improving socioeconomic outcomes has been amply documented in the literature. At the aggregate level, the World Health Organization estimates the cost of mental health to the global economy to total around 1 trillion USD in lost productivity per year (WHO, 2019). At the individual level, depression and anxiety and other mental health disorders have been found to affect financial empowerment, educational attainment and child investment (Currie and Stabile, 2006; Baranov et al., 2020; Haushofer and Fehr, 2014), and to have large and negative intergenerational effects on children's socio-economic outcomes later in life (Johnston et al., 2013). Further, given that women are almost twice as likely as men to suffer from mental health disorders (WHO, 2000; DeRubeis et al., 2008), the rapid rise in mental disorders is particularly worrying in the context of gender equality.

Despite the increasing contribution of mental disorders to the global burden of disease, relatively little is known about what affects mental well-being over the lifetime. Recently, attention has been drawn to the role of new technologies, namely Internet, smartphones and social media, in contributing to the rise of mental disorders, especially among the population of young adults. In the second chapter of this dissertation, I contribute to the ongoing debate on the link between new technologies and psychological wellbeing by quantifying the impact of having access to broadband Internet on mental health in the initial phase of DSL adoption in Germany.

To answer my research question, I combine restricted-access data on the coordinates of respondents to the German Socio-Economic Panel (SOEP) with publicly available information on the characteristics of the network infrastructure in Germany to construct indicators of supply-side constraints to DSL adoption. I use these constraints to instrument for DSL availability at the household level. The findings from Chapter 2 show that having access to broadband Internet at home significantly and negatively affects the self-reported mental health of women, but not that of men. Looking at which aspects of psychological wellbeing are most affected, I find that the results are driven by a worsening of women's socializing behavior and ability to cope with emotional problems. Moreover, the negative effects are concentrated among the younger cohorts, which suggests that the impact of DSL Internet on mental health is larger, the heavier the use of Internet. To tackle concerns related to the fact that women might be using the Internet to search for health information more than men, I show that having access to broadband Internet has no effect on self-reported physical health for either gender. I also perform an additional robustness check to rule out the possibility that my results are driven by unobserved characteristics that are linked to the local area of residence, and the effect of which may be captured by the instrumental variables used throughout. In this alternative specification, I exploit information on mental health from the pre-DSL period and use a difference-in-difference design, where broadband Internet at the household level is instrumented with the same set of supply-side constraint indicators interacted with a post-DSL dummy. Results from this robustness check confirm the negative impact of DSL Internet availability on women's mental health and no impact for men. Finally, looking at time-use data from respondents to the German SOEP, I provide suggestive evidence that the negative effect of broadband Internet on psychological well-being could be driven by a negative impact of high-speed Internet on the sleep behavior of women.

The results from this chapter contribute to the growing debate on the societal effect of Internet and accompanying technologies. Whilst this paper cannot speak to the question of which online activities are particularly damaging for mental health, or what characterises an addictive or problematic online behavior, this constitutes a promising avenue for future research. Finally, in the context of an ever-increasing use of the Internet and smartphones in all aspects of our daily lives, future research should look at which policies or interventions are most effective in raising awareness about the downsides of online activities, and what tools are effective in managing or correcting problematic online behavior.

Chapters on the Unequal Impact of Covid-19

The last three chapters of this dissertation focus on inequalities that have been generated or exacerbated by the Covid-19 crisis.

Since its discovery in December 2019, the novel coronavirus has spread around the world at alarming speed. To combat the outbreak, many countries have implemented decisive measures to protect workers in their workplace and the general population from the risk of contagion. Such measures included strict lockdowns and workplace closures, which imposed large constraints on people's movements and were accompanied by an unprecedented economic crisis. As of January 2021, more than 90% of the world's workforce lived in countries where business closures were still in place for at least some sectors of the economy (ILO, 2021).

The resulting labor market consequences of the coronavirus crisis have been severe, with large declines in economic activity and employment, and downward adjustments in working hours all around the world. While the unemployment rate has increased in many countries affected by the Covid-19 crisis, focusing on unemployment figures alone does not capture the full extent of the economic downturn: many workers who have suffered job losses during the Covid-19 pandemic are not actively looking to find new jobs, and are therefore classified as out of the labor force in official statistics. Moreover, many workers, although still in paid work, have stopped working or reduced their working hours as a result of the introduction of new, or ramp up of existing, job retention schemes, which aim at preserving firm-worker matches during periods of financial hardships. As a result, looking at declines in work hours offers a more complete picture of the economic impact of the current crisis. According to recent estimates from the ILO (2021), 8.8% of global working hours were lost in 2020 (or about 255 million full-time jobs), relative to the fourth quarter of 2019.

Whilst by now the magnitude of the economic impacts of the Covid-19 crisis is well established, analyzes of the immediate labor market consequences of the pandemic have been held back by data limitations. Official statistics on labor markets only became available with a lag, and large national survey data with a focus on how Covid-19 affected the life of individuals also became available only a few months into the crisis. To fill in this data gap and document the short-term impacts of the pandemic on workers, Abi Adams-Prassl, Teodora Boneva, Christopher Rauh and I launched a series of rapid-response online surveys which we administered to geographically representative samples of the working population in the United States, the United Kingdom and Germany. Overall, we collected information on more than 28,000 workers across the US, the UK and Germany, at three points in time between late March and May 2020.

In Chapter 3 of this thesis we exploit these novel survey data to document inequalities both across and within countries in the labor market impacts of Covid-19. We highlight three main sets of results. First, the short-run economic impacts of the crisis have been highly unequal across countries: our individual-level survey data collected at the height of the crisis show that job losses by early April had been much more pronounced in the UK and the US compared to Germany. Second, we show that, even within countries, not all workers were affected equally by the crisis. Notably, the unprecedented nature of the measures taken to combat the spread of the virus has meant that workers who could do less of their tasks from home have been severely hit. This has resulted in large differences in job loss across occupations with different possibilities for telework (Adams-Prassl et al., 2020d). However, and perhaps more interestingly, the negative relationship between job loss and ability to switch to the home office survives even within occupations. Further, workers employed under unstable work arrangements have also been significantly more likely to suffer job losses than workers employed under stable contracts. Third, looking at which background characteristics predict job loss, we find that women and workers without a college degree have been particularly badly affected. Whilst the educational gap in job loss can be explained by workers with different educational attainment sorting into different types of jobs, the gender gap in job loss remains significant even when controlling for job characteristics and the occupation workers are employed in.

The results on gender gaps in job losses during the first months of the crisis chime in with findings from Chapter 4 on the role of the furloughing scheme in the UK in moderating the negative economic shock. The evidence from this chapter shows that employers made widespread use of the furloughing scheme in the first months of the pandemic: by late May, 35% of respondents in our sample that were in work in February 2020 report being currently furloughed from their main job. This is in line with official statistics from HMRC that show that around 9.4 million claims were made to the furloughing scheme by late June, which corresponds to roughly 34% of the employed population in the UK. However, not all workers were furloughed equally under the Coronavirus Job Retention Scheme. In particular, we document inequalities in the terms under which workers have been furloughed, focusing on three dimentions of heterogeneity. First, we look at what fraction of workers had their salary topped up beyond the 80% contribution from the government. Whilst the vast majority of furloughed workers had their salary topped up beyond the 80% subsidy paid for by the government, women were significantly less likely than men to receive the 20% discretionary top up. Second, we look at who initiated the decision to be furloughed, and find that mothers were 10 percentage points more likely than fathers to report having initiated the decision to be furloughed as opposed to it being fully or mostly the employer's choice. Notably, we find no significant gender gap among childless workers. This result speaks to the role of childcare responposibilities in exacerbating the negative economic impacts of the crisis for women. Third, when looking at the working hours of furloughed workers, we find that the provision of not doing any work for the employer whilst on furlough was routinely ignored. We measure workers' behavior during furlough by both asking survey participants directly whether they had been asked by their employer to keep working whilst furloughed, and by looking at the hours they report working. Both metrics suggest that a large share of furloughed employees continued doing some work for their employer whilst on furlough, although their work hours were significantly lower at the time of our data collections than in February 2020. Interestingly, men were significantly more likely than women to continue working whilst on furlough.

Finally, Chapter 5 of this thesis turns to the impact of Covid-19 on the division of unpaid work between parents in opposite-gender couples. Beyond the labor market impacts of the crisis, the outbreak of Covid-19 and the stay-at-home measures that have been adopted to contain the spread of the virus have also led to drastic changes to the daily lives of individuals all over the world. Parents in particular have experienced a sharp increase in the volume of childcare responsibilities as a result of the closure of schools and childcare center. To examine how the Covid-19 pandemic has affected the lives of parents of school-aged children, in Chapter 5 I leverage novel survey data collected in June 2020 from a geographically representative sample of married or cohabiting parents in England. My focus lies on understanding how the pandemic has changed parental time allocation to different unpaid work activities, including home-schooling and other childcare duties, for married or cohabiting opposite-gender couples. First, I show that large gender gaps were present even before the pandemic in how parents divide unpaid work activities, with women spending a significantly higher amount of time on both childcare activities and house chores than men. Second, consistent with the hypothesis that mothers have shouldered the majority of the additional childcare load, I find that, during the Covid-19 pandemic, mothers have increased the time they spend on childcare activities significantly more than fathers, thus leading to a widening gender gap in time dedicated to childcare, and to educational activities with children in particular. Notably, the gender gap in home schooling time only reduces for families where the father has stopped working during the first months of the pandemic, but never closes entirely or reverses. The rest of the chapter examines the role of different sets of variables in explaining the widening gender gap in educational activities with children. In particular, I focus on the role of perceived gender roles and perceived returns to maternal (*versus* paternal) time investment in home-schooling in explaining changes in the way couples allocate time to educational activities with children during the pandemic.

To document parental beliefs about the returns to maternal (*versus* paternal) time investment in educational activities with children, I make use of hypothetical scenarios. The scenarios describe a hypothetical British family with two-working parents who have to decide whether the mother or the father alone will dedicate time to home schooling their only child. For each scenario, I elicit respondents beliefs about maternal and paternal life satisfaction and productivity at work, as well as child outcomes measured as school performance and earnings at age 30. Participants to my survey clearly perceive home-schooling activities as detrimental for parental productivity and life satisfaction, both for mothers and fathers. However, the negative effects are more pronounced for mothers, which suggests that parents do not perceive mothers as intrinsically better at multi-tasking. Furthermore, survey participants do not perceive mothers as more effective in home schooling children, as captured by the lack of difference in perceived returs to maternal *versus* paternal time investment in terms of child outcomes.

To measure perceived gender roles, survey participants are shown similar vignettes to the above, and are asked to state what share of tasks they think the hypothetical mother should take care of, relative to her partner, in two alternative cases where she or her partner is the main earner in the couple. I classify respondents as having traditional attitudes towards gender roles is the average share of tasks they think mothers should do across the two scenarios is above 50%. In my sample, nearly half of participants hold traditional views about gender roles.

I then turn to examining the role of perceived gender roles and beliefs about returns to maternal time investment in explaining changes in the home-schooling gender gap. I find that beliefs about parental life satisfaction and attitudes towards gender roles are important determinants of changes in time allocation during the pandemic, over and beyond the effect of changes in the employment status of partners in the couple.

Taken together, the last three chapters of this dissertation contribute to a growing body of literature investigating the economic and social impacts of Covid-19. The work in this thesis makes several contributions to existing literature. First, the novel survey data used in the analysis allow to shed light on the short-term consequences of the Covid-19 crisis across multiple countries and, within countries, across different groups of workers. Second, the purposely designed survey modules make us able to document new inequalities arising along dimensions that are specific of the current crisis, namely workers' ability to do their tasks from home and disruptions to work life caused by additional childcare responsibilities arising from school closures. Finally, I develop new measurement tools to quantify parental beliefs about the returns to maternal *versus* paternal time investment and respondents' attitudes towards gender roles, and show these beliefs to be important predictors of how parents share childcare responsibilities when opportunities for outsourcing are limited. Turning to avenues for future research, it is plausible that the disruptions to family life caused by Covid-19 may also alter the way in which couples share unpaid work going forward. This could be especially true for families were fathers have been forced at home, either due to telework or to job loss, during the pandemic. To the extent that these forced and abrupt changes could accelerate the evolution of gender norms towards more gender-equal opinions, future research should examine how shifts in attitudes towards gender roles will affect the future redistribution of responsibilties within the household.

Chapter 1

Can Perceived Returns Explain Enrollment Gaps in Postgraduate Education?

with **Teodora Boneva**, University of Zurich, and **Christopher Rauh**, University of Cambridge

Abstract To understand students' motives to obtain postgraduate qualifications, we elicit intentions to pursue postgraduate education and beliefs about its returns in a sample of 1,002 university students. We find large gaps in perceptions about the immediate and later-life benefits of postgraduate education, both between first- and continuing-generation students and within the latter group. Differences in student beliefs about returns can account for 70% of the socioeconomic gaps in intentions to pursue postgraduate studies. We document large differences in students' current undergraduate experiences by socioeconomic background and find these to be predictive of perceived returns to postgraduate education.

Acknowledgements We thank seminar participants at the University of Montreal and the Tinbergen Institute Amsterdam as well as participants of the EALE/SOLE/AASLE Conference, the briq Workshop on Beliefs, the Warwick Applied Workshop, the Berlin Workshop on Expectations and Decisions and the HCEO SSSI for helpful comments and suggestions. Boneva acknowledges support from the Jacobs Foundation. Golin acknowledges support from the ESRC. Rauh acknowledges support from the SSHRC. Part of this research was conducted during Boneva's visit at the CIREQ Montreal. This study has been approved by the Department's Research Ethics Committee (DREC) at the University of Oxford (Project ID number: ECONCIA18-19-13).

1.1 Introduction

In many countries, including the US and the UK, intergenerational mobility is low (Blanden et al. 2001, 2007; Chetty et al. 2014a,b). At the same time, wage inequality has been increasing rapidly, especially at the upper tail of the wage distribution (Lemieux 2006; Autor et al. 2008; Machin 2011). These increases at the upper tail of the wage distribution have been linked to skill-biased technological change (e.g. Autor et al. 1998; Krusell et al. 2000; Acemoglu 2002a,b), which has led to a steadily rising college-earnings premium.[1] Traditionally, studies examining college earnings premia and skill-biased technological change have focused on differences between college-educated workers and workers without a college degree.[2] More recently, attention has been drawn to the rising wage inequality *within* the group of college-educated workers and the role of postgraduate education in explaining this pattern (Eckstein and Nagypal 2004; Lindley and Machin 2016; Altonji and Zhong 2021).

In recent decades, an increasing share of first-degree holders also obtain postgraduate qualifications. At the same time, earnings growth for postgraduate-degree holders has been much steeper than for workers who only hold a first degree.[3] Postgraduate-degree holders now comprise a significant share of the workforce. As of 2018, in the US and the UK, around 15% and 14% of employees have postgraduate qualifications (or around 37% of employed first-degree holders in both countries).[4] They earn significantly more than employees who only have a first degree (see Appendix Figure 1A.1) and they are over-represented in the upper tail of the earnings distribution. In the UK the share of individuals in the top earnings decile who hold a postgraduate degree is 32%. Given the rising levels of wage inequality and the high intergenerational persistence in earnings, this raises the question of who invests into postgraduate education and what drives individual decisions to obtain a postgraduate degree. Despite the fact that postgraduate-degree holders are the most educated and most highly-skilled group in the population (Lindley and Machin 2016), surprisingly little is known about what drives this educational choice.

In this paper, we aim to fill this gap in the literature and shed light on students' motives to obtain postgraduate education. In order to do so we proceed in three steps. First, we survey

[1] See Mincer (1996); Deschênes (2001); Katz and Murphy (1992); Card and Lemieux (2001); Autor et al. (2008); Goldin and Katz (2009); Carneiro and Lee (2011); Acemoglu and Autor (2010).

[2] Similarly, the literature estimating the elasticity between workers of different skill levels (e.g., Dustmann et al. 2009; Ciccone and Peri 2005) generally focuses on college vs non-college workers, thereby ignoring the difference within college graduates.

[3] This pattern has been documented by several different studies, e.g. Eckstein and Nagypal (2004); Autor et al. (2008); Acemoglu and Autor (2010); Lindley and Machin (2016). See Altonji et al. (2016) for an overview of this literature, and detailed enrollment statistics and returns to graduate degrees in the US.

[4] See Appendix 1A for a description of the data.

a representative sample of 1,002 undergraduate students in England and elicit beliefs about the returns to postgraduate education as well as intentions to enroll in a postgraduate degree. This unique dataset allows us to document individual heterogeneity in perceptions about different immediate and later-life benefits and costs of postgraduate education and investigate whether beliefs differ with the socioeconomic background of the respondent. Second, we estimate a choice model adapted from Zafar (2013) in which we allow for differences in beliefs and preferences across socioeconomic groups and we examine to what extent differences in beliefs about returns can account for the socioeconomic gap in students' intentions to pursue postgraduate education. Finally, we investigate whether students with different socioeconomic background differ in their experiences during their undergraduate studies, and examine whether their actual experiences are predictive of their perceptions about the immediate benefits and costs of continuing to postgraduate education.

We elicit individual beliefs about the returns to postgraduate education using hypothetical investments scenarios. This allows us to overcome the problem that educational choices are consistent with many different combinations of preferences and beliefs (Manski 2004). More specifically, we ask students to imagine scenarios in which they enroll or do not enroll in postgraduate education. We then elicit their perceptions about a range of different immediate and later-life outcomes that are of pecuniary and non-pecuniary nature. To get a better sense of how students experience studying towards their undergraduate degrees, we administer a novel questionnaire designed to capture students' actual experiences.

Several results emerge from our study. First, undergraduate students who are the first generation in their family to go to university state a 5 percentage point lower likelihood of continuing to postgraduate education relative to continuing-generation students. First-generation students in our sample also perceive a range of different benefits of postgraduate education to be lower. This is especially true for the immediate benefits associated with attendance. Second, the estimates of our choice model and results of our decomposition analysis reveal that around 70% of the first-generation vs. continuing-generation gap in students' intentions to enroll in a postgraduate degree can be accounted for by differences in beliefs about returns, with the majority of the gap being explained by differences in beliefs about immediate non-pecuniary factors.

We also find striking differences *within* the group of continuing-generation students. Students who have at least one parent with a postgraduate degree state an 8 percentage point higher likelihood of enrolling in a postgraduate degree relative to students who have at least one parent with a first degree, but no parent with a postgraduate degree. Within the group of continuing-generation students, a large share of the gap can be explained by differences in beliefs about parental approval.

Our last set of results relate to students' actual experiences at university. We document that there are sizeable socioeconomic gaps in how students experience their undergraduate life, how they finance their studies, and how they allocate their time across different activities. In particular, first-generation students are significantly less likely to enjoy their coursework or have received parental support in their choice of attending university, and are more likely to struggle financially and work alongside their studies. Finally, students' current experiences are predictive of beliefs about the immediate non-pecuniary benefits of postgraduate education, which is consistent with a theory in which current experiences shape beliefs about likely future experiences.

The socioeconomic gaps in students' experiences draw attention to an important dimension of inequality. First-generation students enjoy many aspects of university life less. This finding is consistent with the beliefs documented in Boneva and Rauh (2019) showing that secondary school students, who would be the first generation in their family to go to university, perceive the immediate non-pecuniary benefits of going to university as lower compared to students from better educated backgrounds. This raises the question of *why* students' experiences are different and which policies can mitigate this socioeconomic gap. Speculating about potentially effective policies, the fact that first-generation students work more alongside their studies suggests that grants/bursaries could help first-generation students fully take part in student life. Improving students' actual experiences at university may result in more first-generation students wanting to enroll in a first degree and may also shift students' beliefs about their potential experiences during postgraduate education.

Regarding the gaps in students' beliefs about the benefits of postgraduate education, a question which emerges is whether there are actual gaps in the returns to postgraduate education by students' socioeconomic background. Given the socioeconomic differences we find in terms of how students experience their lives as undergraduates, it may very well be that there are also gaps in the returns to postgraduate education, especially when it comes to the immediate non-pecuniary factors. Similarly, the returns to postgraduate degrees in terms of labor market outcomes may also vary with the students' socioeconomic background. We provide suggestive evidence on differences in earnings premia by parental education. More research will be needed to understand how the lives of postgraduate students differ and how the later-life benefits of postgraduate education vary with the students' socioeconomic background.

Our study builds on and contributes to several strands of the literature. First, it contributes to the large and growing literature on the role of beliefs in decision-making. The role of beliefs has been studied in many different contexts.[5] Our study most closely relates to the work which examines the role of beliefs in students' decisions to obtain further schooling (e.g., Dominitz and Manski 1996; Jensen 2010; Attanasio and Kaufmann 2014; Kaufmann 2014; Almas et al. 2016; Attanasio and Kaufmann 2017; Boneva and Rauh 2019; Belfield et al. 2019). To the best of our knowledge, we are the first to investigate the role of beliefs in students' decisions to obtain postgraduate education.

Second, our study relates to the role of students' beliefs in their choice of major, high school track and occupation, or which specific university to attend (e.g., Arcidiacono et al. 2012; Zafar 2012, 2013; Wiswall and Zafar 2015; Hastings et al. 2016; Giustinelli 2016; Hastings et al. 2017; Giustinelli and Pavoni 2017; Giustinelli and Manski 2018; Wiswall and Zafar 2018; Delavande and Zafar forthcoming; Arcidiacono et al. 2020). Similar to many of the studies in this literature, we find that non-pecuniary factors, including considerations related to family dynamics (e.g., parental approval), play a major role in the decision to obtain postgraduate education. In contrast to these studies, we examine an extensive rather than an intensive margin choice.

Third, we contribute to the literature on the importance of personal experience in belief formation. While other studies have shown that personal experiences can shape beliefs in other domains (e.g., Malmendier and Nagel 2011; Hyll and Schneider 2013; Giuliano and Spilimbergo 2013; Malmendier and Nagel 2016; Laudenbach et al. 2019, 2020), we show that personal experiences are also predictive of beliefs in an educational context. Shedding light on the relationship between experiences and beliefs is crucial for our understanding of how beliefs are formed.

Finally, we contribute to the literature on postgraduate education which has examined postgraduate earnings premia and other benefits of postgraduate education (Eckstein and Nagypal 2004; Lindley and Machin 2016; Gu 2019). Altonji and Zhong (2021) estimate the returns to a broad set of graduate degrees in the US. Relatedly, a number of studies have investigated the returns to specialized postgraduate programs such as MBAs (Graddy and Pistaferri 2000; Arcidiacono et al. 2008; Bertrand et al. 2010) and medical degrees (Bhattacharya 2005; Chen and Chevalier 2012; Ketel et al. 2016). While these studies examine the benefits of postgraduate education, we contribute to this literature by examining students' motives for obtaining it.

[5] For example, Kaufmann and Pistaferri (2009) and Armantier et al. (2015) show that individual beliefs are important for consumption decisions and financial investment decisions, respectively.

1.2 Survey Design

To study students' perceptions about postgraduate education and their current experience at university, we design a survey that we administer to a large representative sample of undergraduate students in England. We survey students prospectively rather than retrospectively to minimize potential biases that could arise from ex-post rationalization. Section 1.2.1 describes how we elicit students' intentions to enroll in a postgraduate degree as well as students' beliefs about their likely future performance. Section 1.2.2 describes the hypothetical scenarios we use to elicit individual beliefs about different immediate and later-life returns to postgraduate education, while Section 1.2.3 presents the survey module we design to measure students' current experiences at university. The questionnaire can be found in Appendix 1B.

1.2.1 Students' Intentions to Obtain Postgraduate Education

To elicit students' intentions to obtain postgraduate education, we ask students to state how likely they think it is that they will enroll in a postgraduate degree if they obtain the necessary grades. We elicit student beliefs using a probabilistic 0-100% scale.[6] We chose to ask students to state their intentions on a probabilistic scale because that allows individuals to express uncertainty about their decisions. Previous work investigating students' intentions to obtain university education has shown that students' self-reported intentions to pursue further education correlate strongly with their actual application decisions (Boneva and Rauh 2019). The study further documents that the test-retest correlation of this survey measure is high and does not vary with socioeconomic background.

In addition to beliefs about the likelihood of enrolling in postgraduate education, we elicit students' beliefs about the likelihood that they will obtain the necessary qualifications to enroll in a postgraduate degree. More specifically, we ask respondents to state how likely they think it is that they will complete their undergraduate degree and how likely they think it is that they will obtain First-class honors conditional on completing it. We also elicit individual beliefs about the likelihood of graduating conditional on enrolling in a postgraduate degree. This allows us to document whether students from different socioeconomic backgrounds differ in terms of their perceptions of whether they can succeed in obtaining the postgraduate degree of their choice. While the focus of this paper does not lie on understanding what may be driving students' beliefs about their own performance, we use this information to perform robustness checks in which we

[6] When using the probabilistic scale, we use sliders to elicit students' beliefs. These questions are preceded by an example question that illustrates the use of the probabilistic scale.

limit the analysis to only those students for whom enrolling in a postgraduate degree is likely to be a realistic option.

Finally, while we do not model subject choice in this paper, we also ask students to state which subject they would choose if they were to enroll in a postgraduate degree. When we ask students to imagine their lives in the hypothetical scenario in which they enroll in a postgraduate degree, we explicitly make it clear that they should think about enrolling in their subject of choice.

1.2.2 Beliefs about Returns to Postgraduate Education

To elicit student beliefs about the pecuniary and non-pecuniary returns to postgraduate education, we ask students about (the likelihood of) potential outcomes (i) if the student continues to postgraduate education and (ii) if the student does not continue to postgraduate education but starts working instead.[7] For each of these two different scenarios, students are asked about a range of different outcomes, which are summarized in Panel A of Table 1.1. We group the outcomes into two categories, namely *immediate outcomes* that are realized during the 1-2 years during which the student may or may not be enrolled in postgraduate education and *later-life outcomes* that are realized when the student has entered the labor market. For the latter, we ask students about potential outcomes at age 35 as by this age most individuals will have completed their education and will have entered the labor market.

To elicit beliefs about immediate outcomes, we ask students to think about what their lives are likely to be like during the 1-2 years after completing their undergraduate degree. We use probabilistic questions to elicit their perceptions about the likelihood of different binary outcomes occurring (see Manski 2004 for a review of this methodology). More specifically, we ask students how likely they think it is that they will enjoy their social life, enjoy their study/work, feel stressed, struggle financially and have enough money to do what they enjoy depending on whether they are enrolled in a postgraduate degree or not. We also ask them about their expected earnings if they started to work, the amount they would have to pay in tuition fees if they enrolled in a postgraduate degree, and the probability of having to work alongside their studies if enrolled in a postgraduate degree.

For outcomes at age 35, we ask students what their likely earnings will be (conditional on working full-time) and how likely they think it is that they will be working full-time, depending on whether their highest level of education is a postgraduate degree or an undergraduate degree.

[7] We explicitly ask students to think that the alternative is to start working because we did not want students to think about the possibility of doing a gap year before continuing into postgraduate education.

For each of the two scenarios, we also elicit subjective probabilities about career satisfaction, having a high status in society, and contributing to society, as well as individual perceptions about the likelihood of having a good work-life balance, and having children. While perceived growth or variance of earnings within certain scenarios conditional on full-time work could be useful information, we do not elicit this information to keep the survey compact and not too complicated. We do, however, capture important sources of uncertainty by allowing for differences in beliefs about the probability of completing postgraduate education and finding a full-time job.

Table 1.1: Overview of Belief Elicitation and University Experience Questions

Panel A: Belief elicitation questions	
Scenarios	*Outcomes*
Immediate Outcomes	
(1) If you enrol in your preferred postgr. degree	Enjoy social life (0-100%)
(2) If you start working	Enjoy study/work (0-100%)
	Feel stressed (0-100%)
	Struggle financially (0-100%)
	Have parental support in your choice (0-100%)
	Exp. tuition fees + foregone earnings
Later-life Outcomes	
Highest qualification is:	Earnings (conditional on working full-time)
(1) postgraduate degree	Work full time (0-100%)
(2) undergraduate degree	Be satisfied with professional career (0-100%)
	Have a high status in society (0-100%)
	Contribute to society (0-100%)
	Have good work-life balance (0-100%)
	Have children (0-100%)
Panel B: University experience questions	
Category	*Questions*
Social life	Enjoy social life and activities (0-100)
	Meet people with whom I get along (0-100)
	Have little contact with family / friends from school (0-100)
	Feel lonely and not part of a group (0-100)
Course material	Enjoy studying for my course (0-100)
	Find the material covered in my course interesting (0-100)
Stress	Find the material too hard / workload too high (0-100)
	Feel stressed (0-100)
Financial situation	Struggle financially (0-100)
	Have enough money to do what I enjoy (0-100)
Parental support	Parental support in decision to go to university (0-100)
Life better than expected	Life at university is better than expected (0-100)

Notes: In the belief elicitation module, students are asked about potential immediate outcomes occurring during the 1-2 years after completing their undergraduate degree as well as potential later-life outcomes relating to their lives at age 35. The university experience questions instead refer to students' current life as undergraduate students.

1.2.3 Student Experiences, Time Allocation and Finances

University students may vary in how they experience studying towards their undergraduate degree. To understand whether there are systematic differences across socioeconomic groups and to investigate whether perceived current experiences are associated with students' beliefs about the benefits and costs of postgraduate education, we present students with twelve statements and ask them to rate to what extent these statements apply to them on a 0-100 scale. The twelve statements are summarized in Panel B of Table 1.1 and relate to students' social lives, their course work, their financial situation, and the support they received from their parents in their decision to go to university. We further ask students to what extent they agree with the statement that life at university is better than expected.

To obtain a clearer picture of how the lives of students differ, we elicit information on how students allocate their time across different activities and we collect information on students' finances. More specifically, we ask students how many hours they spent on (i) attending lectures, seminars or tutorials, (ii) studying or preparing for lectures and exams, (iii) participating in student societies, (iv) socializing with friends, (v) working for pay and (vi) working without pay in the previous week. We also ask students about the work they do alongside their studies and the work they did during the last summer break. We further collect information on how much they pay in tuition fees (per year), how they finance their studies, and how much they spend in a typical month during term time.

1.3 Data

To examine how students perceive the benefits and costs of postgraduate education and to study which motives are important in students' decisions to obtain a postgraduate degree, we collect primary survey data on a large representative sample of undergraduate students in England. The data were collected by a professional survey company in the fall semester 2018.[8] The sample consists of 1,002 university students aged 18-27 who had to be currently enrolled in a full-time undergraduate course, and was selected to be representative in terms of regions in England. Within each region, we used quota-based sampling to ensure an equal representation of first- and continuing-generation students. Throughout the text we refer to the former group as students from low socioeconomic status, and to the latter group as students from high socioeconomic status. This sampling procedure has the advantage that we have sufficient power to detect differences between the different socioeconomic groups. For each region and socioeconomic group, we sampled an equal number of male and female students. Table 1C.1 in the Appendix shows the distribution of respondents across regions and the comparison to the national distribution of university students across regions in England. As can be seen from the table, the two distributions are very similar.

[8] All participants were part of the company's online panel and participated in the survey online. The survey was scripted in the online survey software Qualtrics. Students received modest incentives for completing the survey.

Table 1C.2 shows the characteristics of our sample. By construction, 50% of the undergraduate students in our sample are first-generation students and 50% are women. 16% of all respondents report that they have at least one parent who has obtained a postgraduate degree. On average, participants are 20 years old and they are in the second year of their undergraduate course. They are enrolled at 114 different universities across England.[9] 39% of the undergraduate students in our sample attend a university that is part of the Russell Group, which is an association of 24 universities in the UK that are considered as leading in research and teaching. 14% of the students in our sample report that they attended a private school before starting university. Unlike state schools, private schools are fee-charging institutions.[10] 18% of all students in our sample report that they study in their home town.

There are noteworthy differences across socioeconomic groups. While 47% of continuing-generation students currently attend a university that is part of the Russell Group, the corresponding number is 31% for first-generation students (p-value< 0.001). Similarly, 23% of continuing-generation students attended a private secondary school, against a figure of 5% for first-generation students (p-value< 0.001).

We also ask students to indicate which subject field they are currently studying. Table 1C.3 in the Appendix shows the distribution of individuals across different subject fields for the whole sample, and separately for first- and continuing-generation students as well as male and female students. Interestingly, there is no significant difference in the distribution of students across subject fields by socioeconomic status (p-value for Pearson's test of equality of distribution=0.656). At the same time, consistently with other studies documenting that men and women sort into different majors and subject fields (Wiswall and Zafar 2018), we find a significant difference in the distribution of female and male students across subject groups (p-value< 0.001). When asked about which subject field they would choose if they were to continue to postgraduate education, 83% of the students in our sample report they would continue to a degree in the same subject field.

[9] 5% of the students in our sample either did not provide us with information on the university they attend or provided the name of an institution outside England. Our results are robust to dropping those individuals from the analysis.

[10] In the UK these schools are referred to as public/independent schools. As a comparison, in the academic year 2017-2018, 91% of all UK-domiciled full-time undergraduate students enrolled in higher education had attended a state-funded school, while 28% of all full-time undergraduate students attended a university that is part of the Russell Group.

1.4 Student Beliefs and Experiences

1.4.1 Gaps in Students' Intentions to Obtain Postgraduate Education

While a significant body of research has examined students' decision to apply to university, not much is known about how university students think about postgraduate education. We start by documenting differences in students' intentions to enroll in postgraduate education. As explained in Section 1.2, we ask students to state how likely they think it is they would enroll in a postgraduate degree if they obtained the necessary grades. Panel A in Figure 1.1 shows the distribution of responses to this question, separately for first-generation students (dashed line) and continuing-generation students (solid line). There are several patterns worth noting. First, there is a large amount of heterogeneity in individual responses within both of these groups. While some students seem to be very certain that they would like to pursue a postgraduate degree, other students are unsure about it or almost certain they do not wish to enroll in one. Second, there are significant differences across the two groups, with continuing-generation students stating significantly higher likelihoods of continuing to postgraduate education.[11] As can be seen in Panel A of Table 1.2, the mean stated likelihood for first-generation students is 47%, while it is 52% for continuing generation students (p-value=0.013). This gap in intentions to enroll cannot be explained by differences in the subjects students study or the universities they currently attend. When we control for subject and university fixed effects, as well as other observable characteristics such as gender and age, we estimate a conditional gap of 4.73 percentage points in students' intentions to enroll, which is remarkably similar to the unconditional gap (see Table 1.2 column 6, Panel A). Our results are consistent with findings from Wakeling and Hampden-Thompson (2013) who document a 4 percentage point gap in progression to postgraduate degrees between students whose parents do and do not have higher qualifications.[12]

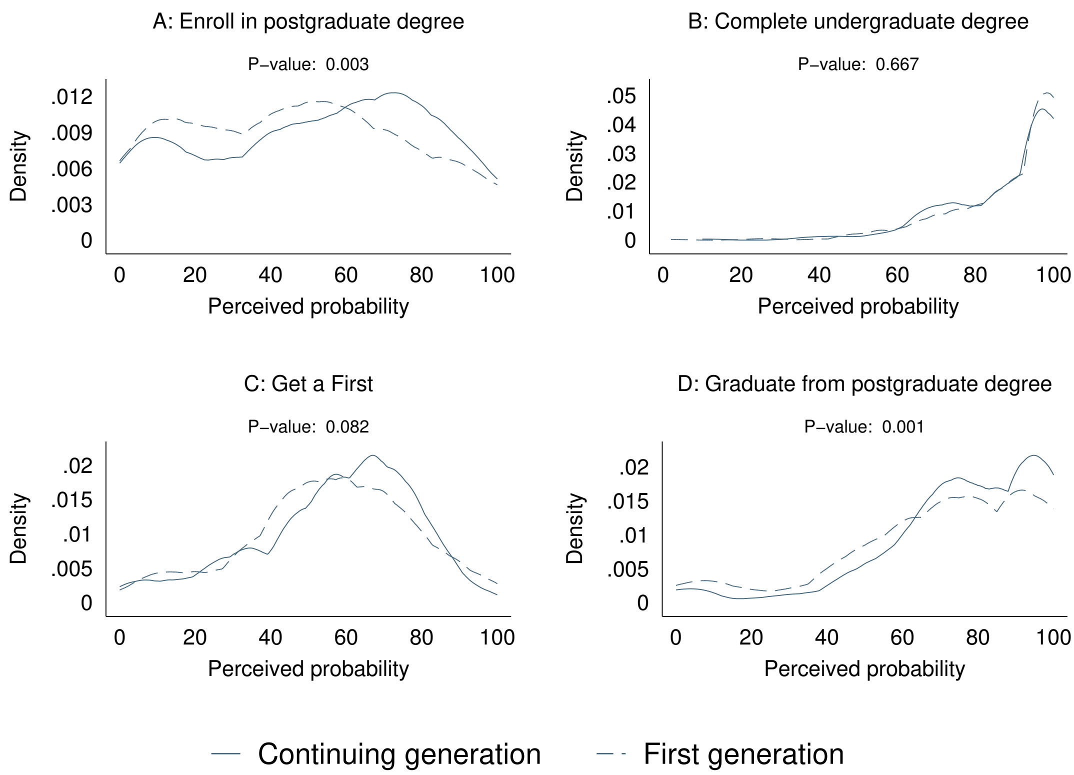
In addition to eliciting students' beliefs about how likely they are to enroll in a postgraduate degree if they get the grades, we also elicit students' perceptions about the likelihood they will complete their undergraduate degree, the probability they will obtain First-class honors if they graduate, as well as the likelihood they will graduate if they enroll in a postgraduate degree. When we compare the responses of first- and continuing-generation students, we find no significant differences in students' average beliefs regarding the likelihood they will complete their

[11] The Kolmogorov-Smirnov test of equality of distributions rejects the null hypothesis that the two distributions are the same at the 1% level.

[12] Figures from Wakeling and Hampden-Thompson (2013) refer to immediate progression to taught postgraduate degrees of full-time UK- and EU-domiciled first-degree graduates who successfully completed their studies in the 2009-2010 and 2010-2011 academic years.

undergraduate degree or graduate with First-class honors (see Panel A of Table 1.2). We do, however, find that first-generation students perceive the likelihood of graduating from a postgraduate degree to be about 6 percentage points lower (p-value< 0.001). In Panels B-D of Figure 1.1, we depict the distributions of individual responses to these three questions, separately for first- and continuing-generation students.

Figure 1.1: Differences in Beliefs by Parental Education



Notes: The different panels depict the kernel densities of individual beliefs about the likelihood of enrolling in a postgraduate degree (Panel A), graduating from their undergraduate degree (Panel B), getting a First in their undergraduate degree (Panel C), and graduating from their postgraduate degree (Panel D). The densities are depicted for first-generation students (dashed line) and continuing-generation students (solid line), respectively. Reported p-values are from Kolmogorov-Smirnov tests of equality of distributions.

The distinction between first- and continuing-generation students is arguably a relevant one and captures important differences in terms of socioeconomic background. At the same time, it masks an additional source of potentially relevant heterogeneity, which is that 33% of the parents of continuing-generation students also have postgraduate qualifications. Given the focus of this paper, we also study whether continuing-generation students who have at least one parent with a postgraduate degree have different beliefs compared to continuing-generation students whose parents do not have postgraduate qualifications (see Panel B of Table 1.2 and Figure 1C.1). The differences across these two groups are striking. Students whose parents hold a postgraduate qualification report a 8.2 percentage point higher probability of enrolling in a postgraduate degree, compared to continuing-generation students whose parents only have an undergraduate degree. Again we find that this gap cannot be explained by differences in subject choice or the university students attend. The conditional gap we estimate is in fact somewhat larger than the unconditional gap (9.9 percentage points). Regarding perceived performance, we find some differences in students' perceptions about the probability of completing their undergraduate degree but no differences in beliefs regarding the probability of obtaining First-class honors or completing the postgraduate degree. Once we control for individual characteristics as well as subject and university fixed effects, we find no significant differences in any of the three perceived performance measures. While numerous studies have investigated the persistence of university education across generations, these results point to an additional channel that has received little attention in the literature: the intergenerational persistence of postgraduate education.

Given the educational context we study, we further investigate whether continuing-generation students who attended a private secondary school report higher intentions to enroll in a postgraduate degree compared to continuing-generation students who attended a state school.[13] Remarkably, we find no significant differences across the two groups, neither in terms of intentions to enroll in a postgraduate degree nor in terms of the three perceived performance measures we elicit (see Table 1C.4 in Appendix 1C). These results are surprising in light of the fact that students educated in private schools have a much more privileged background. As we will see in Section 1.6.1, students from private schools are significantly less likely to struggle financially, and yet they are no more likely to want to continue with their education. This pattern highlights the importance of factors unrelated to financial standing in their choice.

Before we turn to socioeconomic differences in beliefs about the benefits and costs of postgraduate education, we comment briefly on how students' average beliefs reported in this section compare to actual statistics on enrollment and performance. On average, students state a 49% likelihood of enrolling in a postgraduate degree if they get the grades (Table 1.2). Using data from the Quarterly Labour Force Survey, we document that 37% of employed first-degree holders also hold postgraduate qualifications (see Appendix 1A). Consistent with data on actual continuation rates, we find students' intentions to enroll in postgraduate education to be heterogeneous

[13] Only 25 first-generation students in our sample attended a private school. For all analyses by school type we restrict the sample to continuing-generation students only.

Table 1.2: Differences in Beliefs by Parental Education

Panel A: Full sample						
	All	Parental background				Cond. gap
Belief		First	Continuing	Diff	P-value	
Enroll post-gr. degree	49.380	47.016	51.739	-4.723	0.013	-4.727**
	[29.969]	[29.573]	[30.204]	(1.890)		(2.183)
Complete undergr. degree	88.670	89.216	88.124	1.092	0.239	0.188
	[14.667]	[14.537]	[14.790]	(0.927)		(1.044)
Get a First	56.076	55.461	56.691	-1.230	0.372	-1.241
	[21.772]	[22.044]	[21.502]	(1.376)		(1.578)
Graduate (post-gr.)	73.602	70.611	76.606	-5.994	0.000	-6.129***
	[24.549]	[26.162]	[22.444]	(1.545)		(1.711)
Observations	1002	501	501			
Panel B: Continuing-generation students						
	All	Parental background				Cond. gap
Belief		No postgr.	Postgr.	Diff	P-value	
Enroll post-gr. degree	51.739	49.053	57.256	-8.203	0.004	-9.922***
	[30.204]	[29.864]	[30.241]	(2.855)		(3.408)
Complete undergr. degree	88.124	87.107	90.213	-3.107	0.027	-2.099
	[14.790]	[15.231]	[13.648]	(1.403)		(1.661)
Get a First	56.691	57.662	54.695	2.967	0.147	1.700
	[21.502]	[21.269]	[21.904]	(2.045)		(2.605)
Graduate (post-gr.)	76.606	75.488	78.896	-3.408	0.112	-2.595
	[22.444]	[22.351]	[22.529]	(2.141)		(2.841)
Observations	501	337	164			

Notes: Standard deviations given in square brackets, standard errors given in round brackets. Panel A separately provides mean beliefs for the whole sample (Column 2), by whether at least one parent has a degree (Columns 3 and 4), the unconditional difference in beliefs between first- and continuing-generation students (Column 5), and the conditional difference in beliefs (Column 7). Column 3 refers to first-generation students, whilst Column 4 refers to continuing-generation students. P-values for a test of difference in means are provided in Column 6. The conditional gaps refer to the coefficients of a first-generation-student dummy variable, in an OLS regression where each belief variable is regressed on the first-generation dummy, a gender dummy, age of the respondent, and university and subject fixed effects. Panel B shows a similar analysis for the sample of continuing-generation students: the breakdown by parental background distinguishes between students whose parents have a postgraduate degree and students whose parents only have a first degree.

across subjects. In our sample, the reported probability of enrolling in a postgraduate degree spans from 19% and 34% for students currently studying Veterinary Science or Medicine and Dentistry to 58% for students studying Physical Sciences (see column 6 of Table 1C.3). This is in line with the data presented in Wakeling and Hampden-Thompson (2013), showing that Physical Sciences is the subject area with the highest progression rate towards postgraduate degrees, whereas Medicine and Dentistry is the discipline with the lowest.

Turning to average beliefs about performance, students believe there is a 89% chance they will complete their undergraduate degree. This estimate is fairly consistent: in the UK, the percentage of full-time first-degree students who are projected not to obtain a degree ranges between 10.1% and 10.7% for full-time first-degree students starting their undergraduate degree in 2011 or after (Higher Education Statistics Agency 2018). Interestingly, students in our sample seem very optimistic about their performance in terms of final grades obtained for their undergraduate degree. On average, students believe that the likelihood of obtaining First-class honors conditional on graduating is 56%. In the UK, conditional on starting a degree and graduating, only 28% of all full-time first-degree qualifiers obtain First-class honors, while 49% obtain Upper Second-class honors (2.1) and 23% obtain Lower Second-class honors (2.2) or Third-class honors (Higher Education Statistics Agency 2019b).

1.4.2 Heterogeneity in Perceived Returns

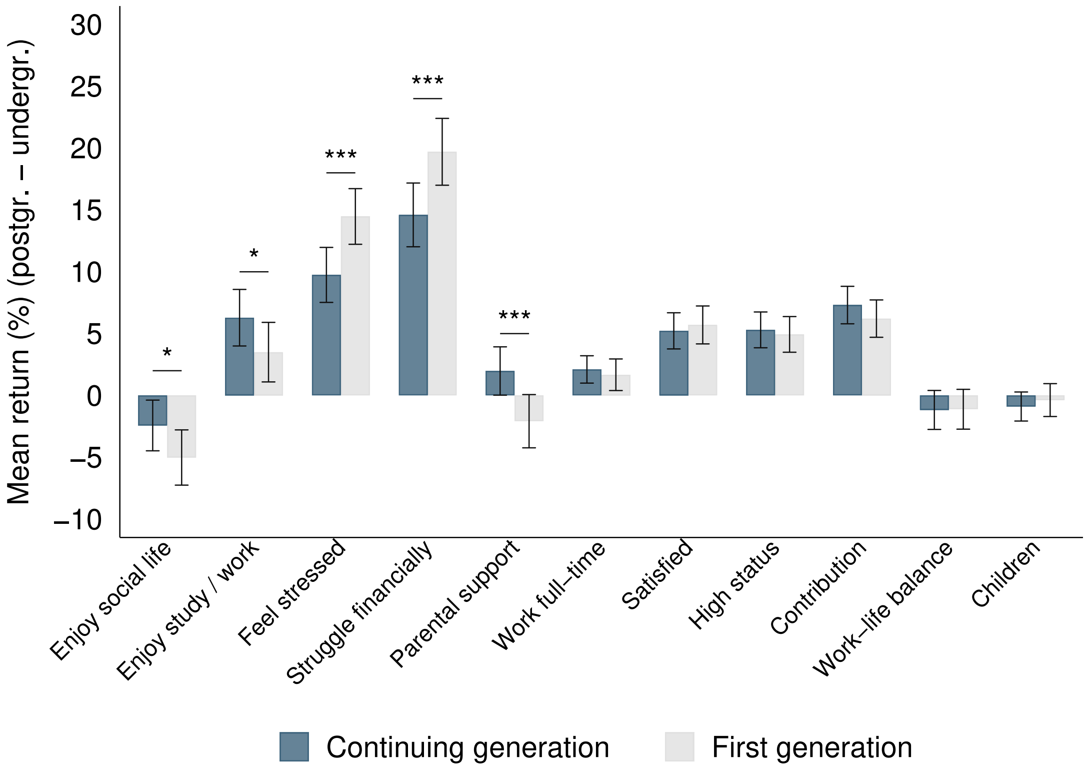
To understand what may be driving the socioeconomic gaps in enrollment rates, we investigate whether students from different backgrounds perceive the immediate and later-life outcomes of postgraduate education as different. We first examine how first- and continuing-generation students perceive the immediate returns to postgraduate education. Panel A of Table 1.3 shows the average stated likelihoods in each of the two scenarios for the different binary outcomes we elicit, both for the whole sample as well as separately for first- and continuing-generation students. Figure 1.2 shows the mean difference in beliefs by SES for all binary outcomes.[14]

Looking at differences across socioeconomic status, we note that both low and high SES students report a lower probability of enjoying their social life in the 1-2 years after graduating from the undergraduate degree if they pursue a postgraduate degree compared to the scenario in which they start working instead.[15] This difference is significantly larger for low SES students. However, both groups of students also report a higher probability of enjoying what they do if they enroll in a postgraduate degree. Individuals are also more likely to report they will feel stressed and struggle financially if they continue on to a postgraduate degree, with perceived costs being significantly larger for low SES students. However, we note that no significant differences between first- and continuing-generation students exist in the self-reported probability of having to work alongside their studies. Furthermore, low SES students report lower costs of postgraduate education, calculated as the sum of expected tuition fees and forgone earnings (see also Figure

[14]Figure 1C.2 shows the kernel densities of individual beliefs about returns to postgraduate education in terms of the different binary outcomes 1-2 years after graduation and at age 35, separately for first- and continuing-generation students.

[15]These results contrast with the findings in Boneva and Rauh (2019) who find that both low and high SES secondary school students believe their social lives will improve on average if they enroll in an undergraduate degree instead of starting to work instead.

Figure 1.2: Returns to Postgraduate Education by Parental Education



Notes: The Figure shows average perceived difference in the probability of immediate and later-life binary outcomes between obtaining a postgraduate degree or only obtaining an undergraduate degree by first-generation students (gray bars) and continuing-generation students (blue bars). The black caps represent 95% confidence intervals and stars indicate statistical significance of differences by parental background: * p<0.10, ** p<0.05, *** p<0.01.

1C.3 in Appendix 1C). It is worth mentioning that, unlike undergraduate studies, tuition fees for postgraduate degrees are not capped and vary significantly across universities and subject fields. Furthermore, governmental student loans for masters courses have only been introduced in the academic year 2016-2017, and are limited to a maximum of £10,609 (for 2018-2019) for the entire duration of the course.[16] Before the introduction of postgraduate student loans, around 80% of first-degree qualifiers progressing to postgraduate degrees were self-funding their studies (Wakeling and Hampden-Thompson 2013). Strikingly, even concerns about parental support unrelated to finances show large differences. While high SES students report they will be more likely to have parental support if they continue with their education, the opposite holds true

[16] Government loans for doctoral studies have been introduced for courses starting in or after 1 August 2018, for a maximum of £25,000.

for low SES students, and the difference across socioeconomic groups is highly significant. It is worth noting that the perceived parental support for continuing-generation students is driven by the subgroup of students whose parents have a postgraduate qualification.[17]

We then analyze the self-reported likelihood of outcomes at age 35, as well as expected earnings at age 35 conditional on working full-time. Panel B of Table 1.3 shows mean beliefs for outcomes at age 35 for the full sample as well as separately for first- and continuing-generation students. The outcomes refer to the two scenarios in which the highest educational qualification is an undergraduate or postgraduate degree, respectively. Both first- and continuing-generation students expect a higher income at age 35 if they obtain a postgraduate qualification. On average in our sample, expected earnings are £41,863 and £48,332, for the scenarios in which the highest educational qualification is an undergraduate and a postgraduate degree, respectively. We note that the difference in earnings across the two scenarios for continuing-generation students is significantly higher than for first-generation students.

Turning to returns about non-pecuniary later-life outcomes, both first- and continuing-generation students in our sample report a higher likelihood of being satisfied with their career, having a high status in society and being able to contribute to society if they obtain a postgraduate qualification. No significant differences are found, for either group, in the likelihood of having a good work-life balance or having children at age 35. We find no significant differences by SES for these later-life non-pecuniary returns.

We also look at differences in perceived returns for both immediate and later-life outcomes, between the subsamples of continuing-generation students whose parents did and did not complete postgraduate education (see Table 1C.5 and Figures 1C.4 and 1C.5). Results show that the only significant difference in terms of immediate outcomes is in perceived parental support if they do or do not enroll in a postgraduate degree. While continuing-generation students, whose parents do not have postgraduate qualifications, think it less likely that their parents will approve of their choice if they continue to higher education than if they start working instead, the opposite holds true for students who have at least one parent with postgraduate qualifications. Looking at outcomes at age 35, students whose parents have a postgraduate degree perceive a larger difference in earnings and in the probability of having a high status in society if they continue with a postgraduate degree compared to the other continuing-generation students.

[17] The difference in perceived support between the two subgroups of high SES students is significant at the 1% level. See Table 1C.5 for the full set of results for the continuing-generation group.

Finally, we also examine differences in perceived returns by whether continuing-generation students have attended a private or state school. Results are presented in Appendix Table 1C.6 and indicate that continuing-generation students who attended different school types only differ in their perception of financial benefits and costs to postgraduate education. Continuing-generation students who attended a state school perceive a larger difference in the probability of struggling financially if they pursue postgraduate education than students who attended a private school, despite perceiving the immediate costs of postgraduate education as significantly lower. Looking at earnings at age 35, students who attended a state school perceive a smaller difference in earnings if they continue with a postgraduate degree compared to the rest of the continuing-generation group.

Table 1.3: Mean Beliefs for Immediate and Later-Life Outcomes by Parental Education

	All			First generation			Continuing generation			Diff-in-diff
Belief	Undergr	Postgr	Diff	Undergr	Postgr	Diff	Undergr	Postgr	Diff	
Panel A: Immediate Outcomes										
Enjoy social life	63.134	59.409	-3.725	61.922	56.902	-5.020	64.345	61.916	-2.429	-2.591*
	[21.004]	[21.650]	0.000	[21.517]	[22.670]	0.000	[20.427]	[20.296]	0.020	(1.543)
Enjoy study / work	63.533	68.424	4.890	63.148	66.647	3.499	63.920	70.204	6.284	-2.785*
	[21.638]	[21.005]	0.000	[22.100]	[21.960]	0.004	[21.181]	[19.866]	0.000	(1.691)
Feel stressed	61.366	73.473	12.107	59.988	74.458	14.470	62.744	72.488	9.744	4.726***
	[23.343]	[21.793]	0.000	[24.394]	[22.220]	0.000	[22.182]	[21.335]	0.000	(1.611)
Strugle financially	42.936	60.086	17.150	41.784	61.483	19.699	44.090	58.687	14.596	5.103***
	[26.528]	[26.492]	0.000	[26.684]	[27.091]	0.000	[26.348]	[25.829]	0.000	(1.900)
Parental support	79.002	78.944	-0.058	78.495	76.409	-2.086	79.510	81.484	1.974	-4.060***
	[24.021]	[24.263]	0.938	[25.252]	[26.354]	0.057	[22.735]	[21.700]	0.048	(1.480)
Immediate cost	0.000	36433.622	36433.622	0.000	35330.329	35330.329	0.000	37539.122	37539.122	-2208.793**
	[.]	[13646.167]	0.000	[.]	[13879.052]	0.000	[.]	[13331.214]	0.000	(860.226)
Panel B: Later-Life Outcomes										
Earnings	41862.980	48332.258	6469.278	40329.152	46050.956	5721.804	43399.876	50618.122	7218.246	-1496.442**
	[17473.994]	[17841.247]	0.000	[17641.394]	[17776.079]	0.000	[17185.267]	[17629.888]	0.000	(714.046)
Work full-time	83.650	85.536	1.886	84.305	85.976	1.671	82.994	85.096	2.102	-0.431
	[18.061]	[17.428]	0.000	[18.597]	[17.961]	0.010	[17.502]	[16.884]	0.000	(0.860)
Satisfied with career	68.940	74.400	5.460	69.010	74.709	5.699	68.870	74.092	5.222	0.477
	[19.749]	[17.647]	0.000	[21.033]	[18.639]	0.000	[18.396]	[16.610]	0.000	(1.079)
High status	54.249	59.366	5.117	52.536	57.470	4.934	55.958	61.257	5.299	-0.365
	[23.943]	[23.452]	0.000	[24.101]	[23.542]	0.000	[23.686]	[23.233]	0.000	(1.039)
Contribution	65.459	72.219	6.759	65.427	71.639	6.212	65.491	72.798	7.307	-1.096
	[22.662]	[20.951]	0.000	[23.345]	[21.294]	0.000	[21.981]	[20.606]	0.000	(1.089)
Work-life balance	63.781	62.636	-1.146	62.687	61.569	-1.118	64.876	63.703	-1.174	0.056
	[20.665]	[21.140]	0.046	[21.585]	[21.473]	0.173	[19.663]	[20.769]	0.144	(1.147)
Children	61.992	61.354	-0.638	61.986	61.608	-0.378	61.998	61.100	-0.898	0.520
	[31.198]	[30.331]	0.157	[32.139]	[31.058]	0.576	[30.262]	[29.616]	0.134	(0.902)

Notes: Standard deviations given in square brackets, standard errors given in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. This table provides mean beliefs for the whole sample and by the education level of the respondent's parents. Columns 1-3 provide results for the whole sample. Columns 4-6 are for respondents for whom neither parent went to university, while Columns 7-9 are for respondents for whom at least one parent went to university. Within each group, the first two columns give mean beliefs for the respective characteristic under the scenarios of having an undergraduate or postgraduate degree as highest qualification respectively. Mean beliefs are given on a 0-100 scale other than for expected earnings and immediate costs, which are in pounds. The third column gives the mean difference between these two beliefs, with the p-value for a t-test of difference in means reported underneath. Column 10 (Diff-in-diff) gives the average difference for respondents for whom neither parent has a degree minus the average difference for respondents for whom at least one parent has a degree.

1.5 Choice Model Estimation

To investigate the role of beliefs in explaining socioeconomic differences in students' intentions to pursue postgraduate education, we estimate a choice model in which students' intentions to enroll in a postgraduate degree are modelled as a function of perceived returns.[18] We first estimate the choice model under the assumption of homogeneous preferences to investigate the relative importance of different motives in the choice. We then allow for heterogeneous preferences across socioeconomic groups and examine to what extent the socioeconomic enrollment gap can be explained by differences in beliefs and preferences.

1.5.1 The Choice Problem

We analyze the choice problem of a student i who is currently enrolled in an undergraduate degree. The student has to choose whether to continue with postgraduate education $(g = 1)$ or start working instead $(g = 0)$. Each level of human capital investment results in different immediate and later-life outcomes, which can be of a binary or continuous nature. Immediate outcomes refer to outcomes that materialize during the 1-2 years following the completion of the undergraduate degree. Later-life outcomes refer to outcomes which materialize at age 35, i.e. once the student has entered the labor market. The student derives utility from these different outcomes and discounts later-life utility at a rate $\beta^{\tau_i} < 1$, where $\tau_i > 0$ is the difference between age 35 and the student's current age.

The student forms beliefs about the likelihood that each of these outcomes will occur, and chooses whether to continue with postgraduate education so as to maximize her subjective expected utility derived from the choice. Let $\{b^I_{n_I} \in \{0,1\}\}_{n_I=1}^{N_I}$ and $\{b^L_{n_L} \in \{0,1\}\}_{n_L=1}^{N_L}$ denote the immediate and later-life binary outcomes respectively, with $N_I + N_L = N$. The former set of binary variables includes whether the student enjoys their social life, enjoys their study/work, feels stressed, struggles financially, has parental support in their choice and completes a postgraduate degree, while the latter includes whether the student works full-time, is satisfied with their professional career, has a high status in society, contributes to society, has a good work-life balance and has children (see Table 1.1). If the student decides to enroll in postgraduate education, she incurs a continuous immediate cost c, which we define as the sum of tuition fees

[18] Our approach follows Zafar (2013) who investigates what drives gender differences in subject choice.

and forgone earnings.[19] At age 35, the student has earnings y (conditional on working full-time), which depend on whether the student has pursued a postgraduate degree or not.

We allow utility to be a function of the different immediate and later-life outcomes as well as individual characteristics Z_i. The individual chooses alternative g so as to maximize her (discounted) subjective expected utility (SEU):

$$SEU_{ig} = \int U_i(b^I, c, Z_i) dP_{ig}(b^I, c) + \beta^{\tau_i} \int U_i(b^L, y, Z_i) dP_{ig}(b^L, y) + \epsilon_{ig}$$

where $P_{ig}(X)$ denotes the subjective probability of outcomes X occurring if alternative g is chosen and ϵ_{ig} is a random error term.

Under the assumption that the error terms ϵ_{ig} have a Type-I extreme value distribution, and assuming utility is additively separable across outcomes, we can write the probability of alternative $g = 1$ being chosen as:

$$\Lambda(\sum_{n_I=1}^{N_I} [P_{ig=1}(b_{n_I} = 1) - P_{ig=0}(b_{n_I} = 1)]\Delta u_{n_I}(Z_i) + [E_{ig=1}(c) - E_{ig=0}(c)]\gamma_c(Z_i)$$
$$+ \beta^{\tau_i} \left[\sum_{n_L=1}^{N_L} [P_{ig=1}(b_{n_L} = 1) - P_{ig=0}(b_{n_L} = 1)]\Delta u_{n_L}(Z_i) + [E_{ig=1}(y) - E_{ig=0}(y)]\gamma_y(Z_i) \right]).$$

where $\Lambda(.)$ is the logistic function. $\Delta u_{n_I}(Z_i)$ and $\Delta u_{n_L}(Z_i)$ capture the differences in utility which arise from the occurrence of the different binary outcomes for an individual with characteristics Z_i. This difference is defined as $\Delta u_{n_I}(Z_i) \equiv u_{n_I}(b_{n_I} = 1, Z_i) - u_{n_I}(b_{n_I} = 0, Z_i)$ and it is defined analogously for later-life binary outcomes.[20] $\gamma_c(Z_i)$ and $\gamma_y(Z_i)$ are the weights an individual with characteristics Z_i places on expected immediate costs and later-life earnings. In this framework, the utility derived from the vector of outcomes can differ across individuals with different characteristics Z_i. This flexible functional form allows us to capture socioeconomic differences in the utility individuals derive from the different outcomes.

We elicit individual beliefs using the hypothetical investment scenarios described in Section 1.2. More specifically, we elicit subjective probabilities of the various immediate and later-life binary outcomes occurring, $P_{ig}(b_{n_I} = 1)$ and $P_{ig}(b_{n_L} = 1)$, as well as individual beliefs about expected costs and earnings, $E_{ig}(c)$ and $E_{ig}(y)$. In most cases, we elicit those beliefs separately for the scenario in which the student decides to pursue a postgraduate degree and the scenario

[19] In this model, financial costs enter the choice problem as a cost to the student's immediate utility. We assume students are not budget constrained, which is consistent with the institutional setting in which we conduct the study as students in the UK can take out loans to finance their education.

[20] $u_{n_I}(b^I_n, Z_i)$ and $u_{n_L}(b^L_n, Z_i)$ is the utility an individual with characteristics Z_i derives from the immediate and later-life binary outcomes.

in which the student decides not to pursue postgraduate education. Two notable exceptions are the perceived probability of graduating from a postgraduate degree if the student does not enroll in one and the immediate costs incurred if the student chooses not to obtain postgraduate education. These are both assumed to be zero.

The parameters to be estimated are the $\Delta u_{n_I}(Z_i)$'s and $\Delta u_{n_L}(Z_i)$'s as well as $\gamma_c(Z_i)$ and $\gamma_y(Z_i)$. We set the discount rate to $\beta = 0.96$. We estimate the preference parameters by maximum likelihood, using the method proposed by Papke and Wooldridge (1996) for continuous dependent variables in the 0-1 range.

1.5.2 Choice Model Estimates - Homogeneous Preferences

Column 1 of Table 1.4 presents the estimation results assuming homogeneous preferences.[21] Several non-pecuniary aspects that relate to students' lives during the 1-2 years after finishing their undergraduate degree significantly predict students' plans of pursuing a postgraduate education. Perceived returns in terms of enjoying one's social life, one's study/work, and parental support significantly and positively predict the perceived likelihood of enrolling in a postgraduate degree. We look at the relative magnitudes of the coefficients to get a sense of the importance of each binary outcome in the choice. The most important immediate factor for students in our sample is enjoying their study/work during the 1-2 years after finishing their undergraduate degree followed by having parental support. These results highlight the importance of perceived immediate non-pecuniary factors in students' educational investment decisions, and are consistent with findings from Zafar (2013), Belfield et al. (2019) and Boneva and Rauh (2019) that non-pecuniary motives drive students' decisions about their education. However, financial considerations play a role as well. We find that concerns about struggling financially as well as the expected immediate costs, i.e. sum of expected tuition fees and forgone earnings, are negatively related to students' plans to enroll in a postgraduate course.

Looking at binary outcomes at age 35, what matters most is whether students will be satisfied with their professional career, and whether they will have a high status in society. In contrast, the point estimate for the weight placed on contributions to society is a precisely estimated zero. Concerns about family formation seem to play a role as well as the perceived possibility of having

[21] Table 1C.7 in Appendix 1C shows that our results are robust to excluding outliers. For each return variable, we consider those observations as outliers that are in the top and bottom percentile of the return distribution. Tables 1C.8 and 1C.9 in Appendix 1C show that the results are also robust to estimating the choice model on the subsample of students whose current university is in England and students for whom the self-reported probability of graduating from their undergraduate degree is above 50%, respectively.

children also positively correlates with the decision to enroll in a postgraduate degree. Finally, we find that pecuniary returns at age 35 (i.e. expected earnings conditional on working full-time) matter for students' decisions about postgraduate education. Overall, the results suggest that both perceived immediate and perceived later-life returns to postgraduate education are important in students' choices.

To provide some interpretation of our parameter estimates, we provide a back-of-the-envelope calculation of the willingness-to-pay (WTP) for each binary outcome. The WTP can be interpreted as the amount of yearly gross earnings a student would be willing to forgo for a one-percentage-point change in the probability of the binary outcome n occurring.[22] Willingness-to-pay estimates are reported in column 2 of Table 1.4 and expressed in units of £.[23] Our results indicate that students are willing to accept a lower income at age 35 for a one-percentage-point change in the probability of several non-pecuniary immediate outcomes. For example, students are willing to forgo £608 in annual gross income for a one-percentage-point increase in the probability of enjoying what they do in the 1-2 years after their undergraduate degree, and £530 for an equivalent change in the probability of having parental support in their choice. Finally, students are also willing to accept £674 and £545 lower earnings for a one-percentage-point increase in the probability of being satisfied with their professional career and having a high status in society at age 35, respectively. While these estimates have to be interpreted with caution as the calculation rests on a number of assumptions (e.g. we abstract from earnings growth over the life cycle), they do highlight the economic relevance of non-pecuniary factors in the choice. We also calculate the WTP for the immediate expected costs of pursuing a postgraduate degree. This captures the gross annual earnings at age 35 students would have to be compensated with, for a one £ increase in the immediate costs of pursuing a postgraduate education.[24] We see that students would be willing to trade-off £0.38 in immediate costs for a one £ increase in earnings at age 35.

1.5.3 Choice Model Estimates - Heterogeneous Preferences

We now turn to the question of whether students from low and high SES backgrounds differ in their preferences over the different attributes. For this purpose, we split the sample by whether or not students have at least one parent who attended university, and we estimate the choice model

[22]The WTP for outcome n can be calculated as: $WTP_n = \frac{0.01\Delta u_n}{\gamma_y}$, where Δu_n is the coefficient attached to the binary outcome of interest, and γ_y is the coefficient on earnings at age 35.

[23]Standard errors of these non-linear combinations of estimators are calculated using the Delta method.

[24]The WTP is calculated as $\frac{\gamma_c}{\gamma_y}$, where γ_c is the coefficient on the immediate costs of a postgraduate degree.

separately for the two groups. Results are reported in columns 3-6 of Table 1.4. We find sizeable differences in the point estimates of the preference parameters we estimate, although most of these differences are statistically insignificant (see columns 7-8 of Table 1.4). Nonetheless, some notable patterns emerge. For example, expected earnings and career satisfaction at age 35 only seem to matter for continuing-generation students, whereas low SES students place more weight on enjoying their social life and not feeling stressed in the 1-2 years after the completion of their undergraduate degree. Interestingly, despite perceiving a lower immediate cost of postgraduate education, first-generation students' intentions to enroll in a postgraduate degree significantly depend on their expected costs of such investment, while this is not the case for continuing-generation students. This suggests that for first-generation students budget constraints might be binding, while for continuing-generation students they appear not to be.[25]

Finally, we investigate whether, among high SES students, differences exist in their preferences over the different attributes based on whether their parents obtained postgraduate education or not. For this purpose, we focus on the subsample of continuing-generation students, split the subsample by whether or not students have at least one parent who holds a postgraduate qualification, and estimate the choice model separately for these two subgroups. The results are reported in columns 3-6 of Table 1.5. Although most of the differences between the estimated preference parameters are again statistically insignificant (see columns 7-8 of Table 1.5), we note that students from the highest socioeconomic background seem to place more weight on whether they will be satisfied with their career at age 35 and whether they will have a good work-life balance. Parental support, on the other hand, plays a significant role in the choice of high SES students whose parents do not have a postgraduate degree, but does not significantly enter the choice model for students whose parents went through postgraduate education.

[25]We note that the probability of working full-time at age 35 negatively enters the choice model for first-generation students. This result is driven by the subsample of female respondents that are the first-generation in their family to go to university.

Table 1.4: Choice Model Estimation by Parental Education

	All		First generation		Continuing generation		Difference (p-value)	
	Coef.	WTP	Coef.	WTP	Coef.	WTP	Coef.	WTP
Expected earnings at age 35 ($10000\gamma_y$)	0.193***		0.083		0.306***		0.093	
	(0.066)		(0.092)		(0.096)			
Enjoy social life (Δu_1)	0.456**	235.787*	0.749***	904.316	0.172	56.192	0.125	0.427
	(0.188)	(129.654)	(0.238)	(1064.756)	(0.291)	(98.197)		
Enjoy study / work (Δu_2)	1.178***	608.803***	0.926***	1117.802	1.584***	517.916***	0.063	0.632
	(0.181)	(221.525)	(0.237)	(1238.350)	(0.263)	(180.298)		
Feel stressed (Δu_3)	-0.288*	-148.582	-0.372*	-448.959	-0.241	-78.824	0.678	0.495
	(0.152)	(90.580)	(0.217)	(536.747)	(0.229)	(79.051)		
Struggle financially (Δu_4)	-0.527***	-272.418**	-0.473**	-570.778	-0.494**	-161.450*	0.939	0.540
	(0.136)	(117.692)	(0.193)	(663.608)	(0.193)	(84.253)		
Parental support (Δu_5)	1.026***	530.239***	0.913***	1102.408	1.106***	361.577**	0.609	0.565
	(0.185)	(203.485)	(0.248)	(1280.104)	(0.282)	(143.594)		
Immediate cost ($10000\gamma_c$)	-0.074***	-0.383**	-0.104***	-1.252	-0.027	-0.090	0.092	0.410
	(0.023)	(0.162)	(0.031)	(1.406)	(0.033)	(0.107)		
Work full time at age 35 (Δu_6)	-0.679	-351.092	-1.889**	-2280.337	0.599	195.812	0.017	0.370
	(0.550)	(308.242)	(0.736)	(2750.617)	(0.734)	(254.648)		
Satisfied with career at age 35 (Δu_7)	1.305**	674.319*	0.930	1122.832	1.844***	603.029**	0.384	0.766
	(0.536)	(383.714)	(0.797)	(1720.207)	(0.683)	(302.474)		
High status at age 35 (Δu_8)	1.056**	545.930	1.128*	1361.706	0.889	290.833	0.806	0.566
	(0.474)	(340.223)	(0.681)	(1848.878)	(0.691)	(265.356)		
Contribute to society at age 35 (Δu_9)	-0.017	-9.016	0.948	1143.823	-0.908	-296.981	0.058	0.369
	(0.486)	(250.960)	(0.715)	(1588.732)	(0.670)	(228.036)		
Work-life balance at age 35 (Δu_{10})	0.713	368.255	0.352	425.446	1.036*	338.879	0.440	0.928
	(0.456)	(269.393)	(0.629)	(927.599)	(0.624)	(224.850)		
Have children at age 35 (Δu_{11})	1.156**	597.491	0.250	301.762	1.738**	568.503*	0.180	0.816
	(0.560)	(370.432)	(0.836)	(1106.713)	(0.730)	(307.514)		
Postgraduate graduation probability	0.405***	209.316**	0.596***	720.025	0.091	29.883	0.044	0.410
	(0.126)	(99.331)	(0.165)	(835.742)	(0.188)	(62.789)		
Observations	989	989	495	495	494	494		
Variance explained	0.269		0.283		0.283			

Notes: Standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Column 1 presents the estimates of the choice model for the whole sample, while column 2 presents the willingness-to-pay calculations. Columns 3-4 present the results for first-generation students, columns 5-6 present the results for continuing-generation students. For the willingness to pay calculations, standard errors are calculated using the delta method. Continuing-generation students are defined as those students who have at least one parent with university education. The last row reports the R-Squared from a regression of the dependent variable on the fitted values predicted by our model.

Table 1.5: Choice Model Estimation by Parental Education - Continuing-generation Students

	Continuing gen.		Parents no postgr. qual.		Parents have postgr. qual.		Difference (p-value)	
	Coef.	WTP	Coef.	WTP	Coef.	WTP	Coef.	WTP
Expected earnings at age 35 ($10000\gamma_y$)	0.306***		0.360***		0.248*		0.565	
	(0.096)		(0.126)		(0.148)			
Enjoy social life (Δu_1)	0.172	56.192	0.158	43.870	0.223	89.866	0.910	0.833
	(0.291)	(98.197)	(0.387)	(109.295)	(0.431)	(188.772)		
Enjoy study / work (Δu_2)	1.584***	517.916***	1.640***	456.030**	1.624***	654.767	0.977	0.664
	(0.263)	(180.298)	(0.332)	(180.782)	(0.445)	(421.630)		
Feel stressed (Δu_3)	-0.241	-78.824	-0.511*	-142.056	0.258	103.876	0.095	0.173
	(0.229)	(79.051)	(0.306)	(97.538)	(0.345)	(151.958)		
Struggle financially (Δu_4)	-0.494**	-161.450*	-0.548**	-152.285*	-0.470*	-189.534	0.842	0.852
	(0.193)	(84.253)	(0.265)	(92.398)	(0.286)	(176.984)		
Parental support (Δu_5)	1.106***	361.577**	1.099***	305.544**	0.809	326.152	0.656	0.947
	(0.282)	(143.594)	(0.328)	(141.112)	(0.564)	(278.601)		
Immediate cost ($10000\gamma_c$)	-0.027	-0.090	-0.007	-0.019	-0.095	-0.382	0.233	0.263
	(0.033)	(0.107)	(0.040)	(0.111)	(0.062)	(0.305)		
Work full time at age 35 (Δu_6)	0.599	195.812	0.176	49.029	1.483	598.003	0.398	0.437
	(0.734)	(254.648)	(0.973)	(272.433)	(1.204)	(652.665)		
Satisfied with career at age 35 (Δu_7)	1.844***	603.029**	1.385	385.089	2.403**	969.148	0.483	0.480
	(0.683)	(302.474)	(0.895)	(287.335)	(1.148)	(777.837)		
High status at age 35 (Δu_8)	0.889	290.833	0.711	197.628	0.706	284.532	0.997	0.888
	(0.691)	(265.356)	(0.832)	(256.892)	(1.208)	(565.310)		
Contribute to society at age 35 (Δu_9)	-0.908	-296.981	-0.884	-245.915	-0.802	-323.360	0.952	0.883
	(0.670)	(228.036)	(0.953)	(265.652)	(1.003)	(452.679)		
Work-life balance at age 35 (Δu_{10})	1.036*	338.879	0.680	189.041	1.865**	751.918	0.350	0.367
	(0.624)	(224.850)	(0.845)	(244.981)	(0.949)	(574.383)		
Have children at age 35 (Δu_{11})	1.738**	568.503*	1.822**	506.765	1.280	516.280	0.739	0.989
	(0.730)	(307.514)	(0.851)	(325.969)	(1.392)	(590.613)		
Postgraduate graduation probability	0.091	29.883	-0.050	-13.874	0.521	210.248	0.158	0.263
	(0.188)	(62.789)	(0.232)	(64.408)	(0.332)	(189.776)		
Observations	494	494	331	331	163	163		
Variance explained	0.283		0.257		0.352			

Notes: Standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Column 1 presents the estimates of the choice model for the subsample of continuing-generation students, while column 2 presents the willingness-to-pay calculations. Columns 3-4 present the results for continuing-generation students whose parents do not hold a postgraduate qualification, columns 5-6 present the results for continuing-generation students whose parents hold a postgraduate qualification. For the willingness to pay calculations, standard errors are calculated using the delta method. Continuing-generation students are defined as those students who have at least one parent with university education. The last row reports the R-Squared from a regression of the dependent variable on the fitted values predicted by our model.

1.5.4 Decomposition of Gaps in Enrollment

The results point to two explanations for why we observe gaps in intentions to enroll in a postgraduate degree between students from different socioeconomic backgrounds. First, results from the choice model suggest that students from different socioeconomic backgrounds may have different preferences over the different factors. Second, depending on their background characteristics, students hold different beliefs about the returns to postgraduate education in terms of both pecuniary and non-pecuniary outcomes, especially for outcomes that accrue in the immediate future. To the extent that beliefs are malleable and possibly formed on the basis of incorrect or incomplete information, it is important to quantify how much differences in beliefs contribute to the socioeconomic gaps in people's intention to pursue postgraduate education. In other words, in this section we calculate how much the gaps would be reduced if everyone in our sample had the same beliefs about the different pecuniary and non-pecuniary returns to postgraduate education.

For this purpose, we use the estimates from Section 1.5.3 to calculate the gaps in intentions to enroll that our model predicts, and decompose these gaps into a composition effect and a preference effect (or coefficients effect). The former captures the effect of differences in the distribution of our covariates (i.e. beliefs about the returns to postgraduate education) across groups, while the latter captures the effect of differences in preference-parameter estimates. Denote as G_i the socioeconomic group student i belongs to, where $G_i = L$ for first-generation students and $G_i = H$ for continuing-generation students. Further let X_i be a vector of all the perceived returns that enter our choice model estimation, and δ be the vector of preference parameters associated to the different returns. The gap in our outcome variable predicted by the model can be written as:

$$\Delta^{SES} = \underbrace{E[\Lambda(X_i\delta^H)|G_i = H] - E[\Lambda(X_i\delta^L|G_i = H)]}_{\Delta^{\delta} \text{ (preference effect)}} + \underbrace{E[\Lambda(X_i\delta^L)|G_i = H] - E[\Lambda(X_i\delta^L|G_i = L)]}_{\Delta^{X} \text{ (composition effect)}}$$

We first look at the gap between first- and continuing-generation students, and then focus on differences by parental background for the sample of continuing-generation students in isolation. When we perform the decomposition exercise using the parameter estimates obtained for first- and continuing-generation students, results show that our model including perceived returns to postgraduate education 1-2 years after graduation and at age 35 predicts a socioeconomic gap in students' intentions to continue to a postgraduate degree of 3.9 percentage points, which corresponds to 75% of the actual gap (the actual, unconditional gap by SES is 5.2 percentage points in the sample of respondents for whom we have non-missing information for all the returns). Furthermore, the decomposition analysis shows that of the 3.9 percentage-point SES gap predicted by the model, 91% can be explained by socioeconomic differences in beliefs (composition effect), and the remaining 9% can be explained by differences in preferences. These results are graphically illustrated in Figure 1C.6. Putting the numbers together, we find that differences in beliefs about the returns to postgraduate education across socioeconomic groups can explain around 70% of the actual gap in students' intentions to enroll in postgraduate education.

We further investigate which beliefs play the dominant role in explaining the gaps by SES in intentions to enroll in a postgraduate degree. To do this, we follow Kaiser (2015) and, for each perceived return, we examine by how much the socioeconomic gap would be reduced if the distribution of beliefs was the same across low and high SES students, keeping the distributions for all other outcomes constant.[26] In other words, we decompose Δ^X into the contributions from each explanatory variable by examining how switching the value of variable n for first-generation individual i with $G_i = L$ with that of continuing-generation individual j with $G_j = H$, holding her preference parameters (δ^L) constant, affects the conditional-expectation function for the outcome of interest. The conditional contribution of variable n is defined as

$$\Delta_n^X(X_i, X_j) = \frac{\Lambda(X_j\delta^L) - \Lambda(X_i\delta^L)}{(X_j - X_i)\delta^L}(X_{jn} - X_{in})\delta^L$$

and the unconditional contribution is then obtained by integrating $\Delta_n^X(X_i, X_j)$ over the distribution of covariates in the two groups. The results from this exercise are presented in columns 1 and 2 of Table 1.6. Looking at the decomposition of the SES gap, we note that shifting the distribution of beliefs about enjoying the activity students will be doing in the 1-2 years after graduation would reduce the SES gap by 0.67 percentage points, whereas differences in beliefs about the likelihood of struggling financially can account for 0.55 percentage points of the SES gap in intentions to enroll in a postgraduate degree. Beliefs about parental support also play a vital role in explaining the gap between first- and continuing-generation students, which would be reduced by 0.92 percentage points if first- and continuing-generation students held the same beliefs. We note that students' perceptions about their professional career and status in society at age 35 do not drive differences in intentions to pursue a postgraduate education. Finally, neither differences in beliefs about earnings at age 35 nor about employment can explain socioeconomic differences in enrollment into postgraduate education. Taken together, the results suggest that

[26] This approach has the advantage of taking into account the impact of differences in higher order moments of X_i, not only differences in means, and of ensuring path independence.

the driving factors behind gaps in enrollment are differences in beliefs regarding the immediate non-pecuniary benefits of postgraduate education.

Table 1.6: Decomposition of Predicted Gaps in Intentions to Enroll

	Gap by SES		Gap by postgr. qual.	
	Gap	P-value	Gap	P-value
Actual gap	5.212	0.006	8.036	0.005
Total predicted gap	3.916	0.046	8.753	0.001
Composition effect	3.618	0.001	4.588	0.012
	Coef.	P-value	Coef.	P-value
Expected earnings at age 35 ($10000\gamma_y$)	0.165	0.416	0.699	0.191
	(0.203)		(0.534)	
Enjoy social life (Δu_1)	0.563	0.114	0.033	0.895
	(0.356)		(0.255)	
Enjoy study / work (Δu_2)	0.666	0.095	1.044	0.276
	(0.399)		(0.959)	
Feel stressed (Δu_3)	0.405	0.172	-0.081	0.810
	(0.297)		(0.340)	
Struggle financially (Δu_4)	0.548	0.100	-0.389	0.376
	(0.334)		(0.439)	
Parental support (Δu_5)	0.925	0.021	2.687	0.008
	(0.401)		(1.007)	
Immediate cost ($10000\gamma_c$)	-0.490	0.148	-0.001	0.992
	(0.339)		(0.135)	
Work full time at age 35 (Δu_6)	-0.136	0.515	0.041	0.877
	(0.208)		(0.262)	
Satisfied with career at age 35 (Δu_7)	-0.045	0.789	0.376	0.325
	(0.167)		(0.382)	
High status at age 35 (Δu_8)	0.040	0.828	0.357	0.468
	(0.185)		(0.492)	
Contribute to society at age 35 (Δu_9)	0.109	0.552	-0.216	0.476
	(0.184)		(0.303)	
Work-life balance at age 35 (Δu_{10})	-0.002	0.987	0.051	0.825
	(0.108)		(0.231)	
Have children at age 35 (Δu_{11})	-0.022	0.869	0.020	0.951
	(0.135)		(0.322)	
Postgraduate graduation probability	0.891	0.014	-0.033	0.861
	(0.364)		(0.190)	
Observations	989		494	

Notes: The relative contributions of beliefs to the predicted gaps in enrollment by SES for the full sample, and by whether or not at least one parent has a post-graduate degree for the subsample of continuing-generation students are presented in columns 1 and 3 respectively. Columns 2 and 4 presents p-values for a test of sinigificance of the coefficients. The first three rows of the table report, for each model, the actual gap observed in the data, the total gap predicted by our model, and the gap predicted from the composition effect. Bootstrapped standard errors calculated from 500 repetitions are provided in parentheses.

We repeat the exercise looking at the continuing-generation subsample only and decomposing the gap between students whose parents have a postgraduate qualification and students whose parents only have an undergraduate degree. Results for this exercise are presented in columns 3-4 of Table 1.6. The actual gap in intentions to enroll that we observe in the subsample of students for whom we have non-missing information about all the returns is 8.04 percentage points. Our model that accounts for differences in perceived returns and differences in preferences predicts a gap in intentions to enroll of 8.75 percentage points, which is more than the actual gap observed in the data. The decomposition analysis shows that 52% of the gap predicted by the model can be explained by differences in beliefs alone (composition effect). We note that none of the coefficients from the decomposition analysis apart from the one associated with parental support are significant at conventional levels, possibly due to a lack of power. Interestingly, the single most important factor in explaining gaps in intentions to enroll among continuing-generation students are beliefs about whether or not they would have parental approval in their choice. Shifting the distribution of beliefs of students whose parents did not obtain postgraduate education would reduce the gap by 2.69 percentage points. The second most important factor are beliefs about whether students will enjoy what they will be doing in the 1-2 years after completing their undergraduate degree. Differences in the distribution of this perceived return account for 1.04 percentage points of the gap within continuing-generation students.

1.6 Discussion

When examining individual beliefs about the immediate non-pecuniary benefits and costs of postgraduate education, a natural question to ask is whether individual characteristics and experiences are predictive of students' beliefs about their short-term future. In particular, one important factor influencing how students form their beliefs about the returns to postgraduate education might be their current experiences of life at university, which we turn to next. In Section 1.6.1 we investigate how students from different backgrounds differ in how they experience university education, while in Section 1.6.2 we examine the determinants of students' beliefs about their short-term future. Finally, in Section 1.6.3 we discuss the accuracy of students' perceived returns to postgraduate education.

1.6.1 Heterogeneity in Students' Current Experiences

To elicit information on students' current experiences, we ask students to what extent different statements about life at university apply to them on a 0-100 scale. For the purpose of this analysis, we group the survey items into six different categories, as summarized in Panel B of

Table 1.1, and construct summary indices by extracting a factor from the different item responses in each category.[27] Figure 1.3 displays the mean values of the extracted factors separately for first- and continuing-generation students. The factors measure the extent to which students have a good social life, enjoy their course work, find studying hard/stressful, struggle financially, benefit from parental support and think their life is better than expected.

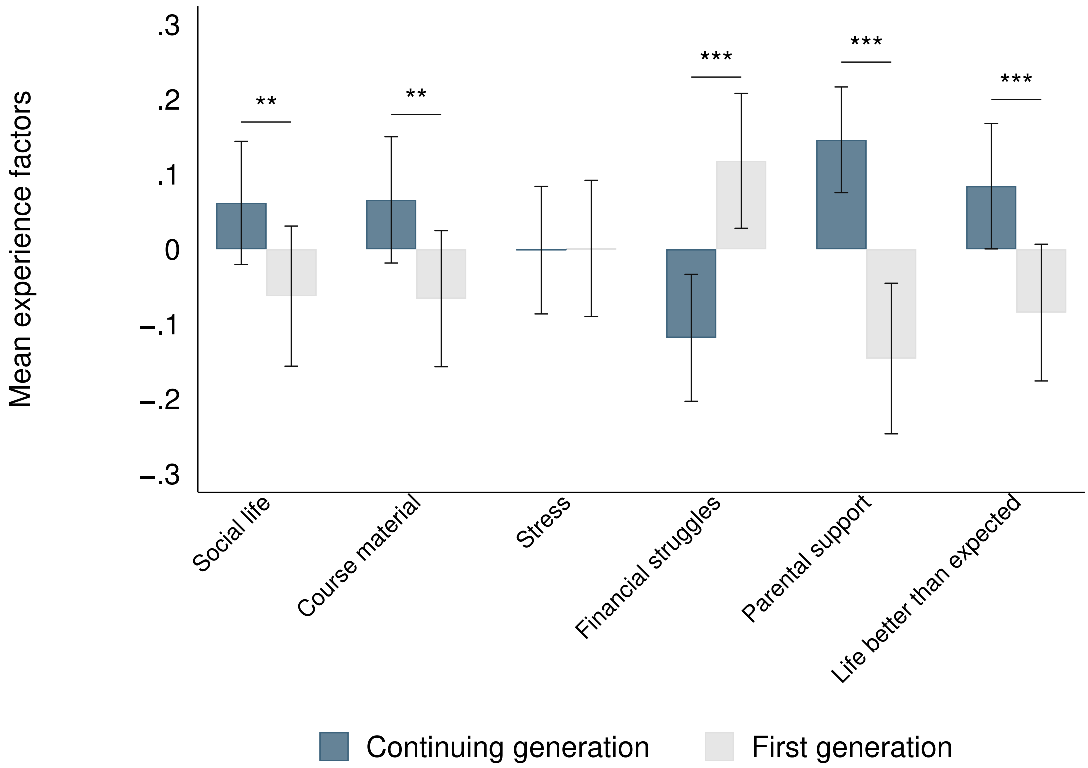
We find significant differences by socioeconomic status in how students perceive their life at university. Continuing-generation students are more likely to enjoy their course work, and they are more likely to report that life at university is better than expected. High SES students are also more likely to state that they have parental approval in their choice to go to university, and they are less likely to struggle financially. Among continuing-generation students, students whose parents have postgraduate qualifications on average report significantly higher levels of parental support but are also less likely to state that their life is better than expected (see Appendix Figure 1C.7). Comparing continuing-generation students with private and state school education, we find that privately-educated students are less likely to struggle financially, but do not significantly differ from students who attended a state school in any other measure of experience of life at university (see Appendix Figure 1C.8).

We also investigate how students allocate their time across various activities in a typical week during term time, and how they finance their tuition fees and living expenses (see Appendix Tables 1C.12-1C.15). First-generation students work more than continuing-generation students (12.5 vs. 8.8 hours per week), they are more likely to work for pay and less likely to engage in work that is related to their studies. Compared to continuing-generation students, they spend less time in student societies. When looking at the work students did over the last summer break, we find that continuing-generation students worked a smaller number of weeks, but the work that they did was more likely to be related to their studies. Furthermore, parents of continuing-generation students were more likely to know the employer their children were working for, and to help them with their application for the job. These findings highlight the importance of parental networks in students' ability to access career-enhancing employment opportunities during their studies.

Turning to the ways in which students finance their tuition fees and living expenses, we find that 82% of continuing-generation students took out a loan, while the corresponding figure for

[27] Tables 1C.10 and 1C.11 in Appendix 1C report the average answers to how much each single statement about life at university applies to the respondents, on a 0-100 scale, for the full sample and for the subgroup of continuing-generation students. Breakdowns by parental education are also provided in both tables.

Figure 1.3: Experience of Life at University by Parental Education



Notes: The figure shows the average value for the first factor from a factor analysis of the variables related to the social life, positive and negative aspects of the course work and financial situation, as well as the standardized variables for having parental support and perceiving life at university as better than expected. Parental background is split between students who have at least one parent with university education (blue bars) and those who do not (gray bars). The black caps represent 95% confidence intervals and stars indicate statistical significance of differences by parental background: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

the low SES group is 95%. Out of those who did not take out a loan, 50% and 85% of first- and continuing-generation students report being helped financially by their family, respectively. Overall, we conclude that first-generation students experience life at university very differently compared to continuing-generation students.

1.6.2 Predictors of Perceived Returns

We now turn to the question of whether students' individual characteristics and experience of life at university during their undergraduate year are predictive of their beliefs about the immediate future. Table 1C.16 shows the results from regressing individual perceived returns to postgraduate education on students' characteristics (first generation, whether at least one parent has a postgraduate qualification, age, gender), the student's self-reported probability of getting a First in her undergraduate degree, the extracted factors capturing students' current experiences at university which we describe in Section 1.6.1, as well as field of study and university fixed effects.

Looking at differences in beliefs by background characteristics, we note that female students report a higher probability of being stressed and struggling financially if enrolling in a postgraduate degree versus not, but also a higher likelihood of enjoying what they will be doing. Having at least one parent with postgraduate qualification and the self-reported probability of getting a First in their undergraduate degree are positively and significantly correlated with the perceived degree of parental approval if pursuing a postgraduate degree.[28]

Further, individual beliefs about the immediate non-pecuniary benefits and costs of graduate education may be influenced by students' actual experiences of studying towards an undergraduate degree. A student who does not enjoy social life while being enrolled in an undergraduate degree may perceive it to be less likely that she will enjoy social life if she decides to enroll in a postgraduate degree. Consistent with this hypothesis whereby current experiences shape students' beliefs about future experiences, we find that the coefficients associated to variables capturing undergraduate experiences are positive and significant along the main diagonal, i.e. the more one statement applies during undergraduate years, the more likely students think it will also apply during their postgraduate education. For example, students who report that they currently enjoy their social life are also more likely to believe that the return to enrolling in a postgraduate degree in terms of their social life is going to be greater. Similarly, students who currently enjoy studying towards their degree also believe that the return in terms of enjoying what they will do will be higher. However, having parental approval in their choice of pursuing a first degree is not associated with students believing that their parents would also support them in their decision to obtain postgraduate education. Perceiving life at university as better than expected is correlated with a higher perceived benefit in terms of enjoying one's social life and lower perceived costs in terms of stress and financial struggles.

1.6.3 Are students' beliefs accurate?

Another important question is whether students' beliefs regarding pecuniary returns to postgraduate education are accurate. While we cannot comment on this with our survey data, we

[28]For brevity, we do not report results for the determinants of perceived returns at age 35 of postgraduate education, for which we find little relation to current experiences.

can compare students' beliefs with information on realized differences in earnings around age 35 across workers with different educational qualification. Data from the LFS show that full-time employees around age 35 on average earn £39,932 and £43,637 if their highest qualification is an undergraduate or postgraduate degree, respectively. We also compare perceived monetary returns to postgraduate earnings premia observed in the UK Household Longitudinal Study for individuals aged 32-38 in waves 6-8, corresponding to the period between 2014 and 2018. More concretely, we estimate postgraduate earnings premia for the sample of respondents with at least a first degree or equivalent and employed full-time, and allow these returns to differ by parental education. We classify respondents as first generation if at least one of their parents has a university degree or higher, and take as dependent variable annual gross labour earnings.

Results from this exercise are reported in column 1 of Table 1C.17, and show that the average earnings premium for university-educated workers with a postgraduate qualification and aged around 35 years in the UK is £6,035.23. Further, we note that the interaction coefficient between being a first-generation student and having a postgraduate degree is negative at £2,892.62 but not significant. We compare the observed earnings premium with perceived returns for students in our sample (see column 2 of Table 1C.17). To compute the perceived returns, we consider two observations per respondent. The first observation refers to the scenario in which the highest educational qualification achieved is an undergraduate degree, and the second refers to the case in which the student successfully completes a postgraduate degree. The dependent variable is expected earnings at age 35, conditional on working full-time. Results show that the average perceived return to a postgraduate degree for students in our sample is £7,218.25. The interaction between postgraduate qualification and first generation is negative and significant at £1,496.44. We further note that the perceived earnings difference for first-generation students with an undergraduate degree compared to their continuing-generation counterpart is negative and significant at £3,052.03 in our data, and significant albeit smaller in magnitude in the UK HLS data.

1.7 Conclusion

In this paper, we investigate to what extent differences in beliefs about the returns can explain the observed gap in intentions to obtain postgraduate education across socioeconomic groups. To answer this question, we collect novel survey data from a representative sample of undergraduate students in the UK. We elicit students' beliefs about the pecuniary and non-pecuniary benefits of postgraduate education, both in the immediate future and later in life, as well as students' intentions to pursue a postgraduate degree. By surveying students prospectively, we minimize biases that can arise due to ex-post rationalization. We also administer a questionnaire that is designed to capture students' actual experience of life at university. This allows us to investigate whether students with different background characteristics differ in their experience of studying towards their undergraduate degree and whether current experiences are predictive of students' beliefs about the immediate non-pecuniary returns to postgraduate education.

We document that undergraduate students, who are the first generation in their family to go to university, state a 5 percentage point lower likelihood of continuing on to postgraduate education relative to continuing-generation students. They also perceive a range of both pecuniary and non-pecuniary returns to postgraduate education to be lower, and this is especially true for returns that would accrue within the 1-2 years of postgraduate studies. Differences in beliefs about the returns to postgraduate education can explain 70% of the observed first-generation/continuing-generation gap in students' intentions to enroll in a postgraduate degree. We also find that the majority of the gap can be explained by differences in beliefs about immediate non-pecuniary outcomes.

We document that large heterogeneities in intentions to enroll in a postgraduate degree exist *within* the continuing-generation group. Students who have at least one parent who holds a postgraduate qualification report an 8 percentage point higher likelihood of pursuing postgraduate education relative to the group of students whose parents have an undergraduate qualification, but not a postgraduate degree. We find that the single most important factor that drives this gap in students' intentions to obtain postgraduate education is parental approval. Finally, we document that there are sizeable differences in how students from different backgrounds experience their lives at university, and that these differences are predictive of the perceived returns to postgraduate education.

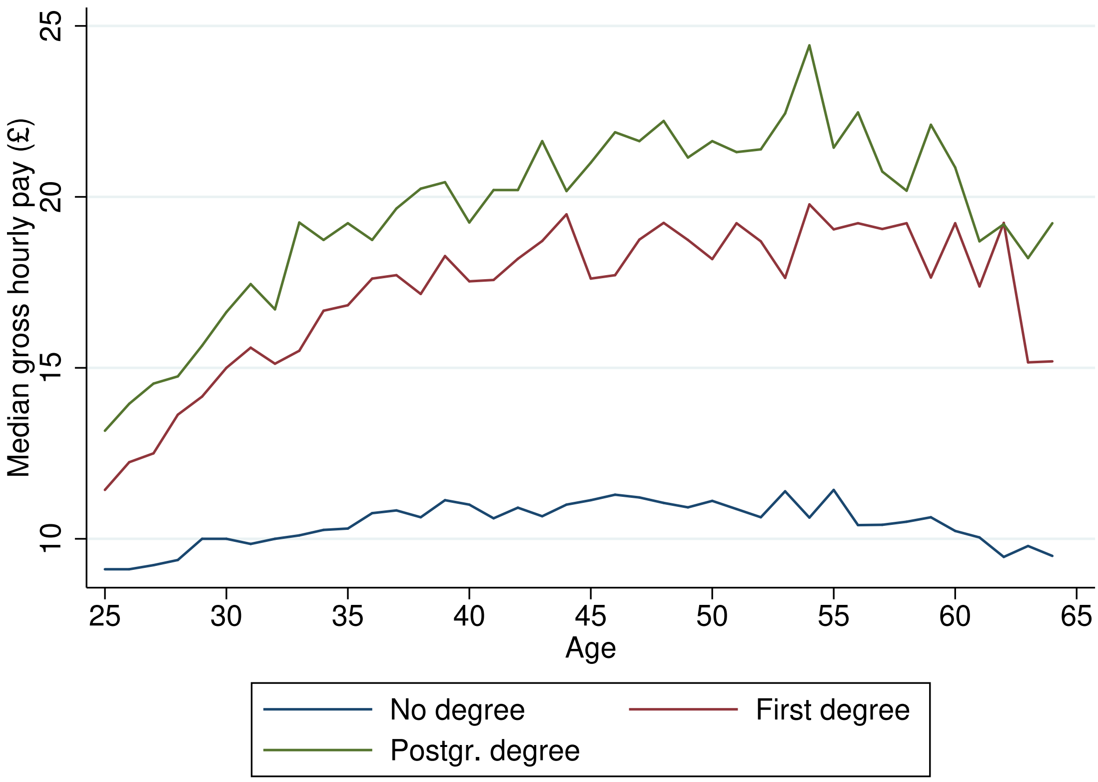
Taken together, the results from this paper shed new light on the growing debate on what drives socioeconomic differences in educational attainment. The socioeconomic gaps we find in students' actual experiences at university are alarming and raise the question of what governments and universities can do to narrow these socioeconomic gaps in actual student experiences. It will also be crucial to understand whether the socioeconomic gaps in students' beliefs about the benefits of postgraduate education are reflective of actual differences in the returns to postgraduate education by socioeconomic status. More research will be needed into whether and potentially why the returns to postgraduate education differ across socioeconomic groups and which policies could be effective in narrowing the gaps in returns to postgraduate education.

Appendices of Chapter 1

1A Supplementary Data

UK Data Data on labour market outcomes and composition of the workforce for the UK come from the quarterly Labour Force Survey (LFS), from Q1 2018 to Q4 2018. The sample includes all first-time respondents aged 25-64 included, who are not in full-time study and for whom information on their highest educational qualification is available. We classify First degrees and other equivalent degrees as "First degree", all higher qualifications as "Post-graduate degree", and other non-university qualifications as "No degree". Income weights, as provided in the LFS dataset, are used throughout.

Figure 1A.1: Gross Hourly Pay by Educational Qualification



Notes: The figure shows median gross hourly pay from the main job by age, for individuals with no university degree, a first degree only and a postgraduate degree respectively. The sample is restricted to individuals aged 25-64 included, who are first-time respondents to the QLFS and employed. We exclude full-time students. Source: QLFS, from Q1 2016 to Q4 2018. Data are weighted with the income weights provided in the QLFS.

US Data Figures for the US come from `https://www.bls.gov/cps/lfcharacteristics.htm#laborforce`. Data on characteristics of the labour force come from the Current Population Survey (CPS), and refer to the population of employed individuals, 25 years and over. We classify Bachelor's degree holders as "First degree", individuals with advanced degrees as "Post-graduate degrees", and any qualification lower than a Bachelor's degree as "No university degree". Figures refer to annual averages for 2018.

1B Questionnaires

1B.1 Experience Questionnaire

Think about your life at university. To what extent do the following statements apply to you? You can select any number between 0 and 100.

- I enjoy the social life and activities I engage in.
- I meet people with whom I easily get along with.
- I have little contact with my family and friends from school.
- I sometimes feel lonely and not part of a group.
- I enjoy studying for my course.
- I find the material covered in my course interesting.
- I find the material too hard and/or the workload too high.
- I am stressed and sometimes feel that I cannot cope.
- I struggle financially.
- I have enough money to do what I enjoy.
- My parents supported me in my decision to go to university.
- Life at university is better than expected.

1B.2 Time Allocation

Now we would like to ask you how much time you spend on different activities. Think about last week and consider which activities you engaged in. If last week was not a typical week (e.g. because of sickness) please think of a typical week during term time. How many hours did you spend on the following activities? (enter hours per week)

- Attending lectures/seminars/tutorials
- Studying/preparing for lectures and exams
- Participating in student societies
- Socialising with friends
- Work/internship (for pay)
- Work/internship (not for pay)

[If working at least 1 hour per week, either for pay or not for pay] To what extent do the following statements apply to you?

- The work I do alongside my studies is closely related to the subject I study.

- The work I do alongside my studies will help me in my future career.

Think about the last summer break. How many weeks did you engage in work / internships?

[If worked at least one week] On a scale from 0 to 100, how related was this job to your studies?

[If worked at least one week] Did your parents know your employer or somebody working for the same employer?

[If worked at least one week] Did your parents help you write your application?

1B.3 Finances

Now we would like to ask you some questions about your current expenses and how you finance your undergraduate studies.

Did you take out a loan to finance your tuition fees? [Yes, No]

[If 'No' selected] How do you finance your tuition fees? (select all which apply)

- Money from parents/family
- Work alongside my studies
- Savings
- Other sources

In a typical month during term time, how high are your living expenses (including rent)? [amounts in £]

1B.4 Plans for the Future

How likely do you think it is that you will complete your undergraduate degree?

Assuming that you complete your undergraduate degree, how likely do you think it is you will get a First?

Assuming that you get the necessary grades, how likely do you think it is you will enrol in a postgraduate degree?

If you enrol in a postgraduate degree, how likely do you think it is you will graduate?

Which field of study would you be most likely to choose?

1B.5 Hypothetical Scenarios

Now we would like you to think about the 1-2 years of your life that will come after you complete your undergraduate degree. Imagine that during these 1-2 years you enrol in your most preferred postgraduate degree. What do you think your life during these 1-2 years will be like? If you enrol in your preferred postgraduate degree, how likely do you think it is that you will...

- ...enjoy your social life?
- ...enjoy studying for your course?
- ...feel stressed?
- ...struggle financially?
- ...have parental support in your choice?
- ...work alongside your studies?

How high do you think the tuition fees for your course would be per year?

Now imagine that during the 1-2 years after you complete your undergraduate degree you do not enrol in a postgraduate degree but start working instead. What do you think your life during these 1-2 years will be like? If you start working, how likely do you think it is that you will...

- ...enjoy your social life?
- ...enjoy the work you will be doing?
- ...feel stressed?
- ...struggle financially?
- ...have parental support in your choice?

If you do not enrol in a postgraduate degree but start working instead, what do you think your pre-tax annual earnings would be during those 1-2 years? [in £]

Now we would like you to think about your life at age 35. Imagine that your highest qualification is a postgraduate degree in your preferred field of study. How likely do you think it is that you will...

- ...be working full-time?
- ...be satisfied with your professional career?
- ...have a high status in society?
- ...have a career in which you can contribute to society?
- ...have a good work-life balance?
- ...have children?

Assuming that you work full-time, what do you think your pre-tax annual earnings would be at age 35 if your highest qualification is a postgraduate degree in your preferred field of study? [in £]

Now we would like you to think about your life at age 35. Imagine that your highest qualification is an undergraduate degree in your current field of study. How likely do you think it is that you will...

- ...be working full-time?
- ...be satisfied with your professional career?
- ...have a high status in society?
- ...have a career in which you can contribute to society?
- ...have a good work-life balance?
- ...have children?

Assuming that you work full-time, what do you think your pre-tax annual earnings would be at age 35 if your highest qualification is an undergraduate degree in your current field of study? [in £]

1C Supplementary Analyses

Table 1C.1: Distribution of Students Across Regions in England (%)

Region	**Sample**	**National**
East of England	6.89	6.69
East Midlands	10.08	9.90
London	17.96	17.86
North East	5.69	5.74
North West	13.47	13.53
South East	14.07	14.17
South West	9.88	10.01
West Midlands	10.78	10.86
Yorkshire and The Humber	11.18	11.24

Notes: National figures come from the Higher Education Statistics Agency (HESA) and refer to the percentage of all students enrolled full-time in a first degree or other undergraduate degree in England. Data source: Higher Education Statistics Agency (2019a).

Table 1C.2: Summary Statistics

	Mean	St. Dev.	N
First generation	0.500	0.500	1002
Female	0.496	0.500	1002
Parent with graduate degree	0.164	0.370	1002
Age	19.909	1.692	1002
Year	1.947	0.902	1002
Russell Group	0.386	0.487	976
Private school	0.141	0.348	1001
Hometown	0.184	0.387	1002

Notes: First-generation students are defined as those whose parents do not have a university degree. Parent with postgraduate degree is a binary variable equal to one if either parent obtained a postgraduate degree. Year is the year of undergraduate course respondents are currently attending. Russell Group is a binary variable indicating whether the university currently attended by the respondent is part of the Russell Group.

Table 1C.3: Distribution of Students Across Subject Disciplines

Subject cateogry	% All	% First	% Cont.	% Female	% Male	% Enroll postgr.
Medicine and Dentistry	5.21	4.01	6.41	5.45	4.97	33.92
Subjects allied to Medicine	6.71	7.41	6.01	10.71	2.78	49.42
Biological Sciences	13.23	13.03	13.43	17.37	9.15	57.77
Veterinary Science	0.90	0.80	1.00	1.41	0.40	19.00
Agriculture and Related Subjects	0.60	0.60	0.60	0.81	0.40	40.33
Physical Sciences	5.31	4.81	5.81	3.23	7.36	57.94
Mathematical Sciences	4.01	4.41	3.61	3.43	4.57	51.45
Computer Science	5.61	5.81	5.41	2.42	8.75	48.54
Engineering and Technology	8.22	8.02	8.42	2.42	13.92	50.29
Architecture	1.60	1.40	1.80	1.62	1.59	48.62
Social Studies	11.32	12.42	10.22	12.73	9.94	48.93
Law	4.71	6.21	3.21	5.05	4.37	51.72
Business and Administrative Studies	10.22	9.62	10.82	7.27	13.12	47.60
Mass Communications and Documentation	1.60	2.00	1.20	1.21	1.99	54.06
Languages	3.51	3.61	3.41	4.24	2.78	43.34
Historical and Philosophical Studies	4.91	4.21	5.61	4.85	4.97	49.00
Creative Arts and Design	8.92	8.02	9.82	11.11	6.76	46.11
Education	3.41	3.61	3.21	4.65	2.19	48.44
Observations	998	499	499	495	503	997

Notes: Subject categories refer to JACS 3.0 Principal subject codes. Column 1 reports the distribution of students in our sample across subjects. Columns 2 and 3 report the distribution for first- and continuing-generation students respectively. Columns 4 and 5 report the distribution separately for female and male respondents. P-value for a Pearson's test of equality of distribution across SES is 0.656. P-value for a Pearson's test of equality of distribution across gender is 0.000. Column 6 reports average state likelihood of continuing to postgraduate education, by subject field.

Table 1C.4: Differences in Beliefs by School Type - Continuing-Generation Students

	All	School type				Cond. gap
Belief		State	Private	Diff	P-value	
Enroll post-gr. degree	51.739	52.621	51.505	1.115	0.728	0.181
	[30.204]	[30.751]	[30.105]	(3.206)		(3.770)
Complete undergr. degree	88.124	88.276	88.068	0.208	0.895	0.267
	[14.790]	[13.507]	[15.190]	(1.570)		(1.614)
Get a First	56.691	58.026	56.302	1.724	0.450	1.720
	[21.502]	[22.334]	[21.285]	(2.281)		(2.634)
Graduate (post-gr.)	76.606	77.877	76.353	1.524	0.524	0.514
	[22.444]	[21.111]	[22.734]	(2.388)		(2.957)
Observations	500	384	116			

Notes: Standard deviations given in square brackets, standard errors given in round brackets. The sample is restricted to continuing generation students only. This table separately provides mean beliefs for the whole sample (Column 1), by whether the student attended a private or state school (Columns 2 and 3), the unconditional difference in beliefs between the two groups (Column 4), and the conditional difference in beliefs (Column 6). Column 2 refers to students who attended a state school, whilst Column 3 refers to students who attended a private school. P-values for a test of difference in means are provided in Column 5. The conditional gaps refer to the coefficients of a dummy variable for whether the student went to a private school, in an OLS regression where each belief variable is regressed on the high school type dummy, a gender dummy, age of the respondent, and university and subject fixed effects.

Table 1C.5: Mean Beliefs for Immediate and Later-Life Outcomes by Parental Education - Continuing-generation Students

	All			No postgr. qual.			Postgrad. qual.			Diff-in-diff
Belief	Undergr	Postgr	Diff	Undergr	Postgr	Diff	Undergr	Postgr	Diff	
Panel A: Immediate Outcomes										
Enjoy social life	64.345	61.916	-2.429	64.169	61.350	-2.819	64.707	63.079	-1.628	-1.191
	[20.427]	[20.296]	0.020	[19.650]	[19.663]	0.017	[21.997]	[21.553]	0.438	(2.224)
Enjoy study / work	63.920	70.204	6.284	63.958	69.193	5.235	63.841	72.274	8.433	-3.198
	[21.181]	[19.866]	0.000	[20.692]	[20.188]	0.000	[22.213]	[19.083]	0.000	(2.477)
Feel stressed	62.744	72.488	9.744	62.747	72.318	9.571	62.738	72.835	10.098	-0.526
	[22.182]	[21.335]	0.000	[21.189]	[20.233]	0.000	[24.156]	[23.493]	0.000	(2.414)
Strugle financially	44.090	58.687	14.596	46.039	59.734	13.695	40.122	56.555	16.433	-2.738
	[26.348]	[25.829]	0.000	[25.892]	[24.113]	0.000	[26.900]	[28.976]	0.000	(2.791)
Parental support	79.510	81.484	1.974	80.363	78.720	-1.643	77.762	87.146	9.384	-11.027***
	[22.735]	[21.700]	0.048	[21.285]	[22.540]	0.157	[25.431]	[18.690]	0.000	(2.063)
Immediate cost	0.000	37539.122	37539.122	0.000	37461.654	37461.654	0.000	37697.837	37697.837	-236.182
	[.]	[13331.214]	0.000	[.]	[13171.379]	0.000	[.]	[13692.327]	0.000	(1271.112)
Panel B: Later-Life Outcomes										
Earnings	43399.876	50618.122	7218.246	43428.601	50029.062	6600.461	43341.024	51824.976	8483.951	-1883.490*
	[17185.267]	[17629.888]	0.000	[18194.990]	[18023.244]	0.000	[14957.241]	[16784.397]	0.000	(1061.281)
Work full-time	82.994	85.096	2.102	81.831	83.267	1.436	85.384	88.854	3.470	-2.033*
	[17.502]	[16.884]	0.000	[17.964]	[17.971]	0.027	[16.306]	[13.697]	0.002	(1.197)
Satisfied with career	68.870	74.092	5.222	68.872	73.276	4.404	68.866	75.768	6.902	-2.499
	[18.396]	[16.610]	0.000	[17.756]	[16.937]	0.000	[19.703]	[15.834]	0.000	(1.585)
High status	55.958	61.257	5.299	57.172	61.139	3.967	53.463	61.500	8.037	-4.069***
	[23.686]	[23.233]	0.000	[23.031]	[23.258]	0.000	[24.865]	[23.250]	0.000	(1.560)
Contribution	65.491	72.798	7.307	66.068	72.665	6.596	64.305	73.073	8.768	-2.172
	[21.981]	[20.606]	0.000	[21.359]	[20.725]	0.000	[23.228]	[20.419]	0.000	(1.642)
Work-life balance	64.876	63.703	-1.174	65.033	63.588	-1.445	64.555	63.939	-0.616	-0.829
	[19.663]	[20.769]	0.144	[18.904]	[20.381]	0.127	[21.195]	[21.606]	0.681	(1.710)
Children	61.998	61.100	-0.898	62.926	61.955	-0.970	60.091	59.341	-0.750	-0.220
	[30.262]	[29.616]	0.134	[28.523]	[28.371]	0.202	[33.565]	[32.041]	0.433	(1.275)

Notes: Standard deviations given in square brackets, standard errors given in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The sample is restricted to continuing-generation students. This table provides mean beliefs for the whole subsample and by the education level of the respondent's parents. Columns 1-3 provide results for the whole sample. Columns 4-6 are for respondents for whom neither parent holds a postgraduate degree, while Columns 7-9 are for respondents for whom at least one parent holds a postgraduate qualification. Within each group, the first two columns give mean beliefs for the respective characteristic under the scenarios of having an undergraduate or postgraduate degree as highest qualification respectively. Mean beliefs are given on a 0-100 scale other than for expected earnings and immediate costs, which are in pounds. The third column gives the mean difference between these two beliefs, with the p-value for a t-test of difference in means reported underneath. Column 10 (Diff-in-diff) gives the average difference for respondents for whom neither parent has a postgraduate degree minus the average difference for respondents for whom at least one parent has a postgraduate degree.

Table 1C.6: Mean Beliefs for Immediate and Later-Life Outcomes by School Type - Continuing-generation Students

	All			Private school			State school			Diff-in-diff
Belief	Undergr	Postgr	Diff	Undergr	Postgr	Diff	Undergr	Postgr	Diff	
Panel A: Immediate Outcomes										
Enjoy social life	64.345	61.916	-2.429	66.862	63.422	-3.440	63.630	61.466	-2.164	-1.276
	[20.427]	[20.296]	0.020	[19.400]	[17.812]	0.079	[20.701]	[21.014]	0.079	(2.476)
Enjoy study / work	63.920	70.204	6.284	64.948	69.931	4.983	63.601	70.285	6.684	-1.701
	[21.181]	[19.866]	0.000	[18.788]	[16.244]	0.018	[21.893]	[20.882]	0.000	(2.762)
Feel stressed	62.744	72.488	9.744	64.017	72.612	8.595	62.368	72.520	10.151	-1.557
	[22.182]	[21.335]	0.000	[21.566]	[19.488]	0.000	[22.406]	[21.873]	0.000	(2.686)
Strugle financially	44.090	58.687	14.596	45.617	54.626	9.009	43.632	59.906	16.274	-7.265**
	[26.348]	[25.829]	0.000	[26.186]	[25.945]	0.001	[26.414]	[25.703]	0.000	(3.099)
Parental support	79.510	81.484	1.974	76.879	81.078	4.198	80.402	81.608	1.206	2.992
	[22.735]	[21.700]	0.048	[21.874]	[19.113]	0.059	[22.908]	[22.473]	0.278	(2.352)
Immediate cost	0.000	37539.122	37539.122	0.000	40597.036	40597.036	0.000	36561.227	36561.227	4035.809***
	[.]	[13331.214]	0.000	[.]	[13761.851]	0.000	[.]	[13050.407]	0.000	(1400.883)
Panel B: Later-Life Outcomes										
Earnings	43399.876	50618.122	7218.246	47452.802	56564.267	9111.466	42092.799	48759.856	6667.057	2444.408**
	[17185.267]	[17629.888]	0.000	[17688.674]	[17520.379]	0.000	[16806.633]	[17266.660]	0.000	(1179.896)
Work full-time	82.994	85.096	2.102	82.284	84.319	2.034	83.234	85.307	2.073	-0.038
	[17.502]	[16.884]	0.000	[17.154]	[16.301]	0.104	[17.637]	[17.086]	0.001	(1.335)
Satisfied with career	68.870	74.092	5.222	67.966	72.991	5.026	69.138	74.479	5.341	-0.315
	[18.396]	[16.610]	0.000	[16.378]	[14.777]	0.002	[18.998]	[17.115]	0.000	(1.766)
High status	55.958	61.257	5.299	59.543	64.724	5.181	54.971	60.341	5.370	-0.189
	[23.686]	[23.233]	0.000	[22.541]	[20.894]	0.000	[23.904]	[23.717]	0.000	(1.748)
Contribution	65.491	72.798	7.307	66.526	73.034	6.509	65.294	72.831	7.536	-1.028
	[21.981]	[20.606]	0.000	[19.782]	[17.720]	0.000	[22.532]	[21.352]	0.000	(1.832)
Work-life balance	64.876	63.703	-1.174	63.845	62.431	-1.414	65.180	64.078	-1.102	-0.312
	[19.663]	[20.769]	0.144	[19.908]	[20.403]	0.338	[19.630]	[20.916]	0.246	(1.905)
Children	61.998	61.100	-0.898	59.828	59.060	-0.767	62.690	61.784	-0.906	0.139
	[30.262]	[29.616]	0.134	[30.839]	[29.893]	0.499	[30.126]	[29.550]	0.197	(1.419)

Notes: Standard deviations given in square brackets, standard errors given in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. This table provides mean beliefs for the whole sample and by whether or not the student attended a private school. The sample is restricted to continuing-generation students only. Columns 1-3 provide results for the whole sample. Columns 4-6 are for respondents who attended a private school, while Columns 7-9 are for respondents who attended a state school. Within each group, the first two columns give mean beliefs for the respective characteristic under the scenarios of having an undergraduate or postgraduate degree as highest qualification respectively. Mean beliefs are given on a 0-100 scale other than for expected earnings and immediate costs, which are in pounds. The third column gives the mean difference between these two beliefs, with the p-value for a t-test of difference in means reported underneath. Column 10 (Diff-in-diff) gives the average difference for respondents who attended a private school minus the average difference for respondents who attended a state school.

Table 1C.7: Removing Outliers

	All		First generation		Continuing generation		Difference (p-value)	
	Coef.	WTP	Coef.	WTP	Coef.	WTP	Coef.	WTP
Expected earnings at age 35 ($10000\gamma_y$)	0.250***		0.063		0.346***		0.068	
	(0.076)		(0.116)		(0.104)			
Enjoy social life (Δu_1)	0.710***	283.341**	0.924***	1472.991	0.595*	171.775	0.425	0.638
	(0.207)	(122.134)	(0.263)	(2769.221)	(0.318)	(108.323)		
Enjoy study / work (Δu_2)	1.085***	433.169***	0.730***	1163.730	1.527***	441.316***	0.054	0.735
	(0.212)	(146.313)	(0.265)	(2129.063)	(0.318)	(151.732)		
Feel stressed (Δu_3)	-0.257	-102.573	-0.127	-202.838	-0.330	-95.299	0.582	0.842
	(0.180)	(78.512)	(0.244)	(534.030)	(0.276)	(84.800)		
Struggle financially (Δu_4)	-0.478***	-190.821**	-0.517**	-824.574	-0.340	-98.212	0.567	0.632
	(0.153)	(85.771)	(0.212)	(1517.903)	(0.226)	(75.276)		
Parental support (Δu_5)	1.169***	466.807***	1.280***	2041.164	0.981***	283.528**	0.501	0.649
	(0.216)	(169.999)	(0.304)	(3862.326)	(0.325)	(125.977)		
Immediate cost ($10000\gamma_c$)	-0.066**	-0.264**	-0.114***	-1.810	-0.003	-0.008	0.037	0.596
	(0.026)	(0.129)	(0.039)	(3.398)	(0.036)	(0.105)		
Work full time at age 35 (Δu_6)	-0.377	-150.543	-1.270	-2024.732	0.809	233.821	0.130	0.583
	(0.702)	(281.507)	(1.004)	(4105.360)	(0.937)	(287.884)		
Satisfied with career at age 35 (Δu_7)	0.890	355.193	0.368	587.438	1.503*	434.141	0.342	0.933
	(0.589)	(265.707)	(0.846)	(1803.706)	(0.843)	(282.275)		
High status at age 35 (Δu_8)	0.868	346.434	0.592	943.985	0.988	285.523	0.756	0.794
	(0.629)	(291.042)	(0.954)	(2512.298)	(0.846)	(277.003)		
Contribute to society at age 35 (Δu_9)	0.339	135.538	1.011	1611.104	-0.433	-125.137	0.249	0.604
	(0.620)	(256.530)	(0.864)	(3342.898)	(0.906)	(257.154)		
Work-life balance at age 35 (Δu_{10})	1.037*	414.005	1.438*	2292.543	0.669	193.218	0.506	0.652
	(0.586)	(271.445)	(0.798)	(4652.575)	(0.837)	(244.878)		
Have children at age 35 (Δu_{11})	1.077	430.108	1.520	2423.725	0.585	169.093	0.497	0.638
	(0.704)	(314.663)	(0.936)	(4779.069)	(1.012)	(300.056)		
Postgraduate graduation probability	0.292**	116.617	0.605***	963.928	-0.093	-26.947	0.014	0.593
	(0.142)	(71.084)	(0.194)	(1855.570)	(0.208)	(59.430)		
Observations	823	823	404	404	419	419		
Variance explained	0.233		0.263		0.225			

Notes: Standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Column 1 presents the estimates of the choice model for the whole sample, while column 2 presents the willingness-to-pay calculations. Columns 3-4 present the results for first-generation students, columns 5-6 present the results for continuing-generation students. For the willingness to pay calculations, standard errors are calculated using the delta method. Continuing-generation students are defined as those students who have at least one parent with university education.

Table 1C.8: Removing Respondents from Non-English Institutions

	All		First generation		Continuing generation		Difference (p-value)	
	Coef.	WTP	Coef.	WTP	Coef.	WTP	Coef.	WTP
Expected earnings at age 35 ($10000\gamma_y$)	0.223***		0.103		0.326***		0.115	
	(0.070)		(0.098)		(0.102)			
Enjoy social life (Δu_1)	0.499***	223.881*	0.805***	781.624	0.217	66.681	0.124	0.370
	(0.191)	(114.599)	(0.234)	(792.320)	(0.302)	(96.937)		
Enjoy study / work (Δu_2)	1.139***	510.765***	0.880***	854.367	1.583***	485.732***	0.055	0.657
	(0.186)	(175.660)	(0.243)	(813.043)	(0.276)	(172.223)		
Feel stressed (Δu_3)	-0.299*	-134.276*	-0.460**	-446.586	-0.180	-55.081	0.391	0.404
	(0.157)	(80.335)	(0.221)	(463.300)	(0.241)	(75.461)		
Struggle financially (Δu_4)	-0.440***	-197.555**	-0.283	-275.129	-0.486**	-149.197*	0.479	0.695
	(0.143)	(89.656)	(0.199)	(310.628)	(0.207)	(81.464)		
Parental support (Δu_5)	1.031***	462.312***	0.914***	887.454	1.090***	334.443**	0.645	0.540
	(0.187)	(167.059)	(0.247)	(892.371)	(0.291)	(133.620)		
Immediate cost ($10000\gamma_c$)	-0.091***	-0.408***	-0.119***	-1.159	-0.045	-0.139	0.142	0.357
	(0.025)	(0.151)	(0.033)	(1.102)	(0.038)	(0.116)		
Work full time at age 35 (Δu_6)	-0.842	-377.736	-2.062***	-2001.516	0.499	153.188	0.020	0.308
	(0.571)	(283.090)	(0.737)	(2097.941)	(0.817)	(261.025)		
Satisfied with career at age 35 (Δu_7)	1.302**	584.252*	0.910	883.538	1.895***	581.227**	0.366	0.816
	(0.561)	(333.115)	(0.820)	(1267.357)	(0.717)	(296.093)		
High status at age 35 (Δu_8)	0.997**	447.307	1.089	1057.591	0.866	265.524	0.824	0.554
	(0.494)	(290.377)	(0.702)	(1315.249)	(0.725)	(258.788)		
Contribute to society at age 35 (Δu_9)	-0.102	-45.550	0.763	740.445	-0.918	-281.711	0.094	0.339
	(0.499)	(223.434)	(0.726)	(1046.584)	(0.695)	(224.679)		
Work-life balance at age 35 (Δu_{10})	0.778*	349.135	0.452	438.593	1.049	321.782	0.510	0.886
	(0.469)	(242.206)	(0.643)	(781.885)	(0.639)	(221.833)		
Have children at age 35 (Δu_{11})	1.108*	497.240	0.199	193.200	1.671**	512.568*	0.190	0.722
	(0.572)	(316.676)	(0.829)	(848.896)	(0.759)	(295.354)		
Graduate postgr.	0.460***	206.298**	0.628***	609.446	0.162	49.619	0.084	0.358
	(0.134)	(89.020)	(0.172)	(605.535)	(0.207)	(65.624)		
Observations	939	939	473	473	466	466		
Variance explained	0.269		0.282		0.284			

Notes: Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Column 1 presents the estimates of the choice model for the whole sample, while column 2 presents the willingness-to-pay calculations. Columns 3-4 present the results for first-generation students, columns 5-6 present the results for continuing-generation students. For the willingness to pay calculations, standard errors are calculated using the delta method. Continuing-generation students are defined as those students who have at least one parent with university education. The sample only includes students for whom we have information on the university currently attendend, and the institution is in England.

Table 1C.9: Removing Respondents For Whom the Probability of Completing Undergraduate Degree is Below 50%

	All		First generation		Continuing generation		Difference (p-value)	
	Coef.	WTP	Coef.	WTP	Coef.	WTP	Coef.	WTP
Expected earnings at age 35 ($10000\gamma_y$)	0.180***		0.060		0.303***		0.075	
	(0.067)		(0.095)		(0.098)			
Enjoy social life (Δu_1)	0.458**	254.529*	0.735***	1229.670	0.181	59.807	0.145	0.561
	(0.190)	(146.282)	(0.239)	(2010.709)	(0.296)	(101.233)		
Enjoy study / work (Δu_2)	1.157***	643.463**	0.929***	1552.941	1.529***	504.849***	0.091	0.668
	(0.182)	(255.228)	(0.238)	(2435.645)	(0.265)	(183.413)		
Feel stressed (Δu_3)	-0.270*	-150.382	-0.362*	-605.989	-0.220	-72.694	0.655	0.589
	(0.152)	(98.671)	(0.220)	(983.543)	(0.230)	(79.652)		
Struggle financially (Δu_4)	-0.521***	-289.418**	-0.482**	-806.341	-0.461**	-152.145*	0.938	0.615
	(0.136)	(134.321)	(0.193)	(1297.543)	(0.194)	(84.326)		
Parental support (Δu_5)	1.066***	592.480**	0.886***	1482.150	1.236***	407.933**	0.362	0.655
	(0.188)	(243.016)	(0.247)	(2401.990)	(0.293)	(158.490)		
Immediate cost ($10000\gamma_c$)	-0.074***	-0.409**	-0.104***	-1.731	-0.024	-0.079	0.096	0.549
	(0.024)	(0.185)	(0.032)	(2.757)	(0.036)	(0.116)		
Work full time at age 35 (Δu_6)	-0.674	-374.812	-1.840**	-3078.056	0.512	168.883	0.027	0.522
	(0.562)	(340.820)	(0.753)	(5066.735)	(0.749)	(259.336)		
Satisfied with career at age 35 (Δu_7)	1.327**	737.929*	0.897	1500.736	1.941***	640.888**	0.323	0.771
	(0.541)	(434.988)	(0.799)	(2937.844)	(0.691)	(319.783)		
High status at age 35 (Δu_8)	1.080**	600.373	1.153*	1927.923	0.888	293.331	0.788	0.637
	(0.480)	(389.580)	(0.686)	(3454.168)	(0.707)	(276.920)		
Contribute to society at age 35 (Δu_9)	0.049	27.103	1.108	1853.524	-0.887	-292.925	0.043	0.508
	(0.491)	(273.922)	(0.720)	(3239.311)	(0.678)	(233.717)		
Work-life balance at age 35 (Δu_{10})	0.697	387.463	0.344	574.568	1.027	339.180	0.441	0.872
	(0.458)	(295.740)	(0.630)	(1441.918)	(0.626)	(229.140)		
Have children at age 35 (Δu_{11})	1.149**	638.782	0.238	398.558	1.775**	586.181*	0.173	0.909
	(0.570)	(417.456)	(0.838)	(1614.930)	(0.754)	(326.028)		
Postgraduate graduation probability	0.403***	224.303**	0.596***	996.600	0.072	23.663	0.042	0.549
	(0.129)	(113.090)	(0.167)	(1623.118)	(0.197)	(65.460)		
Observations	971	971	489	489	482	482		
Variance explained	0.268		0.282		0.283			

Notes: Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. The sample is restricted to respondents for whom the self-reported probability of completing their undergraduate degree is 50% or above. Column 1 presents the estimates of the choice model for the whole sample, while column 2 presents the willingness-to-pay calculations. Columns 3-4 present the results for first-generation students, columns 5-6 present the results for continuing-generation students. For the willingness to pay calculations, standard errors are calculated using the delta method. Continuing-generation students are defined as those students who have at least one parent with university education.

Table 1C.10: Differences in Experiences by Parental Education

	All		Parental background		
Experience	N		First	Continuing	P-value
Enjoy social life	1002	67.918	65.002	70.834	0.000
		(24.249)	(25.534)	(22.542)	
Meet people	1001	68.563	67.389	69.740	0.088
		(21.771)	(22.967)	(20.458)	
Little contact	998	38.844	37.507	40.170	0.148
		(29.091)	(29.407)	(28.742)	
Feel lonely	998	47.203	45.325	49.074	0.054
		(30.787)	(31.818)	(29.639)	
Enjoy studying	1002	68.246	67.048	69.443	0.087
		(22.153)	(23.149)	(21.064)	
Material interesting	1002	70.107	68.651	71.563	0.029
		(21.138)	(21.761)	(20.415)	
Material too hard	999	47.974	47.643	48.304	0.682
		(25.488)	(26.000)	(24.988)	
Feel stressed	997	52.000	52.478	51.523	0.596
		(28.406)	(29.207)	(27.605)	
Struggle financially	998	43.794	45.284	42.297	0.126
		(30.791)	(30.925)	(30.614)	
Have enough money	1000	53.044	48.623	57.447	0.000
		(27.367)	(27.270)	(26.772)	
Parental support	1001	86.962	83.976	89.954	0.000
		(20.468)	(23.452)	(16.447)	
Life better than expected	999	59.934	57.752	62.112	0.008
		(25.826)	(26.815)	(24.635)	

Notes: Standard deviations given in parentheses. This table separately provides mean university experiences on a 0-100 scale for the whole sample (Column 2) and by whether at least one parent has a degree (Columns 3 and 4). Column 3 refers to first-generation students, whilst Column 4 refers to continuing-generation students. P-values for a test of difference in means are provided in Column 5. The number of observations is reported in Column 1.

Table 1C.11: Differences in Experiences by Parental Education - Continuing-generation Students

	All		Parental background		
Experience	N		No postgr.	Postgr.	P-value
Enjoy social life	501	70.834	70.718	71.073	0.869
		(22.542)	(22.520)	(22.655)	
Meet people	500	69.740	69.493	70.252	0.698
		(20.458)	(20.037)	(21.357)	
Little contact	501	40.170	41.341	37.762	0.191
		(28.742)	(28.177)	(29.812)	
Feel lonely	500	49.074	50.286	46.591	0.191
		(29.639)	(28.947)	(30.950)	
Enjoy studying	501	69.443	69.662	68.994	0.740
		(21.064)	(19.993)	(23.167)	
Material interesting	501	71.563	72.030	70.604	0.464
		(20.415)	(19.153)	(22.822)	
Material too hard	500	48.304	49.350	46.141	0.179
		(24.988)	(24.792)	(25.328)	
Feel stressed	499	51.523	51.497	51.577	0.976
		(27.605)	(27.159)	(28.585)	
Struggle financially	498	42.297	44.863	37.025	0.007
		(30.614)	(29.893)	(31.485)	
Have enough money	501	57.447	58.359	55.573	0.275
		(26.772)	(25.506)	(29.195)	
Parental support	500	89.954	88.491	92.951	0.004
		(16.447)	(17.144)	(14.512)	
Life better than expected	500	62.112	64.509	57.201	0.002
		(24.635)	(23.229)	(26.697)	

Notes: Standard deviations given in parentheses. This table separately provides mean university experiences on a 0-100 scale for the subsample of continuing-generation students (Column 2) and by whether at least one parent has a postgraduate degree (Columns 3 and 4). Column 3 refers to students whose parents only have an undergraduate degree, whilst Column 4 refers to students for whom at least one parent has a postgraduate degree. P-values for a test of difference in means are provided in Column 5. The number of observations is reported in Column 1.

Table 1C.12: Differences in Time Allocation by Parental Education

	All		Parental background		
Time Allocation	N		First	Continuing	P-value
Time lectures	956	11.768	12.283	11.271	0.042
		(7.679)	(7.516)	(7.809)	
Time studying	960	12.747	12.186	13.296	0.102
		(10.509)	(10.372)	(10.623)	
Time student societies	958	2.137	1.617	2.643	0.000
		(3.464)	(3.099)	(3.720)	
Time socialising with friends	955	10.234	10.537	9.936	0.406
		(11.165)	(11.540)	(10.788)	
Time work for pay	952	3.479	3.998	2.975	0.015
		(6.520)	(7.046)	(5.929)	
Time work not for pay	951	0.372	0.362	0.383	0.850
		(1.697)	(1.793)	(1.599)	
% Work for pay	952	0.335	0.318	0.352	0.263
		(0.472)	(0.466)	(0.478)	
% Work not for pay	951	0.078	0.057	0.098	0.020
		(0.268)	(0.233)	(0.297)	
Total time work	338	10.568	12.494	8.837	0.000
		(7.547)	(7.052)	(7.576)	
Work related to study	368	37.008	31.503	42.110	0.003
		(34.585)	(35.208)	(33.283)	
Work will help in future career	368	51.842	46.254	57.021	0.001
		(32.083)	(32.954)	(30.434)	
Summer: Number of weeks engaged in work	1001	4.287	4.579	3.994	0.066
		(5.026)	(5.339)	(4.679)	
Summer work: related to studies	563	36.197	31.727	40.033	0.006
		(35.744)	(36.436)	(34.742)	
Summer work: parents knew employer	567	0.280	0.225	0.328	0.007
		(0.450)	(0.419)	(0.470)	
Summer work: parents helped with application	567	0.150	0.103	0.190	0.004
		(0.357)	(0.305)	(0.393)	

Notes: Standard deviations given in parentheses. This table separately provides mean values for the time allocation variables for the whole sample (Column 1) and by whether at least one parent has a degree (Columns 2 and 3). Column 2 refers to first-generation students, whilst Column 3 refers to continuing-generation students. P-values for a test of difference in means are provided in Column 4.

Table 1C.13: Differences in Time Allocation by Parental Education - Continuing-generation Students

Time Allocation	Cont. gen. N		Parental background No postgr.	Postgr.	P-value
Time lectures	486	11.271	10.836	12.164	0.079
		(7.809)	(7.960)	(7.436)	
Time studying	485	13.296	13.742	12.373	0.184
		(10.623)	(10.980)	(9.811)	
Time student societies	485	2.643	2.701	2.522	0.621
		(3.720)	(3.815)	(3.522)	
Time socialising with friends	482	9.936	9.298	11.269	0.060
		(10.788)	(11.153)	(9.883)	
Time work for pay	483	2.975	2.933	3.064	0.820
		(5.929)	(5.956)	(5.892)	
Time work not for pay	481	0.383	0.308	0.538	0.139
		(1.599)	(1.353)	(2.014)	
% Work for pay	483	0.352	0.371	0.312	0.204
		(0.478)	(0.484)	(0.465)	
% Work not for pay	481	0.098	0.095	0.103	0.804
		(0.297)	(0.294)	(0.304)	
Total time work	178	8.837	8.645	9.246	0.623
		(7.576)	(7.960)	(6.736)	
Work related to study	191	42.110	45.539	35.143	0.042
		(33.283)	(31.327)	(36.207)	
Work will help in future career	191	57.021	59.016	52.968	0.197
		(30.434)	(28.701)	(33.559)	
Summer: Number of weeks engaged in work	500	3.994	3.958	4.067	0.808
		(4.679)	(4.566)	(4.915)	
Summer work: related to studies	303	40.033	41.609	36.635	0.247
		(34.742)	(34.712)	(34.745)	
Summer work: parents knew employer	305	0.328	0.349	0.281	0.241
		(0.470)	(0.478)	(0.452)	
Summer work: parents helped with application	305	0.190	0.220	0.125	0.050
		(0.393)	(0.415)	(0.332)	

Notes: Standard deviations given in parentheses. This table separately provides mean values for the time allocation variables for the sample of continuing-generation students (Column 1) and by whether at least one parent has a post-graduate degree (Columns 2 and 3). Column 2 refers to students whose parents do not have a postgraduate qualification, whilst Column 3 refers to students for whom at least one parent has a postgraduate degree. P-values for a test of difference in means are provided in Column 4.

Table 1C.14: Differences in Student Finances by Parental Education

Finances	All N		Parental background First	Continuing	P-value
Loan for tuition fees	1002	0.883	0.948	0.818	0.000
		(0.321)	(0.222)	(0.386)	
Money from parents / family	117	0.769	0.500	0.846	0.000
		(0.423)	(0.510)	(0.363)	
Money from work	117	0.299	0.192	0.330	0.180
		(0.460)	(0.402)	(0.473)	
Savings	117	0.171	0.154	0.176	0.795
		(0.378)	(0.368)	(0.383)	
Other sources	117	0.179	0.308	0.143	0.054
		(0.385)	(0.471)	(0.352)	
Living expenses (£)	1001	600.100	552.200	647.904	0.000
		(382.217)	(372.576)	(386.084)	

Notes: Standard deviations given in parentheses. This table separately provides mean values for student finances for the whole sample (Column 1) and by whether at least one parent has a degree (Columns 2 and 3). Column 2 refers to first-generation students, whilst Column 3 refers to continuing-generation students. P-values for a test of difference in means are provided in Column 4.

Table 1C.15: Differences in Student Finances by Parental Education - Continuing-generation Students

	Cont. gen.		Parental background		
Finances	N		No Postgr.	Postgr.	P-value
Loan for tuition fees	501	0.818	0.825	0.805	0.586
		(0.386)	(0.381)	(0.398)	
Money from parents / family	91	0.846	0.898	0.750	0.062
		(0.363)	(0.305)	(0.440)	
Money from work	91	0.330	0.441	0.125	0.002
		(0.473)	(0.501)	(0.336)	
Savings	91	0.176	0.186	0.156	0.722
		(0.383)	(0.393)	(0.369)	
Other sources	91	0.143	0.119	0.188	0.376
		(0.352)	(0.326)	(0.397)	
Living expenses (£)	501	647.904	646.291	651.220	0.893
		(386.084)	(387.444)	(384.435)	

Notes: Standard deviations given in parentheses. This table separately provides mean values for student finances for the sample of continuing-generation students (Column 1) and by whether at least one parent has a post-graduate degree (Columns 2 and 3). Column 2 refers to students whose parents do not have a postgraduate qualification, whilst Column 3 refers to students for whom at least one parent has a postgraduate degree. P-values for a test of difference in means are provided in Column 4.

Table 1C.16: Determinants of Perceived Returns 1-2 Years after Graduation

	Social life	Study / work	Stressed	Struggle	Parents
First generation	0.002	-0.010	0.026	0.026	-0.004
	(0.019)	(0.022)	(0.020)	(0.024)	(0.020)
Parent with graduate degree	0.041	0.041	-0.028	0.014	0.121***
	(0.026)	(0.029)	(0.028)	(0.032)	(0.025)
Get a First	0.048	0.076	-0.024	-0.074	0.087*
	(0.046)	(0.050)	(0.050)	(0.056)	(0.047)
Female	-0.019	0.032*	0.052***	0.050**	-0.006
	(0.018)	(0.019)	(0.019)	(0.023)	(0.018)
Age	0.001	0.007	-0.005	0.011*	-0.007
	(0.005)	(0.006)	(0.005)	(0.007)	(0.005)
Social life	0.019*	-0.011	0.030***	0.035***	0.004
	(0.010)	(0.011)	(0.011)	(0.013)	(0.011)
Course material	0.006	0.052***	-0.014	0.010	-0.008
	(0.011)	(0.012)	(0.011)	(0.013)	(0.010)
Stress	-0.012	-0.010	0.029***	0.003	0.010
	(0.009)	(0.010)	(0.010)	(0.011)	(0.009)
Financial struggles	0.004	0.016	-0.001	0.083***	0.009
	(0.009)	(0.011)	(0.010)	(0.012)	(0.010)
Parental support	-0.019**	-0.014	0.009	0.022*	0.015
	(0.009)	(0.011)	(0.010)	(0.012)	(0.010)
Life better than expected	0.036***	0.002	-0.033***	-0.027**	0.002
	(0.011)	(0.013)	(0.011)	(0.013)	(0.012)
Observations	962	961	961	961	961
R Squared	0.222	0.237	0.217	0.248	0.187
University fixed effects	Y	Y	Y	Y	Y
Subject fixed effects	Y	Y	Y	Y	Y

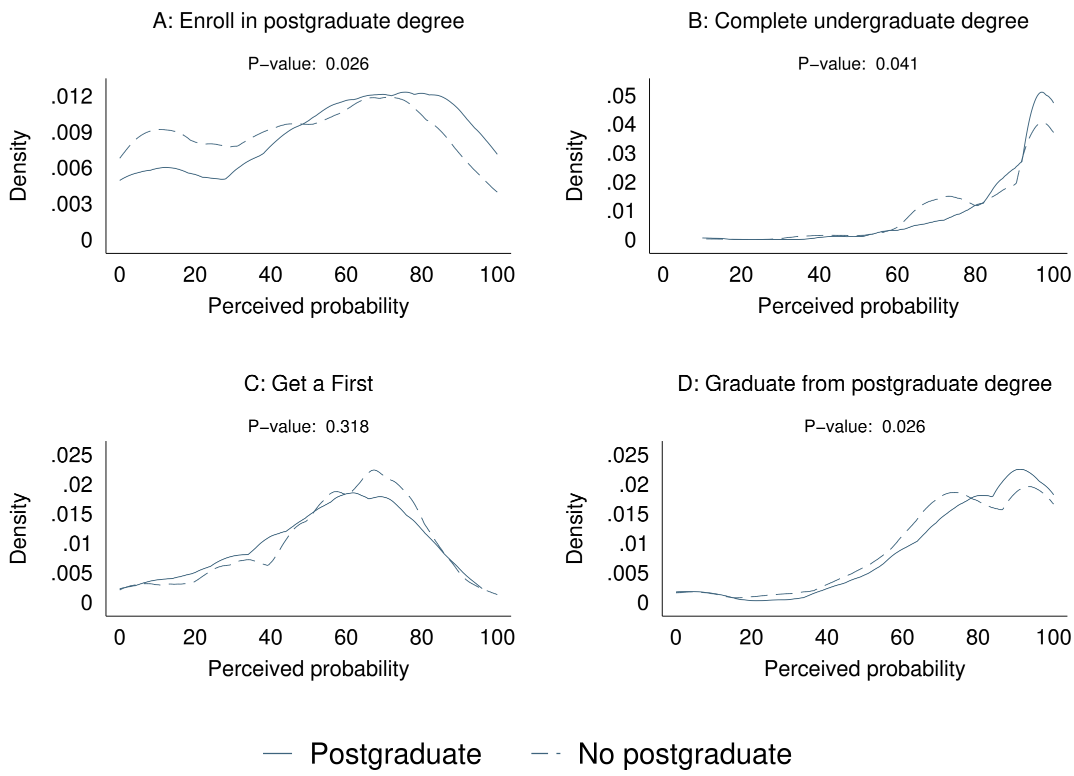
Notes: Robust standard errors from OLS estimation in parentheses. * p<0.10, ** p<0.05, *** p<0.01. All dependent variables are beliefs about returns (postgraduate - work), see overview of elicited beliefs about returns in Table 1. The dependent variable is indicated in the column heading. Social life, course material, stress, and financial situation refer to the first factor from the related variables.

Table 1C.17: Observed and perceived returns to postgraduate education in terms of annual earnings

	UK HLS	Beliefs
Postgraduate degree	6,035.234***	7,218.246***
	(1,843.651)	(499.577)
First gen. × Postgr. degree	-2,892.623	-1,496.442**
	(2,205.555)	(714.386)
First generation	-2,425.178*	-3,052.030***
	(1,406.900)	(1,085.339)
Female	-7,263.812***	-6,218.855***
	(1,026.562)	(1,033.451)
Constant	39,476.855***	46,471.991***
	(1,313.952)	(894.828)
Observations	1,108	2,002
R-squared	0.086	0.074

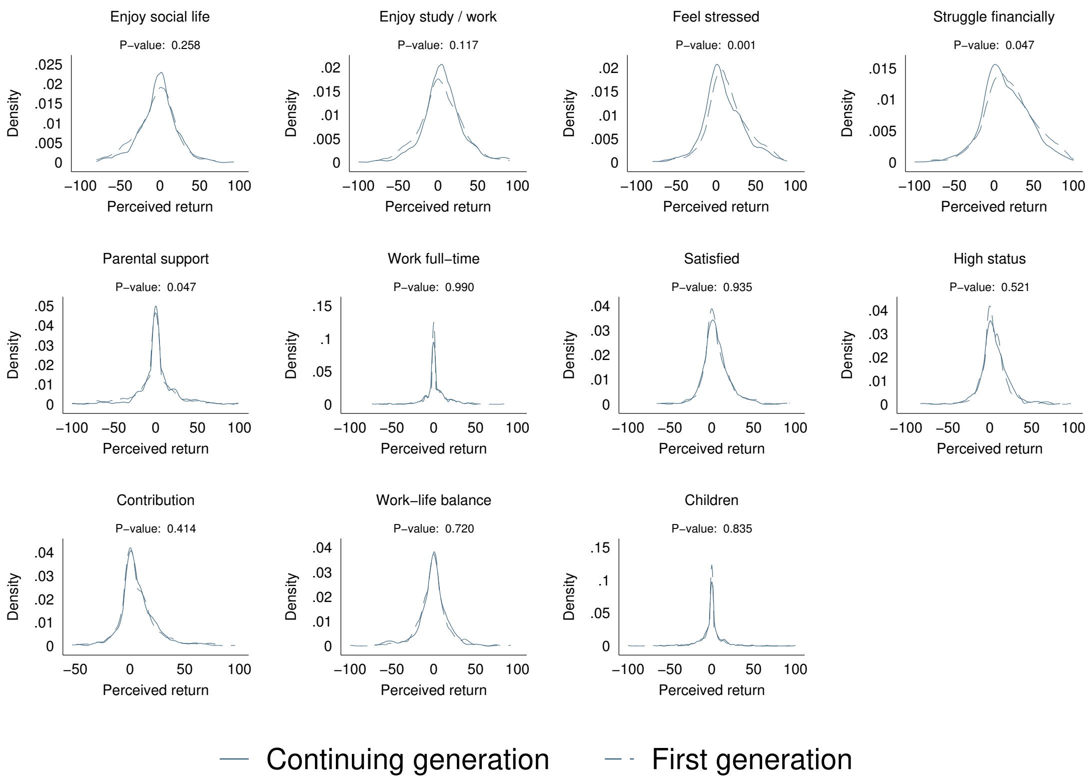
Notes: The first column is estimated using waves 6-8 of the UK Household Longitudinal Study. The sample is restricted to individuals aged 32-38 with at least a first degree or equivalent and employed full time. The dependent variable is total gross annual labour earnings (averaged over the period of observation), for individuals who report strictly positive earnings. We control for age distance from 35. The second column is estimated using our sample while taking each individual twice, once for each scenario. OLS estimation technique is used. Standard errors in parentheses, and clustered at the individual level in column 2. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Figure 1C.1: Differences in Beliefs by Parental Education - Continuing-Generation Students



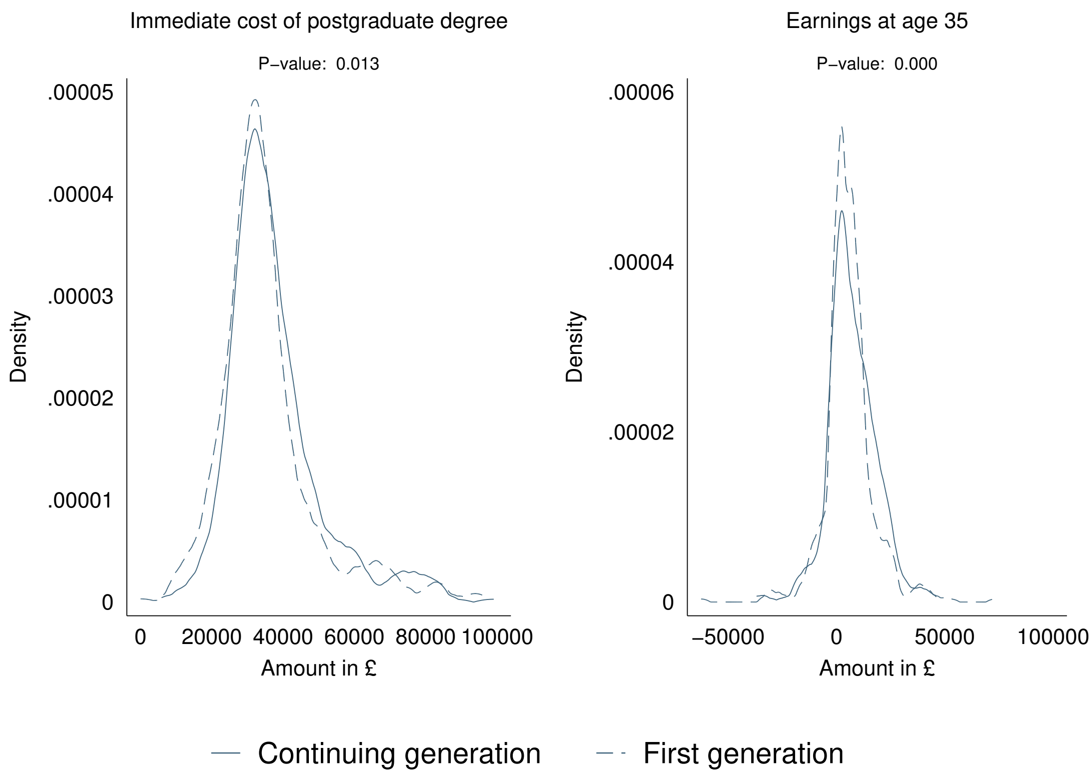
Notes: The different panels depict the kernel densities of individual beliefs about the likelihood of enrolling in a postgraduate degree (Panel A), graduating from their undergraduate degree (Panel B), getting a First in their undergraduate degree (Panel C), and graduating from their postgraduate degree (Panel D). The densities are depicted for students whose parents do not (dashed line) and do (solid line) hold a postgraduate qualification, respectively. The sample is restricted to continuing-generation students only. Reported p-values are from Kolmogorov-Smirnov tests of equality of distributions.

Figure 1C.2: Distribution of Perceived Returns to Postgraduate Education by Parental Education



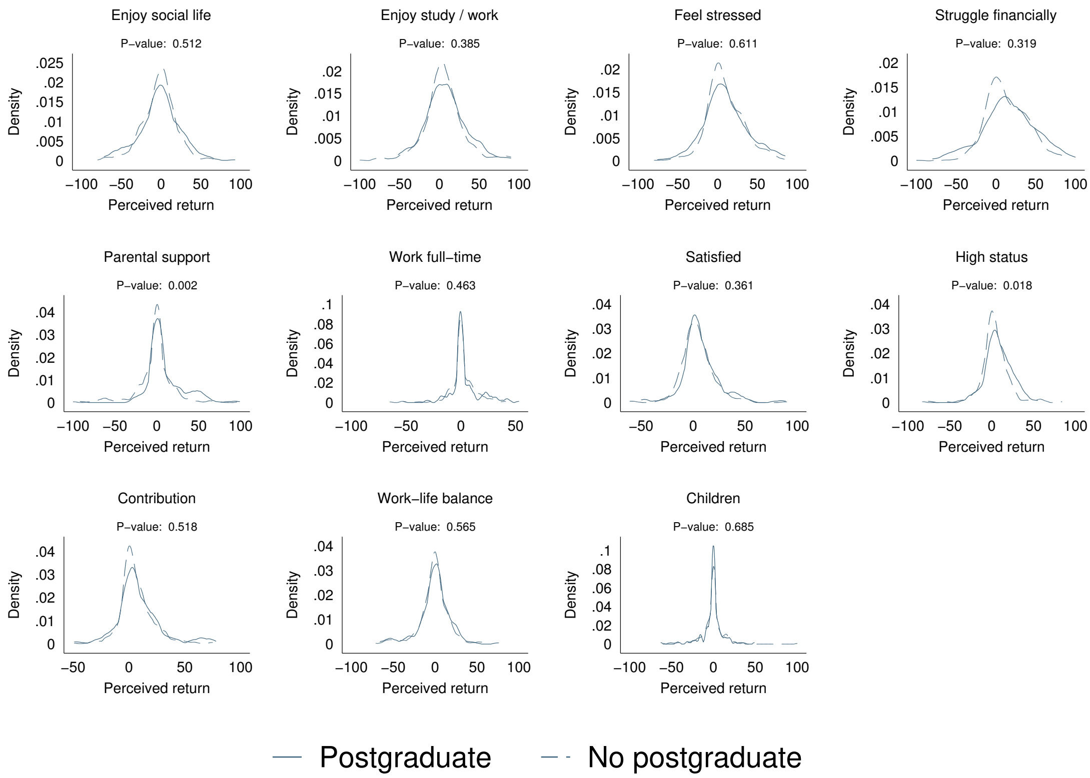
Notes: The different panels depict the kernel densities of individual beliefs about returns to postgraduate education in terms of the different binary outcomes 1-2 years after graduation and at age 35. The densities are depicted for first-generation students (dashed line) and continuing-generation students (solid line). Reported p-values are from Kolmogorov-Smirnov tests of equality of distributions.

Figure 1C.3: Distribution of Immediate Costs and Expected Earnings by Parental Education



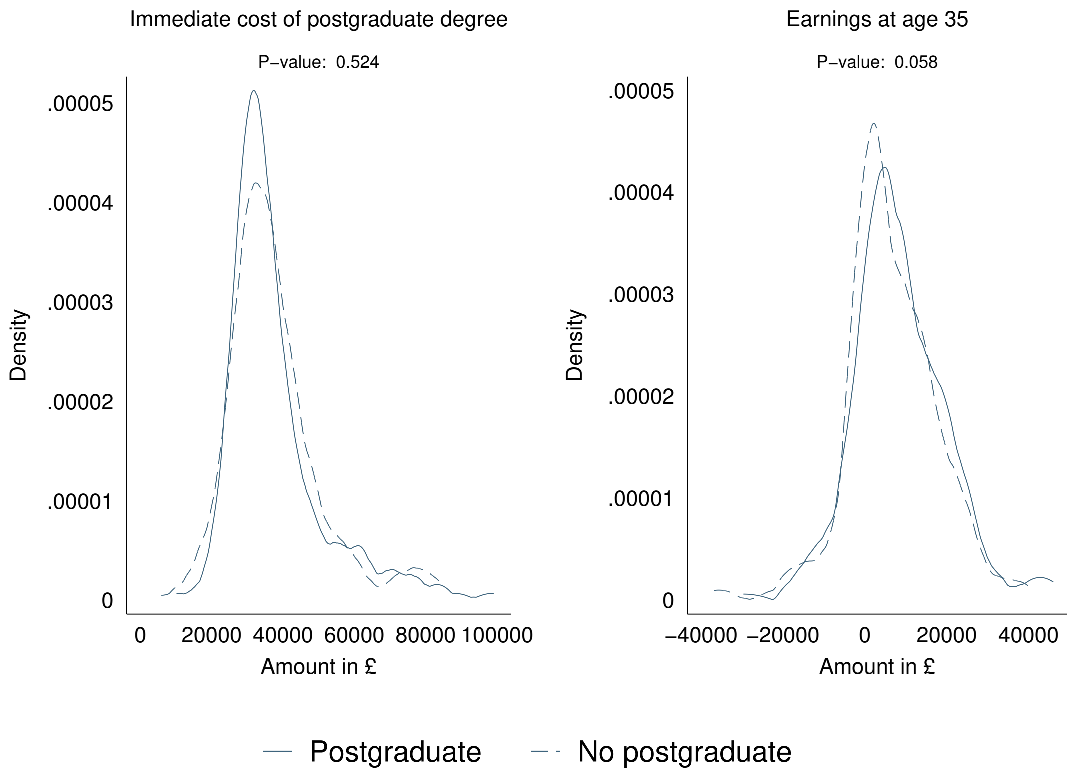
Notes: The two panels depict the kernel densities of individual beliefs about expected immediate costs of postgraduate education, calculated as the sum of expected tuition fees and forgone earnings in the 1-2 years after finishing the undergraduate degree, and expected earnings at age 35 conditional on working full-time. The densities are depicted separately for first-generation students (dashed line) and continuing-generation students (solid line). Reported p-values are from Kolmogorov-Smirnov tests of equality of distributions.

Figure 1C.4: Distribution of Perceived Returns to Postgraduate Education by Parental Education - Continuing-generation Students



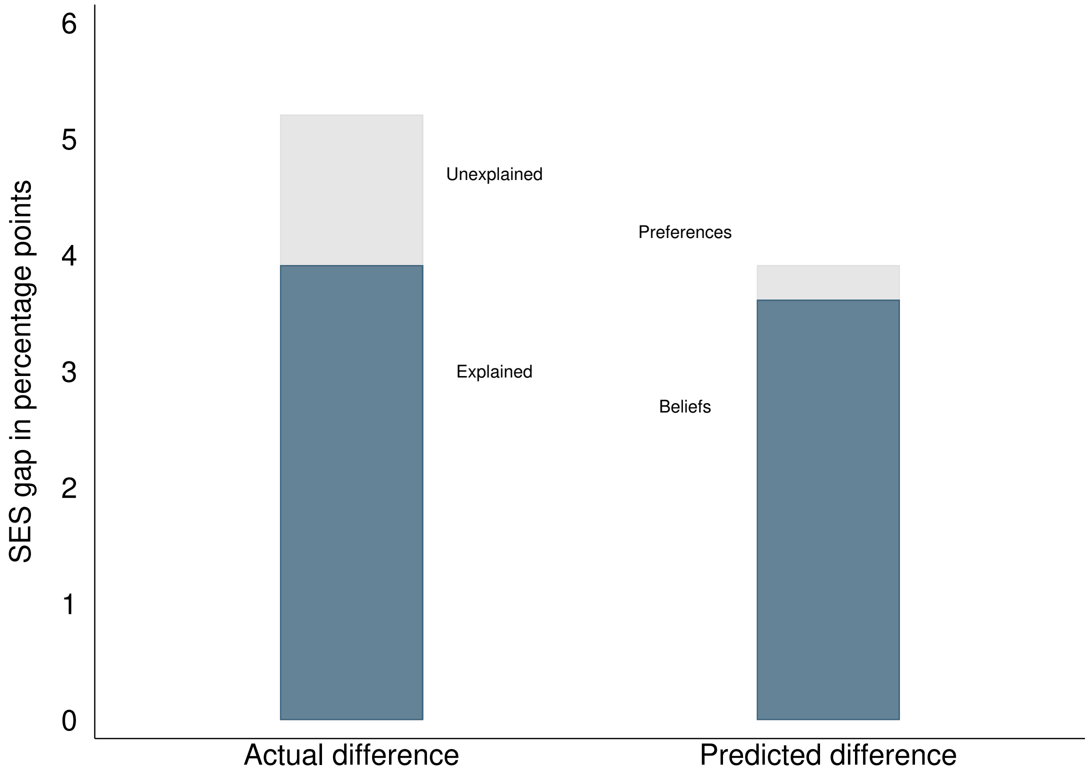
Notes: The different panels depict the kernel densities of individual beliefs about returns to postgraduate education in terms of the different binary outcomes 1-2 years after graduation and at age 35. The densities are depicted for students whose parents do not (dashed line) and do (solid line) hold a postgraduate qualification, respectively. The sample is restricted to continuing-generation. Reported p-values are from Kolmogorov-Smirnov tests of equality of distributions.

Figure 1C.5: Distribution of Immediate Costs Expected Earnings by Parental Education - Continuing-Generation Students



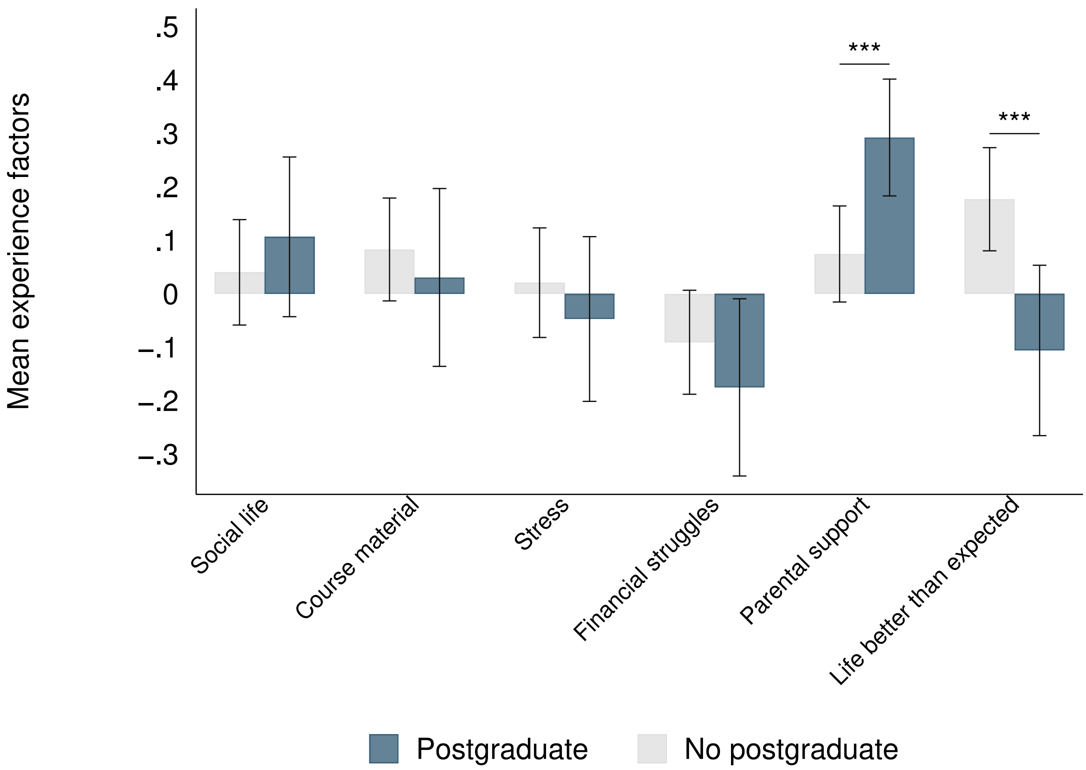
Notes: The two panels depict the kernel densities of individual beliefs about expected immediate costs of postgraduate education, calculated as the sum of expected tuition fees and forgone earnings in the 1-2 years after finishing the undergraduate degree, and expected earnings at age 35 conditional on working full-time. The densities are depicted for continuing-generation students separated by whether their parents do (solid line) or do not (dashed line) hold a postgraduate qualification. Reported p-values are from Kolmogorov-Smirnov tests of equality of distributions.

Figure 1C.6: Decomposition of Predicted SES Gap in Intentions to Enroll



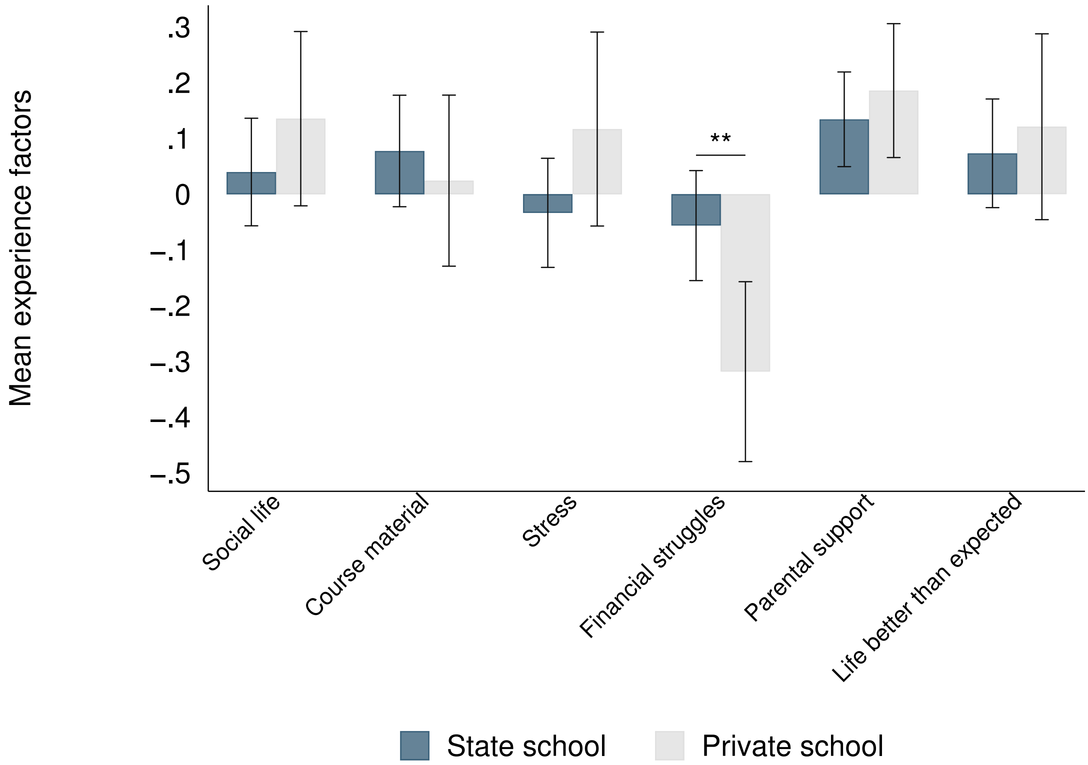
Notes: SES is split by whether at least one parent has university education. The first column decomposes the actual difference between low and high SES students' intention to enroll in a postgraduate degree into that which can be predicted by the model and that which is unexplained. The second column decomposes the predicted SES gap into differences in preferences and differences in beliefs.

Figure 1C.7: Experience of Life at University by Parental Education - Continuing-generation Students



Notes: The figure shows the average value for the first factor from a factor analysis of the variables related to the social life, positive and negative aspects of the course work and financial situation, as well as the standardized variables for having parental support and perceiving life at university as better than expected. The sample is restricted to continuing-generation students only, and students are divided according to whether their parents do (blue bars) or do not (gray bars) hold a postgraduate qualification. The black caps represent 95% confidence intervals and stars indicate statistical significance of differences by parental background: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Figure 1C.8: Experience of Life at University by School Type - Continuing-gen. Students



Notes: The figure shows the average value for the first factor from a factor analysis of the variables related to the social life, positive and negative aspects of the course work and financial situation, as well as the standardized variables for having parental support and perceiving life at university as better than expected. The sample is restricted to continuing-generation students only. School type is split between students who attended a state school (blue bars) and those who attended a private school (gray bars). The black caps represent 95% confidence intervals and stars indicate statistical significance of differences by school type: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Chapter 2

The Effect of Broadband Internet on the Gender Gap in Mental Health: Evidence from Germany

Abstract Mental health disorders are among the leading causes of disease burden worldwide. In this paper, I analyze the causal effect of broadband Internet access on mental health. I leverage confidential information on the coordinates of GSOEP respondents and exploit technological features of the German telecommunication network to instrument for DSL Internet access. Broadband Internet leads to significantly worse mental health for women, but not for men, thus widening the gender gap in mental disorders. Women's mental health decreases by almost 50% of a standard deviation. The results are driven by a worsening of socializing behavior and ability to cope with emotional problems, and are mostly concentrated within the younger cohorts. DSL access also leads to a higher probability of smoking for women, but has no significant effect on physical health for either gender. Looking at potential mechanisms, high-speed Internet access leads to a decrease in the number of hours women sleep during weekdays.

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2.1 Introduction

Mental health conditions, together with substance-use disorders, account for a significant share of the global disease burden (Collins et al., 2011; Vos et al., 2012). This share is particularly large among the population aged 10-24, and has significantly increased over time between 1990 and 2017.[1] Further, women are almost twice as likely as men to experience episodes of depression (WHO, 2000; DeRubeis et al., 2008). The economic costs of mental health and substance-use disorders are large. The World Health Organization estimates the current cost to the global economy of depression and anxiety to be around US$ 1 trillion per year in lost productivity (Patel et al., 2016; WHO, 2019)[2] and a large body of evidence highlights the negative consequences of mental illness on individual economic outcomes.[3] Yet, despite the significant societal and economic burden of mental health and substance-use disorders, to date relatively little is known about the determinants of mental health and factors affecting well-being over the lifetime. Recently, attention has been drawn to the role of Internet and mobile technologies in contributing to the rise of mental disorders, especially among the population of young adults.[4] The scientific evidence on the effect of these new technologies is however scant. In this paper, I aim to fill this gap in the literature and look at the causal effect of broadband Internet access on mental and substance use disorders, and the role of technology in contributing to the gender gap in mental health.

To answer the research question at hand, this paper draws on data from the German Socio-Economic Panel (SOEP), a large longitudinal dataset of German households that has been running since 1984. The focus on Germany is dictated by the availability of a rich micro-dataset and the possibility of applying an instrumental variable (IV) approach which exploits publicly available data on the characteristics of the pre-existing telephone infrastructure across the country. Indeed, the main empirical challenge in the analysis is the endogeneity of DSL access. The

[1] Disability-Adjusted Life Years (DALYs) are a common measure of disease burden. The World Health Organization defines one DALY as one lost year of "healthy" life. The share of 10-24 year-olds' DALYs that is attributable to mental health disorders has risen from around 9.5% in 1990 to almost 12.5 % in 2017. Further, mental health disorders consistently rank first among the contributors to the DALYs of the same population, and sustance-use disorders have also climbed the ladder of contributors to the global burden of disease over 2000-2017. See Figures 2B.1 and 2B.2 in Appendix 2B.

[2] Corresponding figures for Europe and the United States alone are 76 bn and $31 bn respectively (Stewart et al., 2003; Sobocki et al., 2006).

[3] See for example Baranov et al. (2020) for the effect of mental health on financial empowerment and child investment, Haushofer and Fehr (2014); De Quidt and Haushofer (2016) for models of causal links between depression and biased decision-making, and Currie and Stabile (2006) for the effect of poor mental health on educational attainment.

[4] See also Castellacci and Tveito (2018) for a review of the literature on Internet and well-being.

decision to purchase high-speed Internet access may be correlated with unobservable individual characteristics that simultaneously influence subjective well-being and mental health, and also be itself the product of certain individual character traits. To tackle these potential biases, I follow the identification strategy proposed by Falck et al. (2014) and later replicated by Bauernschuster et al. (2014); Billari et al. (2018, 2019). The identification relies on idiosyncrasies of the voice-telecommunication network, which was built in the 1960s and later used for the supply of broadband Internet. At the time, the location of the main distribution frames across Germany was determined by logistical considerations such as the availability of buildings. Crucially, the position of the main distribution frames and their catchment areas did not depend on the distance of households from their assigned main distribution frame. While this distance is a crucial factor affecting the quality and supply of DSL Internet, it does not affect the quality of the voice-telecommunication service, and as such can be considered exogenous to high-speed Internet demand. In this paper, I leverage confidential information on the residential geo-coordinates of the SOEP households to calculate the distance of each household from the main distribution frame they were originally assigned to. I then construct a binary variable capturing whether or not the distance between the household and its assigned main distribution frame is greater than 4.2 km. Beyond this threshold, the quality of the signal that is carried through the copper wires decays to the point of it not being feasible for DSL providers to guarantee a minimum standard and speed for broadband Internet connections without incurring substantial additional costs for replacing the wires. Furthermore, I exploit a "technological mistake" that affects roughly 11% of the municipalities in East Germany, which adopted the optical access line (OPAL) technology in the early 1990s. This infrastructure, which was considered state-of-the-art at the time, turned out to be incompatible with the increasing demand for bandwidth that followed the development of the Internet, and which led to the diffusion of the DSL technology for high-speed Internet access. Thus, municipalities that adopted the OPAL technology faced higher costs to high-speed Internet deployment, which to date still affect the supply of DSL Internet. In the main part of the analysis, I rely on the variation in high-speed Internet access induced by a combination of these characteristics of the German telecommunication network to identify and quantify the causal impact of broadband Internet on the mental health of German adults.

This study highlights a number of interesting findings. First, results from the instrumental variable approach show that access to DSL Internet reduces the mental health of women, but not that of men. Results on gender differences in the effect of Internet access on measures of mental health and wellbeing are consistent with findings from Devine and Lloyd (2012); McDool et al. (2020), who show that Internet-based activities and high-speed Internet access lead to a significant decrease in the subjective well-being of adolescent girls, and a smaller or negligible decrease in wellbeing for boys. The estimated effects are sizeable: women's mental health decreses by almost 50% of a standard deviation with access to broadband Internet. Consistently with the hypothesis that the magnitude of broadband Internet's negative effect on mental health is proportional to usage intensity, I find that the negative impact is mostly concentrated among the younger cohorts. Interestingly, DSL access has no effect on physical health, which suggests that the results are not purely driven by informational asymmetries across households with or without broadband Internet access. Second, looking at the sub-facets of mental health which are most affected by broadband Internet access, I find that most of the negative relationship between mental health and a DSL connection is driven by a worsening of women's socializing behavior and an increased probability of suffering from emotional problems. Importantly, the latter leads to a decrease in women's perceived ability to carry out work. High-speed Internet availability within the household also significantly increases smoking behavior, but not alcohol consumption. Overall, the evidence points towards a significant and negative effect of high-speed Internet access on the mental health of adult women, with potentially severe consequences for their productivity as workers in the labour market and the gender gap in mental health. Results are consistent across a comprehensive set of robustness checks and are in line with other findings from the literature on social media use and subjective well-being (see, e.g., Allcott et al., 2020; Mosquera et al., 2020). Finally, in an attempt to explore the mechanisms through which Internet access may affect mental health, I examine whether having a DSL connection changes the allocation of time across different tasks. I look at data on average hours spent per day during a normal weekday on a range of activities, from paid work to housework and sleep. I find that women who have a DSL connection within the household sleep around 43 minutes less than their counterpart without broadband access. The latter result speaks to the literature on the effect of mobile and Internet technologies on sleep (see Billari et al., 2018) and, consistently with Giuntella and Mazzonna (2019); Jin and Ziebarth (2020), suggests that the effect of DSL access on the mental health of German women may be driven by a reduction in hours slept. Results for men instead show that having a DSL connection does not affect sleeping time.

This work contributes to three main strands of literature. First, it adds to the body of evidence on the determinants of mental health and its evolution over the lifetime. Most of the literature on the origins of mental health focuses on the relationship between economic circumstances and mental illness and documents an association between negative shocks and increased probability of mental disorders, especially depressive symptoms.[5] Evidence on the intergenerational transmission of mental health from parents to offspring also points to the importance of early-life circumstances in affecting children's and adolescents' well-being and their mental health as adults.[6] More recently, both the economics and psychology literature have highlighted associations between mental health disorders and Internet use for personal purposes, video-gaming, the use of information communication technology (ICT), screen-time activities and the use of mobile phones.[7] Closest to the focus of this study is the work by Mosquera et al. (2020) and Allcott et al. (2020). Both papers analyze the causal effect of social networking sites on well-being and find significant increases in subjective well-being following a decrease in the time users spend on Facebook. In this paper, I look at the effect of Internet access more broadly. I exploit a natural experiment in the context of the German telecommunication network infrastructure to examine the *causal* impact of Internet access on a variety of outcomes, namely substance use, mental health and its sub-facets (vitality, socializing behavior, reactions to emotional problems and mood).

Relatedly, this paper speaks to the literature on the gender gap in mental health and its contributors. Several papers have documented a decrease in the wellbeing and mental health of women over time, both in absolute terms and relative to men (see for example Klose and Jacobi, 2004; Stevenson and Wolfers, 2009; Grant and Weissman, 2007; Eaton et al., 2012). However, to date little is known about the social and economic determinants of gender differences in the incidence of mental disorders.[8] Offer and Schneider (2011) examine differences in time use across genders and how these affect psychological distress. They find that women spend more time multitasking than men, and this extra time is mostly spent on housework and childcare; further,

[5] Recent papers include for example Goenjian et al. (2001); Katz et al. (2001); Kahneman and Krueger (2006); Kahneman et al. (2006); Kahneman and Deaton (2010); Sacks et al. (2012); Marcus (2013); McInerney et al. (2013); Stevenson and Wolfers (2013); Mendolia (2014); Haushofer and Shapiro (2016). An exception to the positive relationship between economic circumstances and mental well-being is Bertrand (2013), who finds that having a career worsens the mental health of college-educated women with a family. Relatedly, a large literature explores the relationship between economic conditions and incidence of suicide. See for example Stevenson and Wolfers (2006); Campaniello et al. (2017); Becker and Woessmann (2018); Christian et al. (2019).

[6] See Almond and Mazumder (2011); Johnston et al. (2013); Dinkelman (2017); Persson and Rossin-Slater (2018); Adhvaryu et al. (2019); Graeber and Schnitzlein (2019).

[7] See for example Young and Rogers (1998); Thomée et al. (2007); Gentile et al. (2011); Thomée et al. (2011, 2012); Deters and Mehl (2013); Kayi et al. (2016); Aboujaoude (2017); Rotondi et al. (2017); Shakya and Christakis (2017); Hunt et al. (2018); Twenge et al. (2018b,a); Boers et al. (2019); Brailovskaia et al. (2019); Twenge (2019); McDool et al. (2020).

[8] Relatedly, Batz and Tay (2018) provide a comprehensive summary of research on the determinants of gender differences in subjective wellbeing.

increased multitasking negatively affects the wellbeing of women, but not that of men. Andrés (2004) uses data from the British Household Panel Survey to examine gender differences in the effect of individual characteristics on self-reported mental health and finds that women and men respond differently to education, income and marital status. Further, patterns of self-reported mental health over the lifetime differ significantly across genders. In this paper, I examine the importance of a novel factor contributing to gender differences in mental health, namely access to broadbad Internet, and I do so by addressing endogeneity concerns related to DSL Internet availability. I also provide suggestive evidence that differential effects of DSL Internet access on mental health across genders could be due to differences in Internet usage between men and women, and different allocation of time to various activities during the day.

Finally, this work builds on and contributes to the literature on the effect of computer use and Internet consumption on socio-economic and health outcomes, from fertility, sleep patterns and demand for health care to social capital, cognitive development and voting preferences. Whilst results are somewhat mixed and vary with the context and type of Internet use, there is suggestive evidence that Internet access crowds out other forms of social capital (Bauernschuster et al., 2014; Geraci et al., 2018) and decreases political participation (Falck et al., 2014; Campante et al., 2017). Looking at health-related outcomes, Internet access has been found to affect fertility decisions of highly-educated women (Billari et al., 2019), reduce sleep duration and sleep satisfaction, and increase body weight (Billari et al., 2018; DiNardi et al., 2019), as well as increase the demand for healthcare during pregnancy (Amaral Garcia et al., 2019).[9] Similar to these studies, I exploit physical constraints in the supply of DSL Internet to quantify its causal effect. To the best of my knowledge, this study is the first to provide causal evidence on the effect of broadband Internet access on validated measures of individual mental health and its facets.

The rest of the chapter is structured as follows. Sections 2.2 and 2.3 describe the data and empirical methodology. Sections 2.4 and 2.5 present results for the main specification and robustness checks respectively. Section 2.6 discusses the implications of my findings and Section 2.7 concludes.

[9] For studies on the effect of Internet on academic performance, see also Malamud and Pop-Eleches (2011); Baert et al. (2020); Malamud et al. (2019).

2.2 Data

I make use of data from the German SOEP, a large representative longitudinal dataset of private households in Germany.[10] The SOEP started in 1984 and has since been carried out annually. Each wave surveys approximately 15,000 households and more than 25,000 individuals living in Germany. The dataset combines extensive sociodemographic information on, among other topics, household composition, occupational biographies, employment and earnings, with various measures of physical and mental health (see Schupp and Wagner, 2002; Goebel et al., 2019, for a description of the dataset). Crucially, the 2008 wave was the first in which respondents were asked whether they had a (high-speed) broadband Internet connection in their household. The same question was repeated in 2010 and in all subsequent waves until 2013 included. In the main part of the analysis, I exploit information from waves collected in the years 2008, 2010 and 2012, when information on the main outcome variables of interest is also available.[11] I also restrict the sample to adults aged 18-59 to avoid the problem of changes in mental health as induced by reduced social interactions post retirement (Dave et al., 2006).

2.2.1 Sample characteristics

Table 2A.1 in Appendix 2A presents descriptive statistics for the full sample of adult respondents to the 2008 wave of the SOEP and aged 18-59. The sample includes all individuals with non-missing information on the control variables included in the table. The average respondent is around 41 years old and the sample is split almost evenly between men and women. Around 22% of the sample has obtained tertiary education, whereas only 10% of respondents only achieved lower secondary education. 55% of the respondents are employed full-time at the time of observation. Full-time employment significantly differs across genders, with 36% of female respondents being employed full-time against 77% of male respondents. The vast majority of the sample was born in Germany, with only around 11% of the sample being a first-generation immigrant. Around 60% of respondents are married, 51% of respondents are home owners and 76% live in West Germany.

[10]The data version used in this paper is SOEPv34. DOI: 10.5684/soep.v34

[11]In the 2008-2012 period, broadband Internet was the dominant technology through which Internet users went online. Mobile phone penetration was low in these years: in 2011, only 18% of Internet users in Germany reported accessing the Internet via a mobile device (see Figure 2B.3 in Appendix 2B.)

2.2.2 Broadband Internet

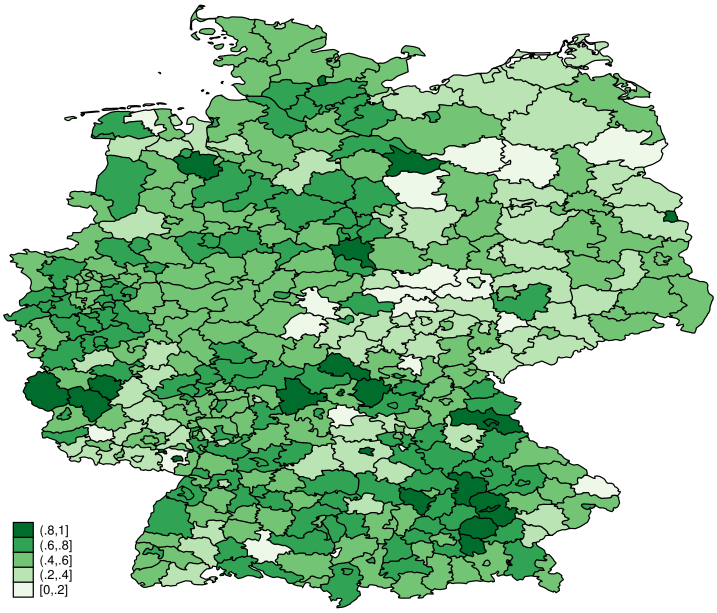
Turning to broadband Internet connection in the household, about 68% of respondents to the 2008 wave have Internet access via DSL at home (see Table 2.1). Figure 2.1 shows the share of SOEP households with access to broadband Internet for the survey year 2008 across all 401 German counties. In 2008, there was large heterogeneity in the level of broadband Internet access across German counties. East Germany was on average behind West Germany in DSL adoption at the household level, with many counties having 40% or less of their households with a DSL connection at home. High-speed Internet access increased rapidly all over the country over 2008-2012: on average, 50% of SOEP households had DSL Internet access in 2008, against 75% in 2012. Heterogeneity in DSL adoption across counties, however, remains sizeable in 2012 (see Figure 2A.1 in Appendix 2A). Of the respondents in my sample, around 7% live in households that are located more than 4.2 km away from their assigned main distribution frame, and 4% live in households that are assigned to a main distribution frame with OPAL technology.

Table 2.1: Broadband Internet availability

	Full sample		Women		Men		P-value
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	
DSL connection in HH	0.68	0.47	0.67	0.47	0.69	0.46	0.006
OPAL technology	0.04	0.20	0.04	0.20	0.04	0.20	0.977
MDF $>$ 4.2 km away	0.07	0.26	0.07	0.26	0.08	0.27	0.237

Notes: SOEP 2008 - Number of observations = 11,447. The sample includes all respondents aged 18-59, with non-missing information on the above variables and control variables included in Table 2A.1. Columns 1-2 show summary statistics for the full sample, Columns 3-4 show results for female respondents and Columns 5-6 report summary statistics for male respondents. The last column shows the p-value for a t-test of equality of means across the two subgroups.

Figure 2.1: Percentage of households with a broadband Internet connection across counties in 2008



Notes: The map shows the fraction of SOEP households with access to broadband Internet for the survey year 2008 across all 401 German counties. Darker green areas indicate higher levels of broadband Internet access.

2.2.3 Mental health and substance use

Starting in 2002, the SOEP introduced a health module in the individual questionnaire, which is administered every second year. The module includes 12 Likert-scale questions (SF-12) on various health aspects, which are grouped into two broad summary scales for physical and mental health.[12] The questions refer to health-related aspects as experienced within the four weeks preceding the interview and can therefore be interpreted as proxies for current health status. Summary scales for physical and mental health as provided in the Health module are calculated using explorative factor analysis, from self-reported answers to the SF-12 module. Although the mental health scale and its sub-facets are constructed from subjective reports about recent experiences and conditions, the SF-12 questions, and in particular the mental health summary scale, have been found to be highly predictive of mental illness (Salyers et al., 2000).[13] All measures for mental and physical health and their sub-facets are originally calibrated to have mean value of 50 for the SOEP 2004 population, and standard deviation of 10 points, with higher scores indicating better health. In what follows, I re-standardize the variables to have

[12]See Appendix 2C for the exact wording of the questions.
[13]In what follows, I use the term "mental health" to refer to these self-reported, validated survey measures.

mean 0 and standard deviation of 1 for the 2004 population for ease of interpretation. Hence, a negative value corresponds to worse mental health compared to the average respondent to the 2004 SOEP questionnaire, and lower values correspond to worse mental health overall.

For the purpose of this analysis, I make use of the continuous summary scale for mental health of the respondents as one of my main dependent variables.[14] Further, I examine specific sub-facets of mental health to analyze which dimensions are most affected by the availability of broadband Internet. More specifically, I look at measures of self-reported vitality, reactions to emotional problems, socializing behavior and an indicator for gloomy and agitated mood. All sub-facets of mental health are constructed from Likert-scale answers to the SF-12 questions and also standardized to have mean 0 and standard deviation of 1 for the 2004 SOEP population. Lower values correspond to worse mental health. I also look at the sub-components of the emotional problem indicator - namely whether one has felt less thorough than usual at work or has achieved less than usual due to emotional problems. For these two variables, which are also standardised to have mean 0 and standard deviation of 1 for the 2004 SOEP population, higher values correspond to worse outcomes.

As potential manifestations of mental health disorders, I look at measures of substance use by focusing on current smoking behavior and alcohol consumption.[15] More precisely, I construct a binary variable indicating whether the individual is currently smoking and an indicator summarizing the frequency of consumption of different alcoholic beverages, respectively. The latter were elicited on a 5-point Likert scale, with frequencies going from "Daily" to "Never".

Summary statistics for the outcome variables are presented in Table 2.2, for the whole sample as well as by gender. The sample in Table 2.2 refers to respondents to the 2008 wave of the SOEP with non-missing information on all the control variables and Internet access, and aged 18-59. Both smoking and alcohol consumption are less prevalent among women than they are among men, and all measures of mental health and its sub-facets indicate worse mental health for the subsample of women compared to their male counterpart. All gender differences in outcomes are significant at conventional levels.

Table 2A.2 reports summary statistics for the outcome variables for the full sample, as well as their split by whether or not the respondent has a DSL Internet connection at home. As it is clear from Panel A, there is positive selection into broadband Internet: people with a DSL

[14] Results on the effect of broadband Internet on physical health are presented in Appendix 2B and discussed in Section 2.4.

[15] See, for example, Friedman (2020) for the relationship between smoking and mental disorders.

Table 2.2: Summary statistics - Outcome variables

	Full sample			Women		Men		P-value
	Mean	St. Dev.	N	Mean	St. Dev.	Mean	St. Dev.	
Mental health								
Mental Health	-0.02	0.95	11234	-0.11	0.99	0.07	0.89	0.000
Socializing behavior	0.08	0.95	11234	0.00	1.00	0.16	0.88	0.000
Vitality	0.04	0.93	11234	-0.01	0.93	0.10	0.92	0.000
Mood	-0.07	0.94	11234	-0.14	0.95	0.01	0.92	0.000
Emotional problems	0.11	0.95	11234	0.02	1.00	0.21	0.89	0.000
Accomplished less	-0.11	0.96	11234	-0.01	1.00	-0.21	0.89	0.000
Less thorough	-0.11	0.94	11234	-0.03	0.99	-0.19	0.89	0.000
Substance abuse								
Currently smoking	0.33	0.47	11430	0.30	0.46	0.37	0.48	0.000
Alcohol consumption	0.00	1.00	11288	-0.23	0.94	0.26	1.00	0.000

Notes: SOEP 2008. The sample includes all respondents aged 18-59, with non-missing information on the control variables presented in Table 2A.1. All mental health variables are standardised to have mean 0 and standard deviation of 1 for the sample of respondents to the 2004 wave of the SOEP. Alcohol consumption is standardised to have mean 0 and standard deviation of 1 for the sample of reference. Columns 1-2 show summary statistics for the full sample, Columns 3-4 show results for female respondents and Columns 5-6 report summary statistics for male respondents. The last column shows the p-value for a t-test of equality of means across the two subgroups.

connection within the household have on average better mental health and less frequent substance consumption.[16]

2.2.4 Evolution of the gender gap in mental health

Table 2.2 highlights a large gender gap in mental health for respondents to the 2008 wave of the SOEP. When studying the effect of technology adoption on mental health, it is interesting to descriptively document how this gender gap evolved over time, and to what extent (and in which direction) attrition may bias the results. I start by discussing the issue of selection and attrition and then move on to document trends in mental health levels over time for respondents to the SOEP.

Columns 1-9 in Table 2A.3 reports summary statistics for mental health variables, as measured for the entire 2004 SOEP population, the subsample aged 18-59 for which we have information on all relevant control variables of interest, and the sub-sample which we also observe both in 2004 and in 2008. All figures refer to answers to the mental health questions in 2004, which is the base wave for standardisation of the outcome variables. For the 2004 population, there exists a large gender gap in mental health and its subfacets, with women reporting more frequent incidence of mental health problems than men. When restricting the sample from the entire 2004

[16] In terms of background characteristics, respondents with a DSL connection within the household are on average younger, more educated, work more hours, are more likely to be married, and have more children and higher household income.

population to individuals aged 18-59 with non-missing information on all control variables used in the analysis, the summary measure of mental health decreases both for the entire subsample and for each gender separately. This indicates that the subsample with comprehensive information on all background characteristics of interest may be negatively selected on levels of mental health. However, while average scores for the mood subfacet also decrease both for the whole sample and for women and men separately, scores for all other subfacets increase. Hence, there is no clear pattern for selection on specific facets of mental health. When it comes to attrition, we compare columns 4-6 to columns 7-9, which further restrict the 2004 sample to individuals that are also observed in 2008 and for which we have non-missing observations on background characteristics in 2008. While summary statistics for the mental health variables are fairly similar across the two subsamples and the gender gap in mental health is stable, it is important to note that individuals with worse mental health are more likely to drop out of the panel. Finally, columns 7-9 and 10-12 show that the gender gap in mental health remains fairly stable over the period 2004-2008.

2.2.5 Time-use data

Starting in the year 2000, the SOEP questionnaire also includes a module on time use, where respondents are asked how many hours a day on average they dedicate to various activities, namely their job, running errands, doing houseworks, training, childcare, doing repairs in the house or garden, leisure activities and sleep. Summary statistics for the time-use variables are presented in Table 2.3, for the whole sample as well as by gender. As above, the sample refers to respondents to the 2008 wave of the SOEP with non-missing information on all the control variables as well as the mental health indicator, and aged 18-59.

On average, individuals in the sample spend around 7 hours on their job every day, and around 4 hours cumulatively on errands, housework and childcare. Leisure time amounts to roughly 2 hours a day on average, and people in the sample sleep around 7 hours on an average night during weekdays. 31% of respondents sleep less than 7 hours on an average weekday.[17] The averages for the whole sample hide large gender differences in time allocation across different activities. Consistent with figures on employment, women in the SOEP spend on average less hours on their job than men do, but more time running errands, taking care of their children and doing housework. They also dedicate more time to sleep during weekdays than men do.

[17] For both variables related to sleep, I exclude observations with extreme values: both variables are classified as missing if respondents report sleeping less than 2 or more than 16 hours on an average weekday.

Table 2.3: Summary statistics - Time-use variables

	Full sample			Women		Men		P-value
	Mean	St. Dev.	N	Mean	St. Dev.	Mean	St. Dev.	P-val
Job	6.95	4.06	10858	5.64	3.97	8.37	3.67	0.000
Errands	0.99	0.70	11006	1.15	0.66	0.80	0.69	0.000
Housework	1.57	1.39	10997	2.21	1.47	0.84	0.82	0.000
Childcare	1.62	3.70	10514	2.48	4.71	0.66	1.59	0.000
Training	0.60	1.81	10329	0.60	1.83	0.61	1.79	0.890
Repairs	0.73	0.89	10692	0.61	0.81	0.87	0.96	0.000
Leisure	2.07	1.74	11044	1.99	1.59	2.16	1.89	0.000
Care	0.14	0.99	10256	0.20	1.20	0.08	0.70	0.000
Sleep	6.95	1.09	11221	7.03	1.10	6.86	1.08	0.000
Sleep <7 hrs	0.31	0.46	11221	0.27	0.45	0.35	0.48	0.000

Notes: SOEP 2008. The sample includes all respondents aged 18-59, with non-missing information on the control variables presented in Table 2A.1 and on mental health. All time-use variables are measured as number of hours per day. The variable "Sleep" only includes respondents that report sensible values of sleep time. Columns 1-2 show summary statistics for the full sample, Columns 3-4 show results for female respondents and Columns 5-6 report summary statistics for male respondents. The last column shows the p-value for a t-test of equality of means across the two subgroups.

2.3 Empirical methodology

The main empirical specification for the contemporaneous effect of high-speed Internet on the various outcome variables considered is:

$$y_{ist} = \beta_0 + \beta_1 Broadband_{ist} + \beta_2 X_{ist} + \mu_s + \lambda_t + \eta_s t + \epsilon_{ist} \tag{2.1}$$

where y_{ist} is the outcome of individual i living in state s at time t and $Broadband_{ist}$ is a binary variable that takes value 1 if the respondent has a broadband Internet connection in the household in the year of observation. The coefficient β_1 thus captures whether addictive behaviors are more prevalent or mental health is lower for individuals who have access to broadband Internet at home. X_{ist} is a vector of time-varying socio-demographic characteristics that includes age and its squared term, gender, indicators for different educational qualifications and occupations, marital status, number of children and household type, migration background, the logarithm of net household income, an indicator for whether the respondent is a home owner, and a dummy variable for whether the respondent works full time. μ_s and $\eta_s t$ represent State fixed-effects and a vector of state-specific linear trends respectively. The state-specific linear trends control for unobserved (cross-state) differences in the outcome variables over time, whilst the state fixed effects control for time-invariant differences across federal states that are unobserved to the econometrician and which may affect mental health or substance use. λ_t is a vector of year fixed-effects that account for possible trends in mental health over time that are common across states. Standard errors are clustered at the household level, which is the same level at which information on broadband Internet is recorded.

Estimating the specification using OLS would be problematic given different endogeneity concerns. In particular, the choice to subscribe to broadband Internet could be correlated with other unobservable determinants of health and behaviors (e.g. genetics, personality traits, knowledge about mental health and substance use disorders). Reverse causality could also bias OLS estimates, to the extent that health conditions could affect preferences regarding leisure activities, and hence demand for broadband Internet. Controlling for a broad set of background characteristics and for state fixed-effects and linear trends partially addresses this concern. However, the OLS estimates of β_1 might still be biased by unobserved confounders. I therefore follow Falck et al. (2014) and make use of identification strategies that exploit characteristics of the telephone infrastructure in Germany that pre-date the period of analysis. I leverage publicly available data on the German telephony network structure from Falck et al. (2014) and exploit two potential sources of exogenous variation in the provision of DSL connection. These are based on the distance of each household to its assigned main distribution frame and the type of wires that connect the household to its assigned main distribution frame. More details on the German telephony infrastructure are provided below.

2.3.1 The German voice telephony network

The German voice telephony network was designed and rolled out in the 1960s, when the provision of telephone services was a state monopoly with the declared goal to provide universal telephone service to all German households. The network is structured around main distribution frames, which households were originally connected to with copper wires. Crucially, the length of the copper wires was irrelevant for the quality of the telephone service, and therefore did not factor into the choice of main distribution frame locations in neither rural nor urban areas. In the initial phases of its development, the supply of DSL Internet relied heavily on the pre-existing subsurface wires from the voice telephony network. However, unlike with telephone services, distance from the main distribution frame significantly affects the quality of broadband Internet connection. In particular, when surpassing a threshold of about 4.2 km, the supply of DSL Internet is no longer feasible via copper wires, and it becomes much more costly for DSL Internet suppliers to provide households with an Internet connection of at least their minimum guaranteed speed.[18] Given this supply-side constraint, I expect that households that are located further than 4.2 km away from their main distribution frame will have more difficulties accessing broadband Internet in the early phase of its development. Combining information on the geographical coordinates of each household in the SOEP with data on the catchment areas and coordinates of each main distribution frame in Germany, I calculate the geographic distance of a household from the main distribution frame it was originally assigned to. I then construct a binary indicator that takes value 1 if the household is located further than 4.2 km away from its assigned main distribution frame and 0 otherwise. I use this variable as a proxy for the level of supply side constraints to the provision of DSL Internet. It is worth noting that the linear distance I calculate between each household and its assigned main distribution frame is likely to be smaller than the actual length of the copper wires. As a result, the proportion of households that in my dataset are identified as living beyond the 4.2 km threshold from their assigned main distribution frame is likely to be lower than the true fraction, if the actual length of the copper wires were to be used instead.[19] The original identification strategy proposed by Falck et al. (2014) leverages a second instrument constructed from whether a MDF exists that is closer to a given household than the one the household is assigned to, and within the 4.2 km threshold. There are few households in the data for which a closer MDF exists that would allow access to high-speed Internet when this is not possible from the originally assigned MDF. Therefore in my main specification I do not include this instrument in my instrumental variable vector.

The second instrumental variable is based on the type of technology used for the telephone infrastructure in each municipality in Germany. After the German reunification in 1990, many parts of Eastern Germany were lacking telephone access lines. To provide telephone services to households in these parts of Eastern Germany, a new telephony infrastructure was rolled out which was built on the basis of a special type of fiber wires - the optical access line (OPAL) technology - instead of the traditionally used copper wires. Roughly 11% of Eastern German municipalities are served by main distribution frames that use this technology (see Figure 2.2 for a map of the locations of these main distribution frames). At the time, the OPAL technology was thought to

[18]After the 4.2 km threshold, copper wires would need to be replaced by fiber wires. Replacing the wires involves costly constructions, with costs increasing with the length of the wires to be substituted.

[19]The discontinuous decay of the quality of DSL Internet around a 4.2 km threshold could in principle also support the use of a regression discontinuity design. However, the SOEP data does not contain enough observations on households that are located approximately 4.2 km away from the main distribution frame. Further, from a technical perspective, the distance from the main distribution frame determines the maximum bandwidth that a household can have, but it is only the 4.2 km threshold that determines DSL availability (Falck et al., 2014).

be the state-of-the-art technology for ICT. However, it could not support the high bandwidths that were required once Internet services became a mass phenomenon. The growing demand for bandwidth led to the development of the DSL technology, which is incompatible with the OPAL technology. Providing OPAL-municipalities with broadband Internet became extremely costly, to the point that, to date, some municipalities in Eastern Germany that are served by OPAL technology still cannot access broadband Internet. Exploiting information on the technology used for each main distribution frame, I construct a binary variable that takes value one if the household is located in an area where infrastructure was built with the OPAL technology and zero otherwise, and expect it to have a negative effect on DSL availability.

Figure 2.2: Main distribution frames with OPAL technology

Notes: The figure shows the location of main distribution frames that use the OPAL technology across German states.

Household and individual characteristics for different features of the telephony infrastructure

In this section, I provide details on the characteristics of households and individuals living either side of the 4.2 km threshold, and who are assigned to MDFs that use different wire technologies. Descriptive statistics and a test of equality of means between subgroups are presented in Tables 2A.4 and 2A.5 in Appendix 2A. Respondents living either side of the 4.2 km threshold are similar on many dimensions, including employment status and educational attainment. Note that households living either side of the 4.2km threshold do not significantly differ in terms of net household income (see Table 2A.4). While individuals living closer to their assigned main distribution frame are younger, more likely to be of non-German descent and to work in white collar jobs, most of these differences are small in magnitude and economic significance. Similarly, individuals living more than 4.2 km away from their assigned main distribution frames are more likely to live in bigger households with more children, and are more likely to be home owners, but the differences are small. In line with my identification, households that are located further than 4.2km away from their assigned MDF display a significantly lower probability of having DSL Internet access at home.

I then compare characteristics of households and respondents in Eastern Germany that are assigned to main distribution frames with different wire technologies (Table 2A.5). Again, consistent with my identification assumption, DSL Internet access is significantly less prevalent in OPAL than in non-OPAL households. Other household characteristics are however substantially similar across the two groups, with the exception of home ownership, which is more prevalent among non-OPAL households, and household size, which is larger for non-OPAL households than their OPAL counterpart. Consistently with the latter point, individuals living in households assigned to an MDF with an OPAL technology are less likely to be married. All other individual characteristics, with the exception of tertiary education, do not significantly differ across subgroups. The limited differences in individual and household characteristics between the OPAL and non-OPAL samples lends credibility to the assumption of 'as-good-as-random' allocation of households across OPAL and non-OPAL areas.

In the regression analysis, I control for all individual and household characteristics presented in the Tables to address concerns about the non-random assignment of the instruments.

2.3.2 First-stage equation

I use the plausibly exogenous variation in the supply of DSL Internet described above to instrument for broadband Internet connection within the household in equation 2.1. The first stage of my instrumental variable specification has broadband availability within the household regressed on the two instrumental variables for whether a household is located more than 4.2 km away from the main distribution frame it is assigned to, and whether it is located in an area served by OPAL technology, as follows:

$$Broadband_{ist} = \gamma_0 + \gamma_1 Z_{ist} + \gamma_2 X_{ist} + \mu_s + \lambda_t + \eta_s t + u_{ist} \tag{2.2}$$

where Z_{ist} is the vector containing the two binary instruments, and the remaining variables are identical to those specified in equation 2.1.[20] This identification strategy mostly exploits within-state cross-sectional variation in residential addresses and their distance from the assigned MDF. Note that the only variation in the instrument vector that occurs within household and over time is through residential mobility. This variation occurs, for example, when a household previously located within 4.2 km of an MDF moves to a location that is further way from its (potentially different) assigned MDF. Similarly, households in Eastern Germany that were previously connected to an MDF through copper wires could relocate within the catchmen area of an MDF with OPAL technology (or vice versa). Whilst the instrument vector can in principle vary within household and over time, residential mobility that induces such variation is in practice rather limited.

As discussed in section 2.3.1, all regressions control for a broad set of individual and household characteristics in order to address concerns about the assumption of 'as-good-as-random' allocation of the intrument vector across households. However, even controlling for a broad battery of background characteristics, I cannot exclude that other unobserved determinants of mental health and substance use might be correlated with the threshold dummy and the OPAL binary variable. In other words, concerns about the validity of the instruments could arise if the characteristics of the voice telephony network affect the outcome variables through channels other than the supply of DSL Internet. For the first instrument for example, we may think that the population living more than 4.2 km away from a given main distribution frame is intrinsically different from that living within a 4.2 km radius from the main distribution frame (think, e.g., of urban vs rural populations), and that these differences could also affect health outcomes of the individuals. To address this concern, I proceed in two ways. First, the use of two instrumental variables will allow to run an over-identification test to check for the validity of the instruments. However, this test relies on the fact that at least one instrument is valid. Here, I will assume that at least the instrument constructed on the basis of the existence of the OPAL technology is valid. Indeed, as detailed above and shown in Table 2A.5, household and individual characteristics do not significantly differ for respondents that are assigned to main distribution frames using different wires technologies. As further evidence of the credibility of the 'as-good-as-random'

[20]Note that the limited within-person over-time variation in the instruments as well as the DSL variable does not allow the use of individual fixed effects in the regression.

allocation of the OPAL instrument vector, Bauernschuster et al. (2014) compare municipalities in Eastern Germany that were served by OPAL technology in 2001 to those which were not, and present evidence that the two groups are identical with respect to observables, with the exception of the rate of home ownership.

Second, in Section 2.5 I conduct a number of robustness checks that attempt to address the concern of other unobserved determinants of the outcomes variables being correlated with my instrument vector. Concretely, I saturate the model with region fixed-effects and region-specific linear trends, and exploit within-region (as opposed to within-state) variation in residential addresses and their distance from the assigned MDF. I also control for characteristics of the municipality respondents are living in to account for differences across local areas that could drive gaps in mental health. Given the period over which the analysis is conducted, this robustness check is also useful to address concerns related to a differential impact of the 2008 financial crisis across local areas, and its effect on mental health and related variables. Further, I exclude movers to avoid the issue of endogenous selection into areas with better DSL availability. In an additional robustness check, I also exploit information on the outcome variables in the pre-Internet period in a difference-in-difference design that relies on interacting the two instrumental variables for DSL Internet availability with an indicator for the post-Internet period. With this approach, identification comes through the change in the impact of the location of residence on the outcome variable, under the assumption that the correlation between the latter and other unobservable characteristics that influence the outcomes of interest did not change with the introduction of the DSL technology. More details and a discussion of the results are presented in Sections 2.5.1 and 2.5.2.

2.4 Results

In the following, I first present results for the main specification from equations 2.1 and 2.2 for my main outcome variables, namely the summary scale for mental health and the indicators for smoking behavior and alcohol consumption (Section 2.4.1). I then analyze which sub-facets of the mental health scale are driving the results in Section 2.4.2.

2.4.1 Broadband Internet and main outcomes

Panels A and B of Table 2.4 present the 2SLS and first-stage estimates for the impact of broadband Internet access within the household on mental health, smoking behavior and alcohol consumption, using the SOEP data for years 2008, 2010 and 2012.[21] Each regression includes a large set of individual controls, as well as state and survey year fixed-effects and state-specific linear trends. The first-stage results displayed in Panel B confirm that both instruments are significantly and negatively related to broadband Internet access at the household level. The F-statistic reported at the bottom of the Table also confirms that the instruments are strong, and results from the overidentification test for all specifications do not reject the null hypothesis that the instruments are jointly valid.

Columns 1-3 of Panel A in Table 2.4 report the 2SLS estimates of the effect of DSL Internet access on measures of substance use and mental health for the full sample. DSL Internet overall has no significant effect on the mental health or alcohol consumption of German adults, but it significantly increases smoking behavior. Whilts substance use disorders are often a manifestation of poor mental health (Friedman, 2020), it is worth noting that, given the lack of a significant effect of broadband Internet on mental health for the full sample, the significant effect of DSL Internet on smoking behavior may not be driven by a deterioration in mental health as caused by high-speed Internet access. Rather, it is plausible to assume that access to broadband Internet can be itself a direct risk factor for addictive behaviors, such as smoking or alcohol consumption. Longitudinal studies on young Internet users have highlighted an association between addictive Internet use during adolescence and smoking and drinking behavior at age 20 (Chiao et al., 2014; Lee and Lee, 2017; Mo et al., 2019).

Looking at heterogeneities by gender, columns 4-9 in Table 2.4 show that the effect of DSL Internet access on the mental health and substance use of men is insignificant, whilst access to

[21] Table 2B.1 in Appendix 2B presents OLS estimates for the same specification.

broadband Internet significantly increases women's probability of being currently smoking. Further, access to broadband Internet leads to a deterioration in women's mental health (column 6). Whilst only significant at the 10% level, the coefficient for the effect of broadband Internet on the mental health of women is significantly different from the equivalent coefficient from a regression run on the male subsample (p-value 0.032). The magnitude of the coefficient for the women subsample is also sizeable. This suggests that high-speed Internet access may lead to lower mental health for women, but not for men. This is consistent with results from Devine and Lloyd (2012) who analyze adolescents' use of online technologies in Northern Ireland and find that the consumption of social networking sites and online games is correlated with lower subjective well-being for girls, but not for boys. The magnitude of the effect is large: mental health decreases by almost 50% of a standard deviation if women have access to high-speed Internet. To put this number into perspective, an invidual with a mental health score of -0.25 would typically have answered "Sometimes" to the question on whether they felt they were limited socially by mental health issue, and "Sometimes" or "Often" to the question on whether they felt they had used up a lot of energy. In contrast, an individual with a mental health score of +0.25 - i.e. a score that is 50% of a standard deviation higher - would typically have answered "Never" to the social functioning question, and "Sometimes" or "Rarely" to the vitality question.

Note that the negative effect of DSL Internet on the mental health of women cannot be explained by differences in mental health in the pre-Internet period across individuals with and without access to DSL Internet at home in 2008. Table 2B.2 presents results from a placebo test where mental health in 2002 and 2004 is regressed on having broadband Internet in 2008. The same IV specification as in Table 2.4 is used. The placebo test shows that, as expected, having access to DSL Internet in 2008 does not significantly affect mental health in previous years, neither for the full sample, nor for the sub-samples of women and men.

The 2SLS estimates point to a large effect of broadband Internet on mental health. One explanation for this sizeable impact is that the 2SLS coefficients refer to the effect of having high-speed Internet access for the compliers, i.e. the local average treatment effect (LATE). In this context, compliers are respondents belonging to either of the following two groups: individuals who live in fairly rural areas, and who have (do not have) access to broadband Internet because they live within (outside) a threshold of 4.2 km from the main distribution frame; or individuals living in East German households with (without) a DSL connection and that are connected to their main distribution frame with standard (OPAL) wires. For this population, compared to urban residents, having access to a broadband Internet connection may constitute a significant increase in the level of amenities they can benefit from. In this sense, the magnitude of the coefficients can be explained by the importance that Internet plays as a source of information and exposure to different realities. It is also important to highlight that the magnitude of the 2SLS coefficients is significantly larger than that of the equivalent OLS coefficients. This suggests a positive correlation between unobservable drivers of mental health (and related behaviors) and availability of high-speed Internet connection. Robustess checks presented in Section 2.5 attempt to tackle the issue of unobservables by controlling for additional variables capturing local area characteristics. It is also worth noting that the OLS estimates might be biased towards zero in case of measurement error in the main explanatory variable, i.e. DSL Internet access. Given the self-reported nature of this variable, measurement error cannot be excluded.

A possible threat to the estimation of unbiased coefficients associated to having a DSL Internet connection at home would arise if the instrumental variables were capturing not only the effect of supply-side constraints to the provision of broadband Internet, but also location effects or the effect of unobserved characteristics. One could think, for example, that individuals living in rural or relatively underserviced areas, such as those identified by the threshold and OPAL instruments, may suffer from overall worse health compared to the rest of the sample. Alternatively, we could think that individuals who have access to broadband Internet are more informed about health problems, and would therefore have a higher probability of identifying and reporting health issues. If that were the case, we would expect to find a significant and negative 2SLS coefficient when estimating the effect of having a DSL connection within the household on the physical health of respondents to the SOEP. Reassuringly, the coefficient of interest in a regression where the outcome variable is the summary scale for physical health is insignificant, both for the whole sample and for the subsamples of men and women separately. This is shown in Table 2.5 below.

While I cannot provide causal evidence on what type of activity or behavior associated with broadband Internet leads to a decrease in mental health for female adults, I can test whether the effect of broadband Internet access is stronger for younger individuals, who are likely to be heavier consumers of the technology. For this purpose, I divide the subsample of women into two groups: those aged 18-30 (henceforth "young") and those aged 31-59 (henceforth "old"). Results from this exercise are reported in Table 2B.4 in Appendix 2B. The estimates from Panel A for the subsample of women aged 18-30 are significantly larger than those reported in Panel B for the older group, and provide suggestive evidence confirming the hypothesis that heavier usage of the Internet leads to larger effects on mental health and substance use.

Table 2.4: Broadband Internet and mental health

	Full sample			Women			Men		
	Smoking	Alcohol	Mental H.	Smoking	Alcohol	Mental H.	Smoking	Alcohol	Mental H.
Panel A: IV regressions - Second stage									
DSL connection in HH	0.262**	-0.125	-0.173	0.328**	-0.202	-0.499*	0.188	-0.027	0.151
	(0.107)	(0.179)	(0.209)	(0.133)	(0.222)	(0.263)	(0.143)	(0.246)	(0.250)
Panel B: IV regressions - First stage									
Threshold	-0.142***	-0.167***	-0.133***	-0.144***	-0.167***	-0.133***	-0.141***	-0.167***	-0.133***
	(0.016)	(0.019)	(0.015)	(0.018)	(0.020)	(0.016)	(0.018)	(0.022)	(0.017)
OPAL technology	-0.059***	-0.063**	-0.049**	-0.065***	-0.060**	-0.049**	-0.051**	-0.064**	-0.048*
	(0.022)	(0.026)	(0.021)	(0.025)	(0.028)	(0.022)	(0.025)	(0.029)	(0.025)
Mean of dep. variable	0.385	0.000	-0.049	0.349	-0.230	-0.133	0.424	0.257	0.046
SD of dep. variable	0.487	1.000	0.971	0.477	0.943	1.001	0.494	0.999	0.926
Observations	29,172	21,925	33,365	15,187	11,553	17,692	13,985	10,372	15,673
State FE and linear trends	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Overidentification test (p-value)	0.941	0.139	0.540	0.844	0.341	0.342	0.627	0.168	0.949
F-stat.	49.811	48.971	48.059	38.979	38.612	38.096	32.091	32.758	31.582
Equality of coefficients (p-value)	-	-	-	-	-	-	0.425	0.562	0.032

Notes: 2SLS regressions. The sample includes all respondents aged 18-59. Standard errors clustered at the household level are reported in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Control variables include age and its squared term, gender, indicators for different educational qualifications and occupation, marital status, number of children and household type, migration background, the logarithm of net household income and an indicator for whether the respondent is a home owner, and a dummy variable for whether the respondent works full time. State and survey year fixed-effects are also included, as well as state-specific linear trends. The F-statistics refers to the Kleibergen-Paap F-statistic from a test for excluded instruments. The last row refers to the p-value for a test of equality of coefficients for broadband Internet across the female and male subsamples.

Table 2.5: Broadband Internet and physical health

	Full sample	Women	Men
Panel A: IV regressions - Second stage			
DSL connection in HH	-0.233	-0.352	-0.101
	(0.170)	(0.223)	(0.222)
Panel B: IV regressions - First stage			
Threshold	-0.133***	-0.133***	-0.133***
	(0.0152)	(0.0162)	(0.0173)
OPAL technology	-0.0489**	-0.0489**	-0.0477*
	(0.0209)	(0.0224)	(0.0246)
Observations	33,365	17,692	15,673
State FE and linear trends	Y	Y	Y
Individual controls	Y	Y	Y
F-stat.	40.69	36.35	30.79
Overidentification test (p-value)	0.183	0.361	0.253

Notes: 2SLS regressions. The sample includes all respondents aged 18-59. Standard errors clustered at the household level are reported in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Control variables include age and its squared term, gender, indicators for different educational qualifications and occupation, marital status, number of children and household type, migration background, the logarithm of net household income and an indicator for whether the respondent is a home owner, and a dummy variable for whether the respondent works full time. State and survey year fixed-effects are also included, as well as state-specific linear trends. The F-statistics refers to the Kleibergen-Paap F-statistic from a test for excluded instruments.

2.4.2 Broadband Internet and sub-facets of mental health

In order to shed light on what dimensions of mental health are most affected by exposure to high-speed Internet, I make use of questions related to specific sub-facets of the mental health scale and the emotional problems indicator (see Appendix 2A for a summary of the variables of interest). More specifically, I examine the effect of broadband Internet on the socializing behavior, vitality, mood and reaction to emotional problems of women in the SOEP, as well as their subjective reporting of being less accurate and achieving less than usual at work in the past four weeks due to mental health or emotional problems. Results from this exercise are presented in Table 2.6 below. While the sign of the 2SLS coefficient associated to high-speed Internet access is negative for all dimensions of mental health, it is interesting to note that the negative effect of Internet access on mental health is mostly driven by worse socializing behavior (Column 1) and ability to handle emotional problems (Column 3). Relatedly, the lower ability to react to perceived emotional problems is driven by a higher likelihood of reporting to have achieved less than usual at work in the past four week, and Internet access is also found to be positively (but insignificantly) associated with a higher probability of reporting to be less accurate at work.[22] Billari et al. (2019) analyze the effect of a DSL connection on the labor supply of highly-educated women aged 25-45 in Germany. Consistent with an effect of broadband Internet on the labor market outcomes of women, they find that having broadband Internet significantly increases the probability of working from home. Broadband Internet also significantly reduces the average number of weekly hours worked and increases the probability of working part-time *versus* full-time for the same group. Results for the effect of high-speed Internet access on the sub-facets of men's mental health are presented in Table 2B.5 in Appendix 2B. The evidence again confirms that broadband Internet access does not negatively affect men's likelihood of suffering from mental illness, nor does it affect their sense of self-productivity at work.

I again look at heterogenous effects by age group in Table 2B.6 in Appendix 2B. Results for the young and older group are presented in Panels A and B respectively. Consistent with the theory that heavier users are likely to suffer more from having access to broadband Internet, I find that the effect of DSL access within the household on various sub-facets of mental health is concentrated among younger women. More specifically, women aged 18-30 with a high-speed Internet connection within the household have one standard deviation lower scores for socializing behavior and emotional problems (Columns 1 and 3), and also have 80% of a standard deviation lower score for their mood (Column 4). Finally, women aged 18-30 are more likely to report both having achieved less than usual in the previous four weeks and having been less accurate due to emotional problems (Columns 5 and 6 respectively). Conversely, the effect of having a DSL Internet connection on the mental health of female respondents aged 31-59 is smaller in magnitude than the effect for the younger cohorts, and only significant for socializing behavior and the likelihood of reporting to have achieved less than usual in the previous four weeks (see Panel B of Table 2B.6 in Appendix 2B). Taken together, these results raise concerns about the potential consequences of technology consumption in terms of women's productivity and labor market attachment, especially so for women in the early phases of their careers. Given recent evidence that the economic costs of mental health disorders in terms of lost productivity are 76 bn in Europe alone, it is imperative to further our understanding of whether technological advancements may be a contributing factor driving productivity losses worldwide.

[22] All significant coefficients are also significantly different from those estimated on the subsample of men, as shown in the last row of Table 2.6.

Table 2.6: Broadband Internet and facets of mental health - Female respondents

	First stage	Mental Health				Emotional Problems	
	DSL in HH	Socializing	Vitality	Emotional	Mood	Achieve less	Less thorough
DSL connection in HH	-	-0.722***	-0.283	-0.608**	-0.267	0.765***	0.420
	-	(0.260)	(0.252)	(0.257)	(0.262)	(0.266)	(0.260)
Threshold	-0.133***						
	(0.0162)						
OPAL technology	-0.049**						
	(0.022)						
Observations	17,692	17,692	17,692	17,692	17,692	17,692	17,692
State FE and linear trends	Y	Y	Y	Y	Y	Y	Y
Individual controls	Y	Y	Y	Y	Y	Y	Y
Overidentification test (p-value)	-	0.507	0.124	0.992	0.660	1	0.984
F-stat. Test of excluded instruments	38.10						
Equality of coefficients (p-value)	-	0.075	0.318	0.050	0.026	0.025	0.149

Notes: 2SLS regressions. The sample includes all female respondents aged 18-59. Standard errors clustered at the household level are reported in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Control variables include age and its squared term, indicators for different educational qualifications and occupation, marital status, number of children and household type, migration background, the logarithm of net household income and an indicator for whether the respondent is a home owner, and a dummy variable for whether the respondent works full time. State and survey year fixed-effects are also included, as well as state-specific linear trends. The F-statistics refers to the Kleibergen-Paap F-statistic from a test for excluded instruments. The last row refers to the p-value for a test of equality of coefficients for broadband Internet across the female and male subsamples.

2.4.3 Broadband Internet and time use

In order to shed light on potential channels through which Internet access affects mental health, I look at the allocation of time across different activities during the day, and how this is affected by the availability of high-speed Internet. I exploit data from the 2008, 2010 and 2012 wave to examine differences in the number of hours per day respondents spend on different activities during weekdays, as induced by having a DSL connection within the households. I present evidence below that broadband access affects the time allocation across various daily tasks differently for men and women. Table 2.7 shows results separately for women and men (Panel A and B respectively), for hours spent on the following activities during an average weekday: job, running errands, housework, childcare, job training, house repairs and garden work, leisure time, care for other persons, sleep. First, sample means across subgroups reveal large gender differences in time allocation: women spend significantly more time than men running errands, doing housework and taking care of children or other dependent persons, while they work less hours than men and enjoy slightly less leisure time. Second, having a broadband connection within the household significantly reduces the number of hours women spend doing housework, whereas it significantly increases the leisure time of men and time men spend on house chores.[23] Further, women who have a DSL connection within the household sleep roughly 43 minutes less compared to women without broadband Internet access. Men's sleep patterns are instead unaffected by broadband Internet access. Qualitatively similar gender differences in the effect of high-speed Internet on sleep are obtained when using a binary indicator for sleeping less than 7 hours as a measure of sleep deprivation, as shown in Column 10. This last result highlights a potential channel through which Internet access may lead to worse mental health for women, but not for men. Indeed, sleep deprivation, which is considered a major public health challenge and one of the most prevalent risky behaviors today (Billari et al., 2018), has been found in the literature to be associated with negative effects on productivity as well as self-reported and objective measures of health (De Quidt and Haushofer, 2016; Giuntella and Mazzonna, 2019; Jin and Ziebarth, 2020). In line with these findings, Table 2B.7 shows that sleep time during workdays is significantly and positively correlated with better mental health for the full sample of SOEP respondents, as well as for both subsamples of men and women. Taken together, this evidence points to the importance of sleep disruptions in explaining part of the effect of broadband Internet on mental health.

[23]Similarly, work from Aguiar et al. (2021) shows that since 2004 young men in the US have been shifting their leisure activities towards video and computer games.

Table 2.7: Broadband Internet access and time allocation

	Job	Errands	Housework	Childcare	Training	Repairs	Leisure	Care	Sleep	Sleep <7 hrs
Panel A: Women										
DSL connection in HH	-0.346	0.075	-0.572*	-0.258	-0.008	-0.996***	0.520	0.194	-0.734**	0.393***
	(0.494)	(0.165)	(0.318)	(1.118)	(0.370)	(0.255)	(0.455)	(0.306)	(0.301)	(0.115)
Observations	17,113	17,558	17,618	16,752	16,413	16,905	17,445	16,391	17,660	17,660
State FE and linear trends	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
F-stat. Test of excluded instruments	35.56	35.60	36.25	34.76	36.17	37.58	35.80	35.38	37.02	37.02
Overidentification test (p-value)	0.0190	0.520	0.751	0.107	0.402	0.125	0.325	0.326	0.114	0.200
Mean of dep. var.	5.660	1.141	2.138	2.417	0.606	0.599	1.958	0.195	6.973	0.297
Panel B: Men										
DSL connection in HH	-0.628	0.059	0.367*	0.241	0.162	-1.371***	0.814*	0.273**	-0.395	0.146
	(0.481)	(0.173)	(0.205)	(0.341)	(0.388)	(0.319)	(0.454)	(0.116)	(0.307)	(0.132)
Observations	15,301	15,277	15,224	14,775	14,597	15,153	15,398	14,470	15,645	15,645
State FE and linear trends	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
F-stat. Test of excluded instruments	29.61	30.65	30.51	30.41	28.68	30.54	30.45	28.54	30.76	30.76
Overidentification test (p-value)	0.736	0.203	0.00970	0.0486	0.452	0.00692	0.468	0.480	0.158	0.477
Mean of dep. var.	8.233	0.810	0.879	0.671	0.611	0.856	2.133	0.0744	6.824	0.360

Notes: 2SLS regressions. The sample includes all respondents to the 2008, 2010 and 2012 aged 18-59 and with non-missing information on mental health. Standard errors clustered at the household level are reported in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The sleep variables are recorded as missing for individuals who report extreme values of sleep (more than 16 or less than 2 hours per night). Control variables include age and its squared term, indicators for different educational qualifications and occupation, marital status, number of children and household type, migration background, the logarithm of net household income and an indicator for whether the respondent is a home owner, and a dummy variable for whether the respondent works full time. State and survey year fixed-effects are also included, as well as state-specific linear trends. The F-statistics refers to the Kleibergen-Paap F-statistic from a test for excluded instruments.

2.5 Robustness

I perform a number of robustness checks to assess how my results change when restricting the sample to specific subgroups or changing the model specification. These are described in Section 2.5.1 and presented in Tables 2B.8 to 2B.11 in Appendix 2B. All results refer to estimates for the subsample of female respondents. I also adopt a second identification strategy to tackle issues arising from a potential violation of the exclusion restrictions. In particular, I exploit information from the pre-Internet period to assess whether the results presented above are driven by unobserved characteristics that are linked to the local area of residence, and the effect of which may be captured by the two instrumental variables used throughout. This is described in Section 2.5.2 below.

2.5.1 Changing the sample or model specification

Tables 2B.8 and 2B.9 present robustness checks where I either modify the sample or the empirical specification of equation (2.1). First, I add region fixed effects and region-specific linear trends instead of state-level variables (Panel A), to control for unobservable time-invariant specificities of the 97 regional policy regions in Germany.[24] Here, the identification strategy exploits within-region cross-sectional variation in the residential addresses of SOEP households and the characteristics of their assigned MDF. Second, I control for local area characteristics meant to capture the effect of the local environment (or neighborhood) the respondents live in (Panel B). More specifically, I control for the unemployment rate, average net household income (in logarithm) and the percentage of foreign residents in the respondents' county (*Kreis*) and for indicators of area type based on the number of inhabitants.[25] Third, in Panel C, I exclude those individuals who moved county of residence between 2001 and 2008, to avoid endogeneity arising from selectively moving to locations with better Internet connection. Fourth, I cluster the standard errors at the county level in Panel D. Results for smoking behavior, socializing behavior and emotional problems are remarkably robust across all specifications, with coefficients retaining significance and varying little in magnitude across the different models. Looking at the summary scale for mental health, while the DSL connection coefficient significantly enters the

[24] The 97 regional policy regions (*Raumordnungsregionen*) are defined by the Federal Office for Building and Regional Planning on the basis of economic interlinkages between different areas - see Knies and Spiess (2007) for the definition of these spatial units in the SOEP.

[25] Beyond these observed characteristics of the local area, unobserved, time-invariant county characteristics may also bias the estimates of my coefficient of interest. Similarly, cross-county variation in mental health and substance use patterns over time is not controlled for and may affect the estimated 2SLS coefficients. Further analyses should include the full set of county fixed-effects and county-specific linear trends to tackle this concern.

model only in Panels B and D, it's worth noting that it remains fairly stable in magnitude across all specifications.

Tables 2B.10 and 2B.11 present results for rubustness checks where I change the instruments used. Since the OPAL instrument is only relevant for Eastern Germany respondents, in Panel A I exploit variation uniquely in the distance of households from their assigned MDF and include only the threshold variable as instrument for DSL access within the household. In Panel B I use only the linear distance of the household from the main distribution frame it is assigned to as instrument for broadband Internet access. Whilst the 4.2 km threshold constitutes a sharp discontinuity in DSL availability, the distance from the main distribution frame determines the maximum bandwidth that a household can have and affects the quality of the Internet connection. It is thus closely related to whether or not households can access high-speed Internet from their home. Results for smoking behavior and socializing behavior survive these modifications of the model specification.

2.5.2 Difference-in-Difference approach

As a further robustness check, I follow the approach of Campante et al. (2017) and make use of information on mental health, its sub-facets and smoking behavior for the pre-Internet period to estimate a difference-in-difference specification. As discussed above, the choice of location of the MDFs and the technology used to connect these to households within their catchment areas predates the development of high-speed in Germany. However, Tables 2A.4 and 2A.5 indicate that the spatial distribution of the MDFs and the wire technology may not be completely random. To address concerns arising from both time-varying and time-invarying confounding factors, I pool answers to the 2002, 2004, 2008, 2010 and 2012 waves and estimate the following 2SLS model:

$$y_{ist} = \beta_0 + \beta_1 Broadband_{ist} + \beta_2 X_{ist} + \mu_s + \lambda_t + \eta_s t + \epsilon_{ist} \tag{2.3}$$

where

$$Broadband_{ist} = \gamma_0 + \gamma_1 Z_{ist} \times Post\_Internet_t + \gamma_2 X_{ist} + \mu_s + \lambda_t + \eta_s t + u_{ist} \tag{2.4}$$

Here, $Post\_Internet_t$ is a binary variable that takes value 1 for the 2008, 2010 and 2012 waves, when broadband Internet technology was already developed in Germany, and 0 otherwise; by assumption, I let $Broadband_{ist}$ take value 0 for the 2002 and 2004 waves, when DSL technology was still in its early phases; all other variables are defined as above.[26]

The use of state fixed-effects together with the use of observations from both before and after the introduction of DSL in Germany allows to overcome estimation biases due to unobserved time-invarying state characteristics.[27] However, time-varying unobserved characteristics may still affect both my outcome variables and access to DSL Internet at the household level. This is why in the first-stage of the 2SLS estimation I instrument access to broadband Internet with the same instrument vector used throughout, but this time interacted with a post-Internet dummy. The identification assumption here is that any correlation between the instrument vector and confounding (unobserved) characteristics of the residential area did not change after the introduction of DSL Internet. To give an intuition of the assumption behind this identification strategy, let's consider the simpler case where only one instrument is used - the threshold indicator. The difference-in-difference identification strategy relies on the assumption that any change in the relationship between living more than 4.2 km away from the main distribution frame and the outcomes of interest was induced only by the development of the DSL technology. As an example, let's assume that living beyond the 4.2 km threshold is correlated with an unobservable measure of social isolation, which in turn affects mental health. The identifying assumption here is that, while the correlation between social isolation and the residential location of the household did not change with the introduction of high-speed Internet, the relationship between mental health and the residential location did, only because of the development of DSL technology.

I now turn to examining 2SLS results for this alternative specification that pools together information from both the pre- and post-Internet period. These are presented in Table 2.8 and refer to estimated effects for the subsample of women respondents. The first stage results refer to the interaction of the two binary instruments with a post-Internet dummy, that takes value one from 2008 onwards and 0 otherwise.

The first-stage diagnostics confirm the validity of the instruments. Turning to the second-stage estimates, it is worth stressing that the coefficients associated to having a DSL connection in the household from the difference-in-difference specifications are remarkably similar to those from the baseline specification. Results from this second identification strategy are consistent with findings from Section 2.4.1 that women's mental health decreases if they have access to

[26] I exclude the 2006 wave as I do not have household-level information on DSL availability for this period, and the assumption of no broadband Internet throughout Germany is unlikely to hold.

[27] Note that unobserved county-level confounders may still bias the estimation of the 2SLS coefficient. Further analyses should include the full set of county fixed-effects instead of state fixed-effects.

broadband Internet, and the negative effect mostly comes through a worse socializing behavior, lower ability to cope with emotional problems and increased feeling of having achieved less and having been less accurate in the past four weeks due to emotional or mental health problems.

Results for men, displayed in Table 2B.12 in Appendix 2B, also confirm the previous findings that broadband Internet access only significantly influences the mental health of women, but not that of men. Taken together, the evidence presented here suggests that broadband Internet is a contributing factor to the widening of the gender gap in mental health.

Table 2.8: Difference-in-difference specification - Female respondents

		Mental health				Emotional problems	
	Mental H.	Socializing	Vitality	Emotional	Mood	Achieved less	Less thorough
Panel A: IV regressions - Second stage							
DSL connection in HH	-0.490*	-0.674***	-0.264	-0.627**	-0.311	0.792***	0.442*
	(0.262)	(0.258)	(0.250)	(0.256)	(0.261)	(0.269)	(0.261)
Panel B: IV regressions - First stage							
Threshold × Post-Internet	-0.129***						
	(0.0163)						
OPAL × Post-Internet	-0.0701***						
	(0.0229)						
Observations	31,562	31,562	31,562	31,562	31,562	31,562	31,562
State FE and linear trends	Y	Y	Y	Y	Y	Y	Y
Individual controls	Y	Y	Y	Y	Y	Y	Y
Overidentification test (p-value)	0.332	0.379	0.142	0.845	0.739	0.842	0.859
F-stat. Test of excluded instruments	37.67						

Notes: 2SLS regressions. The sample includes all female respondents aged 18-59. Standard errors clustered at the household level are reported in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Control variables include age and its squared term, indicators for different educational qualifications and occupation, marital status, number of children and household type, migration background, the logarithm of net household income and an indicator for whether the respondents is a home owner, and a dummy variable for whether the respondent works full time. State, survey year fixed-effects are also included, as well as state-specific linear trends. The F-statistics refers to the Kleibergen-Paap F-statistic from a test for excluded instruments.

2.6 Discussion

The 2SLS estimates presented in sections 2.4.1 and 2.4.2 point to a negative association between high-speed Internet access and mental health, and to large differences in the effect of Internet on psychological well-being by gender. Several channels could explain the results presented in this chapter.

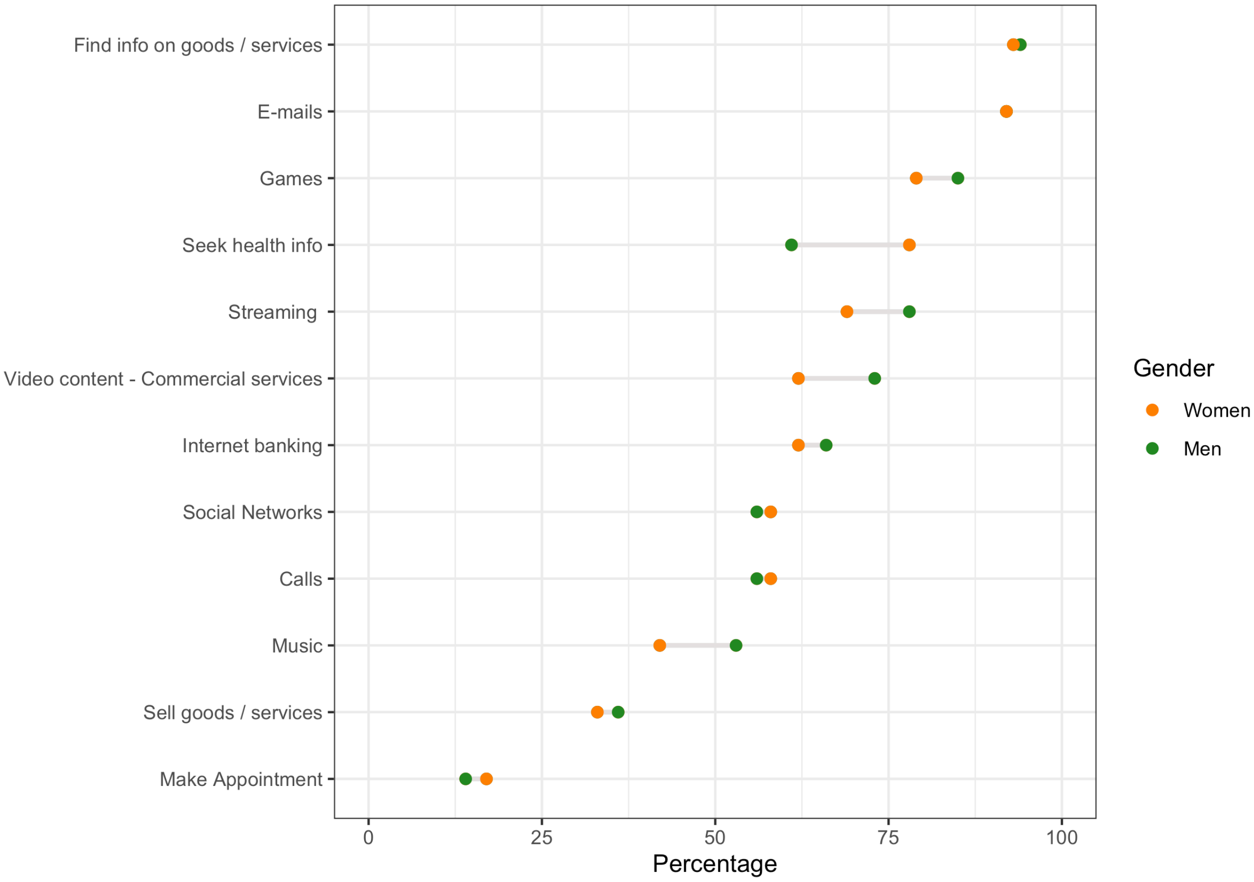
First, Internet access may affect individual time allocation across different activities and induce changes in time use that lead to a deterioration in mental wellbeing and other addictive behaviors. This channel is explored in section 2.4.3. Estimates from 2SLS regressions on time allocation across various activities during weekdays suggest that broadband Internet significantly and negatively affects the sleeping time of women, but not that of men. Previous literature has found changes in sleep patterns to be closely linked with symptoms of depression and anxiety (Jones et al., 1987; De Quidt and Haushofer, 2016; Giuntella and Mazzonna, 2019; Jin and Ziebarth, 2020), which points to a reduction in sleep as a potential mechanism behind the gender differences in mental health due to high-speed Internet access. Beyond sleep, access to broadband Internet might crowd out other activities that influence mental health. As an example, Internet users might substitute in-person interactions or outdoor leisure activities for online alternatives. Whether leisure time spent online leads to worse mental health compared to other forms of leisure activities that may be crowded out by DSL Internet access is an interesting question for future research.

Second, an explanation for the large gender gap in the effect of Internet access on mental health could come from differences in the way broadband Internet is used between men and women. Jackson et al. (2001) and Ipsos MORI (2009) draw on survey data from samples of Anglo-American undergraduate students and Irish adolescents respectively, and document that women tend to use Internet-based communication technologies significantly more than men, who instead make larger use of the Internet's transactional functions like gaming or web searching. While I cannot directly test this hypothesis with SOEP data, which do not contain information on online activities and intensity of Internet use, I use data from Eurostat to provide suggestive evidence that similar differences in Internet usage across genders may be present also in the German context. I collect data on performance of different online activities at the extensive margin from the "Digital Economy and Society Statistics" database. This database has information on the percentage of individuals who carried out different online activities, out of all those who used the Internet in the three months previous to the data collection. Figures are available for the totality of Internet users in the sample, as well as broken down by gender. I compile data for Germany from 2018, when information on the largest number of online activities is available. Figure 2.3 shows the gender breakdown of online activities at the extensive margin, where activities are ordered from the least popular (bottom) to the most popular (top) among female users. Almost the totality of both male and female users make use of the Internet to find information on goods or services, and to use their email. Most of the remaining activities that one could carry out online display gender gaps in the extensive margin of performance. In particular, the share of men performing each activity is higher than the corresponding figure for women for all activities, with the exception of seeking health information, using social networks and making calls. While this evidence does not speak to the intensity with which individuals carry out individual activities, it points to the existence of gender differences in the type and number of activities that Internet users carry out online. Note that such differences may be more or less pronounced across groups with different background characteristics. For example, gaming and the use of Internet to access social networks might be less prevalent amongst the older population of Internet users, with gender differences in this type of activities also being less pronounced amongst this group.

In the context of this paper, it is interesting to note that a higher proportion of women than men seek health information online. This may suggest that the gender gap in the effect of Internet access on mental health could be driven by women having better knowledge of (and being able to identify) symptoms of mental health disorders, as a consequence of them seeking more information online. While I cannot rule out this explanation, results for the effect of Internet access on physical health presented in Table 2.5 suggest there are other reasons behind the gender differences in the effect of DSL access within the household on health-related outcomes. Indeed, one would expect that, if women use the Internet to seek health information more than men do, their knowledge of both mental *and* physical health should improve. If an increased ability to recognize symptoms of diseases and disorders leads to increased reporting of health problems, one would expect DSL access to be related to worse mental *and* physical health for women. However, this is not the case in my data.

It is also important to acknowledge that information seeking behavior might vary with other background characteristics, such as educational attainment. Under the assumption that highly educated individuals are more likely to seek health-related information online than their low educated counterpart, the absence of differences in the impact of Internet access on women's mental health across education groups would be suggestive evidence that the information seeking

Figure 2.3: Breakdown of Internet activities by gender - Individuals aged 16-74



Notes: The graph shows, for each activity carried out on the Internet, the fraction of individuals who performed that action, among German adults aged 16-74 who used the Internet in the three months previous to the data collection. Orange dots indicate the share of women who performed a given action, over the total number of female users of the Internet aged 16-74; green dots indicate the corresponding figure for men.

channel is not the main driver of the results presented in this chapter. Further analyses should investigate the existence of heterogeneities in the impact of DSL Internet across individuals with different levels of educational attainment.

Finally, a higher intensity of Internet usage is likely to exacerbate the negative impact of DSL Internet on mental wellbeing. One dimension along which usage intensity varies significantly is age. As shown in sections 2.4.1 and 2.4.2, the effect of high-speed Internet access on the mental health of women is larger for younger cohorts (age 18-30) than for older groups, which suggests that higher usage intensity leads to a larger deterioration in psychological wellbeing. An alternative dimension along which Internet usage intensity may vary is time use at baseline. For example, individuals who have work activities out of the house may have less time to spend on the Internet compared to those who work from home or are out of paid work. This incapacitation effect would lead to a smaller impact of DSL access on mental health for individuals with limited opportunities for Internet consumption for leisure purposes. It is plausible to assume that similar heterogeneities in the impact of DSL Internet on mental health could arise along other dimensions of time use or individual characteristics at baseline (e.g. presence of young children in the household). Future work should explore how the impact of DSL Internet access varies along different baseline characteristics of individuals, beyond age and gender.

2.7 Conclusion

In this paper, I investigate to what extent having access to broadband Internet affects the mental health and substance use of German adults aged 18-59. To answer this research question, I leverage publicly available data on the telephony network in Germany, and combine these with restricted information on the exact geo-coordinates of households of respondents to the German SOEP. To address the endogeneity concerns related to DSL Internet access within the household, I exploit characteristics of the pre-existing telephony network to instrument for broadband access at the household level. More precisely, I construct two instrumental variables for whether the respondent lives in a household that is more than 4.2 km away from the main distribution frame it is assigned to, and for whether the main distribution frame the respondent's household is assigned to makes use of OPAL technology. In the baseline specification, I use information from the years 2008, 2010 and 2012 and control for a large number of individual characteristics, as well as state and year fixed effects. In a second identification strategy that aims at addressing concerns related to the validity of my instruments, I exploit information from the pre-Internet period (survey years 2002 and 2004) and construct two instruments that are the interaction of the binary indicators described above with a post-Internet dummy that takes value one from 2008 onwards, and zero otherwise. Results show that having broadband Internet access leads to a significant decrease in the mental health of women, but not that of men, as well as significantly increases women's probability of smoking. Interestingly, high-speed Internet access has no effect on physical health, neither for men nor for women. The results are alarming and point to the fact that Internet access is a contributing factor to the gender gap in mental health. The negative effect on women's mental health is mostly concentrated among younger cohorts, which is consistent with the hypothesis that larger use of the Internet would amplify its impact. Further, I provide suggestive evidence that the negative effect on women's mental health is driven by a worsening of women's socializing behavior and ability to cope with emotional problems. The latter has potentially negative repercussions on women's productivity at work. Indeed, I find that female respondents to the SOEP who have a broadband connection within the household more frequently report being less accurate and thorough at work. Finally, I exploit SOEP data on the allocation of time across different activities during weekdays to show that women who have access to DSL Internet within the household sleep significantly less than their counterpart without a broadband connection. No effect on sleep patterns is detected for men, who instead spend significantly more time on leisure activities when having access to high-speed Internet. Recent evidence associating sleep quality and duration to wellbeing and mental health suggests that the reduction in sleep time may be a channel through which broadband Internet affects the incidence of mental disorders.

Taken together, the results from this paper shed new light on potential determinants of mental health disorders and contribute to the growing debate on the societal effect of Internet technology. The large negative effects documented here raise the question of what policies can be implemented to increase awareness of the downsides of online activities. Further research is needed to understand the effect of specific activities that consumers of the Internet carry out online, and whether providing people with information about the effect of Internet use may change their consumption patterns and ultimately affect their subjective well-being and mental health. Finally, the potentially negative side-effect of Internet access on workers' productivity, as induced by an increase in mental health disorders, calls for further investigation.

Appendices of Chapter 2

2A Data description

Table 2A.1: Sample characteristics by gender - Num. of observations = 11,447

	Full sample		Women		Men		P-value
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	
Female	0.53	0.50	1.00	0.00	0.00	0.00	.
Age in years	40.94	11.22	40.90	11.15	40.98	11.29	0.723
Lower sec. education	0.10	0.30	0.11	0.31	0.09	0.29	0.000
Upper sec. education	0.51	0.50	0.50	0.50	0.52	0.50	0.053
Tertiary education	0.22	0.42	0.22	0.41	0.23	0.42	0.134
Employed full-time	0.55	0.50	0.36	0.48	0.77	0.42	0.000
Not employed[a]	0.21	0.40	0.26	0.44	0.14	0.35	0.000
White collar worker	0.31	0.46	0.33	0.47	0.29	0.46	0.000
Blue collar worker	0.22	0.41	0.13	0.34	0.31	0.46	0.000
First-gen. immigrant	0.11	0.31	0.11	0.32	0.10	0.30	0.055
Second-gen. immigrant	0.05	0.22	0.05	0.22	0.05	0.22	0.828
Married	0.60	0.49	0.61	0.49	0.59	0.49	0.009
Single	0.30	0.46	0.27	0.44	0.33	0.47	0.000
Num. of children in HH	0.94	1.03	0.95	1.02	0.93	1.04	0.198
HH net income (Log)	7.85	0.58	7.83	0.58	7.87	0.58	0.001
West Germany	0.76	0.43	0.76	0.42	0.75	0.43	0.204
Home owner	0.51	0.50	0.50	0.50	0.52	0.50	0.036

Notes: SOEP 2008. The sample includes all respondents aged 18-59, with non-missing information on the control variables presented in the above table and information on broadband Internet availability. Columns 1-2 show summary statistics for the full sample, Columns 3-4 show results for female respondents and Columns 5-6 report summary statistics for male respondents. The last column shows the p-value for a t-test of equality of means across the two subgroups.
a: The category "Not employed" comprises non-working individuals (including those in education or training), those in military or community service, those on maternity leave, and employed persons in a phased retirement scheme working zero hours.

Table 2A.2: Sample characteristics by whether or not the respondent has DSL Internet

	Full sample		DSL		No DSL		
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	P-value
Panel A: Outcome variables							
Mental Health	-0.02	0.95	-0.00	0.92	-0.07	1.00	0.000
Socializing behavior	0.08	0.95	0.11	0.92	0.01	1.01	0.000
Vitality	0.04	0.93	0.06	0.91	0.00	0.97	0.001
Mood	-0.07	0.94	-0.05	0.91	-0.11	0.98	0.002
Emotional problems	0.11	0.95	0.14	0.93	0.05	1.01	0.000
Accomplished less	-0.03	0.98	-0.07	0.95	0.03	1.03	0.000
Less thorough	-0.03	0.98	-0.06	0.95	0.03	1.03	0.000
Currently smoking	0.33	0.47	0.31	0.46	0.39	0.49	0.000
Alcohol consumption	0.00	1.00	0.07	1.00	-0.13	0.98	0.000
Panel B: Control variables							
Female	0.53	0.50	0.52	0.50	0.54	0.50	0.006
Age in years	40.94	11.22	40.55	11.00	41.77	11.61	0.000
Lower sec. education	0.10	0.30	0.08	0.28	0.14	0.35	0.000
Upper sec. education	0.51	0.50	0.48	0.50	0.56	0.50	0.000
Tertiary education	0.22	0.42	0.26	0.44	0.15	0.35	0.000
Employed full-time	0.55	0.50	0.57	0.49	0.52	0.50	0.000
Not employed[a]	0.21	0.40	0.18	0.38	0.26	0.44	0.000
White collar worker	0.31	0.46	0.35	0.48	0.23	0.42	0.000
Blue collar worker	0.22	0.41	0.18	0.39	0.29	0.45	0.000
First-gen. immigrant	0.11	0.31	0.09	0.29	0.13	0.34	0.000
Second-gen. immigrant	0.05	0.22	0.05	0.22	0.05	0.22	0.730
Married	0.60	0.49	0.63	0.48	0.53	0.50	0.000
Single	0.30	0.46	0.29	0.45	0.33	0.47	0.000
Num. of children in HH	0.94	1.03	1.04	1.05	0.73	0.97	0.000
HH net income (Log)	7.85	0.58	7.97	0.54	7.60	0.59	0.000
West Germany	0.76	0.43	0.81	0.39	0.66	0.48	0.000
Home owner	0.51	0.50	0.55	0.50	0.43	0.49	0.000

Notes: SOEP 2008. The sample includes all respondents aged 18-59, with non-missing information on the control variables presented in the above table, and non-missing observations for the outcome variables in Panel A. Columns 1-2 show summary statistics for the full sample, Columns 3-4 show results for respondents with a DSL connection at home, and Columns 5-6 report summary statistics for respondents without a DSL connection at home. The last column shows the p-value for a t-test of equality of means across the two subgroups.
a: The category "Not employed" comprises non-working individuals (including those in education or training), those in military or community service, those on maternity leave, and employed persons in a phased retirement scheme working zero hours.

Table 2A.3: Evolution of the gender gap in mental health

	2004 All			2004 - No miss.			Observed also in 2008			2008 stats.		
	All	Men	Women	All	Men	Women	All	Men	Women	All	Men	Women
Mental Health - Summary Scale	0.000	0.114	-0.106	-0.039	-0.039	-0.039	-0.031	0.069	-0.119	-0.021	0.071	-0.102
	(1.000)	(0.963)	(1.021)	(0.961)	(0.961)	(0.961)	(0.953)	(0.910)	(0.982)	(0.946)	(0.894)	(0.983)
Socializing behavior	0.000	0.083	-0.077	0.085	0.085	0.085	0.108	0.176	0.048	0.069	0.148	-0.001
	(1.000)	(0.954)	(1.035)	(0.930)	(0.930)	(0.930)	(0.912)	(0.864)	(0.947)	(0.942)	(0.880)	(0.989)
Vitality	0.000	0.072	-0.067	0.088	0.088	0.088	0.096	0.159	0.041	0.035	0.081	-0.006
	(1.000)	(0.996)	(1.000)	(0.953)	(0.953)	(0.953)	(0.956)	(0.963)	(0.948)	(0.923)	(0.914)	(0.930)
Mood	-0.000	0.121	-0.113	-0.069	-0.069	-0.069	-0.065	0.029	-0.148	-0.065	0.006	-0.127
	(1.000)	(0.985)	(1.000)	(0.967)	(0.967)	(0.967)	(0.967)	(0.957)	(0.968)	(0.932)	(0.914)	(0.944)
Emotional	-0.000	0.109	-0.102	0.086	0.086	0.086	0.114	0.207	0.032	0.096	0.189	0.013
	(1.000)	(0.947)	(1.036)	(0.939)	(0.939)	(0.939)	(0.923)	(0.871)	(0.959)	(0.955)	(0.899)	(0.995)
Accomplished less	-0.000	-0.109	0.101	0.002	0.002	0.002	-0.022	-0.119	0.064	-0.014	-0.119	0.079
	(1.000)	(0.953)	(1.031)	(0.997)	(0.997)	(0.997)	(0.988)	(0.943)	(1.018)	(1.008)	(0.943)	(1.054)
Less thorough	-0.000	-0.101	0.094	-0.004	-0.004	-0.004	-0.039	-0.131	0.042	-0.009	-0.093	0.065
	(1.000)	(0.944)	(1.041)	(0.994)	(0.994)	(0.994)	(0.970)	(0.908)	(1.015)	(1.008)	(0.955)	(1.047)
N	21,248	10,236	11,012	12,787	6,342	6,750	8,387	3,938	4,449	8,058	3,786	4,272

Notes: SOEP 2004 and 2008. Columns 1-3 show summary statistics for the entire 2004 population, and separately by gender. Columns 4-6 restrict the 2004 sample to individuals aged 18-59 with non-missing information on all the control variables presented in Table 2A.1. Columns 7-9 further restrict the sample to individuals that are observed both in 2004 and 2008. Columns 10-12 show summary statistics for the same respondents as in Columns 7-9, but for the year 2008. All mental health variables are standardised to have mean 0 and standard deviation of 1 for the sample of respondents to the 2004 wave of the SOEP.

Table 2A.4: Background characteristics for households living either side of the threshold

	Full sample			>4.2 km		<4.2 km		P-value
	Mean	St. Dev.	N	Mean	St. Dev.	Mean	St. Dev.	
			Household characteristics					
DSL connection in HH	0.52	0.50	10739	0.40	0.49	0.53	0.50	0.000
Number of people in HH	2.28	1.17	10739	2.48	1.21	2.27	1.16	0.000
Number of children in HH	0.55	0.90	10735	0.62	0.99	0.55	0.89	0.031
Single HH	0.28	0.45	10739	0.21	0.41	0.29	0.45	0.000
Couple HH	0.34	0.48	10739	0.38	0.49	0.34	0.47	0.051
Single Parent	0.06	0.24	10739	0.05	0.22	0.06	0.24	0.137
Family w Children	0.30	0.46	10739	0.34	0.47	0.29	0.46	0.007
Other	0.01	0.12	10739	0.02	0.15	0.01	0.11	0.021
HH net income (Log)	7.65	0.62	10145	7.69	0.59	7.65	0.62	0.163
Home owner	0.48	0.50	10739	0.68	0.47	0.47	0.50	0.000
			Individual characteristics					
Female	0.53	0.50	13143	0.51	0.50	0.53	0.50	0.428
Age in years	39.99	11.88	13143	40.64	11.80	39.93	11.89	0.074
Lower seconday education	0.10	0.30	12389	0.10	0.29	0.10	0.30	0.590
Upper seconday education	0.51	0.50	12389	0.56	0.50	0.51	0.50	0.002
Tertiary education	0.22	0.42	12389	0.16	0.36	0.23	0.42	0.000
Employed full-time	0.53	0.50	13143	0.52	0.50	0.53	0.50	0.522
Unemployed	0.23	0.42	13143	0.25	0.43	0.23	0.42	0.134
White collar worker	0.29	0.46	13082	0.27	0.44	0.30	0.46	0.064
Blue collar worker	0.21	0.41	13082	0.23	0.42	0.21	0.40	0.079
First generation immigrant	0.10	0.31	13143	0.05	0.22	0.11	0.31	0.000
Second generation immigrant	0.06	0.24	13143	0.03	0.17	0.06	0.24	0.000
Married	0.57	0.49	13105	0.60	0.49	0.57	0.50	0.045
Single	0.33	0.47	13105	0.30	0.46	0.34	0.47	0.020

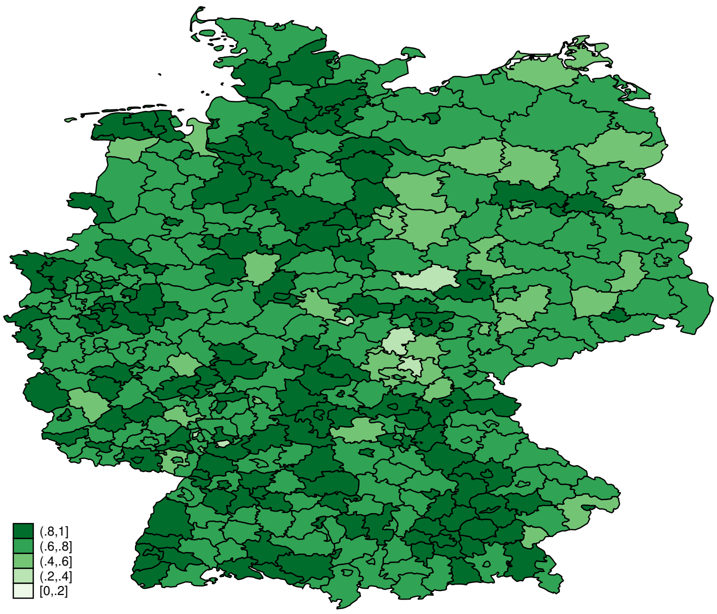
Notes: SOEP 2008. The sample for individual characteristics includes all respondents aged 18-59. Columns 1-3 show summary statistics for the full sample, Columns 4-5 show results for respondents living beyond the threshold and Columns 6-7 report summary statistics for respondents living within the threshold. The last column shows the p-value for a t-test of equality of means across the two subgroups.

Table 2A.5: Background characteristics for households assigned to main distribution frames with different wire technologies

	Full sample			OPAL		No OPAL		P-value
	Mean	St. Dev.	N	Mean	St. Dev.	Mean	St. Dev.	
Household characteristics								
DSL connection in HH	0.37	0.48	2380	0.34	0.47	0.39	0.49	0.054
Number of people in HH	2.19	1.08	2380	2.09	1.04	2.21	1.09	0.034
Number of children in HH	0.47	0.82	2378	0.45	0.80	0.49	0.83	0.373
Single HH	0.29	0.45	2380	0.31	0.46	0.28	0.45	0.224
Couple HH	0.37	0.48	2380	0.39	0.49	0.36	0.48	0.266
Single Parent	0.06	0.24	2380	0.07	0.26	0.06	0.24	0.504
Family w Children	0.27	0.44	2380	0.21	0.41	0.28	0.45	0.002
Other	0.01	0.11	2380	0.02	0.14	0.01	0.11	0.181
HH net income (Log)	7.45	0.56	2292	7.43	0.57	7.45	0.56	0.529
Home owner	0.42	0.49	2380	0.32	0.47	0.43	0.50	0.000
Individual characteristics								
Female	0.52	0.50	3137	0.53	0.50	0.51	0.50	0.395
Age in years	39.82	12.21	3137	39.40	12.35	39.81	12.20	0.472
Lower seconday education	0.06	0.24	2974	0.06	0.23	0.06	0.24	0.812
Upper seconday education	0.55	0.50	2974	0.53	0.50	0.56	0.50	0.298
Tertiary education	0.26	0.44	2974	0.29	0.45	0.25	0.43	0.073
Employed full-time	0.55	0.50	3137	0.55	0.50	0.54	0.50	0.863
Unemployed	0.26	0.44	3137	0.27	0.44	0.26	0.44	0.639
White collar worker	0.27	0.44	3122	0.28	0.45	0.26	0.44	0.499
Blue collar worker	0.23	0.42	3122	0.20	0.40	0.23	0.42	0.118
First generation immigrant	0.01	0.10	3137	0.01	0.09	0.01	0.10	0.444
Second generation immigrant	0.01	0.12	3137	0.02	0.13	0.01	0.12	0.620
Married	0.50	0.50	3123	0.46	0.50	0.50	0.50	0.038
Single	0.39	0.49	3123	0.42	0.49	0.38	0.49	0.094

Notes: SOEP 2008. Sample restricted to observations for East Germany only. The sample for individual characteristics includes all respondents aged 18-59. Columns 1-3 show summary statistics for the full sample, Columns 4-5 show results for respondents being served by an OPAL main distribution frame, and Columns 6-7 report summary statistics for respondents being served by a non-OPAL main distribution frame. The last column shows the p-value for a t-test of equality of means across the two subgroups.

Figure 2A.1: Percentage of households with a broadband Internet connection across counties in 2012



Notes: The map shows the fraction of SOEP households with access to broadband Internet for the survey year 2012 across all 401 German counties. Darker green areas indicate higher levels of broadband Internet access.

2B Supplementary analyses

Table 2B.1: Broadband Internet and mental health - OLS estimates

	Full sample			Women			Men		
	Smoking	Alcohol	Mental H.	Smoking	Alcohol	Mental H.	Smoking	Alcohol	Mental H.
DSL connection in HH	-0.011	0.077***	-0.019	-0.004	0.092***	-0.029	-0.017	0.065**	-0.009
	(0.009)	(0.018)	(0.017)	(0.011)	(0.022)	(0.022)	(0.012)	(0.026)	(0.022)
Observations	29,172	21,925	33,365	15,187	11,553	17,692	13,985	10,372	15,673
State FE and linear trends	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual controls	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: OLS regressions. The sample includes all respondents aged 18-59. Standard errors clustered at the household level are reported in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Control variables include age and its squared term, gender, indicators for different educational qualifications and occupation, marital status, number of children and household type, migration background, the logarithm of net household income and an indicator for whether the respondent is a home owner, and a dummy variable for whether the respondent works full time. State and survey year fixed-effects are also included, as well as state-specific linear trends.

Table 2B.2: Broadband Internet and mental health - Placebo test

	Full sample	Women	Men
Panel A: IV regressions - Second stage			
DSL connection in HH	-0.197	-0.323	-0.057
	(0.233)	(0.263)	(0.307)
Panel B: IV regressions - First stage			
Threshold	-0.142***	-0.153***	-0.130***
	(0.027)	(0.028)	(0.030)
OPAL technology	-0.098***	-0.113***	-0.080**
	(0.035)	(0.037)	(0.039)
Observations	17864	9101	8763
State FE and linear trends	Y	Y	Y
Individual controls	Y	Y	Y
Overidentification test (p-value)	0.6387	0.4409	0.0999
F-stat.	17.59	19.23	11.74

Notes: 2SLS regressions. The dependent variable is the composite index for mental health. The sample includes all respondents to the waves 2002 and 2004, aged 18-59. Standard errors clustered at the household level are reported in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Control variables include age and its squared term, gender, indicators for different educational qualifications and occupation, marital status, number of children and household type, migration background, the logarithm of net household income and an indicator for whether the respondent is a home owner, and a dummy variable for whether the respondent works full time. State and survey year fixed-effects are also included, as well as state-specific linear trends. The F-statistics refers to the Kleibergen-Paap F-statistic from a test for excluded instruments.

Table 2B.3: Broadband Internet and facets of mental health - OLS estimates, Female respondents

	Mental Health				Emotional Problems	
	Socializing	Vitality	Emotional	Mood	Achieve less	Less thorough
DLS connection in HH	-0.259	-0.203	-0.290	-0.315	0.039*	0.017
	(0.219)	(0.202)	(0.219)	(0.207)	(0.022)	(0.022)
Observations	17,692	17,692	17,692	17,692	17,958	17,938
State FE and linear trends	Y	Y	Y	Y	Y	Y
Individual controls	Y	Y	Y	Y	Y	Y

Notes: OLS regressions. The sample includes all female respondents aged 18-59. Standard errors clustered at the household level are reported in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Control variables include age and its squared term, indicators for different educational qualifications and occupation, marital status, number of children and household type, migration background, the logarithm of net household income and an indicator for whether the respondent is a home owner, and a dummy variable for whether the respondent works full time. State and survey year fixed-effects are also included, as well as state-specific linear trends.

Table 2B.4: Heterogeneous effect by age group - Main outcomes

	Smoking	Alcohol	Mental H.
Panel A: Women 18-30, 2SLS estimates			
DSL connection in HH	0.359*	0.205	-1.168***
	(0.213)	(0.491)	(0.440)
Observations	3,136	2,501	3,711
State FE and linear trends	Y	Y	Y
Individual controls	Y	Y	Y
F-stat. Test of excluded instruments	12.10	10.69	13.68
Overidentification test (p-value)	0.227	0.526	0.973
Panel B: Women 31-59, 2SLS estimates			
DSL connection in HH	0.304**	-0.319	-0.263
	(0.150)	(0.235)	(0.299)
Observations	12,051	9,052	13,981
State FE and linear trends	Y	Y	Y
Individual controls	Y	Y	Y
F-stat. Test of excluded instruments	31.86	33.99	31.17
Overidentification test (p-value)	0.746	0.436	0.325
Equality of coefficients (p-value)	0.825	0.324	0.080

Notes: 2SLS regressions. The sample includes all respondents aged 18-59. Standard errors clustered at the household level are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Control variables include age and its squared term, gender, indicators for different educational qualifications and occupation, marital status, number of children and household type, migration background, the logarithm of net household income and an indicator for whether the respondent is a home owner, and a dummy variable for whether the respondent works full time. State and survey year fixed-effects are also included, as well as state-specific linear trends. The F-statistics refers to the Kleibergen-Paap F-statistic from a test for excluded instruments. The last row refers to the p-value for a test of equality of coefficients for broadband Internet across the young and old subsamples.

Table 2B.5: Broadband Internet and facets of mental health - Male respondents

	First stage	Mental Health				Emotional Problems	
	DSL in HH	Socializing	Vitality	Emotional	Mood	Achieve less	Less thorough
DSL connection in HH	-	-0.176	0.035	-0.027	0.449*	0.062	-0.013
	-	(0.254)	(0.264)	(0.248)	(0.258)	(0.256)	(0.252)
Threshold	-0.133***						
	(0.017)						
OPAL technology	-0.048*						
	(0.025)						
Observations	15,673	15,673	15,673	15,673	15,673	15,673	15,673
State FE and linear trends	Y	Y	Y	Y	Y	Y	Y
Individual controls	Y	Y	Y	Y	Y	Y	Y
Overidentification test (p-value)	-	0.730	0.271	0.423	0.186	0.427	0.446
F-stat. Test of excluded instruments	30.79						

Notes: 2SLS regressions. The sample includes all male respondents aged 18-59. Standard errors clustered at the household level are reported in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Control variables include age and its squared term, indicators for different educational qualifications and occupation, marital status, number of children and household type, migration background, the logarithm of net household income and an indicator for whether the respondent is a home owner, and a dummy variable for whether the respondent works full time. State and survey year fixed-effects are also included, as well as state-specific linear trends. The F-statistics refers to the Kleibergen-Paap F-statistic from a test for excluded instruments.

Table 2B.6: Heterogeneous effect by age group - Sub-facets of mental health

	Mental Health				Emotional problems	
	Socializing	Vitality	Emotional	Mood	Achieve less	Less thorough
Panel A: Women 18-30, 2SLS estimates						
DSL connection in HH	-1.011**	-0.609	-0.998**	-0.861*	1.121**	0.839**
	(0.420)	(0.415)	(0.407)	(0.447)	(0.449)	(0.401)
Observations	3,711	3,711	3,711	3,711	3,711	3,711
State FE and linear trends	Y	Y	Y	Y	Y	Y
Individual controls	Y	Y	Y	Y	Y	Y
Overidentification test (p-value)	0.270	0.0779	0.926	0.985	0.930	0.754
F-stat. Test of excluded instruments	14.45	14.45	14.45	14.45	14.45	14.45
Panel B: Women 31-59, 2SLS estimates						
DSL connection in HH	-0.569**	-0.216	-0.465	-0.0994	0.631**	0.271
	(0.288)	(0.277)	(0.293)	(0.280)	(0.301)	(0.296)
Observations	14,322	14,322	14,322	14,322	14,322	14,322
State FE and linear trends	Y	Y	Y	Y	Y	Y
Individual controls	Y	Y	Y	Y	Y	Y
Overidentification test (p-value)	0.123	0.435	0.854	0.608	0.858	0.860
F-stat. Test of excluded instruments	33.23	33.23	33.23	33.23	33.23	33.23
Equality of coefficients (p-value)	0.355	0.380	0.294	0 .125	0.385	0.248

Notes: 2SLS regressions. The sample includes all female respondents aged 18-59. Standard errors clustered at the household level are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Control variables include age and its squared term, indicators for different educational qualifications and occupation, marital status, number of children and household type, migration background, the logarithm of net household income and an indicator for whether the respondent is a home owner, and a dummy variable for whether the respondent works full time. State and survey year fixed-effects are also included, as well as state-specific linear trends. The F-statistics refers to the Kleibergen-Paap F-statistic from a test for excluded instruments. The last row refers to the p-value for a test of equality of coefficients for broadband Internet across the young and old subsamples.

Table 2B.7: The effect of sleep on mental health

	All	Women	Men
Hours of sleep	0.073***	0.073***	0.074***
	(0.009)	(0.012)	(0.012)
Observations	33759	17887	15872
R^2	0.019	0.022	0.026
State FE and linear trends	Y	Y	Y
Individual FE	Y	Y	Y
Individual controls	Y	Y	Y

Notes: OLS regressions with individual fixed effects. The sample includes all respondents aged 18-59 to survey waves 2008, 2010 and 2012 with non-missing information on mental health. Robust standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01. The dependent variable is the summary scale for mental health. Control variables include age and its squared term, indicators for different educational qualifications and occupation, marital status, number of children and household type, migration background, the logarithm of net household income and an indicator for whether the respondent is a home owner, and a dummy variable for whether the respondent works full time. State, survey year and individual fixed-effects are also included, as well as state-specific linear trends.

Table 2B.8: Modifying sample or specification - Main outcomes

	Smoking	Alcohol	Mental H.
Panel A: Region fixed-effect and region-specific time trends			
DSL connection in HH	0.292**	-0.172	-0.383
	(0.134)	(0.224)	(0.267)
Observations	15,187	11,553	17,692
F-stat. Test of excluded instruments	37.042	36.925	36.558
Overidentification test (p-value)	0.661	0.515	0.252
Panel B: Control for local area characteristics			
DSL connection in HH	0.342**	-0.106	-0.513*
	(0.146)	(0.236)	(0.290)
Observations	15,187	11,553	17,692
F-stat. Test of excluded instruments	33.007	33.685	32.686
Overidentification test (p-value)	0.958	0.495	0.150
Panel C: Exclude movers			
DSL connection in HH	0.379***	-0.149	-0.427
	(0.135)	(0.225)	(0.273)
Observations	10,848	9,114	12,273
F-stat. Test of excluded instruments	37.637	36.876	36.373
Overidentification test (p-value)	0.842	0.245	0.402
Panel D: SE clustered at county level			
DSL connection in HH	0.328**	-0.202	-0.499*
	(0.132)	(0.267)	(0.300)
Observations	15,187	11,553	17,692
F-stat. Test of excluded instruments	34.098	35.288	30.979

Notes: 2SLS regressions. The sample includes all female respondents aged 18-59. Standard errors clustered at the household level, unless otherwise specified, are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Control variables in all panels include age and its squared term, indicators for different educational qualifications and occupation, marital status, number of children and household type, migration background, the logarithm of net household income and an indicator for whether the respondent is a home owner, and a dummy variable for whether the respondent works full time. State and survey year fixed-effects are also included as well as state-specific linear trends, except in Panel A where regional controls are used instead. The F-statistics refers to the Kleibergen-Paap F-statistic from a test for excluded instruments.

Table 2B.9: Modifying sample or specification - Sub-facets of mental health

	Mental Health				Emotional problems	
	Socializing	Vitality	Emotional	Mood	Achieve less	Less thorough
Panel A: Region fixed-effect and region-specific time trends						
DSL connection in HH	-0.518**	-0.253	-0.443*	-0.214	0.591**	0.268
	(0.262)	(0.255)	(0.262)	(0.267)	(0.271)	(0.265)
Observations	17,692	17,692	17,692	17,692	17,692	17,692
Overidentification test (p-value)	0.432	0.0826	0.915	0.492	0.886	0.955
F-stat. Test of excluded instruments	36.56	36.56	36.56	36.56	36.56	36.56
Panel B: Control for local area characteristics						
DSL connection in HH	-0.734**	-0.307	-0.632**	-0.291	0.794***	0.438
	(0.286)	(0.276)	(0.282)	(0.287)	(0.294)	(0.284)
Observations	17,692	17,692	17,692	17,692	17,692	17,692
Overidentification test (p-value)	0.252	0.0483	0.660	0.405	0.649	0.694
F-stat. Test of excluded instruments	32.69	32.69	32.69	32.69	32.69	32.69
Panel C: Exclude movers						
DSL connection in HH	-0.642**	-0.209	-0.383	-0.187	0.499*	0.247
	(0.267)	(0.256)	(0.267)	(0.269)	(0.272)	(0.274)
Observations	12,273	12,273	12,273	12,273	12,273	12,273
Overidentification test (p-value)	0.374	0.331	0.742	0.782	0.920	0.567
F-stat. Test of excluded instruments	36.37	36.37	36.37	36.37	36.37	36.37
Panel D: SE clustered at county level						
DSL connection in HH	-0.722***	-0.283	-0.608**	-0.267	0.765***	0.420
	(0.268)	(0.330)	(0.281)	(0.290)	(0.294)	(0.274)
Observations	17,692	17,692	17,692	17,692	17,692	17,692
F-stat. Test of excluded instruments	30.98	30.98	30.98	30.98	30.98	30.98

Notes: 2SLS regressions. The sample includes all female respondents aged 18-59. Standard errors clustered at the household level, unless otherwise specified, are reported in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Control variables in all panels include age and its squared term, indicators for different educational qualifications and occupation, marital status, number of children and household type, migration background, the logarithm of net household income and an indicator for whether the respondent is a home owner, and a dummy variable for whether the respondent works full time. State and survey year fixed-effects are also included as well as state-specific linear trends, except in Panel A where regional controls are used instead. The F-statistics refers to the Kleibergen-Paap F-statistic from a test for excluded instruments.

Table 2B.10: Modifying the instruments - Main outcomes

	Smoking	Alcohol	Mental H.
Panel A: Only threshold used as instrument			
DSL connection in HH	0.319**	-0.254	-0.569**
	(0.139)	(0.231)	(0.268)
Observations	15,187	11,553	17,692
F-stat. Test of excluded instruments	69.76	71.38	70.51
Panel B: Only distance of HH from MDF used as instrument			
DSL connection in HH	0.400***	-0.273	-0.187
	(0.144)	(0.256)	(0.268)
Observations	15,187	11,553	17,692
F-stat. Test of excluded instruments	68.17	59.88	71.69

Notes: 2SLS regressions. The sample includes all female respondents aged 18-59. Standard errors clustered at the household level, unless otherwise specified, are reported in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Control variables in all panels include age and its squared term, indicators for different educational qualifications and occupation, marital status, number of children and household type, migration background, the logarithm of net household income and an indicator for whether the respondent is a home owner, and a dummy variable for whether the respondent works full time. State and survey year fixed-effects are also included as well as state-specific linear trends. The F-statistic refers to the Kleibergen-Paap F-statistic from a test for excluded instruments.

Table 2B.11: Modifying the instruments - Sub-facets of mental health

	Mental Health				Emotional problems	
	Socializing	Vitality	Emotional	Mood	Achieve less	Less thorough
Panel A: Only threshold used as instrument						
DSL connection in HH	-0.770***	-0.388	-0.608**	-0.297	0.765***	0.419
	(0.265)	(0.259)	(0.264)	(0.267)	(0.272)	(0.268)
Observations	17,692	17,692	17,692	17,692	17,692	17,692
F-stat. Test of excluded instruments	70.51	70.51	70.51	70.51	70.51	70.51
Panel B: Only distance of HH from MDF used as instrument						
DSL connection in HH	-0.541**	-0.232	-0.204	0.0165	0.320	0.0702
	(0.264)	(0.251)	(0.266)	(0.260)	(0.272)	(0.273)
Observations	17,692	17,692	17,692	17,692	17,692	17,692
F-stat. Test of excluded instruments	71.69	71.69	71.69	71.69	71.69	71.69

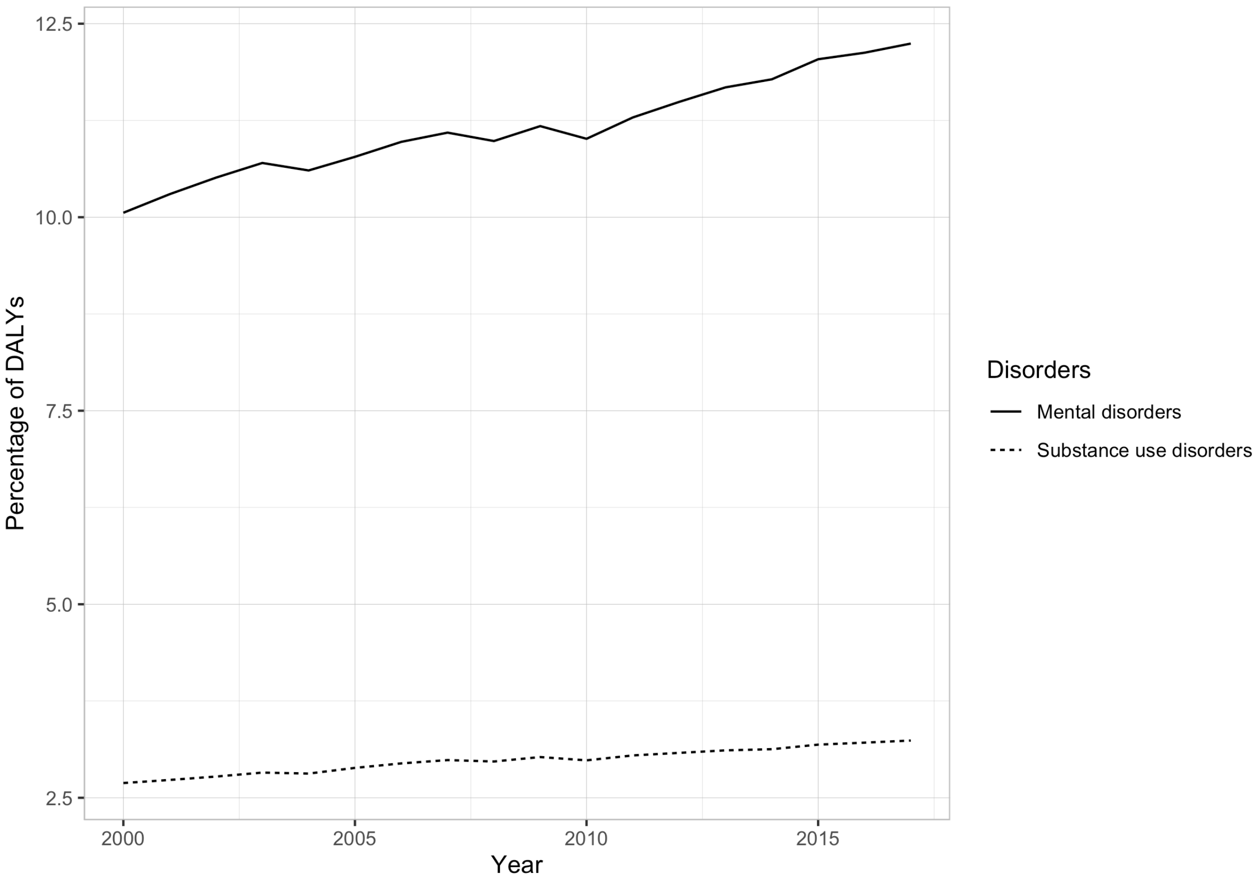
Notes: 2SLS regressions. The sample includes all female respondents aged 18-59. Standard errors clustered at the household level, unless otherwise specified, are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Control variables in all panels include age and its squared term, indicators for different educational qualifications and occupation, marital status, number of children and household type, migration background, the logarithm of net household income and an indicator for whether the respondent is a home owner, and a dummy variable for whether the respondent works full time. State and survey year fixed-effects are also included as well as state-specific linear trends. The F-statistics refers to the Kleibergen-Paap F-statistic from a test for excluded instruments.

Table 2B.12: Difference-in-difference specification - Male respondents

		Mental health				Emotional problems	
	Mental H.	Socializing	Vitality	Emotional	Mood	Achieved less	Less thorough
Panel A: IV regressions - Second stage							
DSL connection in HH	0.193	-0.100	0.0344	0.0283	0.438*	0.00257	-0.0624
	(0.239)	(0.243)	(0.252)	(0.239)	(0.246)	(0.248)	(0.244)
Panel B: IV regressions - First stage							
Threshold × Post-Internet	-0.134***						
	(0.0175)						
OPAL × Post-Internet	-0.0699***						
	(0.0252)						
Observations	28,913	28,913	28,913	28,913	28,913	28,913	28,913
State FE and linear trends	Y	Y	Y	Y	Y	Y	Y
Occupation FE	Y	Y	Y	Y	Y	Y	Y
Individual controls	Y	Y	Y	Y	Y	Y	Y
Overidentification test (p-value)	0.867	0.588	0.222	0.393	0.0993	0.417	0.396
F-stat. Test of excluded instruments	33.33						

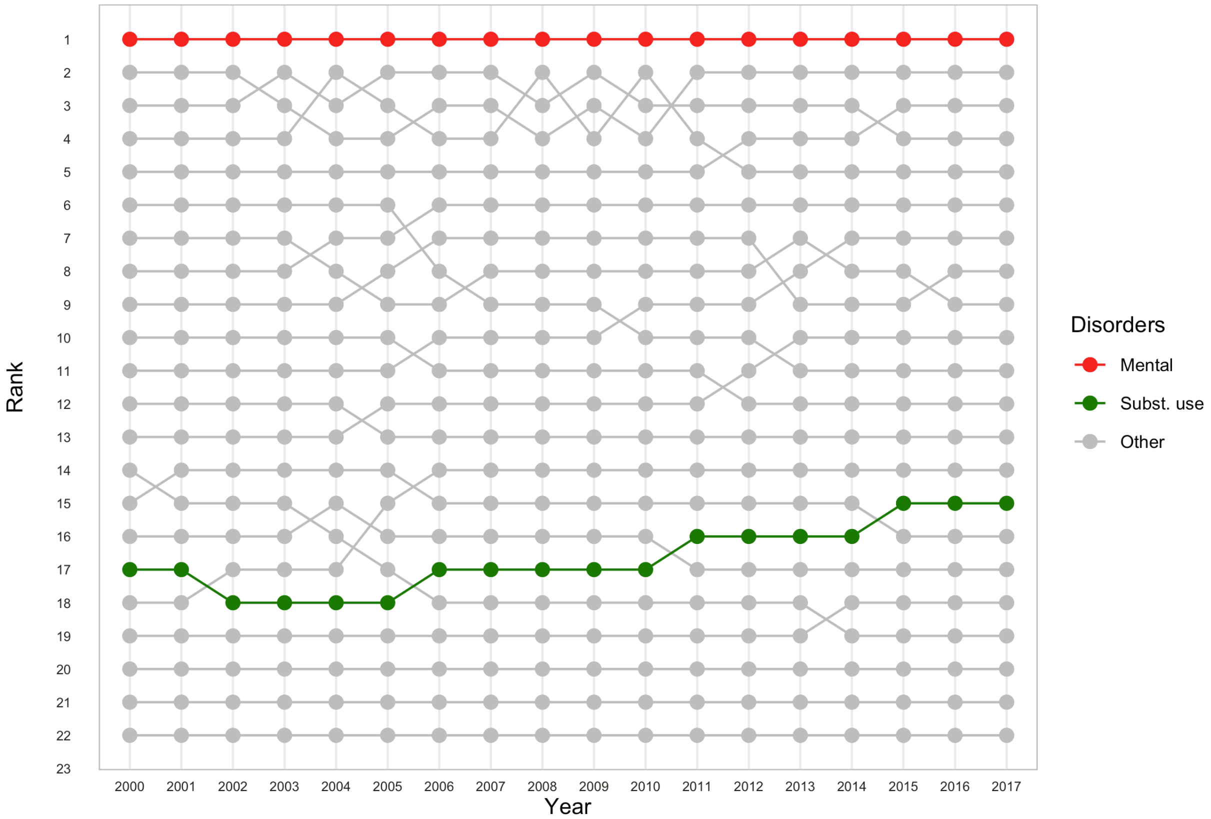
Notes: 2SLS regressions. The sample includes all male respondents aged 18-59. Standard errors clustered at the household level are reported in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Control variables include age and its squared term, indicators for different educational qualifications and occupation, marital status, number of children and household type, migration background, the logarithm of net household income and an indicator for whether the respondents is a home owner, and a dummy variable for whether the respondent works full time. State, survey year fixed-effects are also included, as well as state-specific linear trends. The F-statistics refers to the Kleibergen-Paap F-statistic from a test for excluded instruments.

Figure 2B.1: Contribution of mental health and substance use disorders to DALYs - Individuals aged 10-24



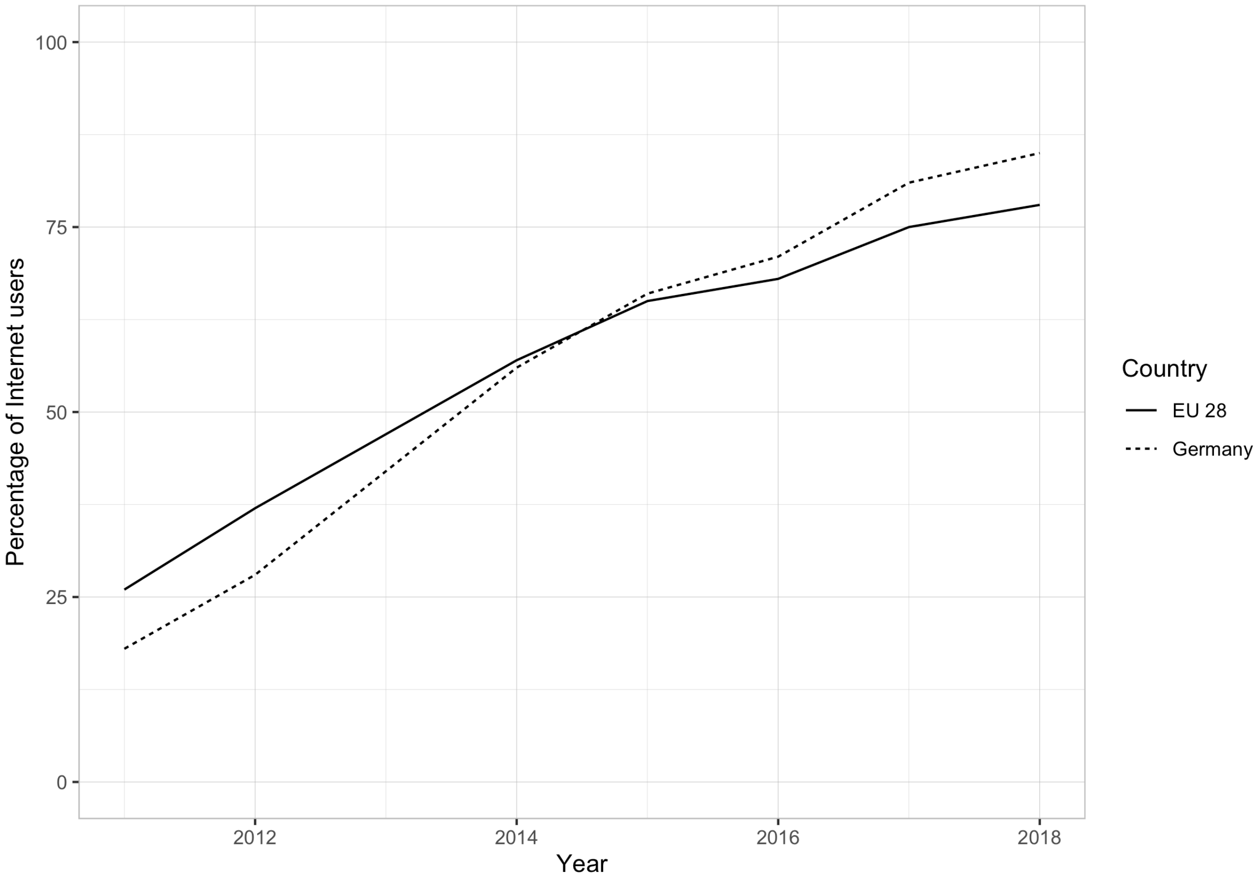
Notes: The graph shows the evolution over time of the contribution of mental and substance-use disorders to the Global Disease Burden. The metrics used to calculate the Global Disease Burden is Disability-Adjusted Life Years (DALYs). Figures refer to the world population of individuals aged 10-24. Source: `http://www.healthdata.org/gbd`

Figure 2B.2: Ranking of causes of DALYs - Individuals aged 10-24



Notes: The graph shows the ranking over time of different categories of disorders as contributors to the Global Disease Burden. The ranking is based on the percentage of Disability-Adjusted Life Years (DALYs) that is caused by a given disorder. Figures refer to the world population of individuals aged 10-24. Source: `http://www.healthdata.org/gbd`

Figure 2B.3: Mobile phone usage in Germany and EU 28



Notes: Source: Eurostat. The figure shows the percentage of Internet users that reported accessing the Internet via their mobile phone in Germany and the corresponding average figure for EU 28 countries. The population of reference is all adults aged 16 or above.

2C Questionnaire

The following refers to the actual wording of the questions as per the SOEP individual questionnaire for the year 2008. Squared brakets indicate answer options.

Do you currently smoke, be it cigarettes, a pipe or cigars? [Yes, No]

How often do you drink the following alcoholic beverages? [Regularly, Occasionally, Seldom, Never]

- Beer
- Wine, Champagne
- Spirits (schnaps, brandy etc.)
- Mixed drinks (alcopops, cocktails etc.)

Please think about the last four weeks. How often did it occur within this period of time,...[Always, Often, Sometimes, Rarely, Never]

- that you felt run-down and melancholic?
- that you felt relaxed and well-balanced?
- that you used up a lot of energy?
- that due to mental health or emotional problems:
  - you achieved less than you wanted to at work or in everyday tasks?
  - you carried out your work or everyday tasks less theroughly than usual?
- that due to physical or mental health problems you were limited socially, i.e. in contact with friends, acquantances or relatives?

How does a typical weekday look like for you? How many hours do you spend on the following activities?

- Job, apprenticeship, second job (including travel time to and from work)
- Errands (shopping, trips to government agencies etc.)

- Housework (washing, cooking, cleaning)
- Child care
- Care and support for persons in need of care
- Education of further training (also school, university)
- Repairs on or around the hours, car work, garden work
- Hobbies and other free-time activities

How many hours of sleep do you average on a normal day during the working week?

Chapter 3

Inequality in the Impact of the Coronavirus Shock: Evidence from Real Time Surveys

with **Abi Adams-Prassl**, University of Oxford, **Teodora Boneva**, University of Zurich, and **Christopher Rauh**, University of Cambridge

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Abstract We present real time survey evidence from the UK, US and Germany showing that the immediate labor market impacts of Covid-19 differ considerably across countries. Employees in Germany, which has a well-established short-time work scheme, are substantially less likely to be affected by the crisis. Within countries, the impacts are highly unequal and exacerbate existing inequalities. Workers in alternative work arrangements and who can only do a small share of tasks from home are more likely to have lost their jobs and suffered falls in earnings. Women and less educated workers are more affected by the crisis.

Acknowledgements Ethics approval was obtained from the Central University Research Ethics Committee (CUREC) of the University of Oxford: ECONCIA20-21-09. We thank Toke Aidt and Hamish Low for valuable feedback. We are grateful to the Economic and Social Research Council, the University of Oxford, the University of Zurich, the Keynes Fund, and the Cambridge INET for generous financial support, and Marlis Schneider for excellent research assistance.

3.1 Introduction

The Covid-19 outbreak has caused severe disruptions to labor supply in many countries around the world, bringing whole economies grinding to a halt. As a result, individuals are suffering large and immediate losses in terms of income and employment. Different public policies are put in place to buffer the economic consequences of the shock. Obtaining a better understanding of the distribution of impacts of the Covid-19 crisis is crucial for designing policy responses that target those individuals who have been most affected by the crisis. In this paper, we provide evidence from real time surveys conducted in the US, the UK and Germany in March and April 2020. We examine which workers were most likely to lose their jobs, be furloughed or on short-time work, reduce their hours, and experience a decrease in their earnings. Our focus lies on documenting cross-country differences as well as understanding which job characteristics allow individuals to buffer the shock of the crisis.

The impacts of the Covid-19 crisis are large and unequal within and across countries. There are several key results that emerge from our study. First, we find staggering cross-country differences in the labor market impacts of the Covid-19 epidemic. By early April, 20% and 17% of individuals in work at the onset of the pandemic lost their jobs in the US and the UK, respectively, compared to only 5% in Germany. The countries differ in the labor market policies that were introduced or extended in response to the crisis. Germany has a well-established short-time work (STW) scheme and we find that 34% of employees in work at the onset of the pandemic have been asked to reduce their hours to benefit from this scheme. Furloughing has been relatively prevalent in the UK but not as prevalent in the US; 36% and 25% of employees in the UK and US respectively report having being furloughed in their main job. Though it might be too early to claim that the "German economic miracle" witnessed during the Great Recession (Rinne and Zimmermann, 2012) is repeating itself, we find that the shock has been much smaller for German workers thus far.

Second, there are striking differences in the impacts within countries depending on job and worker characteristics. In all three countries, workers who report that they can do a high share of tasks from home are substantially less likely to have lost their job. Moreover, we find large differences in job loss probabilities across industries and occupations, mostly owing to the fact that the average percentage of tasks workers can do from home varies substantially across industries and occupations. Interestingly, the percentage of tasks workers can do from home is a significant predictor of job loss, over and above what can be explained by industry, occupation or other job characteristics. In all three countries, employees on permanent contracts have been significantly less likely to lose their jobs compared to employees with temporary work arrangements.

Turning to individual differences in job loss probabilities, in the US and the UK there are marked differences between men and women and between people with and without university education. Women and workers without a college degree are significantly more likely to have lost their jobs. Remarkably, while occupation fixed effects and the percentage of tasks one can do from home can account for all of the gap in job loss between college-educated workers and workers without a college degree, this is not the case for the gender gap. The gender gap persists even once we control for these job characteristics, indicating that other factors play a role. This does not only contrast with usual recessions in which men tend to be more likely to lose their jobs.[1] It also stands in contrast with the results from Germany, where neither gender nor having a college degree significantly predict job loss. Turning to time use data, we note that amongst the population working from home, women spend significantly more time homeschooling and caring for children.

Individual outlooks on the future are bleak. The average perceived probability of losing one's job within the next months is 35% in the US and 31% in the UK. Even in Germany, where the share of workers who have lost their job already is much smaller than in the anglophone countries, the average perceived probability of losing one's job before August 2020 is 25%. Individuals are worried about being able to pay their usual bills and expenses. 47% in the US, 40% in the UK, and 32% in Germany already have struggled to pay their usual bills.

Our paper contributes to several strands of the literature. First, it contributes to the literature on the impact of economic downturns on labor market outcomes (e.g., Hoynes et al. 2012; Christiano et al. 2015) and the importance of short-time work schemes to buffer economic shocks (e.g., Giupponi and Landais 2020; Cahuc et al. 2018; Kopp and Siegenthaler 2018). Second, it closely relates to the literature on alternative work arrangements and the role of firms in providing workers insurance against shocks to labor demand (Malcomson 1999; Koustas 2018; Mas and Pallais 2020). We show that firms are sheltering permanent workers more than those on temporary contracts. Third, our paper contributes to the economics literature documenting the immediate impact of the Covid-19 pandemic. Research using real time data has studied the relationship between the outbreak and stock returns and volatility (Alfaro et al. 2020; Baker et al. 2020b), subjective uncertainty in business expectations surveys (Baker et al. 2020a), business

[1] See, for instance, Hoynes et al. (2012) and Bredemeier et al. (2017).

closures (Bartik et al. 2020), worries regarding the aggregate economy (Fetzer et al. 2020), household spending (Baker et al. 2020c; Carvalho et al. 2020), and labor market impacts in specific countries relying on administrative data (Cajner et al. 2020), data from businesses (Chetty et al. 2020), job ads (Forsythe et al. 2020), public survey data (e.g. Coibion et al. 2020), and own data collected through survey agencies (Bick and Blandin 2020; von Gaudecker et al. 2020). Other research using data collected before the crisis has discussed channels through which the current crisis may affect workers differently depending on their gender and occupation (Alon et al. 2020; Dingel and Neiman 2020; Mongey and Weinberg 2020). We provide real time evidence on the effect of the pandemic on labor market outcomes in three major economies. Moreover, our survey is tailored to capture elements specific to the Covid-19 recession such as furloughing and short-time work.

3.2 Data

We use real-time survey data collected as part of the COVID Inequality Project to study the labor market impacts of the pandemic.[2] The analyses presented in this paper are primarily based on data collected between April 9-14 in the US ($N = 4,000$), UK ($N = 4,931$) and Germany ($N = 4,002$).[3] We also provide additional insights using survey data collected between March 24-26 for which we only have information for the US ($N = 4,003$) and the UK ($N = 3,974$). To be eligible to participate in the study, participants had to be at least 18 years old and report having engaged in any paid work during the previous 12 months. To ensure that results are comparable across waves and countries, we chose to draw independent study samples for each wave/country using the same sampling methodology. More specifically, we used quota-based sampling to ensure that the samples are representative in terms of region in each country. Appendix Tables 3C.1 to 3C.3 show the distribution of respondents across regions and the comparison to the national distribution of individuals across the different regions.

Comparison to CPS, LFS and SOEP data: Appendix Tables 3C.4 to 3C.6 compare the characteristics of the April samples to nationally representative statistics from the Current Population Survey (CPS) for the US, the Labor Force Survey (LFS) for the UK, and the Socio-Economic Panel (SOEP) for Germany. The sample distributions are comparable in terms of occupations

[2]The surveys were conducted by a professional survey company. All participants were part of the company's online panel and participated in the survey online using their computers, tablets or mobile phones. The survey was scripted in Qualtrics. The median time to complete the survey was about 10 minutes.

[3]All dates refer to the year 2020. The results presented in this paper are based on the April wave of the survey, unless stated otherwise.

and industries, although some categories (e.g. "Computer and Mathematical" occupations) are over-represented. In terms of individual characteristics, women and workers with a university degree are over-represented. While there are some differences between our data and the nationally representative statistics, we note that our results are robust to re-weighting the sample using survey weights.[4]

Survey design: We collect detailed information on respondents' work arrangements and work history. Importantly, the data allow us to make two key distinctions. First, we can distinguish between workers who kept their jobs and workers who lost their jobs in the recent crisis. Second, we explicitly ask employees to report whether they have been furloughed (US&UK) or put on STW (Germany). Taken together, this information allows us to distinguish between three different groups of employees: those who are still regularly employed (i.e. not on furlough or STW), furloughed (US&UK) or on STW (Germany), and employees who were laid off. This distinction is important given the recent policy responses to the crisis (see Section 3.3).

The data include information on a range of individual (e.g. age, gender, education) and job characteristics (e.g. occupation, industry). To study the importance of workers' ability to work from home, we elicit information on the percentage of tasks workers could do from home (0-100%). The data further include information on respondents' net earnings in the previous months, as well as on the number of hours worked in a typical week in February and April. Appendix 3A provides more details on the survey design, while Appendix 3B includes the questionnaire.

Sample: To study the impact of the coronavirus crisis on the labor market, we limit the analysis to workers who are still in work in April or lost their job in the previous month due to the coronavirus outbreak. Individuals who did not have a job at the onset of the pandemic are not included in any of the analyses.

3.3 Context

Given the speed at which events unfolded, it is important to situate our study into the existing context. In all three countries, the first Covid-19 cases were confirmed towards the end of January and the first deaths in the beginning of March. The countries differed, however, in the intensity and speed at which lockdown measures and public policies were introduced.[5] Germany announced the first nationwide social distancing measures on March 12th, closed schools on

[4]To calibrate the weights, we use an iterative proportional fitting (or raking) procedure (Deville and Särndal, 1992; Kolenikov, 2014) to ensure that the distributions of gender, education, age, occupation, industry and region in our samples match those of the economically active population in each respective country.

[5]The timeline presented in Appendix Figure 3D.1 illustrates the exact timing of events.

March 16th and announced a nationwide lockdown on March 22nd. In the UK, a nationwide lockdown was announced on March 23rd, and schools were also closed from that date. In the US, national emergency was declared on March 13th. There was a substantial degree of heterogeneity across US states with regard to the introduction of lockdown measures. California was the first to issue state-wide stay-at-home orders, which took effect on March 19th. The majority of US states followed, and by the time of our April data collection 40 US states had introduced similar lockdown measures.[6] In all three countries, visits to retail spaces and workplaces started dropping sharply on March 18th (Appendix Figure 3D.2).

To buffer the labor market impacts of the pandemic, the countries introduced different policy measures. Germany, which already had one of the oldest and most comprehensive short-time work (STW) schemes, passed a law on March 13th, making the eligibility criteria for STW less stringent.[7] On March 20th, the UK government announced the Coronavirus Job Retention Scheme, which allowed firms to furlough workers. In contrast to the German STW scheme, furloughed workers are not allowed to undertake any work for their employer. In the US, where a similar furloughing scheme has been in place, the Coronavirus Aid, Relief, and Economic Security (CARES) Act was signed into law on March 27th. The CARES Act includes provisions to expand unemployment benefits to furloughed workers, gig workers, and freelancers, with unemployment benefits increased by $600 per week, as well as additional direct payments to families. Small businesses could obtain forgivable loans through the Payroll Protection Program (PPP). Germany and the UK also made provisions for the self-employed. On March 23rd, the German government agreed on an emergency assistance program to support small businesses, freelancers and the solo self-employed, which was accessible immediately. On March 26th, the UK announced the Self-Employment Income Support Scheme which offered grants to self-employed workers not to be paid out before June.

The three countries we study do not only differ in their policy responses to the crisis. Most notably, there is also considerable variation in employment protection legislation (OECD 2020). The OECD Employment Protection Legislation (EPL) index, which summarizes core aspects of dismissal regulation such as procedural requirements and severance pay, is 0.09 in the US, 1.35 in the UK and 2.60 in Germany. Existing institutional differences are likely to have contributed to the large cross-country disparities in job loss we document in our study.

[6] An overview of the different lockdown measures US states introduced (with corresponding dates) can be found on this website: `https://github.com/nytimes/Covid-19-data`.

[7] STW allows firms affected by temporary shocks to reduce their employees' hours instead of laying them off. Government subsidies pay short-time compensation to employees who reduce their hours (up to a cap).

3.4 Results

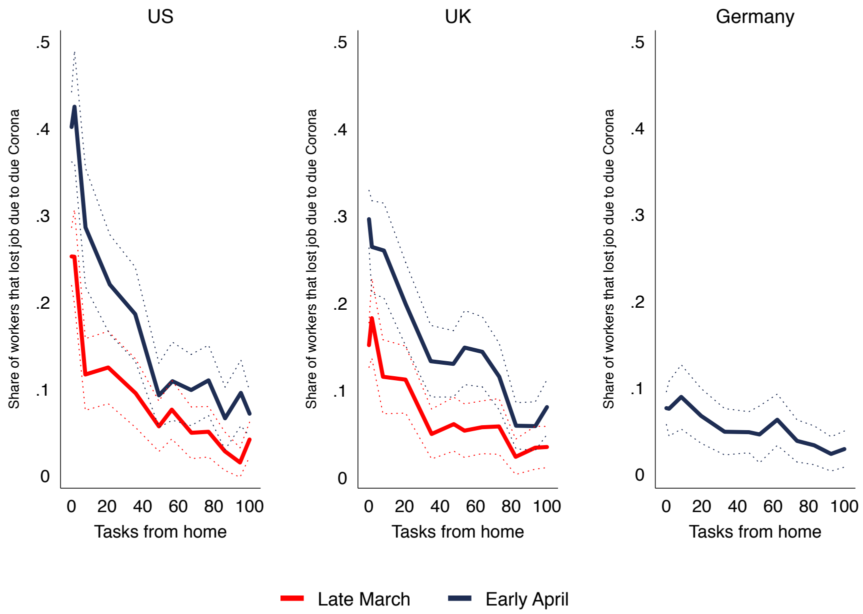
3.4.1 Job Loss

There are staggering cross-country differences in the percentage of workers who lost their jobs due to the Covid-19 pandemic. While 20% and 17% of US and UK workers lost their jobs by early April, the corresponding figure is 5% for Germany.[8] Within each country, the labor market impact of the pandemic was highly unequal. There are some notable similarities across countries in terms of who was most likely to be affected. In all waves and countries, there is a clear negative relationship between job loss and the ability to work from home (panel (a) of Figure 3.1). The most salient cross-country differences in job loss can be observed in the bottom part of the distribution. While more than 40% of workers who cannot work from home lost their jobs in the US by early April, the corresponding figure is below 10% in Germany. Panel (b) of Figure 3.1 displays the proportion of employees who lost their job by work arrangement. Again we observe a similar pattern in all three countries. Employees with permanent, salaried, fixed hour contracts were less likely to lose their jobs.

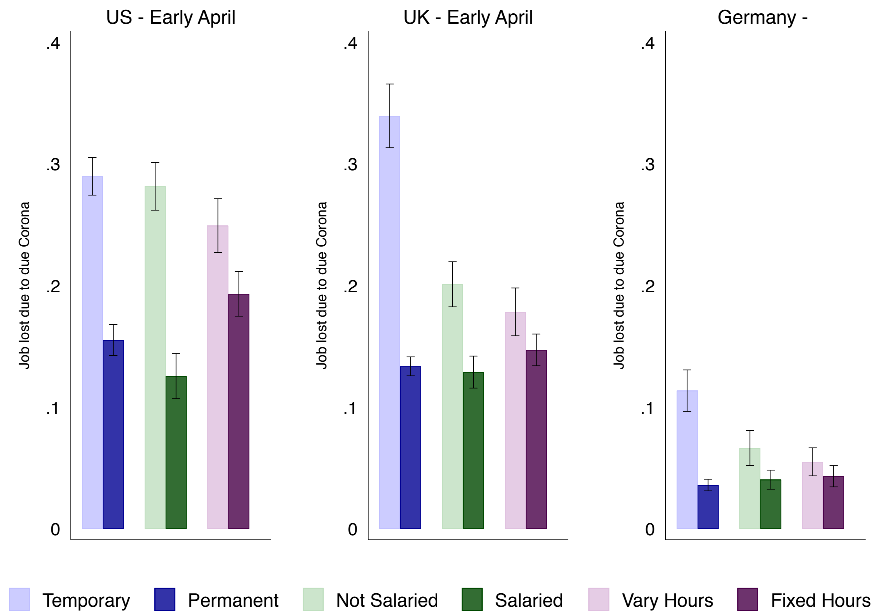
[8] We note that our results are broadly comparable to aggregate statistics obtained from other sources. For the US for example, data from the Household Survey show that in April 2020 total employment fell by 22.4 million, or around 14% of total employment in March 2020. Data from the Establishment Survey show a similar decline in total nonfarm employment, which was particularly concentrated in the leisure and hospitality sector (Bureau of Labor Statistics, 2020). Finally, Bick and Blandin (2020) find that 16.5% of workers in the US lost their jobs.

Figure 3.1: Job loss probability due to Covid-19 by percentage of tasks that can be done from home and work arrangement

(a) Job loss by percentage of tasks that can be done from home

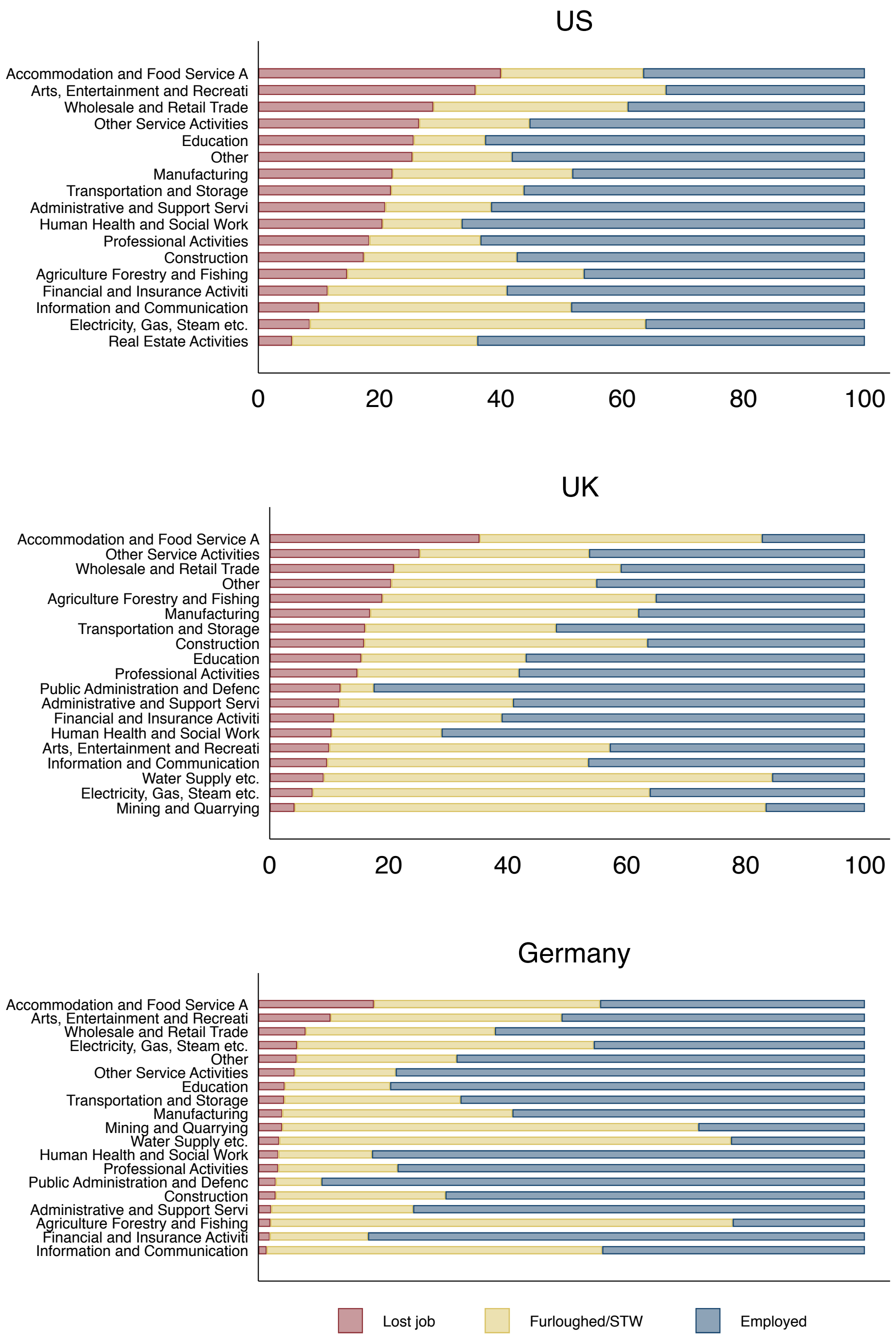


(b) Job loss by work arrangement



Notes: The dotted line in panel (a) and the thin black bars in (b) represent the 95% confidence intervals. The figures show the share of individuals who were in paid work four weeks before data collection that lost their job due to Covid-19.

Figure 3.2: Employment status by industry (early April)



Notes: The figure shows the share of workers who are employed (blue - right), furloughed for the US/UK or on STW for Germany (yellow - middle) or lost their job due to the Covid-19 crisis (red - left), by industry. The sample is restricted to employees (in their current or last job) only.

There are also large differences in job loss across industries and occupations.[9] Figure 3.2 presents the percentage of employees who lost their jobs, were furloughed (US&UK) or on STW (Germany), or still employed in early April. Employees in the 'Accommodation and Food Service Activities' industry were most likely to lose their jobs in all three countries. The 'Arts, Entertainment and Recreation' industry as well as the 'Wholesale and Retail Trade' industry were also considerably affected. Other industries such as 'Information and Communication' experienced lower declines. We also see sizeable differences in the percentage of workers furloughed or on STW. We investigate furloughing/STW in more detail in Section 3.4.3. Appendix Figure 3D.3 shows the large differences in job loss by occupation. Employees in 'Food Preparation and Serving' were substantially more likely to lose their jobs than employees in 'Computer and Mathematical' occupations.

There are substantial differences in workers' ability to work from home both across as well as within industries and occupations (see Appendix Figures 3D.4 and 3D.5).[10] The mean share of tasks workers can do from home is lowest in the 'Accommodation and Food Service Activities' industry and highest in 'Information and Communication'. For occupations, the lowest average share can be observed in 'Food Preparation and Serving' while 'Computer and Mathematical' occupations have the highest share. In Appendix Figure 3D.6 we show that there is a strong relationship between the average share of tasks workers can do from home within a given industry and the percentage of workers who lost their jobs in that industry. The average share of tasks that can be done from home explains 66%, 44% and 24% of the variation in job loss across industries in the US, UK and Germany, respectively. For occupations, this relationship is similarly strong (Appendix Figure 3D.7). These patterns also hold for occupation-industry pairs.[11]

Table 3.1 (columns (1)-(3)) shows the results of linear probability models (LPM) in which we regress job loss on a range of job characteristics. Job loss is defined as a binary variable which equals one if the worker lost their job and zero otherwise. All specifications control for region, occupation and industry fixed effects.[12] The share of tasks that can be done from home

[9] We use NACE Rev. 2 codes to classify industries. Occupations are classified using O*NET SOC 2018 codes for the US&UK, and ISCO-08 codes for Germany. Differences in occupation classifications need to be kept in mind when comparing R^2 statistics across regressions with occupation fixed effects.

[10] In Adams-Prassl et al. (2020d) we document that the variation within and across occupations and industries is remarkably consistent across countries and survey waves.

[11] Appendix Figure 3D.8 shows heatmaps of the average share of tasks that can be done from home by occupation (y-axis) and industry (x-axis), while Appendix Figure 3D.9 shows the share of jobs lost due to Covid-19. Comparing the two figures highlights that occupations in industries in which the average share of tasks that can be done from home is lower experienced larger declines in employment.

[12] Region fixed effects refer to states for the US and Germany. For the UK, we include fixed effects for the nine regions of England, as well as Scotland, Wales and Northern Ireland.

significantly predicts job loss over and above what can be explained by occupation and industry fixed effects, highlighting the importance of differences in the ability to work from home within occupations and industries. The results presented in this table also speak to the importance of contractual arrangements in sheltering workers form the economic downturn. Controlling for workers' ability to work from home and the occupation and industry they work in, we find that employees in less secure work arrangements are more likely to have lost their jobs. In all three countries, employees on permanent contracts were less likely to lose their jobs compared to employees on temporary contracts. Salaried employees were less likely to lose their jobs in the US and Germany compared to non-salaried employees. Finally, self-employed workers were more likely to lose their jobs in the US and the UK compared to employees.[13] The same patterns are found when using both waves for the US and the UK (Appendix Table 3D.1) or using survey weights in the analysis (Appendix Table 3D.2) which account for differences in gender, education, age, occupation, industry and region between our samples and nationally representative samples of the economically active population in each respective country.

Next we explore whether individuals' background characteristics and job characteristics relate to differences in job loss. We explore heterogeneity in job loss with respect to gender, education and age groups. Table 3.2 presents the results of an LPM in which we first regress job loss on individual characteristics only, and then add controls to account for job characteristics.[14] In the US and the UK, women were 6.5 percentage points (p.p.) and 4.8 p.p. more likely to lose their jobs. Differences in job characteristics between male and female workers can account for about half of the gender gap in job loss in both countries. We note, however, that a significant gender gap remains even once we control for job characteristics, suggesting that other factors we are not capturing in this regression play a role in driving the gender gaps.

[13]Note that the definition of job loss is the same for employees and self-employed workers (see Appendix 3A).
[14]Appendix Table 3D.3 presents weighted results. The results are robust to the use of weights.

Table 3.1: Job and earnings loss probability

	Job loss			Earnings loss		
	US	UK	DE	US	UK	DE
	(1)	(2)	(3)	(4)	(5)	(6)
Tasks from home	-0.2617***	-0.1917***	-0.0397***	-0.1328***	-0.0737***	-0.0202
	(0.0216)	(0.0195)	(0.0128)	(0.0303)	(0.0267)	(0.0233)
Self-Employed	-0.0996***	-0.0463*	0.0051	0.0224	0.0945**	0.0615*
	(0.0228)	(0.0257)	(0.0174)	(0.0320)	(0.0373)	(0.0322)
Permanent	-0.0659***	-0.1711***	-0.0546***	-0.0116	-0.0224	0.0030
	(0.0165)	(0.0205)	(0.0114)	(0.0233)	(0.0302)	(0.0210)
Salaried	-0.0632***	0.0110	-0.0193*	-0.0911***	-0.0455**	-0.0629***
	(0.0181)	(0.0154)	(0.0108)	(0.0248)	(0.0207)	(0.0197)
Fixed hours	0.0022	-0.0094	0.0035	-0.0714***	-0.1108***	-0.0927***
	(0.0164)	(0.0151)	(0.0097)	(0.0232)	(0.0203)	(0.0175)
Constant	0.4475***	0.2720***	0.1288***	0.3757***	0.3765***	0.2933***
	(0.0875)	(0.0667)	(0.0355)	(0.1208)	(0.0886)	(0.0645)
Observations	2995	3760	3354	2396	3111	3165
R^2	0.1600	0.1138	0.0654	0.1057	0.0890	0.0671
Region F.E.	yes	yes	yes	yes	yes	yes
Occupation F.E.	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes

Notes: OLS regressions. Standard errors in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01. The dependent variable in Columns (1) - (3) is a binary variable for whether a respondent lost their job within the past month and attributed the job loss to the coronavirus outbreak. The dependent variable in Columns (4) - (6) is a binary variable for whether a respondent earned less in March 2020 than the average earnings over January and February 2020. In Columns (4) - (6) the sample is restricted to those who were in work at the time of data collection. Tasks from home is the fraction of tasks respondents could do from home in their main or last job. Self-employed is a binary variable for being self-employed in the main or last job. Permanent, salaried and fixed hours take value 1 for employees with permanent contracts, who are salaried and whose work hours are fixed, respectively. Region fixed effects refer to state fixed effects for the US and Germany, and fixed effects for regions as reported in Table 3C.1 for the UK.

Table 3.2: Job loss probability - Individual characteristics

	United States		United Kingdom		Germany	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.0652***	0.0321**	0.0483***	0.0242*	0.0015	-0.0002
	(0.0151)	(0.0157)	(0.0124)	(0.0129)	(0.0077)	(0.0084)
University degree	-0.0789***	-0.0050	-0.0629***	-0.0070	-0.0130	0.0053
	(0.0151)	(0.0161)	(0.0123)	(0.0131)	(0.0086)	(0.0102)
30-39	-0.0325	-0.0043	0.0222	0.0304*	-0.0432***	-0.0186*
	(0.0201)	(0.0195)	(0.0156)	(0.0156)	(0.0097)	(0.0103)
40-49	-0.0286	-0.0087	0.0259	0.0229	-0.0343***	-0.0141
	(0.0214)	(0.0209)	(0.0171)	(0.0173)	(0.0115)	(0.0124)
50-59	0.0005	0.0171	0.0036	-0.0074	-0.0342***	-0.0204
	(0.0247)	(0.0241)	(0.0215)	(0.0216)	(0.0120)	(0.0127)
60+	0.0135	0.0111	0.0256	0.0111	0.0319	0.0290
	(0.0257)	(0.0253)	(0.0366)	(0.0359)	(0.0201)	(0.0207)
Tasks from home		-0.2574***		-0.1913***		-0.0400***
		(0.0219)		(0.0197)		(0.0131)
Self-employed		-0.1003***		-0.0477*		0.0059
		(0.0230)		(0.0260)		(0.0176)
Permanent		-0.0639***		-0.1720***		-0.0510***
		(0.0166)		(0.0206)		(0.0116)
Salaried		-0.0592***		0.0112		-0.0192*
		(0.0185)		(0.0156)		(0.0109)
Fixed hours		0.0018		-0.0123		0.0056
		(0.0165)		(0.0152)		(0.0097)
Constant	0.2371***	0.4311***	0.1191***	0.2454***	0.0860***	0.1320***
	(0.0689)	(0.0888)	(0.0253)	(0.0678)	(0.0132)	(0.0358)
Observations	3025	2995	3816	3760	3584	3354
R^2	0.0448	0.1618	0.0169	0.1161	0.0171	0.0679
Region F.E.	yes	yes	yes	yes	yes	yes
Occupation F.E.	no	yes	no	yes	no	yes
Industry F.E.	no	yes	no	yes	no	yes

Notes: OLS regressions. Standard errors in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01. The dependent variable is a binary variable for whether a respondent lost their job within the past month and attributed the job loss to the coronavirus outbreak. Tasks from home is the fraction of tasks respondents could do from home in their main or last job. Self-employed is a binary variable for being self-employed in the main or last job. Permanent, salaried and fixed hours take value 1 for employees with permanent contracts, who are salaried and whose work hours are fixed, respectively. Region fixed effects refer to state fixed effects for the US and Germany, and fixed effects for regions as reported in Table 3C.1 for the UK.

In terms of education, we find that workers with a university degree were 7.9 p.p. and 6.3 p.p. less likely to lose their jobs in the US and the UK, respectively.[15] Once we account for job characteristics, we no longer find a significant difference in job loss between workers with/without a university degree. Workers with different levels of education sort into different types of jobs, and sorting is a likely explanation for the insignificant coefficient we find in the regressions controlling for job characteristics.[16] The results contrast with the results for Germany, where we do not find significant gender or education gaps in job loss. Turning to the age patterns in job loss, we find no association between age and job loss in the US and the UK. In Germany, younger workers seem to have been more likely to lose their jobs.

Once we control for differences in individual background characteristics, we still find similar differences in job loss by job characteristics. The share of tasks that can be done from home is still highly significant in all three countries, though the relationship is much steeper in the US (-0.26) and the UK (-0.19) than in Germany (-0.04).[17] The differences we find in job loss between employed and self-employed workers as well as between employees with different work arrangements are similar to the differences reported in Table 3.1.[18]

Why are women in the US and the UK more likely to lose their jobs than men? While we cannot provide a definite answer to this question, we provide suggestive evidence that differences in care responsibilities might play a role. When we additionally control for whether the respondent had to change their work patterns to care for others, the number of kids in the household and an interaction between the number of kids and the female dummy, we find that in the UK the coefficient on the interaction term is positive and significant (Appendix Table 3D.5), while the opposite seems to be true for Germany where we did not find a significant gender gap in job loss. The presence of care responsibilities is positively associated with job loss in both the US and Germany. We further provide evidence that childcare responsibilities are not shared equally between working parents who work from home. Mothers working from home spend considerably more time homeschooling and caring for children than fathers working from home (Appendix

[15] There might be other differences in education and/or skill levels across workers which are not captured by this classification. Workers with different types of skills may have been more/less affected independent of whether they had a university degree or not.

[16] As illustrated in Appendix Figures 3D.10 and 3D.11, university graduates tend to sort into occupations and industries in which a high share of tasks can be done from home.

[17] To illustrate the explanatory power of the working-from-home measure, we refer to Appendix Table 3D.4. Working from home alone can explain 10%, 6% and 1% of the variation in job loss for the US, UK and Germany, respectively.

[18] Appendix Figures 3D.12 and 3D.13 display the industry and occupation fixed effects from columns (2), (4) and (6) of Table 3.2 resembling the unconditional patterns in Figures 3.2 and 3D.3.

Figure 3D.14). This relationship also holds when we control for a broad range of individual and job characteristics (Appendix Table 3D.6).

At the time the April survey was conducted, there was high uncertainty about the speed at which the virus would be contained and the economy would rebound. Focusing on workers who had a job in early April, we find that in all three countries individual outlooks on the future are bleak. On average, those still in work perceive the likelihood of losing their job in the near future to be 35% and 31% in the US and the UK, and 25% in Germany. To shed light on what might be driving differences in perceptions about job loss, we elicited individual beliefs about the likelihood of social distancing measures being in place on August 1st. The average response to this question was 59% in the US, 62% in the UK, and 53% in Germany. Appendix Table 3D.7 presents the results from an LPM in which we regress perceptions about job loss on individual and job characteristics as well as perceptions about the likelihood of social distancing measures being in place in August. Younger workers and employees on less secure work contracts perceive the probability of losing their job to be higher. Women and workers who can do fewer tasks from home are more optimistic about their chance of keeping their job in the US and the UK. This stands in contrast to the realized experience of these groups so far, and might be explained by strong demand for work in 'essential sectors' (Forsythe et al. 2020). Finally, we find that individuals who believe social distancing measures will still be in place in August perceive the probability of losing their job to be significantly higher.

Given the differences in the way the policies were administered, it is possible that workers who were laid off face a different probability of being rehired in the three different countries. While we cannot directly speak to this question because we do not observe respondents over time, we do have information on workers' perceptions of being rehired by the same employer. We do not find large cross-country differences in the perceived likelihood of returning to the same employer. The average perceived likelihood is 57% and 51% in the US and the UK, and 55% in Germany.

3.4.2 Earnings Loss

Many workers lost a substantial proportion of their income as a result of this recession. As in the Great Recession (Guvenen et al. 2014), the drop in earnings experienced by workers is not evenly spread across the initial earnings distribution. The percentage drop in earnings is greater at the bottom of the earnings distribution in all three countries (Appendix Figure 3D.15).[19] While it is not surprising that workers who lost their jobs experienced drops in income over this time period, one striking pattern in the data is that a very high proportion of workers who still had a job in April also experienced earnings losses. 35% (US), 29% (UK) and 20% (Germany) of respondents still in work in April report lower earnings in March (compared to Jan-Feb). Columns (4)-(6) of Table 3.1 show which job characteristics predict earnings losses for those still in work.[20] In the US and the UK, workers who can do fewer tasks from home are more likely to experience a drop in earnings. Self-employed workers were more likely to experience earnings losses in the UK and Germany. In all three countries, employees on salaried and fixed hour contracts were less likely to experience a decline in earnings. We further explore which individual characteristics predict earnings losses (Appendix Tables 3D.8 and 3D.9). We find no significant differences by gender. In the US, workers with a university degree were significantly less likely to experience earnings losses. In all three countries, we find evidence that younger workers were more likely to experience a decline in their income.

All respondents, irrespective of their current employment status, were further asked about their perceived likelihood of struggling to pay their usual bills and expenses in the near future (before August 1st). The average response to this question was 50% in the US, 45% in the UK, and 32% in Germany, indicating that many individuals think they will struggle financially.[21] Indeed, 47%, 40%, and 32% of individuals in the US, UK, and Germany report that they *already* struggle to pay their usual bills and expenses.

3.4.3 Furloughing and Short-time Work

A prominent feature of the coronavirus crisis has been the introduction and increased use of furloughing and STW schemes. 25% (US), 36% (UK) and 34% (Germany) of employees in work

[19] To conduct this analysis, we compare individuals' net monthly income in March to their average net monthly income of January and February.

[20] Earnings loss is defined as a binary variable which takes on a value of one if net income in March is lower than the average net income of January and February.

[21] Appendix Figure 3D.16 displays the distribution of responses to this question separately for the US, UK and Germany.

at the onset of the pandemic report being furloughed or in STW in early April.[22] As with job loss, there is considerable variation in the percentage of workers furloughed or on STW across industries (Figure 3.2) and occupations (Appendix Figure 3D.3).

Appendix Tables 3D.10 and 3D.11 show the determinants of furlough in an LPM and a multinomial logit framework, respectively. Across all countries, workers on permanent contracts have been significantly more likely to be furloughed rather than laid off, and salaried workers have been significantly less likely to lose their job or be furloughed, when controlling for occupation, industry and background characteristics. The relationship between the ability to work from home and furloughing is less strong than that for job loss, with the exception of Germany. This is to be expected given that furloughed workers are not supposed to do any work for their employers under the US and UK schemes, while they can under the German scheme.[23] Turning to background characteristics, women are less likely to be on furlough in the US but more likely to be put on STW in Germany (controlling for job characteristics). We do not find significant differences in the likelihood of being on furlough between workers with/without a university degree, whereas across all countries older workers are significantly less likely to be on furlough or STW.

In the UK, employers can choose to top up the wage of their furloughed employees and 70% of respondents on furlough report that their employer offered to do so. However, 50% of employees in the UK were asked to take annual leave and 15% of them were asked to work while on furlough. In the US, 53% of furloughed employees lost their health insurance coverage. In Germany, we find a high correlation of 0.81 between the percentage of hours that employees were officially asked to work while on STW (51% on average) and the hours that they actually work (50% on average).

3.4.4 Hours Worked

Among those who still had a job in early April, we observe a stark decline in the number of hours worked. The average change in hours worked per week for those working non-zero hours (com-

[22]In Germany, between early March and end of April, around 20% of the labor force applied for the STW scheme (Bundesagentur für Arbeit, 2020). In the UK, just under 4 million jobs were furloughed by April 23, 2020 and this figure rose to 6.3 million by May 3, 2020 and 9.4 million (or around a third of total employment) by July 12, 2020 (HMRC, 2020).

[23]In Appendix Table 3D.12 we present the R^2 from linear probability models of job loss and furloughing separately for each country, controlling for different sets of covariates. Across all countries, occupation fixed effects explain more of the variation in job loss compared to industry fixed effects, while the opposite holds true for a model of furloughing (see columns (1) and (2)). Contractual arrangement variables have similar explanatory power to industry fixed effects.

pared to a typical week in February) was 5 hours (US), 7 hours (UK) and 4 hours (Germany).[24] Figure 3.3 shows the average change in hours worked per week by industry, amongst workers who still have a job in early April. Across all industries there is large variation in the reduction in hours of those in paid work. Industries which require high in-person contact such as 'Education' or 'Art, Entertainment and Recreation' were disproportionately more affected. Industries that experienced the largest drop in hours also saw the largest share of workers laid off (Appendix Figure 3D.17). This is not a mechanical effect as the reduction in hours worked is calculated for those who are still working non-zero hours, so the change in hours only reflects the intensive but not the extensive margin. In Appendix Figures 3D.18 and 3D.19 we document similar patterns by occupation.

As explained in Section 3.3, different labor market policies were put in place in the three different countries to buffer the economic impact of the pandemic. Given the differences in the way these policies were administered, a broader question which emerges is whether the different policy responses mask actual cross-country differences (or similarities) in the impact of Covid-19 on the labor market. To shed more light on this question, we conduct an additional analysis which does not rely on how workers' status is defined. Instead, we study how hours worked changed between February and April for workers who had a job in February (irrespective of their current work status). The results are reported in Appendix Figure 3D.20. The figure shows the proportion of workers who reported working zero hours when surveyed in April (this includes people who lost their jobs), worked fewer (but positive) hours, the same, or more hours compared to a typical week in February, separately for each country. As illustrated by this graph, the lower job loss figures we find for Germany are not a mere artefact of how workers' status is defined in the different countries. In Germany, a much smaller share of workers who had a job in February worked zero hours in April, and a much higher share worked the same number of hours or more.[25] These patterns cannot be explained by labelling differences across countries. We further illustrate the change in hours worked in all three countries in Appendix Figure 3D.22. Hours worked dropped considerably across the distribution of usual hours worked for the UK and the US, whereas for Germany a large proportion of workers worked the same number of hours in April as in a typical week in February.

[24] Similarly, Brewer et al. (2020) find that the average change in hours worked for those in employment was 7 hours between early March and late April 2020.

[25] In Appendix Figure 3D.21 we limit the sample to the self-employed and split by median labor income in 2019. In all three countries, self-employed workers who had low earnings before the pandemic were considerably more likely to work zero hours in April. Low-wage gig workers, who are subsumed under that category, seem to be more affected compared to entrepreneurs with higher earnings.

Figure 3.3: Change in hours worked by industry

Notes: The thin black bars represent the 95% confidence intervals. The figure shows the change in hours worked between a usual work week in February and the last work week amongst those still working for the US (top), the UK (center) and Germany (bottom).

3.5 Conclusion

The Covid-19 crisis has had large impacts on the economy. The results from our study suggest that the impacts are unequally distributed. The percentage of tasks workers can do from home is highly predictive of job loss and so are individual work arrangements. Firms have played some role in smoothing the shock for permanent and salaried employees, and for those who usually work on fixed schedules.

In the US and UK, women and workers without a college degree are significantly more likely to have lost their jobs, while younger individuals are significantly more likely to experience a fall in their earnings. The outlook on the future is bleak with many workers expecting to lose their jobs in the near future.

Finally, we find large differences in the magnitude of the shock between the anglophone countries, the US and the UK, and Germany. The anglophone countries have seen much more employment ties cut. This might not only lead to an increase in the number of people suffering hardship at the moment, but it could also prove important for the period of economic recovery as match-specific human capital might be lost. The pandemic is likely to bring about a large reallocation of workers. Understanding the forces at work and how they interplay with institutional factors is of high policy importance.

Appendices of Chapter 3

3A Survey Design

Work status and hours worked We collect detailed information on respondents' current work arrangements. We ask respondents to report how many jobs they have been working in over the past 7 days, either as employees or as self-employed. We made it explicit that individuals should count *all* jobs, including the ones in which they have been furloughed (US & UK) or on short-time work (Germany). Individuals who report not having a job are asked since when they have not had a job and whether their job loss was related to the coronavirus outbreak. Workers are classified as having lost their job in the recent crisis if they lost their job in the last four weeks and report 'definitely yes' or 'probably yes' to the question on whether their job loss was related to the coronavirus outbreak.[26] To study changes in the number of hours worked, we ask all respondents how many hours they worked in the previous week and how many hours they worked in a typical week in February.

Information on furloughing/STW To obtain a better understanding of the use of furloughing (US & UK) and STW schemes (Germany), we include questions on furloughing into the US & UK surveys, and questions on STW into the German survey. In the US and the UK, if respondents report being employed in their main job we ask them to report whether they have been furloughed, and, if yes, whether they have still been asked by their employer to do any work. In the UK, respondents provided us with additional information on whether their employer is topping up the government wage support, and whether they lost any annual leave entitlements. In the US, we additionally ask whether employees lost their health insurance coverage. In Germany, we ask employees whether they were on the STW scheme. We further ask respondents to state the official share of their usual hours that they are asked to work, and for the share of hours that they actually work.

[26] Note that the definition of job loss is the same for employees and self-employed workers, as it is based on the same information.

Job characteristics Individuals who report having a job are asked detailed questions about their main job. First, they are asked whether they are employed or self-employed in this job. If they report being employed they are asked to provide more details on their employment. In particular, employees are asked to report whether they are on a permanent or temporary contract, whether their work schedule is fixed or flexible, and whether they are salaried or non-salaried, i.e. paid in a different way for their work (e.g. by the hour). All respondents with a job are further asked to provide information on the industry and occupation they work in. Occupations are classified using O*NET SOC 2018 codes for the US&UK, and ISCO-08 codes for Germany. Industries are classified using NACE Rev. 2 industry codes in all three countries. To study the importance of the ability to work from home, we ask all respondents what percentage of their tasks they could do from home. Answers are recorded using a slider ranging from 0-100%. To ease comprehension of this question, we provide participants with some examples. 'E.g. Andy is a waiter and cannot do any of his work from home (0%). Beth is a website designer and can do all her work from home (100%)'. Individuals who report not having a job are asked the same questions about their last job.

Income To obtain a clearer picture of the impacts of the crisis and the earnings lost, we ask all individuals in the early April survey wave to report their net monthly earnings from all sources for the months of January, February, and March. Throughout the paper, we define 'earnings loss' as a binary variable that takes a value of one if a respondent earned less in March 2020 compared to their average earnings over the months of January and February 2020. In addition, we ask respondents about their gross annual earnings in 2019. We also ask respondents to state whether they have already struggled to pay their usual bills or expenses.

Time use We ask respondents to report the time they spend on different activities on a typical working day over the past week. For individuals with children living in the household, we ask about the number of hours and minutes spent on active childcare and on homeschooling.

Expectations To obtain a better sense of how individuals think about their future, we ask respondents how likely they think it is that certain events will occur before August 1, 2020, on a 0-100% chance scale. Most notably, those include whether respondents think they will lose their job or shut their business (if self-employed), and have trouble paying their usual bills and expenses. To understand how long individuals think the crisis will last, we also ask individuals to report how likely they think it is that some form of social distancing measures will still be in place on August 1, 2020, using a 0-100% scale. Finally, former employees are asked how likely they think it is that their next job will be with their last employer.

3B Questionnaire

Employment status and hours worked

How many jobs, where self-employment activity counts as a job, did you have in February 2020? Please think of any work you did other than completing surveys. If you were furloughed from a job, please count this as a job.
Many people work as employees, where they have an employment contract with an employer, or in self-employment. There is a lot of variation in self-employment, some people might be selling goods or services in their own business, or working through a digital platform such as Uber or Upwork. In addition to working a regular job for an employer, sometimes people do other things to earn money. These activities also count as self-employment. [None, 1, 2, 3 or more]

[If worked at least one job in February] *Think about a typical week in February for you at work (in all of your jobs). How many hours did you work in a typical week in February?* [Answers in 5-hour increments, from 0 to "More than 55 hours"]

How many jobs, where self-employment activity counts as a job, have you had last week? Please think of any work you did other than completing surveys. If you were furloughed from a job, please count this as a job.
Many people work as employees, where they have an employment contract with an employer, or in self-employment. There is a lot of variation in self-employment, some people might be selling goods or services in their own business, or working through a digital platform such as Uber or Upwork. In addition to working a regular job for an employer, sometimes people do other things to earn money. These activities also count as self-employment. [None, 1, 2, 3 or more]

[If worked at least one job last week] *Now think about all the work you did last week (in all of your jobs). How many hours did you work last week?* [Answers in 5-hour increments, from 0 to "More than 55 hours"]

[If reports working zero jobs last week] *Please think about your last job. In your last job, were you working as an employee or self-employed?* [Employee, Self-employed]

[If reports working at least one job last week] *In your main job, that is the job that you usually spend the most time working in, are you working as an employee or self-employed?* [Employee, Self-employed]

[For current employees] *Have you been furloughed?*[27] [Yes, No]

[If reports working zero jobs last week] *For how long have you not had a job?* [Recorded in weeks/months]

[If reports working zero jobs last week] *If you lost your job recently, do you think this was related to the coronavirus outbreak?* [Answers on 5-item scale, from "Definitely yes" to "Definitely no", with additional option "I did not lose my job recently"]

Income

Which category represents your total individual annual income (before taxes) in 2019? This should include money from all jobs, net income from a business or farm, and any rent, pensions, dividends, interest, social security payments or other money income you received. [Answers on 12-point scale, from "Less than $10,000" to "$150,000 or more"]

Please think about your earnings from all your jobs over the last few months. After tax, how much did you approximately earn in the following months? [Number in local currency for January 2020, February 2020 and March 2020]

Job characteristics: Questions phrased to refer to main or last job, depending on the respondent's employment status.

What sort of occupation best describes this job? [O*NET SOC 2018 major groups for US and UK; ISCO-08 major groups for Germany]

What category best describes the industry you work in? [NACE Rev. 2 industry classification]

[27] For Germany, we asked whether you have been on short-time work.

[For current or former employees] *Do you have a permanent contract?* [Yes, No]

[For current or former employees] *Is your job salaried or how do you get paid?* [Salaried, Hourly, Paid by the job, Commission or tips only, Other]

[For current or former employees] *Are the number of hours you work fixed or do they vary?* [Fixed, Vary - I choose how many hours I work, Vary - My employer decides how many hours I work but I am guaranteed some work each week, Vary - I am an on-call worker]

In your job, what percentage of the tasks could you do from home? Examples: Andy is a waiter and cannot do any of his work from home (0%). Beth is a website designer and can do all her work from home (100%). [Answer on 0-100 slider]

Time use

Please think about last week and the time you spent on various activities. On a typical working day, how many hours did you spend... [Answers in hours and minutes]

- *... outside your home for work?*
- *... outside your home for leisure?*
- *... working from home?*
- *... home-schooling children?*
- *... actively caring for children (other than home-schooling)?*

Expectations

On a scale of 0-100%, how likely do you think it is that some form of social distancing measures will be in force in your state [country] on 1st August 2020?

On a scale of 0-100%, how likely are the following scenarios to occur before 1st August 2020?

- *I will lose my job or shut my business if self-employed*
- *I will have troubles paying my usual bills and expenses*

[For former employees] *On a scale of 0-100%, how likely do you think it is that your next job will be with your last employer?*

3C Comparison with nationally representative data

Table 3C.1: Distribution of respondents across regions - UK

Region	National	March	April
Scotland	8.42	8.48	8.54
Northern Ireland	2.76	2.57	2.80
Wales	4.79	4.83	4.87
North East	4.06	4.08	4.12
North West	11.00	11.02	11.11
Yorkshire and the Humber	8.24	8.28	8.34
West Midlands	8.80	8.86	8.92
East Midlands	7.27	7.32	7.38
South West	8.59	8.63	8.70
South East	13.70	13.79	13.87
East of England	9.29	8.91	8.03
Greater London	13.15	13.24	13.32
Observations		3974	4931

Notes: National figures refer to the latest available estimates for the population of residents aged 18 or above. Data source: Office for National Statistics (2019).

Table 3C.2: Distribution of respondents across area codes - US

Region	National	March	April
Area code 0	7.40	7.39	7.40
Area code 1	10.33	10.32	10.32
Area code 2	10.04	10.04	10.05
Area code 3	14.41	14.41	14.40
Area code 4	10.02	10.02	10.03
Area code 5	5.25	5.25	5.25
Area code 6	7.17	7.17	7.18
Area code 7	11.94	11.94	11.95
Area code 8	7.13	7.12	7.13
Area code 9	16.30	16.34	16.30
Observations		4003	4000

Notes: National figures refer to the latest available estimates for the population of residents aged 18 or above. Data source: U.S. Census Bureau, Population Division (2019).

Table 3C.3: Distribution of respondents across states - Germany

Region	National	April
Baden-Württemberg	13.33	13.29
Bayern	15.75	15.74
Berlin	4.39	4.40
Brandenburg	3.03	3.02
Bremen	0.82	0.82
Hamburg	2.22	2.22
Hessen	7.55	7.55
Mecklenburg-Vorpommern	1.94	1.97
Niedersachsen	9.62	9.62
Nordrhein-Westfalen	21.60	21.59
Rheinland-Pfalz	4.92	4.92
Saarland	1.19	1.20
Sachsen	4.91	4.90
Sachsen-Anhalt	2.66	2.65
Schleswig-Holstein	3.49	3.50
Thüringen	2.58	2.60
Observations		4002

Notes: National figures refer to the latest available estimates for the population of residents. Data source: Statistische Ämter des Bundes und der Länder (2018).

Table 3C.4: Demographics of the population and surveys

	US		UK		DE	
	CPS	April	LFS	April	SOEP	April
Female	0.480	0.582	0.471	0.552	0.479	0.475
University	0.394	0.494	0.361	0.488	0.272	0.287
<30	0.234	0.255	0.222	0.281	0.171	0.398
30-39	0.225	0.264	0.232	0.333	0.210	0.284
40-49	0.201	0.215	0.220	0.238	0.209	0.146
50-59	0.197	0.136	0.220	0.114	0.267	0.132
60+	0.143	0.130	0.105	0.033	0.144	0.040

Notes: The table shows the mean demographic characteristics of economically active individuals in our April samples, as well as nationally representative samples, for the US, UK and Germany. For the US, we use the February 2020 monthly CPS data, for the UK the 2019 LFS data, and for Germany the 2018 SOEP data as a benchmark.

Table 3C.5: Distribution across occupations of the population and surveys

	US		UK		DE		
	CPS	April	LFS	April		SOEP	April
Management	0.092	0.114	0.146	0.102	Management	0.050	0.116
Business and Financial Operations	0.060	0.087	0.068	0.089	Academic	0.199	0.110
Computer and Mathematical	0.038	0.073	0.030	0.065	Technician, comparable non-tech.	0.248	0.155
Architecture and Engineering	0.022	0.019	0.032	0.030	Office and administration	0.095	0.190
Life, Physical, and Social Science	0.011	0.023	0.018	0.020	Service and retail	0.152	0.190
Community and Social Service	0.018	0.019	0.019	0.023	Farming, fishing, and forestry	0.011	0.019
Legal	0.011	0.018	0.010	0.016	Craftsmen and women	0.095	0.077
Educational Instruction and Library	0.063	0.078	0.072	0.085	Mechanical	0.061	0.027
Arts, Design, Entertainment, Sports, Media	0.023	0.035	0.027	0.039	Auxiliary	0.085	0.103
Healthcare Practitioners and Technical	0.064	0.043	0.052	0.038	Military	0.003	0.012
Healthcare Support	0.033	0.045	0.015	0.042			
Protective Service*	0.021	0.011	0.024	0.014			
Food Preparation and Serving	0.055	0.072	0.036	0.073			
Building, Grounds Cleaning, Maintenance	0.029	0.016	0.032	0.017			
Personal Care and Service	0.026	0.051	0.043	0.026			
Sales and Related	0.100	0.101	0.072	0.101			
Office and Administrative Support	0.109	0.074	0.129	0.105			
Farming, Fishing, and Forestry	0.008	0.010	0.012	0.004			
Construction and Extraction	0.056	0.032	0.044	0.023			
Installation, Maintenance, and Repair	0.031	0.019	0.022	0.013			
Production	0.050	0.032	0.038	0.041			
Transportation and Material Moving	0.080	0.029	0.059	0.034			

Notes: The table shows the breakdown by occupation of economically active individuals in our April samples, as well as nationally representative samples, for the US, UK and Germany. For the US, we use the February 2020 monthly CPS data, for the UK the 2019 LFS data, and for Germany the 2018 SOEP data as a benchmark. For the UK, we match UK SOC 2010 codes to O*NET SOC 2018 codes by first matching the UK codes to the ISCO-08 codes and then onto O*NET SOC 2018 codes for major groups. (*) Includes Military occupations, which the CPS data does not record among its occupation codes.

Table 3C.6: Distribution across industries of the population and surveys

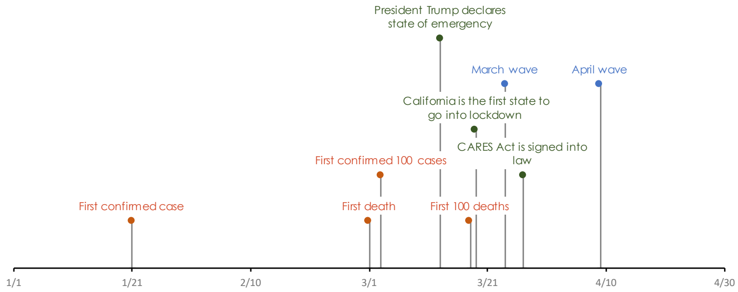
	US		UK		DE	
	CPS	April	LFS	April	SOEP	April
Agriculture, forestry and fishing	0.016	0.022	0.011	0.012	0.011	0.037
Mining and quarrying	0.005	0.011	0.004	0.016	0.002	0.022
Manufacturing	0.095	0.082	0.092	0.089	0.198	0.090
Electricity, gas, air cond supply	0.095	0.082	0.092	0.089	0.198	0.090
Water supply, sewerage, waste	0.005	0.013	0.007	0.023	0.006	0.055
Construction	0.071	0.064	0.072	0.063	0.050	0.068
Wholesale, retail, repair of vehicle	0.130	0.073	0.122	0.092	0.114	0.052
Transport and storage	0.050	0.033	0.049	0.042	0.052	0.050
Accommodation and food services	0.071	0.067	0.053	0.059	0.036	0.050
Information and communication	0.018	0.083	0.043	0.066	0.039	0.125
Financial and insurance activities	0.049	0.067	0.040	0.062	0.032	0.036
Real estate activities	0.021	0.023	0.013	0.013	0.009	0.012
Prof, scientific, technical activ.	0.079	0.065	0.079	0.044	0.051	0.024
Admin and support services	0.035	0.043	0.047	0.048	0.045	0.032
Public admin and defence*	0.046	0.012	0.067	0.039	0.070	0.059
Education	0.094	0.103	0.105	0.120	0.079	0.046
Health and social work	0.141	0.081	0.136	0.090	0.152	0.096
Arts, entertainment and recreation	0.019	0.044	0.026	0.037	0.017	0.023
Other service activities	0.043	0.084	0.028	0.051	0.021	0.058
Households as employers	0.005	0.012	0.001	0.007	0.006	0.009

Notes: The table shows the breakdown by industry of economically active individuals in our April samples, as well as nationally representative samples, for the US, UK and Germany. For the US, we use the February 2020 monthly CPS data, for the UK the 2019 LFS data, and for Germany the 2018 SOEP data as a benchmark. The industry groups refer to the NACE Rev. 2 industry codes. For the US, we matched the Census Codes from the CPS into NACE Rev. 2 codes. (*) Includes "Extraterritorial organisations", which the CPS data does not record among the industry codes.

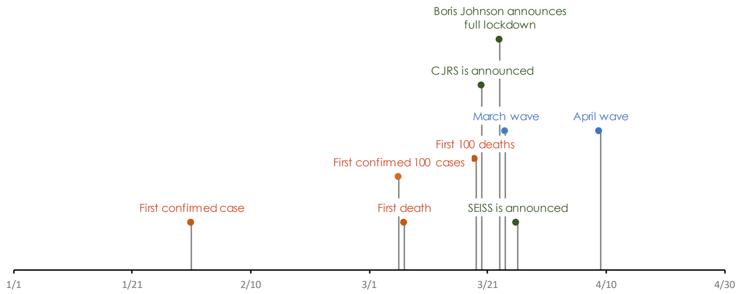
3D Additional Tables and Figures

Figure 3D.1: Timeline of coronavirus outbreak and policy responses

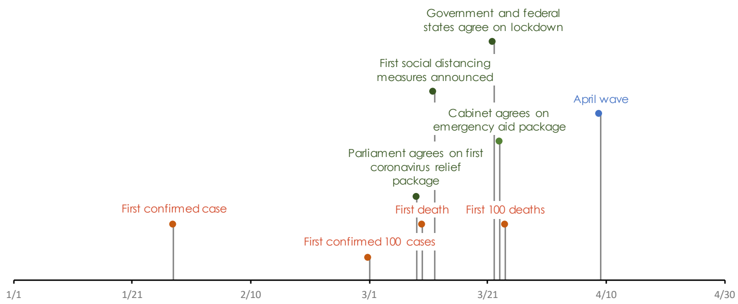
(a) US



(b) UK

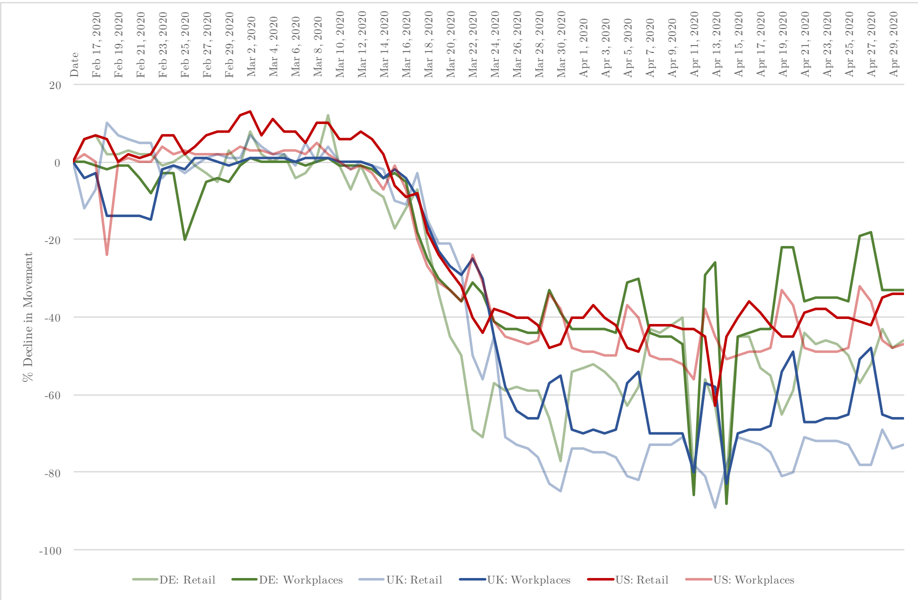


(c) Germany



Notes: This figure illustrates the exact timing of events with regard to the coronavirus outbreak (red) and the main policy responses (green) in (a) the US, (b) the UK, and (c) Germany. The dates when the surveys were launched are marked in blue.

Figure 3D.2: Change in community mobility

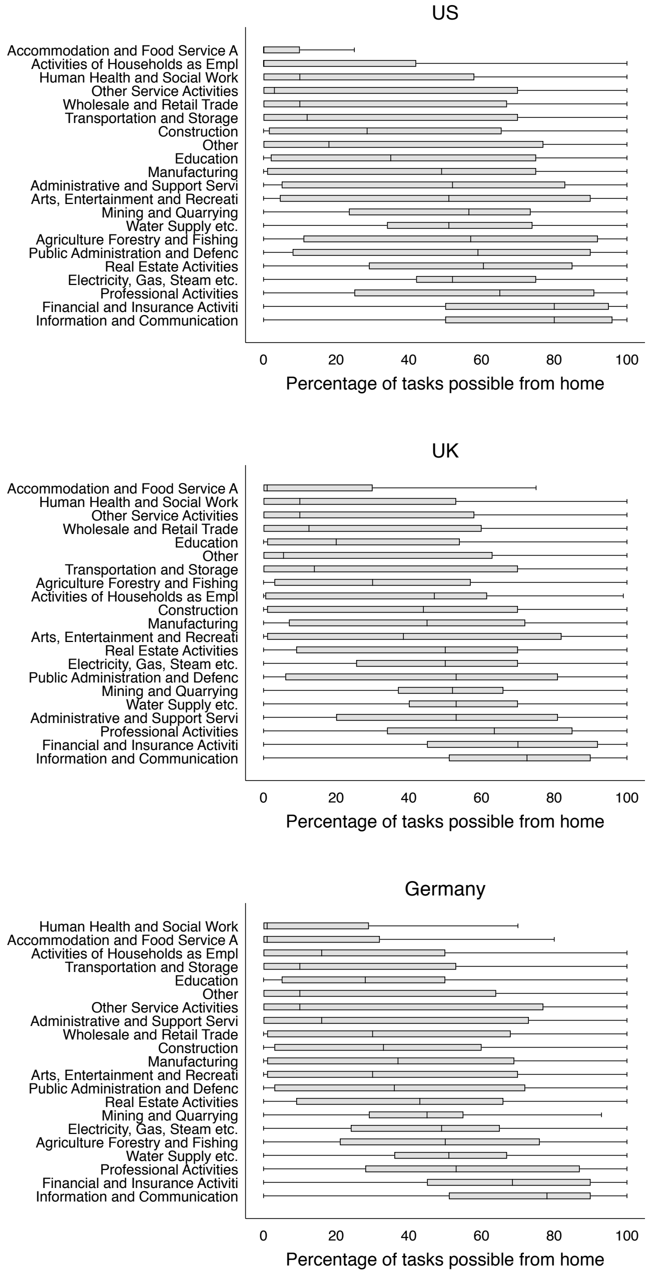


Notes: The figure shows the percentage change in retail and workplace mobility using data from the Google COVID-19 Community Mobility reports. Google uses anonymized location data provided by apps such as Google Maps to construct these measures. The retail trend shows the change in visitors at places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters. The workplaces trend shows how the number of visitors to workplaces has changed relative to the period before the pandemic.

Figure 3D.3: Employment status by occupation (early April)

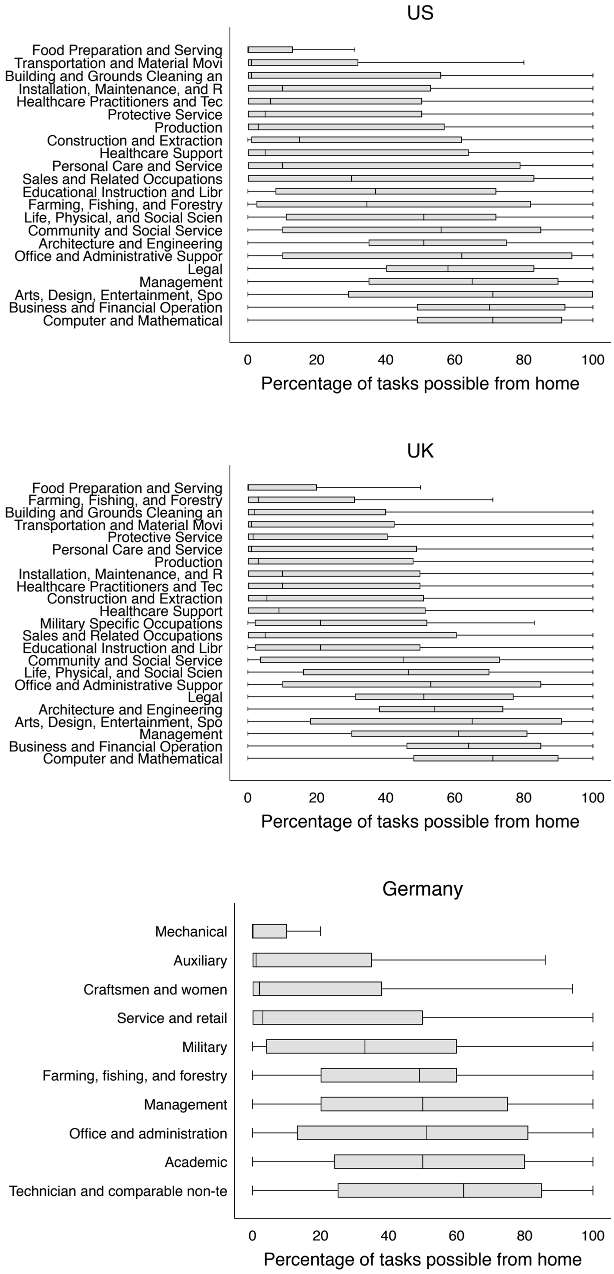
Notes: The figure shows the share of workers who are employed (blue - right), furloughed for the US/UK or on STW for Germany (yellow - middle) or lost their job due to the Covid-19 crisis (red - left), by occupation. The sample is restricted to employees (in their current or last job) only.

Figure 3D.4: Share of tasks that can be done from home by industry



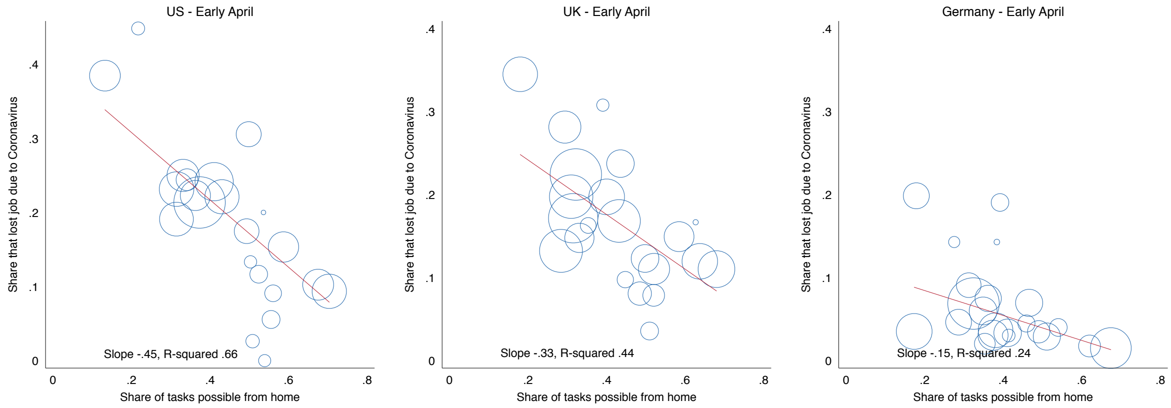
Notes: The figure shows box plots for the share of tasks that workers in each industry can do from home, separately for the US (left), UK (center) and Germany (right). The industries are ordered by the mean share of tasks that can be done from home. The gray boxes illustrate the 25^{th} to the 75^{th} percentile, the black line the median, and the whiskers are the values that are furthest away from the median on either side of the box, but are still within a distance of 1.5 times the interquartile range from the nearest quartile.

Figure 3D.5: Share of tasks that can be done from home by occupation



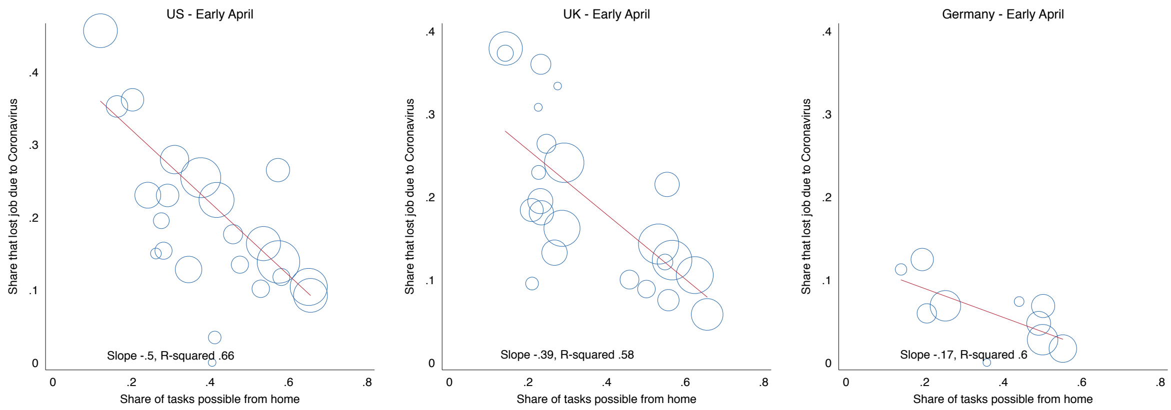
Notes: The figure shows box plots for the share of tasks that workers in each occupation can do from home, separately for the US (left), UK (center) and Germany (right). The occupations are ordered by the mean share of tasks that can be done from home. The gray boxes illustrate the 25^{th} to the 75^{th} percentile, the black line the median, and the whiskers are the values that are furthest away from the median on either side of the box, but are still within a distance of 1.5 times the interquartile range from the nearest quartile.

Figure 3D.6: Share of tasks that can be done from home versus job loss probability due to Covid-19 by industry



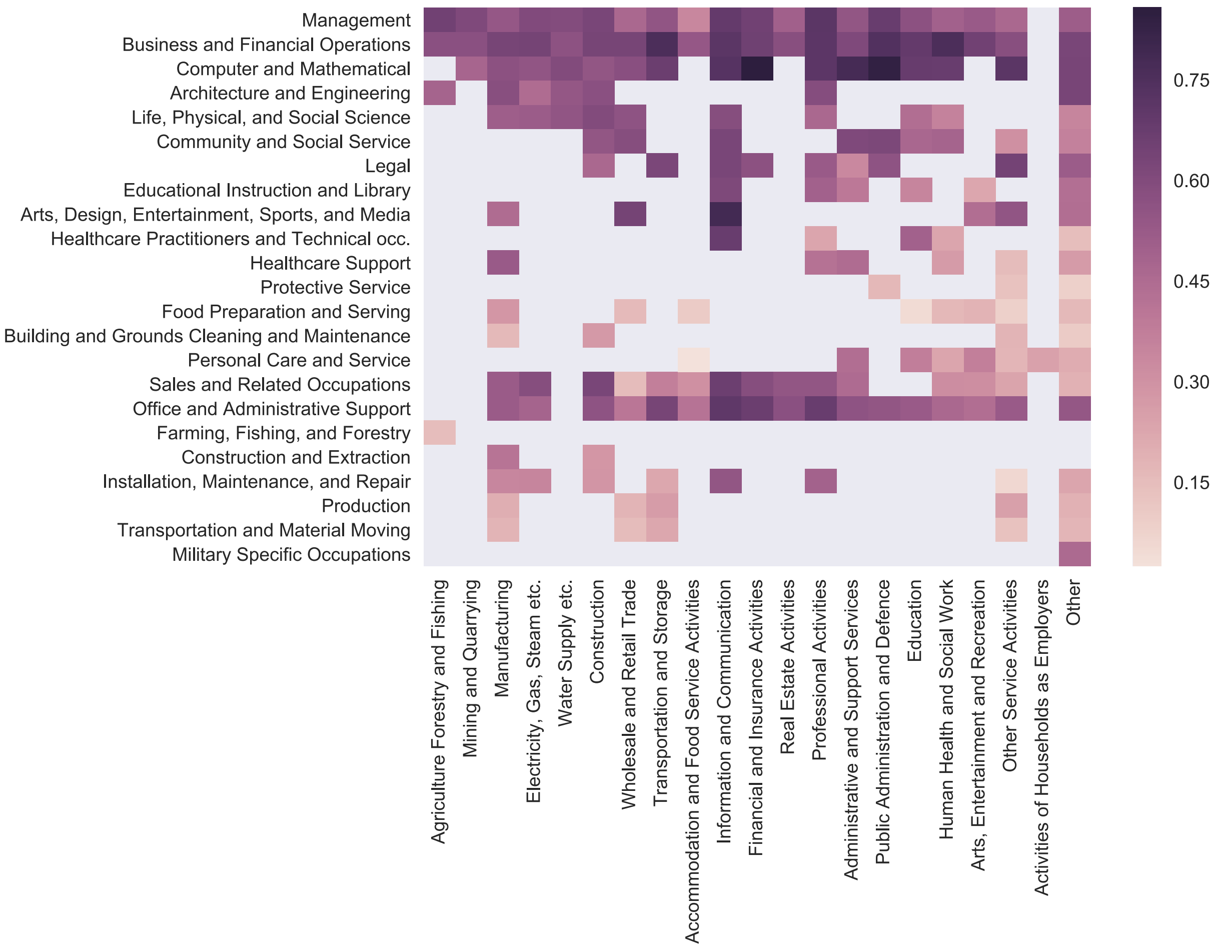
Notes: Each bubble represents an industry and the size is proportional to the number of observations we have for that industry. The figure shows the average share of tasks that can be done from home by industry on the x-axis and the share of workers that their jobs due to Coronavirus on the y-axis.

Figure 3D.7: Share of tasks that can be done from home versus job loss probability due to Covid-19 by occupation



Notes: Each bubble represents an occupation and the size is proportional to the number of observations we have for that occupation. The figure shows the average share of tasks that can be done from home by occupation on the x-axis and the share of workers that their jobs due to Coronavirus on the y-axis.

Figure 3D.8: Share of tasks that can be done from home by occupation-industry pairs

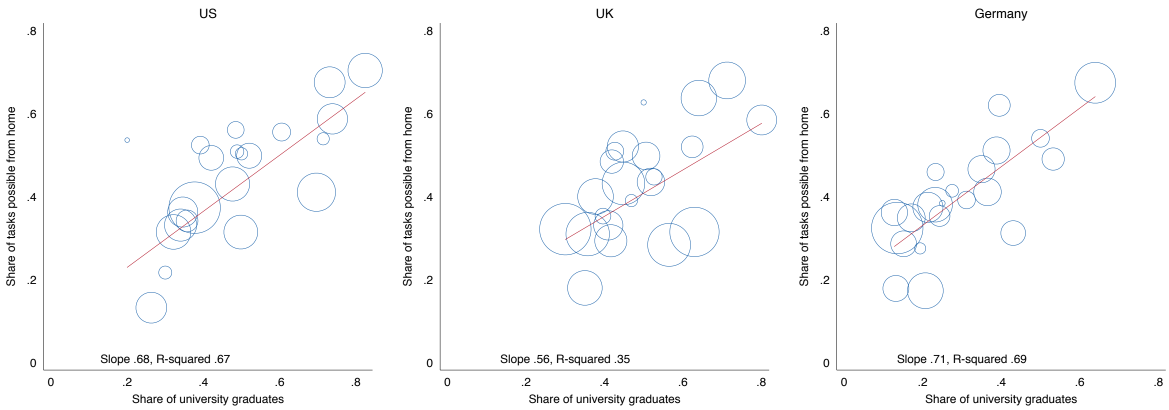


Notes: Joint data for US and UK from the April wave of the surveys. Cells with less than 10 observations are dropped. The darker the color of a cell, the higher the share of tasks that can be done from home. The legend on the right indicates the levels of the share of tasks that can be done from home.

Figure 3D.9: Jobs lost due to Coronavirus by occupation and industry

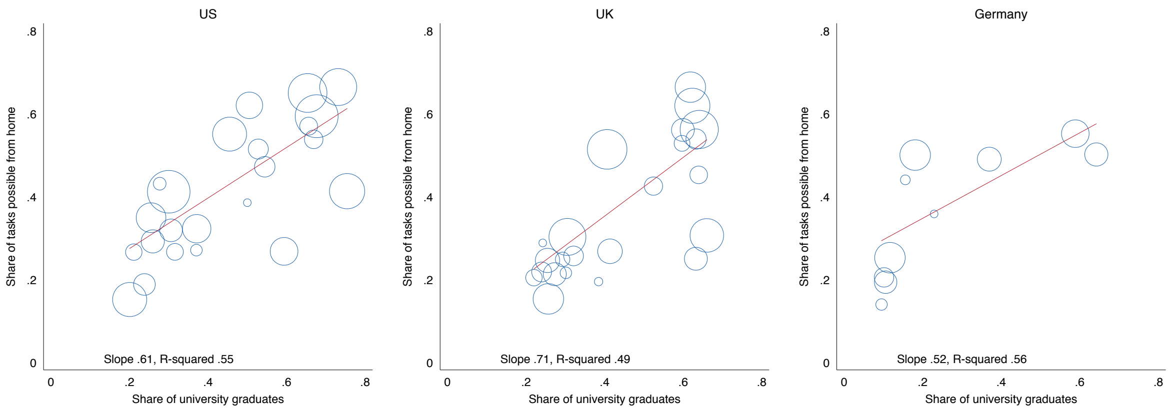
Notes: Joint data for US and UK from the April wave of the surveys. Cells with less than 10 observations are dropped. The darker the color of a cell, the higher the job-loss probability. The legend on the right indicates the levels of the job-loss probabilities.

Figure 3D.10: Share of workers with a university degree versus share of tasks that can be done from home by industry



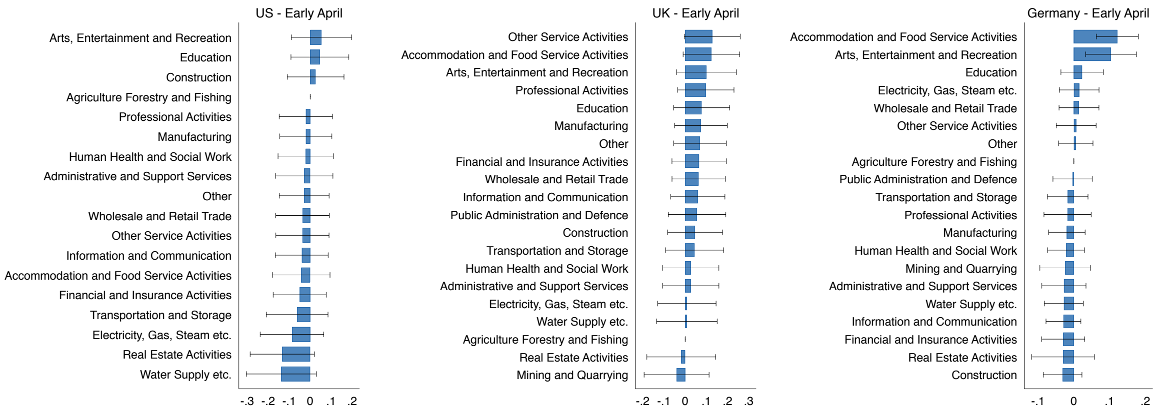
Notes: Each bubble represents an industry and the size is proportional to the number of observations we have for that industry. The figure shows the share of workers with a university degree by industry on the x-axis and the share of tasks that can be done from home on the y-axis.

Figure 3D.11: Share of workers with a university degree versus share of tasks that can be done from home by occupation



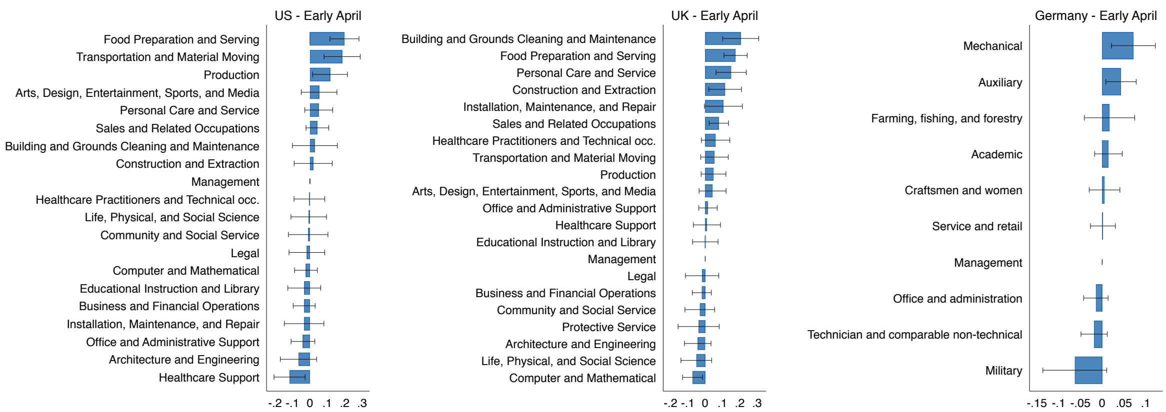
Notes: Each bubble represents an occupation and the size is proportional to the number of observations we have for that occupation. The figure shows the share of workers with a university degree by occupation on the x-axis and the share of tasks that can be done from home on the y-axis.

Figure 3D.12: Industry fixed effect for job loss



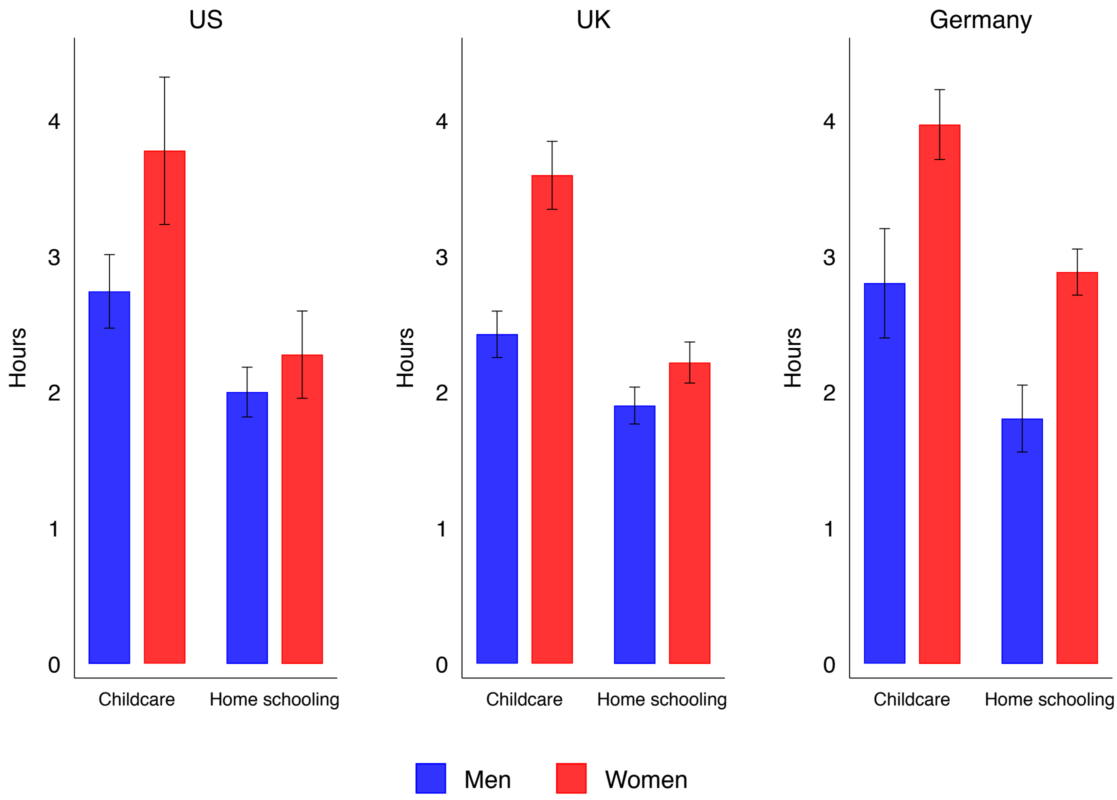
Notes: The thin black bars represent the 95% confidence intervals. The bars represent coefficients for occupation fixed effects from the regressions in Table 3.2 columns (2), (4), and (6) for the US, UK and Germany, respectively. Agriculture, forestry and fishing is the baseline industry.

Figure 3D.13: Occupation fixed effect for job loss



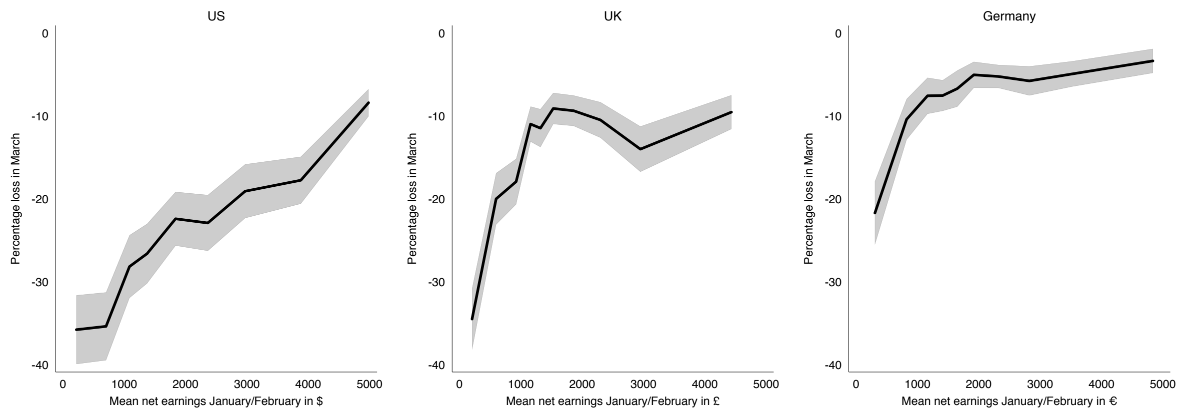
Notes: The thin black bars represent the 95% confidence intervals. The bars represent coefficients for occupation fixed effects from the regressions in Table 3.2 columns (2), (4), and (6) for the US, UK and Germany, respectively. Management is the baseline occupation.

Figure 3D.14: Hours spent on a "typical" work day during the past week on active childcare and home schooling



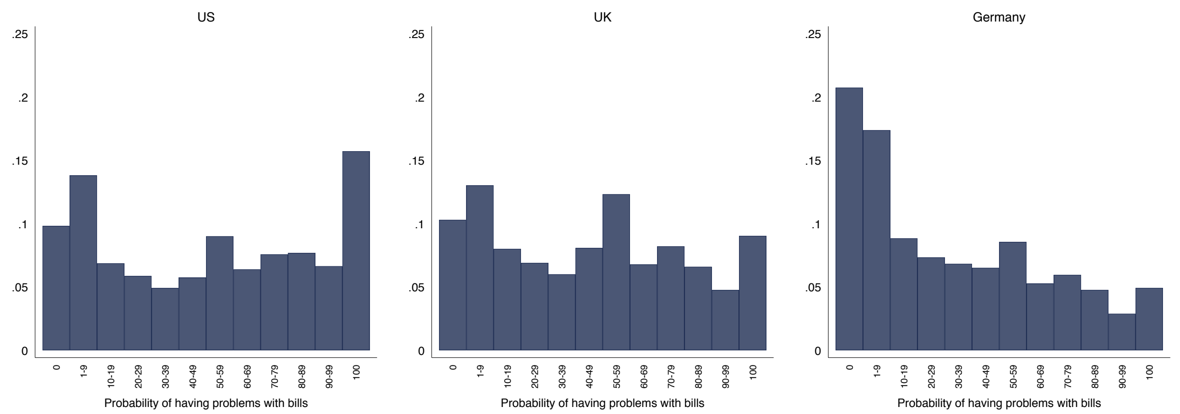
Notes: Data from the April wave of the surveys. The thin black bars represent the 95% confidence intervals. The figure shows average number of hours that men and women reported spending on childcare and homeschooling. We restrict the sample to individuals with children who report working from home, and whose answers to the time use questions combined do not exceed 24 hours.

Figure 3D.15: Average percentage drop in earnings from January/February to March



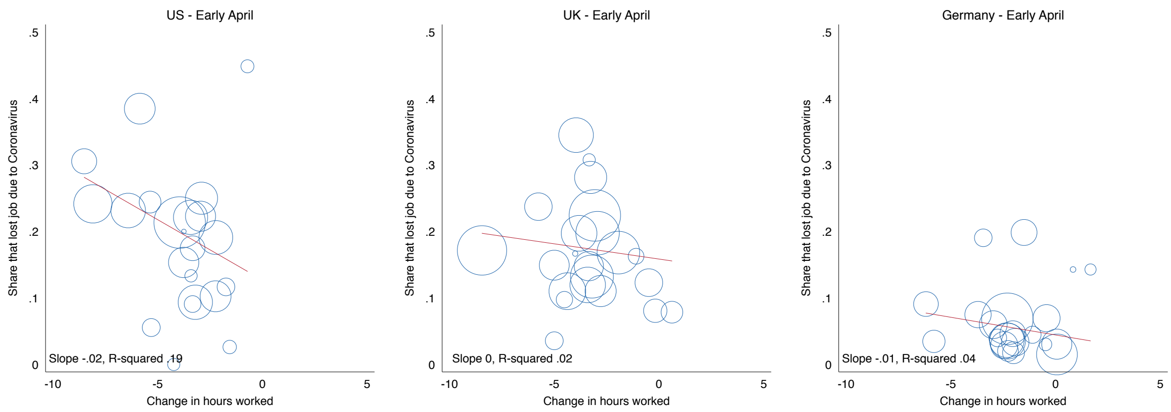
Notes: The line is computed by splitting respondents with average earnings between 10 and 5000 in the respective currency into earnings deciles and the gray area is the 95% confidence interval.

Figure 3D.16: Distribution of perceived likelihood of struggling with bills/expenses



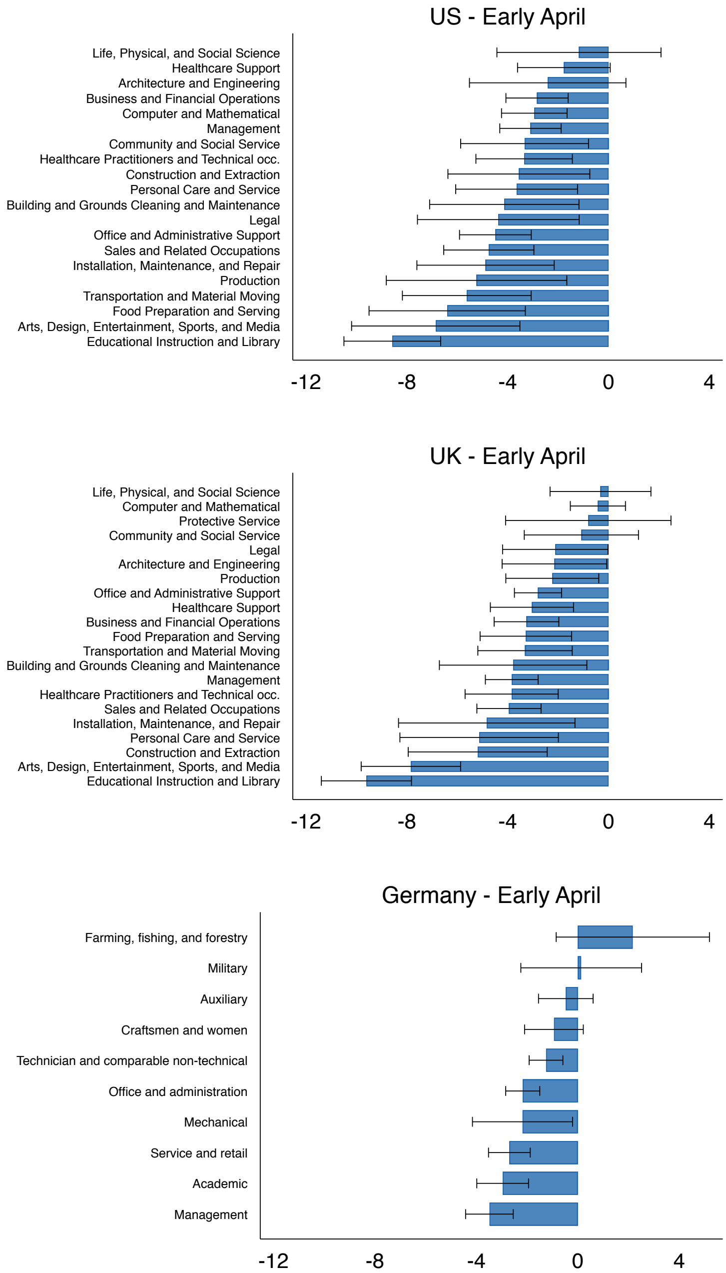
Notes: Data from the April wave of the surveys. This figure displays the distribution of the perceived likelihood of struggling to pay usual bills/expenses in the near future (before August 1st) in the US (left), UK (center) and Germany (right). Responses to this question are recorded on a 0-100% scale.

Figure 3D.17: Change in hours worked (conditional on working) vs jobs lost due to Coronavirus by industry



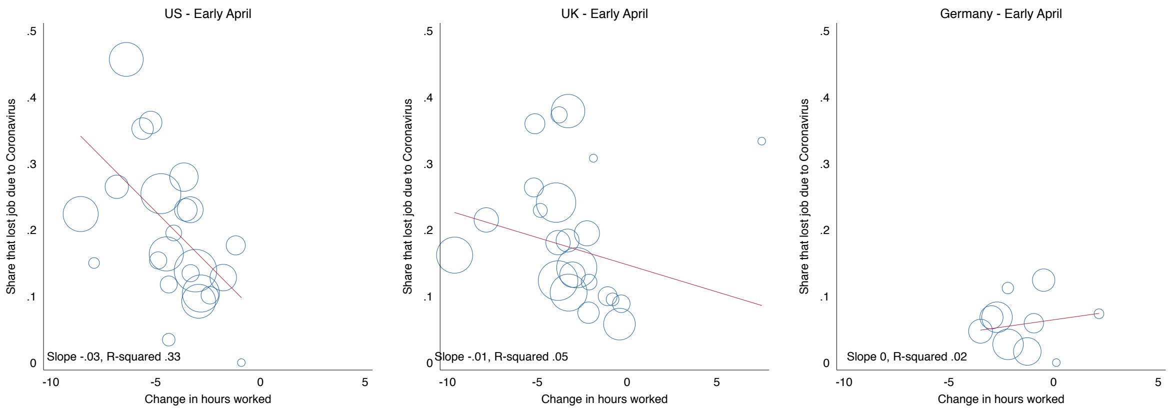
Notes: Each bubble represents an industry and the size is proportional to the number of observations we have for that industry. The figure shows the average change in hours between a usual and the last work week by industry on the x-axis and the share of workers that their jobs due to Coronavirus on the y-axis.

Figure 3D.18: Change in hours worked by occupation



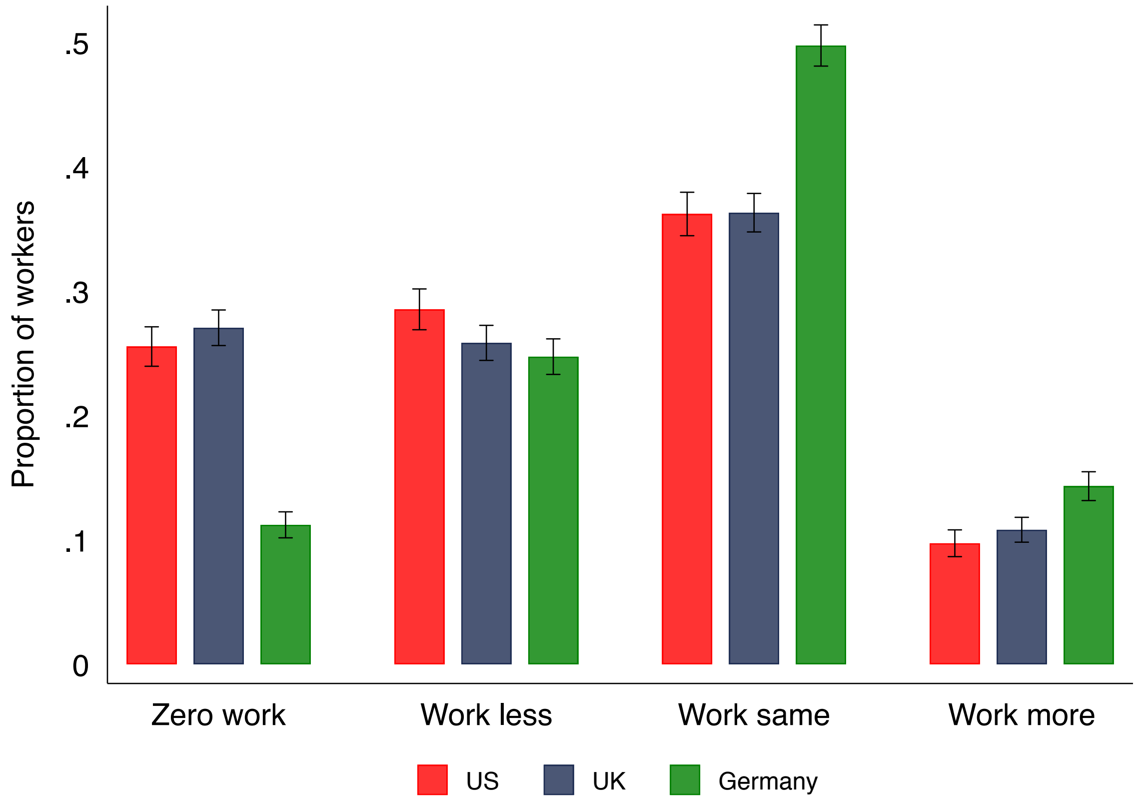
Notes: The thin black bars represent the 95% confidence intervals. The figure shows the change in hours worked between a usual work week in February and the last work week amongst those still working for the US (top), the UK (center) and Germany (bottom).

Figure 3D.19: Change in hours worked (conditional on working) vs jobs lost due to Coronavirus by occupation



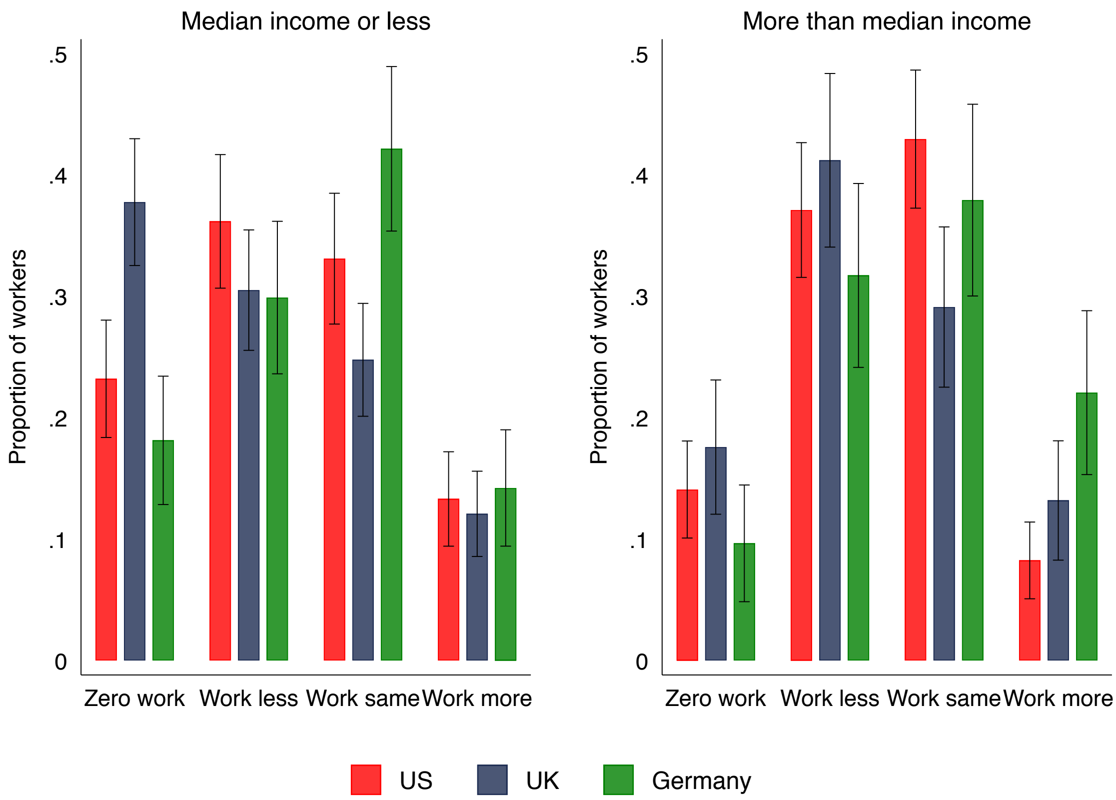
Notes: Each bubble represents an occupation and the size is proportional to the number of observations we have for that occupation. The figure shows the average change in hours between a usual and the last work week by occupation on the x-axis and the share of workers that their jobs due to Coronavirus on the y-axis.

Figure 3D.20: Hours worked compared to a typical week by country



Notes: Data from the April wave of the surveys. The thin black bars represent the 95% confidence intervals. Whether a worker works less or the same as usual is judged compared to a typical week in February before the pandemic. Those working zero hours include those that have lost their job.

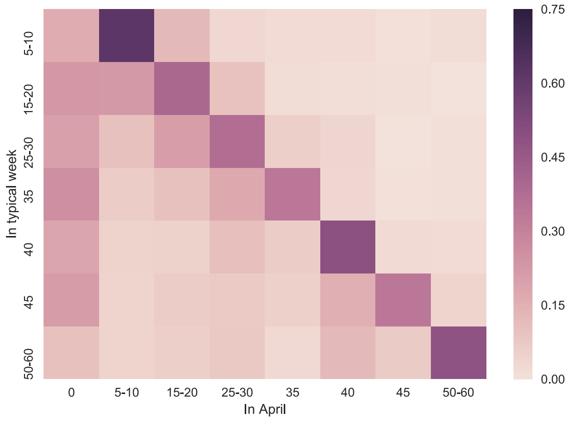
Figure 3D.21: Hours worked of the self-employed compared to a typical week by country



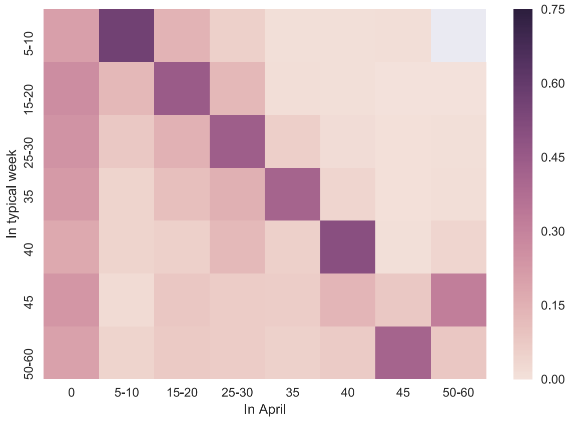
Notes: Data from the April wave of the surveys. the self-employed are split by median total labor income in 2019. The thin black bars represent the 95% confidence intervals. Whether a worker works less or the same a usual is judged compared to a typical week in February before the pandemic. Those working zero hours include those that have lost their job.

Figure 3D.22: Hours worked in a typical week compared to in April

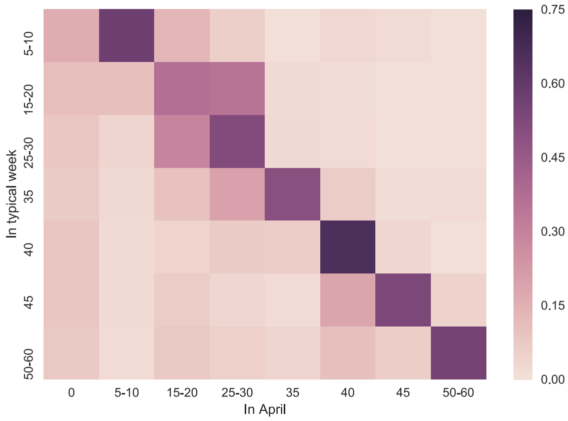
(a) US



(b) UK



(c) Germany



Notes: The figure shows the conditional probabilities of working a certain amount of hours in the April survey given the amount of hours normally worked in a typical week in February for (a) the US, (b) the UK, and (c) Germany. The darker the color of a cell, the higher the probability. The legend on the right indicates the levels of the transition probabilities. Each row sums to one.

Table 3D.1: Job loss probability - Waves 1 and 2

	United States			United Kingdom		
	(1)	(2)	(3)	(4)	(5)	(6)
Tasks from home	-0.2685***	-0.2436***	-0.2395***	-0.1858***	-0.1503***	-0.1581***
	(0.0117)	(0.0129)	(0.0129)	(0.0112)	(0.0126)	(0.0126)
Wave 2 (April)	0.0905***	0.0940***	0.0929***	0.0882***	0.0889***	0.0879***
	(0.0088)	(0.0087)	(0.0087)	(0.0080)	(0.0080)	(0.0079)
Female		0.0423***	0.0394***		0.0214**	0.0213**
		(0.0097)	(0.0097)		(0.0086)	(0.0085)
University degree		0.0028	0.0101		-0.0064	-0.0039
		(0.0097)	(0.0100)		(0.0086)	(0.0086)
30-39		-0.0049	-0.0034		0.0050	0.0148
		(0.0118)	(0.0118)		(0.0104)	(0.0103)
40-49		0.0044	0.0037		-0.0061	0.0009
		(0.0129)	(0.0130)		(0.0114)	(0.0114)
50-59		0.0015	-0.0016		-0.0242*	-0.0206
		(0.0148)	(0.0148)		(0.0135)	(0.0134)
60+		0.0241	0.0211		0.0039	-0.0021
		(0.0160)	(0.0160)		(0.0195)	(0.0193)
Permanent			-0.0301***			-0.1162***
			(0.0097)			(0.0110)
Salaried			-0.0335***			0.0048
			(0.0113)			(0.0101)
Fixed hours			0.0337***			-0.0035
			(0.0097)			(0.0098)
Constant	0.2557***	0.2178***	0.2330***	0.1363***	0.1003***	0.1996***
	(0.0401)	(0.0431)	(0.0434)	(0.0148)	(0.0219)	(0.0232)
Observations	6289	6282	6280	7024	7010	7009
R^2	0.1007	0.1257	0.1296	0.0553	0.0801	0.0994
Region F.E.	yes	yes	yes	yes	yes	yes
Occupation F.E.	no	yes	yes	no	yes	yes

Notes: OLS regressions. Standard errors in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01. The sample includes respondents to the March and April survey waves for the US and the UK. The dependent variable is a binary variable for whether a respondent lost their job within the past month and attributed the job loss to the coronavirus outbreak, and zero if they did not. Tasks from home is the fraction of tasks respondents could do from home in their main or last job. Permanent, salaried and fixed hours take value 1 for employees with permanent contracts, who are salaried and whose work hours are fixed, respectively. Region fixed effects refer to state fixed effects for the US, and fixed effects for regions as reported in Table 3C.1 for the UK.

Table 3D.2: Job and earnings loss probability (weighted)

	Job loss			Earnings loss		
	US	UK	DE	US	UK	DE
Tasks from home	-0.2395***	-0.1928***	-0.0761***	-0.1180***	-0.0774**	-0.0035
	(0.0283)	(0.0258)	(0.0237)	(0.0367)	(0.0332)	(0.0371)
Self-employed	-0.0942***	-0.0290	0.0514	0.0018	0.0552	0.0563
	(0.0305)	(0.0386)	(0.0450)	(0.0422)	(0.0523)	(0.0669)
Permanent	-0.0648***	-0.1726***	-0.1036***	0.0142	-0.0515	-0.0281
	(0.0225)	(0.0302)	(0.0325)	(0.0281)	(0.0410)	(0.0369)
Salaried	-0.0596**	0.0193	0.0009	-0.1410***	-0.0107	-0.1040***
	(0.0233)	(0.0198)	(0.0179)	(0.0299)	(0.0259)	(0.0353)
Fixed hours	0.0155	0.0017	0.0056	-0.0949***	-0.1628***	-0.0729***
	(0.0224)	(0.0187)	(0.0146)	(0.0296)	(0.0265)	(0.0274)
Constant	0.3856***	0.3571***	0.1108**	0.5211***	0.3535***	0.3021***
	(0.1138)	(0.1282)	(0.0519)	(0.1504)	(0.1056)	(0.0995)
Observations	2995	3760	3354	2396	3111	3165
R^2	0.1607	0.1131	0.1471	0.1350	0.1160	0.1106
Region F.E.	yes	yes	yes	yes	yes	yes
Occupation F.E.	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes

Notes: OLS regressions. Standard errors in parentheses. ***** p< 0.1, ****** p< 0.05, ******* p< 0.01. The dependent variable in Columns 1 - 3 is a binary variable for whether a respondent lost their job within the past month and attributed the job loss to the coronavirus outbreak. The dependent variable in Columns 4 - 6 is a binary variable for whether a respondent earned less in March 2020 than the average earnings over January and February 2020. In Columns 4 - 6 the sample is restricted to those who were in work at the time of data collection. Tasks from home is the fraction of tasks respondents could do from home in their main or last job. Self-employed is a binary variable for being self-employed in the main or last job. Permanent, salaried and fixed hours take value 1 for employees with permanent contracts, who are salaried and whose work hours are fixed, respectively. Region fixed effects refer to state fixed effects for the US and Germany, and fixed effects for regions as reported in Table 3C.1 for the UK.

Table 3D.3: Job loss probability - Individual characteristics (weighted)

	United States		United Kingdom		Germany	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.0484**	0.0383*	0.0325**	0.0330**	-0.0208	-0.0164
	(0.0198)	(0.0202)	(0.0162)	(0.0163)	(0.0138)	(0.0145)
University degree	-0.0852***	-0.0010	-0.0632***	-0.0025	-0.0225	-0.0116
	(0.0196)	(0.0202)	(0.0154)	(0.0160)	(0.0140)	(0.0200)
30-39	-0.0160	-0.0016	0.0034	0.0133	-0.0290*	-0.0001
	(0.0261)	(0.0255)	(0.0197)	(0.0203)	(0.0159)	(0.0157)
40-49	-0.0133	-0.0036	-0.0011	0.0006	-0.0139	0.0089
	(0.0274)	(0.0280)	(0.0208)	(0.0218)	(0.0181)	(0.0182)
50-59	0.0364	0.0467	-0.0010	-0.0024	-0.0305*	-0.0109
	(0.0341)	(0.0322)	(0.0264)	(0.0271)	(0.0160)	(0.0155)
60+	0.0064	0.0009	-0.0231	-0.0265	0.0653*	0.0647*
	(0.0318)	(0.0313)	(0.0361)	(0.0340)	(0.0368)	(0.0360)
Tasks from home		-0.2365***		-0.1939***		-0.0694***
		(0.0285)		(0.0260)		(0.0221)
Self-employed		-0.0988***		-0.0257		0.0363
		(0.0304)		(0.0390)		(0.0452)
Permanent		-0.0630***		-0.1700***		-0.1078***
		(0.0227)		(0.0303)		(0.0326)
Salaried		-0.0551**		0.0187		-0.0007
		(0.0240)		(0.0202)		(0.0178)
Fixed hours		0.0133		-0.0001		0.0100
		(0.0225)		(0.0186)		(0.0144)
Constant	0.2206**	0.3628***	0.1537***	0.3451***	0.0973***	0.1296**
	(0.0952)	(0.1147)	(0.0334)	(0.1289)	(0.0229)	(0.0539)
Observations	3016	2995	3804	3760	3541	3354
R^2	0.0550	0.1644	0.0153	0.1156	0.0703	0.1572
Region F.E.	yes	yes	yes	yes	yes	yes
Occupation F.E.	no	yes	no	yes	no	yes
Industry F.E.	no	yes	no	yes	no	yes

Notes: OLS regressions. Standard errors in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01. The dependent variable is a binary variable for whether a respondent lost their job within the past month and attributed the job loss to the coronavirus outbreak. Tasks from home is the fraction of tasks respondents could do from home in their main or last job. Self-employed is a binary variable for being self-employed in the main or last job. Permanent, salaried and fixed hours take value 1 for employees with permanent contracts, who are salaried and whose work hours are fixed, respectively. Region fixed effects refer to state fixed effects for the US and Germany, and fixed effects for regions as reported in Table 3C.1 for the UK.

Table 3D.4: Job loss probability - Individual characteristics

	United States		United Kingdom		Germany	
	(1)	(2)	(3)	(4)	(5)	(6)
Tasks from home	-0.3313***		-0.2308***		-0.0524***	
	(0.0182)		(0.0168)		(0.0111)	
Female		0.0372**		0.0306**		-0.0012
		(0.0161)		(0.0130)		(0.0081)
University degree		-0.0240		-0.0210		0.0003
		(0.0164)		(0.0130)		(0.0092)
30-39		-0.0116		0.0306*		-0.0214**
		(0.0199)		(0.0157)		(0.0099)
40-49		-0.0152		0.0291*		-0.0129
		(0.0213)		(0.0174)		(0.0119)
50-59		0.0217		0.0020		-0.0173
		(0.0246)		(0.0218)		(0.0123)
60+		0.0272		0.0186		0.0323
		(0.0257)		(0.0361)		(0.0202)
Self-employed		-0.1720***		-0.0795***		-0.0052
		(0.0226)		(0.0260)		(0.0169)
Permanent		-0.0789***		-0.1784***		-0.0556***
		(0.0169)		(0.0207)		(0.0113)
Salaried		-0.0853***		-0.0111		-0.0169
		(0.0187)		(0.0156)		(0.0105)
Fixed hours		-0.0032		-0.0074		0.0066
		(0.0168)		(0.0153)		(0.0094)
Constant	0.3564***	0.3200***	0.2721***	0.1718**	0.0775***	0.1352***
	(0.0111)	(0.0904)	(0.0094)	(0.0681)	(0.0059)	(0.0309)
Observations	3006	3014	3772	3804	3393	3536
R^2	0.0990	0.1228	0.0475	0.0947	0.0065	0.0674
Region F.E.	no	yes	no	yes	no	yes
Occupation F.E.	no	yes	no	yes	no	yes
Industry F.E.	no	yes	no	yes	no	yes

Notes: OLS regressions. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is a binary variable for whether a respondent lost their job within the past month and attributed the job loss to the coronavirus outbreak. Tasks from home is the fraction of tasks respondents could do from home in their main or last job. Self-employed is a binary variable for being self-employed in the main or last job. Permanent, salaried and fixed hours take value 1 for employees with permanent contracts, who are salaried and whose work hours are fixed, respectively. Region fixed effects refer to state fixed effects for the US and Germany, and fixed effects for regions as reported in Table 3C.1 for the UK.

Table 3D.5: Probability of job loss II

	United States		United Kingdom		Germany	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.0261	0.0269	-0.0047	-0.0042	0.0099	0.0110
	(0.0193)	(0.0193)	(0.0208)	(0.0208)	(0.0101)	(0.0101)
Number of kids	-0.0103	-0.0120	0.0027	0.0028	0.0033	0.0022
	(0.0105)	(0.0105)	(0.0090)	(0.0091)	(0.0056)	(0.0057)
Number of kids x female	0.0072	0.0074	0.0215*	0.0210*	-0.0164*	-0.0177*
	(0.0134)	(0.0134)	(0.0122)	(0.0123)	(0.0091)	(0.0092)
Changed work patterns for care		0.0257*		0.0113		0.0221**
		(0.0151)		(0.0127)		(0.0086)
University degree	-0.0036	-0.0049	-0.0067	-0.0071	0.0051	0.0036
	(0.0163)	(0.0163)	(0.0131)	(0.0131)	(0.0102)	(0.0103)
30-39	-0.0022	0.0007	0.0242	0.0241	-0.0163	-0.0158
	(0.0198)	(0.0198)	(0.0158)	(0.0158)	(0.0104)	(0.0104)
40-49	-0.0055	-0.0013	0.0169	0.0186	-0.0132	-0.0110
	(0.0212)	(0.0212)	(0.0174)	(0.0176)	(0.0124)	(0.0125)
50-59	0.0159	0.0230	-0.0043	-0.0020	-0.0212*	-0.0169
	(0.0242)	(0.0244)	(0.0216)	(0.0218)	(0.0127)	(0.0128)
60+	0.0078	0.0165	0.0138	0.0172	0.0280	0.0336
	(0.0255)	(0.0259)	(0.0362)	(0.0365)	(0.0207)	(0.0208)
Tasks from home	-0.2573***	-0.2587***	-0.1929***	-0.1945***	-0.0390***	-0.0414***
	(0.0219)	(0.0219)	(0.0197)	(0.0199)	(0.0132)	(0.0132)
Self-employed	-0.1001***	-0.1010***	-0.0485*	-0.0496*	0.0051	0.0059
	(0.0230)	(0.0230)	(0.0260)	(0.0261)	(0.0176)	(0.0176)
Permanent	-0.0626***	-0.0642***	-0.1732***	-0.1740***	-0.0511***	-0.0515***
	(0.0166)	(0.0167)	(0.0206)	(0.0207)	(0.0116)	(0.0116)
Salaried	-0.0588***	-0.0586***	0.0129	0.0127	-0.0198*	-0.0189*
	(0.0185)	(0.0185)	(0.0156)	(0.0157)	(0.0109)	(0.0109)
Fixed hours	0.0009	0.0023	-0.0114	-0.0104	0.0052	0.0071
	(0.0165)	(0.0165)	(0.0152)	(0.0153)	(0.0097)	(0.0098)
Constant	0.4376***	0.4236***	0.2450***	0.2423***	0.1299***	0.1133***
	(0.0891)	(0.0894)	(0.0685)	(0.0710)	(0.0359)	(0.0368)
Observations	2995	2993	3759	3746	3354	3348
R^2	0.1621	0.1631	0.1180	0.1183	0.0689	0.0708
Region F.E.	yes	yes	yes	yes	yes	yes
Occupation F.E.	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes

Notes: OLS regressions. Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. The dependent variable in Columns 1 - 6 is a binary variable for whether a respondent lost their job within the past month and attributed the job loss to the coronavirus outbreak. Tasks from home is the fraction of tasks respondents could do from home in their main or last job. Self-employed is a binary variable for being self-employed in the main or last job. Permanent, salaried and fixed hours take value 1 for employees with permanent contracts, who are salaried and whose work hours are fixed, respectively. Region fixed effects refer to state fixed effects for the US and Germany, and fixed effects for regions as reported in Table 3C.1 for the UK.

Table 3D.6: Hours spent on a "typical" work day during the past week on active childcare or home schooling

	United States		United Kingdom		Germany	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	1.0663**	0.9021*	1.2538***	1.2373***	1.8465***	1.8568***
	(0.4758)	(0.4818)	(0.2238)	(0.2236)	(0.4508)	(0.4480)
University degree	0.1077	0.1043	0.1961	0.2005	-0.1497	-0.3216
	(0.4910)	(0.4902)	(0.2302)	(0.2301)	(0.5032)	(0.5049)
Number of kids	0.0790	0.0786	0.6184***	0.6249***	-0.3323	-0.3005
	(0.2359)	(0.2356)	(0.1288)	(0.1286)	(0.2595)	(0.2589)
Married	0.4534	0.4647	0.3673	0.3758	1.4849***	1.6198***
	(0.5525)	(0.5524)	(0.2602)	(0.2603)	(0.4655)	(0.4669)
30-39	-0.4830	-0.4904	0.6391**	0.6397**	1.3540**	1.1695**
	(0.5743)	(0.5759)	(0.2699)	(0.2702)	(0.5226)	(0.5272)
40-49	-0.0719	-0.0982	-0.0413	-0.0413	-0.0911	-0.0024
	(0.6219)	(0.6290)	(0.3043)	(0.3069)	(0.6182)	(0.6157)
50-59	-1.6476*	-1.8368*	-2.2041***	-2.1552***	-2.4099**	-2.4477**
	(0.9919)	(1.0013)	(0.4440)	(0.4457)	(1.2040)	(1.1962)
60+	-1.6823	-1.7829	-2.9806***	-3.0226***	1.5229	1.3897
	(1.1566)	(1.1550)	(0.9515)	(0.9509)	(3.5818)	(3.5957)
Tasks from home	-0.7789	-0.8137	-1.0187***	-1.0978***	-0.7983	-0.7194
	(0.7520)	(0.7647)	(0.3928)	(0.4018)	(0.7514)	(0.7820)
Hours worked outside home		-0.0631		-0.1137**		-0.2074**
		(0.0814)		(0.0472)		(0.0879)
Hours worked from home		0.1067		-0.0520		-0.1076
		(0.0678)		(0.0367)		(0.0841)
Constant	1.1854	1.2252	2.7605**	3.0701***	3.3157**	3.8524**
	(2.3639)	(2.3616)	(1.1043)	(1.1092)	(1.6472)	(1.6568)
Observations	429	429	1273	1273	343	343
R^2	0.2726	0.2810	0.1530	0.1575	0.4044	0.4166
Region F.E.	yes	yes	yes	yes	yes	yes
Occupation F.E.	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes

Notes: OLS regressions. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is the number of hours spent on child care or home schooling on a typical day during the last week. Tasks from home is the fraction of tasks respondents could do from home in their main or last job. Region fixed effects refer to state fixed effects for the US and Germany, and fixed effects for regions as reported in Table 3C.1 for the UK.

Table 3D.7: Perceived probability of job loss

	United States		United Kingdom		Germany	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.0998***	-0.0590***	-0.0533***	-0.0100	0.0220**	0.0449***
	(0.0138)	(0.0141)	(0.0106)	(0.0107)	(0.0102)	(0.0095)
University degree	0.0198	0.0167	0.0136	0.0092	0.0589***	0.0237**
	(0.0140)	(0.0146)	(0.0106)	(0.0108)	(0.0117)	(0.0118)
30-39	0.0129	0.0075	-0.0491***	-0.0243*	0.0009	0.0161
	(0.0185)	(0.0176)	(0.0135)	(0.0129)	(0.0129)	(0.0117)
40-49	0.0084	0.0022	-0.1407***	-0.0873***	-0.0897***	-0.0208
	(0.0195)	(0.0189)	(0.0147)	(0.0144)	(0.0153)	(0.0140)
50-59	-0.1269***	-0.0849***	-0.2361***	-0.1571***	-0.1444***	-0.0596***
	(0.0229)	(0.0220)	(0.0183)	(0.0177)	(0.0156)	(0.0143)
60+	-0.2102***	-0.1505***	-0.2514***	-0.2087***	-0.1854***	-0.1116***
	(0.0239)	(0.0232)	(0.0317)	(0.0299)	(0.0271)	(0.0241)
Tasks from home		0.1105***		0.1180***		0.1409***
		(0.0200)		(0.0166)		(0.0152)
Self-employed		0.0059		-0.1077***		-0.0932***
		(0.0206)		(0.0231)		(0.0205)
Permanent		0.0443***		-0.0778***		0.0026
		(0.0152)		(0.0186)		(0.0135)
Salaried		-0.0244		-0.0297**		-0.1080***
		(0.0163)		(0.0129)		(0.0125)
Fixed hours		-0.0368**		-0.0587***		-0.0299***
		(0.0150)		(0.0125)		(0.0111)
Measures still in August		0.3562***		0.2170***		0.2154***
		(0.0238)		(0.0203)		(0.0164)
Constant	0.3804***	0.1608**	0.4165***	0.3478***	0.3407***	0.3378***
	(0.0639)	(0.0801)	(0.0214)	(0.0563)	(0.0182)	(0.0420)
Observations	2402	2382	3115	3094	3179	3116
R^2	0.1320	0.2713	0.0831	0.2333	0.0766	0.3075
Region F.E.	yes	yes	yes	yes	yes	yes
Occupation F.E.	no	yes	no	yes	no	yes
Industry F.E.	no	yes	no	yes	no	yes

Notes: OLS regressions. Standard errors in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01. The dependent variable is a binary variable for whether a respondent lost their job within the past month and attributed the job loss to the coronavirus outbreak. Tasks from home is the fraction of tasks respondents could do from home in their main or last job. Self-employed is a binary variable for being self-employed in the main or last job. Permanent, salaried and fixed hours take value 1 for employees with permanent contracts, who are salaried and whose work hours are fixed, respectively. 'Measures still in August' refers to the perceived probability of some social distancing measures being in place in August. Region fixed effects refer to state fixed effects for the US and Germany, and fixed effects for regions as reported in Table 3C.1 for the UK.

Table 3D.8: Earnings loss probability - In-work respondents

	United States		United Kingdom		Germany	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.0126	0.0143	0.0082	0.0273	0.0104	0.0130
	(0.0202)	(0.0217)	(0.0166)	(0.0174)	(0.0145)	(0.0151)
University degree	-0.1501***	-0.0758***	-0.0206	0.0287	-0.0022	0.0325*
	(0.0209)	(0.0226)	(0.0169)	(0.0176)	(0.0165)	(0.0177)
30-39	-0.0129	-0.0044	-0.0777***	-0.0447**	-0.0567***	-0.0288
	(0.0271)	(0.0272)	(0.0209)	(0.0211)	(0.0182)	(0.0185)
40-49	-0.0484*	-0.0676**	-0.0686***	-0.0219	-0.0302	0.0019
	(0.0286)	(0.0291)	(0.0229)	(0.0235)	(0.0218)	(0.0223)
50-59	-0.0973***	-0.1084***	-0.0994***	-0.0612**	-0.0465**	-0.0121
	(0.0335)	(0.0339)	(0.0285)	(0.0290)	(0.0222)	(0.0228)
60+	-0.1044***	-0.1290***	-0.1045**	-0.0861*	-0.1176***	-0.1072***
	(0.0349)	(0.0356)	(0.0491)	(0.0485)	(0.0382)	(0.0382)
Tasks from home	-0.1224***	-0.1258***	-0.0990***	-0.0785***	-0.0280	-0.0281
	(0.0274)	(0.0304)	(0.0236)	(0.0269)	(0.0213)	(0.0239)
Self-employed		0.0293		0.1045***		0.0678**
		(0.0319)		(0.0377)		(0.0326)
Permanent		-0.0230		-0.0147		0.0078
		(0.0234)		(0.0303)		(0.0214)
Salaried		-0.0683***		-0.0472**		-0.0641***
		(0.0252)		(0.0210)		(0.0198)
Fixed hours		-0.0699***		-0.1087***		-0.0901***
		(0.0231)		(0.0204)		(0.0176)
Constant	0.4013***	0.4164***	0.3640***	0.3751***	0.1789***	0.2812***
	(0.0939)	(0.1225)	(0.0347)	(0.0901)	(0.0272)	(0.0650)
Observations	2405	2396	3123	3111	3201	3165
R^2	0.0661	0.1207	0.0214	0.0932	0.0139	0.0712
Region F.E.	yes	yes	yes	yes	yes	yes
Occupation F.E.	no	yes	no	yes	no	yes
Industry F.E.	no	yes	no	yes	no	yes

Notes: OLS regressions. Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Sample is restricted to those who were in work at the time of the survey. The dependent variable is a binary variable for whether a respondent earned less in March 2020 than the average earnings over January and February 2020. Tasks from home is the fraction of tasks respondents could do from home in their main or last job. Self-employed is a binary variable for being self-employed in the main or last job. Permanent, salaried and fixed hours take value 1 for employees with permanent contracts, who are salaried and whose work hours are fixed, respectively. Region fixed effects refer to state fixed effects for the US and Germany, and fixed effects for regions as reported in Table 3C.1 for the UK.

Table 3D.9: Earnings loss probability - In-work respondents (weighted)

	United States		United Kingdom		Germany	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.0199	0.0286	0.0082	0.0359*	0.0015	0.0056
	(0.0253)	(0.0266)	(0.0209)	(0.0206)	(0.0219)	(0.0226)
University degree	-0.1550***	-0.0837***	-0.0162	0.0357*	-0.0442*	0.0020
	(0.0260)	(0.0284)	(0.0211)	(0.0212)	(0.0268)	(0.0283)
30-39	-0.0327	-0.0179	-0.0924***	-0.0511*	-0.0193	0.0151
	(0.0358)	(0.0359)	(0.0265)	(0.0264)	(0.0293)	(0.0311)
40-49	-0.0963***	-0.1036***	-0.0830***	-0.0342	0.0138	0.0591
	(0.0366)	(0.0377)	(0.0286)	(0.0288)	(0.0349)	(0.0374)
50-59	-0.1604***	-0.1629***	-0.1110***	-0.0680**	-0.0008	0.0446
	(0.0414)	(0.0417)	(0.0341)	(0.0327)	(0.0319)	(0.0339)
60+	-0.1474***	-0.1560***	-0.1400***	-0.1224**	-0.0598	-0.0479
	(0.0449)	(0.0452)	(0.0498)	(0.0499)	(0.0393)	(0.0393)
Tasks from home	-0.1136***	-0.1150***	-0.0965***	-0.0899***	-0.0037	-0.0039
	(0.0333)	(0.0366)	(0.0296)	(0.0331)	(0.0322)	(0.0385)
Self-employed		0.0241		0.0723		0.0608
		(0.0411)		(0.0529)		(0.0682)
Permanent		-0.0026		-0.0383		-0.0284
		(0.0279)		(0.0417)		(0.0376)
Salaried		-0.1099***		-0.0150		-0.1087***
		(0.0301)		(0.0266)		(0.0357)
Fixed hours		-0.0894***		-0.1614***		-0.0780***
		(0.0290)		(0.0263)		(0.0271)
Constant	0.4849***	0.5682***	0.3458***	0.3615***	0.1251***	0.2591**
	(0.1251)	(0.1482)	(0.0398)	(0.1056)	(0.0377)	(0.1042)
Observations	2398	2396	3111	3111	3169	3165
R^2	0.1025	0.1587	0.0251	0.1244	0.0371	0.1178
Region F.E.	yes	yes	yes	yes	yes	yes
Occupation F.E.	no	yes	no	yes	no	yes
Industry F.E.	no	yes	no	yes	no	yes

Notes: OLS regressions. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Sample is restricted to those who were in work at the time of the survey. The dependent variable is a binary variable for whether a respondent earned less in March 2020 than the average earnings over January and February 2020. Tasks from home is the fraction of tasks respondents could do from home in their main or last job. Self-employed is a binary variable for being self-employed in the main or last job. Permanent, salaried and fixed hours take value 1 for employees with permanent contracts, who are salaried and whose work hours are fixed, respectively. Region fixed effects refer to state fixed effects for the US and Germany, and fixed effects for regions as reported in Table 3C.1 for the UK.

Table 3D.10: Probability of being furloughed

	United States		United Kingdom		Germany	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.1497***	-0.1131***	-0.0367**	0.0252	0.0210	0.0276*
	(0.0179)	(0.0193)	(0.0166)	(0.0175)	(0.0161)	(0.0166)
University degree	0.0096	-0.0057	-0.0215	-0.0066	0.0875***	0.0092
	(0.0179)	(0.0198)	(0.0167)	(0.0178)	(0.0182)	(0.0208)
30-39	-0.0217	-0.0157	-0.1693***	-0.1276***	0.0655***	0.0519**
	(0.0234)	(0.0234)	(0.0209)	(0.0209)	(0.0204)	(0.0202)
40-49	-0.0111	0.0173	-0.2183***	-0.1454***	-0.0467*	-0.0500**
	(0.0250)	(0.0251)	(0.0231)	(0.0235)	(0.0242)	(0.0246)
50-59	-0.1108***	-0.0578*	-0.2912***	-0.1884***	-0.1830***	-0.1166***
	(0.0299)	(0.0297)	(0.0296)	(0.0299)	(0.0252)	(0.0251)
60+	-0.1512***	-0.0914***	-0.2830***	-0.2237***	-0.2239***	-0.1651***
	(0.0308)	(0.0312)	(0.0516)	(0.0508)	(0.0438)	(0.0423)
Tasks from home		0.0940***		0.0246		0.0871***
		(0.0274)		(0.0276)		(0.0265)
Permanent		0.1486***		0.1698***		0.0509**
		(0.0181)		(0.0259)		(0.0218)
Salaried		-0.0549***		-0.1091***		-0.1311***
		(0.0206)		(0.0198)		(0.0206)
Fixed hours		-0.0426**		-0.0649***		-0.0509***
		(0.0180)		(0.0192)		(0.0183)
Constant	0.3706***	0.3041***	0.5939***	0.5541***	0.5267***	0.6088***
	(0.0822)	(0.1078)	(0.0337)	(0.0905)	(0.0278)	(0.0753)
Observations	2415	2391	3289	3238	3221	3000
Region F.E.	yes	yes	yes	yes	yes	yes
Occupation F.E.	no	yes	no	yes	no	yes
Industry F.E.	no	yes	no	yes	no	yes

Notes: OLS regressions. Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. The dependent variable is a binary variable for whether a respondent reported being on furlough / STW at the time of our April survey wave. The sample is restricted to current or former employees only. Tasks from home is the fraction of tasks respondents could do from home in their main or last job. Permanent, salaried and fixed hours take value 1 for employees with permanent contracts, who are salaried and whose work hours are fixed, respectively. Region fixed effects refer to state fixed effects for the US and Germany, and fixed effects for regions as reported in Table 3C.1 for the UK.

Table 3D.11: Multinomial logit - Employment status

	United States		United Kingdom		Germany	
	No job	Furloughed	No job	Furloughed	No job	Furloughed
Female	1.0835	0.5151***	1.1968	1.1888*	1.0901	1.1584
	(0.1470)	(0.0652)	(0.1479)	(0.1113)	(0.2108)	(0.1121)
University degree	0.9127	0.9559	0.9048	0.9510	0.9869	1.0202
	(0.1230)	(0.1278)	(0.1125)	(0.0909)	(0.2538)	(0.1216)
30-39	0.9971	0.8912	0.7829*	0.5142***	0.6866	1.2604**
	(0.1612)	(0.1352)	(0.1142)	(0.0570)	(0.1668)	(0.1407)
40-49	0.8808	1.0553	0.6641**	0.4601***	0.5115**	0.7225**
	(0.1540)	(0.1715)	(0.1083)	(0.0576)	(0.1619)	(0.1040)
50-59	0.9096	0.6051**	0.3937***	0.3177***	0.4724**	0.4262***
	(0.1780)	(0.1330)	(0.0860)	(0.0527)	(0.1468)	(0.0702)
60+	0.8013	0.4567***	0.4076**	0.2696***	1.0231	0.2959***
	(0.1626)	(0.1094)	(0.1469)	(0.0766)	(0.4104)	(0.0953)
Tasks from home	0.1730***	1.1496	0.2065***	0.7861	0.6297	1.5582***
	(0.0357)	(0.2114)	(0.0420)	(0.1163)	(0.2082)	(0.2398)
Permanent	0.8158	2.4630***	0.4268***	1.6128***	0.4681***	1.1912
	(0.1014)	(0.3089)	(0.0673)	(0.2420)	(0.0951)	(0.1517)
Salaried	0.5902***	0.6502***	0.8305	0.5647***	0.5782**	0.5063***
	(0.0882)	(0.0872)	(0.1119)	(0.0590)	(0.1265)	(0.0570)
Fixed hours	0.9409	0.7536**	0.8009*	0.6893***	1.0752	0.7623***
	(0.1161)	(0.0893)	(0.1061)	(0.0696)	(0.2201)	(0.0791)
Constant	1.5753	0.6466	1.3592	2.7972**	0.2172	2.0793*
	(1.2493)	(0.4330)	(0.8594)	(1.3312)	(0.2481)	(0.8286)
Observations	2391		3238		3000	
Region F.E.	yes		yes		yes	
Occupation F.E.	yes		yes		yes	
Industry F.E.	yes		yes		yes	

Notes: Multinomial logit regressions. The coefficients represent relative risk ratios. The base category is working and not being furloughed / on STW. The sample is restricted to former or current employees only. Standard errors in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01. Tasks from home is the fraction of tasks respondents could do from home in their main or last job. Permanent, salaried and fixed hours take value 1 for employees with permanent contracts, who are salaried and whose work hours are fixed, respectively. Region fixed effects refer to state fixed effects for the US and Germany, and fixed effects for regions as reported in Table 3C.1 for the UK.

Table 3D.12: Probability of job loss & furlough

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
United States								
Job loss R^2	0.0946	0.0706	0.1088	0.0565	0.0734	0.1173	0.1290	0.1331
Furlough R^2	0.0784	0.0937	0.1116	0.0904	0.0899	0.1342	0.1414	0.1614
Observations	2406	2406	2406	2406	2406	2406	2406	2406
United Kingdom								
Job loss R^2	0.0581	0.0360	0.0652	0.0160	0.0408	0.0688	0.0911	0.0937
Furlough R^2	0.0527	0.0868	0.1018	0.0528	0.0567	0.1244	0.1268	0.1463
Observations	3280	3280	3280	3280	3280	3280	3280	3280
Germany								
Job loss R^2	0.0283	0.0369	0.0491	0.0199	0.0273	0.0543	0.0607	0.0636
Furlough R^2	0.1305	0.1795	0.2044	0.1122	0.1196	0.2309	0.2301	0.2529
Observations	3181	3181	3181	3181	3181	3181	3181	3181
Occupation F.E.	yes	no	yes	no	no	yes	yes	yes
Industry F.E.	no	yes	yes	no	no	yes	yes	yes
Demographics	no	no	no	yes	no	yes	no	yes
Contract type	no	no	no	no	yes	no	yes	yes
Region F.E.	yes	yes	yes	yes	yes	yes	yes	yes

Notes: OLS regressions. Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. The dependent variables are a binary variable for whether a respondent lost their job within the past month and attributed the job loss to the coronavirus outbreak, and a binary variable for whether the respondent is currently on furlough / STW. The sample is limited to respondents without missing answers on all control variables in (8). Demographic characteristics are age, and binary variables for whether a respondent is female and has at least university level education. Job contract characteristics are binary variables for whether a job is permanent, salaried or had fixed hours. Region fixed effects refer to state fixed effects for the US and Germany, and fixed effects for regions as reported in Table 3C.1 for the UK.

Chapter 4
Furloughing

with **Abi Adams-Prassl**, University of Oxford, **Teodora Boneva**, University of Zurich, and **Christopher Rauh**, University of Cambridge

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Abstract Over 9 million jobs were furloughed in the UK during the Coronavirus pandemic. Using real time survey evidence from the UK in April and May, we document which workers were most likely to be furloughed and analyze variation in the terms on which they furloughed. We find that women were significantly more likely to be furloughed. Inequality in care responsibilities seem to have played a key role: mothers were 10 percentage points more likely than fathers to initiate the decision to be furloughed (as opposed to it being fully or mostly the employer's decision) but we find no such gender gap amongst childless workers. The prohibition of working whilst furloughed was routinely ignored, especially by men who can do a large percentage of their work tasks from home. Women were less likely to have their salary topped up beyond the 80% subsidy paid for by the government. Considering the future, furloughed workers without employer-provided sick pay have a lower willingness to pay to return to work, as do those in sales and food preparation occupations. Compared to non-furloughed employees, furloughed workers are more pessimistic about keeping their job in the short to medium run and are more likely to be actively searching for a new job even when controlling for detailed job characteristics. These results have important implications for the design of short-time work schemes and the strategy for effectively reopening the economy.

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4.1 Introduction

The coronavirus outbreak has brought about a severe economic recession. With lockdown measures and business closures in place to contain the spread of the virus, many businesses have seen their activities coming to a halt. This has led to a sharp rise in unemployment rates in many countries affected by the coronavirus pandemic. To counteract the economic consequences of the current crisis and partially shield workers from the economic downturn, many countries have introduced or expanded existing furloughing or short-time work schemes (Giupponi and Landais 2020). In the UK, the government launched the Coronavirus Job Retention Scheme (CJRS) on 20 April 2020. The scheme allows employers to furlough workers for a minimum of three weeks, with the government contributing 80% of employees' salaries. By 14 June 2020, more than 9 million jobs had been furloughed under the CJRS, for a total value of claims of more than £20bn.[1]

While a third of UK employees have been enrolled in the CJRS, little is known about the operation and effectiveness of the policy. It is thus difficult to assess when the scheme should optimally end, and the degree to which furloughing should feature in the policy response to any future waves of infection. Further, the CJRS leaves a lot of room for employer discretion in the terms on which workers are furloughed. Whether the exercise of such discretion is reducing or exacerbating existing dimensions of labor market inequality is important for the design of policies to support the economic recovery.

In this paper, we use survey data that we collected on two independent samples of workers to shed light on the operation of the UK furloughing scheme. We find large variation in the share of workers that have been furloughed across, but also within, occupations and industries. Women have been significantly more likely to be furloughed than men doing the same type of job. There is evidence that childcare responsibilities play an important role in explaining this gender gap. Mothers are 10 percentage points more likely than fathers to have initiated the decision to be furloughed as opposed to the decision being "fully" or "mostly" the employers when controlling for a rich set of job characteristics. However, we find no gender gap in the furlough decision amongst childless workers.

We find that "not all workers are furloughed equally", and document differences in the terms under which workers are put on furlough, including whether employers have agreed to top-up their employees' salary beyond the state contribution. Women and those on low incomes are less

[1] Source: HMRC coronavirus (COVID-19) statistics.

likely to have had their wages topped up beyond the 80% provided by the government. We find that the majority of workers have continued to do some work while furloughed without being formally rotated back into employment. Amongst furloughed workers who can do at least 50% of their job from home, only 17% report working zero hours and their work hours are only 25% lower than they were in February.[2]

Finally, we examine workers' expectations about future unemployment. We find that workers' perceived probability of losing their job before August is 28%, but that furloughed workers perceive a 15 percentage point higher likelihood of job loss in the coming months. We also show that more pessimistic expectations increase on-the-job search, and that having been furloughed further increases the probability of job search by 3 percentage points.

Our results have important implications for the design of the UK furloughing scheme, and short-time work policies more broadly. First, short-time work schemes should allow employees to work on a part-time basis. Indeed, it is odd that the UK scheme originally ruled-out this possibility given that such flexibility is a key reason to prefer short-time work schemes over recall-unemployment. It is very rare for workers to report that they can do precisely zero of their work tasks from home (Adams-Prassl et al. 2020d), and the majority of workers have continued to do some work while on furlough. Perversely, firms breaking the terms of the scheme in this way has likely been welfare-improving, although it has introduced horizontal inequity between compliers and non-compliers; firms will have had more flexibility in maintaining essential business activities and the rate of human capital depreciation should have slowed.

The duration of support is a crucial parameter of STW schemes. These policies should be active long-enough to prevent inefficient layoffs from firms in temporary hardship. However, they should not subsidize low-productivity matches indefinitely and thereby hinder efficient labor market reallocation (Giupponi and Landais 2020). Our results suggest another dimension to consider. Crucially, the duration of the furloughing scheme should be sensitive to continued disruption in schooling and childcare. Mothers have been more likely to request to be furloughed. There is a real risk that these women could be forced out of the labor market if the furloughing scheme ends without viable childcare options being available. Our results also suggest the need for flexibility in the removal of the scheme across different occupations. Furloughed workers who can do a large proportion of their jobs from home are relatively pessimistic about their chance of

[2] These figures exclude furloughed employees who said they were being formally rotated back into work by their employer.

keeping their job. For these workers, social-distancing measures are unlikely to be the only reason for a low-productivity match and they should not be prevented from moving to more viable firms.

Finally, a return to work outside the home provides more opportunities for catching and transmitting the virus. We find wide variation in the willingness to return to work from furlough. Workers without access to employer-provided sick pay have significantly lower willingness to pay to return to work from furlough. Worryingly, we find that workers without sick pay are significantly more likely to continue to work with mild coronavirus symptoms. The UK has one of the least generous statutory sick pay schemes in Europe, which was described as "manifestly inadequate" by the European Committee of Social Rights (European Committee of Social Rights 2017). Our results suggest that the provision of more generous sick pay could help to support the economic recovery by encouraging workers to return to work while infection rates remain above zero, and supporting sick workers to take time off work when they pose a risk to others.

Our paper contributes to several strands of the literature. First, it contributes to the literature on the importance of short-time work schemes to buffer economic shocks (e.g., Giupponi and Landais 2020; Cahuc et al. 2018; Kopp and Siegenthaler 2018) and on the growing literature documenting the immediate economic impact of the Covid-19 pandemic in the UK (e.g. Blundell et al. 2020; Benzeval et al. 2020; Piyapromdee and Spittal 2020). Other research using data collected before the crisis has discussed channels through which the current crisis may affect workers differently depending on their gender and occupation (Alon et al. 2020; Dingel and Neiman 2020; Mongey and Weinberg 2020). Our results are consistent with Andrew et al. (2020a), who also find big differences in the labor supply of mothers and fathers over the pandemic. Finally, our paper contributes to the literature on the positive externalities arising from sick pay coverage (Pichler and Ziebarth 2020; Marie and Vall Castelló 2020; Adams-Prassl et al. 2020c). We show that even amid the pandemic, when the importance of social distancing and self-isolation was particularly salient, workers without sick pay were significantly more likely to work when sick and that workers without sick pay are less willing to return to work from furlough.

4.2 Institutional Features & Design Choices

4.2.1 Policy Motivation

Short-time work (STW) schemes subsidize labor hoarding by firms. They allow firms to reduce employees' hours rather than firing them, with the government stepping in to smooth workers' salaries. STW schemes have been a key pillar of countercyclical policy in several countries for many years. Germany, for example, has one of the oldest and most comprehensive STW programs in the world.[3] The German *Kurzarbeit* scheme allows firms to reduce their employees' hours for up to 12 months. The government replaces 60% of forgone net monthly earnings (up to a cap) for single workers to shield them from the financial impact of the fall in hours.[4] Similar schemes exist in many other European countries and in some US states.[5]

Why implement a STW policy rather than insuring workers directly through unemployment insurance schemes? STW schemes aim to preserve worker-firm matches in the face of temporary negative shocks; firm-specific human capital and hiring costs mean that it can be efficient to keep a worker-firm match intact in periods of low productivity. However, liquidity constraints and/or commitment issues limit the degree to which firms can do this in practice (Giupponi and Landais 2020). This provides a role for governments to subsidize labor hoarding and reduce inefficient layoffs. While firms can fire workers and rehire them when business conditions improve, commitments to recall workers are generally not credible. In their model, Gregory et al. (2020) emphasize the importance of furloughing to avoid job ties being cut for workers who could take years to find stable jobs. STW schemes also allow much more flexibility than so-called temporary or recall unemployment; most STW schemes allow employees to work on a part-time basis, helping to maintain essential business activities and preventing depreciation of human capital.

In an aggregate crisis, STW schemes can relieve the public administration of some of the burden of allocating funds quickly to those in need. In the US, for instance, the reports of long delays in payments and long cues in front of public offices during the Covid-19 pandemic are plentiful.[6] As STW schemes can operate directly through employers, applications can be coordinated around a smaller number of agents and the paperwork burden on workers can be minimized.

To evaluate the overall effects of STW schemes, there are several factors to consider. First, does the scheme reduce inefficient separations? Evidence from the Great Recession suggests that some STW policies can have large positive effects on employment: Giupponi and Landais (2020) and Cahuc et al. (2018) exploit variation in eligibility rules to show that the Italian and French

[3] Short-time work dates back to 1910 when it was first used in the mining industry.

[4] The usual replacement rate is 67% for employees with children. During the Covid-19 pandemic the replacement rate is increased to 70% (or 77% with children) for those working half time from the fourth month onwards and to 80% (or 87% with children) from the seventh month onwards.

[5] See Schulten and Müller (2020) for differences in the regulations across European countries. Some US states also have short-time compensation (STC) schemes. STC programs are implemented at the state level and there are differences among state programs.

[6] See, for instance, `https://www.washingtonpost.com/business/2020/07/13/unemployment-payment-delays/`.

STW schemes respectively have strong positive employment effects on liquidity constrained firms. However, the devil is in the details; schemes must likely provide timely payments and extend for the duration of the shock if liquidity constrained firms are to retain workers into a downturn. It is also important to consider whether all types of labor are covered by the scheme to prevent inefficient substitution between different workers.

Second, how large are moral hazard effects? Moral hazard can take many forms in this context. Firms might take advantage of the scheme by requiring workers to put in their usual hours with their wages subsidized by the state. In the present crisis, this is more likely to be a pressing issue in occupations where working from home is easier. Evidence of significant downturns in production as a condition for wage subsidies could help limit such behavior and is used in practice in some countries (e.g. Germany). Alternatively, firms may accept subsidies and still layoff workers. Take-up should, therefore, be made conditional on retaining workers; the precise terms in which this obligation is made varies across countries (Schulten and Müller 2020).

Third, do STW schemes prevent workers from moving to higher productivity firms? By subsidizing lower productivity matches, STW schemes could prevent workers from leaving failing firms quickly and thus hinder efficient labor market reallocation. Giupponi and Landais (2020) show that this effect is especially important for persistent shocks. In the present context, this question cannot be evaluated at this stage given that the pandemic remains active and the persistence of the downturn remains unknown.

Finally, many schemes leave room for firm discretion regarding how to allocate hours reductions across their workforce, whether wages should be topped up beyond government subsidies, and the removal of non-wage work benefits. As far as we are aware, there is no existing evidence on heterogeneity in the terms on which workers are enrolled in STW schemes. The consequence of employer discretion on these margins for labor market outcomes is an empirical question that we hope to shed light on in this paper.

4.2.2 The UK Coronavirus Job Retention Scheme

In the United Kingdom, the government announced a new STW scheme to protect jobs on March 20, 2020, the *Coronavirus Job Retention Scheme* (CJRS). The operation and expected duration of the scheme have been continuously revised over the crisis. It closed to new applications on 30

June 2020.[7] There are two particularly noteworthy features compared to other European STW schemes: tight restrictions on flexible working and uncertainty over the duration and generosity of the scheme.

The UK scheme initially placed severe restrictions on work for enrolled employees. Until 1 July 2020, workers on the scheme had to be furloughed and do *no* work for their employer for at least three weeks in each four-week period.[8] In return, the government paid 80% of employees' wages, up to a maximum of £2,500 per month. This stands in contrast to the STW schemes in Italy, France, and Germany, which allowed for flexible reductions in hours. In principle, flexible reductions in hours seem preferable as a minimum number of hours may be necessary to sustain critical business operations and prevent depreciation of individual and firm-specific human capital.

On June 12, the UK scheme was revised to permit 'flexible furloughing' from the beginning of July. From 1 July, employers have been able to bring furloughed employees back to work and claim subsidies for typical hours not worked by an employee (with employers paying for hours that are worked). However, note that this arrangement is only available for workers who were previously 'fully' furloughed. The introduction of short-time work within the scheme was previously announced to be available from 1 August but was brought forward by a month to facilitate a return to work with the easing of lockdown measures. From 1 August, employers are also required to make gradually increasing contributions towards labor costs.[9]

As this discussion highlights, firms have faced considerable uncertainty about the length, generosity, and design of the UK scheme. When announced, the UK scheme was guaranteed to last for four months, until the end of June 2020. At the time of writing, the scheme has been extended until the end of October. It remains unclear whether the scheme will operate beyond this point, and if so, under what terms. It is also worth noting the initial delay in payments. While the scheme was announced in late March, the portal to facilitate payments to firms did not open until the end of April.

[7] From 30 June onwards, employers were only able to furlough employees that they had furloughed for a full three week period at any time between 1 March 2020 and 30 June. Thus, the final date by which an employer could have furloughed an employee for the first time was 10 June.

[8] An employee could be furloughed and do no work for three weeks, and then be brought off furlough to work for the employer for a one-week period before potentially being put back on furlough. However, furloughed employees can take on a new job with a different employer, provided this is permitted by their contract of employment in general.

[9] In August, the government contribution towards the employee's pay when on furlough remains at 80% but employers are required to pay employer national insurance and pension contributions. In September, employers are also required to pay 10% of wages and the government contributes 70%. In October, the employer contribution increases to 20% with the government contribution falling to 60%.

4.3 Data

To study variation in the characteristics of workers furloughed, and heterogeneity in the terms under which they have been furloughed, we collected real time survey data on large geographically representative samples of UK workers.[10] The data were collected by a professional survey company; all participants were part of the company's online panel and participated in the survey online.[11] We collected two waves of survey data that included detailed information on furloughing. The first wave of data ($N = 4,931$) was collected on April 9-11, 2020 (approximately 2 weeks after the introduction of lockdown measures in the UK). The second wave ($N = 4,009$) was collected on May 20-21, 2020.[12] To be eligible to participate in the study, participants had to be resident in the UK, be at least 18 years old, and report having engaged in any paid work during the previous 12 months. While our surveys targeted individuals who were or had been engaged in any type of paid work, including self-employment, in the analysis we restrict the sample to respondents who reported being in paid work in February 2020, and who were (had been) employees in their main (last) job.

The samples were selected to be representative in terms of region. Appendix Table 4A.1 shows the distribution of respondents across regions in the UK and the comparison to the national distribution of individuals across the different regions, separately for each survey wave. As can be seen from this table, the distributions are very similar. We compare the characteristics of the respondents in our sample to a nationally representative sample of the economically active population in the UK. Appendix Table 4A.2 shows the demographic characteristics of our samples and of economically active workers in the Labour Force Survey (LFS) in the second quarter of 2019.

Economic Activity & Furloughing In our surveys, we asked respondents about the number of jobs they had in February 2020 and in the week before the survey date. Respondents were asked to think about jobs they had other than completing surveys and were told to count jobs from which they were furloughed as a job. Respondents who worked at least one job in February were then asked for their typical weekly hours in February. Respondents who had at least one job in the survey reference week were asked how many hours they worked last week.

[10] Appendix 4C includes the questionnaire.

[11] The survey was scripted in the online survey software Qualtrics. Participants received modest incentives for completing the survey.

[12] We deliberately chose to survey new participants in the second survey wave, i.e. there are no participants who participated in the survey more than once.

Workers who had at least one job in the week before data collection were asked detailed questions about their main job, including whether they were furloughed.[13] Note that we asked *all* employees if they had been furloughed, i.e. we did not condition this question on whether a respondent reported zero-work hours last week to allow us to analyze compliance with the terms of the CJRS. This is in contrast to some other UK labor market surveys, which have conditioned their question about furloughing on a report of zero-work hours in the survey reference week (Gardiner and Slaughter 2020).

Furloughing Terms We collected information on the terms under which workers have been furloughed. In the April survey, we asked respondents whether their employer had topped up their wage beyond the 80% paid by the government and we also collected information on whether employers were still asking respondents to work, distinguishing between those who were being formally rotated back into work and those who were being asked to work in violation of the terms of the scheme.[14]

In our May survey, we asked questions about whether the worker or their employer made the decision to go on furlough and whether a respondent wanted to return to work. Specifically, we asked about the degree to which furlough was the employer's or respondent's decision on a five-point scale ranging from "Fully [the employer's] decision" to "Fully [the respondent's] decision". Respondents who were currently furloughed in the May survey were also asked whether they would prefer to go back to their usual work hours for 80% of their usual salary.

Economic impacts Furloughing is only effective if it limits inefficient separations. To obtain a better sense of how individuals perceived their future labor market outcomes, we asked respondents how likely they thought it was that they would lose their job before August 1st, 2020, on a 0-100% chance scale. In our second survey, we also asked respondents how likely it was that they would look for a new job in the next 12 months, again on a 0-100% chance scale.

4.4 Who Was Furloughed?

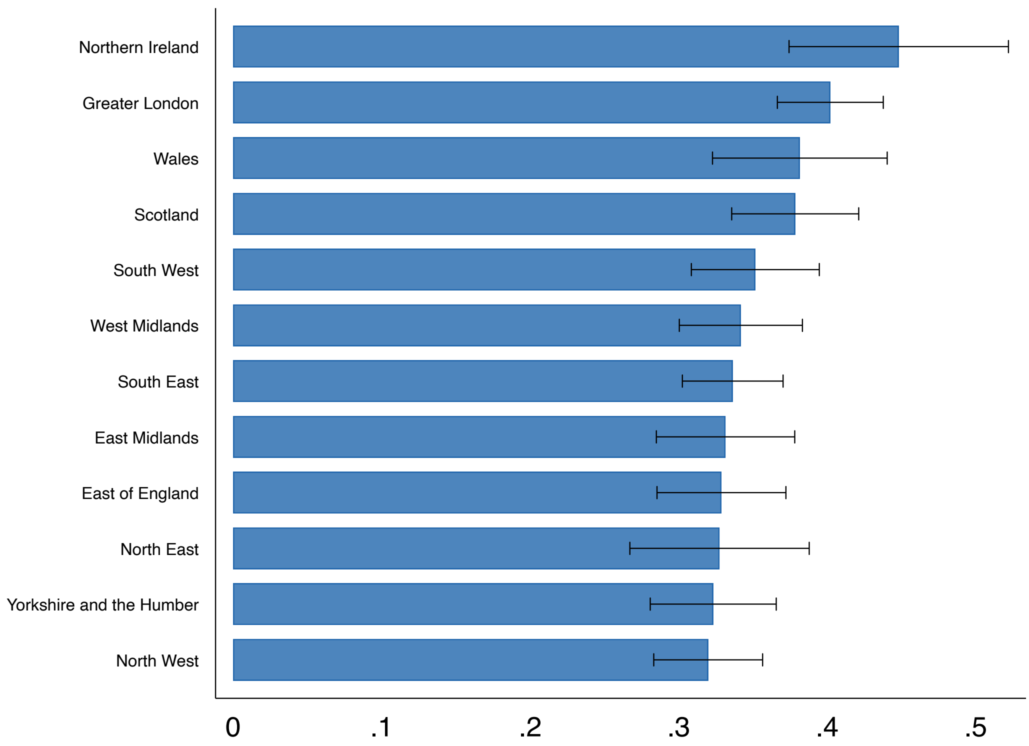
In our sample of UK employees, 35% of those in work in February report being currently furloughed from their main job. This figure is consistent with the best available UK administrative records. Official records show that 9.4 million claims were made to the furloughing scheme by late June

[13] Respondents who had no job in the week before the survey were asked analogous questions about their last job.

[14] Both our surveys took place before the announcement of flexible-furlough.

2020. Assuming that each worker is only furloughed from a single job, this corresponds to 34% of employees.[15] In Figure 4.1 we exhibit the share of furloughed workers by region. The share of workers furloughed across regions varies from 32% in the North West to 45% Northern Ireland.

Figure 4.1: Share of furloughed workers by region



Notes: The horizontal bars show the average share of employees who were furloughed on the survey date for each region. The black bars represent 95% confidence intervals. Survey responses for the April and May survey waves are pooled in this figure.

There is a lot of variation in the extent to which employers made use of the furloughing scheme across both industries and occupations. In Figure 4.2 we report the share of furloughed employees by occupation (top) and industry (bottom) when pooling our April and May survey waves.[16] For occupations, the share of employees who reported having been furloughed ranges from 61% for 'Architecture & Engineering' to 19% for 'Healthcare Support'. Across industries, 76% of those employees in February working in 'Mining and Quarrying' report having been furloughed, against a figure of 8% for 'Public Administration and Defence'.

[15]The UK Office for National Statistics estimates there were 27.7million employees in their February 2020 labor market bulletin. `https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/bulletins/employmentintheuk/february2020`

[16]Most occupations and industries saw little change in the share of furloughed workers across these survey waves - see Appendix Figure 4B.1. Meaningful easing of lockdown did not begin until 4th July in many sectors.

One might have expected the share of furloughed employees to have been greatest in 'Accommodation and Food Services' given that this industry has been particularly affected by sector-specific lockdowns. While 53% of employees working in this industry report being furloughed, which is higher than average, job loss has also been particularly high (29%). In contrast, in many utility industries (e.g. 'Water Supply, Electricity'), a large proportion of workers have been furloughed but few have lost their job.[17] Figure 4.3 shows the relationship between the share of employees that lost their jobs and the share that was furloughed across occupations (left) and industries (right). While there is a significant positive relationship between the rates of job loss and furlough, there is considerable heterogeneity in the furloughing rate amongst occupations and industries with similar levels of job loss.

Turning to differences in the probability of being furloughed by background and job characteristics, Figure 4.4 shows that workers with unstable work arrangements were significantly more likely to be put on furlough. In particular, 48% of workers with varying hours were put on furlough by May 2020, against a corresponding figure of 29% of workers with fixed-hour contracts. Workers under the age of 35 were significantly more likely to be put on furlough by May 2020 compared to workers aged 35 or above.

In Table 4.1 columns (1) to (3) we consider which workers were furloughed within the framework of a linear probability model (LPM). In column (1) we see that occupation and industry are important determinants of whether an employee is furloughed or not: together with region and time fixed effects, they explain 10% of the variation in furloughing. Job characteristics are important predictors of furloughing.[18] Throughout all specifications, workers on variable hours contracts and those who are paid by the hour are much more likely to have been furloughed, while those who can do a greater percentage of their work tasks from home have been less likely to be furloughed. Controlling for job characteristics, as well as a broad set of fixed-effects, we find that women were 3 percentage points (p.p.) more likely to have been furloughed compared to men. Moreover, workers on varying hour contracts, both if the firm or the worker decides on the schedule, are also significantly more likely to have been furloughed. The probability of being furloughed is u-shaped in terms of age with young workers below the age of 30 being the most likely to have been furloughed.

[17] Appendix Figure 4B.2 shows the share of employees that have lost their job, been furloughed, and remained employed and not been furloughed by occupation and industry.

[18] We note that some differences between regions remain significant, even when controlling for job and individual characteristics.

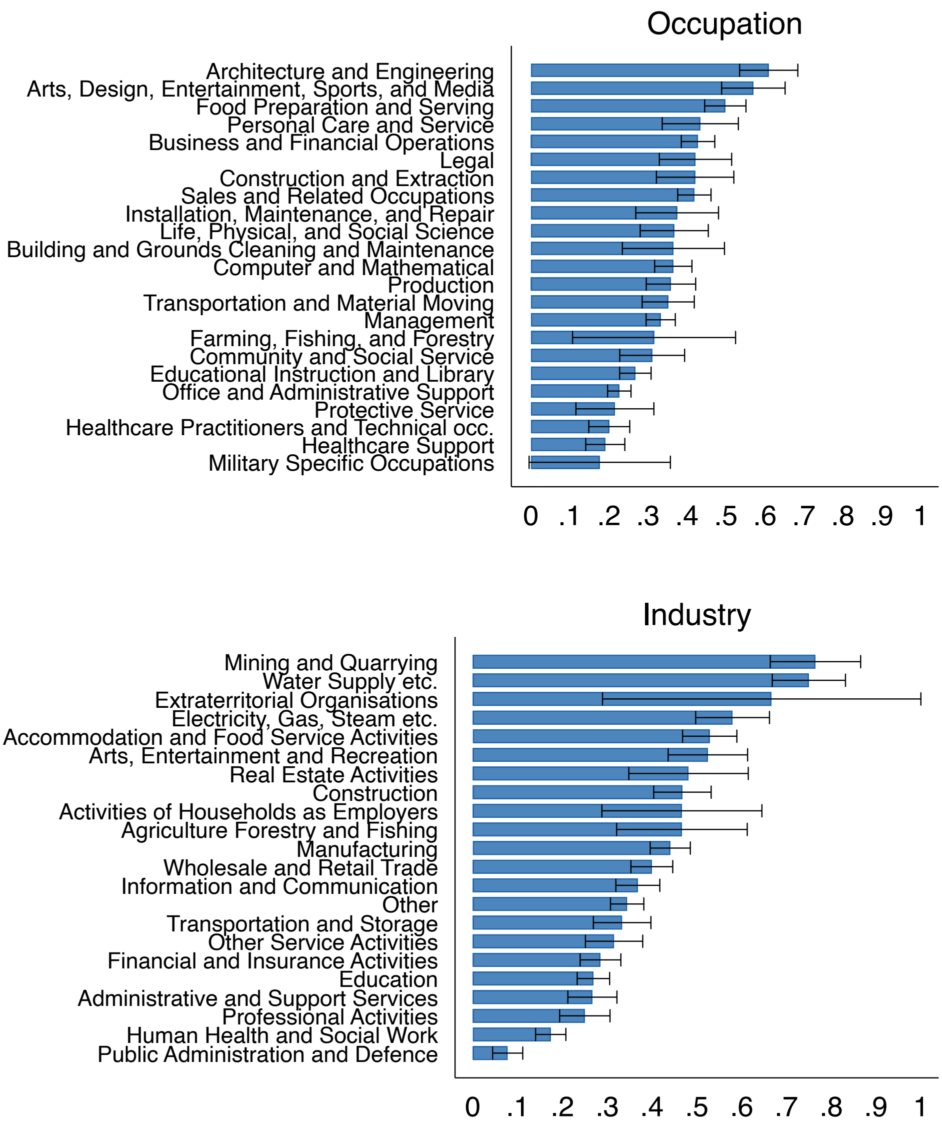
These models ignore the fact that workers can be in three states: furloughed, employed and not furloughed, and not in work. Columns (4) and (5) analyze worker outcomes in a multinomial framework, where "employed & not-furloughed" is the omitted category. Similar patterns arise. Notably, women are significantly more likely to have been furloughed or lost their job. Younger workers and those employed on variable hour contracts are less likely to be in non-furloughed employment. While workers on temporary contracts have been less likely to be furloughed, they are more likely to have been laid off. Those on higher incomes are more likely to have been furloughed relative to remaining in employment or losing their job.

Table 4.1: Furloughing probability - Job and individual characteristics

	LPM - Furloughed			Multinomial Logit	
	(1)	(2)	(3)	Furloughed	Lost Job
Age:					
30-39		-0.1312***	-0.0806***	-0.4575***	-0.3773***
		(0.0172)	(0.0171)	(0.0845)	(0.1324)
40-49		-0.1984***	-0.1164***	-0.6491***	-0.4955***
		(0.0183)	(0.0187)	(0.0961)	(0.1464)
50-59		-0.2695***	-0.1642***	-0.9872***	-0.6940***
		(0.0200)	(0.0206)	(0.1187)	(0.1703)
60+		-0.1982***	-0.1097***	-0.6712***	-0.7919***
		(0.0305)	(0.0306)	(0.1620)	(0.2564)
University degree		-0.0382***	-0.0038	-0.0107	-0.0100
		(0.0128)	(0.0138)	(0.0738)	(0.1129)
Female		-0.0239*	0.0279**	0.2027***	0.3127***
		(0.0128)	(0.0136)	(0.0721)	(0.1132)
Income 2019 (£10,000s)			0.0063**	0.0298**	-0.0034
			(0.0029)	(0.0145)	(0.0263)
Temporary Contract			-0.1262***	-0.3080***	0.9074***
			(0.0223)	(0.1154)	(0.1389)
Varied Hours (Worker)			0.0758***	0.4029***	0.2638*
			(0.0177)	(0.0890)	(0.1415)
Varied Hours (Firm)			0.0682***	0.3822***	0.1488
			(0.0209)	(0.1051)	(0.1505)
Non-Salaried Contract			0.1181***	0.5582***	0.1051
			(0.0161)	(0.0793)	(0.1211)
Work from Home			-0.0554***	-0.6065***	-1.8480***
			(0.0201)	(0.1116)	(0.1851)
No Paid Sick Leave			-0.0439***	0.0295	0.8219***
			(0.0167)	(0.0879)	(0.1136)
Constant	0.4984***	0.5848***	0.5317***	0.3591	-1.6383**
	(0.0854)	(0.0275)	(0.0906)	(0.3965)	(0.6781)
Observations	5522	5540	5476	5476	
R^2	0.1008	0.0465	0.1350		
Region F.E.	yes	yes	yes	yes	
Wave F.E.	yes	yes	yes	yes	
Occupation F.E.	yes	no	yes	yes	
Industry F.E.	yes	no	yes	yes	

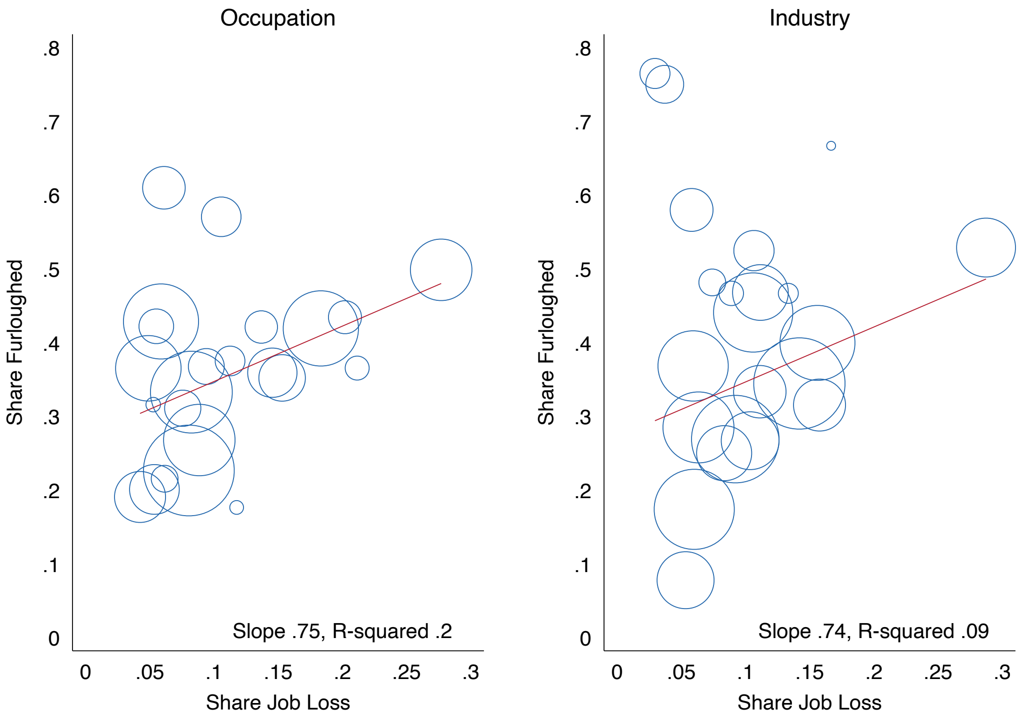
Notes: Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Columns (1)-(3) report linear probability models where the dependent variable is a dummy variable that takes value 1 if the respondent reports that they are currently furloughed from their main job and zero otherwise. Columns (4)-(5) report the coefficients of a multinomial logit model where the omitted category is "Employee - Not Furloughed".

Figure 4.2: Share of furloughed workers by occupation and industry



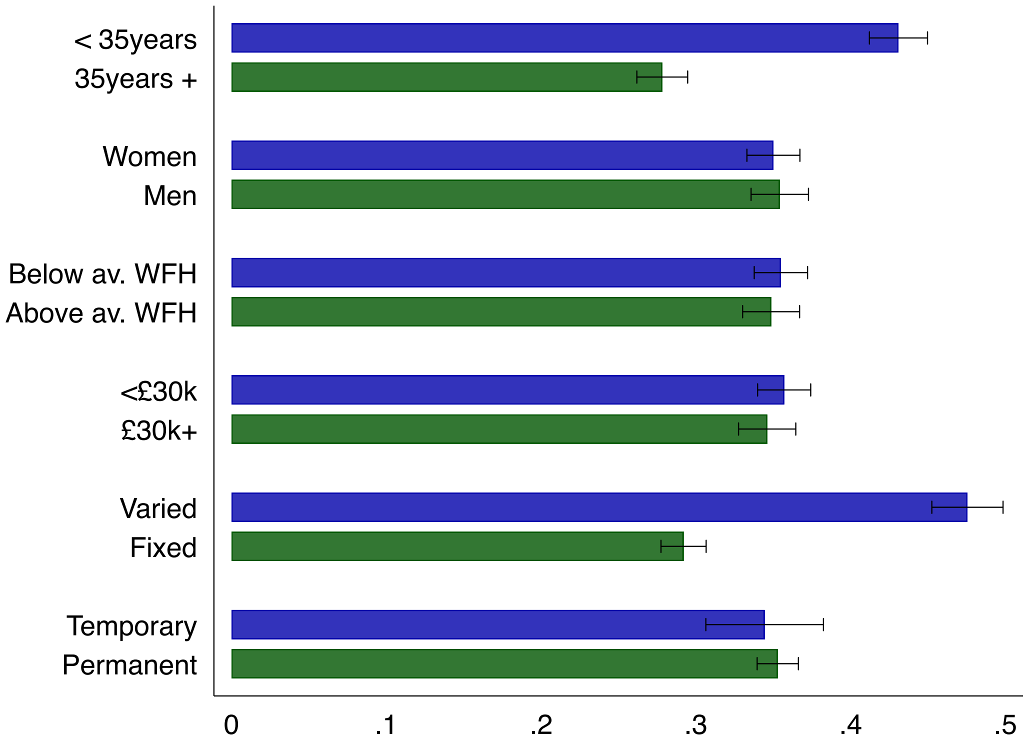
Notes: The horizontal bars show the average share of employees who were furloughed on the survey date for each occupation (top) and industry (bottom). The black bars represent 95% confidence intervals. Survey responses for the April and May survey waves are pooled in this figure.

Figure 4.3: Share of workers furloughed and share that have lost their job across occupations and industries



Notes: Each circle represents either an occupation or industry, with the size proportional to the number of survey respondents who report that either their current or last job was in that occupation or industry. The line gives the line of best fit. Survey responses for the April and May survey waves are pooled in this figure.

Figure 4.4: Share of furloughed workers by individual and job characteristics



Notes: The graph shows the share of workers that are currently furloughed by different individual and job characteristics. Black bars represent 95% confidence intervals. Survey responses for the April and May survey waves are pooled in this figure. 'Below av. WFH' are employees who can do less than average tasks from home, while 'Above av. WFH' are employees who can do more than average tasks from home. '<£30k' refers to respondents with less a yearly gross individual income below £30,000 in 2019, while '£30k+' are those earning more. 'Varied' refers to respondents with varying hour contracts, while 'fixed' refers to those with fixed hour contracts.

4.5 Furloughing Terms

Heterogeneity in the terms on which workers are furloughed arises along several dimensions: did the worker or employer initiate the decision to be furloughed? Are worker incomes "topped-up" by employers beyond the 80% paid for by the government? Do employees continue to work while furloughed even though it is against the terms of the scheme?[19]

Consider first the decision to be put on furlough. We asked respondents to identify whether the decision to be furloughed was "fully [their] employer's decision" to "fully [their] decision" on a five-point scale.[20] Figure 4.5 shows whether an employee had at least an "equal say" in the decision to go on furlough by gender and by whether the respondent has children. We construct a binary variable that takes value 1 if the respondent reports that they had an equal say in the furloughing decision, or the furloughing was initiated mostly or fully by them. Women are more likely to have initiated furloughing and this is mainly driven by women with children at home who are much more likely to have initiated furloughing than men with children. These results highlight an important gender gap in the impact of the pandemic and are consistent with findings that mothers are spending significantly more time on childcare activities than men during the pandemic at the expense of paid work time (Adams-Prassl et al. 2020b; Andrew et al. 2020a; Biroli et al. 2020a; Farré et al. 2020; Sevilla and Smith 2020).

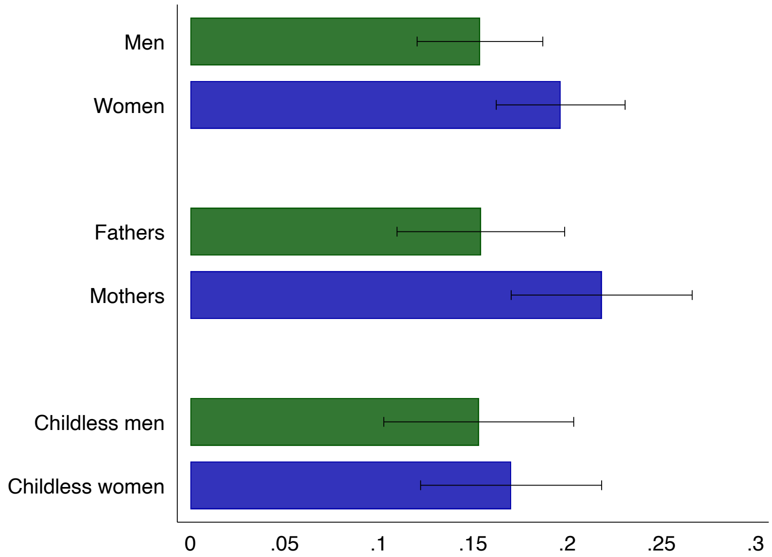
In Table 4.2 we look at which workers are more likely to have initiated the furloughing in a regression framework. In column (1) we find that women are 4 p.p. more likely to have asked to be put on furlough, compared to men. The coefficient on the female dummy remains stable when controlling for occupation and industry fixed effects, as well as a number of job characteristics (column (2)). We then examine whether childcare responsibilities might affect a worker's decision to initiate furloughing. When restricting the sample to parents (columns (3) and (4)), we find that women are almost 10 p.p. more likely to initiate the furloughing, whereas we do not find a gender gap in who initiates furloughing in the group of respondents without children (columns (5) and (6)).

We also find that those on variable hour contracts are more likely to have initiated the decision to be furloughed. This is especially so for those where the employer, rather than the worker, has the discretion to determine working hours: those with employer-determined hours are 14 p.p. more likely to have initiated furlough than those with a fixed hours schedule. This does not seem

[19] Both our survey waves took place before the introduction of flexible furloughing.

[20] See Section 4.3.

Figure 4.5: Share of furloughed employees who asked to be furloughed



Notes: The graph shows the share of currently furloughed employees who initiated furloughing. We construct a binary variable that takes value 1 if the respondent reports that they had an equal say in the furloughing decision, or the furloughing was initiated mostly or fully by them. Mothers or fathers are defined as respondents who have at least one child living in the household. The sample is restricted to respondents to the May survey wave.

related to childcare responsibilities but could be related to more sensitivity to uncertainty during the pandemic.[21] Amongst those without children, workers who set their own working hours are more likely to have initiated the decision.

In principle, the furloughing scheme could result in less pay inequality as it compresses the wage distribution from above by capping the maximum monthly amount at £2,500. However, employers have the choice to top-up salaries of furloughed workers above the 80% state contribution or the maximum limit of £2,500, whichever is lowest. In our April survey wave, we ask furloughed respondents whether their employer topped up their salary beyond the level provided by the government. We find that 70% of furloughed workers receive a discretionary salary top-up by their employer. However, workers on higher incomes are more likely to be topped-up, reducing the inequality-reducing effect of the scheme. Figure 4.6 also shows that (unconditionally) men are more likely to receive discretionary payments.

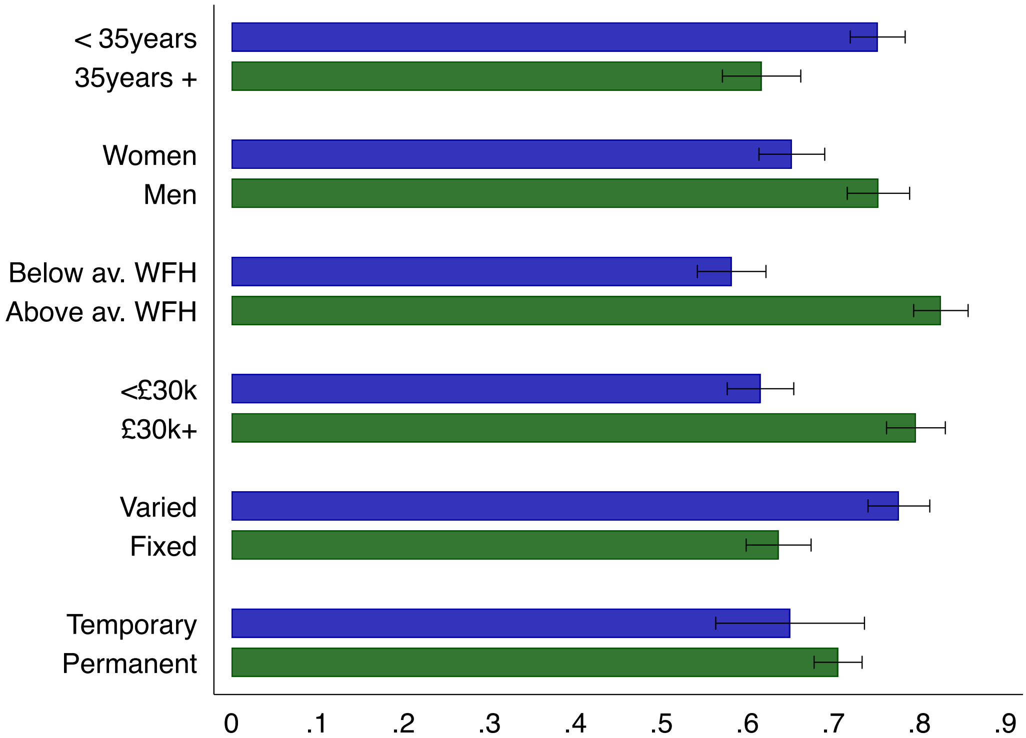
[21] Interactions between gender and hours arrangements are insignificant.

Table 4.2: Who initiated furloughing?

	All		Parents		No children	
	(1)	(2)	(3)	(4)	(5)	(6)
Age:						
30-39	-0.0467	-0.0291	-0.0797**	-0.0501	0.0151	0.0209
	(0.0316)	(0.0315)	(0.0403)	(0.0431)	(0.0571)	(0.0539)
40-49	-0.0277	0.0246	-0.0333	0.0115	-0.0217	0.0401
	(0.0371)	(0.0372)	(0.0502)	(0.0510)	(0.0533)	(0.0550)
50-59	-0.0606	0.0155	-0.1148*	-0.0417	-0.0140	0.0251
	(0.0409)	(0.0422)	(0.0647)	(0.0751)	(0.0577)	(0.0610)
60+	0.0253	0.1064*	0.3032	0.4504**	0.0290	0.0680
	(0.0572)	(0.0594)	(0.1988)	(0.1988)	(0.0653)	(0.0692)
University degree	0.0293	0.0338	0.0549	0.0387	0.0047	0.0192
	(0.0257)	(0.0272)	(0.0338)	(0.0392)	(0.0405)	(0.0425)
Female	0.0432*	0.0537*	0.0711**	0.1048***	0.0240	-0.0176
	(0.0254)	(0.0278)	(0.0351)	(0.0377)	(0.0382)	(0.0445)
Income 2019 (£10,000s)		0.0068		0.0066		0.0142
		(0.0058)		(0.0077)		(0.0110)
Temporary Contract		0.0273		0.0662		0.0224
		(0.0445)		(0.0614)		(0.0676)
Varied Hours (Worker)		0.0817**		0.0545		0.1924***
		(0.0342)		(0.0425)		(0.0666)
Varied Hours (Firm)		0.1394***		0.1437***		0.1277**
		(0.0368)		(0.0512)		(0.0566)
Non-Salaried Contract		0.0509*		0.0132		0.0719
		(0.0283)		(0.0398)		(0.0456)
Work from Home		-0.0174		0.0029		-0.0676
		(0.0403)		(0.0632)		(0.0566)
No Paid Sick Leave		-0.0624**		0.0016		-0.1213***
		(0.0313)		(0.0549)		(0.0403)
Constant	0.0984**	0.2809	0.1051	0.2381	0.0894	0.9117***
	(0.0501)	(0.2019)	(0.0691)	(0.2055)	(0.0746)	(0.1140)
Observations	968	963	537	533	431	430
R^2	0.0203	0.1248	0.0560	0.1636	0.0244	0.2122
Region F.E.	yes	yes	yes	yes	yes	yes
Occupation F.E.	no	yes	no	yes	no	yes
Industry F.E.	no	yes	no	yes	no	yes

Notes: OLS regressions. Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. The sample is restricted to furloughed respondents to the May survey wave. The dependent variable is a dummy variable that takes value 1 if the respondent had an equal say in the decision to initiate the furloughing or if the furloughing was mostly the respondents' decision. The dependent variable takes value 0 if the furloughing was initiated fully or mostly by the employer.

Figure 4.6: Share of furloughed workers receiving top-up by individual and job characteristics



Notes: The graph shows the share of workers that are currently furloughed by different individual and job characteristics who report having their salary topped-up beyond the 80% subsidy provided by the government. Black bars represent 95% confidence intervals. The sample is restricted to respondents to the April survey wave. 'Below av. WFH' are employees who can do less than average tasks from home, while 'Above av. WFH' are employees who can do more than average tasks from home. '<£30k' refers to respondents with less a yearly gross individual income below £30,000 in 2019, while '£30k+' are those earning more. 'Varied' refers to respondents with varying hour contracts, while 'fixed' refers to those with fixed hour contracts.

In the first two columns of Table 4.3, we analyze heterogeneity in salary top-ups. In column (1) we see that the probability of receiving a top-up is decreasing in age and 10 p.p. lower for women. In column (2) we examine heterogeneity in the probability of receiving a top-up across the income distribution and by job characteristics. Workers with higher (individual) incomes in 2019 are more likely to receive a top-up when furloughed. Therefore, the equalizing effect of the furloughing scheme is partially mitigated by employers' decisions to top-up their employees' salaries. While the coefficients on gender is insignificant with the full set of controls, we note that it remains positive and significant if only income is controlled for; it is the inclusion of the full suite of job-characteristics that reduces the magnitude of the effects. Workers with self-determined hours are 5 p.p. more likely to have received a top-up, perhaps reflecting a reward for greater autonomy (discussed in more detail below).

At the time of our surveys, working was forbidden while currently furloughed. However, 19% of employees in our sample report being explicitly asked to work by their employer despite being currently furloughed. In Figure 4B.3 we show how this share breaks down by occupation and industry.[22] There is large variation in the share of furloughed workers who are asked to provide work across occupations. While 44% of furloughed employees working in 'Computer and Mathematical' occupations have been asked to work while on furlough, the corresponding share for 'Transportation and Material Moving' is 3%. Similarly, 35% of workers in the 'Information and Communication Industry' report having been asked to work while on furlough, against 8% for 'Agriculture, Forestry and Fishing'.

Many more furloughed employees report working even if not explicitly compelled to do so by their employer. Two thirds of furloughed workers (who only had one job) report having worked a positive amount of hours over the last week. The regression models reported in columns (3)-(6) of Table 4.3 reveal that women, older workers, and those without paid sick leave are less likely to have continued to work on furlough. Workers on higher incomes but also those on variable hours contracts have been more likely to continue working. Those with self-determined hours flexibility (as opposed to those whose schedule is determined by their employer) that have been more likely to continue working whilst on furlough, suggesting the importance of worker autonomy in the decision to work whilst furloughed (Mas and Pallais 2020).

Workers who can do a large percentage of their jobs from home are especially likely to have continued working whilst furloughed (columns (4) and (6) of Table 4.3). Figure 4.7 shows relative

[22] We exclude employees who report they are being formally rotated into work.

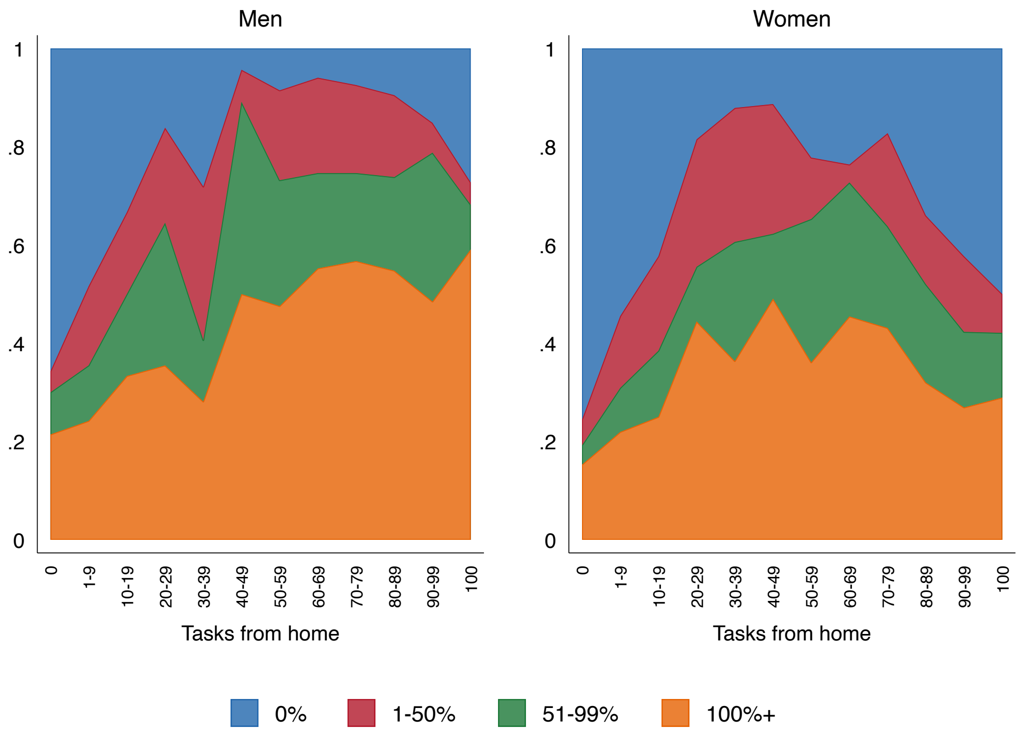
Table 4.3: Terms on which furloughed

	Salary top-up		Positive work hours		% Usual Hours	
	(1)	(2)	(3)	(4)	(5)	(6)
Age:						
30-39	-0.0227	-0.0042	-0.0802***	-0.0648**	-0.0894***	-0.0676**
	(0.0320)	(0.0308)	(0.0277)	(0.0252)	(0.0332)	(0.0307)
40-49	-0.1353***	-0.0396	-0.2355***	-0.1578***	-0.2789***	-0.1854***
	(0.0405)	(0.0399)	(0.0331)	(0.0313)	(0.0352)	(0.0336)
50-59	-0.1980***	-0.0009	-0.3418***	-0.1841***	-0.4054***	-0.2248***
	(0.0617)	(0.0612)	(0.0441)	(0.0440)	(0.0415)	(0.0427)
60+	-0.3038***	-0.1878*	-0.3981***	-0.2469***	-0.3775***	-0.2114***
	(0.1086)	(0.1078)	(0.0533)	(0.0593)	(0.0538)	(0.0591)
University degree	0.0158	-0.0765***	0.0696***	-0.0160	-0.0012	-0.0642**
	(0.0280)	(0.0287)	(0.0237)	(0.0233)	(0.0262)	(0.0254)
Female	-0.0968***	-0.0104	-0.1949***	-0.0975***	-0.1944***	-0.0952***
	(0.0274)	(0.0289)	(0.0225)	(0.0225)	(0.0253)	(0.0253)
Income 2019 (£10,000s)		0.0138***		0.0154***		0.0148***
		(0.0049)		(0.0040)		(0.0053)
Temporary Contract		-0.0243		-0.0177		-0.0307
		(0.0444)		(0.0357)		(0.0396)
Varied Hours (Worker)		0.0536*		0.1020***		0.1000***
		(0.0325)		(0.0265)		(0.0317)
Varied Hours (Firm)		-0.0263		0.0472		0.0507
		(0.0379)		(0.0302)		(0.0353)
Non-Salaried Contract		0.0599**		0.0590**		0.1206***
		(0.0294)		(0.0244)		(0.0287)
Work from Home		0.2878***		0.3272***		0.3690***
		(0.0483)		(0.0402)		(0.0453)
No Paid Sick Leave		-0.3376***		-0.2128***		-0.1928***
		(0.0431)		(0.0306)		(0.0301)
Constant	0.8230***	0.6840***	0.8369***	0.7402***	-0.1710***	-0.6226***
	(0.0547)	(0.1053)	(0.0474)	(0.0860)	(0.0535)	(0.1045)
Observations	1142	1099	1481	1469	1481	1469
R^2	0.0541	0.2514	0.1835	0.3774	0.1663	0.3589
Region F.E.	yes	yes	yes	yes	yes	yes
Wave F.E.	-	-	yes	yes	yes	yes
Occupation F.E.	no	yes	no	yes	no	yes
Industry F.E.	no	yes	no	yes	no	yes

Notes: OLS regressions. Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. In columns (1)-(2) the sample is restricted to respondents to the April survey wave that are currently furloughed in their main job. The dependent variable is a dummy variable that takes value 1 if the respondent reports that their employer has topped up their salary beyond the 80% funded by the government. Columns (3)-(6) pool responses from the April and May survey waves and restrict the sample to those who are currently furloughed in their main job and report having only one job. The dependent variable in columns (3)-(4) is a dummy variable that takes value 1 if the respondent reports positive work hours last week and is zero otherwise. The dependent variable in columns (5)-(6) is the proportion of weekly hours worked last week compared to typical hours in February.

hours worked by the percentage of tasks one can do from home separately for men (left) and women (right). The relationship is striking. Those who can do the majority of their tasks from home are especially likely to have continued working the same or more hours than usual (orange) while on furlough. The gradient is somewhat less striking for women, perhaps because of caring responsibilities. In Appendix Figure 4B.4 we plot the mean and median hours worked amongst furloughed workers by the percentage of tasks that can be done from home, which confirms the patterns.

Figure 4.7: Percentage of usual hours worked while furloughed by the percentage of tasks that could be done from home



Notes: The graph shows the percentage of typical work hours worked last week by respondents who are currently furloughed by the percentage of tasks one can do from home. Survey responses for the April and May survey waves are pooled in this figure.

On average, including zeros, furloughed workers worked 15 hours (10 hours median). While still substantial, this is a decline in work hours of 44% on average compared to a typical week in February. Although some of these workers might have been furloughed very close to our survey date and therefore might have not been furloughed in the previous week when they report working a positive amount of hours, it is unlikely that this scenario applies to a large fraction of respondents. In Table 4.3 we show how the number of hours worked, despite being furloughed, relates to individual and job characteristics. When controlling for job and individual characteristics, as well as region, industry and occupation fixed effects, we find that women, older workers, those on lower incomes and those without paid sick leave are working fewer hours while currently furloughed.

We note that these patterns cannot be explained by formal rotation of employees on and off of furlough: the CJRS originally allowed workers to work one week in every four week period. In our April survey wave, we explicitly asked workers whether their employer was formally rotating them back into work. When we restrict our sample to furloughed employees with a single job who report that their employers is not formally rotating them back into work, we still find that over 60% of furloughed employees report doing some work with a 42% reduction in weekly hours on average. Appendix Table 4B.1 replicates columns (4) and (6) of Table 4.3, restricting the sample to furloughed employees who are not being formally rotated into work.

4.6 Returning to Work & Expectations for the Future

At the time of writing, consumers are being encouraged to leave their homes to spend on the high street and workers are being actively encouraged to return to work.[23] In our May survey wave, we asked furloughed workers whether they would prefer going back to work for 80% of their salary instead of staying on furlough. On average, 61% of respondents said they would prefer to return to work from furlough even at 80% of pay. However, there are large differences in workers' preferences across occupations and industries (see Figure 4.8). Workers in service-sector occupations, for example 'Food Preparation and Serving' or 'Sales and Related' occupations, are significantly less likely to be willing to return to work compared to workers in 'Computer and Mathematical' or 'Architecture and Engineering' occupations.

In Table 4.4 we analyze the determinants of workers' willingness to return back to work. Column (1) shows that women are almost 13 p.p. less likely to report being willing to go back to work for a 20% salary cut, and willingness to return to work decreases with age. In column (2) we analyze heterogeneities in workers' willingness to return to work for a pay cut along the income distribution and for individuals with different contractual arrangements. Workers who can do a larger share of their tasks from home are 17 p.p. more likely to be willing to go back to work instead of being on furlough. Importantly, individuals employed under variable hour work arrangements are significantly more likely to be willing to take a pay cut and return to work, especially for workers who have control of the number of hours they work. This suggests that furloughed workers might value other intangible aspects of their work beyond the monetary compensation.

Employees who do not have access to paid sick leave beyond the statutory minimum are 13 p.p. less likely to be willing to return to work for 80% of their salary, even when a rich set of job characteristics are controlled for. This highlights an important trade-off between health and economic risks; workers without an adequate safety net appear to be more cautious about exposing themselves to health risks at work. Finally, in column (3) we include whether an employee initiated the decision to be furloughed, but we do not find any significant effect.

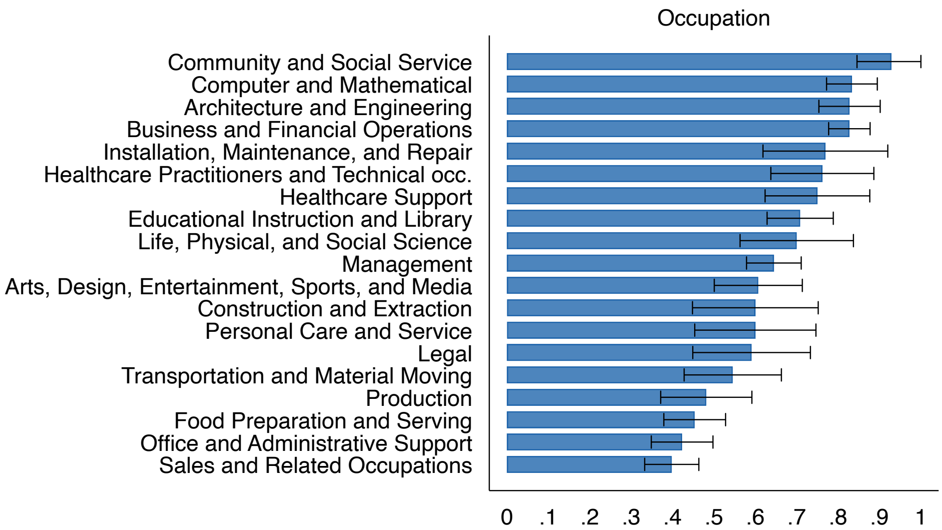
[23] See, for example, the introduction of the "Eat Out to Help Out" scheme on 8th July 2020: https://www.gov.uk/guidance/get-a-discount-with-the-eat-out-to-help-out-scheme.

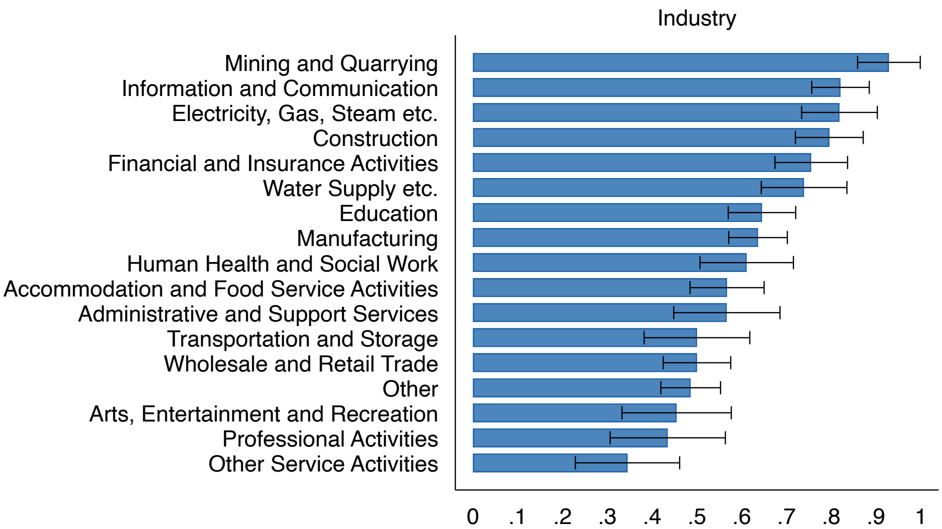
Table 4.4: Prefer to return to work for 80% of pay

	(1)	(2)	(3)
Age:			
30-39	-0.0300	-0.0423	-0.0419
	(0.0412)	(0.0398)	(0.0397)
40-49	-0.1293**	-0.0614	-0.0617
	(0.0506)	(0.0512)	(0.0512)
50-59	-0.1316**	-0.0031	-0.0036
	(0.0609)	(0.0620)	(0.0621)
60+	-0.1845**	-0.0545	-0.0555
	(0.0732)	(0.0798)	(0.0798)
University degree	0.0535	-0.0024	-0.0027
	(0.0347)	(0.0361)	(0.0361)
Female	-0.1302***	-0.0442	-0.0446
	(0.0342)	(0.0349)	(0.0349)
Income 2019 (£10,000s)		0.0163**	0.0163**
		(0.0068)	(0.0068)
Temporary Contract		-0.0008	-0.0006
		(0.0600)	(0.0600)
Varied Hours (Worker)		0.1807***	0.1797***
		(0.0404)	(0.0406)
Varied Hours (Firm)		0.1142**	0.1130**
		(0.0487)	(0.0490)
Non-Salaried Contract		0.0983**	0.0982**
		(0.0391)	(0.0392)
Work from Home		0.1709***	0.1710***
		(0.0621)	(0.0621)
No Paid Sick Leave		-0.1327***	-0.1320***
		(0.0438)	(0.0439)
Initiated Furlough			0.0097
			(0.0409)
Constant	0.6823***	0.4319*	0.4294*
	(0.0732)	(0.2218)	(0.2220)
Observations	806	801	801
R^2	0.0744	0.2690	0.2690
Region F.E.	yes	yes	yes
Occupation F.E.	no	yes	yes
Industry F.E.	no	yes	yes

Notes: OLS regressions. Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. The sample is restricted to currently furloughed respondents in the May survey wave. The dependent variable is a dummy variable that takes value 1 if the respondent would prefer going back to work for 80% of their salary instead of staying on furlough, and is zero otherwise.

Figure 4.8: Would accept pay cut to return to work by occupation and industry





Notes: The graph shows the share of currently furloughed workers who would prefer going back to work for 80% of their salary instead of staying on furlough, by occupation and industry. Black bars represent 95% confidence intervals. The sample is restricted to furloughed respondents of the May survey wave.

Despite the government's effort to cushion the negative impact of the coronavirus crisis on the labor market, many workers fear losing their job before August (Adams-Prassl et al., 2020b), and workers who have been put on furlough may feel perilously close to being laid off. In Table 4.5, we look at workers' expectations about future labor market outcomes. We restrict the sample to individuals who are currently in work and regress workers' self-reported probability of losing their job before August on individual and job characteristics, and an indicator for whether they are currently on furlough. Column (1) shows that the expected probability of losing one's job is decreasing in age, and higher for men and workers with a university degree. Column (2) echoes our findings on returning to work and shows that workers with less secure job contracts are more pessimistic about their future labor market outcomes. Notably, workers who can do a large share of their tasks from home find it more likely that they will lose their job before August. In column (3) we examine heterogeneities in the perceived probability of job loss by whether or not workers are currently furloughed. Furloughed workers are much more likely to fear losing their jobs: they, on average, report a 15 percentage points higher likelihood of losing their job before August, controlling for a broad range of individual and job characteristics. Among furloughed workers, those who can do a larger share of their tasks from home are more pessimistic about future employment (see column (4)). For these workers, social-distancing restrictions on labor supply are unlikely to be the only reason for a low-productivity match and thus firm or demand factors could be stronger drivers of subjective expectations of job loss.

In Table 4.6 we use data from our May survey wave to examine differences in workers' subjective probability of looking for a new job in the next year. Looking at individual and job characteristics, we find that old workers and workers without a university degree are less likely to look for a new job, whereas workers on temporary contracts report significantly higher likelihoods of job search. Column (3) further shows that furloughed workers are around 10 percentage points more likely to be currently looking for a job, even when controlling for individual and job characteristics. Interestingly, in all specifications, workers who do not have access to sick pay beyond the statutory minimum report between 4 and 9 p.p. higher likelihoods of looking for a new job. In column (4) we additionally control for workers' self-reported probability of job loss before August. As expected, fears of job loss strongly correlate with search behavior: workers who are more pessimistic about their abilities to retain their job in the short-term are significantly more likely to report they will be looking for a job in the next year. Moreover, once we control for the subjective probability of job loss, we find that the coefficient on the furlough dummy becomes

Table 4.5: Perceived job loss probability

	In Work			Furloughed	Not Furloughed
	(1)	(2)	(3)	(4)	(5)
Age:					
30-39	-0.0316***	-0.0077	0.0073	0.0445***	-0.0229
	(0.0111)	(0.0106)	(0.0103)	(0.0151)	(0.0142)
40-49	-0.1229***	-0.0659***	-0.0448***	-0.0097	-0.0663***
	(0.0117)	(0.0118)	(0.0115)	(0.0195)	(0.0147)
50-59	-0.2033***	-0.1206***	-0.0909***	-0.0409	-0.1077***
	(0.0119)	(0.0126)	(0.0123)	(0.0252)	(0.0150)
60+	-0.2107***	-0.1343***	-0.1128***	-0.0581*	-0.1341***
	(0.0177)	(0.0183)	(0.0175)	(0.0350)	(0.0200)
University degree	0.0172**	0.0089	0.0094	0.0199	0.0091
	(0.0082)	(0.0086)	(0.0083)	(0.0138)	(0.0103)
Female	-0.0581***	-0.0095	-0.0156*	-0.0370***	-0.0032
	(0.0082)	(0.0086)	(0.0082)	(0.0138)	(0.0101)
Income 2019 (£10,000s)		0.0080***	0.0072***	0.0047*	0.0045*
		(0.0019)	(0.0018)	(0.0025)	(0.0025)
Temporary Contract		0.0721***	0.0818***	0.0308	0.1154***
		(0.0147)	(0.0147)	(0.0192)	(0.0216)
Varied Hours (Worker)		0.0493***	0.0359***	0.0165	0.0421***
		(0.0109)	(0.0106)	(0.0160)	(0.0140)
Varied Hours (Firm)		0.0483***	0.0360***	0.0242	0.0484***
		(0.0130)	(0.0126)	(0.0181)	(0.0178)
Non-Salaried Contract		0.0531***	0.0348***	0.0419***	0.0209*
		(0.0098)	(0.0094)	(0.0142)	(0.0124)
Work from Home		0.1395***	0.1575***	0.3018***	0.0815***
		(0.0133)	(0.0127)	(0.0254)	(0.0145)
No Paid Sick Leave		-0.0040	-0.0039	-0.0201	0.0042
		(0.0109)	(0.0106)	(0.0186)	(0.0128)
Currently Furloughed			0.1554***		
			(0.0087)		
Constant	0.3782***	0.2378***	0.1493***	0.3065***	0.1322**
	(0.0172)	(0.0491)	(0.0451)	(0.0645)	(0.0561)
Observations	4908	4877	4877	1892	2985
R^2	0.0920	0.2178	0.2723	0.2563	0.1814
Region F.E.	yes	yes	yes	yes	yes
Wave F.E.	yes	yes	yes	yes	yes
Occupation F.E.	no	yes	yes	yes	yes
Industry F.E.	no	yes	yes	yes	yes

Notes: OLS regressions. Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. The sample in columns (1)-(3) is restricted to those in work in the April and May survey waves. The sample in column (4) is restricted to those currently on furlough and in column (5) is restricted to employees not on furlough. The dependent variable is the respondent's subjective probability of losing their job before August 1st on a 0-1 scale.

three times smaller, but that it is still significant and around 3 percentage points. Finally, in column (5) we restrict the sample to workers who reported being furloughed at the time of data collection and find that the associations between age, education, and on-the-job search survive within the sample of furloughed workers.

Table 4.6: On the job search

	In Work				Furloughed	Not Furloughed
	(1)	(2)	(3)	(4)	(5)	(6)
Age:						
30-39	-0.0334*	-0.0104	-0.0058	-0.0079	-0.0340	0.0025
	(0.0180)	(0.0182)	(0.0180)	(0.0172)	(0.0254)	(0.0238)
40-49	-0.0743***	-0.0330	-0.0243	-0.0038	0.0009	0.0023
	(0.0205)	(0.0208)	(0.0206)	(0.0195)	(0.0320)	(0.0256)
50-59	-0.1893***	-0.1276***	-0.1145***	-0.0821***	-0.1309***	-0.0675**
	(0.0217)	(0.0227)	(0.0227)	(0.0210)	(0.0373)	(0.0265)
60+	-0.3143***	-0.2536***	-0.2465***	-0.2069***	-0.2133***	-0.2019***
	(0.0265)	(0.0272)	(0.0268)	(0.0240)	(0.0430)	(0.0309)
University degree	0.0531***	0.0631***	0.0623***	0.0607***	0.0418*	0.0683***
	(0.0140)	(0.0147)	(0.0145)	(0.0137)	(0.0220)	(0.0180)
Female	-0.0146	-0.0099	-0.0139	-0.0002	0.0008	-0.0038
	(0.0136)	(0.0143)	(0.0142)	(0.0134)	(0.0221)	(0.0174)
Income 2019 (£10,000s)		-0.0033	-0.0034	-0.0064**	-0.0058	-0.0078**
		(0.0030)	(0.0030)	(0.0025)	(0.0036)	(0.0035)
Temporary Contract		0.0735***	0.0774***	0.0479**	0.0123	0.0682**
		(0.0240)	(0.0240)	(0.0222)	(0.0331)	(0.0314)
Varied Hours (Worker)		0.0400**	0.0317*	0.0118	0.0490*	-0.0139
		(0.0183)	(0.0181)	(0.0163)	(0.0261)	(0.0219)
Varied Hours (Firm)		0.0281	0.0221	0.0032	0.0228	0.0049
		(0.0217)	(0.0216)	(0.0203)	(0.0319)	(0.0286)
Non-Salaried Contract		0.0371**	0.0269	0.0046	-0.0109	0.0128
		(0.0166)	(0.0164)	(0.0152)	(0.0245)	(0.0206)
Work from Home		0.1465***	0.1623***	0.0918***	0.0588	0.1071***
		(0.0217)	(0.0214)	(0.0206)	(0.0395)	(0.0250)
No Paid Sick Leave		0.0706***	0.0671***	0.0615***	0.0840***	0.0423*
		(0.0186)	(0.0184)	(0.0172)	(0.0286)	(0.0224)
Currently Furloughed			0.0964***	0.0291**		
			(0.0145)	(0.0137)		
Perceived Prob. Job Loss				0.4604***	0.4643***	0.4664***
				(0.0249)	(0.0429)	(0.0315)
Constant	0.4394***	0.2650***	0.2114***	0.1335**	0.1977**	0.1541*
	(0.0289)	(0.0808)	(0.0795)	(0.0575)	(0.0855)	(0.0814)
Observations	2292	2282	2282	2278	800	1478
R^2	0.1086	0.1879	0.2029	0.3116	0.3438	0.2882
Region F.E.	yes	yes	yes	yes	yes	yes
Occupation F.E.	no	yes	yes	yes	yes	yes
Industry F.E.	no	yes	yes	yes	yes	yes

Notes: OLS regressions. Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. The sample in columns (1)-(6) is restricted to those in work in the May survey wave. The samples in column (6) and (7) are restricted respectively to those currently on furlough and not on furlough in the May survey wave. The dependent variable is the respondent's subjective probability of looking for a new job in the next year.

4.7 Implications for Policy Design

Given the high likelihood of future waves of coronavirus infection, it is crucial quickly to evaluate the design of the CJRS. It is clear that any future UK policy should allow employees to work on a part-time basis from the introduction of the scheme. The vast majority of workers report that they can do some of their work tasks from home (Adams-Prassl et al. 2020d), and the majority of workers continued to do some work while on furlough even when this was banned by the scheme. While this has likely introduced inequality between firms that fully complied with the scheme and those that did not, having furloughed employees continue to work is likely to have been welfare-improving by allowing economic activity to continue.

Preventing work on furlough might also have slowed the adoption of new technologies to enable working from home: why invest in changing work practices if your employees are not supposed to work? In Adams-Prassl et al. (2020d), we show that improvements in the ability to work from home were the largest in occupations that already had the largest share of workers who could do all tasks from home at the beginning of the crisis. It is plausible that the capacity to work from home could have increased in a wider set of occupations had the furloughing scheme placed fewer restrictions on working.

At the time of writing, the UK government is resisting any extension to the CJRS beyond October 2020. Our results suggest that greater flexibility in the ending of the scheme could be required. Crucially, the duration of the furloughing scheme should be sensitive to continued disruption in schooling and childcare. There is a growing body of evidence that women, and mothers in particular, have been especially hard hit economically by the pandemic (Adams-Prassl et al. 2020b; Andrew et al. 2020a; Benzeval et al. 2020). Even mothers who can work from home face more interruptions to their work time from domestic care responsibilities (e.g. Adams 2020; Andrew et al. 2020a). In this paper, we show that mothers have been more likely to request to be furloughed but there is no gender gap for childless workers. There is a real risk that mothers could be forced out of the labor market if the furloughing scheme ends without viable childcare options being available.

Flexibility in the removal of the scheme across different occupations is also warranted. Our results suggest that support for jobs that can be done from home should be phased out more quickly. Furloughed workers who can do a large proportion of their jobs from home are relatively pessimistic about their chance of keeping their job in the medium-run. For these workers, social-distancing measures are unlikely to be the only reason for a low-productivity match and they should not be prevented from moving to more viable firms. However, in jobs that are relatively difficult to do from home, labor supply restrictions from social distancing measures should be taken into considerations as the match might be efficient outside a pandemic.

Returning to work outside the home brings more opportunities for exposure to, and transmission of, the virus. While the majority of furloughed workers would prefer to return to work even at 80% of their usual pay, workers without employer-provided sick pay have a significantly lower willingness to pay to return to work. Worryingly, we find that workers without additional sick pay are significantly more likely to continue to work even with mild coronavirus symptoms (Appendix Table 4B.2). The UK has one of the least generous statutory sick pay schemes in Europe, which was described as "manifestly inadequate" by the European Committee of Social Rights (European Committee of Social Rights 2017). Complementing findings from causal studies of changes in sick-pay coverage (Pichler and Ziebarth 2020; Marie and Vall Castelló 2020), our results suggest that the provision of more generous sick pay could help to support the economic recovery by encouraging workers to return to work while infection rates remain above zero, and supporting sick workers to take time off work when they pose a risk to others.

4.8 Conclusion

In this paper, we exploit survey data from the UK to document differences in furloughing under the Coronavirus Job Retention Scheme across job and individual characteristics. We show that, while a significant proportion of workers in our sample are currently on furlough, there are large differences in the use of the furloughing scheme across industries and occupations. Further, we document that women, younger workers, and workers with alternative work arrangements have been more likely to be put on furlough.

Relatedly, we provide evidence of differences in the terms under which employees have been furloughed. In particular, our analysis shows that a significant proportion of workers who are on furlough still reports working a positive amount of hours. Further, the number of hours worked while on furlough is increasing in the share of tasks that workers can perform from home, and higher for respondents whose employer agreed to top up their wage beyond the 80% state contribution. Finally, we show that being on furlough is associated with higher self-reported probabilities of job loss before August for respondents who are in paid work at the time of data collection, and a higher likelihood of searching for a new job.

Our results highlight the benefits of allowing employees to work while enrolled in a STW scheme and the need for flexibility in the duration of government support across occupations and in response to childcare disruption. Finally, our results suggest that the provision of more generous sick pay could help to support the economic recovery by encouraging workers to return to work while infection rates remain above zero, and supporting sick workers to take time off work when they pose a risk to others.

For future research it will be important, but challenging, to understand what would have happened to the UK economy under alternative policy responses or with no furloughing scheme at all. This understanding could contribute to the design of short-time work schemes which are kept in place to help stabilize the economy in response to large negative exogenous shocks with mechanisms that contain uncertainty and increase efficiency.

Appendices of Chapter 4

4A Data Description

Table 4A.1: Distribution across regions

Region	National	April	May
Scotland	8.42	8.54	8.48
Northern Ireland	2.76	2.80	2.74
Wales	4.79	4.87	4.79
North East	4.06	4.12	4.04
North West	11.00	11.11	10.95
Yorkshire and the Humber	8.24	8.34	8.21
West Midlands	8.80	8.92	8.78
East Midlands	7.27	7.38	7.26
South West	8.59	8.70	8.61
South East	13.70	13.87	13.69
East of England	9.29	8.03	9.30
Greater London	13.15	13.32	13.15
Observations		4931	4009

Notes: National figures refer to the latest available estimates for the population of residents aged 18 or above and come from the Office for National Statistics. Data source: Office for National Statistics (2019).

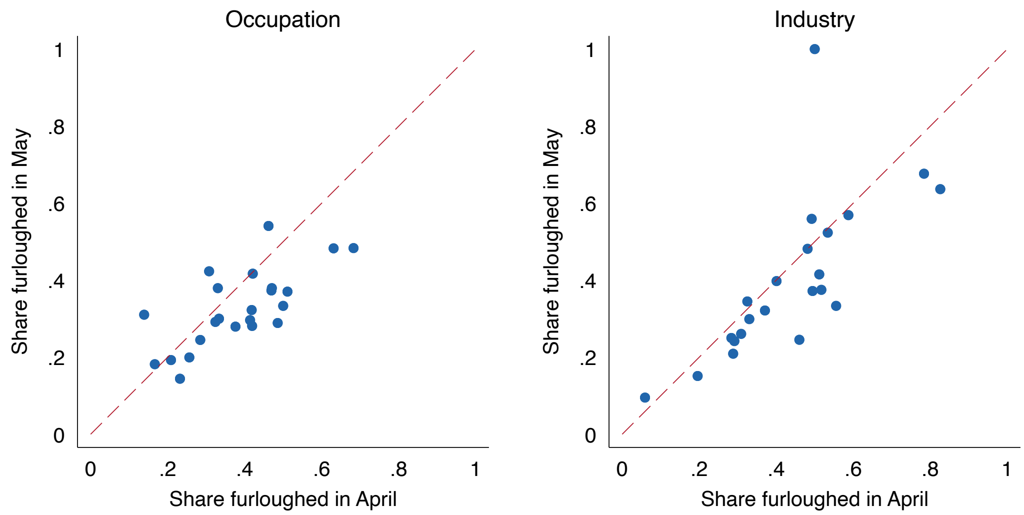
Table 4A.2: Background characteristics

	LFS	April	May
Female	0.47	0.552	0.550
University	0.357	0.488	0.464
<30	0.232	0.281	0.283
30-39	0.230	0.333	0.264
40-49	0.217	0.238	0.196
50-59	0.217	0.114	0.163
60+	0.104	0.033	0.095

Notes: The table shows the mean demographic characteristics of economically active individuals in the UK. These were calculated using the frequency weights provides in the LFS. The unweighted averages of these demographic variables in our survey waves are also reported.

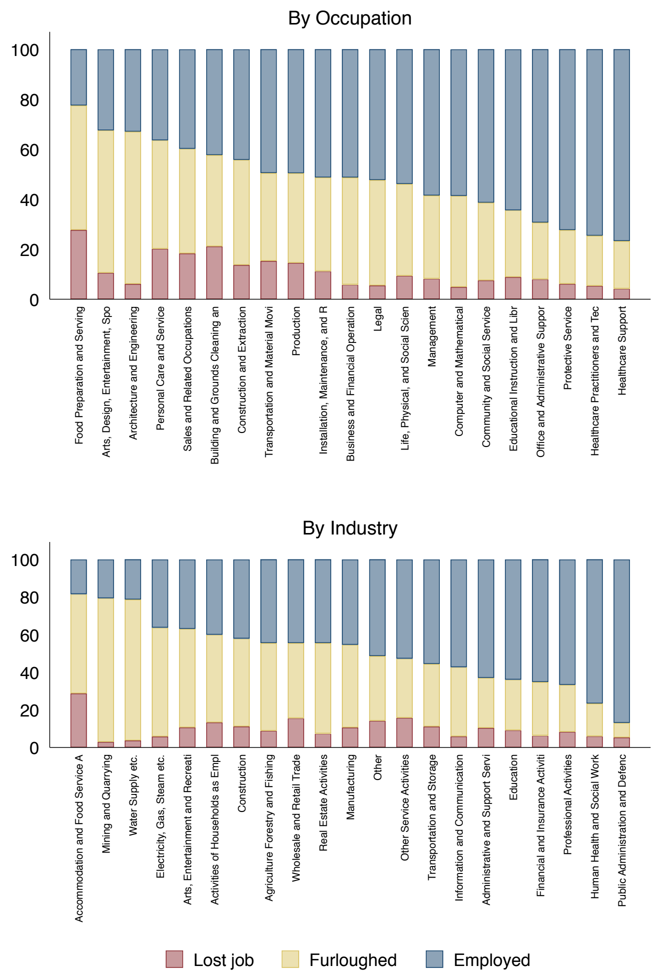
4B Additional Results

Figure 4B.1: Share of furloughed workers by occupation and industry across survey waves



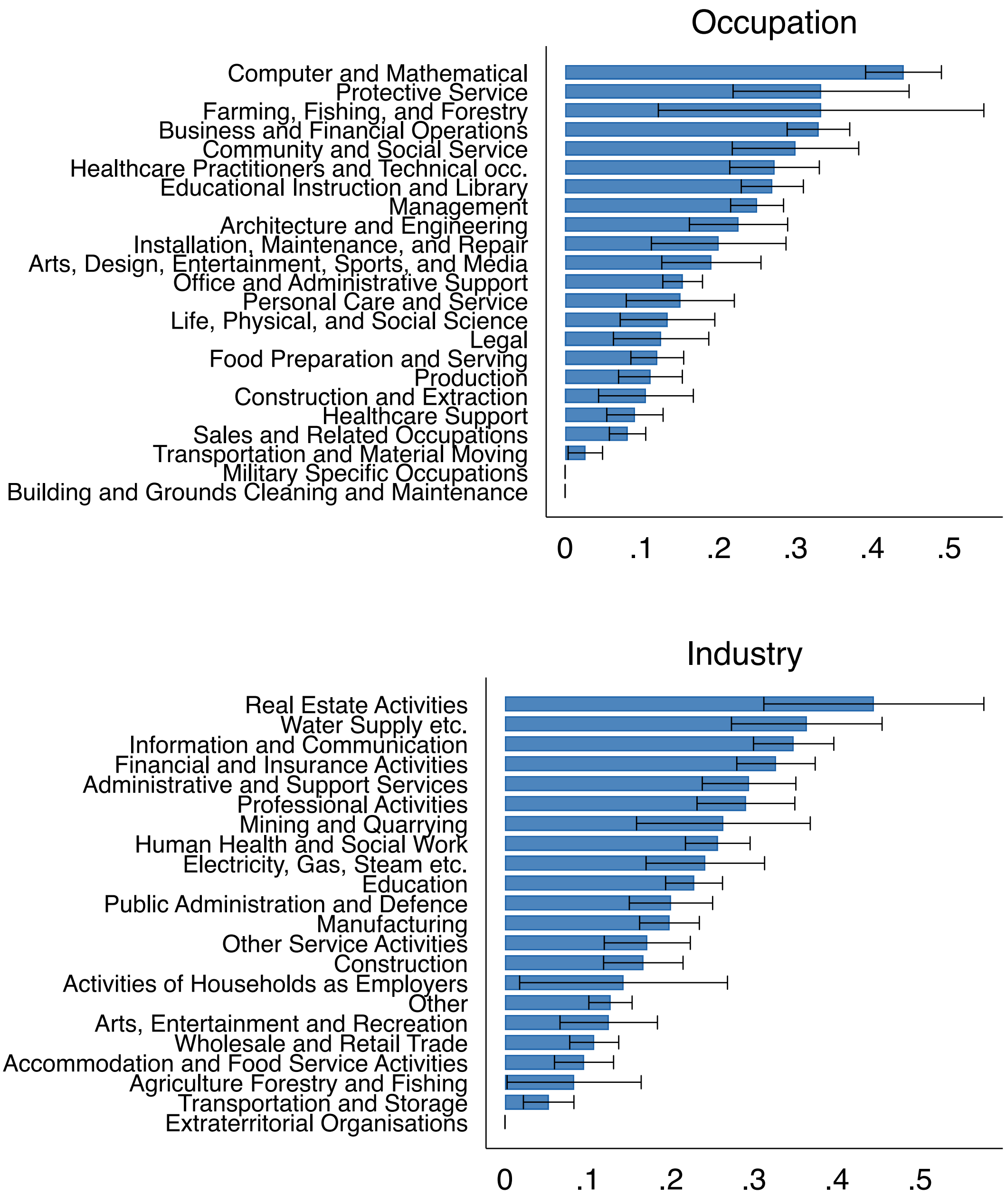
Notes: The graph shows the share of workers that are furloughed by occupation and industry, separately for the April (x-axis) and May (y-axis) survey wave. Each dot represents one occupation (left) or industry (right).

Figure 4B.2: Employment status by occupation and industry



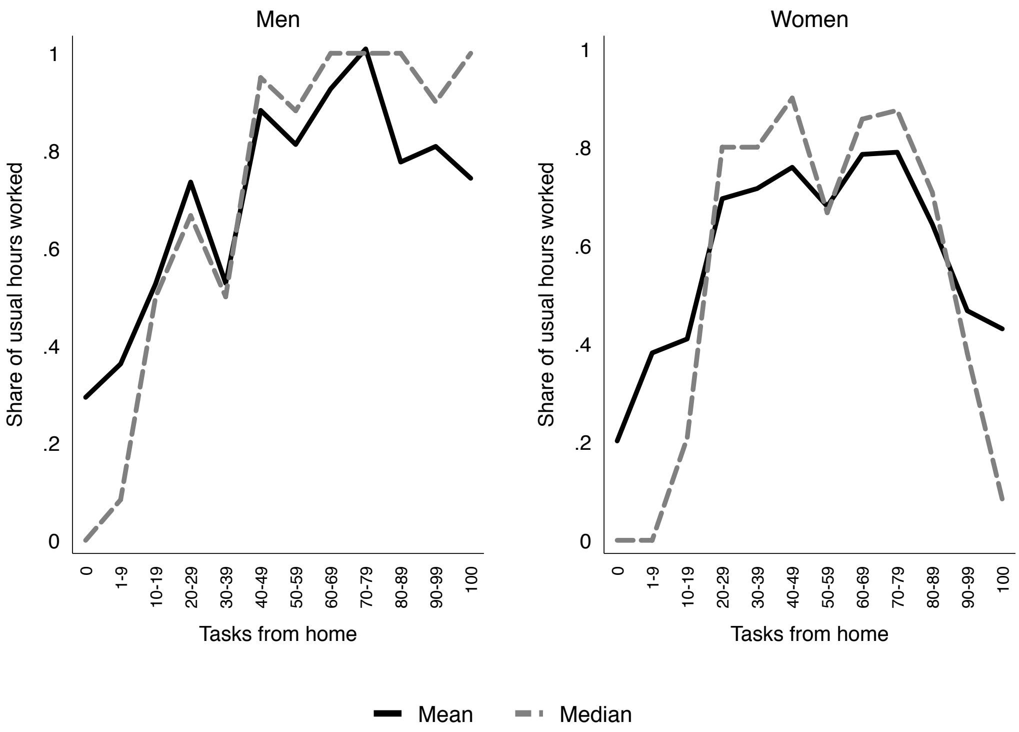
Notes: The figure shows the share of workers who are employed (blue), furloughed (yellow) or lost their job due to the Covid-19 crisis (red), by occupation (top) and industry (bottom). Survey responses for the April and May survey waves are pooled in this figure.

Figure 4B.3: Share of furloughed workers being asked to work



Notes: The sample is restricted to respondents to the April survey wave. The horizontal bars show the average share of furloughed workers who report having been asked to work while on furlough for each occupation (top) and industry (bottom). The black bars represent 95% confidence intervals.

Figure 4B.4: Percentage of usual hours worked while furloughed by percentage of tasks that could be done from home



Notes: The graph shows the mean and median percentage of typical work hours worked last week by respondents who are currently furloughed by the quintiles of the percentage of tasks one can do from home. Survey responses for the April and May survey waves are pooled in this figure.

Table 4B.1: Hours worked while on furlough - Sensitivity to Formal Workplace Rotation

	Positive work hours		% Usual Hours	
	(1)	(2)	(3)	(4)
Age:				
30-39	-0.1100***	-0.1398***	-0.1524***	-0.1787***
	(0.0335)	(0.0420)	(0.0421)	(0.0462)
40-49	-0.1532***	-0.1766***	-0.2252***	-0.2346***
	(0.0405)	(0.0513)	(0.0451)	(0.0514)
50-59	-0.1299**	-0.1685**	-0.2491***	-0.2573***
	(0.0615)	(0.0702)	(0.0614)	(0.0655)
60+	-0.0934	-0.0942	-0.1271	-0.0928
	(0.1312)	(0.1367)	(0.1307)	(0.1332)
University degree	-0.0779**	-0.0834**	-0.1316***	-0.1149***
	(0.0303)	(0.0371)	(0.0347)	(0.0383)
Female	-0.0817***	-0.0884**	-0.0926***	-0.0736*
	(0.0287)	(0.0369)	(0.0348)	(0.0396)
Income 2019 (£10,000s)	0.0223***	0.0263***	0.0184***	0.0241***
	(0.0046)	(0.0066)	(0.0065)	(0.0078)
Temporary Contract	0.0471	0.0413	-0.0138	0.0049
	(0.0455)	(0.0543)	(0.0486)	(0.0552)
Varied Hours (Worker)	0.0627*	0.0488	0.0459	0.0416
	(0.0336)	(0.0443)	(0.0417)	(0.0476)
Varied Hours (Firm)	0.0464	0.0498	0.0231	0.0576
	(0.0409)	(0.0530)	(0.0512)	(0.0590)
Non-Salaried Contract	0.0355	0.0509	0.1154***	0.1023**
	(0.0316)	(0.0414)	(0.0376)	(0.0442)
Work from Home	0.2991***	0.3075***	0.3405***	0.2808***
	(0.0502)	(0.0614)	(0.0586)	(0.0658)
No Paid Sick Leave	-0.1861***	-0.1626***	-0.2034***	-0.1664***
	(0.0455)	(0.0473)	(0.0448)	(0.0460)
Constant	0.7835***	0.7914***	-0.5339***	-0.4612***
	(0.0975)	(0.1137)	(0.1244)	(0.1253)
Observations	823	653	823	653
R^2	0.3397	0.3354	0.3431	0.3466
Region F.E.	yes	yes	yes	yes
Occupation F.E.	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes

Notes: OLS regressions. Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. All specifications restrict responses to April survey wave. Columns (1) and (3) restrict the sample to those who are currently furloughed in their main job and report having only one job. In columns (2) and (4), the dependent variable is further restricted to those who did not report being formally rotated back into work.

Table 4B.2: Working with cold-like symptoms

	(1)	(2)	(3)
Age:			
30-39	0.0540**		0.0215
	(0.0241)		(0.0250)
40-49	0.1388***		0.0917***
	(0.0253)		(0.0272)
50-59	0.1563***		0.0995***
	(0.0308)		(0.0334)
60+	0.0354		-0.0110
	(0.0586)		(0.0592)
University degree	0.0274		-0.0031
	(0.0184)		(0.0206)
Female	0.0299		0.0101
	(0.0183)		(0.0205)
Income 2019 (£10,000s)		-0.0094**	-0.0098**
		(0.0041)	(0.0043)
Temporary Contract		-0.1284***	-0.1172***
		(0.0344)	(0.0344)
Varied Hours (Worker)		-0.0120	-0.0065
		(0.0251)	(0.0251)
Varied Hours (Firm)		-0.0872***	-0.0796**
		(0.0315)	(0.0315)
Non-Salaried Contract		-0.0690***	-0.0603***
		(0.0229)	(0.0232)
Work from Home		-0.0042	0.0061
		(0.0312)	(0.0314)
No Paid Sick Leave		0.0716***	0.0592**
		(0.0250)	(0.0252)
Constant	0.6267***	0.9045***	0.8534***
	(0.0372)	(0.1063)	(0.1103)
Observations	2660	2611	2611
R^2	0.0308	0.0795	0.0861
Region F.E.	yes	yes	yes
Occupation F.E.	yes	yes	yes
Industry F.E.	yes	yes	yes

Notes: OLS regressions. Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Sample restricted to employees April wave and the dependent variable is a dummy variable that takes value 1 if the respondent reports that they would definitely or probably work with cold-like symptoms.

4C Questionnaire

Employment status and hours worked

How many jobs, where self-employment activity counts as a job, did you have in February 2020? Please think of any work you did other than completing surveys. If you were furloughed from a job, please count this as a job.
Many people work as employees, where they have an employment contract with an employer, or in self-employment. There is a lot of variation in self-employment, some people might be selling goods or services in their own business, or working through a digital platform such as Uber or Upwork. In addition to working a regular job for an employer, sometimes people do other things to earn money. These activities also count as self-employment. [None, 1, 2, 3 or more]

[If worked at least one job in February] *Think about a typical week in February for you at work (in all of your jobs). How many hours did you work in a typical week in February?* [Answers in 5-hour increments, from 0 to "More than 55 hours"]

How many jobs, where self-employment activity counts as a job, have you had last week? Please think of any work you did other than completing surveys. If you were furloughed from a job, please count this as a job.
Many people work as employees, where they have an employment contract with an employer, or in self-employment. There is a lot of variation in self-employment, some people might be selling goods or services in their own business, or working through a digital platform such as Uber or Upwork. In addition to working a regular job for an employer, sometimes people do other things to earn money. These activities also count as self-employment. [None, 1, 2, 3 or more]

[If worked at least one job last week] *Now think about all the work you did last week (in all of your jobs). How many hours did you work last week?* [Answers in 5-hour increments, from 0 to "More than 55 hours"]

[If reports working zero jobs last week] *Please think about your last job. In your last job, were you working as an employee or self-employed?* [Employee, Self-employed]

[If reports working at least one job last week] *In your main job, that is the job that you usually spend the most time working in, are you working as an employee or self-employed?* [Employee, Self-employed]

[For current employees] *Have you been furloughed?*[24] [Yes, No]

[For furloughed employees - April wave] *For the period you are being furloughed, has your employer agreed to top up the government wage support? The government will pay 80% of furloughed employees' wages up to a maximum of £2500 per month. Some employers might choose to top up the scheme so that employees receive more than 80% of their usual wages.* [Yes, No]

[For furloughed employees - April wave] *During the period you have been furloughed, have you still been asked to do any work for your employer?* [Yes - I have been asked to do work while still furloughed, Yes - I have been formally rotated back into work, No]

[For furlughed employees - May wave] *Was the decision to be furloughed...?* [5-point scale from "Fully your employer's decision" to "Fully your decision"]

[For furloughed employees - May wave] *If you could go back to work the same number of hours as you did on a typical week in February but be paid 80% of your salary, would you prefer going back to work rather than staying on furlough?* [Yes - I would prefer going back to work, No - I would prefer staying on furlough]

[If reports working zero jobs last week] *For how long have you not had a job?* [Recorded in weeks/months]

[If reports working zero jobs last week] *If you lost your job recently, do you think this was related to the coronavirus outbreak?* [Answers on 5-item scale, from "Definitely yes" to "Definitely no", with additional option "I did not lose my job recently"]

[24] In the May survey wave, the answer options were [Yes - I am currently on furlough, Yes, but I am no longer on furlough, No].

How likely is it that you will look for a new job in the next 12 months?[Answer on a continuous 0-100 scale]

Income

Which category represents your total individual annual income (before taxes) in 2019? This should include money from all jobs, net income from a business or farm, and any rent, pensions, dividends, interest, social security payments or other money income you received. [Answers on 12-point scale, from "Less than $10,000" to "$150,000 or more"]

Job characteristics: Questions phrased to refer to main or last job, depending on the respondent's employment status.

What sort of occupation best describes this job? [O*NET SOC 2018 major groups]

What category best describes the industry you work in? [NACE Rev. 2 industry classification]

[For current or former employees] *Do you have a permanent contract?* [Yes, No]

[For current or former employees] *Is your job salaried or how do you get paid?* [Salaried, Hourly, Paid by the job, Commission or tips only, Other]

[For current or former employees] *Are the number of hours you work fixed or do they vary?* [Fixed, Vary - I choose how many hours I work, Vary - My employer decides how many hours I work but I am guaranteed some work each week, Vary - I am an on-call worker]

In your job, what percentage of the tasks could you do from home? Examples: Andy is a waiter and cannot do any of his work from home (0%). Beth is a website designer and can do all her work from home (100%). [Answer on 0-100 slider]

[For current or former employees] *In addition to statutory sick pay, how many days of paid sick leave are you entitled to per year through this job?* [None, 1-5 days, 6-10 days, 11-15 days, 16-20 days, More than 21 days]

Expectations

On a scale of 0-100%, how likely are the following scenarios to occur before 1st August 2020?

- *I will lose my job or shut my business if self-employed*

Chapter 5

Gender Gaps in Home-Schooling Time

Abstract The COVID-19 pandemic has led to drastic changes to family life, including a significant increase in childcare responsibilities for parents of school-aged children. To examine the effects of the pandemic on time use in opposite-gender couples, I conduct a survey of married or cohabiting parents of school-aged children in England. The total time parents spend on childcare activities significantly increased between February and June 2020, but the gender gap in childcare responsibilities has grown significantly during the first months of the pandemic. The widening of the gender gap has been driven primarily by a more unequal division of educational activities with children. Increases in the home schooling gender gap are more (less) pronounced in couples where the mother (father) stopped working during the first UK lockdown. Perceived returns to maternal (as opposed to paternal) time investment in home schooling are positively correlated with an increase in the home schooling gender gap, even controlling for changes in the employment status of partners. The increase in the home schooling gender gap is also larger in households where the respondent holds traditional attitudes towards gender roles. I provide evidence of widespread conservative opinions about gender roles, as well as a systematic overestimation of the degree of conservatism of other survey participants.

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5.1 Introduction

The rapid spread of COVID-19 and the ensuing stay-at-home orders have led to drastic changes to the daily lives of individuals all over the world. For parents, the closure of schools and childcare centers has translated into a significant increase in total time spent on childcare activities during weekdays and weekends alike (for the UK, see for example Andrew et al., 2020a; Blundell et al., 2020; Sevilla and Smith, 2020).[1] Recent studies on time use during COVID-19 find that women are shouldering a larger share of these additional childcare duties. The growing gender gap in unpaid work has been put forward as a contributor to gender inequalities in the labor market impact of COVID-19 (Adams-Prassl et al., 2020b; Alon et al., 2020; Bangham, 2020). In light of these findings, understanding changes in time-use patterns within families and how parents decide to share additional childcare responsibilities has important implications for policy.

In this paper, I document changes in the time use of parents of school-aged children during the first period of school closures in the UK, and further investigate the determinants of the growing gender gap in parental time allocated to educational activities with children. To answer my research question I proceed in three steps. First, I analyze how the home schooling gender gap reacted to changes in the employment status of parents in the couple during the first months of the COVID-19 crisis. Second, I provide novel evidence on respondents' beliefs about returns to maternal time investment in children and their attitudes towards gender roles. Third, I examine the role of these beliefs in explaining changes in the home schooling gender gap, over and beyond the effect of changes in the employment status of partners.

To shed light on the time use of parents before and during the coronavirus crisis, I administer a novel, geographically representative survey to around 1800 parents in England who are married or cohabiting and with at least one school-aged (5-16) child. In the survey, I collect information on how respondents and their partners allocate time across different activities, including home schooling. With these data, I document how the first period of school closures changed the way in which parents allocate time across paid and unpaid work.

To elicit parental beliefs about the returns and costs to mothers (or fathers) spending time on educational activities with children, I design a novel measurement tool based on hypothetical scenarios. The hypothetical scenarios allow to overcome the problem that a household's choice about time allocation is endogenous to the couple's socio-economic background, labor market

[1] See also Del Boca et al. (2020); Farré et al. (2020) for the impact of COVID-19 on gender differences in paid and domestic work for Italy and Spain, respectively.

status and preferences. I design the scenarios to purposely measure beliefs about both child and parental outcomes. More specifically, I ask respondents to imagine a hypothetical British family where both parents work full-time and have to decide how to allocate home schooling responsibilities for a total of four hours per working day. Survey participants are presented with two scenarios in which either (i) the mother alone takes care of home schooling the child for four hours per day, or (ii) the father alone spends four hours per day on educational childcare activities. For each scenario, I elicit respondents' expectations about a number of paternal, maternal and child outcomes.

To measure attitudes towards gender roles, I make use of vignettes to collect parents' stated preferences about time allocation in a hypothetical family. As in the case of perceived returns to maternal time investment, respondents are presented with scenarios featuring the same hypothetical family having to home school their only child during the period of school closures. However, this time respondents are asked to indicate the share of total home schooling tasks that they think the hypothetical mother should take on, separately for the case where the hypothetical mother earns less or more than her husband.

Several results emerge from this study. The first set of findings relates to changes in time use for parents in England between February and June 2020. Data on self-reported time allocation across different home-production activities show that parents' total time spent on house chores and childcare has significantly increased between February and June 2020. On the other hand, time spent on market work has decreased. While these trends hold for both mothers and fathers, the gender gap in time spent on educational activities with children has widened dramatically during the first months of the pandemic. Second, zooming in on changes in the home schooling gender gap, I find evidence of asymmetric responses to parental job loss. The gender gap widens by more than one hour per day from a baseline of 30 minutes in households where the mother stopped working between February and June 2020. Conversely, in households where the father alone stopped working the gap reduces by 19 minutes from a baseline of 36 minutes per day, but does not fully close.

I then turn to the role of beliefs about returns to maternal (*versus* paternal) time investment in educational activities with children and beliefs about gender roles in explaining the (asymmetry in) changes in time allocation to home schooling activities during the pandemic. First, I document parents' perceptions about the benefits and costs to maternal time investment in educational activities with children. I compare answers to the scenario in which the mother alone takes care of home schooling tasks to answers for the opposite scenario where the father is the sole provider of home schooling. Looking at parental outcomes, I find that both perceived productivity at work and opportunities for career progression decrease when the hypothetical parents have to devote four hours of their day to educational childcare activities. The gradient is however more pronounced for maternal outcomes than paternal outcomes. This suggests that mothers are not thought to be intrinsically better at multi-tasking or balancing work and childcare responsibilities. Similarly, parental satisfaction with life decreases with time spent on home schooling activities, for both genders. Looking at differences in perceived returns by background characteristics, I find that women perceive both the costs for mothers and the benefits for fathers as higher than male respondents, in absolute terms. The number of children is also strongly predictive of more negative (positive) returns in terms of maternal (paternal) outcomes. Turning to child outcomes, respondents to my survey do not report differences in perceived effectiveness of maternal and paternal time investment in home schooling activities.

Looking at beliefs about gender roles, the data reveal the existence of widespread traditional gender identity norms among participants to my study. Around 50% of respondents think mothers should take care of the majority of home schooling tasks, irrespective of who is the main earner in the couple. Female respondents are found to be more conservative in their attitudes about gender roles than male respondents.

Finally, I analyze whether beliefs about returns to maternal time investment and gender roles can explain changes in the home schooling gender gap, over and beyond household characteristics and changes in the work arrangements of parents. I find that increases in the home schooling gender gap are larger in households where the respondent holds traditional views about gender roles. Gender-role attitudes are particularly strong predictors of increases in *maternal* time dedicated to educational activities with children. Returns to maternal time investment in terms of perceived life satisfaction of both parents are also found to be positively associated with increases in the gender gap.

Taken together, the results from this paper contribute to improving our understanding of the unequal impact of COVID-19 across gender, and of the way in which parents in opposite-gender couples share unpaid work. In particular, I highlight a widening gender gap in childcare responsibilities in two-parent households during the first UK lockdown. The labor market status of parents is a strong predictor of the change in time allocation within families but, even in families where fathers stopped working, mothers continue to shoulder around half of all home schooling activities. This paper shows that beliefs about perceived returns to maternal time investment and, most importantly, gender roles appear to have a role in explaining these asymmetries.

This paper relates to three main strands of literature. First, it contributes to recent and ongoing work on gender differences in the impact of the coronavirus pandemic (Adams-Prassl et al., 2020a,b; Oreffice and Quintana-Domeque, Forthcoming; Russell and Sun, 2020). Closest to this study are papers documenting gender differences in the additional workload associated to COVID-19, with mothers bearing the brunt of additional childcare responsibilities (Andrew et al., 2020a,b; Biroli et al., 2020a; Del Boca et al., 2020; Heggeness, 2020; Hupkau and Petrongolo, 2020; Lee and Tipoe, 2020; Mangiavacchi et al., 2020; Sevilla and Smith, 2020). This study sheds new light on the determinants of these gender differences and the role of parental beliefs in determining time allocations within the household.

Second, this paper builds on and expands the growing literature on the importance of beliefs and preferences for parental investment decisions (Dizon-Ross and Jayachandran, 2015; Boneva and Rauh, 2018; Dizon-Ross, 2019; Attanasio et al., 2020). Differently from previous studies that have looked at how parental beliefs shape the amount of investment parents make into their children or the timing of such investment, I examine the intensive margin of choice of whom in the household should take responsibility for childcare activities.

Finally, my paper is related to the literature on the relationship between gender identity norms, female labor supply and home production (Fernandez and Sevilla Sanz, 2006; Bertrand et al., 2015; Bursztyn et al., 2017; Cortés and Pan, 2019; Ichino et al., 2019; Bursztyn et al., 2020; Lassen, 2020; Oh, 2020). I contribute to this literature by examining how perceived gender roles are factored into parental decisions about time allocation to educational activities with children.

The remainder of the paper is structured as follows. Sections 5.2 and 5.3 describe the survey design and data. Section 5.4 presents descriptive evidence on the impact of COVID-19 on time use across families and gender gaps in time allocated to educational activities with children. Section 5.5 analyzes the role of parental beliefs about gender roles and perceived returns to maternal time investment in explaining changes in the gender gap in home schooling activities during the coronavirus pandemic. Section 5.6 discusses the implications of the results and Section 5.7 concludes.

5.2 Survey design

The focus of this study is to examine how parents in two-parent families allocate time across different activities and to analyze parents' perceptions about the potential costs and benefits of different time allocations. To this end, I design a survey that I administer to a large, geographically representative sample of parents in two-parent households in England.[2] While I only survey one person per couple, respondents are also asked detailed information about their partner. The survey consists of several different parts, summarised in the rest of this section. The full list of questions can be found in Appendix 5C.

5.2.1 Time allocation within the household

To measure how couples in two-parent families divide the responsibility of childcare activities and house chores, I administer a time-use module where respondents have to report the number of hours that they spent on different activities on an average weekday during the week before data collection, and during a typical week in February. Similar questions are also asked about the respondent's partner.[3] The activities survey participants are asked about include educational activities with their children, other childcare activities, house chores and work. Answers to these questions allow me to document how families from different socio-economic backgrounds or with different employment situations differ in terms of how partners contribute to various aspects of home production.

5.2.2 Beliefs about returns to maternal home schooling time

I develop a novel survey tool to elicit parental beliefs about the returns to maternal *versus* paternal investment in home schooling. To elicit perceived returns to maternal time investment, I make use of hypothetical scenarios. This methodology has been widely applied for the elicitation of beliefs about returns to different types of parental and other investment towards children (see, e.g., Boneva and Rauh, 2018; Attanasio et al., 2020). I extend this literature to examine beliefs about returns to the intensive margin of choice between maternal and paternal time investment. Participants to this study are presented with two scenarios depicting a hypothetical British family with one child and two working parents of opposite gender. Due to school closures,

[2] I decided to only survey respondents living in England to avoid heterogeneity arising from differences in both the lockdown restrictions and the schooling system across the devolved nations in the UK.

[3] Time use is measured in hours per day to keep the survey a manageable length. These questions offer a coarser measure of time use than the 10-minute intervals generally employed in time-use surveys, such as the 2015 UK Time Use Survey, and hence may yield less precise coefficient estimates for regressions where time-use measures are used as a dependent variable.

the hypothetical parents are faced with the need to spend four hours every day on home schooling activities with their only child and can decide between two time allocations: (i) the mother takes care of home schooling fully by herself for four hours per day, and (ii) the father takes care of home schooling fully by himself for four hours per day. The introductory text to the hypothetical scenarios reads as follows:

> *We will ask you to consider the situation in which, much like today, all schools in the country are closed and have moved their activities online to different degrees. In this context, we will ask you to imagine a British family, the Joneses, who have one child and have to make decisions about who will dedicate time to home schooling their only child. Both Mr and Mrs Jones work full-time. More specifically, we will show you two scenarios and ask for your opinion on certain outcomes. The scenarios will be:*
>
> - *Mrs Jones (Sarah) takes care of all of the home schooling*
> - *Mr Jones (Michael) takes care of all of the home schooling*
>
> *Please think about Michael and Sarah Jones, who both have a university degree and have one child, Emma. Emma is enrolled in Year 5 in an average school in England and has achieved the expected level in the KS1 SATS.*[4] *Sarah and Michael want to dedicate 4 hours every day to home schooling their child, and can decide whether Sarah or Michael alone will take care of all the home schooling activities. Suppose they decide by rolling a dice.*

I deliberately chose to depict a hypothetical couple where both partners work full-time, in order to fix ideas about the time constraints faced by the parents. This simplifying assumption may threaten the external validity of my belief measures. However, by presenting participants with scenarios where both partners work full time, I can isolate the effect of perceived returns to maternal time investment in home schooling and avoid the confounding element of beliefs about the gendered specialisation in paid and unpaid work.

Note that in the hypothetical scenarios it is decided by chance whether the mother or the father will home school the child. Whilst this is a simplifying assumption, if this choice was presented as not random, respondents could, for example, interpret the decision of the mother

[4] Respondents were randomised to see scenarios with a female or male child, and with different levels of educational attainment of the two hypothetical parents.

to take care of home schooling as the mother caring more about her child's education than her partner, or her being more capable of helping the child with homework. Making explicit that who home schools the child is decided by a random draw helps circumvent the issue of respondents making inference about preferences or abilities of the hypothetical parents from the choice they are making.

For each scenario, I ask respondents about (the likelihood of) a range of different parental and child outcomes, summarized in Table 5.1. Comparing responses across the two scenarios allows me to compute a quantitative measure of respondents' beliefs about the benefits and costs of maternal time investment in home schooling.

Table 5.1: Overview of belief elicitation questions

Scenarios
(1) If the mother takes care of home-schooling fully by herself
(2) If the father takes care of home-schooling fully by himself
Child Outcomes
Earnings of child at age 30 (£)
Child achieves the national standard or more in KS2 (0-100%)
Parental Outcomes
Mother enjoys her life (0-100%)
Father enjoys his life (0-100%)
Mother can complete work tasks (0-100%)
Father can complete work tasks (0-100%)
Mother has full-time job one year from now (0-100%)
Father has full-time job one year from now (0-100%)

Notes: Each respondent is presented with two scenarios. For each scenario, parents are asked about child and parental outcomes as detailed above.

I use probabilistic questions to elicit respondents' perceptions about the likelihood of different binary outcomes occurring for the two scenarios described above. More specifically, I ask respondents how likely they think it is that each parent will enjoy their life, be able to complete his / her work tasks, and retain his / her full-time job one year from now. I also ask survey participants about the probability that the hypothetical child achieves the expected standard in the KS2 assessments, and the expected earnings of the hypothetical child at age 30.[5]

[5] The National Curriculum in England is split into four 'key stages' into which children are grouped depending upon their age. This does not include the first Reception year. The second key stage (KS2) ends in Year 6, when pupils sit a test that assesses their abilities in reading, maths, spelling, punctuation and grammar. The KS2 test is a national standardised assessment that all parents should be familiar with, regardless of the age of their child.

5.2.3 Beliefs about gender roles

The division of home schooling tasks between parents may be influenced by parental beliefs about 'who is better at' or 'who should do' a certain activity, i.e., parental beliefs about gender roles. I make use of two additional hypothetical vignettes to construct a measure of traditional beliefs about gender roles. In both vignettes, participants are again asked to think about a hypothetical British family, with two working parents of opposite gender and one child who needs to be home schooled for four hours every day. Respondents are then asked what share of total parental home schooling time they think should fall upon the mother, relative to her partner. Answers are provided on a scale from 0 to 100%, where 100% (0%) corresponds to the case where the mother (father) alone takes care of home schooling. The two vignettes in this module only differ in who is the main earner in the hypothetical couple: in the first vignette, the hypothetical father earns more than the mother, whereas in the second vignette the opposite occurs. The salary difference between parents is fixed for each respondent, and randomised across respondents to be either 2%, 5%, 10% or 20%.[6] To analyze the extent to which individual perceptions deviate from the average expectations of parents in England, I also ask respondents what they think other survey participants would answer to the same questions.

5.2.4 Employment and opinion about the future

I collect information on the employment status of respondents and their partners pre- and during COVID-19. Respondents are asked to report whether they and their partner were working (either full-time or part-time) or out of work at two different points in time - February 2020 and the week before data collection. For June 2020, I further distinguish between workers who are furloughed and those who are out of work for other reasons. For workers (or partners thereof) who report being in work in the week prior to data collection, I collect information on whether they are classified as key workers. To measure the future effect of the lockdown and school closures on parental work patterns, I ask respondents whether they or their partner are considering quitting their job or substantially reducing their work hours to care for their child(ren). Finally, to measure parental perceptions about how COVID-19 will affect the division of childcare responsibilities going forward, I ask participants whether they think the division of childcare in their household will stay the same as it is now, or whether it will become more or less unequal.

[6] In the UK, the gender pay gap among full-time employees was 8.9% in 2019, whereas it was 17.3% among all employees (Smith, 2019).

5.3 Data description

I collect primary survey data on a large, geographically representative sample of parents in England. To participate in the survey, respondents had to be resident in England, be at least 18 years old, married or cohabiting and have at least one school-aged child (5-16). The survey was conducted anonymously and administered online through the professional survey company PureProfile. Participants were offered modest incentives to complete the survey. No personal information is collected that would allow to identify any individual respondent. The data were collected between June 15, 2020 and July 6, 2020.[7]

The original sample consists of 1805 respondents and was selected to be representative of the distribution of the population of individuals aged 18 or above across regions in England. Within each region, I used quota-based sampling to ensure an approximately equal representation of men and women. Throughout the text I interchangeably refer to the former group as men or fathers, and to the latter group as women or mothers. Table 5A.1 in the Appendix shows the distribution of respondents across regions in England and the comparison to the national distribution of the population of adults aged 18 or above. As can be seen from the table, the two distributions are very similar. Table 5A.2 shows the characteristics of respondents in my sample. By construction, around 50% of the sample are women. Respondents are 43 years old on average and have 1.9 children. The youngest child in the household is on average 8.7 years old. Slightly more than half of survey participants have a university degree and 67% of respondents are in work (either full-time or part-time) in the week before the data collection.[8] The share of respondents in work in June 2020 (67%) is significantly lower than the corresponding figure of 84% for February 2020. Around 37% of respondents who are still in paid work in June 2020 identify themselves as key workers. Out of those who were in paid work before the pandemic, 21% stopped working between February and June 2020. Almost the totality of respondents are in opposite-gender couples (97.6%).

For the analysis, I restrict the sample in the following ways. Given that the focus of this paper is in understanding differences in time allocation across men and women in the household,

[7]As COVID-19 spread in the UK, the government closed schools from 23 March 2020, except for key workers' children and vulnerable children. A gradual re-opening of schools started on 1 June 2020 for selected age groups. Parents whose children were in school in the week before data collection were asked to think about the last week in which their child was fully home schooled.

[8]Respondents who report being on furlough in June 2020 are classified as "not working" throughout the paper. At the time of data collection, the furloughing scheme in the UK was such that furloughed employees faced the provision of doing no work at all for their employer. Hence, in principle, furloughed workers faced no constraints to their time allocation to unpaid work as arising from work commitments. In this sense, this lack of constraint is similar to that faced by individuals who are out of work altogether.

I restrict the sample to only include respondents in opposite-gender couples. I further exclude observations for respondents that gave implausible answers to the time use questions.[9] This leads to a final sample size of $N = 1,723$. Table 5A.3 compares the characteristics of my final sample to those of the UK Household Longitudinal Study (UKHLS), where the UKHLS sample has been restricted to respondents to the third wave of the COVID-19 special module that was run in June 2020, and limited to individuals either married or cohabiting, with a partner of opposite gender and with school-aged children.[10] Relative to UKHLS respondents, participants to my study are more likely to have obtained a university degree. Furthermore, the shares of respondents in work in February and June 2020 are slightly lower in my sample compared to the UKHLS, although the two samples are very similar in terms of the share of in-work respondents in February 2020 who stopped working by June 2020. Finally, respondents to my study have on average slightly less children, and their youngest child is half a year older than that of UKHLS respondents.

[9] I exclude respondents whose answers to the time use questions summed to more than 24 hours, either for questions about their own time or their partner's.

[10] For a description of the UKHLS data, see Institute for Social and Economic Research (2020a,b).

5.4 The impact of COVID-19 on time use

In this section, I document how COVID-19 has affected the time use of families with children in England. I start by documenting how parents allocate their time to home-production activities (i.e. educational activities with children, other childcare activities and house chores) and market work before and during the pandemic. I examine gender differences in time allocation and how these have evolved during the first months of the crisis. I then describe the labor market impacts of COVID-19, and discuss heterogeneities in changes to time allocations depending on the employment status of parents.

5.4.1 Parental time use

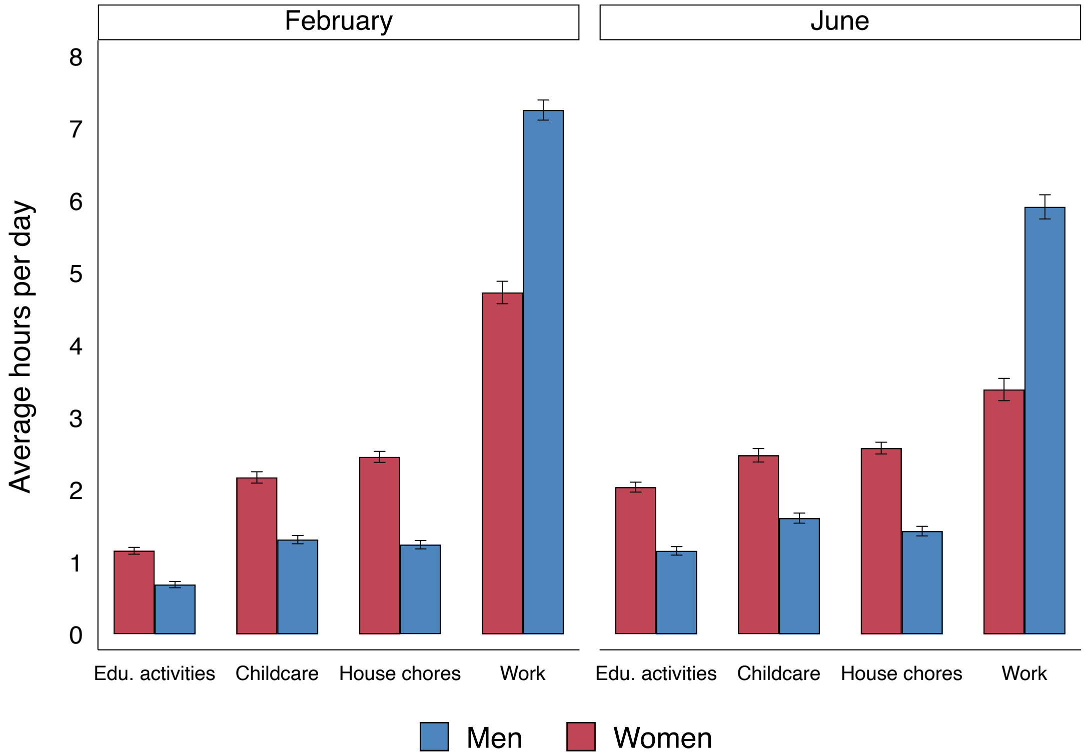
A distinctive feature of the coronavirus pandemic has been the introduction of stay-at-home orders and school closures, which have increased the workload of adult members of the household by limiting the possibility of outsourcing home production tasks and childcare. In what follows, I document how parental time allocation to unpaid and paid work has changed during the coronavirus pandemic, compared to the pre-crisis period.

To allow inter-temporal comparisons of time use, in my survey I ask participants for the number of hours they spent on educational activities with children, other childcare activities, house chores and market work, in the week before data collection and during an average week in February 2020. To gain insights on the division of labor within the household, similar questions are asked about the time allocation of the respondent's partner. Home-production activities, including childcare and house chores, took up a significant amount of parents' time on weekdays already in normal times (see Figure 5B.1). Participants to this study report that the total time they and their partner spent during a typical weekday in February on educational activities with children, other childcare activities and house chores is on average 1.9, 3.6 and 3.8 hours per day, respectively.

During the pandemic, time spent on all of these activities increased significantly. This is especially true for educational activities with children, to which parents devoted 1.4 hours more on average on a weekday in June compared to February, as school closures meant that children needed substantial help from parents for their home-learning. In contrast, the combined time respondents in two-parent families spent on market work is 9.4 hours every day on a typical workday in June, down from around 12 hours of combined market work in February.[11]

[11] Figure 5B.2 shows that there are differences in parental time use along the income distribution. High-income parents devote more time to home schooling activities and market work than low-income parents. Low-income

Figure 5.1: Parental time use before and during COVID-19 by gender



Notes: The graph shows the average number of hours respondents report they and their partner spent in total on educational activities with their child, other childcare activities, house chores and work, separately for men (blue) and women (red). The gender of the two adults in the couple is identified from answers to the question about the respondent's own gender and the gender of their partner. Separate panels show answers for a typical week in February (left) and the week before data collection (right). The black caps show 95% confidence intervals.

Looking at differences in time use within the household, Figure 5.1 provides details on the gender division of paid and unpaid work before (left panel) and during (right panel) COVID-19. Before the pandemic, mothers spent significantly more time than fathers on educational activities with their children (1 hours and 12 minutes versus 43 minutes). Similarly, women spent around 2 hours of a typical workday on other childcare activities, against a corresponding figure of 1 hour and 20 minutes for men. Large gender gaps were also present before the pandemic in house chores, with mothers spending roughly double the amount of time fathers spent on these activities. Finally, consistent with differences in labor force participation across genders, men

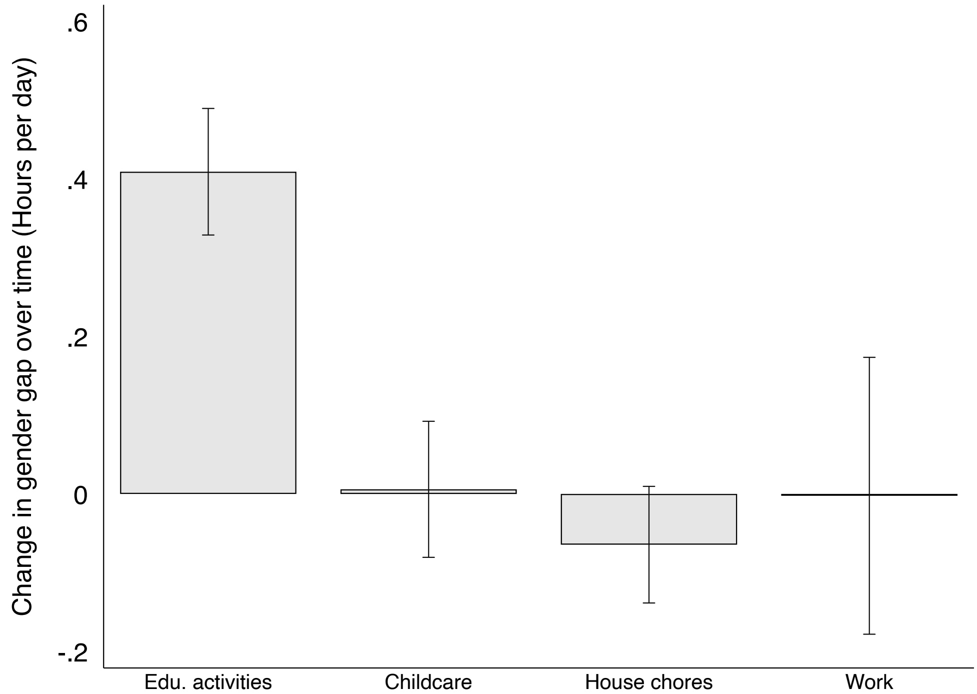
parents devote less time to house chores than the rest of the sample. Further, there is a negative (positive) association between the age of the youngest child in the household and time spent on childcaring activities (market work) - see Figure 5B.3.

spent on average slightly more than seven hours working for pay on a typical workday in February, whereas women spent on average 4 hours and 46 minutes on market work. Table 5B.1 shows that the gender gaps in time use before the pandemic strongly depend on the employment status of the partners. Conditional on a broad set of individual and household characteristics, in couples where the mother was out of work in February 2020 the gender gaps in educational activities, other childcare activities and house chores are 10, 32, and 57 minutes larger, respectively, compared to families where the mother was in paid work before the pandemic. Similarly, when fathers are not in work, the difference in time allocation to childcare activities and housechores between mothers and fathers significantly decreases by 27 and 38 minutes respectively. It is however interesting to note that gender gaps in unpaid work remain positive even in families where fathers are out of work but mothers are doing some positive amount of paid work.

Figure 5.2 shows the evolution of these gender gaps during the first months of the pandemic. The main effect of the COVID-19 crisis has been a widening in the difference in time that mothers and fathers spend on educational activities with children. In particular, mothers, who already before the pandemic were spending significantly more time than fathers helping their children with school work, increased the time they spend on these activities by around 52 minutes per day on average. Hence, in June 2020 mothers were spending around 2 hours every day home schooling their children. These numbers stand in contrast to an increase in home schooling time of only 28 minutes for fathers. Overall, the gender difference in time dedicated to helping children with their school work inreased by around 25 minutes per day between February and June 2020. Turning to other childcare activities, both fathers and mothers in my sample increased the time dedicated to this activity by around 20 minutes, with no significant effect on the gender gap. Notably, fathers' time spent on house chores increased more than mothers' (13 and 9 minutes respectively), thus leading to a small albeit insignificant reduction in the gender gap for house work. Finally, time spent on market work was around 80 minutes lower in June than it was in February for both genders, with again no significant effect on the gender gap.[12] In what follows, I will examine the determinants of the increase in the gender differences in time dedicated to home schooling activities with children.

[12] In my sample, mothers are more likely than fathers to experience a reduction in work hours between February and June 2020. However, changes in work hours are overall smaller in magnitude for women than they are for men. As a consequence, among couples where only one parent lost their job or stopped working, changes in the gender gap were larger (in absolute terms) in households where the father stopped working (5.36 hours) than those where the mother did (3.47 hours), since fathers were working more hours than mothers to begin with. Similarly, in families where both parents stopped working, the gender gap in paid work time reduces due to the larger drop in work hours of men than of women.

Figure 5.2: Change in gender gaps in time allocation between pre- and during-COVID period



Notes: The graph shows the evolution of the gender gap in time dedicated to different activities between February and June 2020. The gender gap is calculated as time devoted by the mother minus time devoted by the father, both expressed in hours per day. Positive numbers correspond to an increase in the gender gap to the disadvantage of women between February and June 2020. The gender of the two adults in the couple is identified from answers to the question about the respondent's own gender and the gender of their partner. Black caps show 95% confidence intervals.

5.4.2 Labor market outcomes and changes in gender gaps

Part of the increase in gender differences in time spent on educational activities with children during COVID-19 can mechanically arise from a differential effect of the pandemic on the labor market outcomes of men and women. If women were more likely than men to stop working, this would give mothers more extra time to dedicate to childcare. In the UK, the latest data show that the overall employment effects of the pandemic have been neutral across gender. However, several studies have highlighted large gender differences in the labor market impact of the pandemic *among parents*, with mothers in a couple being more likely to have stopped working or asked to be furloughed during the early phases of the crisis (Adams-Prassl et al., 2020b; Andrew et al., 2020a; Sevilla and Smith, 2020). Table 5A.4 offers insights on the labor market impacts of COVID-19 for two-parent families in my sample. First, comparing the share of people in work at the time of data collection across gender, we see that only 59% of mothers from households in my sample were in work (either part-time or full-time) during the week before data collection, against a corresponding figure of 79% for fathers. Further, 27% of mothers in my sample who were in work in February 2020 had stopped working by mid June, against a corresponding figure of 15% of fathers.[13]

Table 5.2 and Figure 5.3 show the evolution of the gender gap in time spent on educational activities with children across families with different transitions out of paid work across partners. I classify families depending on whether only the mother or father stopped working between February and June 2020, both parents stopped working or no change occured in the employment status of either parent. For the latter group, I further distinguish between households where the mother remained in work or out of work throughout.[14] Before the pandemic, the home schooling gender gap ranged from 21 to 40 minutes per day across family types. During the first UK lockdown, the gender gap in home schooling activities increased for all groups, with the exception of households where the father stopped working between February and June 2020. The increase is starkest, and around one hour per day, in families where the mother stopped working during the pandemic. However, also noteworthy is the increase in the gender gap in time devoted to educational activities with children for families where *no change* occured in the employment status of either partner, even in families where the mother reports being in paid work both before and during the crisis. Interestingly, we do not observe a reversal or significant reduction in the gender gap in families where the father alone stopped working in the first months of the pandemic.[15]

[13] The share of households where both parents were out of work increased from 4% in February to 12% in June 2020. Overall, 4.5% of households in my sample have seen both partners stop working during the first months of the pandemic. Of the parents still in work at the time of data collection, 44% of mothers and 36% of fathers are key workers.

[14] See Table 5A.5 for the distribution of households across groups.

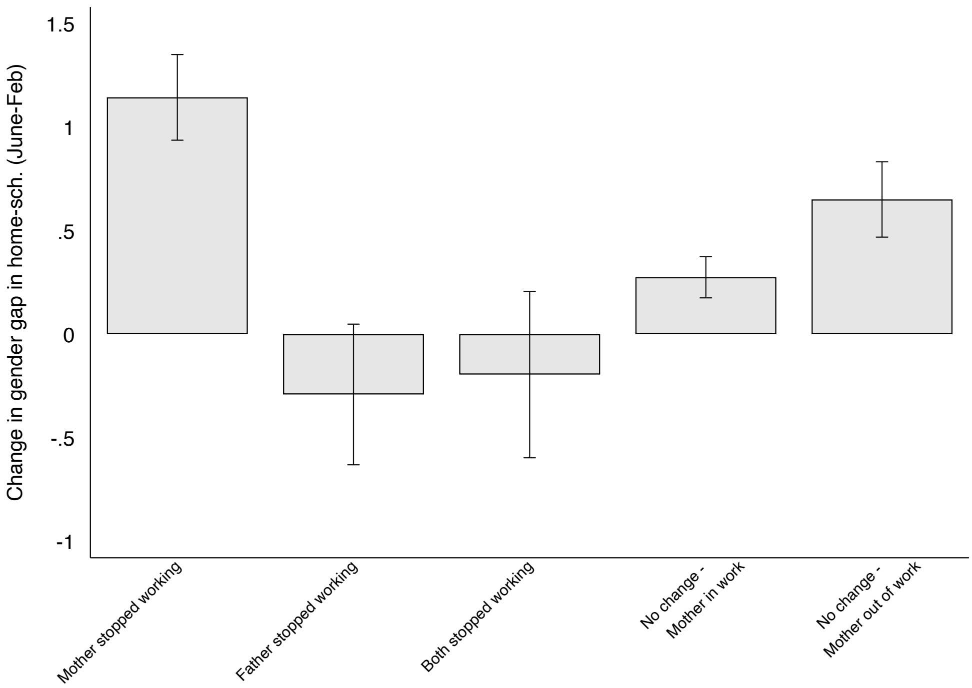
[15] Similar results hold in Table 5B.2 and Figure 5B.4 where I use a more granular definition of family types. Interestingly, in households where the father stopped working but the mother remained in work the gender gap in home schooling activities fully closes but does not significantly reverse.

Table 5.2: The gender gap in home schooling time by changes in labor market outcomes

	Gender gap	
	February	June
Mother stopped working	0.50	1.66
	(0.90)	(1.81)
Father stopped working	0.60	0.31
	(1.02)	(2.45)
Both stopped working	0.47	0.27
	(1.03)	(2.03)
No change - Mother in work	0.36	0.64
	(0.97)	(1.69)
No change - Mother out of work	0.67	1.34
	(1.04)	(1.84)

Notes: Standard deviations given in parentheses. This table provides average gender gaps in educational activities with children by family type. Columns (1) and (2) refer to statistics for February and June 2020, respectively. Gender gaps are constructed as the difference between maternal and paternal time spent on educational activities with children, and are expressed in hours per day. Positive numbers indicate mothers are spending more time than fathers on educational activities with children. Family types are constructed on the basis of the labour market status of both partners in February and June 2020.

Figure 5.3: Change in the gender gap in home schooling time by changes in labor market outcomes



Notes: The graph shows the evolution of the gender gap in time dedicated to educational activities with children between February and June 2020. The gender gap is calculated as time devoted by the mother minus time devoted by the father, both expressed in hours per day. Positive numbers correspond to an increase in the gender gap to the disadvantage of women between February and June 2020. The gender of the two adults in the couple is identified from answers to the question about the respondent's own gender and the gender of their partner. Different bars represent households where the mother, father or both parents stopped working between February and June, or where there was no change in the labor market status of either parents. Black caps show 95% confidence intervals.

Table 5.3 examines the relationship between changes in the employment status of parents and the gender gap in home schooling activities in a multivariate regression framework. The first column only controls for indicators of different family types. The baseline category is the group of families where no change occured in the employment status of either partner, and the mother was in work both before and during the first UK lockdown. In this group, the home-schooling gender gap increased by 0.27 hours (or approximately 16 minutes) between February and June 2020. For families whithout changes in the employment status of either partner, but where the mother was out of work throughout, the home-schooling gender gap increased by an additional 23 minutes, for a total increase of 39 minutes per day on average. In families where only mother stopped working, the gender gap increased by a total of about 70 minutes per day. Conversely, families where the father alone or both parents stopped working saw a decrease in the home-schooling gender gap of 19 and 11 minutes, respectively. Column (2) additionally controls for region fixed effects and income of both parents, as well as indicators for whether the parents are key workers in June. Not surprisingly, when mothers (fathers) are key workers, the increase in the gender gap in home schooling time is significantly smaller (larger). Finally, Column (3) additionally controls for household characteristics, including parental age and educational attainment, number of children and indicators for the presence of children aged 0-4 and 5-10 in the household. Controlling for all these characteristics does not significantly alter the relationship between family types and changes in the home schooling gender gap. The only exception is families where mothers are out of work throughout and no change occured to the employment status of the father. For this group, the increase in the home schooling gender gap is no longer significant when controlling for household characteristics.

As shown in Table 5.3, changes in employment status of parents, whilst important predictors of parental time allocation, cannot fully explain the changes in the home schooling gender gap that happened during the first UK lockdown. In particular, even in families where the father stopped working, mothers still continue to shoulder the majority of home schooling tasks. There could be a number of other reasons for the increasingly gendered division of educational activities with children during the COVID-19 crisis. One potential explanation could be differences in productivity across gender. If parents thought mothers were more used to, and hence better at, helping children with their school work, then both children and parents could be thought to benefit from mothers taking on the majority of home schooling tasks. Similarly, the way in which parents changed their division of childcare tasks might be driven by parental attitudes towards gender roles, i.e., parental beliefs about who should do what in the household. In the rest of the paper, I investigate the role of beliefs about gender roles and returns to maternal time investment in explaining the asymmetric responses to changes in maternal and paternal labor market status.

Table 5.3: Labor market impacts of COVID-19 and changes in the gender gap in educational activities

Sample	All	All	All
Mother stopped working	0.8786***	0.7272***	0.6774***
	(0.1169)	(0.1279)	(0.1296)
Father stopped working	-0.5819***	-0.5355***	-0.6095***
	(0.1799)	(0.1830)	(0.1894)
Both stopped working	-0.4638**	-0.5593***	-0.5616***
	(0.2070)	(0.2167)	(0.2127)
No change - Mother not working	0.3879***	0.2072*	0.1735
	(0.1062)	(0.1235)	(0.1214)
Key worker - Mother		-0.2831***	-0.3202***
		(0.1054)	(0.1053)
Key worker - Father		0.1834*	0.1883**
		(0.0941)	(0.0926)
Income - Mother (£0000's)		-0.0416*	-0.0486**
		(0.0213)	(0.0211)
Income - Father (£0000's)		0.0115	0.0322*
		(0.0173)	(0.0179)
Constant	0.2690***	0.5814**	0.0531
	(0.0508)	(0.2630)	(0.4104)
Mean dep. var.	0.404	0.404	0.404
Observations	1672	1672	1672
R^2	0.061	0.073	0.098
Region F.E.	✗	✓	✓
Household characteristics	✗	✗	✓

Notes: OLS regressions. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. The dependent variable is the change in gender gap in time dedicated to home-schooling activity, between February and June 2020. The gender gap for each period is calculated as the difference between maternal and paternal time devoted to educational activities with children, and expressed in number of hours per day. Positive (negative) coefficients correspond to an increase (decrease) of the gender gap. Household characteristics include age of both partners, indicators for partners having a university degree, the number of children in the household and indicators for the presence of children aged 0-4 and 5-10.

5.5 Beliefs about returns to maternal time investment and gender roles

In this section, I first describe how I measure beliefs about returns to maternal time investment in home schooling activities and perceived gender roles, and discuss their determinants. I then examine the role of these beliefs in explaining changes in the gender gap in time dedicated to home schooling activities, over and beyond constraints imposed by the employment status of parents.

5.5.1 Measuring perceived returns to maternal time investment

To elicit parental beliefs about the returns to maternal time inputs in home schooling, I make use of hypothetical scenarios featuring a British family with one child currently enrolled in Year 5 and two working parents of opposite gender.[16] The scenarios are set during the COVID-19 pandemic when schools are closed and children are at home. The hypothetical parents need to spend four hours every day on home schooling activities with their only child and can decide between two time allocations: (i) the mother takes care of home schooling fully by herself for four hours per day (t_1), and (ii) the father takes care of home schooling fully by himself for four hours per day (t_2). For each scenario, respondents are asked to report their perceived likelihood that different binary outcomes would occur on a 0-100 scale (see Manski (2004) for a review of this methodology). Let $\{b \in \{0,1\}\}_{n=1}^{N}$ denote the vector of binary outcomes. Binary outcomes include parental satisfaction with life, ability to complete their work tasks and ability to retain their full time job for at least a year. All parental outcomes are elicited separately for the mother and the father in both scenarios. Respondents are also asked about the perceived probability that the hypothetical child will score above average in their KS2 examination and the expected earnings of the child at age 30 in both scenarios. Earnings are elicited on a continuous scale using a slider.

Table 5.4 reports the average beliefs for all parental and child outcomes across the two scenarios where the mother or the father alone takes care of home schooling. The table shows substantial perceived costs for mothers from dedicating time to educational activities with children. The perceived life satisfaction of mothers is 20 percentage points higher when the father takes care of home schooling relative to the scenario where the mother does. Similarly, maternal

[16] Year 5 is the year before the hypothetical child takes the KS2 national exam. The Department for Education had cancelled all national assessments for the 2019/2020 academic year. I therefore chose to present respondents with scenarios featuring a child in Year 5 because, with schools closed, parental investment during Year 5 would be particularly important for Year 6 examinations in the academic year 2020/2021.

productivity at work, measured by the probability that she will be able to complete her work tasks, is 33 percentage points higher when she does not have to spend four hours every day home schooling her child. Finally, the perceived probability that the hypothetical mother will be able to retain her job in 12 months' time is around 20 percentage points lower in the scenario where she alone is responsible for home schooling. Simmetrically, maternal time spent on home schooling yields large benefits for fathers. Relative to the scenario where the hypothetical father alone home schools the child, paternal life satisfaction, ability to finish his work tasks and probability to retain his full time job are all significantly higher when the father does not have to spend time on home schooling activities. Interestingly, the perceived costs to mothers are larger in absolute terms than the perceived benefits for fathers. For work-related outcomes, this difference is driven by worse maternal outcomes in the scenario where the mother is responsible for home schooling the child compared to the symmetric outcomes for fathers. In other words, while there is no perceived difference in outcomes across gender when parents do not engage in home schooling activities, gender differences at the disadvantage of mothers arise when parents have to devote four hours every day to home schooling their child.

With regards to child outcomes, respondents believe there is a 60% chance on average that the hypothetical child would achieve the expected standard in their KS2 examination. This figure is not statistically different across the two scenarios (p-value = 0.214). Comparing parental beliefs to the actual performance of pupils in KS2 examinations in England reveals that participants to this study are somewhat pessimistic about exam performance. In 2019, 65% of pupils in England reached the expected standard in all of their KS2 reading, writing and maths examinations, while 11% of pupils reached the higher standard (Department for Education, 2019).[17] The fact that parents perceive the chance of the hypothetical child meeting the required standard as around 60%, and sinigificantly below the national average for 2019, could reflect the fact that respondents perceive home schooling and online learning as less effective than in-person teaching.[18] Looking at long-term child outcomes, the expected earnings of the child at age 30 are around £34,000 and again the figure does not differ across scenarios (p-value = 0.335). Beliefs about expected earnings are in line with findings from previous studies that have used a similar elicitation method

[17] To reach the expected standard in all KS2 reading, writing and maths examinations, pupils must achieve a scaled score of at least 100 in their reading and maths tests and an outcome of 'reaching the expected standard' or 'working at greater depth' in the writing assessment. To reach the higher standard, a pupil must achieve a scaled score of at least 110 in their reading and maths tests, and an outcome of 'working at greater depth' in the writing assessment.

[18] In response to the COVID-19 pandemic, the Department for Education cancelled the 2019/20 national curriculum assessments. It is therefore not possible to assess how the first months of school closure have affected the performance of children in their KS2 examinations.

to examine the role of parental beliefs about the production technology for child outcomes (see, e.g., Boneva and Rauh, 2018; Attanasio et al., 2020). Remarkably, parents are also close in their estimates to the true average: the median annual pay for full-time employees was £31,461 for the tax year ending on 5 April 2020 (Office for National Statistics, 2020).[19] Interestingly, while parents seem to be pessimistic about short-term outcomes, their answers to the earnings questions suggest that, on average, respondents do not perceive a significant earnings penalty due to COVID-19.[20]

Table 5.4: Mean beliefs for parental and child outcomes

	Maternal time		Paternal time		Difference
	Mean	St. Dev.	Mean	St. Dev.	P-val.
Parental outcomes					
Mother enjoys life	51.96	(21.72)	70.40	(20.26)	0.000
Father enjoys life	66.57	(20.64)	51.78	(22.41)	0.000
Mother can finish work tasks	46.41	(23.74)	79.86	(20.44)	0.000
Father can finish work tasks	76.92	(22.61)	51.35	(23.51)	0.000
Mother retains FT job	55.88	(23.68)	76.26	(21.00)	0.000
Father retains FT job	76.85	(21.68)	63.80	(23.37)	0.000
Child outcomes					
Child achieves KS2 standard	60.08	(19.96)	59.24	(19.69)	0.214
Earnings at age 30 (£)	34531.67	(14762.65)	34038.20	(15211.26)	0.335

Notes: Standard deviations given in parentheses. This table provides mean beliefs for the whole sample for all parental and chid outcomes. Columns 1-2 provide the mean and standard deviation of beliefs for the scenario where the hypothetical mother alone takes care of home-schooling activities for four hours every day. Columns 3-4 provide the corresponding figures for the scenario where the hypothetical father dedicates four hours every day to home-schooling activities and the mother dedicates zero hours. Mean beliefs are given on a 0-100 scale other than for expected earnings of the child, which are in pounds. The last column gives the p-value for a t-test of difference in means between the two scenarios.

Next, I calculate individual perceived returns to maternal time inputs for each respondent i. To obtain a measure of individual perceived returns to maternal time investment in terms of a given binary outcome b_n, I first calculate the perceived difference in probability that a certain outcome would occur by comparing a parent's response in the scenario where the mother alone takes care of homeschooling to the parent's response in the corresponding scenario in which it is the father who is responsible for helping the child with school work. I then divide this difference by four to compute a measure of average perceived *hourly* return to maternal time investment:[21]

$$r_{ni} = \frac{Pr(b_{ni} = 1|t_1) - Pr(b_{ni} = 1|t_2)}{4} \tag{5.1}$$

[19] Respondents were not given any information on actual average earnings.

[20] It is possible that the expected earnings of the child in the absence of COVID-19 would be higher than the average expected earnings elicited here. Participants to this study were not asked about their beliefs on how COVID-19 will affect the labor market prospects of children. Therefore, this question cannot be answered with the data at hand.

[21] The difference in maternal time investment across the two scenarios is four hours per day.

Similarly, to calculate perceived hourly returns to maternal time inputs in terms of child earnings, I take the difference between respondent i's expected log earnings in the two scenarios and divide it by four:

$$r_{Yi} = \frac{log(Y_{it_1}) - log(Y_{it_2})}{4} \tag{5.2}$$

Panel (a) of Figure 5.4 shows respondents' perceived returns to maternal time investment in educational activities with their children, relative to paternal time inputs, for parental outcomes. More precisely, Panel (a) plots the perceived returns in terms of binary parental outcomes for the scenario where, in a hypothetical British family, the mother alone takes care of home schooling relative to the case where the father alone helps the child with school work. Positive (negative) numbers indicate a perceived benefit (cost) to the parent. Red and blue bars show perceived returns in terms of maternal and paternal outcomes, respectively. The figure shows substantial perceived costs for mothers to dedicating time to educational activities with children: for every hour that mothers dedicate to home schooling activities, their probability of enjoying life decreases by 4.6 percentage points (p.p.), the probability of finishing their work tasks is 8.4 p.p. lower and their likelihood of retaining their full-time job is around 5.1 p.p. lower. Conversely, the father's likelihood of enjoying life, finishing his work tasks and retaining his full-time job is 3.7, 6.4 and 3.2 p.p. higher for every hour that the mother spends home schooling the child.

Panel (b) instead plots average perceived returns to maternal time inputs in terms of child outcomes. The figure confirms that respondents do not perceive maternal time inputs as significantly more productive than paternal time inputs: every hour that the mother spends home schooling the child (instead of the father doing so) boosts child earnings by 0.01% on average, and the probability that the child will achieve the expected standard in his / her KS2 exam increases by 0.2 percentage points.[22]

Table 5B.3 analyzes how perceived returns to maternal time inputs vary depending on respondents' characteristics. Women perceive both the costs for mothers and the benefits for fathers as higher than male respondents, in absolute terms. Higher income individuals instead report lower perceived costs for mothers and lower perceived benefits for fathers. The number of children is also strongly predictive of more negative (positive) returns in terms of maternal (paternal) outcomes. In particular, the presence of children aged 5-10 in the household is strongly correlated with higher maternal costs in terms of being able to finish her work tasks. Child outcomes are

[22] Figure 5B.5 shows the cumulative distributions of individual perceived returns to maternal time inputs for all parental and child outcomes.

less affected by the respondent's background characteristics, with the exception of out of work parents perceiving maternal time investment as less effective in boosting the child's KS2 score.

5.5.2 Measuring perceived gender roles

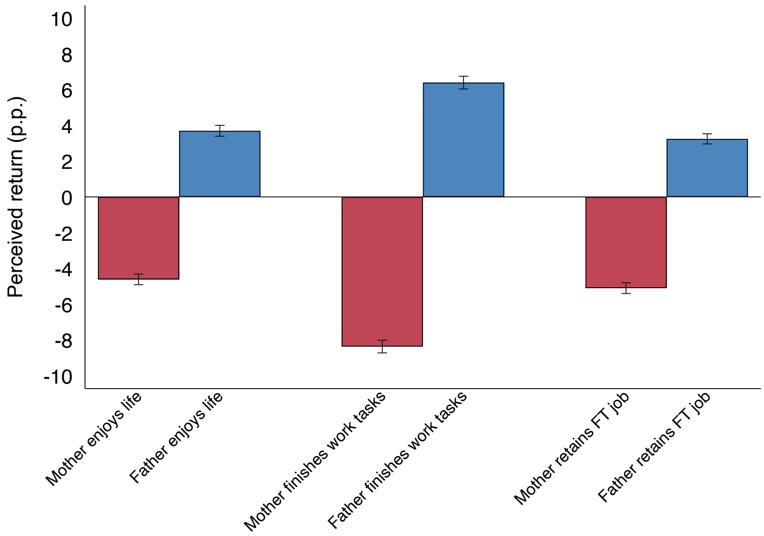
The economics literature has highlighted the importance of attitudes towards gender roles in determining how partners of opposite gender allocate their time between unpaid and paid work (see for example Bertrand et al., 2015; Ichino et al., 2019; Lassen, 2020). To gauge the extent to which respondents to my survey hold a "traditional" view of gender roles, I make use of hypothetical vignettes where participants are asked to state what share of home schooling tasks they think should fall upon the mother in a hypothetical family where both parents are working full-time. The hypothetical family in this set of vignettes is in most aspects identical to the family in the vignettes used to elicit beliefs about the returns to maternal time investment. Differently from before, however, in this set of vignettes respondents are asked to consider two cases: (i) the case where the mother's salary is higher than the father's; and (ii) the case where the father is the main earner. Salary differences between partners are randomised across respondents but kept constant within respondent. More explicitly, respondents would see the same salary difference, randomised between 2, 5, 10 and 20% first in favour of one partner and then in favour of the other. For both cases, respondents to the survey are asked what share of total parental home schooling time they think should fall upon the mother, relative to her partner. Answers are provided on a scale from 0 to 100%, where 100% (0%) corresponds to the case where the mother (father) alone takes care of home schooling.

Figure 5.5 shows respondents' opinion about the share of home schooling tasks that mothers should take care of, for different levels of earning gap between partners. Two facts emerge from this figure. First, the share of tasks respondents think mothers should do is very close to 50% on average when the hypothetical mother is the main earner in the family. Second, when the man is the breadwinner, the distribution of home schooling tasks is instead more unequal and loaded on the mother. Taking the two most extreme cases as illustrative examples, when the hypothetical mother earns 20% more than her partner, respondents believe she should take care of around 47% of home schooling activities; conversely, when the hypothetical father earns 20% more than her partner, respondents believe mothers should contribute 61% of total home schooling time.

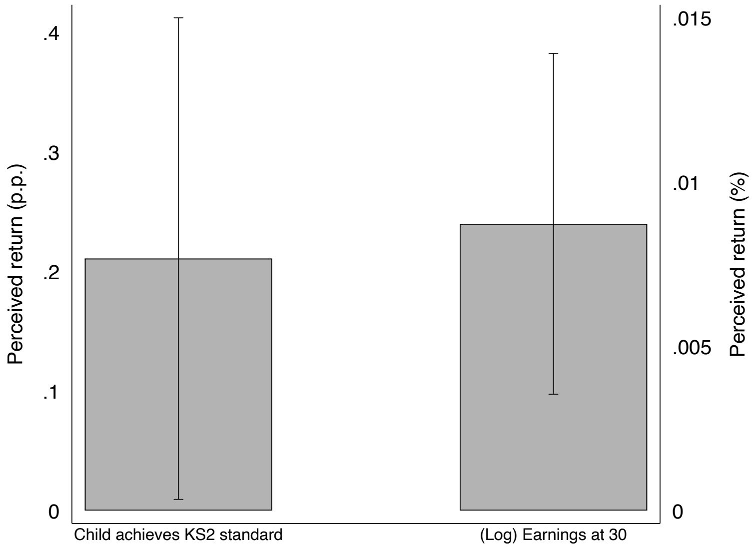
I use respondents' answers for the two different cases where the mother or the father are the main earners in the household to construct a dummy variable indicating whether respondent i holds "traditional" beliefs about gender norms. The variable takes value 1 if the average share of

Figure 5.4: Perceived returns to maternal time investment

(a) Parental outcomes

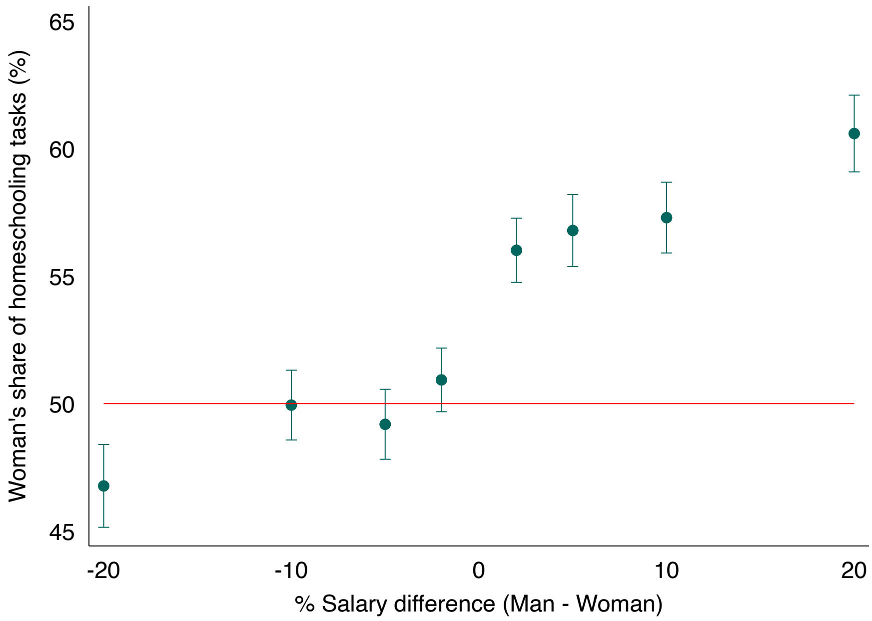


(b) Child outcomes



Notes: Panel (a) shows the average perceived returns to maternal time investment relative to paternal time investment for various paternal and maternal outcomes. Panel (b) shows the average perceived returns for child outcomes. Returns are calculated as the difference between the perceived probability that a given outcome will occur under the scenario where the mother alone takes care of home schooling, and the corresponding probability under the scenario where the father alone is responsible for home schooling the child. For perceived returns in terms of child earnings, these are calculated as the difference in log earnings between the two scenarios. Black caps represent 95% confidence intervals.

Figure 5.5: Perceived gender roles



Notes: The green circles show the average share of tasks respondents think the hypothetical mother should do, relative to her husband, for different levels of salary difference between father and mother. Caps represent 95% confidence intervals.

tasks the respondent thinks the mother should take on across the two scenarios is higher than 50%, and 0 otherwise. 47% percent of parents in my sample are classified as "traditional" or conservative in their opinion about the allocation of time to educational activities with children within the family.[23]

Table 5B.4 shows how respondents' attitudes towards gender roles vary with their background characteristics. The main finding emerging from the table is that women display higher levels of conservatism than men. Results from Column (2) show that the share of home schooling tasks that respondents think the hypothetical mother should do when she is the main earner in the couple is 3 percentage points higher for female respondents compared to male participants. Similarly, as shown in Column (3), women are 9 percentage points more likely to have traditional opinions about gender roles.

[23] 19% of the sample holds 'non-traditional' values (i.e., this group thinks the hypothetical father should home school more than the mother, regardless of the earnings gap). 34% of respondents can be classified as 'pragmatic', with the ideal maternal share of home schooling tasks moving symmetrically around 50% across the two scenarios.

5.5.3 Beliefs and changes in gender gaps

Next, I turn to the question of whether parental beliefs about returns to maternal time investment and attitudes towards gender roles contribute to explaining the change in the way parents of opposite gender share home schooling activities within families during the COVID-19 pandemic. Table 5.5 examines the role of different sets of variables in explaining changes in the home schooling gender gap between February and June 2020. Column (1) only includes as controls region fixed effects, parental beliefs about gender roles and perceived returns to maternal time investment. Changes in the home schooling gender gap are strongly associated with beliefs about parental life satisfaction: the lower the perceived cost for mothers in terms of life satisfaction, and the higher the perceived benefit for fathers, the more the gender gap in home schooling activities increases during the pandemic. In addition, perceived returns in terms of paternal productivity at work are positively associated with increases in the home schooling gender gap. Finally, attitudes towards gender roles are strongly correlated with changes in time use during the pandemic: in households where the respondent is classified as "traditional" in their opinion about gender roles, the increase in gender gap in home schooling time was around 20 minutes larger.[24]

Column (2) additionally controls for household characteristics. The results indicate that parental income and education are important determinants of changes in time allocation within families during the pandemic. In particular, and not surprisingly, maternal income is negatively correlated with changes in the gender gap in home schooling time. Further, families with children aged 5-10 saw larger increases in the home schooling gender gap than families with children in older or younger age ranges. When controlling for household characteristics, the coefficient estimates associated with parental beliefs remain qualitatively unchanged.[25]

Finally, Column (3) further controls for indicators of family types based on the employment status of parents in February and June 2020. Controlling for changes in the employment situation of both partners in the household does not alter the magnitude or the significance of the coefficients associated to the beliefs variables. Perceived gender roles in particular remain a strong determinant of changes in the home schooling gender gap.[26] Table 5B.7 examines heterogeneity

[24] Table 5B.5 shows equivalent regression results where beliefs about gender roles are measured with a continuous variable capturing the average share of home schooling activities respondents believe the hypothetical mother should do across the two scenarios.

[25] For the full set of coefficients of variables not displayed in Table 5.5, see Table 5B.6.

[26] Besides contraints imposed by working hours, household characteristics and differences in perceived beliefs, differences in individual preferences may also affect the way in which parents allocate their time across different activities. Figure 5B.6 plots answers to how much the survey participants report enjoying different activities, separately for male and female respondents. While women report enjoying childcare significantly more than men, and market work significantly less than male respondents, differences by gender in self-reported preferences for

in the importance of beliefs in explaining changes in the home schooling gender gap by gender of respondent. Interestingly, gender-role attitudes of the respondent are significant determinant of changes in the home schooling gender gap only for women, but not for men. All other coefficients for perceived returns to maternal investment are similar across genders, with the exception of perceived paternal life satisfaction, which is more strongly correlated with changes in gender gaps in families of male respondents than it is for the households of female respondents.

The last two columns of Table 5.5 examine whether perceived returns to maternal time investment and gender-role attitudes affect changes in the time allocation of mothers and fathers differently. Column (4) regresses the change in time spent by mothers on home schooling activities between February and June 2020 on the full set of beliefs, household characteristics and indicators for family types. Column (5) presents estimates for an equivalent regression, where the dependent variable is the change in paternal time allocation to home schooling activities. Paternal time is strongly correlated with perceived returns to maternal time investment in terms of parental life satisfaction. In particular, fathers increase their home schooling time by significantly less in households where the respondent believes there are larger benefits for fathers (and lower costs for mothers) to mothers alone taking care of home schooling. Changes in maternal time allocation are instead positively associated with returns in terms of paternal ability to complete work tasks. Lastly, mothers (fathers) increase their home schooling time by significantly more (less) in households where the respondent has traditional opinions about gender roles, but maternal time reacts more strongly to gender-role attitudes than paternal time.

Taken together, these results point to the importance of the relative contribution of partners in a couple to market work as a determinant of gender inequality in the division of childcare and its evolution over the course of the pandemic. Moreover, a consistent picture emerges where gender-role attitudes are significant predictors of changes in the allocation of time to educational activities with children between partners of opposite gender. Changes in maternal time allocation are especially responsive to attitudes towards gender roles. Perceived returns to maternal time investment in terms of life satisfaction of parents are also important, whilst perceived returns in terms of child outcomes play an insignificant role.

various activities (notably home schooling) are quantitatively small, even when significant, and thus unlikely to be the main driver of the gaps in time use that we observe.

Table 5.5: The importance of beliefs for changes in the home schooling gender gap

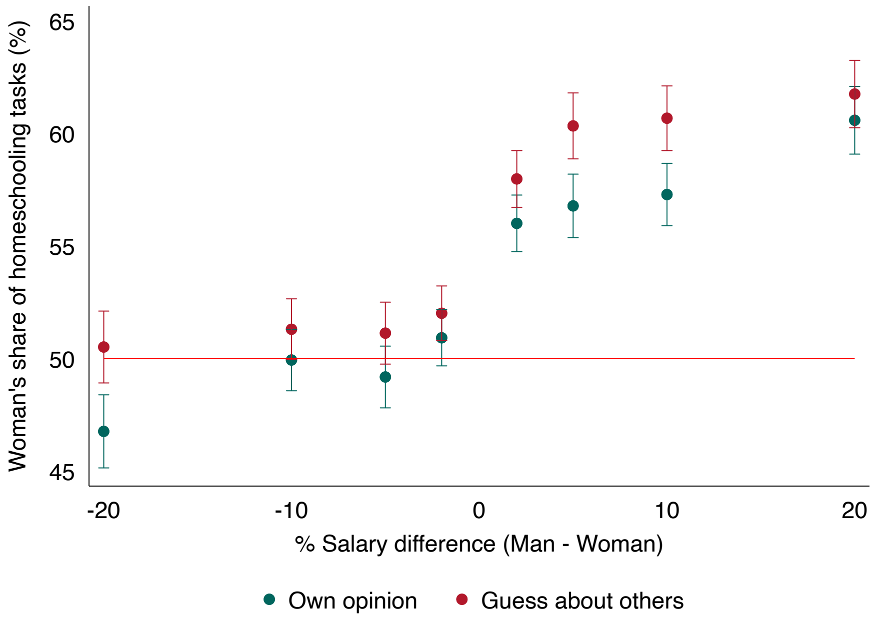
	Changes in				
	Gender gap	Gender gap	Gender gap	Mother time	Father time
Mother enjoys life	0.0210**	0.0227**	0.0212**	0.0096	-0.0116**
	(0.0096)	(0.0096)	(0.0093)	(0.0074)	(0.0057)
Father enjoys life	0.0151*	0.0162*	0.0144*	0.0039	-0.0105*
	(0.0091)	(0.0090)	(0.0088)	(0.0074)	(0.0056)
Mother can finish tasks	-0.0118	-0.0113	-0.0068	0.0010	0.0078
	(0.0086)	(0.0085)	(0.0085)	(0.0071)	(0.0052)
Father can finish tasks	0.0185*	0.0139	0.0160*	0.0241***	0.0081
	(0.0096)	(0.0096)	(0.0096)	(0.0082)	(0.0059)
Mother retains FT job	0.0066	0.0050	0.0019	0.0030	0.0011
	(0.0098)	(0.0096)	(0.0094)	(0.0076)	(0.0057)
Father retains FT job	-0.0054	-0.0042	-0.0081	-0.0140	-0.0059
	(0.0113)	(0.0110)	(0.0109)	(0.0089)	(0.0061)
Child achieves KS2 std.	-0.0017	-0.0027	0.0029	0.0075	0.0046
	(0.0112)	(0.0110)	(0.0110)	(0.0093)	(0.0066)
Child earnings at age 30	-0.5084	-0.3610	-0.3744	-0.1779	0.1965
	(0.3897)	(0.4046)	(0.4033)	(0.3231)	(0.2752)
Traditional gender roles	0.3377***	0.3142***	0.2771***	0.1865***	-0.0907*
	(0.0840)	(0.0828)	(0.0806)	(0.0673)	(0.0501)
Mean dep. var.	0.403	0.403	0.403	0.887	0.485
Observations	1647	1647	1647	1647	1647
R^2	0.029	0.060	0.117	0.082	0.084
Region F.E.	✓	✓	✓	✓	✓
Household characteristics	✗	✓	✓	✓	✓
Labour market controls	✗	✗	✓	✓	✓

Notes: OLS regressions. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. The dependent variable in Columns (1) to (3) is the change in gender gap in time dedicated to home-schooling activity, between February and June 2020. The gender gap for each period is calculated as the difference between maternal and paternal time devoted to educational activities with children, and expressed in number of hours per day. Positive (negative) coefficients correspond to an increase (decrease) of the gender gap over time. The dependent variables in Columns (4) and (5) are the change in maternal and paternal time allocation to home schooling activities between February and June 2020, respectively. Labour market controls include indicators for different family types, where types are defined based on changes in labour market outcomes of both parents between June and February 2020, as well as indicators for whether the mother or father is a key worker. Household characteristics include age and income of both partners, indicators for partners having a university degree, the number of children in the household and indicators for the presence of children aged 0-4 and 5-10.

5.5.4 Own and others' perceived gender roles

Beyond respondents' own attitudes, recent work in economics shows that individuals' behavior might be driven by their perceptions about the opinions of others. In the context of gender norms, Bursztyn et al. (2020) offer a powerful example of how correcting men's beliefs about others' support for female labor force participation increases married men's willingness to let their wives join the labor force. Thus, evaluating the extent to which respondents' own opinion about gender roles differs from their perceptions about the attitudes of others may offer insights

Figure 5.6: Perceived gender roles and perceived opinion of others



Notes: The green circles show the average share of tasks respondents think the hypothetical mother should do, relative to her husband, for different levels of salary difference between father and mother. The red circles represent the average respondents' guess about the opinion of other survey participants. Caps represent 95% confidence intervals.

into possible interventions that could affect parental behavior. As detailed above, I measure respondents' gender-role attitudes by asking them what share of home schooling tasks they think a hypothetical mother in a two-parent family should do in the context of school closures. In addition, to measure how respondents perceive the opinion of others with respect to gender roles, participants to the survey are also asked to guess the average answer of other survey participants. Modest incentives were given to encourage accurate guessing.[27] By comparing respondents' opinions about gender roles to their guesses about the opinions of others, I can examine misperceptions in attitudes towards gender roles among parents in England. Figure 5.6 replicates Figure 5.5, with the addition of red dots representing respondents' guess about the share of home schooling tasks others think the mother should take care of, for different levels of earning gap between partners. The figure shows that on average individuals believe other suvery participants are more conservative than they are when it comes to gender roles within the household.

[27] Respondents were randomly drawn to receive an extra compensation of £5 if their guess about the opinion of others was less than 2 percentage points away from the sample average of own opinions.

An interesting question that emerges when discussing respondents' perceptions of social norms related to gender roles is how accurate individuals are in their guess about what others believe. Comparing the average share of tasks respondents think mothers should take care of to individual participants' guess about the answer of other survey respondents allows me to analyze the accuracy of parents' beliefs about gender norms. In my sample, 47% of survey respondents strictly over-estimate social norms related to gender roles. The average difference between respondents' guess about the answer of others and respondents' actual answers is 2.26 percentage points.[28] These results point to potential biases in perceptions of gender norms that could contribute to a suboptimal division of labor within couples in the case where deviating from widespread attitudes towards gender roles generates substantial disutility. Given that gender-role attitudes play a strong role in the decision-making process of couples, there could be scope for changing parental behavior through information interventions aimed at correcting individuals' misperceptions about gender norms.

[28]Figure 5B.7 shows the distribution of wedges in perceptions, calculated as respondents' guess about the answer of others minus the average answer of survey respondents to the questions on the share of home schooling tasks the hypothetical mother should do relative to her partner.

5.6 Discussion

5.6.1 What are beliefs capturing?

This paper examines the role of beliefs about gender norms and productivity of maternal time investment in explaining the fact that, during the first UK lockdown, mothers have been at the receiving end of the additional childcare responsibilities caused by the COVID-19 pandemic. There are three potential concerns for the external validity of the belief measures presented here. First, parental perceptions elicited in June 2020 may be influenced by the current situation parents are living in, and may not generalise to normal circumstances. In particular, beliefs about child outcomes could incorporate parental perceptions on the effect of home schooling on children's educational attainment and future labor market outcomes. Indeed, as shown in section 5.5.1, participants to this study are relatively pessimistic about the school performance of children relative to actual exam results. Similarly, beliefs about parental outcomes may reflect respondents' opinion about the long-term consequences of the COVID-19 crisis on the labor market (and how these may differ by gender). In the absence of data on parental beliefs before the pandemic, whether or not the measures of beliefs that I present here have external validity beyond pandemic times cannot be verified. Collecting more data on parental beliefs at the end of the pandemic is an important next step.

Second, parental beliefs where elicited by asking respondents about a hypothetical family, rather than the respondents own family. This methodology has the advantage that I can abstract from differences across respondents (and their households) when varying parental inputs into home schooling across scenarios (see section 5.2.2). However, one potential disadvantage of this approach is that respondents can make assumptions about the (unobserved) characteristics of the hypothetical family they are presented with, which may influence their answers to the questions on parental and child outcomes.[29] In the context of this study, respondents may have attributed preferences and behaviors to the hypothetical family of the scenarios based on the fact that both hypothetical parents were described as working full time. For example, if respondents assumed that a mother who works full time enjoys paid work relatively more (and unpaid work relatively less) than women with lower work hours, this could have led to an overestimation of maternal costs in terms of life satisfaction arising from her spending four hours every day home schooling her child. Similarly, respondents' attitudes towards gender roles might reflect their beliefs as

[29] See also Delavande (2014) for a discussion of how the wording of hypothetical questions affects respondents' answers about their mortality expectations.

applicable to the specific context they are presented with. To the extent that couples where the mother works full time could be perceived as less conservative in the way in which paid and unpaid work is divided among partners, elicited attitudes towards gender roles may underestimate the actual level of conservatism among survey participants. The hypothetical scenario approach used in this chapter does not allow to isolate the component of respondents' beliefs that arises from inference about the characteristics of the hypothetical family that features in the scenarios. Future work could exploit a within-subject design to explore how the elicited perceived returns and costs to maternal time investment, as well as attitudes towards gender norms, vary with the characteristics of the hypothetical family respondents are presented with. With this caveat in mind, the fact that recent literature on perceived returns to parential investment finds a strong correlation between elicited beliefs and actual investment decisions lends credibility to the hypothetical scenario approach (see for example Boneva and Rauh, 2018; Attanasio et al., 2020; Biroli et al., 2020b).

Finally, parental attitudes towards gender roles measured in June 2020 may have been influenced by the forced changes to both work and daily life that the pandemic brought about. Previous evidence shows that, already before the pandemic, gender norms were slowly evolving towards increased support for less traditional gendered division of paid and unpaid work (Fortin, 2005; Bertrand, 2018). The large labor market shocks induced by the COVID-19 crisis may have accelerated this evolution, especially in families were fathers have stopped working and are forced home. If that were the case, my measures of beliefs about gender roles, and potentially beliefs about perceived returns to maternal time investment, may already reflect shifts in attitudes that have been brought about by the pandemic. My estimate of the pervasiveness of traditional attitudes towards gender roles would therefore be a lower bound of the real level of conservatism in society before the advent of COVID-19. Whether the COVID-19 crisis has significantly altered the evolution of gender norms remains an important open question for future research.

5.6.2 Implications for gender equality

The results from this and other studies on the impact of COVID-19 on family life highlight an important gender difference in the impact of the pandemic: mothers are spending significantly more time on childcare activities than men, often at the expense of paid work time. As a consequence, the gender gap in childcare activities has increased during the first months of the crisis. Whether or not this larger inequality will persist after the pandemic is yet to be understood. In my survey, I ask respondents whether they think the future allocation of childcare will remain the same as it is now, or whether it will become more or less unequal as a result of the pandemic. 68% of respondents believe the future allocation of childcare will remain the same as it is now, and 26% believe it will become more equal. While only 6% think the split of childcare tasks will become more unequal, women are significantly more pessimistic, with 7% of female and 4% of male respondents thinking inequality in the division of childcare will increase in the future.

The survey also includes a question aimed at investigating the future consequences of the current pandemic on the labor force participation of parents. In-work respondents are asked whether they (and / or their partner) are considering quitting their job or substantially reducing their working hours to care for their children. Around 10% of working parents in my sample report considering reducing their work hours (partially or entirely) due to childcare responsibilities. Alarmingly, women are significantly more likely to consider dropping out of the labor force or reducing their work time than men (12% vs 8%, p-value: 0.0035). This finding echoes results from Adams-Prassl et al. (2020a) that show that furloughed mothers have been more likely than furoughed fathers to initiate the furloughing decision, and suggests that future waves of coronavirus may exacerbate the gender gap in the labor market impact of the pandemic through an increased childcare burden placed on mothers. The provision of adequate support to working parents is therefore paramount to mitigate the already large negative consequences for women in the labor market.

5.7 Conclusion

In this paper, I exploit novel survey data from the UK to document the impact of the pandemic on the time use of parents of school-aged children in opposite-gender couples. I show that the gender gap in time dedicated to educational activities with children has significantly increased in the first months of the pandemic relative to February 2020. Part of this change can be explained by the differential impact of the pandemic on the labor market outcomes of men and women: female survey respondents are more likely to have stopped working between February and June 2020, and gender gaps in home schooling activities are largest (smallest) in families where only the mother (father) has stopped working at some point between February and June. However, even in families where mothers are in work and fathers have stopped working, mothers continue to spend at least as much time on educational activities with children as fathers do.

This gendered division of home schooling activities could be driven by parental beliefs about who should do what in the household, or who is better at performing certain tasks. In the second part of the paper, I present novel evidence on parental beliefs about the returns to maternal, relative to paternal, time investment in home schooling activities and parental attitudes towards gender role. The new data show that parents perceive substantial costs to spending time home schooling children for mothers, and substantial benefits to delegating this task for fathers. Looking at attitudes towards gender roles, I find that almost 50% of my sample holds traditional beliefs about the share of home schooling tasks mothers should perfom.

I then turn to examining the role of beliefs about returns to maternal (*versus* paternal) time investment and gender-role attitudes in explaining changes in the home schooling gender gap during the first UK lockdown. Whether or not respondents hold a traditional opinion about gender roles is found to be strongly and positively correlated with changes in the gender gap in home schooling activities, over and beyond the effect of changes in labor market status of the parents. Finally, I show that respondents on average over-estimate the extent to which others support a traditional split of educational childcare tasks within the household, which suggest that information interventions may have the potential of changing parental behavior through their effect of parents' own beliefs about gender roles. The evidence presented here highlights the importance for policies to take into account the heterogeneity in the impact of the COVID-19 pandemic across genders, and to provide parents with adequate support in the form of childcare.

Appendices of Chapter 5

5A Data Description

Table 5A.1: Distribution of respondents across regions in England (%)

Region	Sample	National
North East	4.99	4.83
North West	13.13	13.04
Yorkshire and the Humber	9.92	9.80
West Midlands	10.53	10.47
East Midlands	8.75	8.65
South West	10.31	10.22
South East	16.51	16.30
East of England	10.97	11.05
Greater London	14.90	15.64

Notes: National figures refer to the latest available estimates for the population of residents aged 18 or above and come from the Office for National Statistics. Data source: Office for National Statistics (2019).

Table 5A.2: Full sample characteristics

	Mean	St. Dev.	N
Female	0.495	0.500	1805
Age	42.978	8.184	1805
University degree	0.542	0.498	1805
In work - June 2020	0.666	0.472	1805
Key worker	0.370	0.483	1202
In work - Feb 2020	0.837	0.370	1805
Stopped working	0.216	0.412	1510
Number of kids	1.879	0.770	1805
Age youngest child	8.695	4.439	1784
Opposite-sex couple	0.976	0.153	1805

Notes: The variable "In work" takes value 1 for respondents who reported being in paid work (either full time or part time) in the reference period (either the week before the interview or February 2020). The variable "Key worker" takes value 1 for in-work respondents who report being employed as essential workers. "Stopped working" takes value 1 for respondents who were in work in February 2020, either full time or part time, but report being out of paid work or on furlough in the week before data collection.

Table 5A.3: Final sample characteristics - Comparison with UKHLS data

	UKHLS			Survey		
	Mean	St. Dev.	N	Mean	St. Dev.	N
Female	0.499	0.500	1851	0.490	0.500	1723
Age	42.473	7.170	1851	43.109	8.180	1723
University degree	0.376	0.484	1758	0.540	0.499	1723
In work - June 2020	0.705	0.456	1851	0.665	0.472	1723
Key worker	0.542	0.498	1354	0.363	0.481	1145
In work - Feb 2020	0.875	0.331	1850	0.836	0.371	1723
Stopped working	0.210	0.408	1627	0.216	0.412	1440
Number of kids	2.203	0.886	1851	1.875	0.766	1723
Age youngest child	8.186	4.056	1851	8.730	4.437	1703

Notes: The first three columns present the characteristics of respondents to the June 2020 wave of the UKHLS Covid-19 module. The sample is restricted to married or cohabiting individuals with school-aged children. Cross-sectional survey weights are used to compute the summary statistics. Columns (4) to (6) refer to the restricted sample from my survey data. The variable "In work" takes value 1 for respondents who report being in paid work (either full time or part time) and not on furlough in the reference period (either the week before the interview or February 2020). The variable "Key worker" takes value 1 for in-work respondents who report being employed as essential workers. "Stopped working" takes value 1 for respondents who were in work in February 2020, either full time or part time, but report being out of paid work or on furlough in the week before data collection.

Table 5A.4: Characteristics of households

	Mean	St. Dev.	N
Mother in work - Feb.	0.780	0.414	1723
Father in work - Feb.	0.921	0.270	1723
Mother in work - June	0.587	0.492	1723
Father in work - June	0.788	0.409	1723
Both partners in work - June	0.490	0.500	1723
Both partners out of work - June	0.115	0.320	1723
Mother key worker	0.439	0.496	1012
Father key worker	0.354	0.478	1357

Notes: The variable "In work" takes value 1 for respondents who reported being in paid work (either full time or part time) in the week before the interview, and 0 if the respondent reports being on furough or otherwise not working. The variable "Essential worker" takes value 1 for respondents who reported being employed as key workers in June 2020. "Stopped working" takes value 1 for respondents who were in work in February 2020, either full time or part time, but report being out of paid work or on furlough in the week before data collection.

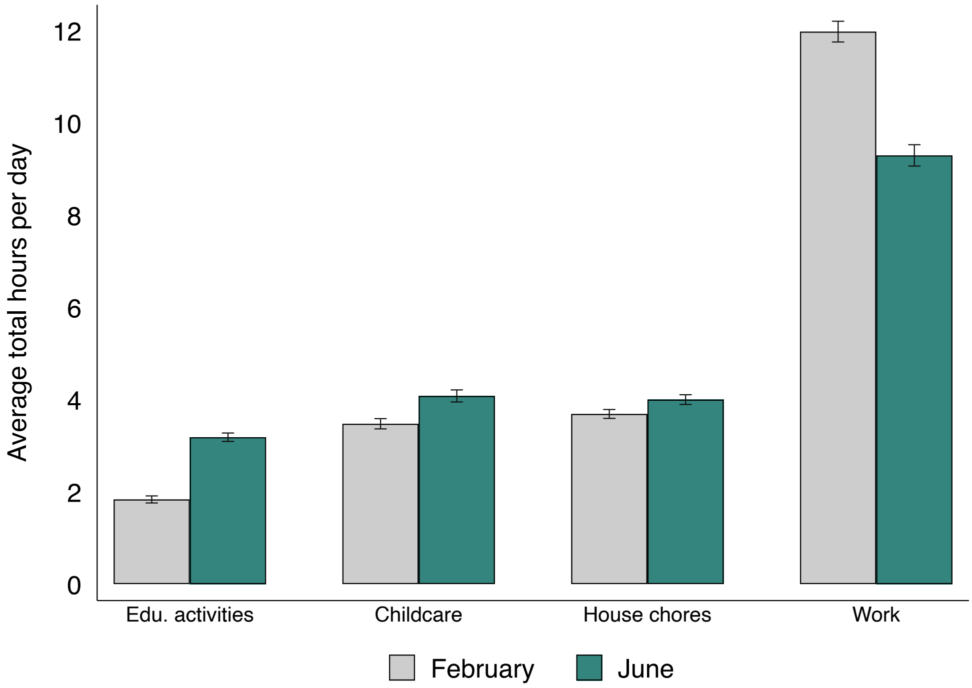
Table 5A.5: Distribution of households by family type

Family type	Share (%)
Mother stopped working - Father works	15.0
Mother stopped working - Father out of work	1.0
Father stopped working - Mother works	7.2
Father stopped working - Mother out of work	2.5
Both stopped working	4.5
No change - Mother in work	50.1
No change - Mother out of work	18.0
Other	1.7

Notes: Parents are classified as "In work" if they were in paid work (either full time or part time) at the relevant point in time, and 0 if they were on furough or otherwise not working. "Stopped working" takes value 1 for respondents (and their partners) who were in work in February 2020, either full time or part time, but report being out of paid work or on furlough in the week before data collection.

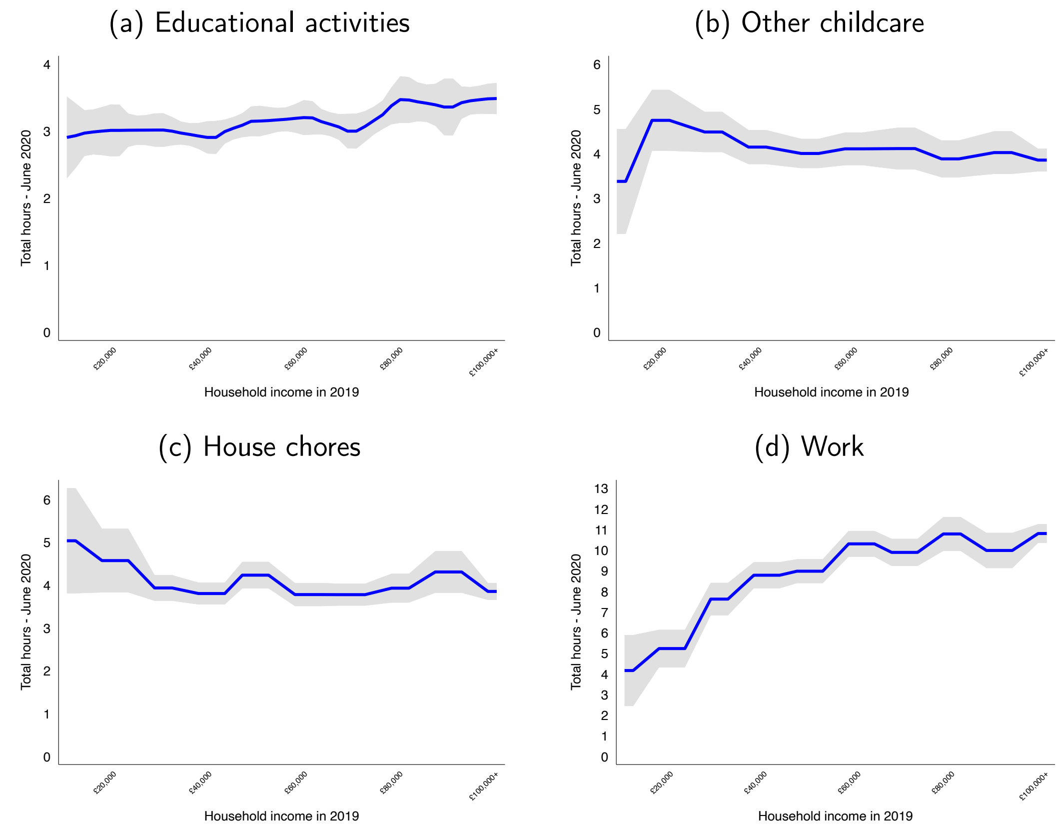
5B Supplementary analyses

Figure 5B.1: Parental time use before and during COVID-19



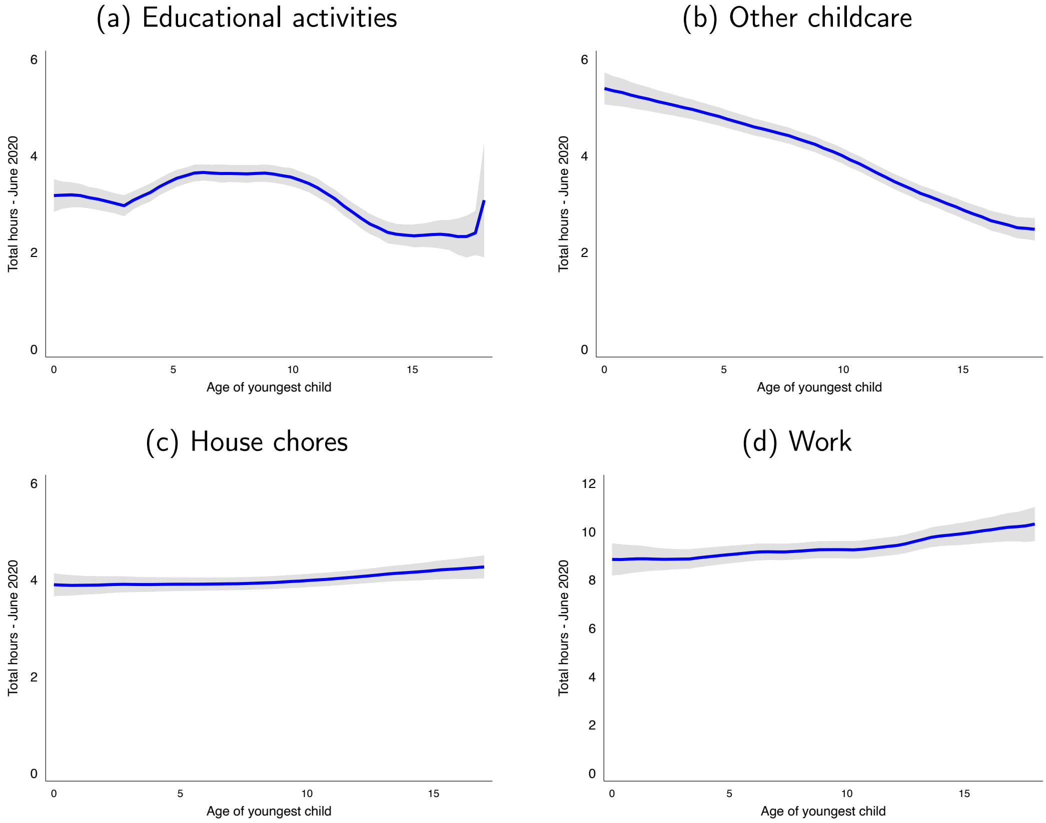
Notes: The graph shows the average number of hours respondents report they and their partner spent in total on educational activities with their child, other childcare activities, house chores and paid work. Separate bars show answers for a typical week in February (gray) and the week before data collection (green). The black caps show 95% confidence intervals.

Figure 5B.2: Total time use by household income



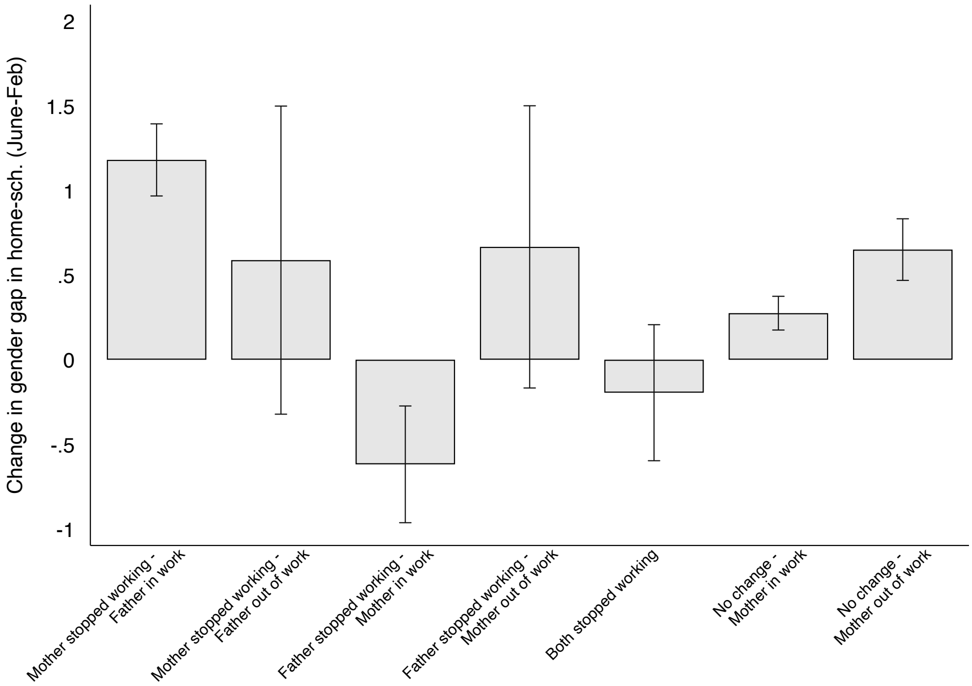
Notes: The graphs show the total number of hours respondents report they and their partner spend in total doing educational activities with their child (a), other childcare activities (b), house chores (c) and on market work (d), for different levels of household income. Household income is calculated as the sum of the respondent's income and the income of their partner in 2019. The gray area shows the 95% confidence interval.

Figure 5B.3: Total time use by age of youngest child



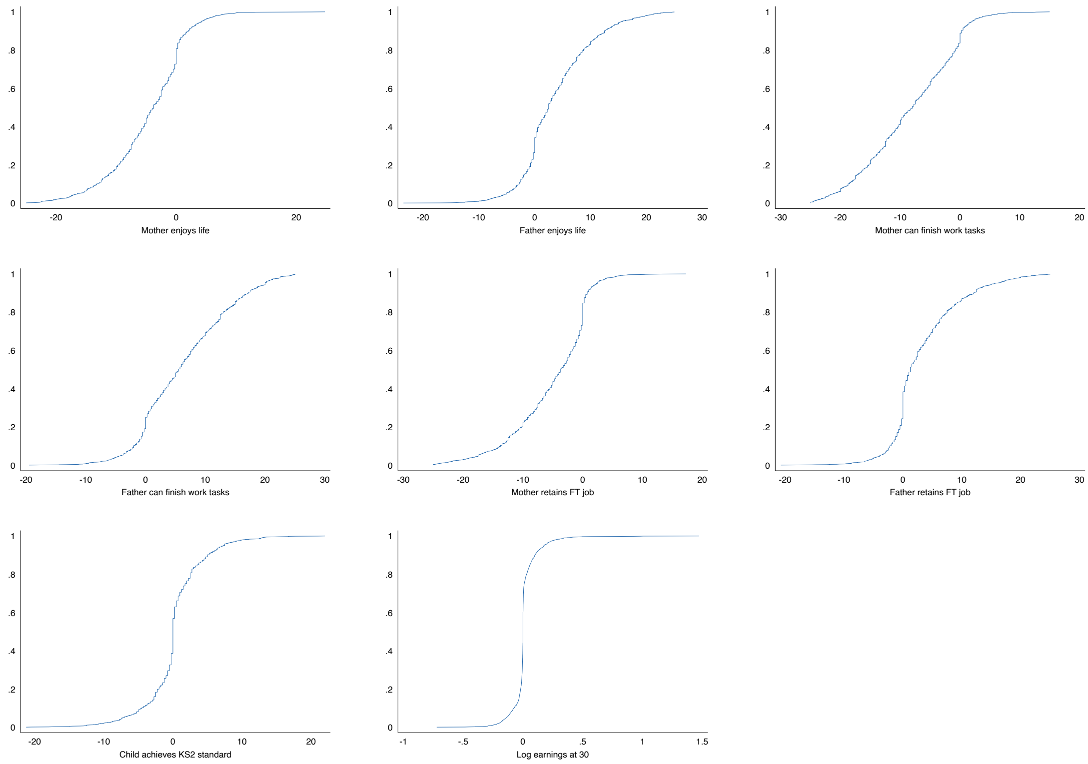
Notes: The graphs show the total number of hours respondents report they and their partner spend in total doing educational activities with their child (a), other childcare activities (b), house chores (c) and on market work (d), by age of the youngest child in the household. The gray area shows the 95% confidence interval.

Figure 5B.4: The gender gap in home schooling time by changes in labor market outcomes - Detailed groups



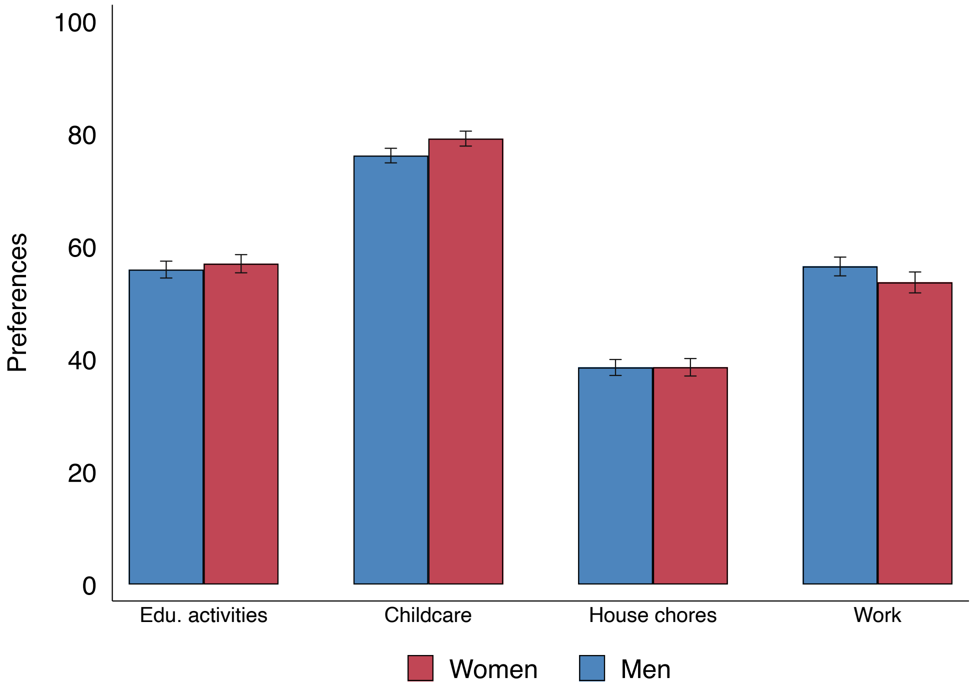
Notes: The graph shows the evolution of the gender gap in time dedicated to educational activities with children between February and June 2020. The gender gap is calculated as time devoted by the mother minus time devoted by the father, both expressed in hours per day. Positive numbers correspond to an increase in the gender gap to the disadvantage of women between February and June 2020. The gender of the two adults in the couple is identified from answers to the question about the respondent's own gender and the gender of their partner. Different bars represent households where only one parent stopped working betweek February and June 2020 (further distinguishing hoseholds depending on the employment status of the other parent) both parents stopped working, or where there was no change in the labor market status of either parent, further distinguishing between households where the mother was in work or out of work throughout. Black caps show 95% confidence intervals.

Figure 5B.5: Cumulative distribution of individual perceived returns to maternal time investment



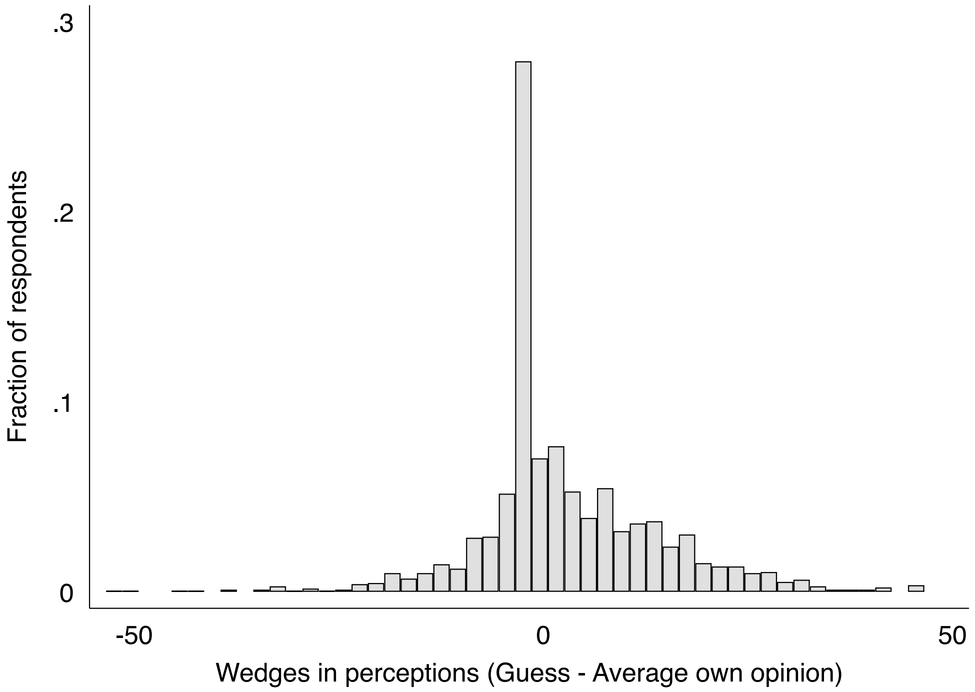
Notes: This figure shows the cumulative distribution of individual perceived returns to maternal time inputs separately for all parental and child outcomes.

Figure 5B.6: Preferences



Notes: The graph shows the respondents' average self-reported level of enjoyment, measured on a continuous scale from 0 to 100, of educational activities with their child, other childcare activities, house chores and work, separately for male and female respondents. The black caps show 95% confidence intervals.

Figure 5B.7: Wedges in perceptions of social norms about gender roles



Notes: The graph shows the distribution of the difference between respondents' guess about others' opinion about gender roles and the average opinion of survey respondents. Positive numbers indicate respondents over-estimate the extent to which others are conservative.

Table 5B.1: Determinants of pre-COVID gender gaps in time allocation

	Edu. activities	Childcare	House chores	Work
Has uni - Father	-0.1043*	-0.0829	-0.0806	-0.0084
	(0.0575)	(0.0998)	(0.1060)	(0.1917)
Has uni - Mother	0.0379	-0.0075	-0.1726	0.6061***
	(0.0572)	(0.0999)	(0.1117)	(0.1993)
Income - Mother	-0.0030*	-0.0136***	-0.0130***	0.0475***
	(0.0015)	(0.0021)	(0.0022)	(0.0045)
Income - Father	0.0007	0.0058***	0.0039*	-0.0365***
	(0.0012)	(0.0017)	(0.0021)	(0.0035)
Has children age 0-4	0.0576	0.5724***	0.2218	-0.2017
	(0.0782)	(0.1513)	(0.1507)	(0.2414)
Has children age 5-10	0.0486	-0.0654	0.0117	0.0469
	(0.0613)	(0.1019)	(0.1094)	(0.1869)
Out of work - Mother	0.1744***	0.5263***	0.9510***	-2.7948***
	(0.0578)	(0.0877)	(0.1097)	(0.2050)
Out of work - Father	-0.1036	-0.4545***	-0.6425***	1.9197***
	(0.0668)	(0.1103)	(0.1459)	(0.2523)
Constant	0.3861**	0.5925*	1.2637***	-1.9734***
	(0.1946)	(0.3310)	(0.3544)	(0.5804)
Mean of dep. var.	0.461	0.854	1.204	-2.473
Observations	1739	1744	1745	1745
R^2	0.029	0.105	0.118	0.303
Individual controls	✓	✓	✓	✓

Notes: OLS regressions. Robust standard errors in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$. The dependent variables are gender gaps in time allocation calculated as the difference between maternal and paternal time devoted to a given activity, and are expressed in number of hours per day. Positive (negative) coefficients correspond to an increase (decrease) of the gender gap. Individual controls include indicators for age groups of both partners.

Table 5B.2: The gender gap in home schooling time by changes in labor market outcomes - Detailed groups

	Gender gap	
	February	June
Mother stopped working - Father in work	0.55	1.74
	(0.88)	(1.78)
Mother stopped working - Father out of work	-0.18	0.41
	(0.81)	(1.87)
Father stopped working - Mother in work	0.50	-0.11
	(0.98)	(2.22)
Father stopped working - Mother out of work	0.88	1.55
	(1.10)	(2.68)
Both stopped working	0.47	0.27
	(1.03)	(2.03)
No change - Mother in work	0.36	0.64
	(0.97)	(1.69)
No change - Mother out of work	0.67	1.34
	(1.04)	(1.84)

Notes: Standard deviations given in parentheses. This table provides average gender gaps in educational activities with children by family type. Columns (1) and (2) refer to statistics for February and June 2020, respectively. Gender gaps are constructed as the difference between maternal and paternal time spent on educational activities with children, and are expressed in hours per day. Positive numbers indicate mothers are spending more time than fathers on educational activities with children. Family types are constructed on the basis of the labour market status of both partners in February and June 2020.

Table 5B.3: Determinants of perceived returns

	Maternal outcomes			Paternal outcomes			Child outcomes	
	Enjoys life	Finish tasks	Keep job	Enjoys life	Finish tasks	Keep job	Achieve KS2 std.	Log earnings
Female	-0.9273***	-2.2705***	-0.4376	1.6335***	2.2077***	0.3323	0.3043	0.0128*
	(0.3326)	(0.3898)	(0.3372)	(0.3426)	(0.3949)	(0.3219)	(0.2266)	(0.0068)
Age	0.0101	-0.0264	-0.0001	-0.0166	0.0201	-0.0181	0.0196	-0.0006
	(0.0225)	(0.0256)	(0.0236)	(0.0217)	(0.0238)	(0.0198)	(0.0159)	(0.0004)
Uni. degree	-0.0714	-1.1213***	-0.8495**	0.4479	1.4720***	0.5286*	0.2521	-0.0055
	(0.3263)	(0.3872)	(0.3362)	(0.3381)	(0.3980)	(0.3120)	(0.2201)	(0.0061)
Income (£'000s)	0.0182***	0.0156**	0.0135**	-0.0214***	-0.0187**	-0.0147**	-0.0084*	0.0001
	(0.0064)	(0.0073)	(0.0064)	(0.0065)	(0.0077)	(0.0062)	(0.0044)	(0.0001)
Out of work	0.0151	0.3806	-0.6388	-0.3591	-0.4327	-0.1986	-0.6158**	-0.0061
	(0.4597)	(0.5302)	(0.4704)	(0.4671)	(0.5517)	(0.4192)	(0.3133)	(0.0069)
Number of kids	-0.4258*	-0.5802**	-0.3845*	0.4012*	0.5462**	0.2210	0.0600	0.0006
	(0.2375)	(0.2513)	(0.2228)	(0.2268)	(0.2564)	(0.2118)	(0.1544)	(0.0039)
Children age 0-4	-0.0739	-0.3299	0.3651	0.2576	0.4779	0.2325	0.1944	0.0039
	(0.4389)	(0.5351)	(0.4310)	(0.4532)	(0.5420)	(0.4414)	(0.2959)	(0.0073)
Children age 5-10	-0.2991	-0.8058**	0.0439	0.0847	0.6506*	0.2498	0.1276	-0.0173***
	(0.3549)	(0.3966)	(0.3426)	(0.3486)	(0.3944)	(0.3242)	(0.2474)	(0.0060)
Constant	-3.3483**	-4.7013***	-3.0565**	3.4371**	2.5598*	2.4717**	-0.7762	0.0374*
	(1.3587)	(1.5635)	(1.4031)	(1.3470)	(1.5352)	(1.2358)	(0.9486)	(0.0211)
Mean dep. var.	-4.609	-8.381	-5.109	3.676	6.389	3.237	0.198	0.009
Observations	1713	1712	1712	1715	1712	1713	1713	1695
R^2	0.036	0.056	0.021	0.043	0.055	0.022	0.010	0.014

Notes: OLS regressions. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. The dependent variables are perceived returns to maternal time investment.

Table 5B.4: Determinants of beliefs about gender roles

	Main earner		Trad. beliefs
	Man	Woman	
Female	0.8444	2.9972***	0.0886***
	(0.7873)	(0.8052)	(0.0266)
Age	-0.0038	-0.0116	0.0013
	(0.0543)	(0.0564)	(0.0017)
Uni. degree	-1.5516**	-0.4659	-0.0507*
	(0.7490)	(0.7487)	(0.0265)
Income (£000's)	-0.0044	0.0488***	0.0008
	(0.0150)	(0.0154)	(0.0005)
In work	-0.3999	0.3847	-0.0063
	(0.8601)	(0.8736)	(0.0279)
Number of kids	-0.0551	-0.2990	-0.0200
	(0.5221)	(0.5287)	(0.0171)
Children age 0-4	-1.4319	0.0967	-0.0476
	(1.0536)	(1.0799)	(0.0348)
Children age 5-10	0.4437	-1.0634	0.0153
	(0.8213)	(0.8282)	(0.0274)
Salary difference 5%	0.9000	-1.9974**	0.0267
	(0.9707)	(0.9430)	(0.0342)
Salary difference 10%	1.1978	-1.3433	0.0234
	(0.9612)	(0.9546)	(0.0338)
Salary difference 20%	4.6407***	-4.2886***	0.0539
	(1.0035)	(1.0450)	(0.0341)
Constant	53.3537***	50.9381***	0.3534***
	(3.3948)	(3.4433)	(0.1117)
Mean dep. var.	57.671	49.240	0.476
Observations	1716	1716	1716
R^2	0.026	0.027	0.015
Region F.E.	✓	✓	✓

Notes: OLS regressions. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. The dependent variables in Columns (1) and (2) are the share of home-schooling tasks respondents think the mother should do in the scenario where the father or the mother are the main earner, respectively. The dependent variable in Column (3) is a binary indicator for whether the respondent holds traditional beliefs about gender roles.

Table 5B.5: The importance of beliefs for changes in the home schooling gender gap - Continuous measure of gender-role attitudes

	Changes in				
	Gender gap	Gender gap	Gender gap	Mother time	Father time
Mother enjoys life	0.0195**	0.0213**	0.0201**	0.0089	-0.0112**
	(0.0096)	(0.0096)	(0.0092)	(0.0073)	(0.0057)
Father enjoys life	0.0156*	0.0168*	0.0152*	0.0044	-0.0107*
	(0.0092)	(0.0090)	(0.0088)	(0.0074)	(0.0056)
Mother can finish tasks	-0.0106	-0.0101	-0.0057	0.0018	0.0074
	(0.0086)	(0.0085)	(0.0085)	(0.0070)	(0.0052)
Father can finish tasks	0.0172*	0.0126	0.0148	0.0233***	0.0085
	(0.0096)	(0.0096)	(0.0096)	(0.0081)	(0.0059)
Mother retains FT job	0.0056	0.0042	0.0011	0.0025	0.0013
	(0.0098)	(0.0095)	(0.0094)	(0.0076)	(0.0057)
Father retains FT job	-0.0055	-0.0042	-0.0082	-0.0141	-0.0058
	(0.0113)	(0.0110)	(0.0108)	(0.0089)	(0.0061)
Child achieves KS2 std.	-0.0001	-0.0012	0.0045	0.0086	0.0041
	(0.0111)	(0.0110)	(0.0110)	(0.0092)	(0.0066)
Child earnings at age 30	-0.4932	-0.3434	-0.3448	-0.1582	0.1866
	(0.3837)	(0.4008)	(0.3989)	(0.3203)	(0.2735)
Avg. maternal % of tasks	1.0034**	0.9374**	0.6920	0.4677	-0.2243
	(0.4462)	(0.4445)	(0.4469)	(0.3749)	(0.2481)
Mean dep. var.	0.403	0.403	0.403	0.887	0.485
Observations	1647	1647	1647	1647	1647
R^2	0.023	0.055	0.112	0.079	0.083
Region F.E.	✓	✓	✓	✓	✓
Household characteristics	✗	✓	✓	✓	✓
Labour market controls	✗	✗	✓	✓	✓

Notes: OLS regressions. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. The dependent variable in Columns (1) to (3) is the change in gender gap in time dedicated to home-schooling activity, between February and June 2020. The gender gap for each period is calculated as the difference between maternal and paternal time devoted to educational activities with children, and expressed in number of hours per day. Positive (negative) coefficients correspond to an increase (decrease) of the gender gap over time. The dependent variables in Columns (4) and (5) are the change in maternal and paternal time allocation to home schooling activities between February and June 2020, respectively. Labour market controls include indicators for different family types, where types are defined based on changes in labour market outcomes of both parents between June and February 2020, as well as indicators for whether the mother or father is a key worker. Household characteristics include age and income of both partners, indicators for partners having a university degree, the number of children in the household and indicators for the presence of children aged 0-4 and 5-10.

Table 5B.6: The importance of beliefs for changes in the home schooling gender gap - Continued

	Changes in				
	Gender gap	Gender gap	Gender gap	Mother time	Father time
Age - Mother		0.0122	0.0143	0.0142	-0.0001
		(0.0114)	(0.0111)	(0.0086)	(0.0076)
Age - Father		-0.0043	-0.0055	0.0031	0.0087
		(0.0100)	(0.0097)	(0.0076)	(0.0065)
Has uni - Mother		0.1075	0.1846*	0.0837	-0.1009*
		(0.0980)	(0.0977)	(0.0827)	(0.0572)
Has uni - Father		-0.3980***	-0.4113***	-0.1398*	0.2715***
		(0.0977)	(0.0977)	(0.0801)	(0.0582)
Number of kids		0.0235	0.0010	0.0238	0.0228
		(0.0595)	(0.0599)	(0.0502)	(0.0372)
Children age 0-4		0.0416	0.0410	-0.0178	-0.0588
		(0.1185)	(0.1139)	(0.0947)	(0.0686)
Children age 5-10		0.4115***	0.4144***	0.5009***	0.0864
		(0.0985)	(0.0972)	(0.0786)	(0.0639)
Income - Mother (£0000s)		-0.0714***	-0.0468**	-0.0303*	0.0165
		(0.0194)	(0.0203)	(0.0174)	(0.0127)
Income - Father (£0000s)		0.0408**	0.0282	0.0196	-0.0086
		(0.0182)	(0.0178)	(0.0154)	(0.0111)
Mother stopped working			0.6714***	0.4006***	-0.2708***
			(0.1297)	(0.1085)	(0.0726)
Father stopped working			-0.5880***	-0.1583	0.4298***
			(0.1954)	(0.1533)	(0.1167)
Both stopped working			-0.5191**	-0.1211	0.3980**
			(0.2210)	(0.1648)	(0.1599)
No change - Mother not working			0.1765	-0.0099	-0.1865**
			(0.1219)	(0.1066)	(0.0742)
Key worker - Mother			-0.3068***	-0.2060**	0.1009
			(0.1062)	(0.0864)	(0.0712)
Key worker - Father			0.1989**	0.0516	-0.1474***
			(0.0933)	(0.0807)	(0.0547)
Constant	0.2231	-0.1373	-0.1396	-0.1704	-0.0308
	(0.2498)	(0.4198)	(0.4211)	(0.3297)	(0.2985)
Mean dep. var.	0.403	0.403	0.403	0.887	0.485
Observations	1647	1647	1647	1647	1647
R^2	0.029	0.060	0.117	0.082	0.084

Notes: OLS regressions. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. The table displays coefficients for the variables not shown in Table 5.5.

Table 5B.7: The importance of beliefs for changes in the home schooling gender gap - Heterogeneity by gender

Sample	Men	Women
Mother enjoys life	0.0185	0.0193
	(0.0120)	(0.0138)
Father enjoys life	0.0264**	0.0047
	(0.0128)	(0.0118)
Mother can finish tasks	-0.0012	-0.0019
	(0.0128)	(0.0113)
Father can finish tasks	0.0163	0.0104
	(0.0161)	(0.0115)
Mother retains FT job	-0.0153	0.0153
	(0.0134)	(0.0131)
Father retains FT job	-0.0133	0.0026
	(0.0157)	(0.0146)
Child achieves KS2 standard	0.0130	-0.0082
	(0.0167)	(0.0146)
Child earnings at age 30	-0.2938	-0.6591
	(0.8217)	(0.4644)
Traditional gender roles	0.1272	0.3335***
	(0.1166)	(0.1112)
Mean dep. var.	0.114	0.706
Observations	844	803
R^2	0.119	0.143
Region F.E.	✓	✓
Household characteristics	✓	✓
Labour market controls	✓	✓

Notes: OLS regressions. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. The dependent variable is the change in gender gap in time dedicated to home-schooling activity, between February and June 2020. The gender gap for each period is calculated as the difference between maternal and paternal time devoted to educational activities with children, and expressed in number of hours per day. Positive (negative) coefficients correspond to an increase (decrease) of the gender gap over time. Columns (1) and (2) restrict the sample to male and female respondents respectively. Labour market controls include indicators for different family types, where types are defined based on changes in labour market outcomes of both parents between June and February 2020, as well as indicators for whether the mother or father is a key worker. Household characteristics include age and income of both partners, indicators for partners having a university degree, the number of children in the household and indicators for the presence of children aged 0-4 and 5-10.

5C Questionnaire

Demographics

Do you have at least one child aged between 5 and 16 living with you? Please only consider children of whom you are a parent or a guardian. [Yes, No]

Are you married or cohabiting? [Yes, No]

Which region do you live in? [Nine regions in England]

[Self and partner] *What is your age?* [Age in years, 18-99]

[Self and partner] *What is your gender?* [Male, Female, Other]

[Self and partner] *What is your highest level of education?* [No qualifications, Fewer than 5 GCSE, 5 or more GCSE, Trade/technical/vocational training, A-levels, Bachelor's degree, Master's degree, Doctoral or professional degree]

How many children aged 18 or less do you have living with you? Please count all children living in your house and of whom you are parent or guardian, including those younger than 5 and aged between 16 and 18.

[For each child] *Please specify their gender and age in years.*

[Self and partner] *Which category represents your total individual income (before taxes) in 2019? This should include money from all jobs, net income from a business or farm, and any rent, pensions, dividends, interest, social security payments or other money income you received.* [Income brackets from £10,000 to £150,000]

Hypothetical scenarios

Next, we are interested in your opinion about how important parental time is for children's future, in these unprecedented circumstances.

We will ask you to consider the situation in which, much like today, all schools in the country are closed and have moved their activities online to different degrees. In this context, we will ask you to imagine a British family, the Joneses, who have one child and have to make decisions about who will dedicate time to home schooling their only child. Both Mr and Mrs Jones work full-time.

More specifically, we will show you two scenarios and ask for your opinion on certain outcomes. The scenarios will be:

- *Mrs Jones (Sarah) takes care of all of the home schooling*
- *Mr Jones (Michael) takes care of all of the home schooling*

We know these questions are difficult. Please try to consider each scenario carefully and tell us what you believe the likely outcome to be.

Child earnings *Please think about Michael and Sarah Jones, who both have a university degree and have one child, Emma. Emma is enrolled in Year 5 in an average school in England and has achieved the expected level in the KS1 SATS.*[30]

Sarah and Michael want to dedicate 4 hours every day to home schooling their child, and can decide whether Sarah or Michael alone will take care of all the home schooling activities. Suppose they decide by rolling a dice.

Assuming that £1 today is worth £1 when the child turns 30, what do you think the child's yearly earnings at age 30 (in £, before taxes) will be, if Sarah and Michael split the home schooling responsibilities as follows? [Sliders for the scenarios described above]

Binary outcomes *Please keep thinking about Michael and Sarah Jones, who have to decide how much time each of them should spend doing educational activities with their child. How likely do you think it is that the following outcomes will occur if Sarah takes care of home schooling for 4 hours every day by herself?* [Repeat the same questions for all scenarios.]

- *The child will achieve more than the expected standard in the KS2 SATs (score above 100)*

[30] Respondents were randomised to see scenarios with a female or male child, and with different levels of educational attainment of the two hypothetical parents.

- *Sarah enjoys her life*
- *Michael enjoys his life*
- *Sarah is able to complete all her work activities*
- *Michael is able to complete all his work activities*
- *Sarah will have a full-time job one year from now*
- *Michael will have a full-time job one year from now*

Gender roles *Please keep thinking about Sarah and Michael Jones, who both work full-time and have one child. Now think about the case in which Michael earns X%*[31] *more than Sarah. With the schools closed, Sarah and Michael have to help their child with home schooling for 4 hours every day. On a scale from 0 to 100, where 0 means Michael takes care all of the home schooling by himself, and 100 means Sarah takes care of all of the home schooling by herself, please tell us:*

- *How you think Sarah and Michael should divide the home schooling responsibilities between themselves*
- *How other survey respondents think Sarah and Michael should divide the home schooling responsibilities between themselves*

We are interested in how your answers would change if now Michael earned X% less than Sarah. [Repeat two questions above with the same answer scale]

Parental time use

On an average school day last week (or the last week in which your child was home schooled), how many hours did you and your partner spend doing the following activities? Please consider only school days (Monday - Friday) and indicate a time in full hours rounding to the closest unit. [Answers in hours, separately for self and partner. A similar question was also asked in reference to a typical week in February.]

- *Doing educational activities with children*
- *Doing other childcare activities*

[31] 'X' randomised between 2, 5, 10 and 20%.

- *Doing house chores*
- *Working*

Employment

[Self and partner] *Which statement best describes your employment status in February 2020 and last week, respectively?* [Working full-time; Working part-time; Not working, furloughed; Not working, Other]

[Self and partner] *Are you a critical worker?* [Yes; No]

If schools and childcare centres remain closed until the beginning of the next academic year, are you or your partner, if applicable, considering quitting your job or significantly reducing your working hours to take care of your children? [Yes, I am; Yes, my partner is; Yes, we both are; No]

Other questions

How do you think this period of school closure will change the way in which you and your partner will divide childcare responsibilities in the future? [We will split tasks more equally than before, We will split tasks in the same way we did before the crisis, We will split tasks less equally than before]

On a scale from 0 to 100, where 0 means "Not at all" and 100 means "A great deal", how much do you enjoy doing the following activities? [Answers on a 0-100 slider]

- *Work*
- *Educational activities with child*
- *Recreational activities with child*
- *House chores*
- *Leisure time*

Thesis Conclusion

This thesis has explored the determinants of inequalities in educational investment, mental health and labor market outcomes. In the first chapter, my co-authors and I examine whether differences in beliefs about the returns to postgraduate education can explain the socio-economic gap in intentions to pursue a postgraduate degree. We show that students from different socio-economic backgrounds perceive returns to postgraduate education very differently, and that differences in perceptions can explain around 70% of the gap in intentions to enroll. Further, we provide suggestive evidence that students' experience during their undergraduate years are important for the formation of beliefs about postgraduate education, and stress the importance of providing support to disadvantaged students from early on in their studies.

In the second chapter, I investigate whether having access to a broadband Internet connection at home affects the mental health of adults in Germany. I leverage restricted access data on the coordinates of respondents to the German SOEP and combine it with publicly available information on the characteristics of the network infrastructure in Germany to construct instruments based on supply-side constraints to broadband access. The results from my instrumental variable strategy suggest that women's mental health is negatively affected by having access to DSL Internet. Consistent with the hypothesis that more frequent use of the Internet would exacerbate its negative effect on mental health, I find that the results are concentrated among the younger cohorts. I also provide suggestive evidence that the mechanism through which high-speed Internet is affecting mental health is through its impact on sleep duration.

The last three chapters of the thesis examine inequalities in the impact of the Covid-19 crisis. Chapters 3 and 4 show that the impacts of Covid-19 on the labor market have been highly unequal, both across and within countries. In particular, women have been more likely to lose their job and to be put on furlough under the UK Coronavirus Job Retention Scheme. In these chapters, my co-authors and I provide suggestive evidence that childcare responsibilities might have played a role in explaining these gender gaps. In the last chapter, I examine how stay-at-home orders and school closures have affected the time allocation of parents with school-aged children in the UK. I find evidence of a widening gender gap in time allocated to educational activities with children. I further show that beliefs about the perceived returns of maternal time investment in childcare activities and perceptions about gender roles are strongly correlated with changes in the gender gap in home-schooling time. Taken together, the results from the last three chapters contribute to our understanding of the impacts of Covid-19 on work and family life, and stress the importance of providing continued support to women.

* * *

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