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Who works in STEM? How degree field of study, gender, and parental occupation shape graduates' likelihood of working in STEM



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Abstract

This thesis explores the broad question of 'who works in STEM?' by investigating aspects of two domains: the role of higher education, which is examined by looking at the gendered association between degree field of study and field of occupation ('horizontal education-job matches'), and the role of social origin, specifically the association between parental STEM occupation and own STEM occupation ('occupational inheritance'). Possible mediators of these associations are considered throughout. The thesis makes several contributions to the literature, the most notable being (i) its focus on taking a work life course perspective, which continues to be relatively scarce both in the study of horizontal education-job matches and in the study of occupational inheritance, and (ii) its exploration of the role of social origin as a determinant of STEM work. The thesis takes a quantitative approach and explores the research questions through logistic cross-sectional and panel regressions using data from the 1970 British Cohort Study (BCS70). Firstly, examining the role of higher education, I demonstrate that gender plays an important role in shaping horizontal education-job matches in what I call 'Core STEM' fields (computer science and IT, engineering, mathematics, and the physical sciences), with women being less likely to 'benefit' from their STEM degree. This pattern persists, and even strengthens, over the work life course. However, despite being important in shaping graduates' likelihood of working in STEM, degree field of study and gender cannot explain a considerable proportion of the variance in graduates' likelihood of being found in STEM work. Hence, secondly, I turn to the role of social origin and show that occupational inheritance plays an important role in determining whether graduates work in STEM. Those with a 'STEM parent' are substantially more likely to enter STEM at labour market entry but are also more likely to leave STEM over the work life course.

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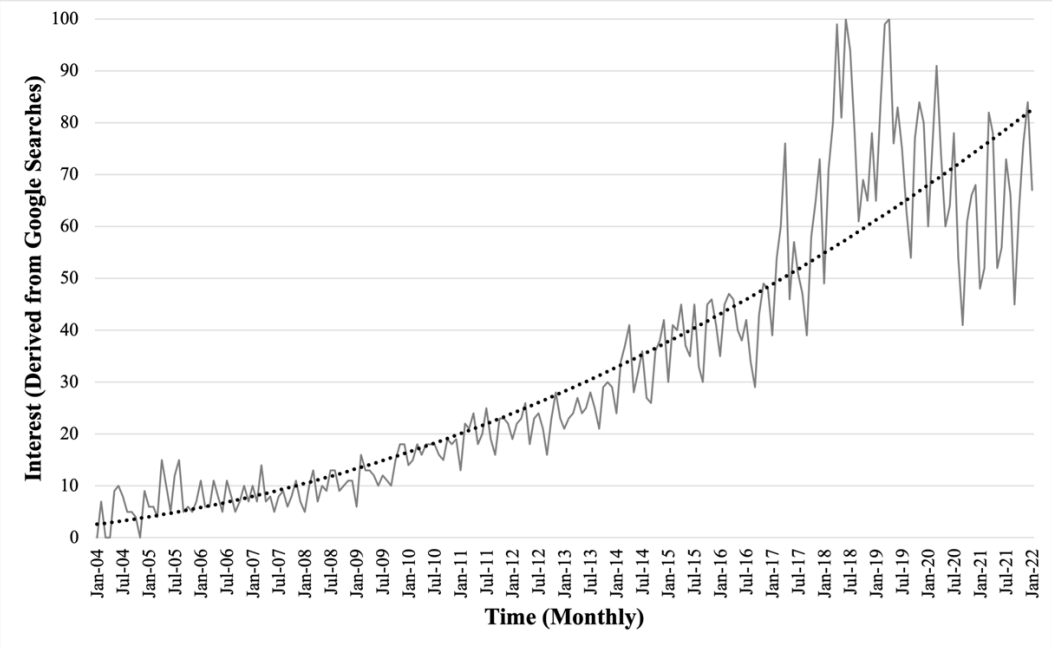
AME	……	Average marginal effect
BCS70	……	British Cohort Study 1970
CATs	……	Colleges of Advanced Technology
CLS	……	Centre for Longitudinal Studies
CNAA	……	Council for National Academic Awards
DES	……	Department of Education and Science
DESO	……	Direct Effect of Social Origin
DfES	……	Department for Education and Skills
DIUS	……	Department for Innovation, Universities and Skills
GIST	……	Girls into Science and Technology
HC Deb	……	House of Commons Debate
HEFCE	……	Higher Education Funding Council for England
HESA	……	Higher Education Statistics Agency
IT	……	Information technology
JACS	……	Joint Academic Coding System
LEMB	……	Law, economics, management, and business
LFS	……	Labour Force Survey
NCDS	……	National Child Development Study
OECD	……	Organisation for Economic Co-operation and Development
O*NET	……	Occupational Information Network
ONS	……	Office for National Statistics
OSSAH	……	Other social sciences, arts, and humanities (including languages)
SOC	……	Standard Occupational Classification
STEM	……	Science, Technology, Engineering and Mathematics
UCAS	……	Universities and Colleges Admissions Service
UGC	……	University Grants Committee
UKCES	……	UK Commission for Employment and Skills
WISE	……	Women into Science and Engineering

1. INTRODUCTION

1.1. Motivation

The concept of Science, Technology, Engineering and Mathematics (STEM) has gained increasing traction over the past couple of decades (figure 1), in large part due to government discourse and policy surrounding the field. STEM has been discussed as a policy issue in the British House of Commons numerous times in recent years, and ministers of all parties seem to be in unanimous agreement that the country should strive to increase the number of people in STEM education and consequently STEM careers.

Figure 1: Google searches for 'Science, Technology, Engineering, and Mathematics' in the United Kingdom, January 2004 - January 2024



Note: Data from Google Trends (2024). Scale: 'Numbers represent search interest relative to the highest point on the chart for the given region and time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. A score of 0 means that there was not enough data for this term.'

STEM is usually discussed in the context of a (presumed) skills shortage, the elimination of which is framed as vital to achieve increased productivity and economic growth. Hence, STEM skills play a central part in the government's industrial strategy

(HM Government 2021), and encouraging people into STEM occupations (through STEM education) has repeatedly been identified as vital for economic growth by British MPs (for example, HC Deb 19 January 2016, HC Deb 27 October 2016, HC Deb 23 March 2017). Increasing the number of people in STEM is also seen as a way of decreasing societal inequality, especially regarding gender. Such arguments are still made from an economic angle - the idea being that obtaining a STEM degree will allow women and other members of underrepresented groups 'to take full advantage of all the opportunities offered by these wonderful [STEM] careers' (HC Deb 19 January 2016). Indeed, MPs have repeatedly named the gender pay gap as a reason to encourage women into STEM (HC Deb 26 May 2016, HC Deb 27 October 2016, HC Deb 23 March 2017).

As a result, between 2007 and 2017, government departments spent almost £1 billion on initiatives that aimed to encourage more young people to consider STEM careers (House of Commons 2018). Despite the substantial amount of time and resources that have been invested in such schemes, remarkably little research has been done into the determinants of STEM work, especially in the UK setting, and therefore many of the policies around STEM seem to have been formulated based on assumptions rather than evidence. Thus, this thesis aims to shed some much-needed light on the question of *Who works in STEM?* by studying two determinants of STEM occupations; the role of higher education, and the role of parents.

Based on this policy discourse regarding STEM, the initial factor shaping one's STEM career that this thesis investigates is higher education, and degree field of study specifically. The majority of government money that has been invested into increasing the STEM work force has gone to schemes and policies regarding STEM education, with girls in particular being targeted (House of Commons 2018), because it is widely assumed that those who obtain a STEM degree enter STEM work, and that encouraging more

women into STEM education will close the gender gap in the STEM labour market. However, the (gendered) relationship between having a STEM degree and working in STEM has not been investigated thoroughly, especially in the UK context and over the work life course. Hence, the first half of my research investigates how the relationship between obtaining a STEM degree and working in STEM, both at the point of labour market entry and over the work life course, varies by gender. Doing so reveals that although degree field of study is an important determinant of being found in a STEM occupation, a large portion of the variance in field of occupation cannot be explained through people's degree field of study and its relationship with gender.

Therefore, in the second half of the thesis I turn to another, presently understudied, factor that might influence people's occupation: the role of parents, and specifically parental STEM occupation. This focus on social origin was in part informed by Torche (2011, 800), who, when investigating the relationship between family background and economic attainment among graduates, concluded that her findings 'invite theories of ascriptive sources of labor [sic] market inequality, currently focused on gender and race, to incorporate class background as a potentially relevant source of disparity' because 'social origins may be a powerful source of advantage among highly qualified workers'. Similarly, the role parents play in shaping (STEM) careers has largely been overlooked in previous research, and is a promising avenue of explaining STEM membership (Plasman et al. 2021). I choose to take a 'microclass approach' (see section 3.2.2.) and focus on parental occupation in particular rather than on parental social class more generally because of my focus on graduates, who are relatively homogenous in terms of 'big class' background. I reveal that parental STEM occupation is an important determinant of being in a STEM occupation, especially at the point of labour market entry.

Together, these findings challenge the current overwhelming focus on STEM education when determining who works in STEM. While degree field of study is undoubtedly an important precursor to a STEM occupation for many, it does not guarantee entry into and persistence in STEM, especially not for women. Furthermore, I demonstrate that there is value in approaches that do not centre education or gender, the two most commonly studied determinants of STEM work. Parental STEM occupation plays an important role in shaping STEM membership, one which should certainly not be overlooked.

Before proceeding, I wish to acknowledge two things. Firstly, the analyses presented in this thesis draw on data from the British Cohort Study (BCS70). All BCS70 respondents were born in a single week in April 1970 and continue to be traced across their life course to date (Chapter 4 discusses the data in more detail). This study was chosen due to my interest in the work life course. While BCS70 provides valuable insights into how respondents' field of work develops as their careers progress, it is important to bear in mind that the graduates studied in this thesis went to school and university in the 1970s and 1980s and entered the labour market in the early 1990s. Therefore, my findings do not fully reflect the experiences of today's STEM graduates, and it is vital to bear the historical context of the time in mind when reading this thesis, as significant changes to the education system and labour market have taken place over the past few decades. To aid with this, the following chapter will outline this context.

Secondly, although discourse surrounding STEM is often concerned with how the STEM workforce can be increased – along the lines of 'how can we get more students to study STEM?', 'how can we get more women to work in STEM?' and 'how can we address the STEM skills shortage'? – this is not the motivation of my thesis, as I am unconvinced of the need for more STEM graduates (see section 2.1.2.). Instead, I wish to

understand how certain individual characteristics (degree field of study, gender, and parental occupation) shape one's likelihood of working in STEM. I believe that this is important in itself.

1.2. Research Questions

Below, I list the research questions I address in this thesis. These will be re-introduced and discussed in more detail in each of my analytical chapters.

Analytical Chapter 1

(i) How does the relationship between obtaining a STEM degree and entry into STEM work vary by gender?

(ii) How do gender differences in the strength of association between being a STEM graduate and working in STEM develop over the work life course?

(iii) To what extent can family obligations, pay and promotion opportunities, and career interests explain gender differences in the association between being a STEM graduate and working in STEM?

Analytical Chapter 2

(i) Are graduates whose parents work in STEM more likely enter the labour market in a STEM occupation themselves?

(ii) Does the effect of having a parent in STEM on determining whether graduates enter the labour market in a STEM occupation differ by degree field of study? If yes, is it larger for STEM graduates, forming a 'boosting effect', or for non-STEM graduates, forming a 'compensatory effect'?

(iii) Through what mechanisms may parental STEM occupation influence their children's (STEM) field of occupation at labour market entry?

Analytical Chapter 3

(i) How does the strength of association between having a 'STEM parent' and working in STEM develop over the first decade of graduates' time in the labour market?

(ii) Through what mechanisms may parental STEM occupation influence their children's (STEM) field of occupation over the first decade of graduates' time in the labour market?

1.3. Contributions

The thesis makes three important and novel contributions. Firstly, in both my first and my third analytical chapters, I take a work life course perspective, examining how the association between degree field of study, gender, and parental STEM occupation develops as graduates' time in the labour market progresses. To date, the majority of studies examining education-job matches, and gender differences in STEM work in particular, have focused on cross sectional analyses, often at the point of labour market entry (for example, E. Smith 2011a; Xie and Shauman 2003). My first analytical chapter, *Gendered education-job (mis)matches in STEM: How do STEM graduates' occupations differ by gender over the work life course?,* highlights that such an approach, although not without merit, misses out a big part of the overall picture, because the association between degree field of study and STEM work varies substantially in its pattern for male and female STEM graduates. When it comes to occupational inheritance, the focus of my second and third analytical chapters, the life course perspective (in the labour market) has only been taken by Gubler, Biemann and Herzon (2017) to the best of my knowledge, and not at all in the context of STEM. As I demonstrate in my third analytical chapter, *Occupational inheritance in STEM over the work life course: The diminishing role of parental occupation*, doing so reveals patterns that a sole focus on the labour market entry misses. Both of my longitudinal chapters therefore highlight the importance of examining phenomena in a dynamic way, as the point of labour market entry, while informative, obscures insights.

My second novel contribution is the focus on the relationship between parental occupation and that of their children (occupational inheritance) in the second part of this thesis. Although not a new concept (for example, Werts 1968; Cutright 1968), the literature on occupational inheritance remains relatively scarce, especially in the context

of STEM work, where only a handful of past papers have explicitly addressed this subject (Cheng, Kopotic, and Zamarro 2017; Werts 1968; Preston 2004; Godwin, Potvin, and Hazari 2014; M.-T. Wang, Degol, and Ye 2015). Therefore, I dedicate two analytical chapters to this topic, examining occupational inheritance in STEM at the point of labour market entry and over the work life course separately. In doing so, I reveal that parental STEM occupation is an important determinant of STEM work, playing a substantial role especially at labour market entry. Furthermore, in my third analytical chapter, I demonstrate that although the point of labour market entry is particularly important in the intergenerational transmission of STEM work, the overall 'picture' changes drastically after only a few years in the labour market.

My focus on occupational inheritance furthermore allows me to contribute to two bodies of sociological literature: (i) the microclass approach and (ii) the direct effect of social origin (DESO). Both are discussed in more depth in Chapter 3, but in short, the microclass approach is a call for an increased focus on the occupation level (as opposed to aggregating occupations as is done in 'big class' schemes), and my findings suggests that this approach has merit in the context I examine. All three of my analytical chapters reveal that while parental STEM occupation shapes the likelihood of people working in STEM, none of the 'big classes' I consider do.[1] The DESO literature examines the effect of social origin on individuals' outcomes, after controlling for education. I highlight that among graduates, parental STEM occupation is an important determinant of STEM work, even when controlling for a variety of school, university, and work-level factors, but that this importance dissipates over the work life course.

[1] It should be noted that I do not mean to argue against the usefulness of 'big class' schemes as some proponents of the microclass approach do (for example, Weeden and Grusky 2005, 2012), I simply wish to highlight the supplementary value of such an approach. The lack of findings regarding 'big classes' may be due to my exclusive focus on graduates.

Finally, my focus on the UK setting is a contribution in itself, as most of the literature investigating horizontal education-job matches, DESO, and occupational inheritance is based on data collected in other (mostly European) countries, while much of the literature surrounding STEM in particular has been US-focused. Because it has been demonstrated that findings regarding all three of these concepts vary by country setting (for example, Bol et al. 2019; Bernardi and Ballarino 2016; Jonsson et al. 2009), in part due to differences in the labour market, it is vital to explore them in the UK context in particular.

1.4. Thesis Overview

In what follows, I first consider the historical context in which the respondents in my data made educational and career choices. This includes a discussion of government policy surrounding science and technology in post-WWII Britain, the (myth of the) 'STEM skills shortage', educational expansion and its implication for STEM participation, and a brief discussion of wider trends in the UK labour market.

Next, my past research and theoretical framework chapter outlines the broader debates surrounding the concepts which I address in my thesis. As aforementioned, the thesis examines two key concepts that may explain who works in STEM. Firstly, addressing the role of higher education, I outline the literature and debates on (horizontal) education-job (mis)matches, including prior research on the role gender plays in moderating these. Secondly, regarding the role that parents play in shaping their children's occupations, I discuss DESO, the microclass approach, and occupational inheritance. The sub-sections in this chapter are based on my key research questions. For example, while I explicitly discuss gender in the education-job (mis)matches section given my interest in the gendered relationship between STEM degrees and STEM

occupations, I do not do so in the sections pertaining to the role of parents, focusing instead on details that are relevant to the analytical chapters which address occupational inheritance in STEM.

Having outlined my theoretical framework, I discuss my data and methods. In this chapter I introduce my data and explain why I believe the 1970 British Cohort Study (BCS70) is appropriate for my purposes. Next, I discuss the key concept I examine in this thesis – STEM – and how it has been defined in various ways in previous literature. Specifically, I outline three common approaches of defining STEM education and work: (i) the categorisation approach, (ii) the skills approach, and (iii) the realised matches approach, before explaining how STEM will be conceptualised and operationalised in this thesis. I then introduce the variables used in this thesis and their coding. This section serves as a resource to refer back to while reading the analytical chapters, should variable definitions be unclear. This thesis utilises multiple imputation, which I also discuss in the data and methods chapter. Finally, after outlining my methodology, the chapter outlines the way in which findings will be presented and interpreted throughout my analytical chapters.

My first analytical chapter, *Gendered education-job (mis)matches in STEM: How do STEM graduates' occupations differ by gender over the work life course?,* investigates the way in which gender shapes the horizontal education-job matches and subsequent labour market patterns of British STEM graduates. I determined that while field of study has a large effect on working in STEM occupations, fewer than half of all STEM graduates enter the labour market in STEM occupations. Furthermore, when looking at a restricted definition of STEM (what I call 'Core STEM': computer science and IT, engineering, mathematics, and the physical sciences), I find large gender differences in the likelihood of STEM graduates entering STEM at the point of labour market entry,

with only one third of women doing so. Additionally, I find large gender differences in how the likelihood of being in Core STEM work develops over the work life course, with women being substantially more likely to drop out of STEM, especially at the beginning of their career. The gender differences in the horizontal education-job matches I observe are shaped by family obligations, a lack of pay and promotion opportunities in the STEM labour market, and career interests among other unobserved factors. This chapter demonstrates that while education plays a vital role in determining who works in STEM, a large proportion of the variance in STEM work is explained by other factors.

Hence, my second analytical chapter, *Does STEM work run in the family? The role of parental field of occupation in shaping graduates' entry into the STEM labour market*, focuses on an understudied factor that may influence people's entry, or lack thereof, into STEM work: the role of parents. Specifically, I examine how having a parent who works in STEM themselves influences graduates' entry into STEM work (referred to as 'occupational inheritance' or 'micro-class immobility'), how this differs by degree field of study, and what factors mediate this relationship. This has, once more, not previously been studied in the UK context, and only rarely in general. I find that having a parent in STEM doubles graduates' likelihood of entering STEM work, an effect that persists across degree subjects and only reduces slightly when controlling for a variety of possible mediator variables.

Building on this finding, my third analytical chapter, *Occupational inheritance in STEM over the work life course: The diminishing role of parental occupation,* investigates the relationship between parental occupation and STEM work further, now taking a life-course perspective exploring whether people whose parents work in STEM are less likely to drop out of STEM. I find that the gap between children of 'STEM' and 'non-STEM parents' narrows to the point of disappearing after 10 years in the labour

market, which is driven by a decreasing likelihood of being found in a STEM occupation among children of 'STEM parents' as time progresses, while the opposite is the case for children of non-STEM parents. Looking at possible mediators of the parental STEM occupation- own STEM occupation relationship reveals that part of the 'STEM parent' effect I observe can be explained through (higher) education, although work-level mediators are more instrumental in shaping this effect. A substantial 'STEM parent' effect remains in the first years following labour market entry after taking into account all mediators, which highlights the importance of parental occupation in shaping the early destinations of graduates in particular. Thus, coupled with the findings of my second analytical chapter, my thesis highlights the vital role parents play at the point of labour market entry, (indirectly) shaping their children's occupation for years.

2. HISTORICAL CONTEXT

This thesis focuses on respondents' work, from the point of labour market entry, which took place between 1989 and 2004 among BCS70 graduates, with the majority of respondents beginning their careers between 1992 and 1995. Hence, it is important to note the context in which the respondents of this study made education and career decisions.

2.1. STEM in post-WWII Britain

The contemporary narrative surrounding the concept of STEM commenced in the late 1990s and early 2000s. In 1998, as a result of growing concerns over a lack of skills among the United States' population, the National Science Foundation (NSF) introduced the acronym 'SMET' to group together the fields of science, mathematics, engineering and technology (McComas 2014), which was renamed 'STEM' in 2001 (Velarde 2019). A year later, in April 2002, the report *SET for success: The supply of people with science, technology, engineering and mathematics skills* was presented to the UK government. In it, Sir Garth Roberts 'identified a number of serious problems in the supply of people with the requisite high quality skills' and called for the government to 'continue to attract the brightest and most creative minds to become scientists and engineers' (Roberts 2002, iii). By 2006, the UK had also adopted the term 'STEM' (Barlex 2011). Since then, the term has gained increasing traction (figure 1). Therefore, despite its contemporary popularity, the people studied in this thesis made educational choices and entered the labour market prior to the conception of the term STEM, and in a somewhat different political climate. However, the governments' focus on science and technology is not unique to the 21st century, having been present throughout Britain's entire post-WWII history.

2.1.1. STEM in Post-WWII Education Policy

Following the Second World War, the position of science in Britain had been transformed as science became increasingly seen as beneficial to the public (Collins 2015). In this context, higher STEM education was viewed as vital for economic growth, which was reflected in several governmental reports calling for more trained engineers and scientists, including the Percy Report (1945) and the Barlow Report (1946). In the 1950s, the UK government under Anthony Eden introduced a number of measures to enhance technical education, including upgrading technical colleges, new Colleges of Advanced Technology (CATs), and 'gentle prods of the University Grants Committee (UGC) to shift the balance of university students from arts to sciences' (Mandler 2015a, 3). By 1960, Britain was 'the scientific and technological powerhouse of Western Europe' as a result of these government efforts (Edgerton 1996). Students were encouraged into science to meet 'national needs' and contribute towards economic growth as Britain recovered from the Second World War, at the time resulting in one of the highest tertiary education science and technology uptakes in the world in an education system that was 'dominated by the sciences' (Mandler 2020, 156).

This changed when, during reforms to the British university system in the 1960s, which was marked by rapid educational expansion (discussed in more detail in section 2.2. below), higher education became increasingly 'consumer'-driven. Rather than expanded for the sake of manpower planning, the new demand for higher education was driven by students' interests and own choices (Mandler 2020). This was in part a product of the expanding (school) education system, which did not require students to take science and mathematics courses until the National Curriculum was introduced in 1989 (Parliamentary Office of Science and Technology 2003). Hence, students who did not choose science early on in their school careers were 'locked out of' pursuing science

education when deciding to remain in post-compulsory education (Duckworth 1978). Coupled with the popularity of new courses such as 'social studies' (which included business and communications) and rising share of female students, this meant that much of the increase in higher education participation was concentrated in the arts and social sciences, rather than sciences, leading to the 'swing away from science' in the 1960s (Mandler 2015a).

The Labour government at the time, which had 'publicly proclaimed enthusiasm for technology and science' while being more cautious behind the scenes (Collins 2015, 54), initially made efforts to reverse this trend by setting up a series of committees concerned with manpower planning in the context of science and technology (A. R. Smith and Bartholomew 1988), which included appointing Fred Dainton to lead an enquiry into the decreasing share of science and technology students. However, in part based on Dainton's 1968 findings that the swing away from science was not unique to Britain, and that Britain was outperforming its European rivals in terms of numbers of science specialists (Mandler 2020), the government ultimately gave in, shifted away from manpower planning, and accepted 'that the agenda for higher education was being set by teenagers and their parents' (Mandler 2015a, 10). This focus on students' individual choices remained throughout the 1970s.

The government's priorities shifted drastically when Margaret Thatcher came to power in 1979. The 1980s, when the BCS70 cohort started to make educational choices, again saw a desire on part of the British government to expand the science and technology workforce in the name of economic growth through shaping higher education (Flanagan et al. 2019). Albeit with limited success, Keith Joseph, Thatcher's Secretary of State for Education and Science between 1981 and 1986, made efforts to increase uptake of science and technology courses at schools and universities, and the general narrative shifted from

students' individual choices to employers' needs and rates of return (Mandler 2020). For example, when the newly elected Thatcher government announced substantial cuts to higher education in 1981, they requested for science to be maintained over arts programmes, despite student demand being focused on the arts (Mandler 2015b). The government's attempts to expand the STEM student body and workforce in the 1980s included a focus on women's underrepresentation in science, and engineering in particular (DES 1980), reflecting contemporary narratives surrounding STEM.

In 1989, when the National Curriculum was introduced, science and mathematics became core (compulsory) subjects up to the age of 16 (Lawton 2008), making STEM skills a central part of the British education system ever since. Therefore, unlike today's school students, the BCS70 respondents were not yet required to take science and mathematics courses for their GCSE (or equivalent) and A-level qualifications. However, given that the number of school students taking science A-levels has not substantially changed since the 1960s (E. Smith and Gordard 2011), it is likely that this did not affect their educational choices as drastically as one may assume.

Subsequent British governments were similarly focused on manpower planning and increasing the proportion of STEM graduates and STEM workers. For example, both the Dearing Report (1997) and the Augar Review (2019) two decades later called for a focus on 'technical' education. In 2006, New Labour launched 'triple science' as a GCSE subject, allowing students to study all three school sciences (Physics, Chemistry and Biology) as separate subjects (Mandler 2020). This was motivated by the continued ambition 'to get more students to do more science, with the long term aim of increasing the supply of scientists, engineers and technologists in the workforce' (Homer, Ryder, and Donnelly 2013, 249). The 2008 financial crisis and Britain's concerns about economic recovery and competitiveness exaggerated these concerns, strengthening the

focus on STEM and the Coalition and Conservative governments that succeeded New Labour resumed the strategy of 'reach[ing] desperately to science education for solutions to economic problems […] with a vengeance' (Mandler 2020, 175).

Hence, although the acronym of STEM was not used until the early 2000s, the focus on science and technology among British policymakers was already well-established prior to its adoption. Tracing the government's attitude towards science and technology education in post-WWII Britain, Mandler (2020, 173) concludes: 'There has remained all along a powerful voice in policy circles arguing in conventional, technocratic terms – often amplified by engineering and other interested employers – for a greater focus on STEM. Although the strength of this voice may have dulled (or been muted) for periods […] it was consistently amplified by politicians' preferences for a quick fix for both educational and economic problems.'

The focus on STEM fields has consistently led to substantial government attention and spending on initiatives aimed at improving the science curriculum and increasing the number of students in STEM. It is therefore likely that at least some of the BCS70 respondents in this thesis were encouraged into science through some of these schemes, but this information was not collected by BCS70. They include the Nuffield Science Project in the 1960s, the GCSE double science award that was introduced in the late 1980s when sciences became a core part of the National Curriculum, the Curriculum 2000 (a reform of A-level examinations), the Twenty First Century Science programme, and programmes aimed specifically at girls and women, such as the 1980s Girls into Science and Technology (GIST) and Women into Science and Engineering (WISE) campaigns (E. Smith and Gordard 2011). In 2004, a review of current STEM activities revealed over 470 initiatives run by government departments and external agencies (DfES 2006). As noted in the Introduction of this thesis, substantial spending on STEM continues, as

between 2007 and 2017, government departments spent almost £1 billion on such initiatives (House of Commons 2018).

2.1.2. The (Myth of the) STEM Skills Shortage

In post-war Britain, much of the higher education policy and spending regarding science and technology was driven by a (perceived) shortage of graduates who could fill STEM jobs. This rhetoric can be traced back all the way to the 1940s and has persisted until now. This is noteworthy, as the 'STEM skills shortage' has been disputed for decades and has seemingly been kept alive by wishful thinking on part of policymakers (that an expanded science and technology workforce will fix Britain's problems) rather than evidence. For example, when writing a report on 'the flow of candidates in science and technology into higher education' in 1968, Dainton concluded that Britain was ahead of other European nations in its supply of STEM workers, but, given he had been commissioned by the British government to make recommendations on ways to increase manpower in these fields, 'he felt obliged to identify ways to raise the profile of science in the education system' (Mandler 2020, 159–60). The 2002 Roberts report similarly found that Britain had a larger share of STEM workers than other countries, but nonetheless made recommendations on how to grow the STEM workforce (Roberts 2002). Thus, the narrative that the number of students in STEM fields needed to be increased to meet labour market demands remained strong despite being contradicted by much of the evidence, including evidence provided in reports initiated with the express purpose of investigating the supply of STEM workers.

Indeed, the concept of an overall 'STEM shortage' that is widely accepted among policymakers has been widely disputed. Shortages that do exist are highly field-specific and short-lived (Xue and Larson 2015; DIUS 2009; Bosworth, Lyonette, and Wilson

2013; E. Smith 2017), but, as Lowell and Salzman (2007, 43) conclude about the US, overall 'labor [sic] market shortages for scientists and engineers are anecdotal and also not supported by the available evidence.' This sentiment is echoed by researchers studying the UK labour market, who conclude that there have been more than sufficient numbers of STEM graduates to fill vacancies in the STEM labour market for decades (E. Smith 2010; E. Smith and Gordard 2011; Bosworth, Lyonette, and Wilson 2013; E. Smith and White 2018a, 2018b). Based on this research, Mandler (2020, 172) summarises: 'There was considerable evidence that the swing away from science was not impairing economic development – that there was no 'STEM skills shortage'.' Nonetheless, today the government continues to focus on increasing STEM skills (HM Government 2021), despite a pattern of continued growth of the STEM workforce (see section 2.4.1. below).

It should be noted that although there continues to be no overall shortage of STEM graduates – with such graduates being in oversupply if anything (E. Smith and White 2018a) – there certainly were, and continue to be, shortages of women working in various STEM fields, amounting to an overall 14:11 ratio of male and female STEM workers. This shortage of women is concentrated in specific fields, however, with computer science and IT, engineering, and the planning and construction-related fields seeing especially large gender gaps. It is not the case that women are underrepresented in every STEM field, with health-related fields being female-dominated, for example (table 1). Hence, while there is a slight shortage of women in STEM overall, this is largely concentrated in traditionally 'male typed' fields, reflecting the persistence of societal gender norms.

Table 1: The share of men and women in STEM work in 2020

Sub-field of Work	Men (%)	Women (%)	N
Computer science and IT	78.4	21.6	1,581
Engineering	78.8	21.2	939
Physical sciences	55.1	44.9	303
Biological sciences	50.9	49.1	171
Medicine, dentistry and veterinary science	42.8	57.2	418
Nursing and other subjects allied to medicine	17.2	82.8	3,386
Planning and construction-related	91.4	8.6	1,969
Agriculture, forestry and other	69.7	30.3	633
STEM	55.7	44.3	9,400
Non-STEM	47.6	52.4	24,300

Note: Based on a sample of respondents in the LFS.

2.2. Educational Expansion since the 1960s

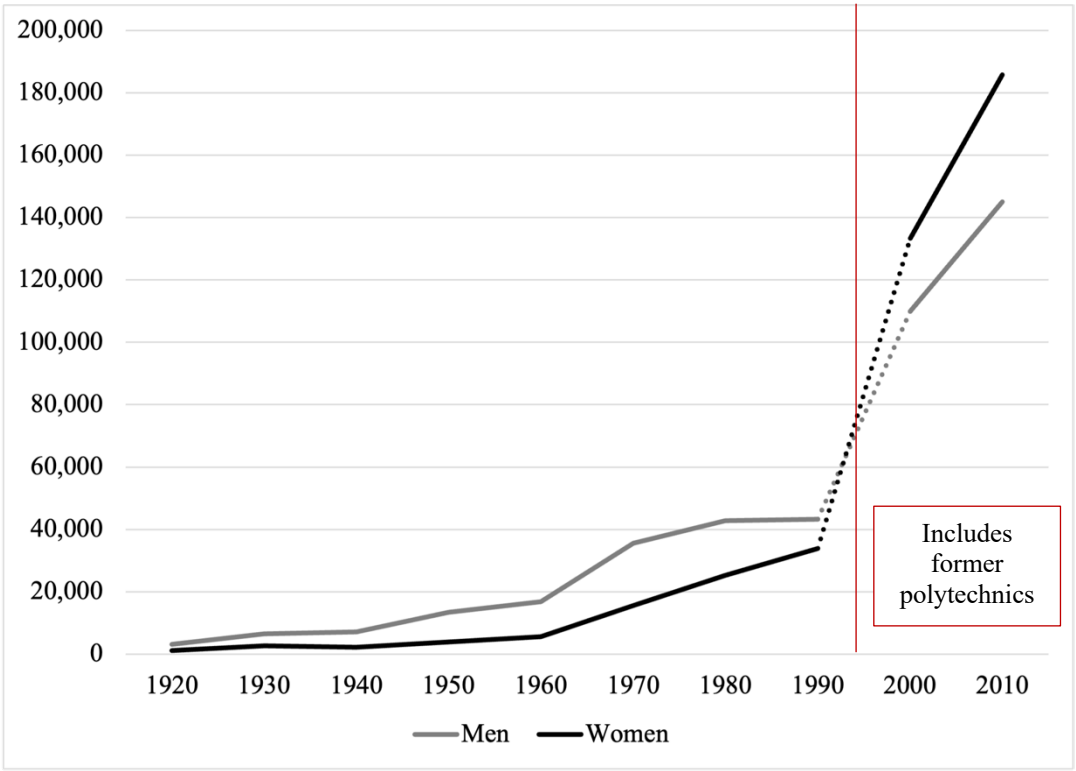
Before discussing how the share of STEM graduates has developed over the past decades, it is important to examine the expansion of higher education which took place during this period. Prior to the Second World War, going to university was reserved for only a small fraction of the British population. This was reflected in Britain's leadership, as Stanley Baldwin was the only interwar Prime Minister to have obtained a degree (Mandler 2015a). However, following the post-war expansion of secondary education, applications to higher education rapidly began to rise in the mid-1950s to early 1960s as people increasingly aspired to more education (Mandler 2015a). Soon, the university system could not keep up with the demand. While in 1956, 80% of qualified applicants were admitted to university, this had dropped down to 60% by 1962 (Mandler 2015a). This increasing demand for higher education paved the way for decades of educational expansion.

In 1961, the British government appointed Lord Lionel Robbins as chair of an expert committee to investigate ways of expanding British higher education. Following

two years of research, the committee released the Robbins report, which made recommendations based on a guiding principle (the 'Robbins principle'): 'that courses of higher education should be available for all those who are qualified by ability and attainment to pursue them and who wish to do so' (Robbins 1963). The recommendations of this report were accepted both by the Conservative government at the time, and by the Labour government that succeeded it (Mandler 2015a). The Robbins principle had long lasting effects on the British education system, which changed drastically following the report, with changes including: (i) an expansion of student numbers and funding, (ii) the creation of new universities, (iii) the transformation of CATs into universities, (iv) the establishment of polytechnics in 1965 and the Open University in 1969, (v) the establishment of the Council for National Academic Awards (CNAA) and of a new Department of Education and Science (DES), and (vi) a substantial increase in international student fees (Liang, Shepherd, and Manhire 2000).

These measures relieved the previous demand pressure on the system through an expansion in the supply of university spaces, but in turn created further demand for higher education as children increasingly aspired to go to university (Mandler 2015a). Hence, in the space of only 7 years in the 1960s, the total number of students enrolled in higher education doubled to more than 50,000 and between 1950 and 1970, overall participation in higher education grew from 3.4% to 8.4% (Bolton 2012, 14). This increase affected both male and female students. While the number of men who obtained undergraduate degrees more than doubled between 1960 and 1970, the number of women – who were substantially underrepresented in higher education at the time – almost tripled (figure 2).

Figure 2: Number of students obtaining undergraduate universities degrees, 1920-2010



Note: Based on table 8 in Bolton (2012, 20), who obtained the data from the following sources: (i) Statistical abstract for the United Kingdom 1935, Board of Trade, (ii) Annual abstract of statistics, ONS/CSO, (iii) Higher Education Statistics Agency (HESA). Students attending polytechnics are only included following 1992.

The trend of increasing higher education participation was interrupted in the 1970s, as the 'Robbins escalator' suddenly 'stopped dead' at the start of the decade (Mandler 2015a, 10).[2] It should be noted that this mainly applied to male students, who continued to make up the majority of graduates (figure 2). Hence, when the financial crisis of 1974 occurred, the Labour government at the time allowed the stagnating rate of higher education uptake to continue in an effort to keep public expenditure low while largely avoiding direct cuts to the sector (Mandler 2015a). This aversion was not shared

[2] A number of explanations have been put forward for this sudden stagnation, including a drop in the 'graduate premium' (salary advantage for graduates), high class barriers limiting the feasible rate of expansion, the development of a 'counter-school' culture, and a reorganisation of the schooling system (Mandler 2015a). Mandler (2015a, 13) additionally emphasises the instrumental nature of the changing image of universities in the media, as their presentation 'shifted sharply from golden places of uplift, aspiration and modernity to very tarnished places of conflict, rebellion and, above all, difference – a space apart from society rather than integrated into it'. This image was undoubtedly influenced by the 1968 student rebellions (Hoefferle 2013).

by Thatcher, who, having come to power in 1979, made higher education ‘a deliberate target for deep cuts’ in the context of the early 1980s recession (Mandler 2015a, 17), aiming to reduce higher education participation.

By the 1980s, the government’s attempts to shrink the higher education sector did not reflect public demand for higher education, however. After a decade of declining higher education participation, the interest in attending higher education suddenly rose sharply, possibly because students attempted to stay in education until the labour market recovered and unemployment rates declined. Because university places were subject to government cuts, much of this increased participation in higher education was concentrated in the polytechnics (which is why it cannot be seen in figure 2) (Mandler 2015a), which, by the late 1980s, ‘had become universities in all but name’ (Wilson 2022). It was clear that the stagnation in higher education participation which marked the 1970s had ended.

The Conservative government ultimately responded to public demand by making a drastic U-turn and embracing higher education. By 1989, the government had ‘ushered in the era of mass higher education’ (Mandler 2015b, 418), leading to a ‘revolution in higher-education participation in the subsequent decades’ (Mandler 2015a, 22). By 1990, overall participation in higher education had risen to 19.3%, by 2000 to 33% (Bolton 2012, 14), and by 1996, the share of women in higher education had reached 50% (Mandler 2020). This focus on higher education was continued under Tony Blair. By 2001, the New Labour government, which placed widening participation and improved retention at the forefront of their policies (E. Smith and White 2011), had set a target of 50% participation in higher education (Mandler 2015b). Higher education policy has reflected this target ever since. Subsequently, the proportion of school leavers entering higher education has continued to grow, only being curbed by the 2010 rise in tuition fees

(Mandler 2015a). As can be seen in figure 2, the redefinition of polytechnics as universities as a result of the Further and Higher Education Act 1992 has not only increased university student numbers drastically, but also contributed to a shifting gender balance in higher education.

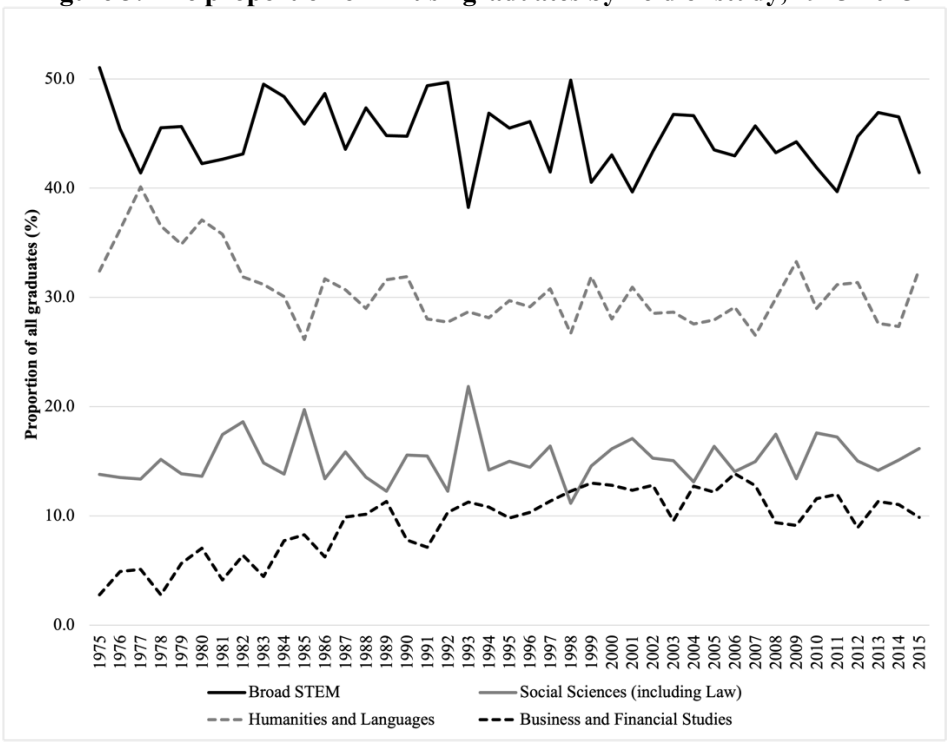
2.3. Trends in Higher Education STEM Participation

In general, educational expansion has had little effect on the proportions of students in science subjects both at school and at university. For example, although the overall number of students that remain in post-compulsory school education has increased since the 1960s, this has not substantially affected numbers of students taking science A-levels (E. Smith and Gordard 2011). The only science field that has steadily been increasing is biology, which is driven by a rise in female students taking the subject (E. Smith and Gordard 2011). In higher education, the proportion of science students remained remarkably stable at around 55% between the late 1930s and 1960s, and it was not until the 'swing away from science' that it decreased (Mandler 2015b). By 1975, the total student population was equally distributed between arts and science degrees, and, following a temporary increase of science degree uptakes in the early years of the first Thatcher government, the proportion of science graduates declined somewhat as a result of educational expansion (Mandler 2020).[3]

The trend which Mandler (2020) identifies is also reflected in figure 3, which is based on a sample of graduates in the Labour Force Survey (LFS). The figure reveals a general pattern of stability with a small reduction in the proportion of graduates completing university with a STEM undergraduate degree between 1975 and 2015. –

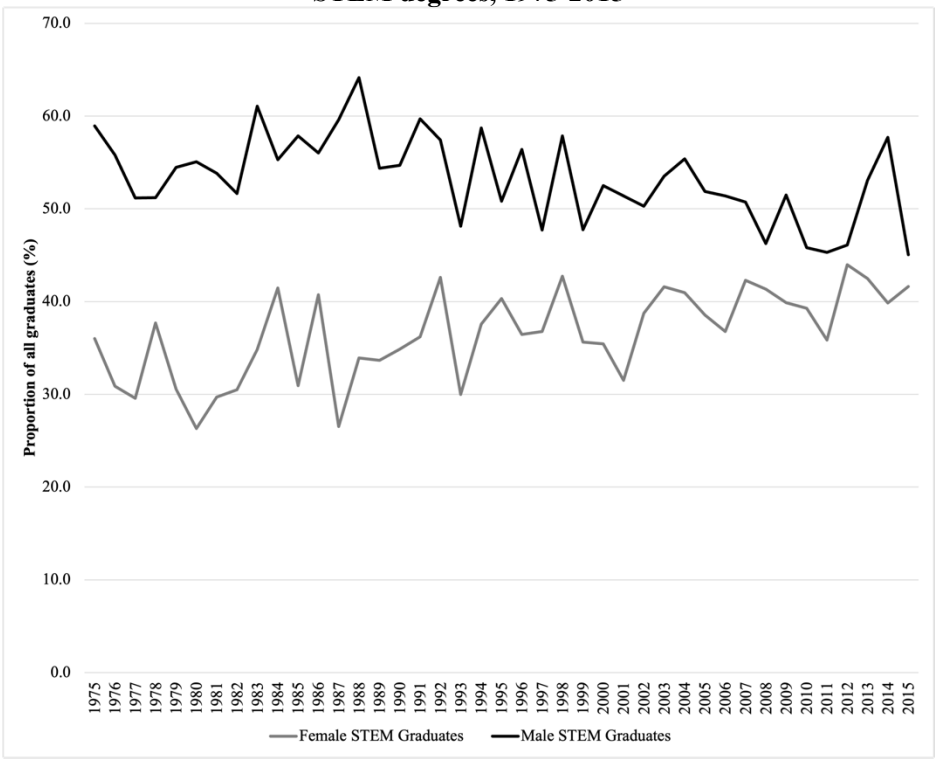
[3] The general subject composition of the polytechnics and universities was relatively similar across this time span, and had increasingly been converging prior to the Further and Higher Education Act 1992 as a result of which polytechnics became universities (Mandler 2020).

Figure 3: The proportion of British graduates by field of study, 1975-2015



Note: Based on a sample of 14,948 graduates in the LFS. Includes polytechnics prior to 1992 (and subsequently Post-92 universities).

Figure 4: The proportion of male and female British undergraduates who graduated with STEM degrees, 1975-2015



Note: Based on a sample of 6,655 male and 8,293 female graduates in the LFS, of whom 3,499 and 3,151 respectively had graduated from a STEM degree. The proportions are calculated relative to the total number of male and female students respectively. Includes polytechnics prior to 1992 (and subsequently Post-92 universities),

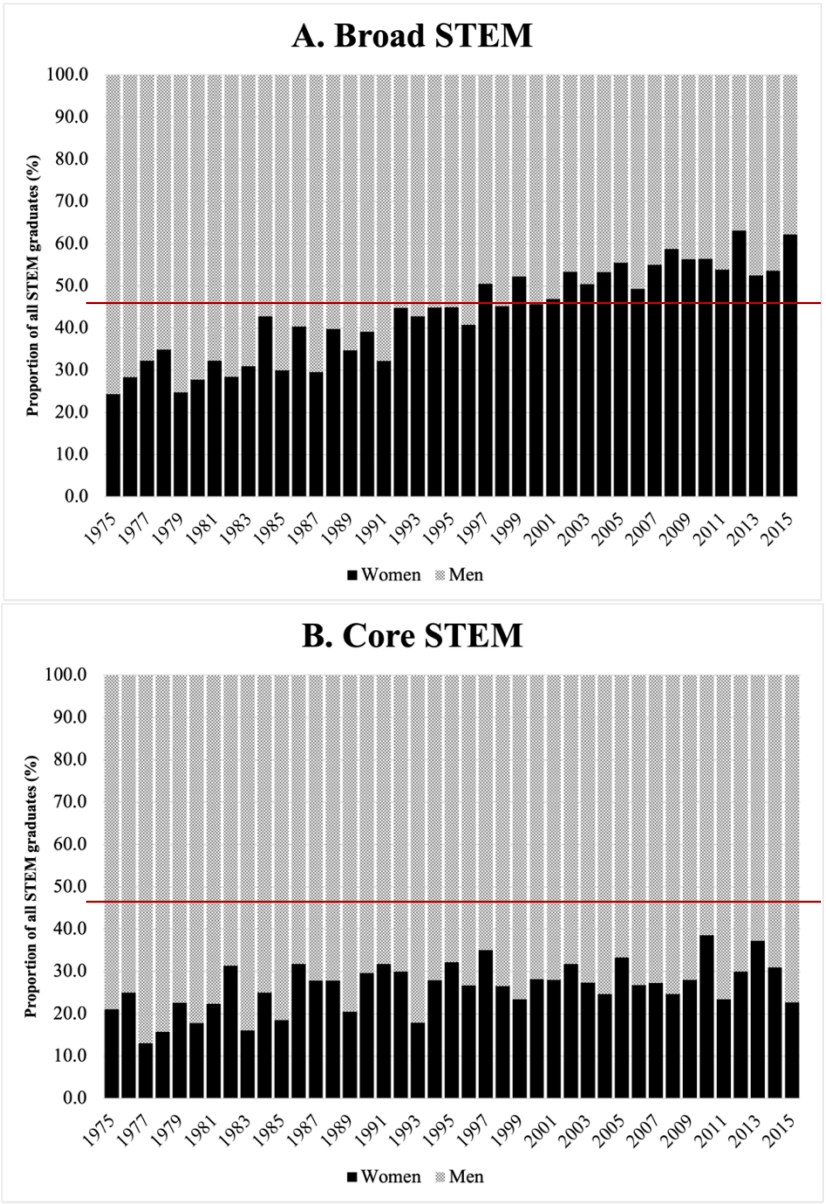
- Figure 4, which breaks down the proportion of STEM graduates by gender, reveals that the proportion of women graduating with a STEM degree (in relation to women graduating from other fields) grew relatively steadily from the mid 1980s until 2015, while the proportion of men graduating with a STEM degree decreased slightly, pointing to increasing gender equality in higher education participation in STEM. This is likely in part driven by the general rise in female students over the observed period (figure 2).

However, figure 5 reveals that this does not apply to all STEM sub-fields. When STEM is defined broadly, including fields such as medicine and architecture as is commonly done (for example, HESA 2018), the share of women in STEM fields (in reference to men in these fields) has grown steadily, and women have in fact overtaken men in graduating with a STEM degree (figure 5a), possibly due to having overtaken - men in graduating from university in general (figure 2). However, when only looking at what I refer to as 'Core STEM' (see Chapter 4), the increase in the share of female STEM graduates becomes considerably less pronounced, as women are underrepresented in these fields over the entire four decades shown (figure 5b).

These patterns call the success of the many STEM initiatives over the past few decades into question. Despite the substantial government interest in shifting higher education away from the arts and towards the sciences, the proportion of STEM graduates has remained relatively stable, and even decreased somewhat. Similarly, despite initiatives such as GIST and WISE which aim to increase the number of women in STEM there was little change in the proportion of women in traditionally male (Core STEM) subjects. This is also reflected in findings of past research; for example, the proportion of women among mechanical engineering undergraduates (7%) did not change between 1986 and 2009 (E. Smith and Gordard 2011). Instead, the increase in women in STEM (both at school and at university) has largely been concentrated in the biological sciences

and medical fields, which are often not the target of STEM initiatives. Furthermore, Banerjee (2016) suggests that improvements in the mathematics and science performance of schools and pupils in England cannot be attributed to STEM enrichment and enhancement activities, as improvements are not limited to schools and pupils involved in STEM interventions.

Figure 5: The share of male and female STEM graduates by definition of STEM, 1975-2015



Note: Based on a sample of 6650 'Broad STEM' and 3122 'Core STEM' graduates in the LFS. The proportions are calculated relative to the total number of STEM graduates. 'Core STEM' here refers to: (i) mathematical sciences and computing, (ii) technology, (iii) engineering and (iv) physical/ environmental sciences, while 'Broad STEM' additionally includes: (v) biological sciences, (vi) medicine and dentistry, and (vii) other subjects allied to medicine, (viii) agricultural sciences, and (ix) architecture and related studies. Includes polytechnics prior to 1992 (and subsequently Post-92 universities).

In sum, despite considerable educational expansion and despite hundreds of STEM initiatives, the proportion of students graduating with a STEM degree has remained remarkably stable for decades, with only a small decline in the proportion of STEM graduates being observed. In line with increased female participation in higher education, there have been advances in the share of female STEM graduates, but these are limited to certain STEM fields, and there has been little change in the share of women graduating from traditionally male-typed Core STEM fields between 1975 and 2015.

2.4. Changes in the Labour Market since the 1970s

In addition to the substantial reforms that took place in the British (higher) education system during the BCS70 cohort's upbringing, the UK labour market was marked by considerable change. This could be seen by the kinds of jobs that increasingly made up the British workforce, with significant growth in the service sector and a simultaneous drop in the production sector since the 1970s (Qayyum et al. 2018). Furthermore, Thatcher's commitment to develop a 'conditional and affordable welfare state' (Stepney 2018 in Albertson and Stepney 2020, 325) led to a long lasting trend of labour market activation, with the focus increasingly shifting to trying to get people into work. This approach has permeated British social policy ever since.

2.4.1. The Structure of the Labour Market

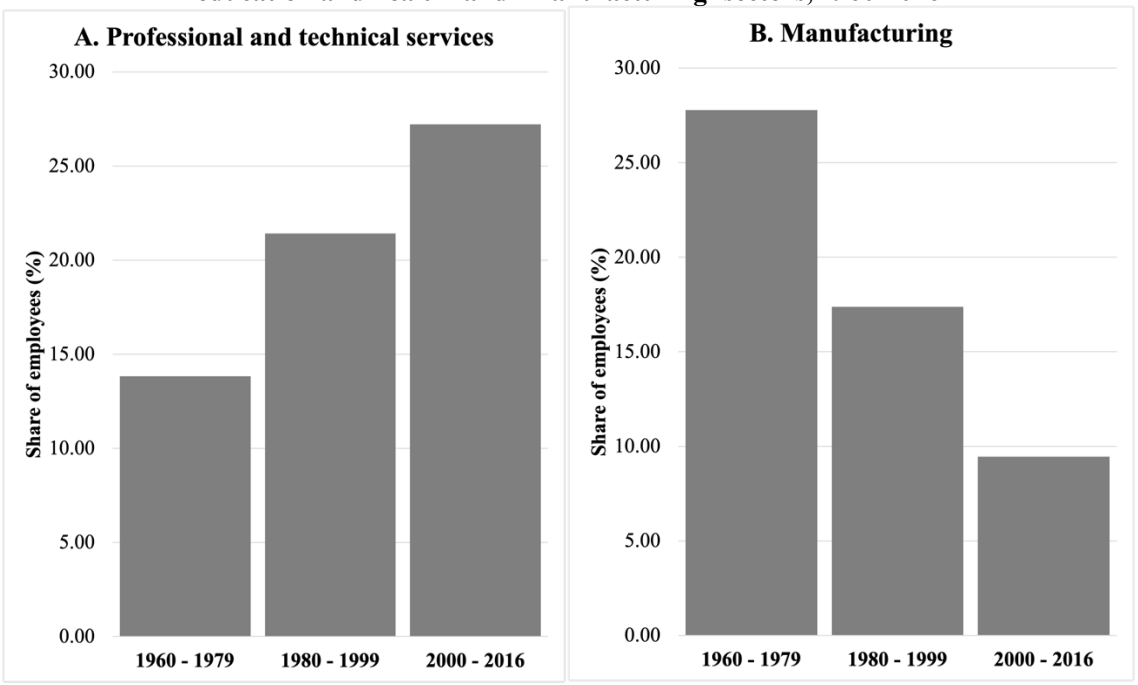
The BCS70 cohort grew up during a period of substantial labour market restructuring. This was largely driven by a shift away from manufacturing and towards the service sector, with the 'professional and technical services' gaining the largest share of the total labour force. While manufacturing made up around 28% of the workforce on average in the 1960-1979 period, this dropped down to only 9.5% on average in the 2000-2016

period. Meanwhile, the share of 'professional and technical services (including education and health)' workers increased from around 14% to around 27% over the same time span (Chiripanhura and Wolf 2019), as can be seen in figure 6. In fact, since 1970, the 'professional scientific and technical services' sector (including education and health) has grown at the fastest rate out of all service sectors (Qayyum et al. 2018).[4] Therefore, while the BCS70 cohort were born and attended school during a time in which manufacturing dominate the British labour market in terms of work force share, their careers were – and continue to be – marked by a shift towards professional and technical services and other knowledge-based sectors.

Simultaneously, and relatedly, the share of private sector employment increased significantly (figure 7). While the private sector has made up the majority of UK employment for the past century, a shift in government priorities and developments in innovation meant that it experienced unusually high growth during the time the BCS70 respondents entered the labour market. Between 1983 and 2018, the share of private sector employment jumped from 72% to 83%, growing by 57.4% (Chiripanhura and Wolf 2019). This growth was in part driven by substantial growth of technology and innovation sectors and was associated with an increase in STEM jobs. Highly skilled STEM workers continue to be largely located in the private sector; while around half of all graduates work in the private sector roles, three quarters of highly skilled STEM positions are located in the sector (E. Smith and White 2018a).

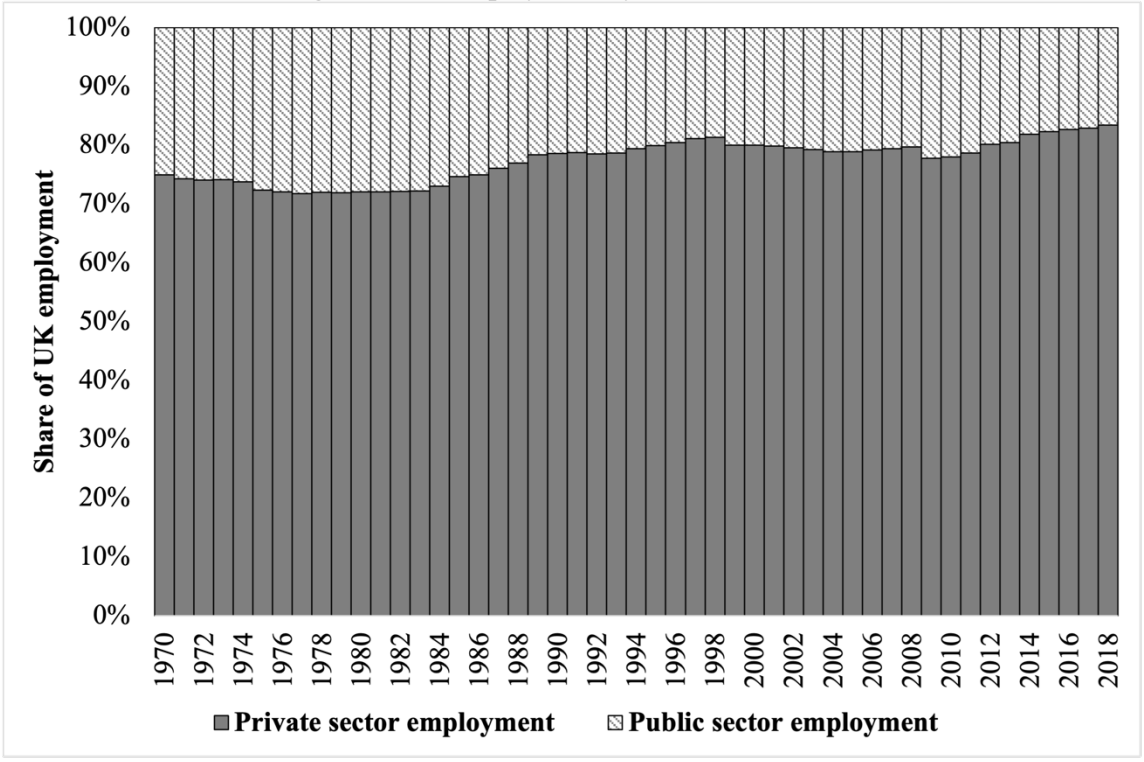
[4] This was the case both for men and women (Qayyum et al. 2018), and was therefore not driven by the increased share of women in the labour market (which is discussed in section 2.4.2. below).

Figure 6: The share of people employed in the 'Professional and technical services (including education and health' and 'Manufacturing' sectors, 1960-2016



Note: Source: ONS (Chiripanhura and Wolf 2019)

Figure 7: UK employment by sector, 1970-2018



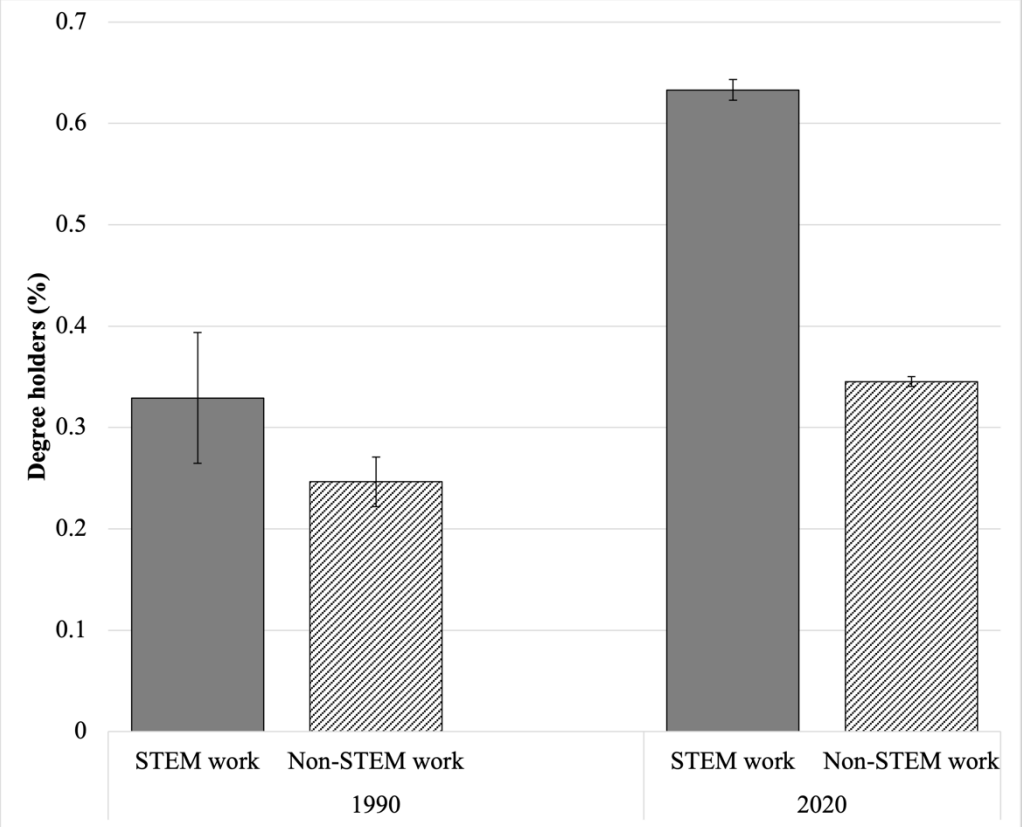
Note: Source: ONS (Chiripanhura and Wolf 2019)

Examining the UK workforce more broadly from 2003 to 2017, Emsi (2018) noted that the number of STEM occupations increased at a higher rate than non-STEM occupations, a pattern which was also found in the US (Fayer, Lacey, and Watson 2017). This disproportionate growth was heavily driven by IT professionals, while the growth in the number of engineers and scientists was proportional to the overall growth of the UK workforce (Emsi 2018). In 2020, STEM occupations made up 17.6% of the overall workforce, having grown by over 3 percentage points in just one decade. [5] Therefore, the STEM sector grew steadily over the entire period the BCS70 respondents have spent in the labour market thus far.

This shift away from manufacturing and towards knowledge-based industries, coupled with the rapid expansion of higher education described above, led to an increased demand for degree-level qualifications on part of UK employers. This was particularly pronounced in STEM jobs. In 1990, when the majority of BCS70 respondents entered the labour market, around 30% of all STEM workers had obtained a degree (figure 8). By 2020, the STEM sector was dominated by graduates (63% of all STEM workers). The share of graduates in non-STEM work also increased, but at a substantially lower rate. While 25% of all non-STEM workers had obtained a degree in 1990, graduates made up 35% of all non-STEM workers in 2020. Therefore, the graduates studied in this thesis entered the labour market at a time during which degrees were not yet a requirement for the majority of jobs, STEM and non-STEM alike.

[5] Based on samples of 47,071 (2011) and 33,700 (2020) LFS respondents.

Figure 8: The share of degree holders by field of work, 1990 versus 2020

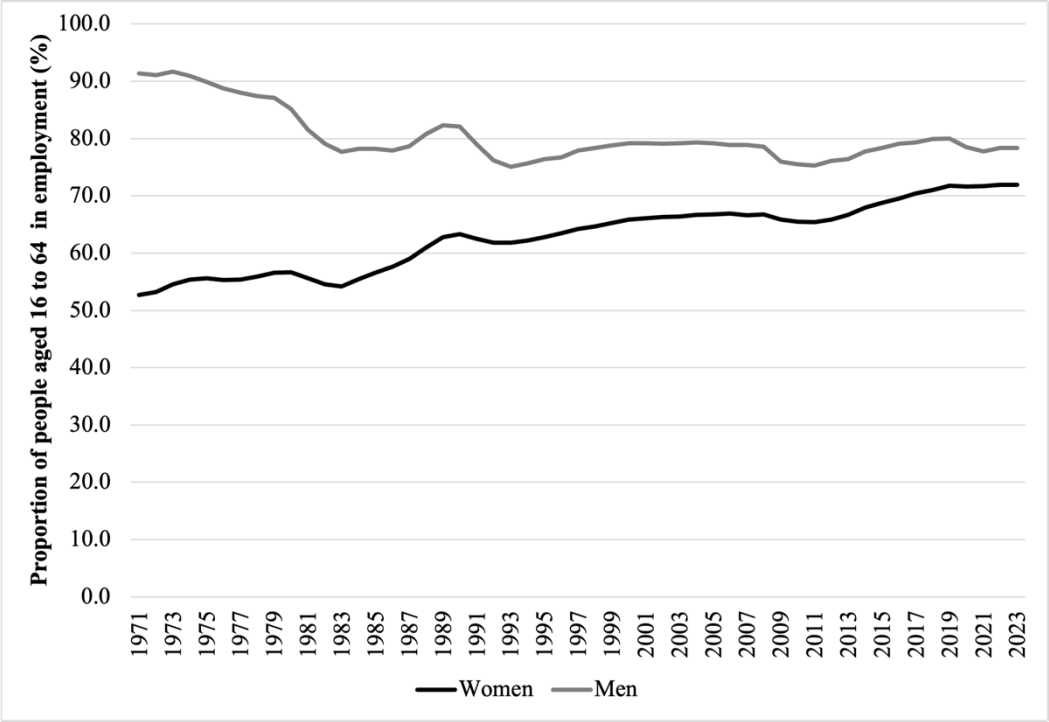


Note: While the 1990 values are based on BCS70 data, the 2020 values are based on a sample of LFS respondents.

2.4.2. Female Participation in the Labour Market

When most of the BCS70 entered the labour market (1992-1995), the female employment rate was 13.7 percentage points lower than the male rate on average (based on data shown in figure 9). This gender gap is considerably larger than the 2023 gap of 6.5 percentage points, but compared to previous years, the BCS70 respondents entered the labour market in a period of unprecedented levels of female employment. The share of women in the labour market rose drastically over the respondents' childhood and time in education; in the year following their birth, only 52.7% of working age women were in employment, which had risen to 62.5% by the time many of them entered the labour market in 1991 (figure 9). Self-employment among women similarly grew substantially, and at a steeper rate than self-employment among men (Qayyum et al. 2018).

Figure 9: The employment rate among men and women aged 16 to 64, 1971-2023



Note: The values shown are seasonally adjusted. Source: ONS (2024a, 2024b)

This sharp rise in female participation in the labour market was driven by a variety of factors. The rapid increase in the share of women attending higher education (figure 2) seems to have contributed, but Roantree and Vira (2018, 6) identify 'a dramatic shift in the working patterns of women across the life cycle' as a key factor driving the trend presented in figure 9. They show that although female employment rates do not differ greatly across the cohorts they study (1930s to 1980s) for women in their 40s, women in 'younger' cohorts (those born since the 1960s) are considerably more likely to work in their 20s and 30s. The female employment rate of 1970s cohorts, for example, was just under 75% across all ages they observe (25 and older), while only 50% of 25-year-olds were in employment in the 1940s cohorts. The employment rate among female BCS70 respondents is therefore substantially higher than that estimated by figure 9.

This increase in women of younger generations entering work at young ages is likely due to changing gender norms, which were reflected in employment provisions.

For example, as a result of the Equal Pay Act of 1970, which aimed to equalised pay between men and women doing similar work, 'the average full-time wage for women in the UK in comparison to men increased by 5%, from 72% to 77%' by 1975 (Choudhry 2020). Soon after, the Employment Protection Act of 1975 introduced provisions such as Maternity Leave and the Right of Reinstatement, which made having children substantially less disruptive to women's careers, and led to higher rates of return to employment within one year following child birth (Gregg, Gutierrez-Domenech, and Waldfogel 2003). As BCS70 cohort members grew up, these provisions were coupled with a move away from the 'male breadwinner' model and towards an 'adult worker' model starting under Thatcher, in which women were increasingly treated as potential workers, and policies were designed to allow them to enter and stay in the labour market (Lewis 2002; Daly 2011).

In this context, women born in the 1970s were considerably less likely than earlier cohorts (especially the 1940s and 1950s ones) to have a child and live with a partner by the age of 25. Those who did have children were substantially more likely to work than mothers in previous generations had been, a trend which was particularly pronounced among women in couples. This was in part driven by the fact that compared to previous generations, women born in 1970 were more likely to switch to part-time work following the birth of their first child rather than leaving the labour market altogether (Roantree and Vira 2018). Hence, the reasons that had led to female underrepresentation in the labour market in previous generations (low female participation in higher education, a traditional view of women as homemakers, and a lack of provisions for women in the labour market) were starting to erode, making female labour market participation more feasible, and actively encouraged by the government.

The increased share of women in the labour market has not eradicated gender differences in the labour market outcomes and experiences of workers, however. For example, although the gender pay gap has generally decreased over the past three decades, women continue to earn less than men (N. J. White 2023). Furthermore, in cohabiting (heterosexual) couples, women continue to do the majority of unpaid work and childcare, while men do more paid work, although gender differences in time spent in unpaid work have reduced since the 1970s as a result of an increase in the time spent doing such work among men (Bangham and Gustafsson 2020). Therefore, although unequal pay and division of labour is likely to have declined since the BCS70 cohort members began work, these patterns are still present in the current labour market.

2.4.3. Economic Crises

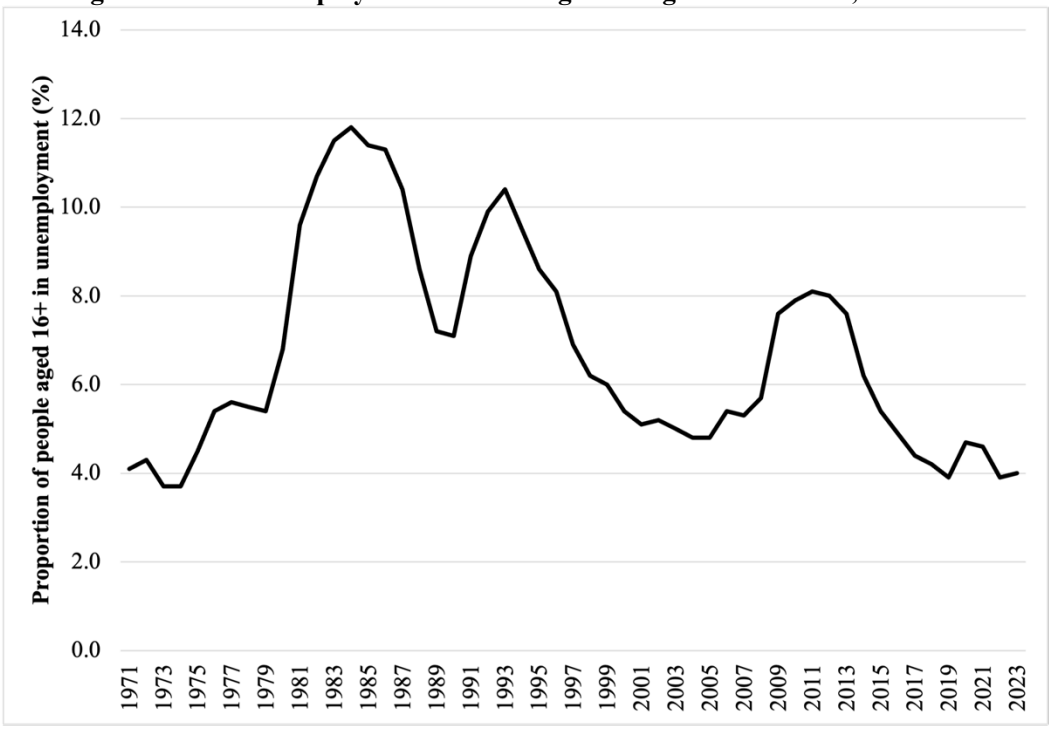
By the age of 40, the BCS70 respondents had lived through four recessions: (i) the Mid-1970s recession when respondents were 3-5 years old, (ii) the early 1980s recession when respondents were 10/11 years old, (iii) the early 1990s recession when respondents were 20/21 years old, and (iv) the Great Recession of 2008/2009 when respondents were 38/39 years old. These economic crises, especially the 1980s and 1990s recessions, led to periods of high unemployment (figure 10), which are likely to have affected the BCS70 respondents' education and labour market choices.

The British economy took 8 years to recover from the 1980s recession in terms of employment (Jenkins 2010). Therefore, the BCS70 cohort was among the group of students for whom post-compulsory education uptake rose as a result of 'parking' – 'staying in further education until the labour market recovered' (Mandler 2015a, 18), which may well in turn have influenced their likelihood of entering higher education. Thus, despite not having entered the labour market yet in the wake of the 1980s recession,

the high unemployment levels that resulted from it might have increased higher education participation among the cohort.

The 1990s recession, which affected the United Kingdom (UK) between July 1990 and September 1991, is likely to have had a greater effect on the BCS70 respondents, however. This recession resulted in yet another substantial drop in employment (figure 10), which the UK labour market did not fully recover from for nearly 9 years (Jenkins 2010). Therefore, the majority of BCS70 respondents entered the workforce in a period of high unemployment, as most graduates in my sample entered the labour market between 1992 and 1995. This is likely to have shaped the job choices available to them, as they faced more obstacles because of the recession.

Figure 10: The unemployment rate among those aged 16 and over, 1971-2023



Note: The values shown are seasonally adjusted. Source: ONS (2024c)

However, it is worth nothing that, recessions, including the 1990s recession, impact graduates differently than lower-educated people. While Clarke (2019)

demonstrates that school-leavers are more likely to be unemployed during a recession, he observes a smaller and (at least initially) statistically non-significant fall in the probability that graduates will be in work. Similarly, in the aftermath of the 1990s recession, the pay of graduates was affected less negatively than that of lower-educated people (Clarke 2019). Therefore, while the 1990s recession certainly created altered labour market conditions, it is likely to have influenced the subjects of this study less than non-graduates.

Furthermore, job loss did not impact UK industries equally, and STEM fields were less affected by the recession. While on average, the workforce declined by 3.7% during the recession, 'professional scientific and technical activities' saw a substantially smaller level of job loss at 1.9%, and jobs in 'human health and social work activities' in fact *increased* by 3.3% (Jenkins 2010, 31). In the subsequent six months, while the overall workforce saw a further 0.6% decrease in jobs, both STEM industries were marked by workforce increases (of 0.2% and 1.6% respectively). These patterns were even more pronounced in the 2008/09 recession, when the workforce grew both during the recession and in the first six months of recovery in both of these STEM industries (Jenkins 2010).[6] Therefore, the main field of interest of this thesis – STEM work – was impacted considerably less by the recessions that occurred during data collection than other occupational sectors.

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[6] Specifically, jobs increased by 1.6% in 'professional scientific and technical activities' and by 5.3% in 'human health and social work activities' in the immediate aftermath of the 2008/09 recession, and by 2.3% and 1.9% in the subsequent six months. At the same time, the overall workforce saw job decreases of 2.7% during the recession, and further decreases of 0.3% during the first six months of recovery (Jenkins 2010, 31).

The BCS70 respondents grew up in a time of substantial educational and economic transformation. They were likely born to parents who, if they attended university, did so during the initial period of rapid expansion to higher education of the 1960s.[7] BCS70 were therefore raised by parents who were more educated than any previous generation had been. By the late 1980s, when the majority of the BCS70 graduates entered university, participation in higher education was once more on the rise, and the number of female students at university was higher than ever before. While higher education participation was still relatively low by today's standards, the BCS70 cohort were the first people to grow up in a context where higher education had become attainable for a large proportion of the population.

Furthermore, although the concept of STEM was not popularised in the UK until the early 2000s, the cohort studied in this thesis entered university at a time of greater focus on STEM fields when compared to the previous decade, and similar political rhetoric of productivity and economic growth to today. Their entire adult lives have taken place in a context in which the British government has prioritised STEM fields. However, while the BCS70 were one of the first cohorts to see a substantial proportion of school pupils proceed to university education, they were not much more (or less) likely to graduate with a STEM degree than the generations that pre- and succeeded them.

In addition to the considerable change in the (higher) education system, BCS70 respondents witnessed quite significant change in the labour market. During their lifetime, the economy shifted away from manufacturing and towards knowledge-based work. With this change came an increasing focus on degrees in the labour market, as employers started to require them more. Provisions such as the right to equal pay for

[7] The average maternal age at first birth in 1970, when the BCS70 respondents were born, was 22 (Thompson et al. 2012), suggesting that the average mother in 1970 entered university in 1966 (I am not aware of the average paternal age, nor of the average age among graduates).

women and Maternity Leave were introduced, and the share of women in work skyrocketed. By the time BCS70 members entered the labour market, it had been normalised for women to work, although women were still responsible for the majority of unpaid work and childcare in the household, as is also the case today. Additionally, the cohort members lived through several economic recessions. These are likely to have shaped their educational choices and the labour market options available to them to some extent. However, it should be noted that graduates and STEM sectors were substantially less affected by the economic impacts of recession. Similarly, the overall underrepresentation of women in work at the time when BCS70 respondents entered the labour market seemed to largely have been driven by older cohorts, affecting the people in my sample less.

3. PAST RESEARCH AND THEORETICAL FRAMEWORK

My research into what determines STEM work connects to a number of broader theoretical debates and concepts within the sociological literature. Below, I outline the most important ones as pertaining to the focus of my research. Specifically, to address the role (higher) education, and in particular degree field of study, plays in determining one's likelihood of being in STEM work, and how this varies by gender, section 3.1. introduces the concept of horizontal education-job (mis)matches, their determinants, outcomes, and how they vary by gender and over the work life course. This section aims to provide background on the more STEM focused discussion in my first analytical chapter. Secondly, to address the role parents play in shaping STEM work (which is explored in the second and third analytical chapters of this thesis), section 3.2. discusses the direct effect of social origin (DESO), the microclass approach to studying social stratification, and occupational inheritance. I provide further detail on how level of education may shape how influential parents are, and how and why this relationship might vary across the work life course.

3.1. The Role of Higher Education

3.1.1. Horizontal Education-Job (Mis)Match

The term 'education-job matches', also called 'congruence', refers to having an occupation closely related to one's degree subject. Understanding the extent to which such (mis)matches occur, what causes them, and what their labour market outcomes are is an important puzzle within the school-to-work transition literature, and – in the policy context – is vital for efficient education and labour market policy. The term 'education-

job matches' has been used to describe both *vertical matches* (working in an occupation that corresponds to one's level of education) and *horizontal matches* (working in an occupation that corresponds to one's field of study). The latter of these two kinds of education-job matches has received less attention in the literature but is increasingly becoming a focus of study. Due to the nature of my research questions, in what follows I will review the literature on horizontal (mis)matches.

Because horizontal, rather than vertical, education-job (mis)matches continue to be relatively understudied (Vecchia et al. 2023), the prevalence of such matches is debated. For example, while Robst (2007b, 2007a) finds that about 20% of his sample of US graduates are in horizontal mismatches, Vecchia et al. (2023) recently demonstrated that nearly 33% of UK graduates were in occupations that did not match their field of study. Part of these discrepancies might be caused by definitional differences, as there are several ways in which education-job (mis)matches are commonly defined (McGuinness, Pouliakas, and Redmond 2018). While some have operationalised such mismatches using subjective questions asking people to what extent their job matches their field of study (Robst 2007a, 2007b; Verhaest, Sellami, and Van der Velden 2017), others have used more statistical operationalisations (Bol et al. 2019; Vecchia et al. 2023), such as the realised matches approach,[8] or by comparing field of study categorisations with occupational codes (for example, Nordin, Persson, and Rooth 2010; Domadenik, Farčnik, and Pastore 2013).

Across these definitions, a consensus has not been reached regarding the likelihood of horizontal (mis)matches varies by field of study (Boudarbat and Chernoff 2009; Robst 2007b; Salas-Velasco 2021), with many finding that graduates from STEM fields are more likely to be in a job matching their field of study (Frenkel and Leck 2017;

[8] This is explained more thoroughly in the context of STEM occupations in section 4.1. below.

Robst 2007a; Xu 2013), although this finding is not universal (Vecchia et al. 2023). Robst (2007a) suggests this is because of a higher supply of STEM jobs when compared to other fields, while others have pointed to strong education-work skill matches in those fields (M. C. Long, Goldhaber, and Huntington-Klein 2014; Salas-Velasco 2021). In the UK context, multiple studies have demonstrated that (at least) half of all UK STEM graduates enter STEM work at the point of labour market entry (Bosworth, Lyonette, and Wilson 2013; Select Committee on Science and Technology 2012; E. Smith and White 2017, 2018a; DIUS 2009; E. Smith 2011a), a pattern which has also been found in the US (for example, Xu 2013; Preston 2004; VanHeuvelen and Quadlin 2021) and Canada (Frank 2019).

Determinants of Horizontal Matches

Researchers have identified a variety of determinants of horizontal education-job (mis)matches. Much of the literature has focused on aspects of people's education and has demonstrated that the circumstances under which one receives a university degree affect one's likelihood to end up in a congruent job. In addition to field of study, other aspects of people's university experience also shape the likelihood of education-job matches. The selectivity of a higher education institution (Xu 2013, 2017), graduates' degree level (i.e., undergraduate/master's/doctoral) (Robst 2007a), and academic performance have all been linked to good matches, although in the case of academic performance this relationship is not as linear for STEM graduates than for people who majored in other fields (Xu 2017).

Horizontal education-job (mis)matches are also shaped by people's demographic characteristics. In addition to gender, the role of which I discuss in section 3.1.3., ethnicity might play a small role in the overall picture that emerges about (mis)matches. For example, Xu (2013) finds that Asian graduates from non-STEM fields are more likely

than white students to be in education-job matches, but finds no relationship between racial group membership and such matches among STEM graduates. Similarly, Robst (2007a) does not find racial differences in the likelihood of education-job matches, but stresses that the reasons for this incongruence differ by racial group. While white graduates often find themselves in mismatched jobs due to career interests, job conditions, job locations and family-related reasons, Black graduates reported job unavailability, and therefore a lack of choice, as the main reason for job mismatches (Robst 2007a). Hence, while the aggregate picture may suggest racial equality in horizontal education-job (mis)matches, there remain stark power imbalances. Robst (2007a) further controlled for disability, and found that it was negatively associated with the likelihood of finding oneself in a good education-job match. He concludes that 'groups facing discrimination are less likely to find a related job' (Robst 2007a, 171).

Finally, some work has started to investigate the role of social origin in shaping horizontal matches, although more often than not, family background has not been taken into account (it was not included in Robst (2007a) and Bol et al.'s (2019) analyses, for example). Where family background has been studied, results are contradictory. While some have found no relationship between family background and horizontal education-job matches (Boudarbat and Chernoff 2009), others have suggested this pattern varies by field of study and by operationalisation of family background. In terms of parental income, Xu (2013, 2017) finds a negative association between family income and the likelihood of working in a congruent job, but only among STEM graduates. When it comes to parental education, Xu (2013) finds only a weak association with horizontal matches and only among STEM graduates. Somewhat contradictorily, in her 2017 paper, she did find that parental highest educational attainment was positively associated with the likelihood of congruence, but only for female graduates (regardless of field of study)

(Xu 2017). It therefore remains unclear whether family background shapes the likelihood of horizontal education-job matches.

Outcomes of Horizontal Matches

Horizontal education-job matches appear to lead to positive labour market outcomes. The better outcomes of those in matching jobs have often been explained with reference to human capital theory (Becker 1962), the key argument being that those in matching jobs will be most able to translate the skills they obtained during their time in education. Hence, horizontal *mis*matches have been framed as an underutilisation of skills (Vecchia et al. 2023).

There is evidence that being in a job that matches one's degree field of study leads to a higher income (Robst 2007a, 2007b; Bol et al. 2019; Xu 2013; Vecchia et al. 2023; Nordin, Persson, and Rooth 2010), although this finding is not universal; once controlling for job characteristics, the negative impact on the salary of mismatched people which Beduwe and Giret (2011) observe disappears. Robst (2007a) finds that although being in a mismatched job negatively affects wages, this does not apply to cases in which people have chosen to enter an incongruent job because of better pay and promotion opportunities. Being in an education-job match has also been linked with non-monetary benefits, such as higher job satisfaction (Lee and Sabharwal 2016; Xu 2013; Robst and VanGilder 2016), higher occupational status (Wolbers 2003), and a higher likelihood of being in full-time employment (Xu 2013). Women appear to benefit more from being in a matching occupation than their male peers (Bol et al. 2019).

The labour market benefits of being in a horizontal match seem to vary by field of study (Robst 2007a; Bol et al. 2019; Robst and VanGilder 2016), with those with degrees which emphasise occupation-specific (rather than general) skills facing more negative consequences when in a mismatched job. This has been demonstrated in the

context of earnings (Robst 2007a; Bol et al. 2019; Robst and VanGilder 2016) and of job satisfaction (Robst and VanGilder 2016). This once more highlights the importance of studying individual fields when it comes to education-job (mis)matches.

3.1.2. Horizontal Education-Job (Mis)Match over the Work Life Course

Horizontal mismatch has rarely been studied over the work life course, and the vast majority of studies investigating it have done so using cross sectional data (for example, Robst 2007a, 2007b; Bol et al. 2019; Vecchia et al. 2023). Using such 2017 data on UK graduates, Vecchia et al. (2023) find that horizontal matches remain stable with labour market experience, with the rate of matches being remarkably similar at labour market entry, 10 and 20 years into people's careers. There are theoretical reasons to believe horizontal (mis)match may also reduce or increase over the work life course, however. Robst (2007a), for example, suggests that one reason for horizontal mismatch is changing career interests over time. As individuals' time in the labour market progresses, they might realise their interest lies in a field that differs from their undergraduate field of study. Younger workers also appear to gain larger wage advantages from being in a matching occupation (Bol et al. 2019), meaning the benefit of being in a good education-job match could deplete, making such matches less desirable over the life course. On the other hand, it is relatively common for recent UK graduates to start working in non-graduate roles (Clegg 2017), which do not necessarily match their field of study, so the prevalence of horizontal matches might increase over the life course, as people enter work that more closely matches their original career ambitions.

In the context of STEM particularly, several studies *have* investigated horizontal matches over the life course, although this continues to not be commonly done and there is a lack of consensus both about the direction in and extent to which the relationship

between STEM study and STEM work changes. The majority of past studies have demonstrated a reduction in the share of STEM graduates in STEM work over the life course (Preston 2004; Hunt 2016; E. Smith and White 2018a, 2020; Deming and Noray 2018; Frank 2019; Glass et al. 2013; Frehill 2009, 2012), but this finding is not universal (Xu 2013; Bosworth, Lyonette, and Wilson 2013; VanHeuvelen and Quadlin 2021). The extent to which this change occurs also varies by study. For example, Frank (2019), who studies Canadian longitudinal census files finds a 12.9% drop after 10 years, while Preston (2004) finds that the share of science graduates working in science in a US sample dropped by 9.7% after 7 years (and 15.5%-31.5% after around 12 years). Hence, while STEM retention among STEM graduates has been studied before, a clear pattern has not yet emerged, even when comparing individual disciplines.

Moreover, the literature on this topic has disproportionally focused on the US. Based on cross-sectional data from the UK LFS, Bosworth, Lyonette and Wilson (2013) find that the share of Core STEM[9] graduates working in Core STEM Sectors and Occupations increased quite substantially with age, jumping from 56% to 68% when comparing 25-29 year olds with 45-49 year olds in 2001, and 44% to 57% when drawing the same conclusion based on 2010 data. Contrarily, when looking at descriptive statistics from the British Cohort Study (BCS70) and the National Child Development Study (NCDS), Smith and White (2018a, 2020) find a considerable decline in STEM graduates in highly skilled STEM jobs as workers got older, with the share dropping from around 50% at age 26 to 40% at age 42.

[9] Which they define as including the following fields: Biological sciences; Agricultural sciences; Physical/ environmental sciences; Mathematical sciences and computing; Engineering, Technology and Architecture.

3.1.3. Does Gender shape Horizontal Education-Job Matches?

To what extent education-job matches are determined by gender remains understudied and disputed, despite gender being the most common demographic characteristic that has been studied in this regard. While some find no statistically significant relationship between gender and the likelihood of education-job matches (Boudarbat and Chernoff 2009; García-Espejo and Ibáñez 2005), others have found that men are less likely than women to find themselves in congruent jobs (Robst 2007a; Xu 2013), although this finding differs by field of study, and may only hold up for non-STEM graduates (Xu 2013).

In the case of STEM graduates, several studies have found that women who have studied STEM subjects at university are less likely than their male peers to find work in a matching job (Sassler, Michelmore, and Smith 2017; Robst 2007a; Xu 2017; E. Smith and White 2018a; Frank 2019), although it should be noted this finding is also not universal. Xu (2013) does not find statistically significant gender differences until 10 years after graduation, when men were somewhat more likely to be in a congruent STEM job than their female counterparts. Xu explains this through delayed attrition of women from STEM fields and thereby highlights the importance of longitudinal study of this issue.

Together, past literature suggests that if gender differences in matches do exist, it seems that in the context of STEM, men are more likely to find themselves in congruent jobs, while in the context of non-STEM work, women are more likely to do so. Both patterns can potentially be explained by looking at the occupational choices available to men and women. Robst (2007a, 174) finds that: 'Men tend to report career-related reasons for mismatch while women are more likely to report amenity/constraint reasons for mismatch.' Because women continue to be societally viewed as primary caregivers, they

are penalised in the labour market even before they are parents, resulting in many 'choosing' to prioritise family over work (Wyn et al. 2017). Women are more likely to consider factors such as being close to family and friends, and the child care policies and programmes offered by potential employers when making decisions about employment (Wilkinson 1996). Doing so might constrain their choices in a way that is not the case for men, making it easier to enter work that matches their education, even in cases where an education-job mismatch may yield higher labour market returns. This could lead to more women being in congruent jobs in non-STEM fields, because such fields tend to be more family-friendly than the often male-dominated STEM occupations (Glass et al. 2013).

Discrimination is also likely to play a role in gender gaps in labour market outcomes by further restraining choice. For example, Joy (2000) demonstrated that female labour market entrants are likely to be in lower quality jobs because women often only get one job offer, and are more likely to be offered only clerical and service work. This could be due to the fact women in male-typed fields, such as STEM, tend to receiver fewer excellent recommendation letters than their male counterparts (Dutt et al. 2016), and are judged to be less competent by possible employers, even when evidence to the contrary is available (Reuben, Sapienza, and Zingales 2014). Such discrimination continues across the work life course, as women in male-typed jobs are less liked and more personally derogated than equivalently successful men (Heilman et al. 2004), which may be why women in STEM, for example, generally earn less and occupy less senior or highly skilled roles than their male peers (E. Smith and White 2018a; Xu 2017; Kalmijn and Lippe 1997; Xu 2015). Taken together, this discrimination might not only prevent

women in STEM from entering good education-job matches but could also affect their desire to remain in a matching occupation.[10]

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In sum, because horizontal education-job (mis)matches continue to be a relatively novel subject of study, there are many aspects of such matches that we do not fully understand yet, including their prevalence. Being in a matching occupation generally leads to positive labour market outcomes, with matches having been linked to higher income, higher job satisfaction and higher occupational status, although this varies by the circumstances in which people choose to enter mismatching occupations. Women appear to particularly benefit from being in a matching occupation, possibly due to men being more likely to choose to enter occupations that do not correspond to their degree field of study for favourable occupational outcomes in other fields. The extent to which horizontal education-job matches are determined by gender remains understudied and debated, however. Similarly, little work has been done on the way in which horizontal matches develop over the life course. It seems that the prevalence of, outcomes from, and gender differences in horizontal education-job matches vary by field, highlighting the importance of studying the way they present in specific fields.

To address some of the gaps in the literature which I have identified above, in my first analytical chapter, I will focus on the prevalence of horizontal STEM matches over the work life course, and gender differences therein. Given the generally positive outcomes that have been linked to being in matching jobs, particularly in skills-specific

[10] Such bias is deeply engrained; when made aware of experimental evidence of science faculty members' gender biases, male respondents in Moss-Racusin et al.'s (2015) study were more likely to respond negatively (for example, by providing justifications for the gender bias) while women were more likely to respond positively (for example, by calling for action).

fields, understanding these relationships in the context of STEM is vital. Next, having discussed the role (field of) education can play in shaping labour market choices and outcomes, I turn to the role parents play.

3.2. The Role of Social Origin

3.2.1. The Direct Effect of Social Origin (DESO)

The direct effect of social origin (DESO) is the association that remains between family background and occupational attainment after controlling for education. This direct effect seems to be widespread, as parental origin has been found to directly affect both occupational status and earnings in a variety of countries (for example, Bernardi and Ballarino 2016; Witteveen and Attewell 2017, 2020a; Tolsma and Wolbers 2014), although in some countries only negligible effects of social origin on earnings have been found (Grätz and Pollak 2016; Blank, Bar-Haim, and Shavit 2016; Mastekaasa 2016). In the UK context, DESO has been demonstrated both in terms of occupational status and earnings. While the majority of these studies find that DESO remains even for the highly educated (Britton et al. 2016; Crawford et al. 2016; Crawford and Vignoles 2014; Gregg et al. 2017; Gugushvili, Bukodi, and Goldthorpe 2017), Vandecasteele (2016) found no such relationship once controlling for education.

These studies looking at DESO among graduates have generally focused on parental class/status, parental education, and parental income as measures of social origin, and socio-economic status and income as outcomes. However, recent work by Bernardi and Gil-Hernandez (2021) suggests that DESO varies by occupation, with high-grade managerial and professional parental occupations being characterised by the largest DESO. Similarly, the work on occupational inheritance among graduates, which I review in section 3.2.3. below, points towards parental occupation being influential in

determining graduates' labour market outcomes, which I will explore further in this thesis.

Does DESO shape graduates' outcomes?

While it is well established that parental occupation, and relatedly income, shape their children's occupational outcomes, it is less clear whether this relationship remains among the highly educated. In fact, education has been argued to be the greatest equaliser, as numerous studies have found that the role parents play in shaping labour market outcomes reduces or even disappears completely among undergraduate degree holders (Hout 1984, 1988; Stolzenberg 1994; Torche 2011, 2016). Torche (2011) demonstrates this pattern across a range of socioeconomic indicators – social class, occupational status, individual earnings, and total family income – highlighting the breadth of the 'meritocratic power' of an undergraduate degree in her findings. Similarly, analysing UK data, Vandecasteele (2016) found that the direct effect of parental occupational status on their offspring's occupational status is weaker among highly educated men.

Nonetheless, academic studies are increasingly highlighting that a direct effect of parental background remains above and beyond (higher) education (Iannelli and Paterson 2007; Jacob, Klein, and Iannelli 2015; Vandecasteele 2016; Witteveen and Attewell 2017, 2020a; Bernardi and Gil-Hernandez 2021; Zhou 2019; Kratz, Pettinger, and Grätz 2022; Tolsma and Wolbers 2014), although education does appear to mediate DESO in many country settings. With some exceptions, the DESO on occupational class is higher for the lower-educated in most countries (Bernardi and Ballarino 2016; Tolsma and Wolbers 2014). Bernardi and Ballarino (2016, 265) explain this through what they call a 'compensatory effect': 'socio-economically advantaged families are more likely to 'lift' their children who are not good students to an acceptable (from their point of view)

occupational level.' Thereby, they suggest, having an advantaged parent may more substantially shape the occupational outcomes of those with low educational attainment.

Furthermore, the way in which DESO is present among the labour market experiences of the highly educated varies by definition of DESO. Although the DESO on occupational class often is higher for the lower-educated, with some exceptions (Ballarino, Cantalini, and Panichella 2021), this is not the case when it comes to income. Studies investigating Norway, Russia, Spain, and the USA have all found larger direct effects of social origin on income for those who are high achievers at school and already at the top of the earnings distribution (Mastekaasa 2016; Bessudnov 2016; Bernardi 2016; Torche 2016). Similar results have been found for Dutch women and Israeli men (Blank, Bar-Haim, and Shavit 2016; Tolsma and Wolbers 2016). Bernardi and Ballarino (2016, 265) label this a 'boosting effect' of social origin and explain that 'socio-economically advantaged families are more likely to 'push' their children who are good students towards the higher part of the income distribution'.

Taken together, there is reason to suspect that DESO remains among the university educated. The extent to which it is present in shaping occupational outcomes might differ by which kind of social transmission of advantage is studied. As discussed above, DESO has only recently been explicitly studied from an occupation-level perspective, so the extent to which the direct effect of parental occupation is present among the highly educated remains to be established.

DESO over the work life course

Based on previous literature there is reason to believe that DESO emerges at the beginning of the career, although this has not been sufficiently studied in the context of occupational inheritance. Less is known about the development of DESO over the life course, which has only relatively recently become a focus in the literature on DESO. After

the point of labour market entry, DESO could either reduce, increase, or remain stable and arguments can be made for all three patterns.

Firstly, one could expect DESO to decline and possibly even disappear over the life course, as individuals establish themselves in the labour market. Cantalini and Ballarino (2023) hypothesise that such a reduction may be observed due to first jobs being less meritocratic. In lieu of work-specific information on people's work-specific skills and productivity, employers need to rely on educational achievements and first impressions during interviews when hiring labour market entrants. Because educational outcomes are influenced by family background (for example, Crawford et al. 2016) and advantaged students tend to have higher non-cognitive skills (Blanden, Gregg, and Macmillan 2007; Heckman and Rubinstein 2001), social origin may play a large role in determining graduates' first jobs. However, as their time in the labour market progresses, employers can rely on work-specific information when making hiring and promotion decisions, possibly making the process more meritocratic, and thereby reducing the importance of family background in shaping job outcomes over time.

The initial advantage people from advantaged social backgrounds have in the labour market could also increase, however. Decisions regarding hiring and promotion are made by people who are (mostly subconsciously) influenced by societal biases, which can influence their choices. Class, for example, has been demonstrated to shape manager's perceptions of the intelligence and socio-emotional skills and therefore worthiness of hire of prospective employees (Sharps and Anderson 2021; Thomas 2018). Such stereotypes and resulting discrimination are likely to affect individuals' career progression throughout their work life course. In this context, those who entered the labour market in relatively privileged position might continue to be rewarded throughout their career. Cantalini and Ballarino (2023, 2) suggest that it could be the case that 'early

success begets later success' – a Matthew effect (Merton 1968, 1973) – and that because it is hard to actually observe work-specific skills and performance, their previous successes (and failures) in the labour market may be used as signals for career advancement decisions. Should this be the case, the role social origin plays in determining labour market entry would affect people for years.

Finally, DESO could remain relatively stable over the work life course as a result of the mechanisms described above 'cancelling each other out'. It may be the case that while some people overcome their initial disadvantage through work outcomes and behaviours that get noticed and rewarded over and above social origin, others might be 'stuck' in the above-described Matthew effect. In such a scenario, social origin would affect both the acquisition of an initial job, and people's career progression more or less equally (Cantalini and Ballarino 2023).

It is unclear from previous literature in which direction DESO develops over the work life course. Thus far, a persisting effect of family background in the first decade of graduates' careers has been demonstrated in the United States, Italy, the Netherlands and West Germany (Witteveen and Attewell 2017; Passaretta et al. 2018; Ballarino, Cantalini, and Panichella 2021; Cantalini and Ballarino 2023; Manzoni, Härkönen, and Mayer 2014). In the context of Italy and the Netherlands, it appears that DESO remains relatively stable over the work life course when investigating the effect of parental social class on occupational status (Passaretta et al. 2018; Ballarino, Cantalini, and Panichella 2021; Cantalini and Ballarino 2023), with some small increases in DESO. Ballarino, Cantalini and Panichella (2021) recently pointed to the importance of first jobs in shaping DESO over the work life course, highlighting that the boosting pattern they observe among highly educated men in Italy is mostly driven by a better allocation at the point of labour market entry. Using West German data, Manzoni et al. (2014) found a substantial rise in

the gap in career progression between people from higher service classes when compared to the lower-grade non-manual and working classes, pointing towards 'permanence in occupational inequality' (1285).

Contrarily, studies focusing on the UK find that DESO disappears in the first decade of graduates' careers, after only 4 years in the case of Jacob and Klein's (2019) paper investigating the link between parental social class and occupational prestige, and after 10 years in Byrne et al.'s (2018) study investigating how occupational earnings are constrained by parents' social mobility during childhood. Furthermore, Duta et al. (2021) find that certain UK graduates' career trajectories do not differ by social class once controlling for age at graduation, type of higher education institution and whether people have a postgraduate degree (Duta, Wielgoszewska, and Iannelli 2021).[11] Similarly, Kratz, Pettinger and Grätz (2022, 877) recently demonstrated that DESO decreases with age for highly educated people in Germany, concluding that 'time spent in the labour market is essential for higher education to function as the 'great equalizer [sic]'.'

Hence, the direction in which DESO develops over time is debated. There may be some country differences at play in the contradictions observed in the previous literature, but even within countries there is disagreement regarding the nature and presence of DESO in shaping career progression. It is therefore unclear how DESO might shape the field of occupation of UK graduates over the work life course, which I will explore in Chapter 6.

[11] Specifically, this applies to the 'Direct and early entry into higher managerial and professional occupations' identified by Duta, Wielgoszewska, and Iannelli (2021), which most STEM graduates would fall into.

3.2.2. The Microclass Approach

In addition to DESO gradually being studied in the context of specific occupations, social stratification research more generally has increasingly focused on occupations, as opposed to broader class categorisations as units of analysis. The case for disaggregation was introduced by Grusky and Sørensen (1998, 2001), and developed into the 'microclass approach' by Grusky and Weeden (2001, 2002; Weeden and Grusky 2004, 2005, 2012) who argued that focusing in on occupations adds nuance to our understanding of a range of individual-level outcomes that prominent 'big class' schemes (for example, that proposed by Erikson and Goldthorpe (1992)) cannot sufficiently address. For instance, in their first *American Journal of Sociology* publication on this matter, Weeden and Grusky (2005), demonstrate that microclasses have a strong association with outcomes within the domains of life chances, culture, lifestyles and demographic composition, and often explain these outcomes better than 'big class' schemes, with some exceptions. In fact, they conclude that 'there is little empirical justification for aggregating occupations, decades of class-analytic practice to the contrary' (Weeden and Grusky 2005, 173). Their second AJS paper on microclasses goes into more detail, highlighting that only the 'life chances' domain (which encompasses education, employment and home ownership), is explained better through 'big class' schemes than a microclass approach, although microclass association is still substantial in this domain (Weeden and Grusky 2012).[12] Furthermore, using US data from the 1970s as a starting point, they highlight that while 'big class' inequality weakened over time in many areas, there has been little change in the prevelance of microclass inequalities.

[12] While 'big class' association is 60%, microclass association is 40% (Weeden and Grusky 2012, 1741–42).

The microclass approach has also been extended to the study of social mobility. Jonsson et al. (2009) demonstrate that it is fruitful to consider the occupation level when studying social reproduction, and reveal rigidities that are obscured when limiting one's work to 'big class' analysis. Examining data from the US, Japan, Germany and Sweden, Jonsson et al. (2009) find that 10-25% of men end up in the same occupation as their father, but that the rate of microclass immobility varies by country. Based on these findings, they propose that 'much of what shows up as big-class reproduction in conventional mobility analyses is in fact occupational reproduction in disguise' (Jonsson et al. 2009, 977). Microclass immobility, also known as occupational inheritance, will be discussed in more detail in section 3.2.3.

Perhaps unsurprisingly, this approach to studying class and social reproduction is not without criticism. Goldthorpe (2002), for example, concludes that while he welcomes Weeden and Grusky's microclass approach as a valuable contibution to occupational sociology, he opposes its framing as a substitute for previous class theories, arguing that there are theoretical and empirical reasons to continue to use 'big class' schemes. Similarly, regarding the study of social reproduction, Erikson, Goldthorpe, and Hällsten (2012) oppose what they call the 'ratcheting down' of mobility analyses by the microclass approach. They argue that that the microclass approach has a restricted use when compared to more traditional class schemes because it is limited to studies of immobility (rather than being able to shed light on mobility also) and does not sufficiently explain women's experiences in the labour market because occupational inheritance is weaker among women.[13] Furthermore, Erikson, Goldthorpe, and Hällsten (2012) question the

[13] It should be noted that Erikson, Goldthorpe, and Hällsten (2012) study older cohorts than I do, which means that the women in their sample are likely to have had fewer labour market opportunities than the women in BCS70.

importance of the microclass approach in revealing social stratification, a debate which I discuss in more detail below.

Whether microclasses are an alternative to more traditional 'big class' schemes or not, Weeden and Grusky's and Jonsson et al.'s work on microclasses certainly makes the case for examining inequalities on the occupation level: 'Because occupations are deeply institutionalized, they tend to develop cultures that reflect the complicated niches and environments they occupy, cultures that then affect what we believe, how we vote, and the lifestyles we lead' (Weeden and Grusky 2012, 1758). This thesis will do so, grouping together various STEM fields, as I argue that similar underlying mechanisms produce the inequalities I examine within them.

3.2.3. Occupational Inheritance

Occupational inheritance – which is also referred to as intergenerational occupational transfer or microclass immobility, as Jonsson et al. (2009) coined it – refers to the phenomenon of children 'inheriting' their occupation from their parents. Such transfers of occupations have been studied for decades (for example, Werts 1968; Cutright 1968), but the literature on the relationship between parental occupation and that of their offspring (on the micro-level) nonetheless remains relatively scarce. Occupational inheritance has been demonstrated among self-employed workers and farmers in the USA (Laband and Lentz 1983; Lentz and Laband 1990), teachers in Switzerland and the USA (Gubler, Biemann, and Herzog 2017; Werts 1968), public sector workers in Italy (Scoppa 2009) and in scientific and medical occupations in the USA (Werts 1968; Cheng, Kopotic, and Zamarro 2017; Preston 2004). Studying the concept more generally using data from the USA, Sweden, Germany and Japan, Jonsson et al. (2009) established that it is common for children to inherit their parents' occupation, which Rahaman et al. (2023) also recently

found in the Ghanaian context. Furthermore, Egerton (1997) finds that professional family origins facilitate entry into professional occupations, a relationship that is independent from educational attainment, which is in line with Ruggera and Barone's (2017) findings that children of licensed professionals are most likely to inherit their parents' occupation. However, a consensus has not been reached regarding the presence of occupational inheritance, with several US studies not finding such a relationship (Aldrich and Kim 2007; Godwin, Potvin, and Hazari 2014; M.-T. Wang, Degol, and Ye 2015). Therefore, more needs to be done to thoroughly understand whether and how parental occupation shapes their offspring's occupation.

Parents may pass their occupation down to their children in a variety of ways. Jonsson et al. (2011) explain micro-class immobility, as they call it, through a number of mechanisms: (i) occupation-specific skills, (ii) occupation-specific culture and tastes (including career interests), (iii) occupation-specific networks and (iv) fixed resources (such as a business), which they illustrate through the example of children of carpenters:

> The children of carpenters, for example, may be especially likely to become carpenters because they are exposed to carpentry skills at home, socialized in ways that render them especially appreciative of carpentry as a vocation, and embedded in social networks that provide them with information about how to become carpenters and how to secure jobs in carpentry (Jonsson et al. 2011, 503).

These mechanisms are likely to apply across a wide range of occupations, including highly skilled ones. For example, family culture and networks play an important role in determining occupational inheritance among doctors (Devine 2010).[14] In fact, it could be the case that occupational inheritance is more common among well-paid, stable, and prestigious occupations, which parents deem to be more desirable for their children, as Devine (2010) finds when comparing doctors to teachers.

[14] Devine's (2010, 49) interviews with doctors revealed that the 'medical world dominated family life'; 'The intrinsic rewards of medicine were discussed at home and amongst their networks of friends who were often medics'.

In addition to the mechanisms outlined by Jonsson et al. (2011), parental expectations might also play a role in shaping children's likelihood of entering their parents' careers. Many of the doctors in Devine's (2010) study wanted their children to enter medicine, with one mother admitting she had exerted 'both implicit and explicit pressure' on her child to do so. This could shape both educational and occupational choices. However, parental expectations seem to play an especially important role in determining people's occupational choices in collectivist cultures (Akosah-Twumasi et al. 2018), and may therefore be less influential in determining occupational outcomes in the UK, which this thesis focuses on.

Together, these skills, tastes, networks and possibly expectations can restrain the occupations people consider, because they aspire to their parent's career, but also because they simply never imagined a world in which they do not enter their parent's occupation,[15] or because following in their parent's footsteps could be the easiest path to take (Mortimer 1974; Gubler, Biemann, and Herzog 2017), an argument which is strengthened by the finding that people with higher risk tolerance are less likely to inherit their careers from their parents (Y. Wang 2020). There are therefore numerous theoretical reasons to expect that people are more likely to enter an occupation if at least one of their parents also works in the field.

Occupational Inheritance over the work life course

Thus far, the literature on occupational inheritance has largely focused on the point of labour market entry. To the best of my knowledge, the only study that has explicitly investigated how occupational inheritance changes over people's life course in the labour market focused on a sample of Swiss teachers' careers between the mid-1960s and late

[15] As one of Devine's (2010, 50) doctor interviewees states: their child 'did not know any other life'.

1990s (Gubler, Biemann, and Herzog 2017). They find that those whose mothers also worked as teachers were substantially more likely to leave the profession as their career progressed, while fathers did not have a statistically significant effect on their offspring's career over the work life course. Gubler, Biemann and Herzog (2017) explain this by stating that individuals become more agentic over the course of their career, meaning their experienced (rather than expected) fit between their values and reality becomes increasingly more important. They further suggest that those whose parents worked as teachers may have entered the profession because of a lack of self-direction, a sense of duty to follow family traditions or due to positive feelings towards their parents, all of which could become less important as people's careers progress, and work values and interest in one's own work becomes more significant. Gubler, Biemann and Herzog (2017) therefore conclude that the link between parents' occupation and their children's occupation weakens over time.

It is certainly feasible for this finding to apply to other cases of occupational inheritance, with the association between parental occupation and own occupation fading over the work life course. As people establish themselves in the labour market, their own experiences are likely to develop their occupation-specific culture and taste, possibly away from those of their parents. Furthermore, they will be able to increasingly rely on their own occupation-specific networks, making their parents' connections less important over time. Therefore, it is possible for the DESO which is observed at labour market entry to dissipate with age.

However, as I discuss above in relation to the development of DESO over the work life course more generally, there are certainly arguments to be made for a continued direct influence of parental occupation on their children's occupation, as parental knowledge, networks, and resources may shape not only entry into- but also progression

or persistence in- an occupation. Hence, parental knowledge and networks might *strengthen* the development of people's skills, tastes, and networks within their parent's occupation.

Does Occupational Inheritance Matter?

Before delving into occupational inheritance in the context of STEM in the analytical section of this thesis, it is important to address a question which has been debated somewhat: *(Why) should we care about occupational inheritance rather than simply focusing on 'big class'?*

One of Erikson, Goldthorpe, and Hällsten (2012)'s biggest criticisms of the increasing focus on individual occupations within social stratification research is that they are unconvinced by the argument that the microclass approach can be used to draw conclusions about inequality of opportunity. Building on an example given by Jonsson et al. (2009), they suggest that ultimately whether the children of truck drivers become truck drivers themselves, or enter another occupation does not matter much in itself, what matters is whether this alternative occupation is higher in the 'big class' scheme. Contrarily, Jonsson et al. (2009) argue that microclass immobility highlights constraints in choice, which is an important aspect of inequality of opportunity, even on the occupational level.[16] They concede that choice of occupation is driven by taste in addition to resources, but argue that tastes themselves can be understood as largely endogenous to class position, an assumption which Erikson, Goldthorpe, and Hällsten (2012) question.[17]

[16] My understanding of this debate was aided by a series of *Inequalities* blog posts by Geiger (2013a, 2013b, 2013c).

[17] There does seem to be a link between family background and education/career choices (Mandler 2020). For example, people from more privileged families are more likely to enter gender a-typical fields (Van de Werfhorst 2017), suggesting they may have had more freedom to explore their interests than less advantaged people.

Although Jonsson et al.'s (2009) defence of the importance of microclass immobility in highlighting the unfairness of our society has been called unconvincing when positioned as an alternative to 'big class' schemes (Erikson, Goldthorpe, and Hällsten 2012; Geiger 2013c), both approaches have their merits. As Devine (2010, 43) points out: 'both Grusky's and Goldthorpe's theories have insights to offer on class and/or social reproduction. Occupational inheritance contributes to class reproduction, and to understand one facilitates an understanding of the other.' In other words, we should care about whether and why the children of truck drivers move out of working-class occupations *and* about whether and why they too become truck drivers; the two questions are not mutually exclusive. This thesis takes a similar stance. I do not suggest that my focus on the occupation level is superior to a focus on broader class categories but argue that given my research questions and relatively homogenous population of interest (graduates), looking at the micro-level is likely to be more insightful than looking at 'big class' schemes.

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In sum, DESO, the association that remains between family background and occupational attainment after controlling for education, has been demonstrated using a variety of measures of social origin. Most commonly, parental social class / occupational status, parental education and parental income have been examined in this regard, with socio-economic status and income being the most studied outcomes. However, recent literature has suggested that a focus on the occupation-level may be fruitful in the study of DESO. The occupation-level, or micro-level, has generally become an increasingly popular area of study in social stratification research, with proponents of the 'microclass approach'

arguing that it leads to a more nuanced understanding of occupational outcomes and the transmission of societal advantages.

In this context, occupational inheritance, the phenomenon of children 'inheriting' their occupation from their parents, promises to be an interesting area of further research. Although occupational inheritance is not a new concept, it remains relatively understudied, and more needs to be done to thoroughly understand whether and how parental occupation shapes their offspring's occupation. Doing so has important implications regarding societal constraints on people's occupational choices. This applies both to the point of labour market entry, and to the work life course, which has rarely been studied when it comes to occupational inheritance and DESO more generally.

There is a debate in the literature on whether DESO, of which occupational inheritance is a subtype, remains among the highly educated. Although it has previously been argued that education is the greatest equaliser, studies increasingly dispute this, demonstrating DESO among graduates. Furthermore, whether DESO decreases with education varies by which measures are examined, with a decline being found in the context of occupational status, but not income. DESO has only recently been explicitly studied from an occupation-level perspective, so the extent to which the direct effect of parental occupation is present among the highly educated remains to be established.

Therefore, we continue to lack a thorough understanding of whether DESO remains when studying the occupation-level, especially among the highly educated, and across the work life course. To address these gaps in the literature, my second and third analytical chapters will focus on occupational inheritance in STEM, investigating it both at the point of labour market entry and throughout the first decade of graduates' time in the labour market.

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In what follows, I situate my investigation of how degree field of study, gender, and parental STEM occupation shape graduates' likelihood of working in STEM both at labour market entry and over the work life course, in the academic debates which I have outlined in this section. I do so in three analytical chapters, the first of which investigates (gendered) horizontal education-job matches in STEM, while the subsequent chapters focus on occupational inheritance in STEM.

4. DATA AND METHODS

4.1. Defining STEM

Before proceeding, it is essential to discuss how I understand the key concept of this thesis: STEM. This is important because there is no universally accepted definition of STEM. In the absence of such consensus, academics and governmental bodies have tended to offer their own definition when writing about the concept, and it is at times unclear what is being discussed and why. Such approaches can be problematic for two reasons. Firstly, the in-/exclusion of certain fields may affect research findings and thus conclusions drawn about issues related to STEM. Therefore, two researchers researching the same phenomenon using different definitions of STEM might find different things due to how STEM was conceptualised. This is highlighted in figure 5 in Chapter 2, for example, which shows that while the overall proportion of STEM graduates in the UK has increased, this is not the case when only looking at the more masculine-typed STEM fields. Secondly, by simply constructing a group of subjects and calling it 'STEM', one can miss differences that exist between STEM-subfields. STEM subjects – however defined – are not a homogenous group (E. Smith and White 2018a), and highlighting differences between them is necessary in order to make nuanced statements about STEM.

4.1.1. Different Approaches to Defining STEM

Although no universal way of defining STEM has been established, three main approaches have become the most common: (i) a categorisation approach, (ii) a skills approach, and (iii) a realised matches approach. The type of approach chosen often depends on the interests of the people or organisations which are defining STEM.

The Categorisation Approach

The most common approach of defining STEM in/excludes specific educational subjects or jobs based on the broader fields they belong to. In the UK, the Joint Academic Coding System (JACS), which was created in 2002/03 as a result of a collaboration between the Higher Education Statistics Agency (HESA) and the Universities and Colleges Admissions Service (UCAS) (HESA 2018), is often used to group educational fields into STEM and non-STEM, although ways of categorisation vary. JACS identifies the following fields as STEM:

1. Medicine and dentistry
2. Subjects allied to medicine
3. Biological sciences
4. Veterinary sciences, agriculture and related subjects
5. Physical sciences
6. Mathematical sciences
7. Engineering
8. Computer sciences
9. Technologies
10. Architecture, building and planning

The categorisation approach is arguably the most intuitive way of defining STEM, which is often understood in terms of specific fields. Critics of JACS have argued it is too broad, as it leads to the inclusion of fields such as sports science that have not traditionally been considered STEM, which are given equal weighting to fields such as engineering. However, JACS can – and has – been adapted accordingly, with the Higher Education Funding Council for England (HEFCE) dropping architecture from their definition, while some Sector Skills Councils exclude medicine and subjects allied to medicine from their definitions (Select Committee on Science and Technology 2012). Alternatively, fields can be distinguished by being grouped into other classifications, such as ‘core’ versus ‘non-core’ or ‘hard’ versus ‘soft’ STEM fields (Select Committee on Science and Technology 2012).

In instances where certain fields are dropped from the definition, subjective choices need to be made. In general, those making choices about which fields they believe to be STEM (or non-STEM) tend to consider which fields are most commonly understood as belonging to STEM in policy discourse and the academic literature. Often, such choices are therefore made on perceived 'STEM-ness' of certain fields, without systematic in/exclusion criteria, and definitions can be heavily influenced by individual interests.

The Skills Approach

Instead of focusing on specific fields, some governmental and non-governmental bodies have started to define STEM by referring to specific skills which are learned in STEM education and used in the STEM workforce. According to the House of Lords' Science and Technology Select Committee (2012), a STEM graduate usually possesses the following skills and characteristics:

> numeracy and the ability to generate, understand and analyse empirical data including critical analysis; an understanding of scientific and mathematical principles; the ability to apply a systematic and critical assessment of complex problems with an emphasis on solving them and applying the theoretical knowledge of the subject to practical problems; the ability to communicate scientific issues to stakeholders and others; ingenuity, logical reasoning and practical intelligence

The Select Committee identifies this approach to be the 'most rational', as they say that these skills are 'needed to generate economic growth', and therefore more important to focus on than individual fields. In the United States, the Occupational Information Network (O*NET) takes a similar approach when defining STEM occupations, which they say 'require education in science, technology, engineering, and mathematics (STEM) disciplines' (O*NET OnLine 2018). However, the skills approach too has shortcomings. For example, through this approach, O*NET include occupations such as 'Sociologists' and 'Political Scientists', due to the quantitative skills which are used in such fields at times, which are arguably not commonly understood to belong to STEM.

The Realised Matches Approach

Lastly, the realised matches approach is similar to the skills approach in terms of being person- rather than field- centred. Instead of defining STEM by field, this approach looks at the behaviour of STEM graduates, defining STEM jobs as those most commonly entered by people with STEM degrees. This approach is taken by the UK Commission for Employment and Skills (UKCES 2011; Bosworth, Lyonette, and Wilson 2013), whose definition(s) Smith and White (2018a) adopt. They define highly skilled STEM occupations based on 'whether an occupation has a high proportion of graduates, a high proportion of STEM-degree holders and a high proportion of STEM-degree holders among graduate entrants' (E. Smith and White 2018a, 54). Similarly, Bol et al. (2019) define degree-work 'matches' based on the top occupations graduates from a given field enter.

Although useful in determining the most common destinations of STEM graduates, this approach has some limitations. Firstly, it relies on pre-defined STEM degree fields, and can therefore only be used to define STEM work. Often, those who use the realised matches approach to define STEM jobs use the categorisation approach to define STEM degrees; Smith and White (2018a) in fact use the JACS subject groups. Secondly, because many STEM graduates enter finance-related work, it leads to occupational groups such as 'Business and Finance Associate Professionals' being defined as STEM jobs (E. Smith and White 2018a). Such fields tend to not be associated with STEM work in general political discourse surrounding the concept.

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The realised matches approach of defining STEM is not unique in claiming that the definition of STEM occupations should be restricted to graduate-level work. In fact,

seemingly the only aspect past studies tend to agree upon when it comes to defining STEM is that STEM occupations require post-compulsory schooling or training. This is either explicitly stated (for example, OECD 2016; Han 2015, 2016; Ulicna and Royale 2015) or implied through the kinds of occupations considered (for example, OECD 2013; Caprile et al. 2015). In some instances, researchers restricting their focus to graduate-level occupations refer to 'highly skilled'/ 'high level' STEM work (E. Smith and White 2018a; UKCES 2011; Bosworth, Lyonette, and Wilson 2013), which implies the presence of 'low level' non-graduate STEM work, but more often than not, definitions of STEM generally pre-suppose degree-level education across the board.

4.1.2. What will I do?

This thesis takes the categorisation approach to defining STEM. My interest in STEM work originated in the political discussions surrounding STEM, which seem to generally define STEM in terms of specific fields. It is rare to see politicians discussing the need for more (quantitative) social researchers in the context of STEM, for example, which is why the skills approach does not fully lend itself to my research aims. Furthermore, due to my interest in the relationship between degree field of study and field of occupation (Chapter 5), defining STEM occupations through the actions of STEM graduates (using the realised matches approach) would introduce bias into my results, whereas the categorisation approach allows me to create independent STEM degree and STEM occupation variables.

Following previous research, I understand STEM work as being highly skilled, usually requiring degree-level education. Given that only 19.3% of school-leavers attended higher education in 1990 (Bolton 2012, 14), when the majority of BCS70 respondents went to university, I relaxed this definition somewhat, focusing on the

occupations with the highest shares of graduates (table 2). This pertained to the first three SOC major groups, namely (i) 'Managers, Directors and Senior Officials', (ii) 'Professional Occupations' and (iii) 'Associate Professionals and Technical Occupations' – the groups which Smith and White (2018a) also define as highly skilled work. Although this approach includes occupations which did not necessarily require a degree in the 1990s, it does narrow my focus down to occupations which require degree-level qualifications in today's labour market. For example, while 31% of BCS70 respondents who worked as technicians had a degree in my sample (table 2), HESA data from 2021/22 revealed that now 77% of technical staff are educated to first degree level or above (Van Essen-Fishman 2024).

Table 2: Proportion of BCS70 graduates by SOC major group

SOC major group		No degree	Has degree	N
1	Managers, Directors and Senior Officials	66.8	33.2	566
2	Professional Occupations	39.3	60.7	843
3	Associate Professionals and Technical Occupations	69.9	30.2	607
	Of which Technicians only	*68.9*	*31.2*	*61*
4	Administrative and secretarial occupations	85.9	14.1	355
5	Skilled trades occupations	92.7	7.3	478
6	Caring, leisure and other service occupations	93.0	7.0	301
7	Sales and customer service occupations	95.6	4.4	160
8	Process, plant and machine operatives	94.3	5.7	176
9	Elementary occupations	91.3	8.7	231
Total		/	/	3310

Note: The values displayed in table 2 refer to the proportion of respondents who worked in each occupational category *at any time point* in the data (T0-T25).

When coding specific fields into STEM subjects and STEM occupations, I based the overall categories I considered on the JACS STEM subject groups.[18] Despite not being

[18] I made small changes to the JACS subgroups; I collapsed 'Medicine and dentistry' and 'Veterinary science' into one group, and combined technology with computer science rather than engineering in my sub-groups. In practice, this did not affect my definitions of STEM, as all of the JACS groups were still included, and was simply done for my ease of coding.

free of criticism (see section 4.1.1.), JACS continues to be commonly used to define STEM subjects across UK government bodies,[19] so using it makes my research most comparable to the outputs of these agencies. Because STEM fields are not homogenous, and to address the broadness of the JACS definition of STEM, I created two definitions of STEM. The first definition, which I call 'Broad STEM', includes all fields defined as STEM by JACS (HESA 2018). This definition was chosen as it includes all subjects that are commonly understood as STEM in past research and policy documents. The second definition, which I call 'Core STEM' is narrower, and only includes 'hard' STEM fields which are universally understood as STEM (i.e., computer science and IT, engineering, mathematics and physical sciences), while some of the 'soft' STEM fields contained in the 'Broad' definition of STEM, such as medicine and architecture, are not. When not explicitly looking at both definitions, as in Chapter 5, I will focus on Broad STEM and use the Core definition in auxiliary analyses. I do so because the majority of government policies surrounding STEM target a broad range of STEM subjects, not just those I include in Core STEM.

4.2. Data

4.2.1. The British Cohort Study (1970)

My analyses rely on the British Cohort Study of 1970 (BCS70), which is collected by the Centre for Longitudinal Studies (CLS). The study is a longitudinal survey that follows the life course of just over 17,000 people born in a single week in April 1970. It covers

[19] For example, it was used by the National Audit Office in the report *Delivering STEM (science, technology, engineering and mathematics) skills for the economy* (Morse 2018), in the Scottish government's (2017) report *STEM Strategy for Education and Training,* and by the Northern Ireland Statistics and Research Agency in recent reports on higher education enrolment in STEM (for example, NISRA 2023), all of which consider perhaps more 'ambiguous' fields such as agriculture and architecture as STEM.

people born in England, Scotland, and Wales (Betthäuser and Bourne 2016),[20] but because of missing educational variables, I will not take Scotland into account. Information about the respondents was collected sporadically during their childhood, and then every 4 years from 1996 onwards, when the respondents were 26 years old. The latest available wave at the time of writing was collected at age 46.

As previously discussed, the respondents of this study were born in 1970, so they made educational and early labour market decisions before the term 'STEM' started to be used in the UK. Nonetheless, BCS70 lends itself to my research aims better than any other available UK data. The later cohort studies, 'Next Steps' and the 'Millennium Cohort Study' follow people born in 1990 and 2000,[21] and their respondents are aged 25 and 17 respectively in the latest available waves (CLS 2023). These studies therefore would not allow me to trace respondents' work over the life course, nor do they contain information on all labour market entrants. Other large longitudinal UK studies such as 'Understanding Society' do not contain information on degree field of study at the time of writing. BCS70 is therefore the only study that contains sufficient detail of respondents' life course both before and after the point of labour market entry. It provides rich information on parental background, childhood, educational trajectories, work trajectories, and respondents' home lives.

4.2.2. Subjects of Study

University Graduates

In line with previous work, I restrict my study to that of people who have graduated from university with at least a bachelor's degree (Glass et al. 2013; Sassler, Michelmore, and

[20] Northern Ireland was additionally included for the birth survey only.
[21] Interestingly, the absence of a 1980s cohort study can be explained by Keith Joseph's (Thatcher's Secretary of State for Education and Science) mission to funnel funding away from the social sciences and towards science and technology (Mandler 2020, 167).

Smith 2017; Xu 2013; De Vita and Giancola 2017; Montmarquette, Cannings, and Mahseredjian 2002; Han 2016, 2015). This is done because of my focus on STEM. While the term STEM does not have a commonly agreed upon definition (see section 4.1.), the majority of studies which investigate STEM labour market outcomes concentrate on occupations that require tertiary education (for example, Ulicna and Royale 2015). Hence, I restrict my population of interest to graduates.[22] Specifically, I look at both undergraduates and postgraduates, defining a 'STEM graduate' as a person who has obtained any type of STEM university degree. Only focusing on graduates will, of course, mean that I can only draw conclusions about the labour market outcomes of people who have attended university. Therefore, my conclusions will not be applicable to less educated people in Britain but will shed light on the highly educated.

Labour Market Entrants

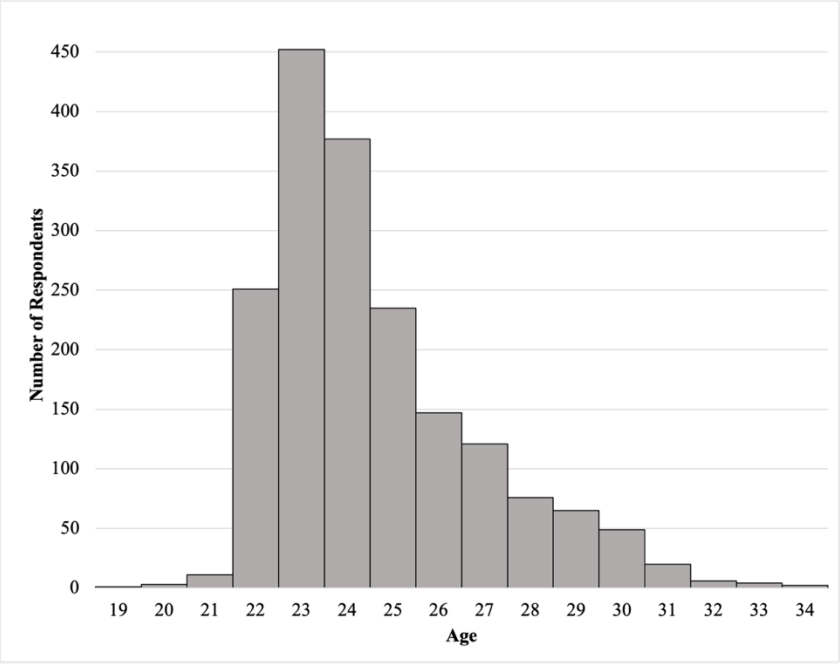
I trace respondents from the point of labour market entry. The definition of labour market entrants varies from study to study. Firstly, there is a wide range of age cut-offs for when people start their first job, with 30 being a common threshold (for example, Murcia, Pepper, and Williams 2020). To compensate for any struggles BCS70 respondents may have had with finding work because of the 1990s recession, I personally decided to pick the slightly older age of 35. Secondly, some studies additionally restrict their definition of labour market entry jobs to ones that respondents have been in for a specified duration of time to exclude 'unserious' work (for example, Jacob and Klein 2019; Gangl 2003). Adapting their approach, I only consider first jobs which people have been in for at least

[22] In this thesis, I will restrict my definition of graduates to university educated people, as has been done by the vast majority of previous literature in this field. In doing so, I am disregarding vocational education equivalents (NVQ5 and 6) which are arguably on the same level of the educational scale as university degrees (Bukodi and Goldthorpe 2013).

3 months, as was recently done by Cantalini and Ballarino (2023).[23] Thirdly, while most past papers studying labour market entrants do not make in/exclusions based on education level or type, I follow Jacob and Klein (2019) in excluding part-time students because 'their educational attainment runs in parallel to their occupational career, and they are likely to have a more stable starting point after graduation when compared to full-time graduates' (Jacob and Klein 2019, 9).

Taken together, I define labour market entrants as people who have left full-time education, who entered the labour market (as employees or self-employees) before the age of 35, and who have been in their first job for at least 3 months. At the point of labour market entry, most respondents are aged 22 or over and the average age at labour market entry is 24.3 (figure 11).

Figure 11: Distribution of respondents at labour market entry (T0) by age



Note: N = 1,820. The average age at labour market entry is 24.3 (standard deviation = 2.3).

[23] Comparing my 3-month definition to people who had been in their first job for at least 6 and 12 months respectively yielded highly similar results, so I considered 3 months sufficient, and chose it over the 6-month cut-off used by Gangl (2003) and Jacob and Klein (2019) for the purpose of increasing my sample size.

Active Labour Market Participants

For the purpose of this thesis, only active labour market participants will be taken into account. My method of analysis does not require complete information on the respondents over the time studied, so only years with information on paid work (in the form of employment or self-employment) are considered. Excluding unemployment should not bias the results, because there is little difference in the unemployment rates of STEM and non-STEM graduates in the UK in general (DIUS 2009; E. Smith and White 2017), and unemployment rates are generally low in the sample; the vast majority of respondents (92%, which rises to 95% when examining the first decade of graduates' careers) did not spend any time over the period I studied in unemployment seeking work.[24] Doing so will, however, limit the conclusions I am able to draw to ones regarding active labour market participation.

✶

Taken together, the population of interest are people who obtained a full-time university degree (undergraduates and postgraduates), have entered the labour market before the age of 35, and are active labour market participants. In Chapter 5, each respondent is included from the point of labour market entry (T0) and followed until the last time they were observed in the BCS70 waves I analyse (which is at age 42 for the vast majority of respondents). On average, each respondent is observed for just over 18 years.

As shown in table 3, 56 respondents were dropped due to missing labour market information, but the final analytical sample consists of 97.1% of all full-time graduates in BCS70 (94.3% when only looking at the 'Core' definition of STEM), and I therefore

[24] This does not take into account people who were out of work for further education, due to sickness or disability, due to family responsibilities or due to retirement.

deem it to be representative of the BCS70 graduates. This is also reflected in table 4, which shows only minor differences in the distribution of degree field of study (by gender) between the wider pool of BCS70 graduates and the analytical sample. Table 4 furthermore reveals that the distribution of the analytical sample across degree field of study and gender is largely highly similar to that of a LFS sample of people born in 1970. This suggests the sample studied in this thesis represents the wider UK population of people born in 1970 well.[25]

Table 3: Cases dropped due to missing values

	Broad STEM		**Core STEM**	
	N	% of total	N	% of total
Full-time degree	1915	100.0	1559	100.0
+ known field of work	1885	98.4	1492	95.7
+ known point of LM entry	1859	97.1	1470	94.3

The final analytical sample size is 1,859 individuals in 30,905 person-year observations. Because of how the field of occupation and degree field of study variables are coded (more detail below), when using the Core Definition of STEM, this decreases to 1,470 individuals in 23,018 person-year observations. In Chapter 6, I only consider the point of labour market entry, and Chapter 7 examines the first decade of graduates' time in the labour market.

[25] The most noteworthy difference is the underrepresentation of women with Broad STEM degrees in BCS70 compared to the LFS (38.3% in the LFS, and 33.7% in the analytical sample).

Table 4: Distribution of graduates by degree subject and gender across different samples

Gender	*Sample*	**Broad STEM**			**Core STEM**		
		STEM degree	Non-STEM degree	N	STEM degree	Non-STEM degree	N
All	Full-time BCS70 graduates	42.9	57.1	1,915	28.6	71.4	1,915
	Analytical sample	43.8	56.2	1,859	28.8	71.2	1,470
	Wider population (LFS sample born in 1970)	44.9	55.1	1,667	28.4	71.6	1,283
Men	Full-time BCS70 graduates	53.2	46.8	1,052	42.4	57.6	869
	Analytical sample	53.5	46.5	1,017	41.9	58.1	812
	Wider population (LFS sample born in 1970)	52.9	47.2	755	42.4	57.6	618
Women	Full-time BCS70 graduates	33.8	66.2	1,010	15.9	84.2	814
	Analytical sample	33.7	66.3	985	15.6	84.4	776
	Wider population (LFS sample born in 1970)	38.3	61.7	912	15.3	84.7	665

Note: The analytical sample is the final sample shown in table 2. The LFS sample is based on people born in 1970 and was drawn from non-secure access LFS data.

4.3. Variables

The variables included in my analyses can be grouped into four categories: (i) dependent variable, (ii) key independent variables, (iii) control variables and (iv) mediator variables. A full list of variables and their basic summary statistics can be found at the end of this section in tables 6 and 7.

4.3.1. Coding STEM

Before discussing individual variables, I want to outline my general approach to coding STEM-related variables (*has STEM A-Level*, *degree field of study*, *field of occupation,* and *parental occupation,* described below). As previously mentioned, my operationalisation of STEM uses the JACS subject groups (HESA 2018) as a jumping off point (see the 'Broad Field Category' column in table 5). To guide me regarding which specific educational subjects and occupations belong to each subject group, I consulted previous classifications (E. Smith and White 2018a; Langdon et al. 2011; Beede et al. 2011), although I did not follow them exactly.[26] If I was uncertain what a specific degree or occupation entailed, I researched them before grouping them into STEM or non-STEM fields. For degree subjects, I mainly relied on university websites to do so, paying attention to subject descriptions and the departments specific degrees belonged to. For occupations, I considered the type of work performed, and whether the occupation seemed to be commonly understood as STEM.

[26] For instance, Smith and White (2018a) include 'Business and Finance Associate Professionals' in their definition of STEM, which I do not.

Table 5: STEM measure compositions

Broad Field Category	Broad STEM	Core STEM
Computer science and IT	✓	✓
Engineering	✓	✓
Mathematics	✓	✓
Physical sciences	✓	✓
Biological sciences	✓	
Medicine, dentistry and veterinary Science	✓	
Nursing and other subjects allied to medicine	✓	
Architecture, building and planning-related	✓	
Agriculture, forestry and other	✓	

For the *has STEM A-Level* and *degree field of study* variables, I include all subjects that fall into the broad fields listed in table 5 in my definition(s) of STEM. For occupations (both respondents' own and parental occupation), I introduce a further restriction by only considering graduate-level work as STEM, as is commonly done (for example, OECD 2016; Ulicna and Royale 2015; E. Smith and White 2018a). I define graduate-level occupations as those belonging to SOC major groups 1 ('Managers, Directors and Senior Officials'), 2 ('Professional Occupations') and 3 ('Associate Professionals and Technical Occupations'), following Smith and White (2018a).

With the exception of *has STEM A-levels*,[27] I code all STEM-related variables twice, once using the Broad definition of STEM, and once using the Core definition of STEM. The Core STEM variables only compare Core STEM fields to fields that do not fall into any definition of STEM. This means that if a respondent works in a job that would be defined as STEM using the Broad definition, but not the Core one, the

[27] This decision was made because the variable *has STEM A-Levels* is not a key variable in this thesis, and the Core versus Broad STEM distinction makes less sense in the context of A-Levels. Therefore, to increase sample-size, I use the Broad definition of STEM when it comes to A-Levels.

respondent's job is coded as STEM for the Broad STEM *degree field of study* / *field of occupation* / *parental occupation* variables, and as missing for the Core STEM ones. This was done to preserve the STEM versus non-STEM distinction.

4.3.2. Dependent Variable

Field of Occupation (STEM versus Non-STEM)

The dependent variable of this study is a dummy capturing whether respondents are in a STEM occupation at a given point in time, where 0 = work in a non-STEM occupation, 1 = work in a (Broad / Core) STEM occupation. This variable was created using 3-digit SOC90 codes and 4-digit SOC2000 codes from Hancock's (2017) Activity Histories file as well as 3-digit SOC2010 codes from BCS70 itself. Unfortunately, due to a lack of nuance in SOC codes, I was unable to determine whether graduates who went into teaching did so in STEM or non-STEM fields. Hence, for the purpose of this thesis, teaching is not considered a STEM job. As explained above, I only consider occupations belonging to SOC major groups 1 ('Managers, Directors, and Senior Officials'), 2 ('Professional Occupations') and 3 ('Associate Professionals and Technical Occupations') as STEM. For an in-depth explanation of my process as well as a full list of occupations considered STEM, see section A1 in appendix A.

4.3.3. Key Independent Variables

Degree Field of Study (STEM versus Non-STEM)

My key independent variable is *degree field of study* at university. This variable captures whether respondents have obtained a STEM degree of any kind (undergraduate or postgraduate), rather than examining undergraduates and postgraduates separately. This decision was made to avoid small-n issues. The degree field of study variable has two levels: 0 = degree obtained but not in STEM, 1 = (Broad / Core) STEM degree obtained.

The majority of people with a STEM degree have obtained their degree at undergraduate level; 87.25% of STEM graduates only have an undergraduate STEM degree, 9.85% have an undergraduate *and* postgraduate STEM degree, and only 2.90% have a postgraduate STEM degree but not an undergraduate STEM degree (this includes people for whom information on undergraduate field of study is missing). For an in-depth explanation of my process as well as a full list of degrees considered STEM, see section A2 in appendix A.

I created the field of degree variable(s) using the age 30, 34, and 42 sweeps. The Age 30 answers were not coded by BCS70, so I manually coded the responses into the Age 34 codes. In cases where I had different information on the first degree (from the Age 30/34 versus 42 surveys) I relied on the earlier surveys as these are likely to be more accurate as less time had passed between respondents' time in higher education and the interview.

Sex

My second key independent variable in Chapter 5 captures respondents' sex (0 = man, 1 = woman), which was collected in the Age 10 sweep. Throughout the text, I refer to sex/gender interchangeably, but it should be noted that I am unable to take differences between these concepts into account, and therefore understand gender as binary due to data restrictions.

Parental Field of Occupation (STEM versus Non-STEM), Age 10

The key independent variable of Chapters 6 and 7 is *parental field of occupation (STEM versus non-STEM)*, a dummy variable measuring whether respondents had at least one parent who worked in STEM at the age of 10. Because of the small sample size, and the historic underrepresentation of women, especially those with children, in the labour

market (as discussed in section 2.4.2.), I do not distinguish between mothers and fathers in STEM.[28] This variable was coded using SOC90 codes from the ESRC project 'An examination of the impact of family socio-economic status on outcomes in late childhood and adolescence' led by Paul Gregg (2012), which created occupational code classifications using the CASCOT (Computer Assisted Structured Coding Tool) software programme (Morris 2012, 7).[29] Using these codes, I grouped mothers' and fathers' occupations into broad fields and subsequently STEM versus non-STEM fields, following the same approach I took for my dependent variable, before creating an overall 'parental STEM' variable.

Time Elapsed Since Labour Market Entry

To investigate change over respondents' work life course, which I address in Chapters 5 and 7, I created a variable that captures the time (in years) that has elapsed since labour market entry. I define labour market entry as the first economic activity respondents partook in (employment or self-employment) after completing full-time education, that lasted at least 3 months and was started by the age of 35.

[28] Past research has found differences in how mothers and fathers influence their male and female children's career aspirations (for example, Paa and McWhirter 2011; Sikora and Pokropek 2012; Bahar and Adiguzel 2016), but given that I do not examine the relationship between gender and occupational inheritance in these chapters, this omission will hopefully not affect my findings.

[29] The project coded SOC90 codes in two steps, as outlined by Morris (2012, 7): Firstly, SOC90 codes as well as confidence thresholds (out of 100) were assigned automatically based on text responses. Secondly, any automatic codes with a low confidence threshold score (<46) were manually assigned by a researcher. A randomised sample of 10% of the data (n=1,211) was also coded by another researcher using the previous two steps, which was then added back into the output file to allow comparison of the manual coding. However, because the 'verification' data are highly correlated with the data from step two above (r=0.92), I chose to only look at the original codes.

4.3.4. Control Variables

Person Characteristics

To control for the respondents' characteristics, I firstly include a variable capturing their age at the point of labour market entry, because age has been shown to affect the likelihood of horizontal education-job matches among (female) STEM graduates (Xu 2017), and the extent of parental influence on graduates' career outcomes (Kratz, Pettinger, and Grätz 2022). Next, I include a measure of migration status (0 = born in UK, 1 = born outside UK), because career attitudes vary by country and culture (Akosah-Twumasi et al. 2018), which could shape decisions regarding STEM. I also include a dummy variable to indicate whether a respondent is a person of colour or white (0 = white, 1 = person of colour). I collapsed ethnicity in this way due to a low number of people of colour in my sample. In Chapters 6 and 7, I additionally control for sex, which is a key independent variable in Chapter 5, because gender is well established as affecting people's likelihood of entering STEM work (Xie and Shauman 2003). In Chapter 7, I control for number of children and partnership status which are mediator variables in Chapter 5, because family responsibilities have been shown to affect people's likelihood of being in STEM (Cheng, Kopotic, and Zamarro 2019).

Social Origin

Parental Social Class, Age 10

For the parental social class variable, I again used data coded as part of the ESRC project 'An examination of the impact of family socio-economic status on outcomes in late childhood and adolescence' led by Paul Gregg (2012). These variables are based on data from 1980, when respondents were 10 years old.

Using SOC90 occupational variables for mothers and fathers, I first coded NS-SEC using conversion matrices. Because I have information both on employment status and the size of organisations parents worked for, I derived NS-SEC using the full method. This method was chosen as it 'achieves the best quality derivation' (when compared to the reduced and simplified methods) (ONS 2010, 20). The detailed NS-SEC variables were then collapsed to create a vertical classification with 7 levels:

1. Higher Managerial & professional occupations
2. Lower managerial & professional occupations
3. Intermediate occupations
4. Small Employers and own account workers
5. Lower technical and supervisory occupations
6. Semi-routine occupations
7. Routine occupations

To create an overall parental class variable based on mother's and father's class, I used the dominance approach following Bukodi and Goldthorpe's (2013, 1037) method: 'husband's class is taken to dominate wife's class unless the latter is higher in the ordering of the classes as 1, 2, 3–5, 6, 7, in which case wife's class dominates'.

Parental Education, Age 10

Following Betthäuser and Bourne's (2016) adaptation of Bukodi and Goldthorpe's (2013) method, I created a 7-level composite measure of parental education incorporating information about both parents' highest level of education:

1. Neither parent has any qualification
2. One parent has secondary or lower qualification; other parent has no qualification
3. Both parents have secondary or lower qualification
4. One parent has higher secondary or lower tertiary qualification; other parent has lower qualification
5. Both parents have higher secondary or lower tertiary qualification
6. One parent has degree-level qualification; other parent has lower qualification

7. Both parents have degree-level qualifications

In the above, 'secondary or lower qualifications' were operationalised using O-Levels and Trade Apprenticeships, and 'higher secondary or lower tertiary' were operationalised as A-Levels or sub-degree qualifications (i.e., Certificate of Education / SRN).

These variables were made up of dummy variables as well as categorical variables contained in the Age 10 survey, to reduce missingness. When a parent's qualifications were recorded as 'other' in BCS70, I coded them as missing. If educational information was only available for one parent, I imputed the other parents' level of education using the 'modal value for partners corresponding to the valid category' (Betthäuser and Bourne 2016, 14). For example, if I had information that a respondents' father was educated to 'higher secondary or lower tertiary' level but had no information on the education of the respondents' mother, I imputed the modal value of education for all mothers whose partners had 'higher secondary or lower tertiary' level education.

Parental Income, Age 16

To create the parental income variable, I followed an adapted version of Betthäuser & Bourne (2016)'s approach. I used information from the Age 16 sweep, which contained the combined gross income of both parents, including all earned and unearned income before tax and national insurance deductions. All other social origin variables I include in my analyses were collected when the BCS70 respondents were 10 years old, but parental income was not collected prior to age 16. Respondents were asked to exclude child benefit, so I manually added this to the gross income measure based on 1986 child benefit rates. To do so, I derived respondents' household structure using information on who the respondents lived with at age 16 (to derive lone-parent status), and information on their number of siblings. The combined gross parental income variable provided in

BCS70 contains 11 weekly income bands, ranging from 'under < £50' to 'over £500'. I took the mid points of each of them (for example, if someone's parents' income is coded as '£50-99', I coded their weekly income as '£75'), assigning £25 to the lowest band and £525 to the highest.[30]

Work Characteristics

Full-Time Work

Because of the relatively small sample size of graduates, I take both full- and part-time work into account in this thesis. This also ensures that women are not disproportionally excluded from the sample, as many women who were born in 1970 switched to part-time work (rather than leaving the labour market) after child birth (Roantree and Vira 2018). All analyses control for this distinction by including a full-time work dummy variable. In total, 92% of all person-year observations in the sample are in full-time work.[31]

4.3.5. Mediator Variables

School-Level Mediators

Number of Good A-Levels

Because having a parent in STEM has been shown to influence people's school performance, in Chapters 6 and 7 I include a variable capturing the number of good A-Levels (A*-C) a respondent obtained. Unfortunately, BCS70 does not break down school performance by subject, so I am unable to determine whether respondents performed well in STEM fields, but I use overall performance as a proxy. Due to my focus on labour

[30] There was high missingness in the variable, so in cases where I did not have any information on siblings, I used the child benefit entitlement for a family with only one child (depending on lone parent status). In cases where I did not have information on lone parent status, I calculated income as if I was calculating it for a couple (since 89.5% of all parents who I do have information on are in couples). The number of respondents remained relatively low, so I also included weekly parental income information plus the child benefit for a couple who are parents of one child for all parents whose household composition was not known.

[31] This increases to 95% when only looking at men and decreases to 89% when only looking at women.

market entrants, the variable was created only using information from the Age 26 and Age 30 sweeps. Because the quality of the educational information in the Age 26 sweep was affected by the low response rate in that sweep (Dodgeon and Parsons 2011), I prioritised Age 30 information, and only use Age 26 if information for Age 30 is missing. This variable is a mediator in Chapters 6 and 7, and a control variable in Chapter 5.

Whether Respondent has STEM A-Level

I include a dummy variable capturing whether the respondents have obtained at least one STEM A-Level, because parental field of occupation plays an important role in their children's school subject choices. School subject information was available for the Age 30 sweep but was not collected at age 26. BCS70 did not code the subject variables at Age 30, instead simply reporting what interviewers had recorded. Hence, I manually coded these variables into the field of study categories I used for the *degree field of study* variable (which were based on those used by BCS70 in the Age 34 sweep), and subsequently created STEM versus non-STEM variables. In total, I did so for 10 A-Level variables. Lastly, I created a dummy variable measuring whether a respondent has at least one (Broad) STEM A-Level. This variable is examined as a possible mediator in Chapters 6 and 7, and a control variable in Chapter 5.

Mathematics Competence, Age 10

Respondents' early mathematics competence was captured at age 10 using the Friendly Maths Test, a test which was developed for BCS70 and consisted of 72 multiple choice questions testing respondents on a wide range of mathematics areas, including arithmetic, number skills, fractions, algebra, geometry and statistics (Parsons 2014). These questions became increasingly harder, and the test was stopped once a respondent failed six consecutive items. This variable is a mediator variable in Chapters 6 and 7.

Aspirational Mediators

Career Aspirations

At age 16, respondents were asked: 'Nearly everyone of your age has some sort of idea of what they will want to do in life. Here is a list of types of jobs/careers/professions for which various amounts of training are necessary. How about your choice(s)?' The options given to students generally do not easily translate into STEM versus non-STEM interests, but I created two dummy variables using the responses to this question, capturing whether respondents showed interest in 'processing work – computing, information technology' and 'health' work. These dummy variables carry a value of 1 if respondents said they were or might be interested into a certain type of work, and otherwise a 0. It is important to note that these dummies do not capture all STEM career aspirations, as children aspiring to work in fields such as engineering or the biological and physical sciences may not have indicated interest in either of these areas. These variables are, however, the best way of capturing STEM career aspirations that I could create based on the measures available in BCS70. These variables are examined as possible mediators in Chapters 5 and 6.

University-Level Mediators

Undergraduate Degree Performance

Additionally, I include respondents' undergraduate degree class to account for the possible effect of having a parent in STEM on academic performance at this stage of respondents' educational careers. This variable has 5 levels: 0 = 'First', 1 = 'Upper Second', 2 = 'Lower Second', 3 = 'Third' and 4 = 'Pass'. Degree class was only collected for undergraduate degrees in BCS70. In cases where respondents obtained several undergraduate degrees, I created an overall degree performance variable that prioritised the respondents' first degree grade and used later grades only if no information on their

first grade was available. This variable is a mediator variable in Chapters 6 and 7, and a control variable in Chapter 5.

Type of Undergraduate University

I include the type of university respondents attended at undergraduate level (0 = 'Other' University, 1 = Post-92 University, 2 = Russell Group University) because parents have been found to influence the kind of university their children attend (Paul 2014), and this might be one way 'STEM parents' can better guide their children into the STEM labour market. This information was obtained from the Age 42 sweep, which asked respondents for the name of the university they attended for their first degree.

It should be noted that this measure is crude for two reasons. Firstly, at the time the majority of BCS70 respondents started their degrees, the Post-92 universities were still polytechnics, and the Russell Group, which was formed in 1994, did not yet exist. Prior to 1992, there was already a distinction between these groups, however, as the majority of Russell group members had been universities or university colleges for decades, while the Post-92 universities were polytechnics. Secondly, there are differences between universities within these groups that may affect graduates' labour market outcomes. For example, the 'golden triangle' of Oxbridge and London-based universities are distinct from other Russell Group universities as they produce a large proportion of elite scientists in the UK (Bukodi, Goldthorpe, and Steinberg 2023), with the University of Cambridge being particularly noteworthy. This measure therefore gives a broad overview of university prestigiousness, without going into detail. *Type of undergraduate university* is a mediator variable in Chapters 6 and 7, and a control variable in Chapter 5.

Has Postgraduate Degree

Because postgraduate study is predominately motivated by career concerns (Mellors-Bourne, Hooley, and Marriott 2014), which could subsequently shape career outcomes, I include a dummy variable capturing whether respondents have a postgraduate degree (0=undergraduate degree only, 1=has undergraduate and postgraduate degree). Due to the small number of respondents with postgraduate degrees, I do not distinguish between STEM and non-STEM degrees at postgraduate level. This variable is a mediator variable in Chapters 6 and 7, and a control variable in Chapter 5.

Work-Level Mediators

Parental Help with Job Searches

To unpack how having parental help may affect their children's early career choices, I use respondents' answers to the question 'Have your parents ever done any of the things on this card to help you to get any job you have ever had? Please include internships and placements, even if unpaid', to construct four variables capturing parents' contribution: (i) parental advice (general and with application forms), (ii) parental recommendation to an employer (including writing a reference), (iii) direct employment through a parent, and (iv) parental network, measuring whether parents used their contacts to find their child a job. This variable was collected at age 42 but will be used as a proxy for parental help at the point of labour market entry. I use these variables as mediator variables in Chapter 6.

Was Promoted to Manager

Using NS-SEC, I created a variable that carries the value of 1 if someone was promoted into either lower or higher 'managerial and administrative occupations' from a lower occupation in the previous year. To ensure I could use NS-SEC in a hierarchical way, I excluded the 'Small Employers and Own account workers' category from this exercise. This measure is somewhat crude, as it does not allow me to account for promotions within

NS-SEC categories, but it is the best way I can operationalise promotion opportunities using BCS70. This variable is included as a possible mediator in Chapters 5 and 7.

Substantial Pay Increase since Last Sweep

BCS70 does not contain information on pay between sweeps. The pay variable is therefore coded on a person-sweep, rather than person-year, basis. For each sweep, hourly net pay was calculated using a variety of BCS70 variables and adjusted to 2015 prices to be able to compare pay across sweeps. Ideally, I would have used a measure of gross pay, as this is not affected by taxation and therefore more accurately reflects labour market returns across the work life course, but gross pay was not collected in the Age 26 sweep, while net pay was. Therefore, to maximise sample size considering this variable is already only available on a sweep basis, I decided to use net pay. Strictly speaking, these variables capture labour market income, not pay, as it applies to both employees and self-employed people. Using these hourly net pay variables, I created a dummy variable that captures whether respondents' pay increased by at least 10% since the last sweep. This threshold was chosen to ensure I measure substantial, non-routine, pay increases, as my aim is to capture the pay and promotion opportunities in STEM. This variable is a mediator in Chapter 5.

Total Number of Labour Market Activities

To establish how often respondents changed their labour market activity, as I anticipate that 'STEM parents' might affect career stability, this variable counts the total number of different labour market activities a respondent found themselves in over the work life course. This variable is used in Chapter 7, which examines the first decade of the graduates' careers, and is therefore created only taking those 10 years into account. A

labour market activity here is defined as either full or part-time employment, or full- or part-time self-employment.

Family Mediators

Number of Children

The number of children respondents had at a given point in time was coded using information from the BCS70 'person grid' dataset, which was created as part of the 2012 sweep, and topped up with data collected in the 2016 sweep. This dataset contains information on respondents' children's birth years, as well as information on when (non-biological) children started living with the respondents, and when children left the household. I take all children under the age of 18 living in a respondents' household into account, including 'own' children, adopted children, current or previous partner's children, fostered children, grandchildren and children of non-related adults living in the household. This variable is a mediator variable in Chapter 5, and a control variable in Chapter 7.

Partnership Status

The variable capturing respondent's partnership status was created using Hancock's (2016) 'Partnership Histories' dataset, as well as additional information from the 2016 sweep. Using the information, I created a yearly partnership variable, distinguishing between people who were not in partnership due to being single, divorced, or widowed (= 0), cohabiting (= 1) or married (= 2). As is the case with *number of children,* this variable is a mediator variable in Chapter 5, and a control variable in Chapter 7.

Career Break due to Family Obligations

To measure whether people's time in the labour market was interrupted by family obligations, this dummy variable captures whether respondents were outside of work

either due to maternity leave, or as a result of looking after home or family more generally at any point over the observed time frame. This variable is used as a mediator in Chapter 5.

Table 6: Summary of continuous measures

Variable	Measure	*Mean*	*Min*	*Max*
Time elapsed since LM entry	Average total number of years in data	18.2	1	26
Number of good A-Levels	Average number of good A-Levels	2.0	0	10
Childhood mathematics competence	Average Score	55.0	12	72
Number of children	Average number of children	0.7	0	6
Age at labour market entry	Average age at LM entry	24.3	19	34
Parental Income	Average weekly household income (£)	302.0	32.1	553.4
Total number of jobs (up to T10)	Average number of jobs	3.0	1	8

Note: Only values for people for whom information on *field of occupation* and *time elapsed since LM entry* is not missing are included in this table. This table displays averages values across all imputed datasets.

Table 7: Summary of categorical measures

Variable	Measure	'Between' percentage
(Categorical) Key Variables		
Field of occupation	% in Core STEM occupation	28.6%
	% in Broad STEM occupation	44.7%
Degree field of study	% have Core STEM degree	28.1%
	% have Broad STEM degree	42.6%
Sex	% women	49.8%
Parental occupation	% have Core STEM parents	6.8%
	% have Broad STEM parents	16.4%
(Categorical) Control Variables		
Migration status	% born outside UK	2.6%
Person of colour	% non-white	5.7%
Parental social class	% Higher managerial & professional occupations	26.2%
	% Lower managerial & professional occupations	29.3%
	% Intermediate occupations	17.9%
	% Small employers and own account workers	7.2%
	% Lower technical and supervisory occupations	7.0%
	% Semi-routine occupations	7.9%
	% Routine occupations	4.5%

Continued on next page.

Table 7 continued: Summary of categorical measures

Variable	Measure	'Between' percentage
Parental education	% Neither parent has any qualification	10.9%
	% One parent has secondary or lower qualification; other parent has no qualification	11.2%
	% Both parents have secondary or lower qualification	17.5%
	% One parent has higher secondary or lower tertiary qualification; other parent has lower qualification	15.5%
	% Both parents have higher secondary or lower tertiary qualification	5.8%
	% One parent has degree-level qualification; other parent has lower qualification	30.7%
	% Both parents have degree-level qualifications	8.5%
Full-time work	% working full-time	97.6%
(Categorical) Mediator Variables		
Partnership status	% not in partnership	87.2%
	% cohabiting	53.7%
	% married	71.0%
Career break due to family obligations	% took time out of labour market to care for family	15.1%
Technology career aspirations	% aspired to technology career	24.3%
Health career aspirations	% aspired to health career	14.2%
Was promoted to manager	% were promoted to manager since last year	13.7%
Substantial pay increase since last sweep	% received a substantial pay increase since last sweep	37.2%
STEM A-Level	% have STEM A-Level	44.8%
Undergraduate degree performance	% First	8.3%
	% Upper Second	43.6%
	% Lower Second	36.4%
	% Third	4.3%
	% Pass	7.4%
Type of undergraduate university	% attended Russell Groups university	30.8%
	% attended Post-92 university	33.7%
	% attended other university	35.4%
Postgraduate degree	% with postgraduate degree	15.1%
Parental advice	% received parental help with job searches in the form of advice	17.6%
Parental recommendation	% received parental help with job searches in the form of recommendation	4.5%
Parental direct employment	% received parental help with job searches in the form of direct employment	5.8%
Parental contacts	% received parental help with job searches in the form of contacts	12.7%

Note: The values displayed here refer to the number/proportion of respondents who fell into a specific category *at any time point* in the data. Only values for people for whom information on *field of occupation* and *time elapsed since LM entry* is not missing are included in this table. This table displays averages values across all imputed datasets.

4.3.6. Missing Data

BCS70 has high missingness on certain variables, which means the number of complete cases available for my analyses is low. This can affect the representativeness of the sample and accuracy of estimates, which is why I address missing data using multiple imputation. When using BCS70, multiple imputation is recommended as a way of addressing missing data by the Centre for Longitudinal Studies (Mostafa and Wiggins 2014), and commonly utilised by researchers working with the study (for example, Bukodi, Bourne, and Betthäuser 2018; Tinner et al. 2021).[32] All regression results presented in this thesis are run using imputed data. The data were imputed in wide format (UCLA 2021), generating 25 imputed datasets. Because several of my models contain a squared term for *time elapsed since labour market entry*, so a non-linear relationship between one of the predictors and the outcome variable, I do not impute the outcome variable to ensure I do not bias the results (van Ginkel et al. 2020). The full list of multiply imputed variables and number of imputed cases can be seen in table 8.

Using multiple imputation does not change the underlying values substantially. For example, in the 'raw' (unimputed) data, 15.9% of respondents have a 'Broad STEM parent', while 16.4% of respondents in the imputed datasets do on average. Similarly, when comparing the proportion of women in the raw data versus the imputed data, the proportions are 49.1% and 49.8% respectively. Even for variables which ended up with a high number of imputed observations, such as the parental help ones (see table 8), estimates do not change much; while 17.0% of respondents in the raw data have received parental help with a job search in the form of advice, 17.6% in the imputed datasets did on average.

[32] I believe multiple imputation to be appropriate here, as I argue the BCS70 data should be seen as a sample of people who were born in 1970 in Great Britain, rather than as a population of people born in a single week.

Due to technical issues which were likely caused by the high number of categorical variables present in the dataset, the variables *number of children*, *partnership status*, *was promoted to manager* and *substantial pay increase since last sweep* could not be imputed. In the case of the family variables, I used nearest neighbour imputation, prioritising previous years, to increase the sample size, but I did not believe this to be a good approach for the work variables because those are less likely to be constant across time. Therefore, the models including these variables have lower sample sizes, as indicated in the corresponding regression tables.

Table 8: Summary of missing and multiply imputed cases

	Variable	Number of missing observations (n=1,859)	Number of imputed observations (n=1,859)
Key variables	Field of occupation (Core STEM)	389	0
	Field of occupation (Broad STEM)	0	0
	Degree field of study (Core STEM)	347	0
	Degree field of study (Broad STEM)	0	0
	Sex	151	151
	Parental occupation (Core STEM)	322	322
	Parental occupation (Broad STEM)	152	152
	Time elapsed since labour market entry	0	0
Control Variables	Average age at LM entry	0	0
	Migration status	244	244
	Person of colour	0	0
	Parental social class	273	273
	Parental education	254	254
	Parental Income	838	838
	Full-time work	0	0
Mediator Variables	Number of children	356	0
	Partnership status	155	0
	Career break due to family obligations	0	0
	Technology career aspirations	675	675
	Health career aspirations	675	675
	Was promoted to manager	204	0
	Substantial pay increase since last sweep	177	0
	Total number of jobs (up to T10)	0	0
	Childhood mathematics competence	505	505
	Number of good A-Levels	588	588
	STEM A-Level	0	0
	Undergraduate degree performance	36	36
	Type of undergraduate university	341	341
	Postgraduate degree	0	0
	Parental advice	712	712
	Parental recommendation	712	712
	Parental direct employment	712	712
	Parental contacts	712	712

4.4. Methodology

4.4.1. Binary Logistic Regression

My research questions concern both the point of labour market entry and graduates' careers over the work life course. Because my interest lies in the strength of association between *degree field of study* / *sex* / *parental occupation (STEM versus non-STEM)* and *field of occupation (STEM versus non-STEM)*, and how these associations change over

the work life course, I use binary logistic regression rather than methods tracing individual respondents' trajectories.

To address the point of labour market entry, which I study in my first and second analytical chapters (Chapters 5 and 6), I use cross-sectional logistic regression, while for research questions concerning the work life course, which are addressed in my first and third analytical chapters (Chapters 5 and 7), I use logistic panel regressions with random effects and include the variable *time elapsed since labour market entry* as well as its quadratic term to capture the effect of time. In the longitudinal models, where applicable, I lag the time-dependent independent variables by one year to ensure basic time ordering. However, due to my definition of labour market entry necessitating that respondents have just completed a degree, I do not lag degree field of study. Furthermore, given that the promotion and pay opportunity related variables already have time ordering built into them, I also do not lag them.

Each of my analytical chapters contains a research question regarding possible explanations for any patterns I observe. To address these types of research questions, I adapt Gugushvili, Bukodi and Goldthorpe's (2017) approach of 'unpacking' a direct effect through a series of nested regression models, including various (groups of) mediator variables to the base models, and assess how they affect the 'main' effect of interest. Because log-odds ratios cannot be compared across models with different independent variables in a sample (Mood 2010), I will look at the change in AMEs and predicted probabilities. It should be noted that the main aim of this thesis is not to provide explanations for the relationships I observe, and this method of 'unpacking' effects cannot be used to draw conclusions regarding causal mechanisms. Rather, my aim here is to examine correlations to give an initial indication of what possible mechanisms may be driving the associations I observe.

4.4.2. A Note on Interpretation

Predicted Probabilities and other Metrics

Although I will at times present log-odds ratios in regression tables when it is not possible to calculate average marginal effects (AMEs), when drawing conclusions about interactions *in longitudinal models*, I will focus on plotted AMEs and predicted probabilities, as recommended by Mize (2019). This is because in binary logit models, the magnitude and statistical significance of a product term can often be misleading and cannot be used to conclude about the presence of an interaction effect, as a single coefficient does not sufficiently reflect the entire predicted probability curve (for a more detailed explanation, see Mize (2019)). Mize (2019, 102) goes so far as to state: 'The coefficient of the product term—although needed in the model—can safely be ignored when testing for and interpreting interaction effects in the predicted probability metric.' Therefore, I will rely on the predicted probabilities and AMEs to draw conclusions.

Predicted probabilities and AMEs have the additional benefit of being more intuitive than metrics such as log-odds or odds ratios (Karaca-Mandic, Norton, and Dowd 2012), and are therefore easier to interpret. When calculating these predicted probabilities, I will use the method of marginal standardisation,[33] which Muller and MacLehose (2014) identify as the best way of calculating predicted probabilities due to allowing inference to the total population (while predictions at the modes or means only allow inference to the relevant stratum of observations).

[33] '[I]n which predicted probabilities of the outcome are calculated for every observed confounder value and then combined as a weighted average separately for each exposure level' (Muller and MacLehose 2014, 963).

Confidence Intervals

When testing the differences between different groups (for example, STEM versus non-STEM graduates) or different time points (for example, t versus t+5), I will not rely on confidence intervals to conclude about non-significance. Although non-overlap of two confidence intervals *does* indicate a statistical significance, an overlap *does not* necessarily indicate a lack of statistical significance (Belia et al. 2005; Mize 2019). This is because the error bars I present as part of my findings are probable ranges for specific point estimates, not for the differences between estimates. As Mize (2019, 91) explains: 'The only way to know for sure whether group differences (for example, men versus women) are statistically significant is to explicitly test for this difference.' I will therefore determine statistical significance based on further tests wherever possible, the results of which I will present as part of the findings section or mention in the notes under graphs.

Significance Level

Because of the relatively small sample size, this thesis uses a significance level of 10%, although all tables will use asterisks to distinguish between p values smaller than 0.1 (*), 0.05 (**) and 0.01 (***). The thesis presents 90% confidence intervals throughout.

5. ANALYTICAL CHAPTER 1

Gendered education-job (mis)matches in STEM: How do STEM graduates' occupations differ by gender over the work life course?

5.1. Introduction

Policies aimed at increasing the number of people working in the STEM labour market have largely focused on increasing student numbers in the field. Many of these policies specifically concentrate on women and girls, as it is widely known that women continue to be underrepresented in both STEM education and STEM work (for example, Xie and Shauman 2003; Blackburn 2017), which I have also shown descriptively in Chapter 2. These policy initiatives rely on several assumptions, a key one being that future STEM workers get to their jobs in a rather straight-forward trajectory choosing STEM fields at school, then studying STEM at university and finally entering horizontal education-job matches by working in STEM occupations. This assumption is also reflected in the academic literature to a certain extent, and much of the work investigating trajectories into STEM and STEM gender gaps has focused on degree field of study choice, repeatedly demonstrating that women are less likely to study STEM subjects than men (for example, Friedman-Sokuler and Justman 2016; Morgan, Gelbgiser, and Weeden 2013).

However, the STEM school-to-work link is more complicated than this assumption suggests (Witteveen and Attewell 2020b; Metcalf 2010), and simply obtaining a STEM degree does not guarantee that one will work in STEM. In the UK context, several studies have found that around half of all STEM graduates do not enter STEM work at the point of labour market entry (Bosworth, Lyonette, and Wilson 2013; Select Committee on Science and Technology 2012; E. Smith and White 2017, 2018a;

DIUS 2009; E. Smith 2011a), a pattern which has also been found in the US (for example, Xu 2013; Preston 2004; VanHeuvelen and Quadlin 2021) and Canada (Frank 2019). Furthermore, the majority of past studies have demonstrated a drop in the share of STEM graduates in STEM work over the life course (Preston 2004; Hunt 2016; E. Smith and White 2018a, 2020; Deming and Noray 2018; Frank 2019; Glass et al. 2013; Frehill 2009, 2012), suggesting that the association between having a STEM degree and working in STEM weakens over the work life course.

The way in which this association varies by gender continues to be debated, with some finding that women in STEM are less likely to be in horizontal education-job matches than their male peers from the point of labour market entry (for example, Sassler, Michelmore, and Smith 2017; Robst 2007a), while others only find small, or no differences when looking at the labour market outcomes of STEM graduates (for example, E. Smith 2011b; Xu 2013). Should women indeed be less likely to benefit from obtaining a STEM degree (in terms of entering STEM work), both at labour market entry and over the work life course, this would have important implications for the current way policies that are aimed at increasing gender equality in STEM work are formulated. It is therefore vital to understand how the relationship between having a STEM degree and working in STEM is shaped by gender. Hence, to establish whether and to what extent gender influences entry into STEM work among people who obtained a STEM degree, I will ask:

(i) How does the relationship between obtaining a STEM degree and entry into STEM work vary by gender?

This first question concerns the point of labour market entry and aims to provide an initial idea of how a STEM degree shapes STEM work, thereby shedding more light on the debate in the literature. The chapter's main contribution(s) lie in my second

research question, however, which addresses the way in which gender differences develop over the work life course:

(ii) How do gender differences in the strength of association between being a STEM graduate and working in STEM develop over the work life course?

Most past research investigating gender differences in the likelihood of working in STEM has focused on the early destinations of graduates, and life course approaches are still relatively uncommon in this area, and in studies of horizontal education-job (mis)matches more generally. Subsequently, a consensus regarding the career patterns of male and female STEM graduates has not been reached. In the UK context, this question has only been addressed using descriptive statistics thus far (E. Smith and White 2018a), while this chapter will utilise more thorough inferential statistics.

Finally, this chapter aims to isolate the mechanisms through which gender may influence STEM graduates' career patterns. To do so, I will focus on the main areas that have been identified as leading to (gendered) attrition of people from STEM work: (i) family obligations, (ii) (a lack of) pay and promotion opportunities, and (iii) career interests, and see what role they might play in gendered occupational choices of UK STEM graduates.

(iii) To what extent can family obligations, pay and promotion opportunities, and career interests explain gender differences in the association between being a STEM graduate and working in STEM?

Unlike in subsequent analytical chapters, I will investigate these questions using two definitions of STEM in this chapter: (i) 'Core STEM' fields (computer science and IT, engineering, mathematics and the physical sciences) and (ii) 'Broad STEM' fields (additionally including biological sciences, medicine, dentistry, veterinary science,

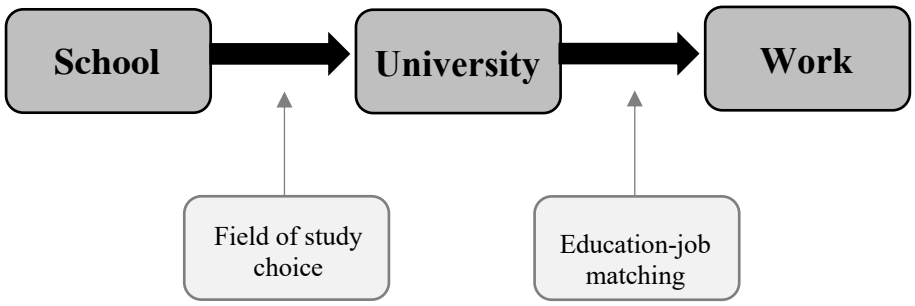
nursing, other health fields including psychology, planning and construction-related fields, agriculture, forestry and any not elsewhere categorised STEM fields). This choice was made due to gender gaps in STEM work varying by STEM sub-field (Hunt 2016). The chapter will discuss the differences I find when using the two definitions of STEM throughout.

5.2. Past Research and Theoretical Framework

5.2.1. The Leaky Pipeline

As mentioned previously, the UK government has funnelled over a billion pounds into various schemes encouraging students to study STEM over the past couple of decades. These policy initiatives rely on several assumptions, a key one being that future STEM workers get to their jobs in a rather straight-forward trajectory (figure 12); choosing STEM fields at school, then studying STEM at university and finally working in STEM occupations that match their STEM degrees. This assumption of a fairly linear trajectory into STEM is also reflected in the academic literature to a certain extent, and much of the work investigating trajectories into STEM *work* has focused on *education*, specifically degree field of study choice, repeatedly demonstrating that women are less likely to study STEM subjects than men (e.g. Friedman-Sokuler and Justman 2016; Morgan, Gelbgiser, and Weeden 2013).

Figure 12: The stages of the perceived (STEM) school to work trajectory



This linear trajectory from STEM education to STEM work is the basis of the 'leaky STEM pipeline' metaphor which is probably the most commonly evoked theoretical framework when discussing women's underrepresentation in STEM, both in research and in policy making. The metaphor was first used by Berryman (1983), popularised by Alper (1993), and has since become widely used in discussions of female (under)representation in STEM (for example, Xie and Shauman 2003). It poses that women are underrepresented in STEM due to progressively 'leaking' out of the 'STEM pipeline', with more and more women leaving STEM as the trajectory unfolds.

Albeit popular, the leaky pipeline metaphor has increasingly been criticised for its oversimplification of trajectories into STEM, as educational STEM trajectories and the STEM school-to-work link is more complicated than the metaphor suggests, with people moving in and out of STEM throughout their educational and work careers (E. Smith and White 2018a, 2020; Witteveen and Attewell 2020b; Metcalf 2010; P. Banerjee and Graham 2023). Research is increasingly highlighting the dynamic nature of STEM education/work membership, stressing that assumptions of linearity mask important processes.

Furthermore, since its inception, the metaphor of the 'leaky pipeline' has largely been applied to the educational trajectories of women in STEM, with early work on the concept explicitly referring to the 'education pipeline' (for example, Berryman 1983; Alper 1993). In this context, Miller and Wai (2015) demonstrate that while female STEM graduates were less likely to proceed to earning a PhD in the 1970s and 1980s, this was no longer the case in the 1990s. They conclude that the leaky pipeline metaphor 'no longer describes current gender differences in the bachelor's to Ph.D. transition in STEM' (Miller and Wai 2015, 1). The usefulness of the metaphor is therefore increasingly in

question, as it not only oversimplifies the dynamics it describes, but also may not apply to more contemporary patterns in STEM.

However, while education gender gaps in STEM seem to gradually be closing, this is not necessarily the case in the workplace. During their time at university, there is little difference in the intentions of male and female STEM students when it comes to entering STEM occupations (Mellors-Bourne, Connor, and Jackson 2011). Nonetheless, female STEM graduates generally are less likely to work in STEM (Xu 2017; E. Smith and White 2018a; Sassler, Michelmore, and Smith 2017; Frank 2019). This is perhaps unsurprising, as it is well documented that women are underrepresented in STEM overall (Xie and Shauman 2003).

5.2.2. Gender Differences at Labour Market Entry

Past research has predominately focused on the early destinations of graduates when studying gender differences in the STEM workplace (for example, E. Smith 2011a; Xie and Shauman 2003), with most finding that female graduates are underrepresented in STEM as soon as they enter the labour market, a pattern that has been demonstrated in the UK (E. Smith and White 2018a; Sassler, Michelmore, and Smith 2017), the US (Xu 2017; VanHeuvelen and Quadlin 2021; Preston 2004; Scott Long 2001) and Canada (Frank 2019). There are some exceptions to this finding; for example, Smith (2011a) only finds slight gender differences in the first destinations of physical and mathematical science graduates in the UK, apart from in the engineering and ICT professions. Similarly, studying US data, Sassler et al. (2017) do not find gender differences in STEM major to STEM work transitions at labour market entry, Hunt (2016) finds gender differences among engineers but not among scientists, while Xu (2013) does not find gender differences in the likelihood of working in STEM 1 and 4 years after graduation from

STEM. Whether or not a STEM degree 'benefits' women less than men as they enter the labour market is therefore yet to be established.

Several reasons have been put forward for the attrition of women from STEM at the point of transition into the labour market, with most focusing on differences in career interests, even among men and women who have studied STEM. Such gendered career interests are often the result of gender stereotypes which are instilled in girls and boys from an early age (Cvencek, Meltzoff, and Greenwald 2011), and are commonly caused by gender bias on part of their parents (for example, Frome and Eccles 1998) and teachers (Cornwell, Mustard, and Van Parys 2013; Lavy and Sand 2015). These childhood lessons can have long-lasting effects, shaping men and women's field of study and later career choices. For example, past research has found that women place more importance on careers that are compatible with family and involve helping others, men are more likely to make choices based on money and power (Eccles 1994; Konrad et al. 2000; Dasgupta and Stout 2014; Su, Rounds, and Armstrong 2009; Mellors-Bourne, Connor, and Jackson 2011). These gendered values can contribute to an underrepresentation of women in STEM because of women's preferences for female-typed occupations. Indeed, Smith and White (2018a) find that female STEM graduates often enter traditionally female-typed caring roles in health and teaching (E. Smith and White 2018a), roles that are often not defined as 'STEM'.

However, Mellors-Bourne et al. (2011) find that the majority of final year STEM students who had applied to a job had applied both to STEM jobs and to more general non-STEM graduate schemes, independent of gender. Hence, even if female STEM graduates have every intention of entering jobs that match their degree, they might not be able to because of gendered stereotypes and discrimination creating greater barriers to entry on the 'demand side' than their male peers. For example, studying STEM graduates

in Poland, Jasko et al. (2020) find that the majority of female STEM graduates only get one job offer, while the majority of men in STEM get multiple offers. Furthermore, they find that women in STEM generally spend more time looking for a job. Because female STEM graduates are slightly more likely to take pragmatic factors into account when entering the labour market, such as the location and the availability of jobs (Mellors-Bourne, Connor, and Jackson 2011), this lack of job offers could lead to female STEM graduates leaving STEM without intending to do so. Indeed, Jasko et al. (2020) find that recent female STEM graduates are less likely to perceive their work as being consistent with their qualifications. When choosing a career path, female STEM graduates entering the labour market might therefore be somewhat more likely than their male peers to be affected by the demand of STEM employers, and in turn more likely to enter non-STEM fields due to their interests or the possibilities available to them.

Therefore, despite some past research having contradictory findings (E. Smith 2011a; Sassler et al. 2017; Hunt 2016; Xu 2013), I expect female STEM graduates to indeed be underrepresented in STEM work at the point of labour market entry, both as a result of their own career choice and due to facing more barriers to entry than their male counterparts, all of which are shaped by the 'wider socio-historical context, institutional factors, social norms, and social inequalities' (Schoon 2023, 245).

5.2.3. Gender Differences Over the Work Life Course

Fewer studies have traced the career patterns of male and female STEM graduates. Those who have done so generally found that both men and women drop out of STEM as their careers progress (Xu 2013; Glass et al. 2013; Frank 2019; Hunt 2016; Preston 2004; Cech and Blair-Loy 2019; Frehill 2009, 2012; E. Smith and White 2018a), and that women generally do so at a higher rate than their male peers (Frank 2019; Hunt 2016; Preston

2004; Cech and Blair-Loy 2019; Frehill 2009, 2012). Should female STEM graduates indeed drop out of STEM work at higher rates than their male peers, this would suggest that obtaining a STEM degree may lead to smaller 'pay offs' for women when it comes to working in STEM, especially as their careers progress.

This finding is not universal, however. Using descriptive data from the UK, including BCS70 data, Smith and White (2018a; P. White and Smith 2022) find no substantial differences in the level of attrition of male and female STEM graduates from STEM work, with the share of female STEM graduates working in highly skilled STEM occupations being around 20 percentage points lower than that of their male peers across their careers. In the US, Hunt (2016) similarly does not find gender differences in attrition among scientists, although she does find some among engineers, and Xu (2013) does find gender differences but only 10 years after graduation.

Attrition from one's career is not limited to STEM work (Duta, Wielgoszewska, and Iannelli 2021), and the general attrition from STEM is not particularly unusual when compared to other fields (Hunt 2016). However, the rate at which women leave STEM work is higher than the rate of attrition from other fields (Glass et al. 2013; Hunt 2016). Hence, gender differences in attrition from STEM may well be unique to STEM work. Past research has generally identified three main explanations of why STEM graduates – and women in particular – might drop out of STEM: (i) pay and promotion opportunities, (ii) family obligations, and (iii) (a change in) career interests.

Firstly, some have argued that STEM occupations are marked by limited opportunities for career development and promotion compared to fields such as Finance (Bosworth, Lyonette, and Wilson 2013), which sits uneasily with Ferriman et al.'s (2009) findings that STEM graduates' values change over their careers, with leadership opportunities and merit-based pay becoming increasingly important over time. Hence,

such STEM graduates could turn to work in non-STEM fields as their time in the labour market progresses, where their technical experience helps them to find work (Anft 2013) and enter managerial roles (Bosworth, Lyonette, and Wilson 2013).

Women might be especially likely to drop out because of a lack of pay and promotion opportunities, as they generally earn less and occupy less senior or highly skilled STEM roles than their male peers (E. Smith and White 2018a; Xu 2017). These gender differences often result from a lack of recognition of women's skills (which can lead to different tasks being performed by female STEM workers), a lack of mentoring support (in the form of female role models), a lack of professional networks, and discrimination by managers and co-workers (Hunt 2016; Fouad et al. 2017; Frehill 2009; Rosser and Taylor 2009), which can ultimately force female STEM graduates out of STEM work (Fouad et al. 2017). Furthermore, those who do get promoted in their STEM jobs (male or female alike) might also find themselves inadvertently leaving 'STEM', because their job roles shift towards managerial and administrative work that is often not included in definitions of STEM as used by many academics and policymakers (Glass et al. 2013; E. Smith and White 2018a).

Secondly, STEM workers who take a career break because of growing family obligations (or other reasons) may end up permanently leaving the field (Bosworth, Lyonette, and Wilson 2013). This can happen both due to STEM graduates' decisions, such as STEM graduates choosing to leave STEM in favour of fields which are more compatible with having a family (W. M. Williams and Ceci 2012), or as a result of labour market barriers as those who have taken a career break can struggle to re-enter STEM as their skills become outdated due to rapid technological and scientific change (Bosworth, Lyonette, and Wilson 2013; Preston 2004). Although parenthood affects both men and women's likelihood of staying in STEM, women are disproportionally impacted by it

(Cech and Blair-Loy 2019). Because women continue to be societally viewed as primary caregivers, they are more likely than men to take a career break due to childcare and other caring or household responsibilities (Xie and Shauman 2003; Cech and Blair-Loy 2019).

Hence, some argue that children and family life more generally is the single most important reason for women leaving STEM (W. M. Williams and Ceci 2012). Fouad et al. (2017) identified a variety of ways in which having children might contribute to women's decision to leave engineering in particular, including that working hours are not conducive to a family life, it is hard to drop down to part-time work in the field, and the pay is often not high enough to cover childcare costs. These reasons are likely to also apply to the other STEM fields. Indeed, Cech and Blair-Loy (2019) found that nearly half of all new mothers left full-time STEM employment, while only a quarter of new fathers did. Therefore, while STEM work appears to not be conducive to parenthood for either gender, women are much more affected by this. This may be because female STEM workers are less likely to be able to rely on their partner to have flexible careers and stay at home to look after children than male STEM workers are (W. M. Williams and Ceci 2012). Hence, they are likely to be disproportionally impacted by the rapid scientific and technological change that makes it hard for STEM graduates to re-enter STEM occupations after taking a career break (Bosworth, Lyonette, and Wilson 2013).

Finally, gendered career interests seem to shape not only people's likelihood of entering STEM work in the first place, as discussed above, but also their likelihood of being in STEM over the work life course. A change in career interests is often cited by female STEM graduates as the reason why they left STEM (Frehill 2012; Preston 2004; Fouad et al. 2017). Changes in career interests might occur as women realise that the reality of the career they entered does not align with their expectations, or as they re-evaluate what is important to them. Because women typically place more importance than

men on a career that allows one to look after one's family, helping others, working with others, doing something worthwhile for society, making friends, self-fulfilment, task enjoyment, and creativity (Eccles 1994; Konrad et al. 2000; Dasgupta and Stout 2014; Su, Rounds, and Armstrong 2009; Mellors-Bourne, Connor, and Jackson 2011), some might leave STEM in the pursuit of more 'meaningful' work (Fouad et al. 2017). These preferences are likely shaped by an array of influences, including structural, institutional and individual level factors (Schoon 2023). Thus, women working in STEM may choose to leave the field at higher rates than their male colleagues due to their disadvantage in STEM roles, or simply because they realise they are more interested in other work.

✶

Together, this past research suggests that it is theoretically more likely for women to be underrepresented in STEM work at the point of labour market entry and leave STEM at a higher rate than men, even after having studied STEM. This suggests that female STEM graduates benefit less from their degree than their male classmates in terms of gaining access to horizontal education-job matches. Gender differences in attrition are likely to be highest in the early to mid- stages of graduates' careers, as promotions, associated pay increases and family formation become increasingly more relevant.

5.3. Data and Methods

5.3.1. Data

As discussed in Chapter 4, the analyses rely on the British Cohort Study of 1970 (BCS70). As mentioned above, because previous research has established that female attrition form STEM work varies by STEM sub-field (Hunt 2016), it is possible that gender differences in the association between having obtained a STEM degree and working in STEM also

vary by type of STEM field considered. The relatively small sample of graduates in BCS70 does not allow me to examine STEM sub-fields individually, which is why I instead distinguish between 'Core' and 'Broad' STEM in this thesis. I examine a sample of 1,859 individuals in 30,906 person-year observations using the Broad definition of STEM, as well as a smaller sample of 1,470 individuals in 23,017 person-year observations when using the Core definition. The latter sample is smaller due to the nature of my Core STEM variables, which are coded as missing for people who obtained a STEM degree / work in STEM using the Broad definition *but not the Core one.*

5.3.2. Variables

The dependent variable of this study is *field of occupation (STEM versus non-STEM)*, a dummy capturing whether respondents are in a STEM occupation at a given point in time, where 0 = work in a non-STEM occupation, 1 = work in a STEM occupation. Because this chapter uses two definitions for STEM, I coded this variable twice, for the Core definition of STEM, (computer science and IT, engineering, mathematics, and the physical sciences) and for the Broad definition of STEM (additionally including biological sciences, medicine, dentistry, veterinary science, nursing, other health fields including psychology, planning and construction-related fields, agriculture, forestry, and any not elsewhere categorised STEM fields). The key independent variables of this chapter are *degree field of study* (0 = non-STEM, 1 = STEM) and *sex* (0 = male, 1 = female). The former of these was once more coded both using the Core and the Broad definition of STEM. The main analyses of this chapter rely on *time elapsed since labour market entry,* which is measured in years, to investigate changes over the work life course.

All models control for respondents' characteristics, taking into account *age at labour market entry*, *migration status* and *ethnicity.* They also all control for schooling

by including *has STEM A-Level, number of good A-levels, type of undergraduate degree, undergraduate degree class* and *has postgraduate degree,* and for *full-time work.* Additionally, I include several measures of social origin, *parental STEM occupation* (age 10), *parental social class* (age 10), *parental education* (age 10) and *parental income* (age 16).

The latter part of the chapter investigates possible mediators, which were chosen based on the factors I identify in the theoretical framework which might be important in mediating the relationship between *degree field of study*, *sex,* and *field of occupation*. To account for family mediators, I include *number of children*, *partnership status* (0 = not in partnership, 1 = cohabiting, 2 = married) and a dummy capturing whether respondents took a *career break due to family obligations* at any point over the observed timeframe. To examine pay and promotion opportunities, I include *substantial net pay increase* (since last sweep) and *was promoted to manager* (since last year). Finally, to capture career interests, I include dummy variables capturing whether respondents indicated *technology* and *health career aspirations* as teenagers. While these variables are imperfect measures of career interests more generally, as they do not account for changes in interests that may occur during the later years of graduates' education journeys or during their time in the labour market, they can give an initial insight into the role aspirations play in mediating the way gender shapes horizontal education-job (mis)matches over the work life course.

5.3.3. Methodology

My research questions concern both the point of labour market entry and graduates' work over the work life course. The questions focus on the association between having obtained a STEM degree and working in STEM, how this association changes across the work life

course, and what may explain this association. To address these questions, I use cross-sectional logistic regression and logistic panel regression with random effects. To establish whether the patterns I observe apply to all STEM fields or just to those I call 'Core STEM' (computer science and IT, engineering, mathematics, and physical sciences), I ran the models twice, once using the Broad definition of STEM and once using the Core one. To address my third research question regarding possible explanations for gender differences in the association between having a STEM degree and working in STEM, I adapt Gugushvili, Bukodi and Goldthorpe's (2017) approach to 'unpacking' a direct effect through a series of nested regression models. As previously mentioned, this approach allows me to examine correlations, but is not a formal analysis of causal mechanisms.

5.4. Empirical Findings

In what follows, I will address my three research questions one after the other, first discussing gender differences in the extent to which STEM graduates enter STEM occupations, then how this develops over graduates' careers, and finally addressing possible mechanisms through which field of study might lead to different occupational outcomes for men and women. Because odds ratios can be misleading in non-linear models (Karaca-Mandic, Norton, and Dowd 2012; Mize 2019; R. Williams 2012), I will focus on predicted probabilities when interpreting the results of my non-linear analyses below, while displaying log-odds for the longitudinal models. I will present average marginal effects (AMEs) in all other results tables.

5.4.1. The Point of Labour Market Entry

My first research interest concerns the point of labour market entry. First, to establish whether my findings are in line with previous research regarding the relationship between obtaining a STEM degree and entering STEM work, model 1 regresses *field of occupation (STEM versus non-STEM)* on *degree field of study (STEM versus non-STEM),* as well as *sex* and the aforementioned control variables. Table 9 shows binary logistic regression results in the form of AMEs for models using the Core definition of STEM (left columns) and the Broad definition (right columns).

As expected, model 1 reveals that at the point of labour market entry, those who have studied STEM (at undergraduate and/or postgraduate level) are more likely to subsequently enter STEM, and women are generally less likely to be found in STEM work (table 9). This is the case using both definitions of STEM. Specifically, entering the labour market with a Core STEM degree, rather than a non-STEM degree, increases the likelihood of entering Core STEM work by 35 percentage points, while the likelihood of entering STEM is 11 percentage points lower among female, rather than male, graduates (model 1, Core STEM). Using the Broad definition of STEM, I find that having a STEM degree increases graduates' likelihood of entering STEM work by 41 percentage points, and being a woman decreases it by 9 percentage points (model 1, Broad STEM).

The associated predicted probabilities presented in figure 13 reveal that at the point of labour market entry, although STEM graduates are substantially more likely than non-STEM graduates to work in STEM, the predicted probability of working in STEM after having graduated from STEM is only around 40% (CI: 0.37 - 0.47) when using the Core definition of STEM, and around 55% (CI: 0.50 – 0.57) when using the Broad definition. The small discrepancies between these findings suggest that obtaining a STEM degree is more important in certain fields that fall into Broad STEM but not Core STEM,

likely to be subjects allied to medicine, dentistry, and veterinary sciences in particular. Hence, I find that STEM graduates are almost equally (if not more) likely to enter non-STEM occupations than STEM occupations after graduating. These results are generally in line with previous findings that half, if not more, of all STEM graduates in the UK do not enter STEM work following graduation (Bosworth, Lyonette, and Wilson 2013; Select Committee on Science and Technology 2012; E. Smith and White 2017, 2018a; DIUS 2009; E. Smith 2011a).

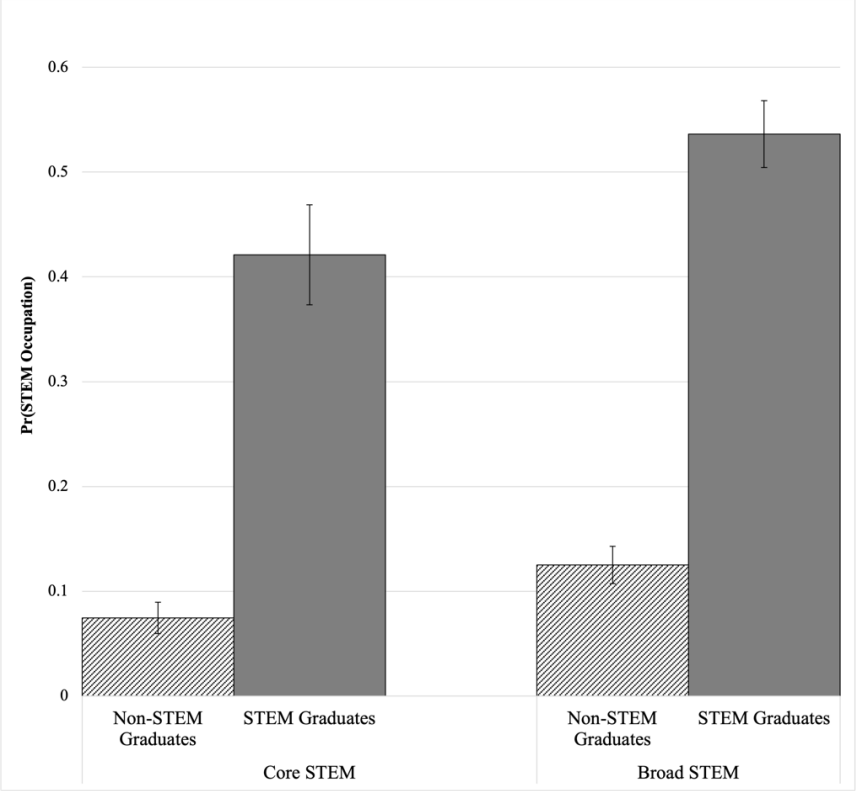
Table 9: The effects of field of study and gender on the likelihood of being found in STEM work at labour market entry (AMEs)

Dependent Variable:	***Core STEM***		***Broad STEM***	
STEM Work	**Model 1**	**Model 2**	**Model 1**	**Model 2**
STEM degree	0.35***	0.41***	0.41***	0.40***
	(0.03)	(0.04)	(0.02)	(0.03)
Female	-0.11***	-0.08***	-0.09***	-0.10***
	(0.02)	(0.02)	(0.02)	(0.02)
STEM degree*Female		-0.10*		0.04
		(0.06)		(0.05)
Number of Observations	1,373	1,373	1,819	1,819

Note: All models control for respondents' A-level performance, whether they obtained a STEM A-Level, the type of university they attended at undergraduate level, their undergraduate degree class, whether they have a postgraduate degree, whether they have a parent in STEM, parental class, parental education, parental income, their age at labour market entry, their migration status, ethnicity, and full-time work. To see the full output, see table B1 in appendix B, standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

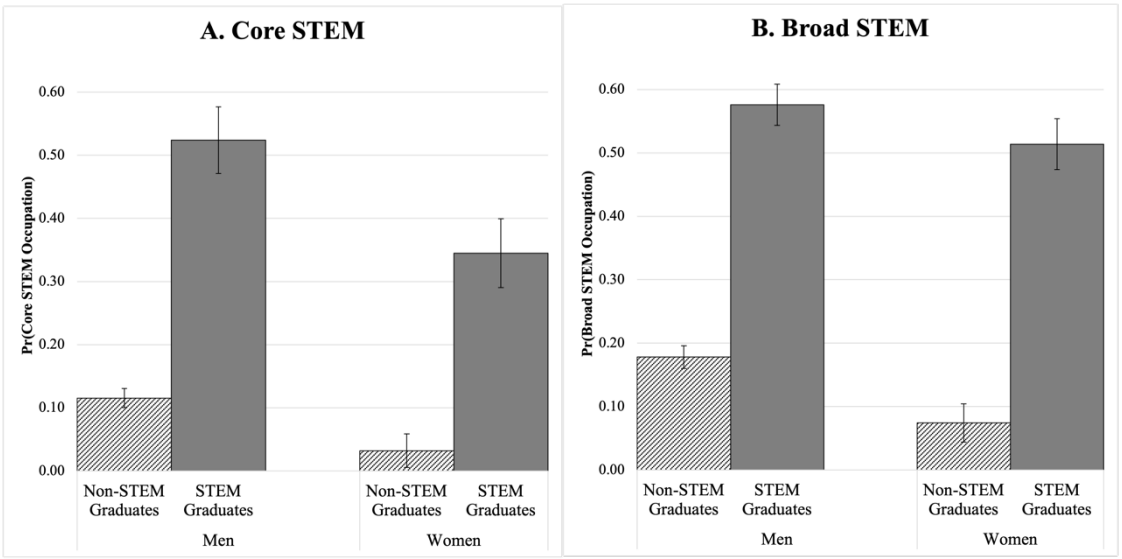
Addressing my first research question regarding how the relationship between STEM degrees and STEM work is moderated by gender, model 2 builds on model 1 by additionally including an interaction between *degree field of study* and *sex* (table 9). This model reveals that at the point of labour market entry, the way the effect of having obtained a STEM degree on working in STEM varies by gender is statistically significant when using the Core definition of STEM, but not when using the Broad definition.

Figure 13: The predicted probability of working in a STEM occupation at labour market entry after graduating with a STEM degree by definition of STEM (based on model 1 in table 9)



When using the Core definition of STEM, the interaction effect is negative, suggesting that male graduates gain more from obtaining a Core STEM degree than female graduates when it comes to entering Core STEM work at the point of labour market entry. When using the Broad definition of STEM, this pattern reverses, and having a STEM degree has a stronger positive effect on working in STEM for female than for male STEM graduates at the point of labour market entry. However, the (non-significant) gender differences I find in entry into Broad STEM work are small, with almost half of all female STEM graduates entering STEM work (see figure 14). Therefore, one should be cautious when discussing gender differences in entry to STEM work at labour market entry, as these differences are largely concentrated in the Core STEM fields.

Figure 14: The predicted probability of working in a STEM occupation at labour market entry after graduating with a STEM degree by gender, degree field of study and definition of STEM (based on model 2 in table 9)



This difference in pattern when using the different definitions of STEM can likely be explained through the nature of the individual fields contained in each definition; Core STEM fields are traditionally seen as 'male-typed', and the literature reviewed above has generally identified them as being particularly difficult to enter for women. The positive interaction effect found when using the Broad definition of STEM is likely driven by more 'female-typed' professions which involve more social interaction and care activities, such as medicine and nursing. Therefore, at the point of labour market entry, the way in which having a STEM degree affects women varies by STEM sub-field. The interaction effect may be non-significant in the Broad models due to the sub-fields not being sufficiently homogenous when it comes to women's experiences at labour market entry. This highlights the importance of being specific about what STEM fields are being discussed when talking about gender differences in STEM occupations.

Panel A in figure 14 reveals that the interaction effect I observe when using the Core definition of STEM is reflected in differences in the predicted probability of working in STEM among Core STEM graduates; the likelihood of working in STEM is around

50% (CI: 0.47 - 0.58) for male STEM graduates and around 35% (CI: 0.26 – 0.43) for female STEM graduates. Hence, looking at Core STEM, around half of all men, and around two thirds of women who have studied STEM do *not* enter STEM work at the point of labour market entry.

Meanwhile, the predicted probabilities that I calculate based on the Broad definition of STEM point towards a much smaller gender difference; the likelihood of entering Broad STEM work at labour market entry is around 60% (CI: 0.54 - 0.62) for male STEM graduates and around 50% (CI: 0.46 – 0.57) for female STEM graduates (figure 14b). The results from the analyses therefore highlight that gendered outcomes vary by STEM sub-field and are largely concentrated in the 'hard' fields which I include in my definition of Core STEM: computer science and IT, engineering, mathematics, and the physical sciences.

5.4.2. The Career Patterns of STEM Graduates

Next, I turn to my second research question, regarding changes over the work life course in the relationship between being a STEM graduate and working in STEM, and how they vary by gender. Table 10 gives an initial indication of the direction and statistical significance of the findings through log-odds which are the result of binary logistic panel regressions. Model 1, which regresses *field of occupation (STEM versus non-STEM)* on *degree field of study (STEM versus non-STEM), sex,* and the time variables (in addition to the controls) reveals that – as was the case at the point of labour market entry – STEM graduates are more likely to work in STEM occupations, while women are less likely than men to do so, especially when using the Core definition of STEM. Furthermore, the coefficient of *time elapsed since labour market entry* indicates a general trend of

increasing likelihood of working in STEM across the work life course among graduates, although this increase is substantially small.

To start to investigate the way in which the association between having a STEM degree and working in STEM is moderated by gender, model 2 builds on model 1 by additionally including a *degree field of study*sex* interaction term. This model reveals that there is a substantial and statistically significant gender difference in the way a Core STEM degree shapes Core STEM work; using this definition, the positive association between having obtained a STEM degree and working in STEM is considerably smaller for female graduates than it is for their male counterparts. Women therefore benefit less from obtaining a STEM degree in the Core STEM fields across the work life course. However, when using the Broad definition of STEM, this gender difference becomes non-significant, and reduces substantially in effect size, indicating that this finding may only apply to the more 'male-typed' STEM fields.

To establish how the moderating relationship between gender and degree field of study develops over the work life course, model 3 builds on model 2 by including a three-way interaction between the key independent variables (*degree field of study* and *sex*), and the quadratic term for *time elapsed since labour market entry* (table 10). I include this interaction because, based on my theoretical framework, I have reason to believe that the way in which degree field of study has a different effect for men and women changes over the work life course.

Table 10: The effects of field of study and gender on the likelihood of being found in STEM work across the work life course by definition of STEM (log-odds)

Dependent Variable: STEM Work	*Core STEM*			*Broad STEM*		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
STEM degree	11.11***	12.38***	12.57***	10.78***	11.19***	11.69***
	(0.99)	(0.93)	(0.77)	(0.49)	(0.65)	(0.72)
Female	-4.32***	-2.32***	-3.18***	-2.48***	-2.29***	-3.34***
	(1.46)	(0.55)	(0.63)	(0.40)	(0.43)	(0.52)
Time Elapsed since LM Entry	0.07***	0.07***	0.05	0.06***	0.06***	0.08**
	(0.02)	(0.02)	(0.06)	(0.02)	(0.02)	(0.04)
Time Elapsed since LM Entry^2	-0.00***	-0.00***	-0.00	-0.00***	-0.00***	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
STEM degree*Female		-5.17***	-2.86**		-0.87	1.52
		(1.34)	(1.12)		(1.25)	(1.60)
STEM degree*Time Elapsed since LM Entry			0.06			0.01
			(0.07)			(0.05)
STEM degree*Time Elapsed since LM Entry^2			-0.01			-0.00
			(0.00)			(0.00)
Female*Time Elapsed since LM Entry			0.17*			0.14**
			(0.09)			(0.06)
Female*Time Elapsed since LM Entry^2			-0.01			-0.00
			(0.00)			(0.00)
STEM degree*Female*Time Elapsed since LM Entry			-0.53***			-0.39***
			(0.15)			(0.10)
STEM degree*Female*Time Elapsed since LM Entry^2			0.02**			0.01***
			(0.01)			(0.00)
Intercept	-15.98***	-16.74***	-16.27***	-14.45***	-14.52***	-14.98***
	(3.42)	(3.14)	(3.27)	(2.45)	(2.44)	(2.50)
Number of Observations	23,017	23,017	23,017	30,906	30,906	30,906
Number of Groups	1,470	1,470	1,470	1,859	1,859	1,859

Note: All models control for respondents' A-level performance, whether they obtained a STEM A-Level, the type of university they attended at undergraduate level, their undergraduate degree class, whether they have a postgraduate degree, whether they have a parent in STEM, parental class, parental education, parental income, their age at labour market entry, their migration status, ethnicity, and full-time work. To see the full output, see table B2 in appendix B, standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

The results indicate that the way in which the association between having a STEM degree and working in STEM changes over the work life course does, indeed, differ by gender. Specifically, as female STEM graduates' time in the labour market progresses, their likelihood of working in STEM decreases, although the magnitude of this effect declines somewhat across the work life course. For male STEM graduates, on the other hand, the likelihood of being in STEM *increases* in the early stages of their career, but the magnitude of this effect once more subsides over the career (although at a slower rate than it does for women), eventually becoming negative. I find this pattern for both definitions of STEM, but it is again much more pronounced when looking at Core STEM fields.

Together, the results shown in table 10 highlight that having a (Core) STEM degree does have a different impact on working in STEM for men and women; as female STEM graduates' careers progress, their likelihood of working in STEM declines steadily, while for men, the strength of association between being a STEM graduate and working in STEM increases initially, but then also declines. Furthermore, the gendered outcomes of having a STEM degree differ substantially by definition of STEM. In fact, as was the case at the point of labour market entry (table 9), the gender differences I observe look to be unique to Core STEM fields.

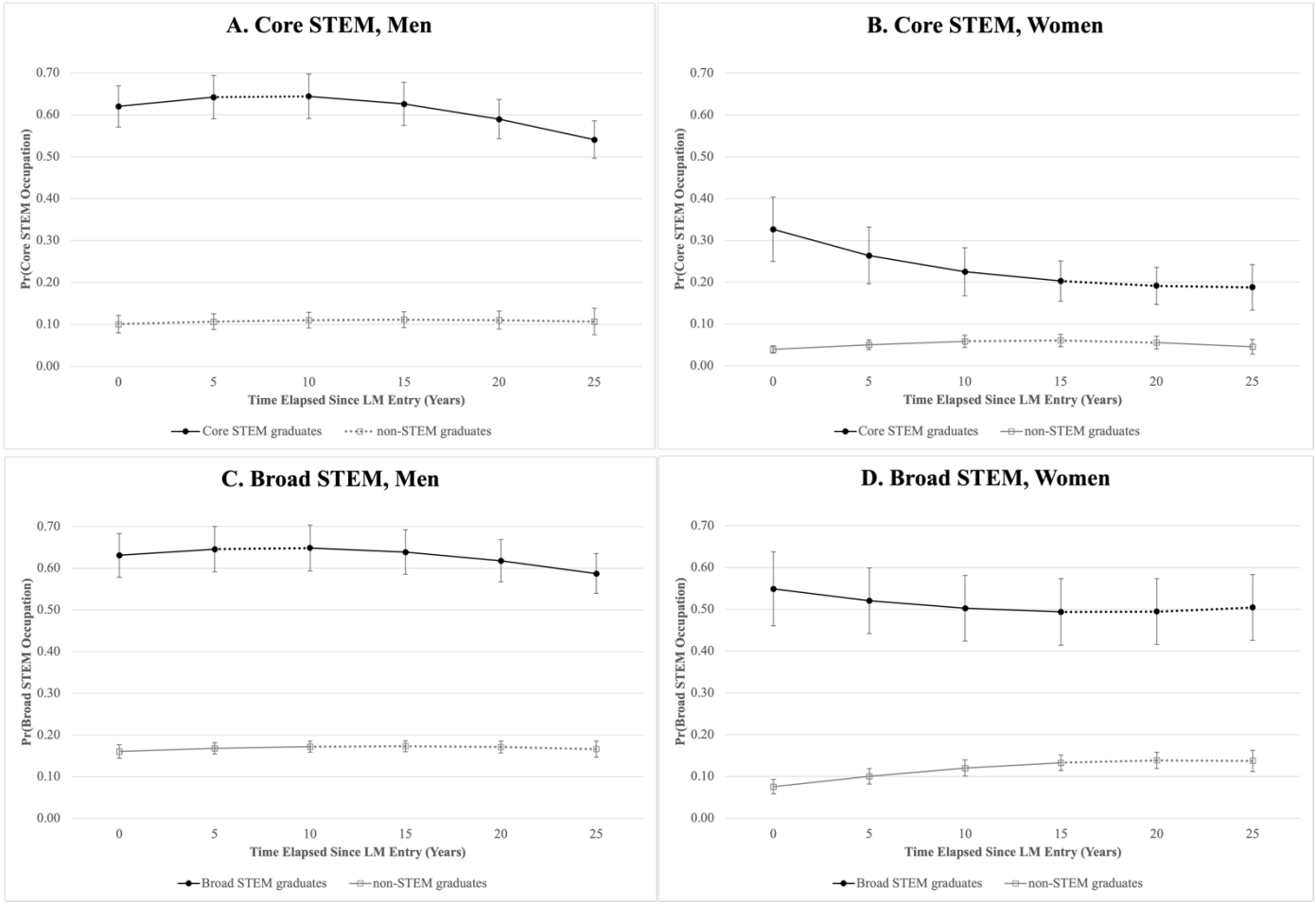
Figure 15, which shows predicted probabilities of working in STEM for male and female graduates, illustrates the results of model 3. It reveals that, as theorised, British women are less likely than men to work in STEM after having studied STEM across their entire career, but that the magnitude of the gender difference in STEM work membership varies as people's careers progress and by definition of STEM. This contradicts Smith and White's (2018a) prior findings that gender differences between male and female STEM graduates in the UK remain relatively stable across the work life course. The

differences in findings between their study and mine are likely driven by differences in how we define STEM, once more highlighting the importance of which STEM sub-fields are included. While I take a categorisation approach to defining STEM, Smith and White take a realised matches approach, which results in occupations such as 'business and finance associate professionals' being defined as STEM work (see section 4.1. for an explanation of these approaches). It is therefore unsurprising that our results differ.

Figure 15 further reveals that the likelihood STEM graduates being in STEM work over the work life course varies quite substantially by gender. In the theoretical framework of this chapter, I suggested that because the knowledge and skills attained by STEM graduates are quickly outdated, it might be difficult for people to move back into STEM after having left it. This does not appear to affect men in their early careers. Instead, male STEM graduates become more likely to work in STEM in the first few years of their career, although this effect levels off and then decreases. The likelihood of men working in STEM after having studied STEM initially increases slightly to around 65% (Core STEM CI: 0.59 – 0.69, Broad STEM CI: 0.59 – 0.70) at T5, remaining stable until T10 (Core STEM CI: 0.59– 0.70, Broad STEM CI: 0.59 – 0.70), and then dropping down somewhat in the later career stages observed in the data.

This drop is more pronounced when using the Core definition of STEM; after 25 years, the likelihood of working in Core STEM for male Core STEM graduates has decreased to around 55% (CI: 0.50 – 0.59), and to around 60% (CI: 0.54 – 0.64) when using the Broad definition of STEM. It could be the case that these men start out in lower-skilled work associated with STEM and subsequently get promoted into STEM work, because it is relatively common for recent UK graduates to start working in non-graduate roles (Clegg 2017). This is backed up by figure B2 in appendix B, which shows the descriptive destinations of STEM graduates in non-STEM work.

Figure 15: The predicted probability of working in a STEM occupation for male and female graduates by degree field of study, time elapsed since labour market entry and definition of STEM (based on model 3 in table 10)



Note: Despite the overlapping confidence intervals when comparing different time-points in figure 15, most changes for STEM graduates are statistically significant as indicated by the solid lines (non-significant changes are indicated using dotted lines).

This pattern may well not be unique to STEM; also using BCS70 data, Duta, Wielgoszewska and Ianelli (2021) find a similar pattern of increased entry into higher managerial and professional occupations up until the age of 32 roughly (which is T7 on average in my sample), and then some movement out of these positions (seemingly into lower managerial and professional occupations) over the subsequent decade among university graduates whose trajectories they class as 'direct and early entry into higher managerial and professional occupations.' Therefore, male STEM graduates' careers follow a relatively 'expected' pattern when compared to the wider body of UK graduates.

However, female STEM graduates' career patterns differ sharply from this 'expected' pattern, as women's likelihood of working in STEM after having obtained a STEM degree decreases across their careers, a drop which is steepest at the start of women's careers, and statistically significant up to T15 using both definitions of STEM (see solid lines in figure 15). This decline is substantially more pronounced when using the Core definition of STEM; from the initial peak of a roughly 35% (T0, CI: 0.25 – 0.40) likelihood of working in STEM, female STEM graduates' likelihood of being in a matching job reduces to only around 20% (T15, CI: 0.15 – 0.25) after 15 years, after which the drop becomes non-significant. Although still statistically significant when using the Broad definition, female STEM graduates' likelihood of working in STEM only drops from around 55% (T0, CI: 0.46 – 0.64) to around 50% (T15, CI: 0.42 – 0.58) after 15 years in the labour market.

This early decline in women's participation in STEM work might be explained through family responsibilities. As Rosser and Taylor highlight (2009, 9): 'Women's biological clocks often mean that decisions about marriage and children cannot be delayed after their careers have been well established.' This is backed up by the fact that the proportion of female STEM graduates in education-related work, which tends to be

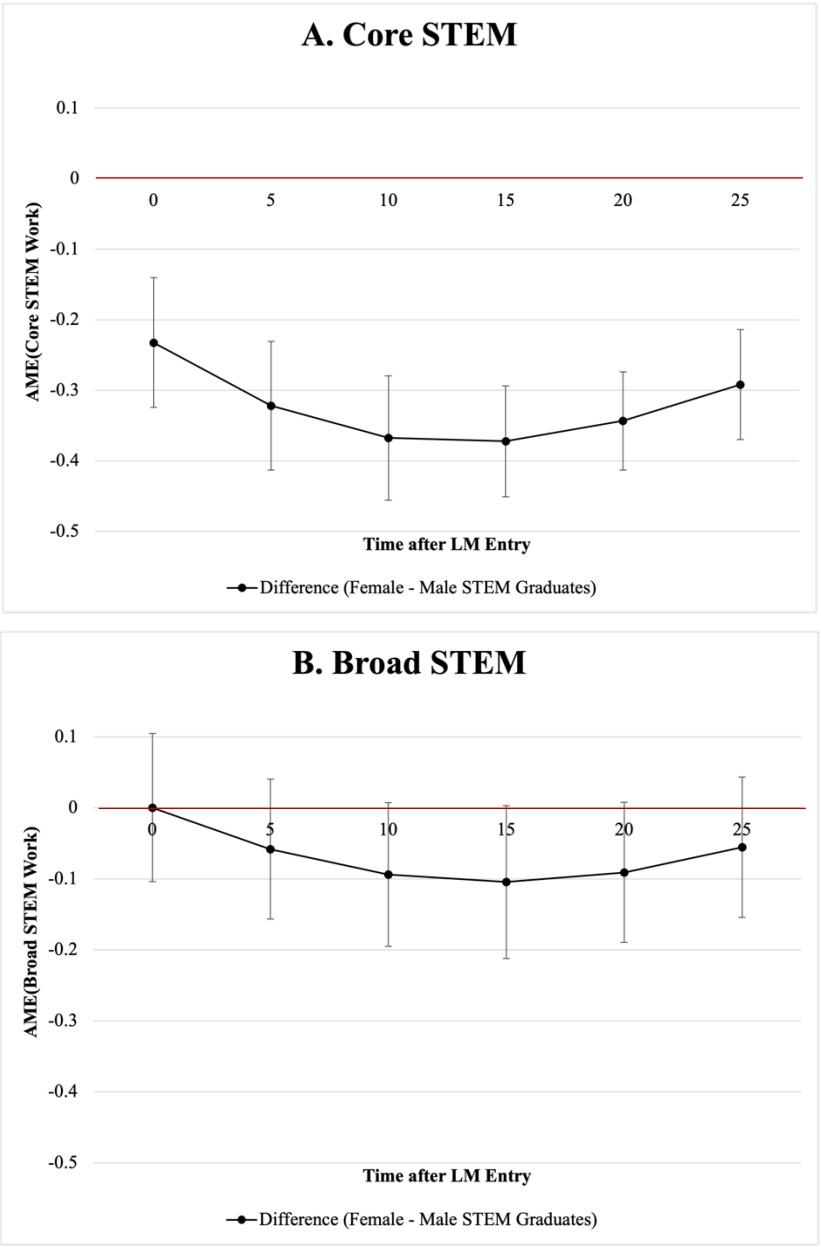
more child-friendly, increases in the initial years of their career (figure B2 in appendix B).

Therefore, while both men and women leave STEM over their careers to some degree, women are more likely to do so relatively early on in their careers, while men are more likely to do so towards the mid-to-late stages of the observed time frame. This suggests that the point of labour market entry is more important in determining women's than men's STEM membership, as the former may be more likely to be 'locked out of STEM.' Overall, using the Core definition of STEM, female STEM graduates' likelihood of working in STEM decreases by around 43% (14 percentage points, CI: -0.19 – -0.08), while that of their male peers drops by 13% (8 percentage points, CI: -0.11 – -0.05) between T0 and T25. There is less difference between the total attrition of male and female STEM graduates when using the Broad definition of STEM; female STEM graduates' likelihood of working in STEM decreases by just over 8% (4 percentage points, CI: -0.08 – -0.01), while that of their male peers drops by 7% (4 percentage points, CI: -0.07 – -0.02) between T0 and T25. I therefore observe attrition from STEM both among men and women, but it can only be described as substantial for women when using the Core definition of STEM.

Together, the trend of women being increasingly less likely to work in STEM while men are initially more likely to be in STEM and subsequently also move out of the field to some extent later on in the work life course, lead to a U-shaped trend in how the gender difference in the AME of having a STEM degree develop over the work life course (figure 16), with differences being largest in the middle of the observed time period. Figure 16 further illustrates that although the general pattern of how the gender difference develops over the work life course can be seen across definitions, I only find a statistically significant moderating effect of gender on the association between having obtained a

STEM degree and working in a STEM occupation when using the Core definition of STEM.

Figure 16: The gender difference in the average marginal effect of having a STEM degree on working in STEM across the work life course by definition of STEM (based on model 3 in table 10)



Overall, as was the case when looking at labour market entry, the results illustrate that the gendered association between obtaining a STEM degree and working in STEM is more pronounced and only statistically significant when examining the 'hard' Core

STEM fields of computer science and IT, engineering, mathematics, and physical sciences. Most notably, while still present, attrition from STEM is substantially less sharp in the early years of female STEM graduates' time in the labour market when using the Broad definition. After 25 years, 1 in 10 female Broad STEM graduates compared to 1 in 2 female Core STEM graduates who started out in STEM work are unlikely to still work in STEM. Similarly, the mid- to late-career stage attrition of male STEM graduates is less pronounced when looking at Broad STEM.

It should also be noted that because my analyses rely on a single cohort of British people, part of what I observe might be due to a possible period effect, as the demand for STEM workers changed over the observed time period (for example, Bosworth, Lyonette, and Wilson 2013). However, while the general (Core) STEM workforce grew quickly in the period I observe (see Chapter 2), I find quite considerable attrition of women from STEM in this chapter. This suggests that what I find is in fact a life course-, rather than a period-, effect. Furthermore, the BCS70 is likely to be representative of later cohorts when it comes to gendered labour market patterns, because there was virtually no difference in the employment rate of women born in the 1970s cohort versus the 1980s cohort nor in the age distribution of child births between women born in 1975 and 1985 (Roantree and Vira 2018, 6–7), for example.

5.4.3. What may explain the observed patterns?

Having established that patterns of horizontal education-job (mis)matches vary among male and female STEM graduates over the work life course, and that gender moderates the association between having a STEM degree and working in STEM when looking at the Core definition of STEM, I now turn to investigating possible mediators that may explain the gender difference in the AME of having a STEM degree on working in STEM.

Because this gender difference is non-significant, and generally less pronounced when using the Broad definition of STEM, I focus on the Core definition only in this section. This also reflects contemporary gender differences in STEM, as gender gaps appear to have largely closed when using the Broad definition, but this is not the case in the Core STEM fields (see figure 5 in Chapter 2). Much of the gender difference I observe is caused by attrition from STEM work, especially among female STEM graduates. Past literature has identified three key factors which explain such attrition: (i) family obligations, (ii) pay and promotion opportunities, and (iii) career interests. Below, I look at the influence of each of these factors in turn.

To establish how these factors might mediate the role gender plays in determining horizontal education-job (mis)matches in STEM across the work life course, I adapt Gugushvili, Bukodi and Goldthorpe's (2017) approach of 'unpacking' a direct effect and run a series of models which add family obligation, pay and promotion, and career aspiration-related mediator variables to model 3 in table 10 (the 'base model') to determine how they influence the gendered effect of having a STEM degree across models. Because log-odds ratios cannot be compared across models with different independent variables in a sample (Mood 2010), I rely on graphs of AMEs to assess how the mediators I consider affect the gender differences in the effect of having a STEM degree on working in STEM. The related regression tables can be seen in table B3 appendix B.

It should be noted that the confidence intervals of the AMEs of different models shown in figure 17 overlap (see figure B1 in appendix B). This does not necessarily mean that the mediating effects I observe are non-significant, as further testing – which I was unable to do given the nature of my data and analyses – would be necessary to establish statistical significance. Therefore, the patterns I observe give an initial indication of

possible mediators of the gender differences which I find, but further research is necessary to understand these mediators better.

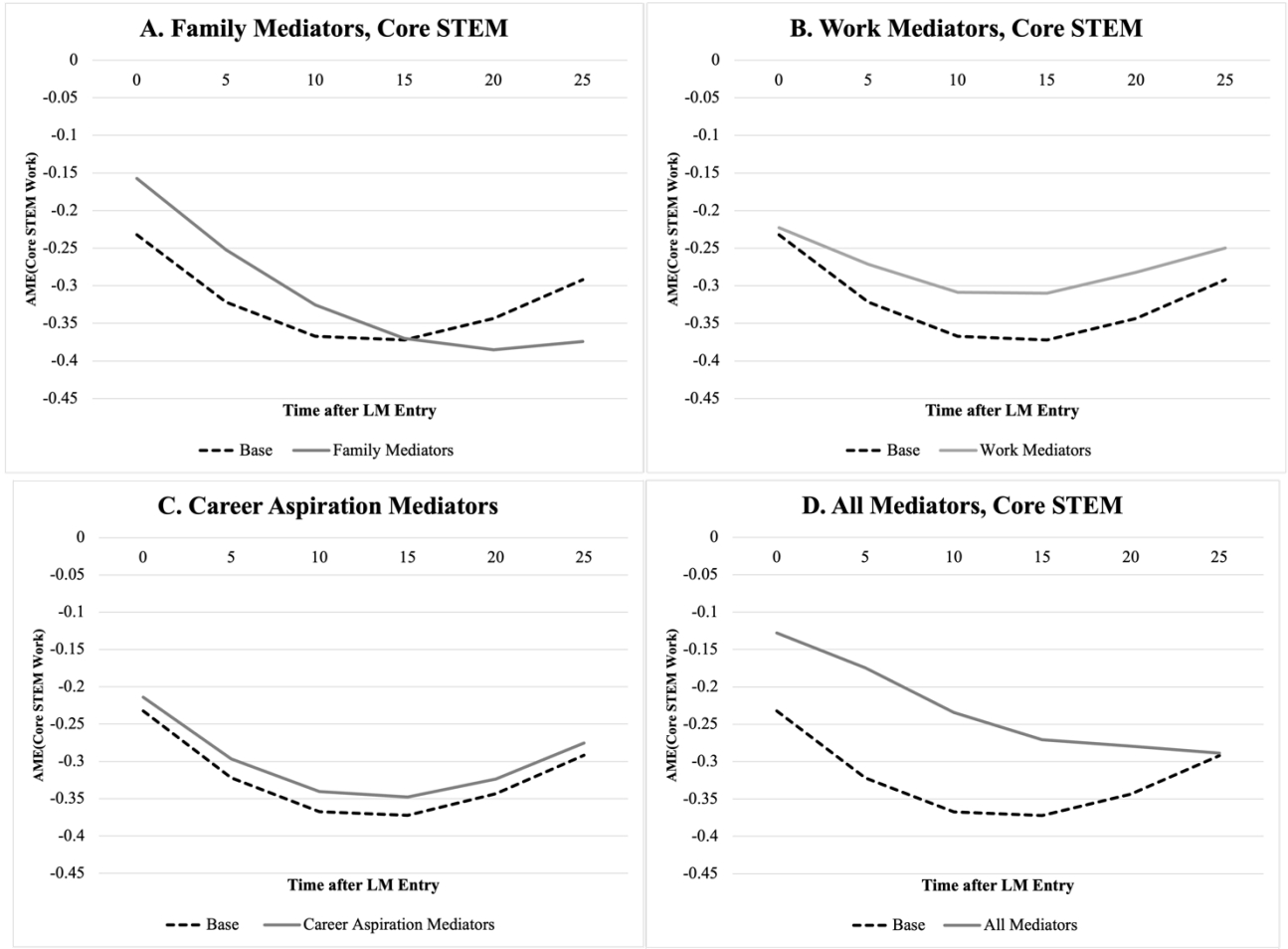
Family Obligations

To investigate the role family can play in mediating the gendered relationship between field of study and field of occupation, model 2 builds on the base model by including three family-related mediators: (i) *number of children*, (ii) *partnership status,* and (iii) a dummy variable capturing whether a respondent took a *career break due to family obligations* at any point over the observed timespan. In general, all the family mediators behave as expected in terms of their association with STEM work. Having children, being in a cohabiting or married relationship, and having taken a career break due to family obligations all decrease graduates' likelihood of working in STEM (table B3 in appendix B).

Panel A in figure 17 shows the way in which the gender difference in the AME of having a STEM degree changes from that estimated in the 'base model' (black dotted line) once the family mediators are included (grey solid line). Family does, indeed, seem to play an important role in the gender differences I observe, and taking these mediators into account reduces the difference, but only in the first decade or so of graduates' careers. Given that these are the years during which I identified the highest reduction in the likelihood of female STEM graduates working in STEM work, this suggests that family obligations do lead to female attrition from STEM, thereby making STEM degrees 'pay off' less for women in Core STEM.

It should be noted, however, that from T15 onwards, family does not mediate the gender difference I observe, instead seemingly *enhancing* it. To investigate this pattern further, I examined how the individual variables I consider mediate the AME (table B3 -

Figure 17: The gender difference (women – men) in the average marginal effect of having a Core STEM degree on working in Core STEM over the work life course as mediated by family, work, and career aspirations (based on models 1 to 5 in table B1)



Note: For legibility, I do not present confidence intervals here, they can be seen in figure B1 in appendix B. Figure 17a includes *number of children*, *partnership status,* and *career break due to family obligations* as family mediators. Figure 17b include *substantial net pay increase* and *was promoted to manager* as work mediators. Figure 17c includes teenage *health* and *technology career aspirations*. Finally, figure 17d includes all of these mediators.

- and figure B1 in appendix B). Doing so reveals that this pattern is driven by how many children the respondents have. Running additional models using a series of dummy variables that distinguish between children of different ages revealed that the age of the children does not matter much, with all ages having a significant negative effect on working in STEM. Having children therefore affects graduates' likelihood of working in STEM beyond the early years during which children require more care. While female STEM graduates are more likely to drop out of STEM when their children are first born (leading to the initial mediation I observe), in the latter years having a higher number of children seemingly leads to a STEM degree benefiting women more than men.

Looking at the destinations of male and female STEM graduates descriptively (figure B2 in appendix B) reveals that the most common non-STEM destination of both groups are what I call 'LEMB' fields (law, economics, management, and business).[34] However, while the share of female STEM graduates in LEMB occupations remains relatively stable over time, the share of male STEM graduates in such occupations increases across the work life course. In fact, after a decade or so in the labour market, all departures from STEM seem to be dominated by male STEM graduates moving into LEMB work. The enhancing effect I observe when including the *number of children* variable may be driven by this pattern. For example, it could be the case that men leave STEM work in favour of higher paying LEMB occupations as a result of a need to financially support their growing family, while the female STEM graduates who stayed in STEM up to T15 are likely to remain in the field. This would explain why the enhancing effect disappears once family obligations and pay and promotion factors are taken into account simultaneously (figure 17d).

[34] This is adapted from Walker and Zhu's (2011) 'LEM' category and includes other subjects associated with Business and Management such as Administration and Finance.

Overall, my analyses indicate that family does mediate the way in which men 'benefit more' from having a STEM degree when it comes to working in STEM, especially in the first decade of graduates' time in the labour market. This is likely driven by women continuing to be primary care givers, which affects them both because of being more likely to take career breaks due to family obligations, but also beyond the early years of their children's lives.

Pay and Promotion Opportunities

Another commonly suggested explanation for STEM graduates' lack of entry to and/or lack of retention in STEM work is pay and promotion opportunities. These factors might also influence the gender differences in the association between being a STEM graduate and working in STEM which I observe, as past research has highlighted that female STEM graduates generally earn less and occupy less senior or highly skilled STEM roles than their male peers (E. Smith and White 2018a; Xu 2017), which may make them more likely to leave the field. Hence, model 3 builds on the base model by including a variable capturing whether respondents have been promoted to manager since the previous year, and a variable capturing whether they received a substantial pay increase since the previous sweep they were in.

Panel B in figure 17 shows that together, these measures of pay and promotion opportunities in the labour market seem to have a relatively substantial mediating effect on the gender differences in the AME of having a STEM degree on working in STEM. Unlike the family mediators, this mediation is largest in the mid- to late- stages of the time period I observe, presumably due to graduates being more likely to be promoted and receive pay increases – or notice the lack thereof – once they have established themselves in the labour market. As a result, once these work variables are included in the model, there is also less change in the gender difference over time; while the U-shape predicted

by the base model remains, with the gender difference being largest in the middle of the observed time period, it is much less pronounced once pay and promotion opportunities are accounted for.

Looking at these mediators individually highlights that they mediate the gender differences I observe in a similar way, with promotion having a slightly larger mediating effect (figure B1 in appendix B). Both pay and promotion reduce graduates' likelihood of working in STEM. This suggests that people leave STEM work to go into higher paying fields with more promotion opportunities, which is backed up by figure B2 in appendix B, which shows that LEMB, which has been argued to have more pay and leadership opportunities than STEM fields (Bosworth, Lyonette, and Wilson 2013), is the most common non-STEM destination for both male and female STEM graduates. Men are particularly likely to leave STEM for LEMB work, so the decrease in the gender differences in the association between being a STEM graduate and working in STEM when including work mediators are likely driven by the behaviour of male STEM graduates.

Career Interests

The final set of mediators I consider concern graduates' career interests. Due to an absence of information on adult career interests in the data, I focus on teenage career aspirations here, and include both *health* and *technology career aspirations* in model 4. I include *health career aspirations* despite focusing on Core STEM only, as these may still indicate a general interest in STEM work. Doing so allows me to capture how graduates' early STEM career interests act as mediators, because differences in career interests, including those formed at an early age, have often been cited as explanations for much of the gendered occupational allocation in the labour market.

As can be seen in panel C of figure 17, I do, indeed, find a small mediating effect of such aspirations on the gender differences in the association between having a STEM degree and working in STEM. Once career aspirations are included in the model, the gender difference in the AME of having a STEM degree decreases somewhat across the entire work life course. Part of this gender difference could therefore be because of women being less motivated to work in STEM, even if they have obtained a degree in the field, and consequently voluntarily choosing to not enter or subsequently leave the field. This mediation is driven by technology career aspirations (figure B1 in appendix B), which is unsurprising given that I focus on Core STEM fields, which do not include subjects allied to health. Teenage (technology) career aspirations therefore shape graduates' likelihood of working in STEM *beyond* shaping their likelihood of studying STEM at university.

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Overall, I find evidence that all three groups of mediators I consider – family obligations, pay and promotion opportunities and career interests – are likely to shape the gender differences in the association between having obtained a STEM degree and working in STEM. The family mediators particularly affect the early differences which I observe, likely due to influencing female attrition from the field, while the pay and promotion mediators play the largest role after a decade or so in the labour market. Teenage career aspirations reduce gender differences across the work life course, but only slightly. Model 5, which includes all mediators simultaneously, shows that the factors I consider do explain a substantial part of the gender differences in the AME of having a Core STEM degree. Once all mediators are included in the analysis, the gender difference increases more or less steadily across the work life course (panel D in figure 17), which suggests

that having a STEM degree 'pays off' less and less for women (compared to men) as their time in the labour market progresses.

Other (unobserved) explanations

The full model (model 5) further reveals that a substantial (and statistically significant) gender difference in the association between having a STEM degree and working in STEM remains after taking into account all of the mediators I consider. Thus, things I do not account for are likely to play an important role in shaping gendered horizontal education-job (mis)matches among STEM graduates. Additional explanations for the patterns I observe are likely related both to the choices of individual STEM graduates, and external labour market circumstances that shape their opportunities and experiences in STEM work.

On the individual choice side, I was unable to take *changes* in people's career interests into account. Given that I do find that teenage career aspirations influence the gender differences in the association between having a STEM degree and working in STEM which I observe, it is likely that adult career interests (and changes therein) play an important role in this dynamic. On the labour market side, commonly cited reasons for leaving STEM among female STEM graduates are a lack of mentoring support and female role models in the workplace, as well as gender discrimination resulting in a lack of recognition of women's skills and limited networking opportunities when compared to the experiences of their male peers workers (Hunt 2016; Fouad et al. 2017; Frehill 2009; Rosser and Taylor 2009). The pay and promotion measures I included in my analyses will have partially captured the effects of such discrimination, but they are not sufficient to take all these workplace factors into account. Additionally, I was unable to account for the number of opportunities STEM graduates have to enter STEM work, which is likely to affect women's underrepresentation in the field in particular, as women generally spend

longer looking for a job out of university, and tend to receive fewer job offers (Jasko et al. 2020).

5.5. Conclusion

Degree field of study and gender are arguably the most commonly discussed – or assumed – determinants of STEM work, both in the academic literature and in the political discourse surrounding the STEM labour market. Nonetheless, little prior research has explicitly studied the way in which gender shapes the relationship between having a STEM degree and working in STEM over the work life course, especially in the UK context. Understanding this relationship is not only important to shed further light on what determines STEM work, but also gives insight into the role gender plays in horizontal education-job (mis)matches, and how these develop across the life course, which is still debated in the literature.

Hence, this chapter asked three research questions. Firstly, I asked how the relationship between obtaining a STEM degree and entry into STEM work varies by gender. Defining a 'STEM graduate' as a person who has obtained any type of STEM university degree at undergraduate and/or postgraduate level, I show that gender moderates the relationship between having obtained a STEM degree and working in STEM for Core STEM fields (computer science and IT, engineering, mathematics and the physical sciences), but not for the 'Broader' set of STEM fields I consider (additionally including biological sciences, medicine, dentistry, veterinary science, nursing, other health fields including psychology, planning and construction-related fields, agriculture, forestry and any not elsewhere categorised STEM fields). Specifically, I find that a Core STEM degree 'benefits' women less than men when it comes to entering Core STEM work. Using the Core definition of STEM, I find that while around 50% of

all male STEM graduates enter STEM work at the point of labour market entry, only around 35% of female STEM graduates do. These predicted probabilities rise to 60% and 50% respectively when using the Broad definition of STEM, and the gender difference becomes non-significant, highlighting that gender plays a larger role in determining entry into the more 'male-typed' Core STEM fields. Gender is therefore an important factor shaping horizontal education-job (mis)matches in STEM, but the extent of this varies by STEM sub-field.

Secondly, I asked whether and how gender differences in the strength of association between being a STEM graduate and working in STEM develop over the work life course. In line with the findings of studies that have investigated this relationship in settings outside of the UK (Frank 2019; Hunt 2016; Preston 2004; Cech and Blair-Loy 2019; Frehill 2009, 2012), my analyses show that the association between being a STEM graduate and working in STEM is stronger for men than for women, and changes over the work life course. Although both men and women are less likely to be in STEM work as their careers progress, the careers of male and female STEM graduates vary quite substantially in their patterns. While male STEM graduates follow a more 'expected' pattern[35] by initially becoming increasingly likely to enter STEM work as time passes, with slight attrition only being observed after 10 years in the labour market, women drop out of STEM from the point of labour market entry, with most attrition being concentrated in the early years of their careers.

This pattern is consistent across definitions of STEM, although the drop in women's likelihood of being found in STEM across the work life course is more pronounced when using the Core definition, and the gender difference in the likelihood

[35] When compared to all graduates who enter higher managerial and professional occupations early on in their careers (Duta, Wielgoszewska, and Iannelli 2021).

of working in STEM among STEM graduates is only statistically significant when examining Core STEM fields. After 25 years in the labour market, when using the Core definition of STEM, female STEM graduates' likelihood of working in STEM decreases by around 40% (14 percentage points), while that of their male peers decreases by 13% (8 percentage points). These findings highlight the importance of studying horizontal education-job matches from a life course perspective, as the point of labour market entry does not sufficiently reflect the way in which male and female graduates' likelihood of being found in STEM changes over time, which likely applies to other fields too.

As aforementioned, when looking at the destinations of STEM graduates who enter non-STEM work descriptively (figure B2 in appendix B), I find that LEMB fields are the most common non-STEM destination for both male and female STEM graduates. However, there are once more gender differences in the career patterns of male and female STEM graduates even when looking at non-STEM work. While the proportion of male STEM graduates in LEMB fields, such as finance, rises steadily as their careers progress, female STEM graduates mainly exhibit an increase of being found in education-related fields such as teaching across the first decade of their career. This increase is in line with the female attrition from STEM which I observe, suggesting that many of the women who drop out of STEM do so in favour of education-related work. This suggests that the underlying mechanisms shaping men's and women's attrition from STEM may differ.

Hence, my third research question asked to what extent family obligations, pay and promotion opportunities and career interests, which are often cited as the main reasons for attrition from STEM, can explain gender differences in the association between being a STEM graduate and working in STEM over the work life course. I demonstrate that all of these mediators do seem to reduce such gender differences, but in slightly different ways. While family mediators mainly mediate the relationship in the

early years of graduates' time in the labour market, pay and promotion opportunities are more important later on in people's careers, while career interests, or teenage career aspirations more specifically, have a small mediating effect throughout. It should be noted that I do not perform explicit analyses of causality, so while my results point towards certain patterns, I cannot establish whether they are indeed causal.

The findings of this chapter again make the case for the importance of studying horizontal education-job mismatches (working in an occupation that corresponds to one's field of study) in addition to the more commonly studied vertical matches (working in an occupation that corresponds to one's level of education). Even among a sample of graduates, there remains substantial heterogeneity in labour market outcomes. Furthermore, I highlight that horizontal matches vary considerably by gender and over the work life course, which should both be taken into account more in future studies investigating the way in which people's degree field of study shapes their field of occupation.

Taken together, these findings suggest that policies that aim to increase gender equality in representation in STEM work should look beyond education. Although degree field of study is an important predictor of STEM work, and despite gender playing an important role in this relationship, a large part of the variance in who does and does not enter (and remain in) STEM work remains unexplained when simply focusing on the link between education and work. Therefore, in what follows I turn to the role of social origin as an additional possible determinant of STEM work.

6. ANALYTICAL CHAPTER 2

Does STEM work run in the family? The role of parental field of occupation in shaping graduates' entry into the STEM labour market

6.1. Introduction

Having established that horizontal education-job matches and gender, albeit important, cannot account for a large part of what determines STEM work, this chapter turns to the role of social origin. In what follows, I will focus on DESO, and occupational inheritance in particular, in the context of parental STEM occupations and investigate the way in which having a parent in STEM can influence own entry into STEM work. As outlined in Chapter 3, occupational inheritance continues to be understudied in general, despite past research suggesting that parental field of occupation may play an important role in shaping their children's field of occupation (for example, Jonsson et al. 2009).

The role that people's parents play in determining how likely they are to work in STEM has rarely been considered. When parental field of occupation has been taken into account, this has mainly been done in regard to school performance (for example, Giannelli and Rapallini 2017; OECD 2007; Anaya, Stafford, and Zamarro 2017), field of study choice (for example, Moakler Jr. and Kim 2014; Cheng, Kopotic, and Zamarro 2017) and career aspirations (for example, Cheng, Kopotic, and Zamarro 2019; Sikora and Pokropek 2012; Dabney, Chakraverty, and Tai 2013; Han 2015; Jacobs, Ahmad, and Sax 2017). It has been generally shown to have an impact on all these areas, with children of 'STEM parents' performing better in STEM-related subjects in school and being more likely to choose and persist in STEM subjects at university. Few have examined how the link between having a parent who works in STEM might influence graduates' career choices *beyond* school and university predictors, however.

Based on this previous literature, it is uncertain whether having a parent in STEM makes one more likely to work in STEM oneself. Although Cheng et al. (2017), Werts (1968) and Preston (2004) find that having a STEM employed parent makes children more likely to work in STEM, Godwin, Potvin and Hazari (2014) found no such relationship when it comes to engineering and mothers, and in fact demonstrated that having a father who is an engineer *decreases* the likelihood of becoming an engineer yourself. Similarly, although Wang, Degol and Ye (2015) initially do find a relationship between parental STEM occupation and own STEM occupation, in their study this effect becomes non-significant once mathematics achievement is controlled for. The adjacent body of literature investigating the impact having a parent in STEM has on career aspirations (rather than observed career patterns) is similarly inconclusive. While some past research finds that the children of parents in STEM occupations are more likely to aspire to working in STEM (Dabney, Chakraverty, and Tai 2013; Holmes et al. 2017), which is also the case in the UK (Schleicher 2007), a variety of studies have found no relationship between parental STEM and children's STEM career aspirations and interest in science (Chen et al. 2022; Japashov et al. 2022; Kjærnsli and Lie 2011; OECD 2007). A consensus regarding occupational inheritance among STEM workers has therefore not been reached.

Furthermore, all prior studies addressing the explicit relationship between parental STEM occupation and own STEM occupation have used data from the USA, and this relationship does not seem to have been studied in another country context. Doing so is vital, as the effect parents have on career aspirations varies by country (Bahar and Adiguzel 2016; Sikora and Pokropek 2012), and parents shape career *aspirations* differently in the USA than they do in the UK (Sikora and Pokropek 2012). It is therefore crucial to study this relationship in another context, which I do in this chapter.

To address these gaps in the literature – in the study of occupational inheritance in general, in the study of occupational inheritance in STEM work, and in the context of the UK – this chapter aims to establish whether a link between parental STEM work and people's own likelihood of entering STEM exists. The chapter focuses on labour market entrants, as my aim here is to gain an initial understanding of how occupational inheritance works in the context of STEM. Chapter 7 studies this relationship over the work life course. Furthermore, first jobs have been identified as playing vital roles in how DESO shapes graduate outcomes (Ballarino, Cantalini, and Panichella 2021), so it is important to understand this point in a graduate's school-to-work transition. First, to establish whether having a 'STEM parent' influences people's STEM career choices, this chapter will ask:

(i) Are graduates whose parents work in STEM more likely enter the labour market in a STEM occupation themselves?

Next, building on my previous finding that having a degree in STEM is an important predictor of entering the STEM labour market, I will investigate whether degree field of study moderates the effect of having a parent in STEM on entering STEM work. Field of study has been shown to be important in shaping DESO; investigating the relationship between parental education and graduates' occupational destinations, Jacob, Klein and Iannelli (2015) conclude that field of study is an important mediator of social inequalities in labour market outcomes, and call for more research investigating the role of field of study in the context of social mobility. It is plausible for degree field of study to also *moderate* the relationship between having a 'STEM parent' and working in STEM. Hence, I ask:

(ii) Does the effect of having a parent in STEM on determining whether graduates enter the labour market in a STEM occupation differ by degree field of study? If yes, is it larger for STEM graduates, forming a 'boosting effect', or for non-STEM graduates, forming a 'compensatory effect'?

Finally, to start to understand how parental STEM occupation can influence graduates' field of occupation at labour market entry, I take an initial look at the mechanisms through which occupational inheritance in STEM operates. In addition to shaping general STEM interest, I anticipate three stages of people's trajectories into the labour market in which having a 'STEM parent' might indirectly shape their field of occupation: (i) secondary schooling, (ii) university level, and (iii) job searching. For example, at secondary level, the influence of 'STEM parents' on STEM school performance may well in turn lead to their children being more likely to consider a STEM career and having a better chance of finding STEM work following graduation. To examine these mechanisms, I ask:

(iii) Through what mechanisms may parental STEM occupation influence their children's (STEM) field of occupation at labour market entry?

6.2. Past Research and Theoretical Framework

6.2.1. Why may graduates whose parents work in STEM be more likely to work in STEM themselves?

Although the literature regarding occupational inheritance in STEM is inconclusive, it is certainly possible that children of parents who work in STEM are more likely to enter STEM themselves. For one, having a parent in STEM can shape children's initial interest in STEM. Parental occupational interest and values have been found to generally shape their children's occupational interests and values (Jodl et al. 2001; Tey, Moses, and Cheah 2020), which is why the children of parents working in STEM are more likely to aspire

to a career in STEM (Dabney, Chakraverty, and Tai 2013; Holmes et al. 2017; Schleicher 2007), although this finding is not universal (Chen et al. 2022; Japashov et al. 2022; Kjærnsli and Lie 2011; OECD 2007). Parental STEM support, which is higher among parents working in STEM (Hsieh and Simpkins 2022), has also been shown to increase interest in STEM among school-aged children (Šimunović and Babarović 2021), which has subsequently been linked to STEM career intentions (Tey, Moses, and Cheah 2020). The children of 'STEM parents' are therefore likely to show more interest in STEM, so it would be unsurprising if they do, indeed, enter STEM jobs at higher rates.

Furthermore, people whose parents work in STEM are more likely to have grown up with a familiarity of the field. Their parents might have demonstrated the realities of what working in STEM entails, leading to higher knowledge of what is required to work in the field. Such knowledge has been linked to a higher likelihood of expressing STEM career aspirations (Blotnicky et al. 2018). More knowledge can also mean that the children of parents in STEM are less negatively affected by stereotypes surrounding the field, which have been shown to have a negative impact on students' STEM career interests (Luo et al. 2021). Indeed, a lack of degree-related work experience has been identified as contributing to STEM graduates choosing non-STEM work such as graduate schemes over entering the STEM labour market following graduation (Mellors-Bourne, Connor, and Jackson 2011). The children of 'STEM parents' may therefore be more likely to enter STEM careers because their parents were able to demystify such jobs, making them feel more accessible.

In addition, some studies suggested that occupational inheritance might occur in part because it is the easiest path to take (Mortimer 1974; Gubler, Biemann, and Herzog 2017), an argument which is strengthened by the finding that people with higher risk tolerance are less likely to inherit their careers from their parents (Y. Wang 2020).

Because children of 'STEM parents' are likely to have grown up with a familiarity with the field, they might feel most comfortable staying in STEM-related education and work. Their parents' field-specific knowledge and connections would furthermore mean that choosing a career in STEM will maximise the parental support available to them. It is therefore feasible that having a parent in STEM may influence interest in, knowledge of, and support in STEM work.

Therefore, I anticipate that having a 'STEM parent' makes people more likely to work in STEM themselves. This is likely for a variety of reasons. Such parents shape their children's interest in and familiarity with the field, making them more likely to go down a STEM related educational and then work path. This could also simply be the easiest field to enter for children of 'STEM parents' due to the knowledge and connections such parents provide, which are likely to help both in education and in the labour market.

6.2.2. How and why might having a parent in STEM work influence STEM and non-STEM graduates differently?

The question of whether the relationship between having a parent in STEM and working in STEM is moderated by degree field of education can be viewed through an adapted version of Ballarino and Bernardi's (2016) 'boosting' versus 'compensatory' effect framework. Looking at income, they explain a 'boosting effect' of social origin as socio-economically advantaged families being 'more likely to 'push' their children who are good students towards the higher part of the income distribution' (Ballarino and Bernardi 2016, 265). A similar dynamic may occur when looking at entry into STEM work among STEM graduates. Because STEM graduates are more likely than non-STEM graduates to work in STEM (see Chapter 4), they might be more able to benefit from the field-specific

knowledge and connections that parents in STEM have. Therefore, having a 'STEM parent' could 'boost' STEM graduates' chances of finding work in STEM.

However, it is feasible that interest in STEM is more important than parental STEM support when it comes to entering STEM work. If this is the case, STEM graduates with 'non-STEM parents' may, in fact, be equally or even more likely to enter STEM work than their peers with 'STEM parents'. Although, as previously discussed, 'STEM parentage' increases interest in STEM in general, this does not necessarily mean that STEM graduates with 'STEM parents' are more interested in the field than those whose parents work in other fields. Because people whose parents do not work in STEM themselves are likely to have received less STEM support when growing up (Hsieh and Simpkins 2022), and STEM is not necessarily the easiest path to take for them, STEM graduates with 'non-STEM parents' might be driven by more genuine interest in the field, making them more likely to apply to STEM work following graduation. This is partially supported by the fact that PISA 2006 data revealed that school children with STEM career aspirations whose parents do not work in STEM perform equally well or better in science-related subjects than children whose parents do work in a STEM career but who do not have STEM career aspirations (OECD 2007). The 'STEM parent' effect may thus be small among STEM graduates.

Therefore, having a 'STEM parent' could, in fact, benefit non-STEM graduates more than STEM graduates. Initially discussed by Bernardi (2014), 'the notion of compensatory advantage predicts that better-off families have the means to compensate for the school failures of their offspring and to help them achieve a good occupational position despite their relatively low educational attainment' (Ballarino and Bernardi 2016, 262). Not having studied STEM subjects at university could be interpreted as such a 'school failure' when it comes to entering the STEM labour market. 'STEM parents'

could compensate for such a 'failure' by ensuring their children have pre-existing knowledge of- and connections into the field, making the field accessible to them despite their lack of a STEM degree. Past literature has repeatedly demonstrated that a substantial proportion of STEM workers do not have STEM degrees (E. Smith and White 2018a; Deming and Noray 2018; Lowell, Salzman, and Bernstein 2009),[36] and it may well be the case that parental occupation plays an important role in making STEM more accessible for non-STEM graduates. This would be in line with Brand and Xie's (2010) 'negative selection hypothesis' that the people who are least likely to obtain a degree (or in this case, a STEM degree in particular), benefit most from obtaining one.

In sum, based on the theoretical arguments presented above, it is unclear in what way (if at all) having a STEM degree is likely to moderate the relationship between having a 'STEM parent' and working in STEM. While STEM graduates might benefit more from having 'STEM parents' via a 'boosting effect', being able to better make use of their parents' knowledge and resources, it is also feasible for non-STEM graduates to benefit more in the form of a 'compensatory advantage'. Such graduates may need their parents' help more to enter the STEM labour market, while STEM graduates can rely on their own knowledge and networks that they gained through their degree. Given these opposing expectations, it is of course also possible for field of study to not moderate the effect of having a 'STEM parent' on STEM work.

6.2.3. What possible mechanisms may drive the relationship between parental STEM occupation and own STEM occupation?

Should 'STEM parents' indeed increase the likelihood of their children working in STEM, as I expect based on the previously discussed literature, this occupational

[36] Indeed, in the previous chapter I too demonstrate that around 10% of non-STEM graduates enter STEM work.

inheritance is driven by a variety of mediators. As aforementioned, Jonsson et al. (2011) explain intergenerational occupational transfer through the following mechanisms: (i) occupation-specific skills, (ii) occupation-specific culture and tastes (including career interests), (iii) occupation-specific networks and (iv) fixed resources (such as a business). All of these mechanisms influence the relationship between having a parent in STEM and working in STEM oneself, in both direct and indirect ways. In addition to shaping (career) interests in STEM during childhood, as described above, it is feasible that parents can influence their children's entry into STEM work through shaping their time at secondary school, at university and during their job search following graduation.

Schooling

Much of the literature investigating the influence parental occupation can have on STEM trajectories has focused on schooling. Together, this research has led to two general findings regarding what may help the children of 'STEM parents' succeed in the STEM labour market: Firstly, having a parent in STEM influences the likelihood of STEM subject choice at high school (Dryler 1998; Plasman, Gottfried, and Williams 2021), although this finding is not universal (Wegemer and S.Eccles 2019). Parental STEM work also influences STEM course persistence at school (Plasman et al. 2021), which might be a result of higher STEM support among 'STEM parents' (Hsieh and Simpkins 2022).

Secondly, the children of parents working in STEM perform better in school, especially in STEM subjects such as mathematics and science (Bowden et al. 2018; Anaya, Stafford, and Zamarro 2017; OECD 2007; Plasman et al. 2021). This could be due to intergenerational transmission of skills; using the Dutch setting, Hanushek et al. (2023) demonstrate that comparative skills advantages (performing better at mathematics rather than language at an early age) are transmitted across generations, and shape both secondary and tertiary field of study choices both within and across generations. In other

words, those with parents who performed well in mathematics at an early age are more likely to perform well in mathematics themselves, and this in turn makes them more likely to choose STEM fields throughout their time in education, and subsequently enter STEM work.

It is likely that these school-level factors may benefit STEM graduates more than non-STEM graduates, forming a 'boosting' effect, as studying STEM at school increases the likelihood of studying STEM at university (De Vita and Giancola 2017; Dilnot 2018), which in turn increases the likelihood of working in STEM (see my previous chapter). Good school performance in these fields also leads to a higher likelihood of majoring in STEM adjacent fields at university (Anaya, Stafford, and Zamarro 2017; Lloyd et al. 2018). On the other hand, school subject choice and performance could contribute to a 'compensatory effect' of parental STEM work, as having some STEM knowledge from school, even if not having studied it at university, might help non-STEM graduates to enter STEM work should they wish to do so.

Higher Education

Parents may also shape their children's STEM career prospects through influencing their time at university. A substantial body of literature has found that having a parent in STEM makes one more likely to study and graduate from STEM at university oneself (Anaya, Stafford, and Zamarro 2017; Cheng, Kopotic, and Zamarro 2017; Plasman et al. 2021; Jarvie-Eggart, Singer, and Mathews 2020; Leslie, McClure, and Oaxaca 1998; Godwin, Potvin, and Hazari 2014; Moakler Jr. and Kim 2014; Sheppard et al. 2010; Astin and Astin 1993; Chise, Fort, and Monfardini 2020) with relatively few studies finding evidence to the contrary (Sheppard et al. 2010; Seymour and Hewitt 1997 in Adelman 1998, 58). In addition, because parents have been found to influence university choice in general (Paul 2014), parents working in STEM might also influence the type of university

their children attend, which may subsequently help them in the STEM labour market. This could occur indirectly through influencing their children's school grades, and directly by using their STEM-specific knowledge to give advice regarding the best degree type and type of university for their children's desired career path. Indeed, Bukodi, Goldthorpe and Steinberg (2023, 553) find that the children of 'STEM parents' are more likely to have attended Cambridge, rather than Oxford, to study STEM fields, pointing towards 'greater awareness of Cambridge's scientific superiority' among parents who worked in STEM themselves, and Jacob, Klein and Iannelli (2015) find that 'type of higher education institution' somewhat reduced the effect of parental education on their children's early labour market destinations in the UK and Germany.

Having a parent who works in one's field of study also seems to improve university performance in said field (Odoh et al. 2017), which points towards a potential advantage the children of STEM workers have when doing STEM degrees. Those whose parents have field-specific knowledge may receive more support or have an easier time acquiring knowledge during their studies because of their familiarity with STEM-adjacent topics and STEM work. These people could therefore have a better chance of academically outperforming their peers whose parents do not work in STEM, which would subsequently help them when entering postgraduate education and/or looking for a job in STEM.

These mechanisms might again differ for STEM and non-STEM graduates. Here, I anticipate university level mediators to contribute towards the 'boosting' effect of having a 'STEM parent'; at university level, it is likely that parents influence their children's STEM labour market destinations by influencing their university choice, degree subject choice, whether they do a postgraduate degree, degree performance in STEM degrees and subsequent STEM destinations.

Parental Help with Job Searches

The children of STEM employed parents may have an advantage when applying to STEM work due to the knowledge and connections of their parents benefiting them in a variety of ways. Parents who have direct knowledge of the STEM labour market might be able to guide their children through the initial job search by giving advice regarding specific employers or broader issues such as how to perform well in interviews. In addition, a parent in STEM may be able to utilise their network to find job opportunities, field-specific work experience, which has been linked to entering STEM work (Mellors-Bourne, Connor, and Jackson 2011), and help with job applications more generally. They might be able to recommend their children to potential employers, or even own STEM-related businesses which their children can inherit, which has been identified as a common form of occupational inheritance in other fields (Lentz and Laband 1990).

Thus, the children of parents in STEM may have higher chances of finding a job in STEM, especially in instances where STEM job opportunities are limited. It is therefore likely that people whose parent(s) work in STEM are more likely to enter STEM than people whose parents work in non-STEM fields. Such direct parental help could benefit non-STEM graduates who want to enter STEM work more than STEM graduates, as parents might be able to compensate for the lack of STEM knowledge and connections that those studying STEM obtain at university.

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Based on the above, I anticipate observing occupational inheritance in the context of STEM, with children of 'STEM parents' being more likely to enter STEM work themselves. This likely operates via a variety of mechanisms, with parental field of occupation shaping STEM interest and STEM skills, which is likely to affect field of

study and performance both at school and at university. Furthermore, 'STEM parents' may be more likely to guide their children through their time at university, ensuring they obtain the best education to enter STEM work (should they so desire), and use their field-specific knowledge and connections to help their children find STEM work at the point of labour market entry. It is unclear whether and how the 'STEM parent' effect is moderated by degree field of study, as I present arguments for both a 'boosting effect' and a 'compensatory advantage'.

6.3. Data and Methods

6.3.1. Data and Sample Specification

As is the case throughout this thesis, this chapter's analyses are based on a sample of graduates in the British Cohort Study of 1970 (BCS70). Due to this chapter's focus on graduates' entry into STEM work, I focus on only one point in time for these analyses; the point of labour market entry. As discussed in Chapter 4, I define labour market entrants as people who have left full-time education, who entered the labour market (as employees or self-employees) before the age of 35, and who have been in their first job for at least 3 months. The year during which labour market entry takes place in the sample therefore varies by respondent, ranging from 1989 to 2004, although most respondents (72%) entered the labour market between 1992 and 1995, in the immediate wake of the 1990s recession. As explained in the Introduction of this thesis, the recession is likely to have had a smaller impact on graduates than less educated labour market entrants, and STEM professions were less affected than other sectors, but it nonetheless forms an important background to this chapter's analyses.

This chapter will focus on Broad STEM fields, while running auxiliary analyses using the more restricted Core definition of STEM. This choice was made because the

theoretical mechanisms I discuss in this chapter are likely to apply across all of the occupations I include in Broad STEM, and also for the practical reason of wanting to maximise the sample size. The analytical sample size for this chapter is 1,819 individuals.

6.3.2. Variables

The dependent variable of this chapter will once more be *field of occupation (STEM versus non-STEM),* where 0 = non-STEM work, and 1 = STEM work. As explained above, for this chapter I will use the Broad definition of STEM. The key independent variable of this chapter is *parental occupation (STEM versus non-STEM),* which is coded in the same way the dependent variable is. This variable was collected when respondents were 10 years old and carries a value of 1 if at least one of the respondents' parents worked in STEM. To address my second research question, I additionally include *degree field of study (STEM versus non-STEM).*

I control for respondents' characteristics, taking into account *sex*, *age at labour market entry*, *ethnicity* and *migration status*. I also control for *full-time work.* Additionally, to isolate the effect of having a 'STEM parent' from other family background factors, I include several measures of social origin, which have all previously been used in studies of DESO: *parental social class* (age 10*)*, *parental education* (age 10) and *parental income* (age 16).

The analyses will include a variety of mediator variables, to establish to what extent the 'STEM parent' effect may be driven by the mechanisms outlined in the theory section. At the school level, to account for the role 'STEM' parents play in school field of study selection, I include a dummy variable capturing whether the respondent has at least one STEM A-Level. To address parents' role in shaping their children's school performance, I include *mathematics competence* (age 10) and *number of good A-levels.*

Unfortunately, BCS70 does not break down A-Level performance by subject, which is why I include childhood mathematics performance and use overall performance as a proxy.

Because STEM career aspirations have been shown to be influenced by STEM parents, I look at the way in which *health career aspirations* and *technology career aspirations* mediate the relationship of interest. As discussed in Chapter 4, these variables offer an insight into STEM career aspirations, but do not cover the full range of STEM fields.

To address mediation at university, and to once more account for parents' influence on field of study choice and academic performance, I include *degree field of study* and *undergraduate degree performance.* Additionally, I include *type of undergraduate university* and a dummy capturing whether respondents have obtained a postgraduate degree, as advice regarding type of university and level of degree may be ways 'STEM parents' can better guide their children into the STEM labour market.

Finally, to further unpack how having parental help might affect their children's early career choices, I include a series of variables measuring parental help with job searches: (i) *parental advice* (general and with application forms), (ii) *parental recommendation* to an employer (including writing a reference), (iii) *direct employment* through a parent, and (iv) *parental network*, measuring whether parents used their contacts to find their child a job. This variable was collected at age 42 but will be used as a proxy for parental help at the point of labour market entry.

6.3.3. Methodology

To address the research questions posed in this chapter, I first examine descriptive statistics before using cross-sectional logistic regression models. To address my second

research question, I examine an interaction effect between 'STEM parent' and 'STEM degree'. For my third research question regarding possible explanations for the association between having a 'STEM parent' and working in STEM, I again adapt Gugushvili, Bukodi and Goldthorpe's (2017) approach of 'unpacking' DESO, in my case parental occupation, through a series of nested regression models. As discussed previously, this approach cannot directly uncover causal mechanisms, but will allow me to infer correlations, which can give an initial indication of possible causality. My main analyses focus on the Broad definition of STEM, while I ran auxiliary analyses using the Core definition. All models presented below are based on multiply imputed data.

6.4. Empirical Findings

6.4.1. Are graduates whose parents work in STEM more likely enter the labour market in a STEM occupation themselves, and does this vary by degree field of study?

The descriptive statistics presented in table 11 give an initial indication that children of parents who work in STEM are, as predicted, more likely to enter the labour market in a (Broad) STEM occupation; at 41%, substantially more children of 'STEM parents' work in STEM than is the case for the children of 'non-STEM parents' (28%). This finding is consistent across degree fields, but table 11 suggests that having a parent in STEM may have a larger impact on working in STEM for STEM graduates. The proportion of STEM graduates in STEM work increases by 19 percentage points when comparing people with 'STEM parents' to those with 'non-STEM parents', while for non-STEM graduates, this proportion only increases by 8 percentage points. This points towards a 'boosting effect' of having a 'STEM parent' when having studied STEM.

Table 11: The distribution of the sample by degree field, parental field of occupation and own field of occupation at labour market entry (Broad definition of STEM)

Degree Field	Parental field of occupation	Field of occupation (%)			*N*
		Broad STEM	Non-STEM	Total	
All	Broad STEM	40.5	59.5	100.0	298
	Non-STEM	28.3	71.7	100.0	1,521
Broad STEM	Broad STEM	64.7	35.3	100.0	143
	Non-STEM	45.6	54.4	100.0	619
Non-STEM	Broad STEM	18.00	82.00	100.0	155
	Non-STEM	10.4	89.6	100.0	903

Note: This table displays averages values across all imputed datasets. Table C7 in appendix C further breaks down these groups by degree level (undergraduate versus postgraduate).

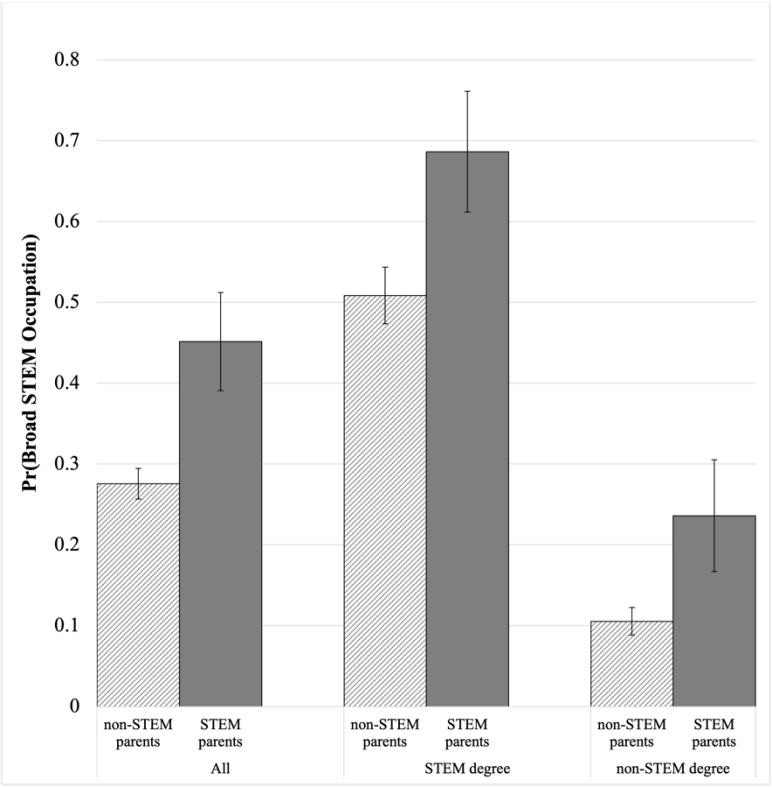
Next, to explore these findings more systematically, I ran cross-sectional logistic regressions (table 12). To address research question 1, which asks whether graduates whose parents work in STEM are more likely to enter the labour market in STEM occupations themselves, model 1 (the 'base model') regresses *field of occupation (STEM versus non-STEM)* on *parental field of occupation (STEM versus non-STEM)* and the control variables. The results of this model confirm that having a parent in STEM has a statistically significant, positive effect on the likelihood of working in STEM. Specifically, the 'STEM parent' effect accounts for an 18-percentage point (CI: 0.11 – 0.24), or around 60%, increase in the likelihood of working in STEM following graduation. To illustrate this, figure 18 shows the predicted probability of entering STEM for children of STEM and non-STEM parents. While graduates whose parents do *not* work in STEM have a likelihood of around 28% (CI: 0.26 – 0.29) of entering STEM work at the point of labour market entry, for children of 'STEM parents', this likelihood is around 45% (CI: 0.39 – 0.51). Auxiliary analyses using the more restrictive Core definition of STEM reveal similar, albeit somewhat less more pronounced, -

Table 12: The average marginal effects of parental field of occupation and field of study on the likelihood of being found in Broad STEM work at labour market entry

Dependent Variable: Broad STEM Work	Model 1	Model 2	Model 3
STEM Parent	0.18***	0.14***	0.13***
	(0.04)	(0.04)	(0.04)
STEM Degree		0.34***	0.40***
		(0.01)	(0.02)
STEM Parent*STEM Degree			0.04
			(0.06)
Number of Observations	1,819	1,819	1,819

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, All models control for sex, migration status, ethnicity, age, parental class, parental education, parental income, and full-time work (see table C1 in appendix C for full results). All STEM variables are operationalised using the Broad definition of STEM.

Figure 18: The predicted probability of working in a Broad STEM occupation at labour market entry by parental field of occupation and degree field of study field of study (based on models 1 and 3 in table 12)



Note: The group comparisons shown here are statistically significant.

- patterns (appendix C4). Hence, in line with Cheng et al. (2017), Werts (1968) and Preston (2004), I find that occupational inheritance is prevalent among STEM workers; people whose parents work in STEM are more likely to go into STEM work at labour market entry than people whose parents do not.[37]

Turning to my second research question regarding possible differences among STEM and non-STEM graduates, model 2 builds on model 1 by additionally including *degree field of study* to give an initial idea of the role having a STEM degree plays in the relationship studied in this chapter, and model 3 additionally adds an interaction effect between *parental field of occupation* and *degree field of study* to directly address my second research question. Model 2 shows that *degree field of study* mediates the relationship between having a 'STEM parent' and working in STEM. I will discuss this relationship in more depth later in this chapter.

For now, it is important to note that model 3 shows that the interaction term between *parental field of occupation* and *degree field of study* is positive but not statistically significant (table 12). The direction of the effect suggests that if anything, the effect of having a 'STEM parent' is somewhat smaller for non-STEM graduates than for STEM graduates, but this difference is substantively small. This is also reflected in the predicted probabilities presented in figure 18; for STEM graduates, having a parent in STEM increases the likelihood of working in STEM by 17 percentage points (CI: 0.08 – 0.26), while for non-STEM graduates, having a 'STEM parent' increases the likelihood of being in STEM by 13 percentage points (CI: 0.05– 0.20). This again provides evidence for a possible small 'boosting effect' of having a 'STEM parent' when not having studied

[37] Looking at the non-STEM destinations of graduates by parental field of occupation (figure C2 in appendix C) further reveals that having a 'STEM parent' also increases the likelihood of working in Law, Economics, Business and Management (LEMB)-related fields, which are known as being marked by high pay.

STEM, although the lack of statistical significance suggests that having a parent in STEM may not affect STEM and non-STEM graduates differently.

It is certainly possible that field of study does not have a moderating effect on the relationship between parental STEM occupation and own STEM occupation. In the context of other measures of social origin, studies have also found at best a weak relationships between horizontal education-job matches and family background (Boudarbat and Chernoff 2009; Xu 2013, 2017). Hence, the mechanisms through which 'STEM parents' can influence their children's likelihood of working in STEM may affect STEM and non-STEM graduates alike.

6.4.2. Through what mechanisms does parental STEM occupation influence their children's field of occupation at labour market entry?

Next, for the purpose of 'unpacking' the direct 'STEM parent' effect to answer my third research question, I ran a series of models which add the secondary schooling (model 4), career aspiration (model 5), university (model 6) and parental help with job searching (model 7) mediator variables to the 'base model' to determine how they influence the effect of having a parent in STEM across models. To get an idea of how much the mediators I identify reduce the effect of having a parent in STEM overall, model 8 simultaneously adds all mediator variables to the 'base model'. Because the interaction effect in model 3 (table 12) was not statistically significant, I build on model 1 – which does not include an interaction term – for this exercise.[38]

As was done by Gugushvili, Bukodi and Goldthorpe's (2017), I focus on how these possible mediators affect the coefficient of my variable of interest; *parental field of*

[38] It should be noted, however, that when trying to 'unpack' the mediators of the *STEM Degree*STEM Parent* interaction in table C6 in appendix C, I find that the (non-significant) interaction effect coefficient was mediated in a similar way to the 'STEM parent' coefficient discussed in this section.

occupation. Table 13 presents an overview of the coefficient across models (highlighted in grey), which reveals the magnitude of the change in the 'STEM parent' effect when comparing models containing mediator variables to the 'base model' (model 1). The first thing to note is that the effect of having a parent in STEM on working in STEM at the point of labour market entry remains positive and statistically significant across all models. I can therefore conclude that a parent's occupation affects their children's (STEM) occupation *beyond* shaping their career aspirations, field of study choices and performance at school and during university, a finding that persists when using a more restrictive Core definition of STEM (appendix C4).

Out of the four groups of mediator variables I consider, the university variables decrease the effect of having a parent in STEM on working in STEM the most (model 6), reducing the 'STEM parent' effect by around 22% (4 percentage points). Model 6 in table 13 suggests that having a STEM degree is the most important university-level mediator I consider, due to its large effect size when compared to the other university mediators' AMEs.[39] To explore these results further, I ran auxiliary models looking at how the AME of 'STEM parent' is mediated by each university-level factor individually (table C4 in appendix C). These auxiliary analyses confirm that *degree field of study* has the largest mediating effect on *parental field of occupation,* a finding which is in line with Jacob, Klein and Iannelli's (2015) work, who identify field of study as one of the most important mediators of social inequalities in labour market outcomes.

[39] The effect sizes are comparable due to the categorical nature of all of the university-level mediators I consider.

Table 13: The average marginal effects of parental field of occupation, field of study, school level factors, university level factors, and parental help factors on the likelihood of being found in Broad STEM work at labour market entry

Dependent Variable: Broad STEM Work	Model 1	Model 4	Model 5	Model 6	Model 7	Model 8
STEM Parent	0.18***	0.17***	0.18***	0.14***	0.18***	0.14***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Childhood Maths Test Score		0.00*				0.00
		(0.00)				(0.00)
Number of good A-Levels (A-C)		-0.01				-0.00
		(0.01)				(0.01)
Has STEM A-Level		0.12***				-0.01
		(0.02)				(0.02)
Health Career Aspiration			0.13***			0.07**
			(0.04)			(0.03)
Technology Career Aspiration			0.10***			0.04*
			(0.03)			(0.03)
STEM Degree				0.34***		0.33***
				(0.01)		(0.02)
Type of University (Ref: Russel Group)						
Other University				0.02		0.01
				(0.03)		(0.02)
Post92 University				0.05**		0.05*
				(0.03)		(0.03)
Degree Class (Ref: Pass)						
First				-0.01		-0.01
				(0.05)		(0.05)
Upper Second				-0.04		-0.05
				(0.04)		(0.04)
Lower Second				-0.10***		-0.10***
				(0.04)		(0.04)
Third				-0.15***		-0.15***
				(0.05)		(0.05)
Has postgraduate degree				0.08***		0.09***
				(0.03)		(0.03)
Parental Advice					0.04	0.02
					(0.03)	(0.03)
Parental Recommendation					0.00	0.04
					(0.06)	(0.05)
Parental Direct Employment					0.01	0.01
					(0.05)	(0.04)
Parental Contacts					-0.01	-0.03
					(0.04)	(0.03)
Number of Observations	1,819	1,819	1,819	1,819	1,819	1,819

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. All models control for sex, migration status, ethnicity, age, parental class, parental education, parental income, and full-time work (see table C1 in appendix C for full results). All STEM related variables are operationalised using the Broad definition of STEM.

In addition, I find a small reduction in the effect size of 'STEM parent' when looking at the impact of *has postgraduate degree* and *degree class* in isolation, while *type of university* seems to do little in mediating the relationship between having a parent in STEM and working in STEM.[40] This suggests that parents do shape their children's career choices through influencing their likelihood of staying on for postgraduate education. The reduction in the 'STEM parent' coefficient when adding *has postgraduate degree* to the base model hints at 'STEM parents' being more likely to encourage graduates into postgraduate study, thereby 'boosting' their chance of obtaining STEM work. Indeed, looking at descriptive statistics (table C7 in appendix C) reveals that the positive effect of having a 'STEM parent' seems to be larger among postgraduates when compared to undergraduates. In addition, a postgraduate degree can possibly 'protect' graduates from starting out in non-graduate level (vocational) roles, as is relatively common in the UK (Clegg 2017). This result suggests that Torche's (2011, 2016) finding that intergenerational associations weaken among undergraduates, but re-emerge among postgraduates, does not apply in the case studied here. Instead, I find some, albeit faint, evidence towards the general trend of DESO reducing with increased education.

Out of the school-level factors I examine, having a STEM A-Level slightly mediates occupational inheritance in the context of STEM (see table C2 in appendix C), while childhood mathematics performance and A-Level performance do not. This once more highlights the importance of parental influence on subject choice when it comes to determining their children's future field of occupation. While the STEM parents' role in subject choice is important both in school and at university, degree subject choice is the more important of the two in determining whether a graduate enters STEM work at the

[40] I find the same pattern using Core STEM fields, although in this case *has postgraduate degree* reduces the 'STEM parent' effect slightly more than does *undergraduate degree class.*

point of labour market entry; once considered in the full model 8 alongside other mediators, the positive effect of obtaining a STEM A-level disappears, while that of obtaining a STEM degree only reduces slightly.

In line with prior work linking STEM career aspirations to working in STEM (Schoon, Ross, and Martin 2007), both kinds of career aspirations I consider – health and technology – have positive and statistically significant effects on graduates' likelihood of being found in STEM work. However, the career aspiration effect sizes are reduced substantially in the full model (8), suggesting that aspirations themselves are mediated by some of the other school, university, and parental help mediators this chapter considers. Somewhat surprisingly, I do not find a mediating effect on the *parent STEM work* coefficient when including career aspiration mediators in model 5. This is unexpected given the body of work that links having a 'STEM parent' to having STEM career aspirations (Dabney, Chakraverty, and Tai 2013; Holmes et al. 2017; Schleicher 2007). It seems that in my sample, while having aspired to work in STEM plays an important role in shaping STEM work, this does not differ by parental field of occupation, and can therefore not explain the 'STEM parent' effect I observe.

Similarly, the parental help with job searches mediators I consider do not reduce the 'STEM parent' effect, and the coefficients for these variables are neither statistically nor substantially significant (models 7 and 8). This lack of parental help effect is rather counterintuitive and might be driven by the specification of the measures I use, as Gugushvili, Bukodi and Goldthorpe (2017) also find a surprisingly small mediating effect of parental help with job searches on DESO when using these variables. Because this measure asked people whether they received help from their parents with job searches at any point before age 42, it may not capture parental help at the point of labour market entry well, both because people might not have a good recollection of their parents' help

– or lack thereof – roughly 20 years ago, and because answers could have been given in relation to other moments in people's careers.

The results indicate that the largest (indirect) impact 'STEM parents' can have on their children's field of occupation is through shaping their subject choice, especially at university level but also at A-Level stage. Additionally, I find that the relationship between having a 'STEM parent' and working in STEM is mediated somewhat when including the obtainment of a postgraduate degree and degree class in the models. Together, these results highlight that (i) the positive and statistically significant effect of having a 'STEM parent' on working in STEM persists across models, pointing towards the presence of DESO when it comes to occupational STEM inheritance, and that (ii) higher education is the most important area in which 'STEM parents' can influence their offspring's STEM labour market outcomes.

It should be noted that all changes in the magnitude of the 'STEM parent' effect I observe are small, including in auxiliary analyses using the Core definition of STEM (table C9 in appendix C). The relative stability in the 'STEM parent' effect as mediator variables are added suggests that some mechanisms not considered here lead to the occupational inheritance of STEM work I observe. There are several mechanisms through which parents may influence their children's career field that I was unable to include in my models.

At the school level, more information on school performance in STEM subjects in particular (especially at older ages) might shed further light on how the 'STEM parent' effect is mediated, because numerous studies have found that having a parent in STEM improves school performance in mathematics and science (Bowden et al. 2018; Anaya, Stafford, and Zamarro 2017; OECD 2007; Plasman et al. 2021) and in Wang, Degol and Ye (2015)'s study the 'STEM parent' effect disappears once 12th grade – which is

equivalent to A-level – mathematics achievement is controlled for. BCS70 does not contain information on how students performed in specific A-level fields.

I was also unable to capture people's interaction with STEM subjects outside of school and university, through extracurricular activities for example, which could be shaped by having a parent in STEM. In general, parents are likely to shape their offspring's interest in- and general knowledge of STEM (work) and the children of parents in STEM fields may also be expected to enter STEM work to continue the 'family tradition'. 'STEM parents' might also pass on relatively unobservable ways of relating to the world, such as the (in)ability to conjure up visual imagery, which has been linked to participation in STEM work (Zeman et al. 2020). All of these explanations are difficult to capture through quantitative measures. I attempted to do so using the career aspiration variables, but as previously noted, they only covered a fraction of possible STEM career aspirations. Moreover, even those who chose not to pursue a STEM path at school and university could be drawn to STEM in general due to their upbringing and the STEM information capital they possess may give them an advantage when trying to enter STEM work.

Some of the lack of mediation I observe might also be a result of the quality of the variables I include, as I discussed in relation to the parental help variables above. For example, given that model 6 reveals a small positive effect for those who attended a Post-92 rather than a Russell Group university, the lack of mediation could be caused by the crudeness of the measure, which may not sufficiently capture institutional prestigiousness within STEM fields.

6.5. Conclusion

Based on the findings of Chapter 5, which revealed that factors other than degree field of study and gender play an important role in determining the allocation of graduates into STEM and non-STEM work, this chapter turned to the role of social origin, and specifically occupational inheritance. Social mobility researchers have highlighted the importance of parental occupation in the intergenerational transfer of work (for example, Jonsson et al. 2009, 2011), but most research investigating the role of parental background has continued to focus on 'big class' schemes. In the context of STEM, past literature has only recently started to consider the role of 'STEM parents' in shaping field of occupation (Plasman et al. 2021), which means that a consensus has not been reached regarding occupational inheritance in STEM. Furthermore, this relationship has not been examined using UK data prior to this thesis, despite past research highlighting country differences in the way 'STEM parents' shape career aspirations (Sikora and Pokropek 2012).

In this context, this chapter set out to answer three questions regarding occupational inheritance among STEM workers. Firstly, I asked whether the children of parents who work in STEM are more likely to enter STEM themselves at the point of labour market entry. I find a persistent and positive 'STEM parent' effect. When using what I call the 'Broad' definition of STEM, I find substantial occupational inheritance; almost half of all children of parents who work in STEM enter STEM jobs themselves. Furthermore, the children of 'STEM parents' are considerably more likely to enter STEM work than children of 'non-STEM parents', suggesting that parental occupation plays an important role in determining people's field of occupation. These findings persist in auxiliary analyses using what I call the 'Core' definition of STEM, which focuses on 'hard' STEM fields, suggesting that (in contrast to the gender differences in horizontal

education-job matches I observed in Chapter 5), occupational inheritance takes place across all STEM fields.

Secondly, I investigated whether the 'STEM parent' effect differs for STEM and non-STEM graduates. I find a small positive, albeit non-significant, relationship, providing evidence that having a parent in STEM may in fact play a more important role for STEM graduates, 'boosting' their chances of entering into STEM work. This finding persists when using Core STEM, with the interaction term remaining non-significant. In both cases, the possible 'boosting' effect of having a 'STEM parent' on STEM graduates' chances of working in STEM is relatively small, suggesting that *if* degree field of study moderates the effect of 'STEM parents' on working in STEM, it only does so marginally. In other words, there seems to only be a weak relationship, if any, between parental occupation and horizontal education-job matches in the context of STEM.

Thirdly, I begin to 'unpack' some of the 'STEM parent' effect I find by investigating mediator variables regarding secondary school, teenage career aspirations, university, and parental help with job seeking. I find that the positive effect of having a parent in STEM persists when controlling for these factors, but that (higher) education does, indeed, seem to be the greatest equaliser; university level factors are most important when it comes to mediating the 'STEM parent' effect in my analyses, with obtaining a STEM degree being particularly important. Field of study choice at A-Level is another mediator of the 'STEM parent' effect, highlighting that help with/influence on field of study choice is a particularly important way in which parents shape their children's field of occupation through field of study choice. I furthermore find a small mediating effect of postgraduate study and degree class. This suggests that in the case of occupational inheritance among STEM graduates, DESO decreases with increased education levels. It should be noted, however, that postgraduate degrees are not homogenous in how they

mediate DESO (Torche 2018), so this finding might not apply to all kinds of postgraduate study. Unfortunately, I am unable to further investigate this finding due to the nature of my data.

Together, these findings highlight the importance of occupational inheritance (and by extension DESO more generally) in the intergenerational reproduction of inequality of opportunity in Britain. Having a parent who works in STEM seems to help graduates overcome possible barriers to entry to STEM work. Based on previous research, this pattern is likely not unique to STEM, and may be a reflection of the importance of parents in the wider UK labour market (although there might be field-dependent differences in the extent of this). The importance of 'STEM parents' stands out as significant, however, because of the numerous policy interventions and initiatives that have encouraged students into science and technology education and work since the 1940s. Despite these interventions, STEM work is most accessible to those with parental guidance in the field.

Furthermore, my findings indicate that the microclass approach to studying intergenerational reproduction, as proposed by Jonsson et al. (2009), is useful in the context of STEM work. While all other measures of social origin – namely parental big' class', parental education, and parental income – which I include as control variables in my analyses do not seem to influence labour market entry into STEM work, parental occupation certainly does. It may be the case that a microclass approach is particularly valuable in the context of relatively homogenous groups, such as graduates, among which other measures of social origin are less diverse.

The conclusions of this chapter come with a few caveats; firstly, the fact that a substantial 'STEM parent' effect remains after including all mediators suggests that it is likely that mechanisms which I was unable to include in my analyses lead to the occupational inheritance of STEM work I observe. Secondly, as is the case throughout

the thesis, I do not explicitly study causal mechanisms, and further research is necessary to establish whether the patterns I observe are indeed causal. Lastly, my findings concern the point of labour market only, as the aim of this chapter was to establish the presence of occupational inheritance in STEM. As Chapter 5 revealed, patterns observed at labour market entry are not necessarily applicable to the work life course, especially given that most of the respondents of this study entered the labour market in the immediate wake of the 1990s recession. Therefore, further analysis is required to better understand the phenomenon of occupational inheritance in STEM fields. In the following chapter, I intend to shed more light on how occupational inheritance develops over the work life course.

7. ANALYTICAL CHAPTER 3

Occupational inheritance in STEM over the work life course: The diminishing role of parental occupation

7.1. Introduction

Research investigating the direct effect of social origin (DESO) has recently started to investigate the way in which DESO develops over the life course. Doing so, several studies have shown that family background, in terms of parental social class, occupational status and income, shapes graduates' labour market outcomes beyond the point of labour market entry (for example, Manzoni, Härkönen, and Mayer 2014; Witteveen and Attewell 2017; Cantalini and Ballarino 2023). Whether DESO persists across the work life course or dissipates after a few years in the labour market continues to be debated, however. Some have found stability and even an increase in DESO over people's careers (Manzoni, Härkönen, and Mayer 2014; Passaretta et al. 2018; Ballarino, Cantalini, and Panichella 2021; Cantalini and Ballarino 2023), pointing towards 'permanence in occupational inequality' (Manzoni, Härkönen, and Mayer 2014, 1285). Others have found that DESO disappears within the first decade in the labour market (Byrne, Chandola, and Shlomo 2018; Jacob and Klein 2019; Kratz, Pettinger, and Grätz 2022), which led Kratz, Pettinger and Grätz (2022, 877) to conclude that 'time spent in the labour market is essential for higher education to function as the 'great equalizer [sic]'.' It is therefore unclear to what extent parents shape their children's labour market outcomes over the work life course.

While no prior study in the UK context has found a persisting or increasing DESO over the life course, a couple of studies have observed that the influence of parents disappears after 4 years when studying the link between parental social class and occupational prestige (Jacob and Klein 2019) and after 10 years when investigating how

occupational earnings are constrained by parents' social mobility during childhood (Byrne, Chandola, and Shlomo 2018). However, more research is necessary to draw conclusions regarding the development of DESO over the work life course, both in the UK context and in general.

Furthermore, while a variety of metrics of social origin and social mobility have been examined over the work life course, this is not the case for occupational inheritance. To the best of my knowledge, only one previous study has explicitly investigated occupational inheritance over the career. Gublier, Biemann and Herzog (2017) did so looking at teachers, but did not distinguish by subject. As far as I am aware, the STEM career patterns of children of 'STEM parents' have not been studied previously. As is the case with DESO more generally (see Chapter 3), there are certainly reasons to believe that occupational inheritance may not remain stable over time, which is why this chapter explores how the direct effect of having a parent who works in STEM, which I demonstrate at the point of labour market entry in Chapter 6, develops over the work life course.

Hence, having established that having a 'STEM parent' is strongly and positively associated with one's likelihood of working in STEM at the point of labour market entry, over and above education, I now turn to studying this relationship over the first decade of graduates' time in work, to determine whether 'the long arm of parental STEM work' strengthens or dissipates across the work life course. Thus, the first research question I address in this chapter is:

(i) How does the strength of association between having a 'STEM parent' and working in STEM develop over the first decade of graduates' time in the labour market?

Secondly, I am once more interested in gaining an initial insight into the mechanisms that shape the relationship between having parental (STEM) occupation and working in STEM, this time over the work life course, to again isolate the direct effect of parental occupation. In addition to the school- and university-level mediators I identified in Chapter 6, which I suspect may also shape occupational STEM inheritance over the work life course, I will take work-specific mediators. To investigate this, I ask:

(ii) Through what mechanisms may parental STEM occupation influence their children's (STEM) field of occupation over the first decade of graduates' time in the labour market?

Together, the answers to these questions will shed further light on the ways in which parental occupation affects field of occupation in the context of STEM. Should parental occupation indeed have a long-lasting effect on the field of occupation people work in over the work life course, this would have important implications regarding the meritocracy of the STEM labour market. This, in turn, would call current assumptions regarding determinants of STEM work into question. My results will also contribute to the as yet understudied wider body of literature regarding how DESO, and occupational inheritance more specifically, develop over the work life course.

7.2. Past Research and Theoretical Framework

7.2.1. How and why might having a parent in STEM work affect graduates' STEM careers over the work life course

Writing about DESO in the context of occupational status, Cantalini and Ballarino (2023) outline a series of possible mechanisms that might lead to a decrease, increase or stability in DESO over the work life course. Many of these mechanisms may well apply in the context of occupational inheritance in STEM. Regarding a possible reduction in DESO

over time, Cantalini and Ballarino (2023) speculate that the allocation of first jobs could be less meritocratic than subsequent hiring and promotion decisions due to a lack of work-specific information available to employers. While the hiring of labour market entrants is often decided based on educational achievements for example, subsequent decisions are likely to be, at least in part, based on job performance and experience. Science, and STEM fields more generally, has long been portrayed as a universalist field (Merton 1973; J. S. Long and Fox 1995), meaning that the allocation of rewards and resources is assumed to be based solely on the merits of an individual's work, a view that is grounded in the image of science (and other STEM fields) as being more objective than the humanities for example. It is therefore entirely possible that the initial 'STEM parent' effect which I observe in Chapter 6 decreases, and possibly even dissipates over the work life course.

A reduction in the association between parental STEM occupation and own STEM occupation could also be driven by more individual-level mechanisms. Studying occupational inheritance among Swiss teachers, Gubler, Biemann and Herzog (2017) found that the children of mothers who were teachers themselves were substantially more likely to leave the profession as their careers progressed, concluding that the link between parents' occupation and their children's occupation weakens over time. They explain this finding by stating that individuals become more agentic over the course of their career, meaning their experienced (rather than expected) fit between their values and reality becomes increasingly more important. They further suggest that those whose parents worked as teachers may have entered the profession due to a lack of self-direction, a sense of duty to follow family-traditions or because of positive feelings towards their parents, all of which might become less important as people's careers progress, and work values and interest in one's own work becomes more significant.

It is certainly feasible that such patterns could also be present in the intergenerational transmission of STEM careers. Indeed, investigating STEM major persistence at university, Seymour and Hewitt (1994, 1997 in Sheppard et al. 2010, 8) find that those who had followed a 'family career tradition' into science and engineering were more likely to drop out of related majors. This might also apply to career patterns over the work life course, with people's own networks, knowledge and achievements becoming increasingly more important determinants of career decisions as they progress in the labour market, making parental occupation less impactful. Furthermore, the possible benefits of having a parent in STEM such as mentoring, parents' networks and knowledge of the field may become outdated as parents age and retire. Hence, although the benefits of these parental connections and expertise might help at the point of labour market entry, they could decrease or even disappear over time. This might mean that children of parents who work in STEM are either more likely to drop out of STEM than people whose parents worked outside of the field, or at least that there is no difference in the likelihood of staying in STEM careers between children of STEM and non-STEM parents.

However, there are also reasons to believe that the children of parents in STEM are *more* likely to persist in their careers should they enter STEM. Cantalini and Ballarino (2023, 2) suggest that it could be the case that 'early success begets later success' – a Matthew effect (Merton 1968, 1973) – and that because it is hard to actually observe work-specific skills and performance, previous successes (and failures) in the labour market may be used as signals for career advancement decisions. Therefore, because children of 'STEM parents' are more likely to start out in STEM, they could also be more likely to remain (and succeed) in STEM should they wish to do so. This may in part explain why, in the context of research scientists, children of 'STEM parents' are more

likely to be recognised as elite scientists by being elected to the Royal Society far into the work life course (Bukodi, Goldthorpe, and Steinberg 2022).

The knowledge and support 'STEM parents' can provide might mitigate two of the main reasons for leaving STEM work which Preston (2004) identified: a lack of mentoring, and discontent with science (/STEM) itself. A variety of past work has identified the importance of mentoring when it comes to STEM retention (Hunt 2016; Fouad et al. 2017; Frehill 2009; Preston 2004), with those who do not have access to mentors in their workplace being more likely to leave the field. Although previous literature has mainly focused on supervisors and colleagues when it comes to mentoring, parents could play an important role in guiding their children through their career, so may mitigate the negative effects not having a mentor can have. Furthermore, the connections of parents who work in STEM may make it easier for their children to have access to mentors. Therefore, the children of 'STEM parents' might be more likely to receive mentoring support, which could prevent them from leaving the field at the same rate as children of 'non-STEM parents'.

A discontent with (aspects of the work encountered in) science has also been referenced by a variety of past studies looking at attrition from STEM work (for example, Frehill 2012; Preston 2004). Often these studies argue that people drop out of STEM because they realise the reality of STEM work is not what they expected based on their school and university experience. Those whose parents work in STEM might be less likely to be surprised by the realities of STEM work, as their parent(s) are likely to have discussed their work at home and taken them to their workplace when they were children; as Zuckerman (1996, 108) puts it, they may have been socialised in the 'ways of science'. Hence, because the children of parents who work in STEM are more likely to know what

STEM work entails before entering it, they could ultimately be less likely to leave STEM due to realising that they are more interested in a non-STEM career.

In sum, it is unclear to what extent and in what direction occupational inheritance in STEM is likely to develop over the work life course. A previous study on occupational inheritance over the work life course has found that the role of parents decreases over time (Gubler, Biemann, and Herzog 2017), and there are certainly reasons to believe that this could also be the case in STEM work. Such a reduction could be driven by work-specific skills being increasingly apparent and valued in the labour market as people's careers progress, thereby making outside signals gained through 'STEM parents' less important. It could also be caused by the disproportionate attrition of children of 'STEM parents' from STEM work. However, some previous research looking into how DESO more generally has found that it remains relatively stable or even increases over the work life course due to path dependency following the initial allocation into occupations, and as a result of continued support in the labour market from 'STEM parents'.

7.2.2. Through what mechanisms may 'STEM parents' determine their children's likelihood of working in STEM over the work life course?

In Chapter 6, I discussed how a variety of school, university and job search level factors may shape the relationship between having a 'STEM parent' and going into STEM at the point of labour market entry. Based on my analyses, I concluded that aspects of people's school and university experiences mediate the initial 'STEM parent' effect, with field of study, especially at university, being particularly important. In addition to shaping entry into STEM, these mediators might also affect the association between parental occupation and own occupation over the work life course. Based on previous literature, I also anticipate work-level mediators playing an important role in occupational inheritance in STEM.

Schooling

Chapter 6 revealed that A-Level STEM subject choice somewhat mediated the 'STEM parent' effect on the likelihood of graduates entering STEM work at the point of labour market entry. As previously mentioned, past literature has indeed demonstrated that those who grew up with at least one parent in STEM are more likely to choose STEM subjects in school (Plasman, Gottfried, and Williams 2021), which can influence subsequent educational and occupational choices. This mediation may affect graduates across the work life course; those who have received an education in STEM subjects, especially at university but also at the school-level, could have an easier time in the STEM labour market than those who have not. For example, those who have obtained a STEM A-Level, but have not subsequently studied STEM at university, might be more likely than non-STEM graduates without a STEM A-Level to find work in STEM due to being able to demonstrate knowledge in the field. People who have obtained a STEM A-Level may also be more interested in the field than those who have not, which could shape their labour market outcomes.

Furthermore, although I did not find a mediating effect of childhood mathematics performance or A-Level performance in Chapter 5, it is feasible for such performance to affect graduates' field of occupation as their career progresses. As previously mentioned, those who grew up with at least one parent in STEM are likely to have higher school grades in STEM subjects (for example, Bowden et al. 2018; Anaya, Stafford, and Zamarro 2017), and comparative skills advantages (performing better at mathematics rather than language at an early age) are transmitted across generations (Hanushek et al. 2023). Good school performance, especially in mathematics, points towards a good base understanding of STEM fields, and an ability to perform well in STEM tasks more generally. Hence, those who have performed better at mathematics, and other STEM-related skills, throughout their time in education are likely to continue to outperform their colleagues in

these areas in the labour market. This could be reflected in job performance. The children of 'STEM parents' therefore may have an advantage when it comes to finding STEM work, as well as staying in, and being promoted in, the field as a result of having a good basis of STEM knowledge which might lead to good job performance.

Higher Education

At the university level, 'STEM parents' may also shape their children's STEM careers through shaping their university choices and performance. The children of 'STEM parents' are more likely to graduate with a STEM degree (for example, Cheng, Kopotic, and Zamarro 2019), which is likely to shape career decisions and options available to graduates beyond the point of labour market entry; as demonstrated in Chapter 5, having a degree in STEM is an important predictor of STEM work across the work life course. I have also previously hypothesised that such children might obtain higher university grades in STEM subjects, because Odoh et al. (2017) show that having a parent who works in one's field of study improves university performance in said field. The underlying skills that shape graduates' performance at university are likely to also shape their performance in the STEM labour market. Degree performance and field of study choice are therefore likely to mediate graduates' STEM work over the work life course in a similar way to school performance and school subject choice, by influencing the job choices and performance-related benefits of the children of 'STEM parents'. I anticipate university-level factors again being more important mediators than school-level factors due to the more advanced and thorough nature of degrees.

Furthermore, 'STEM parents' can use their experience to guide their children when deciding what type of university to attend and whether to pursue postgraduate education, including further education obtained following labour market entry. These choices can have long-lasting effects, as they determine the range of future career options

available to graduates. Indeed, both of these factors have been shown to account for social class differences in career trajectories among UK graduates who entered higher managerial and professional occupations early on in their career (Duta, Wielgoszewska, and Iannelli 2021). Although it is likely for educational credentials to become less important over the work life course, they can nonetheless serve as signals to potential employers throughout a graduate's career.

Work Life

Past studies investigating the way in which DESO more generally develops over the life course have often discussed work-level mechanisms as an explanation for why DESO may de- or increase over time (for example, Cantalini and Ballarino 2023). It might be the case that the children of 'STEM parents' have a higher likelihood of being rewarded in the STEM labour market because of help from their parents. The field-specific knowledge and networks of 'STEM parents' may lead to better job performance on part of their children which can translate into more job and promotion opportunities. For example, in the case of British research scientists, parental STEM occupation influences success at the highest level, with children of 'STEM parents' being more likely to be Fellows of the Royal Society (Bukodi, Goldthorpe, and Steinberg 2022) and within that group being more likely to be international prize winners (Bukodi, Goldthorpe, and Steinberg 2024). Hence, children of parents who work in STEM might (i) be more likely to stay in STEM work over the work life course due to having a more fruitful career, (ii) be more likely to obtain STEM skills even in non-STEM work and therefore have an easier time moving into STEM over the work life course, or (iii) be more likely to be 'promoted out of STEM', because their job roles shift towards managerial and administrative work that is often not included in definitions of STEM as used by many academics and policymakers (Glass et al. 2013; E. Smith and White 2018a). This support

on part of 'STEM parents' may well lead to greater job stability among their children, with fewer episodes of job change over the work life course.

✶

There are theoretical arguments both for a decrease and an increase in the 'STEM parent' effect which I observed at labour market entry in Chapter 6. While Gubler, Biemann and Herzog's (2017) find a reduction in the extent of occupational inheritance over the work life course, research investigating DESO in the context of occupational status has often found stability and even slight increases in the influence of social origin over the work life course (Manzoni, Härkönen, and Mayer 2014; Passaretta et al. 2018; Ballarino, Cantalini, and Panichella 2021; Cantalini and Ballarino 2023). Both de- and increases in occupational inheritance are likely to be driven by 'STEM parents' influencing individuals' choices and experiences both in the education system and in the labour market. Hence, I anticipate that school, university and work level factors will mediate the 'STEM parent' effect over the work life course.

7.3. Data and Methods

7.3.1. Data

As is the case throughout the thesis, this chapter will draw on the sample of graduates from the British Cohort Study of 1970 (BCS70), and again focus on the Broad definition of STEM, as I did in Chapter 6. As I argued in the previous chapter, the potential occupational inheritance mechanisms which I identify are likely to apply across a wide range of STEM fields and are not unique to the Core STEM fields. Considering the

relatively small proportion of respondents with 'STEM parents' in the sample, it therefore makes sense to focus on all STEM fields.

Unlike Chapter 5, which traced respondents' work life course for 25 years, this chapter only focuses on the first decade of graduates' careers. I chose to restrict my analyses here to 10 years, as past research focusing on the UK has highlighted this to be the most important time frame when it comes to possible developments of DESO (Jacob and Klein 2019; Byrne, Chandola, and Shlomo 2018). The first decade of people's careers is likely to be the most important in this regard because it is the prime time during which people explore their own interests (possibly breaking away from those of their parents) and establish themselves in the labour market. For example, in 2004, when, at age 34, the majority of BCS70 respondents had spent around 10 years in the labour market, people aged 30-39 were at the peak of the age-wage curve, receiving the highest median weekly pay in the UK out of all age groups (ONS 2004).[41] The analytical sample size for this chapter is 1,434 respondents in 14,057 person-year observations.[42]

7.3.2. Variables

The dependent variable of this chapter will once more be *field of occupation (STEM versus non-STEM),* where 0 = non-STEM work, and 1 = STEM work. As was the case in the previous chapter, the key independent variable will be *parental occupation (STEM versus non-STEM),* which captures whether respondents had at least one parent in STEM at age 10 and is coded in the same way the dependent variable is. Time is again measured in yearly increments, starting from the point of labour market entry (T0).

[41] Furthermore, due to the nature of the data available to me, taking a longer time frame into account would make the estimates less reliable.
[42] The number of respondents is lower than in Chapter 6 due to the inclusion of *number of children* and *partnership status* as control variables, which I was not able to impute using multiple imputation.

As was the case in previous chapters, I control for respondents' characteristics, taking into account *sex*, *age at labour market entry*, *ethnicity* and *migration status,* and their social origin, including *parental social class* (age 10*)*, *parental education* (age 10) and *parental income* (age 16). Additionally, I control for *full-time work,* and, because Chapter 5 revealed the importance of family responsibilities, and because being in partnership may reduce the influence of parents on occupational outcomes, *number of children* and *partnership status*.

The mediators I consider are as follows: to capture the school-level, I include *childhood mathematics competence* (age 10)*, number of good A-levels* and a dummy capturing whether the respondent has at least one STEM A-Level to take the role parents play in shaping their children's school outcomes into account. Chapter 6 revealed that only the latter of these variables mediated the effect of having a 'STEM parent' at the point of labour market entry, but I nonetheless include all three here because general (mathematics) ability might affect STEM work over the work life course.

To take into account possible university-level mediation, I include *degree field of study, undergraduate degree class, type of undergraduate university* and a dummy capturing whether respondents have obtained a postgraduate degree. Both *degree field of study* and *has postgraduate degree* are time-variant variables, allowing me to account for the possible effect 'STEM parents' could have on later uptake of STEM or postgraduate education. Type of university did not mediate the 'STEM parent' effect in Chapter 6, but may do so over the work life course, as respondents' careers progress.

Lastly, to take into account work-level mediators, I include *was promoted to manager,* as I anticipate that those with 'STEM parents' might benefit from their parents guiding them through the labour market, and *total number of labour market activities* because having a 'STEM parent' might influence STEM work by affecting the stability

of a graduate's career. I do not include a measure of pay rises due to this information only being available on a sweep basis, reducing the sample size substantially. Chapter 5 revealed that being promoted and having had a pay increase work in a similar fashion in mediating the gendered relationship between obtaining a STEM degree and working in STEM, so I anticipate that *was promoted to manager* can sufficiently capture labour market progression.

Furthermore, in this chapter I do not include the measures of parental help which I assessed in Chapter 6 because of the quality concerns I discussed regarding this measure, and their likely impact on the lack of substantial and statistical significance of these variables. This does not mean that I do not suspect that parental advice, recommendation, networks, and direct employment might mediate respondents' likelihood of being in STEM work over the work life course. However, I suspect that much of this help can be captured by the work-level mediators.

7.3.3. Methodology

This chapter analyses the association between having a 'STEM parent' and working in STEM over the first decade of graduates' career. To address my research questions, I use logistic panel regression with random effects. The precise models I specify are outlined below. To address my second research question regarding possible explanations for the change in association between having a 'STEM parent' and working in STEM across the work life course, I once more adapt Gugushvili, Bukodi and Goldthorpe's (2017) approach to 'unpacking' a direct effect through a series of nested regression models, adding possible school, university and work related mediators in a cumulative fashion. As aforementioned, this will allow me to gain insights into possible mechanisms through which parental STEM occupation may influence their children's likelihood of working in

STEM, while not formally testing causal mechanisms. All results presented in this chapter are run using imputed data.

7.4. Empirical Findings

7.4.1. How does having a parent in STEM work affect graduates' STEM careers over the work life course?

To establish the relationship between having a 'STEM parent' and working in STEM over the first decade of graduates' time in the labour market, model 1 regresses *STEM work* on *STEM parent, time elapsed since labour market entry,* the quadratic term of *time elapsed since labour market entry* and the aforementioned control variables. In Chapter 6, I established that, at the point of labour market entry, the children of 'STEM parents' have a considerable advantage over the children of 'non-STEM parents' when it comes to being found in STEM work. The log-odds displayed in table 14 give an initial indication that this effect remains over the first decade of graduates' careers. To determine how the effect of having a 'STEM parent' varies across the work life course, model 2 builds on model 1 by additionally including an interaction between 'STEM parent' and the time variables. The log-odd results are in line with Chapter 6 and indicate that having a parent who works in STEM makes graduates more likely to enter STEM work at the point of labour market entry. However, as the coefficients of the interaction terms reveal, this 'STEM parent' effect decreases over the work life course, a decline which is sharpest in the early years following labour market entry.

Indeed, figures 19 and 20 reveal that the early advantage that children of 'STEM parents' have when it comes to entering STEM work decreases steadily as graduates' time in the labour market progresses. While the difference in likelihood of entering STEM between children of 'STEM' and 'non-STEM parents' which this model predicts is 16

percentage points (CI: 0.11 – 0.20) at the point of labour market entry, this difference drops down to around 4 percentage points (CI: -0.02 – 0.10) and becomes statistically non-significant after 8 years in the labour market (figure 20). Therefore, I find that although having a 'STEM parent' can have an initial substantial positive effect on a graduate's likelihood of being found in STEM work, this effect dissipates within the first decade of graduates' time in the labour market.

Table 14: The effects of having a 'STEM parent' on the likelihood of being found in Broad STEM work in the first decade of graduates' time in the labour market (log-odds)

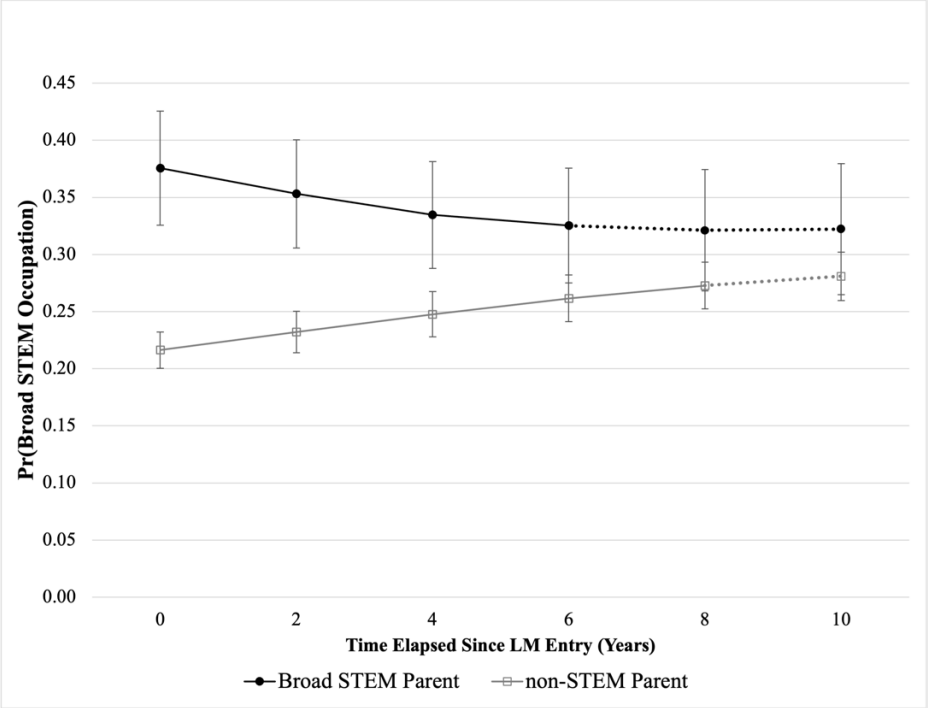
Dependent Variable: Broad STEM Work	**Model 1**	**Model 2**
STEM Parent	2.79***	4.36***
	(0.63)	(0.89)
Time Elapsed since LM Entry	0.19***	0.31***
	(0.05)	(0.06)
Time Elapsed since LM Entry^2	-0.01	-0.01**
	(0.01)	(0.01)
STEM Parent*Time Elapsed since LM Entry		-0.61***
		(0.15)
STEM Parent*Time Elapsed since LM Entry^2		0.03**
		(0.01)
Intercept	-16.11***	-15.38***
	(2.36)	(2.53)
Number of Observations	14,057	14,057
Number of Groups	1,434	1,434

Note: The models control for respondents' sex, number of children (t_{-1}), partnership status (t_{-1}), migration status, ethnicity, age at labour market entry, parental class, parental education, parental income, and full-time work. To see the full output, see table D1 in appendix D, standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

This narrowing of the gap in likelihood of working in STEM between children of 'STEM' and 'non-STEM parents' is driven both by (i) a *decreasing* likelihood of children of 'STEM parents' being found in STEM work as time progresses, and (ii) an *increasing* likelihood of children of 'non-STEM parents' being found in such occupations. The first of these patterns, concerning children of STEM parents, is in line with Gubler, Biemann and Herzog's (2017) conclusion that the link between parents' occupation and their children's occupation weakens over time. As shown in figure 14, the likelihood of

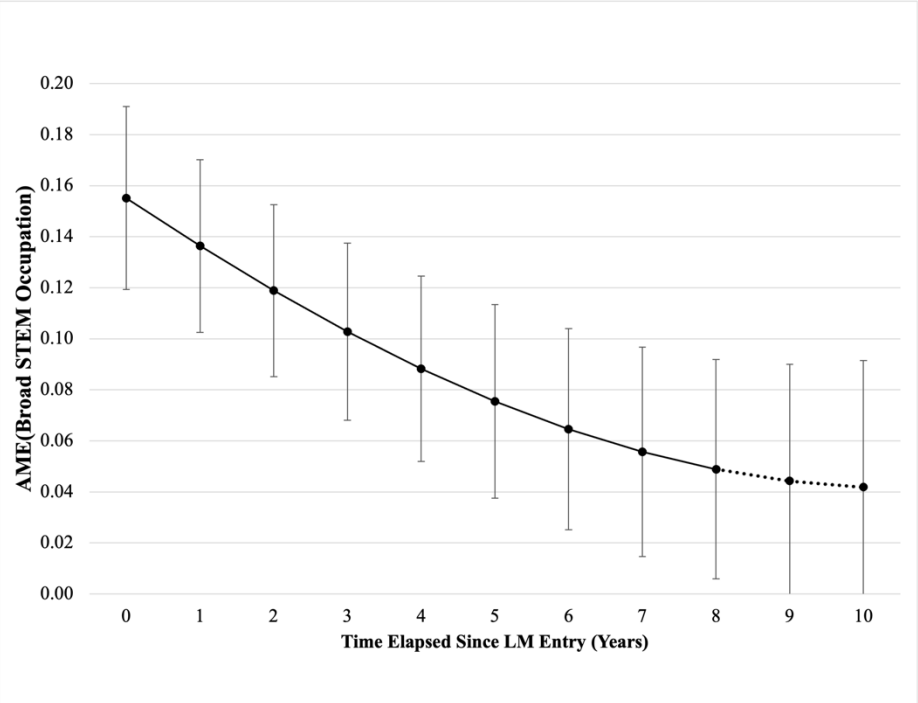
working in STEM among children of 'STEM parents' drops down from an initial peak of around 38% (CI: 0.33 – 0.44) to around 32% (CI: 0.28 – 0.38) after 6 years, after which the decline becomes non-significant. Further testing estimates this drop to amount to a total of 5 percentage points (CI: 0.02 – 0.08) over the decade I study, which is –

Figure 19: The predicted probability of working in a Broad STEM occupation by parental occupation and time elapsed since labour market entry (based on model 2 in table 14)



Note: Despite the overlapping confidence intervals, all group differences up to (and including) T7 are statistically significant, in line with the AMEs illustrated in figure 20 below. When comparing different time-points in figure 19, most changes are statistically significant as indicated by the solid lines (non-significant changes are indicated using dotted lines).

Figure 20: The average marginal effect of having a 'STEM parent' on working in a Broad STEM occupation across the first decade in the labour market (based on model 2 in table 14)



Note: When comparing different time-points in figure 20, most drops are statistically significant as indicated by the solid lines (non-significant changes are indicated using dotted lines).

- equivalent to a decline of just under 15%. In substantive terms, this drop in children of 'STEM parents' working in STEM is therefore relatively small, but it is nonetheless notable in conjunction with the increase in STEM work among children of non-STEM parents.

The drop in the likelihood of working in STEM among children of 'STEM parents' may be driven by a change of career interests and priorities, and by promotion into managerial level work, the latter of which I explore further when addressing my second research question regarding mechanisms. Looking at the destinations of children of 'STEM parents' descriptively reveals that there is a substantial increase in the share of graduates working in LEMB fields[43] over the first decade in the labour market, which is particularly pronounced in the first 5 years (figure D1 in appendix D). It is therefore likely that the decline in children of 'STEM parents' working in STEM, which I observe until T6, is driven by people moving into LEMB fields. These fields have been argued to have

[43] The LEMB category is adapted from Walker and Zhu's (2011) 'LEM' category and includes other subjects associated with Business and Management such as Administration and Finance.

more leadership and pay opportunities than STEM (Bosworth, Lyonette, and Wilson 2013), and might thus be more appealing to graduates, especially those who chose a career in STEM due to family expectations rather than genuine interest in the field.

The second pattern, that of increasing likelihood of working in STEM among children of 'non-STEM parents' is somewhat more unexpected. The likelihood of working in STEM as a child of 'non-STEM parents' increases by a total of 6 percentage points (CI: 0.05 – 0.07) over the first decade of graduates' careers, starting at around 22% (CI: 0.20 – 0.23) and increasing to around 28% (CI: 0.26 – 0.30). The likelihood of being in STEM work as a child of 'non-STEM parents' therefore increases by around 25% over the first decade of graduates' time in the labour market. This pattern might be driven by barriers to entry which children of 'non-STEM parents' face in the STEM labour market. The results of Chapter 6 point towards it being easier for children of 'STEM parents' to enter STEM at the point of labour market entry, which may mean that graduates with less STEM support initially enter non-STEM work and move into STEM work once they have accrued more labour market experience and credentials.

Indeed, descriptive statistics reveal that at the point of labour market entry, about a third of graduates with 'non-STEM parents' (but only around 17% of children with 'STEM parents') start out in vocational occupations (figure D1 in appendix D). The share of people in these vocations drops for both groups, but at a substantially higher rate for those with 'non-STEM parents'. Therefore, having grown up with at least one parent who works in STEM seems to protect graduates from starting out in low-skilled work. Those who did not grow up with such parents on the other hand might either be prevented from entering STEM due to facing more barriers to entry than children of 'STEM parents' or may not desire to enter STEM work at the point of labour market entry and subsequently gravitate towards it.

To investigate whether the patterns I observe are driven by a particular STEM sub-field, I re-ran model 2 (table 14) multiple times, dropping one STEM sub-field at a time. This revealed that the decrease in the likelihood of children of 'STEM parents' working in STEM and the increase among children of 'non-STEM parents' were not observed because of one particular STEM field driving the results. Table 15, which presents the changes in predicted probability of working in STEM between the point of labour market entry (T0) and the tenth year in the labour market (T10), demonstrates that both these patterns remain statistically significant and are therefore robust regardless of which STEM sub-field is dropped.

There are, however, differences in how pronounced these patterns are, with the exclusion of computer science and IT leading to the largest change. When this field is excluded from the analyses, the rise in the likelihood of children of 'non-STEM parents' working in STEM over the work life course reduces substantially. While in the model including all STEM sub-fields the likelihood of working in STEM as a child of 'non-STEM parents' increases by a total of 6 percentage points (CI: 0.05 – 0.07) over the first decade of graduates' careers, in the model that drops computer science and IT I only observe an increase of 3 percentage points (CI: 0.02-0.05).[44] This suggests that a substantial proportion of the increase in children of 'non-STEM parents' in STEM work is driven by such graduates entering computer science and IT work. The fact that there was a simultaneous downward trend in the proportion of children of 'STEM parents' in computer science and IT (figure D2 in appendix D), and a raised graduate unemployment rate in the field during the period studied (E. Smith and White 2018a, 25), suggests that the trend is unlikely to be a period effect involving increasing jobs in the fields.

[44] The confidence intervals do not overlap, despite both including the rounded figure of 0.05.

The large proportion of children of 'non-STEM parents' entering computer science and IT a few years after labour market entry may be due to the nature of the field. Computer science and IT is not only the most common STEM destination of children of non-STEM parents, but also of non-STEM graduates in the Dutch context (Graaf, Hof, and Klaveren 2009), and non-graduates in the UK (E. Smith and White 2018a). Additionally, it is the STEM field in which undergraduates are least likely to take on additional training prior to entering the workforce (E. Smith and White 2018a). Together, this points towards educational credentials being less valued in computer science and IT than in other STEM sub-fields. Hence, those who intended to enter the field from the start but were prevented from doing so might be more able to enter computer science and IT work after several years of accruing less skilled, but possibly related, vocational work experience. The reduced focus on education may also make the field attractive to people who did not intend to enter it, or STEM more generally, at the point of labour market entry (possibly not having studied STEM either) but who had a change of heart after a few years in the labour market. This can explain the pronounced pattern I observe in figure 19, but it is worth remembering that I do observe an increase in children of 'non-STEM parents' in STEM work in every single STEM sub-field across the work life course.

In sum, I find that the substantial 'STEM parent' effect which I observe at the point of labour market entry in Chapter 6 remains for several years, but dissipates within the first decade of graduates' careers. The 'STEM parent' effect becomes increasingly less pronounced due to a decrease in the likelihood of children of parents in STEM working in STEM themselves, and a simultaneous increase in the likelihood of working in STEM among children of 'non-STEM parents'. Furthermore, auxiliary analyses in which I investigate whether degree field of study moderates the 'STEM parent' effect

over the work life course (section D5 in appendix D), reveal that I again do not find a statistically significant difference in how having a parent in STEM affects STEM and non-STEM graduates. Hence, the pattern of decreasing likelihood of being found in STEM work among children of 'STEM parents' and increasing likelihood among children of 'non-STEM parents' is present for both STEM and non-STEM graduates.[45] Therefore, the underlying mechanisms that drive these patterns seem to affect both STEM and non-STEM graduates, even though STEM graduates remain substantially more likely to enter STEM work than non-STEM graduates.

Table 15: Changes in the predicted probability of working in STEM among children of 'STEM' and 'non-STEM parents' over the first decade of graduates' careers (T0 to T10) by dropped STEM sub-field

Dropped Work Field(s)	**Difference between T0 and T10 (PP_{T10} - PP_{T0})**	
	STEM	***Non-STEM***
None (Base)	-0.05* (0.02)	0.06* (0.01)
Computer science and IT	-0.05* (0.02)	0.03* (0.01)
Engineering	-0.05* (0.02)	0.05* (0.01)
Physical sciences and mathematics	-0.04* (0.02)	0.07* (0.01)
Biological sciences, agriculture, forestry and other	-0.05* (0.02)	0.06* (0.01)
Medicine, dentistry and veterinary science	-0.04* (0.02)	0.06* (0.01)
Nursing and other subjects allied to medicine	-0.04* (0.02)	0.06* (0.01)
Architecture, building and planning related	-0.4* (0.02)	0.05* (0.01)

Note: Standard errors in parentheses, $*p < 0.10$, the log-odd results for the models shown here can be seen in table D5 in appendix D. Some sub-categories have been collapsed due to low category sizes.

[45] If anything, these auxiliary analyses once more revealed a possible 'boosting' effect of having a STEM degree, although this remains non-significant. This boosting effect decreases over time, disappearing completely by T10 (see figure D11).

7.4.2. Through what mechanisms does parental STEM occupation influence their children's field of occupation over the work life course?

To explain through which mechanisms having a parent in STEM influences graduates' likelihood of working in STEM, this time across the work life course, I ran a series of additional models which built on the base model (model 2 in table 14) by including the various possible mediators I identified in the theory section. Because of the *STEM parent*time elapsed since LM entry*^{2} interactions, the AME of having a 'STEM parent' on working in STEM varies over the work life course. Hence, instead of displaying results in a regression table, I rely on plotted AMEs (figure 21). A full table displaying the corresponding log-odds can be found in appendix D (table D1), but comes with the caveat that log-odds ratios cannot be compared across models with different independent variables in a sample (Mood 2010).

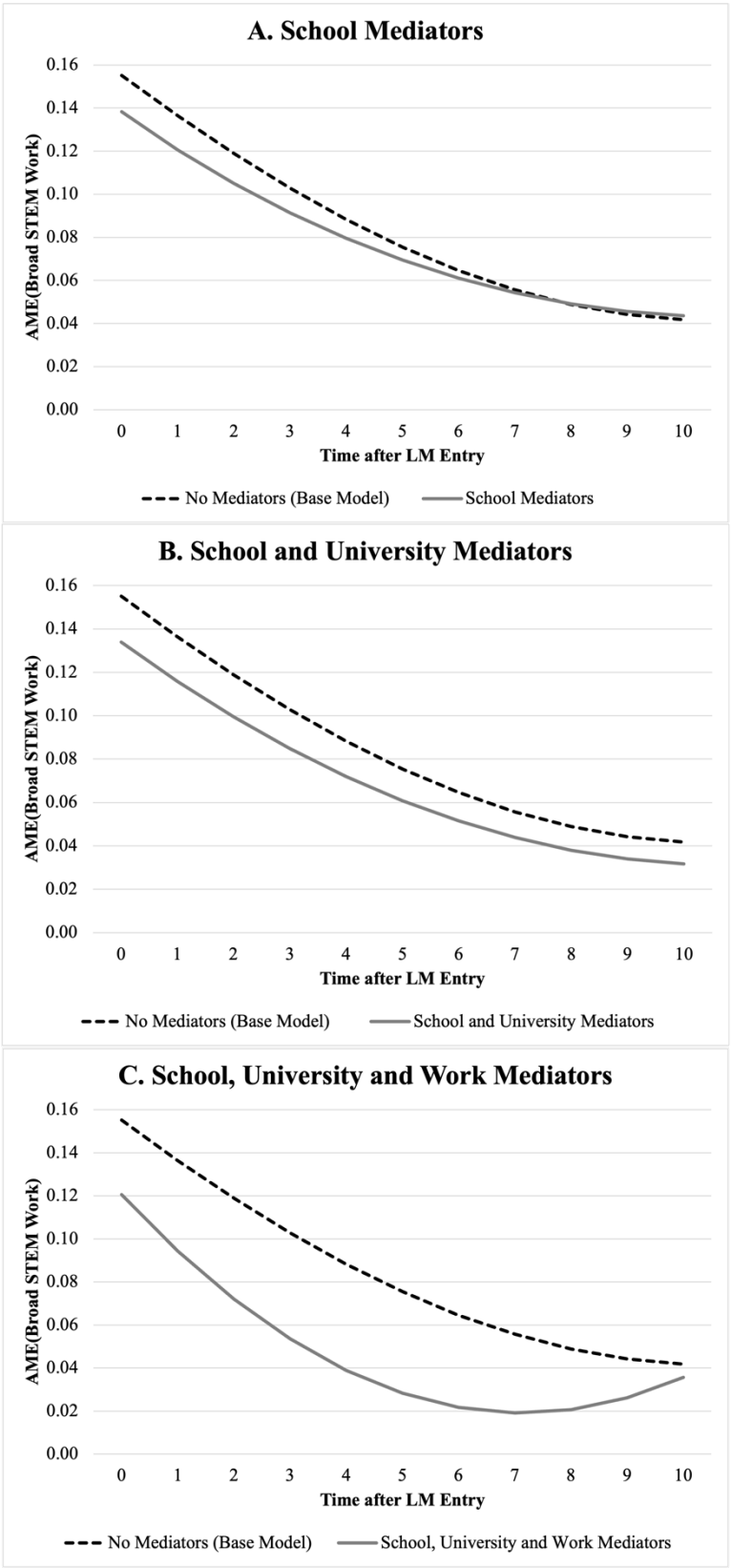
Firstly, to isolate DESO – the 'STEM parent' effect that remains after taking education into account – model 3 includes school-level mediators, and model 4 additionally includes university level mediators. Figure 21 shows the 'STEM parent' effect that the base model predicts (black dotted line), and how this is affected by the inclusion of the various mediators. The AMEs shown in panels A and B demonstrate that after controlling for education, a substantial but reduced 'STEM Parent' effect persists, one which remains statistically significant up to 6 years into the labour market (for legibility, figure 21 does not present confidence intervals, but these can be seen in figure D3 in appendix D).

Looking at the school mediators in isolation (figure 21a) reveals that while school somewhat mediates the 'STEM parent' effect, suggesting that it has some importance in explaining occupational inheritance in STEM, this is concentrated in the early years of graduates' time in the labour market and dissipates across the work life course. School mediators thus only explain part of the early advantage children of 'STEM parents' have,

which is unsurprising given the nature of these variables. In contrast, including university mediators in model 4 (figure 21b) shows that the importance of higher education in mediating the 'STEM parent' effect remains relatively stable across the entire decade. University education is therefore instrumental in shaping occupational inheritance in the context of STEM work across the first decade of graduates' time in the labour market. This mediation declines across the work life course, but only marginally.

Examining the school and university mediators separately (section D3 in appendix D) reveals that the mediation of the 'STEM parent' effect which is shown in figure 21b is almost entirely driven by the university mediators. This suggests that the mediating effect of university-level factors subsumes that of school-level factors, which is also reflected in the fact that school-level mediators become largely non-significant once the university variables are added to the analyses (table D1 in appendix D). The one exception to this is *childhood mathematics performance*, which remains statistically significant ($p < 0.10$), indicating that 'STEM skills' are important in shaping STEM work even after taking university factors into account. Out of the university mediators I consider, *has a postgraduate degree*, *degree field of study,* and *undergraduate degree class* are particularly important in mediating the 'STEM parent' effect. This is in line with the theoretical expectations that are outlined at the beginning of this chapter, as it indicates that parents indeed shape their children's work choices through influencing their field of study, performance, and highest level of education.

Figure 21: The difference between the average marginal effect of having a 'STEM parent' on working in a Broad STEM occupation by included mediators (based on models 2 to 5 in table D1)



Note: For legibility, I do not present confidence intervals here, they can be seen in figure D3 in appendix D. Figure D3 also reveals that the decreases/increases in the 'STEM parent' effect shown here are non-significant between T8 and T10.

However, work-level factors, and promotion in particular, are considerably more impactful in mediating the 'STEM parent' effect than are education factors (figure 21c). When including *was promoted to manager* and *total number of labour market activities* in the analyses, the 'STEM parent' effect decreases rapidly over the work life course, becoming non-significant after only 3 years in the labour market (figure D3 in appendix D), as well as decreasing in substantial magnitude. Lack of statistical significance aside, after 6 years in the labour market, having a 'STEM parent' only increases graduates' likelihood of working in STEM by 2 percentage points, while this effect is estimated at 6 percentage points (and is statistically significant) in the base model at T6. Therefore, the role 'STEM parents' play in shaping graduates' time in the labour market, and likelihood of being promoted in particular explain a substantial proportion of the 'raw STEM parent' effect I identified in figure 20.

This work-level mediation may be due to help 'STEM parents' can provide throughout graduates' first decade in the labour market but could also be partially a result of STEM skills that children have 'inherited' from their parents, which might make them more successful in the labour market. This is supported by the fact that *childhood mathematics performance,* which I use as a proxy for general mathematics skills, becomes non-significant once the work variables are added to the model (table D1 in appendix D). Given that I once more find that being promoted makes graduates less likely to be found in STEM work (table D1), these STEM skills may in fact help the children of 'STEM parents' move out of STEM as their career progresses, as Anf (2013) and Bosworth, Lyonette, and Wilson (2013) have suggested that the technical experience that (STEM) graduates obtain in STEM work helps them to find work and enter managerial roles in non-STEM fields.

In sum, although both school and university contribute to the 'STEM parent' effect at first, over the work life course the importance of school in explaining occupational inheritance dissipates, while that of university mediators remains relatively stable. However, work specific factors quickly overtake the importance of higher education, and explain a substantial proportion of the 'STEM parent' effect, and its decline, which I observe. I find that having a parent who works in STEM increases the likelihood of working in STEM in the first years following labour market entry even when including all mediators in the full model, highlighting the importance of parents in (directly) shaping the early destinations of graduates. Following these first few years, graduates' own education, skills and work experience overtake the importance of 'STEM parents' in shaping their likelihood of being found in STEM work.

It should be noted that the confidence intervals of the AMEs of different models shown in figure 21 overlap (see figure D3 in appendix D), as was the case when I investigated possible mediators of gender differences in Chapter 5. As before, this does not necessarily mean that the mediating effects I observe are non-significant, as further testing – which I was unable to do given the nature of my data and analyses – would be necessary to establish statistical significance. Therefore, the patterns I observe give an initial indication of possible mediators of the 'STEM parent' effect, but further research and a more formal causal analysis is necessary to establish this mediation.

7.5. Conclusion

This chapter built on the finding of substantial occupational inheritance in STEM at the point of labour market entry (Chapter 6) by examining the role parental occupation plays in shaping graduates' own occupation over the first decade of their time in the labour market. Occupational inheritance has only been examined in a longitudinal fashion by

one prior study (Gubler, Biemann, and Herzog 2017), and research on how DESO more generally develops over the work life course remains relatively scarce. Hence, this chapter does not only shed further light on determinants of STEM work, but also contributes to the wider literature on social mobility. My findings highlight that the initial level of occupational inheritance in STEM which I observe at the point of labour market entry is not reflective of the work life course, demonstrating the importance of taking a life course perspective when studying these dynamics.

Having previously established a considerable 'STEM parent' advantage when it comes to graduates' likelihood of working in STEM work at the point of labour market entry, this chapter explored how the relationship between having a parent who works in STEM and working in STEM oneself develops over the first decade of graduates' careers. Based on the findings of Chapter 6, in which I did not find a statistically (or substantially) significant moderating effect of degree field of study in this relationship, I focused on all graduates, independent of their field of study. Auxiliary analyses confirmed the absence of a statistically significant moderating role of degree field of study over the work life course, and that the patterns I find apply to both STEM and non-STEM graduates.

I find that the early advantage that children of 'STEM parents' have when it comes to entering STEM work declines steadily as graduates' time in the labour market progresses, disappearing after 8 years in the labour market. This decrease is driven both by (i) a *decreasing* likelihood of being found in STEM work over the work life course on part of children of 'STEM parents', and (ii) an *increasing* likelihood of being in STEM work among children of 'non-STEM parents'. The first of these patterns could be due to the children of 'STEM parents' becoming more agentic over the work life course, prioritising their own experiences, tastes and networks over the expectations of their parents, as Gubler, Biemann and Herzog (2017) proposed in the case of Swiss teachers.

The second pattern might be driven by barriers to entry which children of 'non-STEM parents' face in the STEM labour market, which may mean that graduates with less STEM support initially enter non-STEM work and move into STEM work once they have accrued more labour market experience and credentials. This pattern could in part be present among BCS70 graduates because of the aftermath of the 1990s recession, which took place close to the point of labour market entry for most respondents and might have resulted in additional obstacles in the labour market, which 'STEM parents' were able to help navigate.

The increase in the proportion of children of 'non-STEM' parents working in STEM over the first decade of their career is particularly pronounced in computer science and IT, as dropping this STEM sub-field from my analyses decreases this pattern substantially. This does not appear to be a period effect due to a simultaneously decreasing likelihood of children of 'STEM parents' working in computer science and IT over the work life course. Instead, these patterns are likely to be driven by an undersupply of jobs in the field (independent of the recession) which disadvantage children of 'non-STEM' parents at the point of labour market entry, and relatively little value being placed on educational credentials in the field, with many people working in computer science and IT having either studied non-STEM fields (Graaf, Hof, and Klaveren 2009) or not attended university altogether (E. Smith and White 2018a). It is likely that similar underlying mechanisms drive these patterns in other STEM fields.

Once more looking at possible mediators of the 'STEM parent' effect revealed preliminary evidence that both school-level and university-level factors may mediate the effect, although the school effect is limited to the early years of people's time in the labour market and is subsumed by the mediating effect of higher education factors. Jointly, education has a stable mediating influence on the 'STEM parent' effect across the entire

first decade of graduates' time in the labour market. Work-level mediation are more important, however, with promotions being particularly influential. This might in part be a result of the intergenerational inheritance of 'STEM skills', which allow children of 'STEM parents' to succeed both in STEM and non-STEM work. Despite this mediation, the 'STEM parent' effect persists in the initial years of graduates' time in the labour market, over and above all of the mediators considered in this chapter. This points towards the importance of the point of labour market entry, as parents play an especially vital role in the early allocation of graduates into STEM and non-STEM work.

Together, these findings highlight the importance of taking the life course perspective into account when studying occupational inheritance (and DESO more generally). The substantial role parental occupation plays in shaping their children's occupation at the point of labour market entry, which I demonstrated in Chapter 6, dissipates within the first decade of graduates' time in the labour market, and is therefore not reflective of graduates' careers on the whole. Additionally, this chapter again highlights the importance of taking social origin into account in addition to higher education and gender, as a considerable 'STEM parent' effect persists for several years of graduates' time in the labour market after controlling for gender and including education mediators. Therefore, despite the decreasing importance of parental occupation across the work life course, I demonstrate that parents have a substantial impact on their children's likelihood of working in STEM.

The finding of a dissipating occupational inheritance across the work life course shows that, although parents play an important role in determining the (early) labour market destinations of graduates, this decreases with age. As Kratz, Pettinger and Grätz (2022, 877) concluded: 'time spent in the labour market is essential for higher education to function as the 'great equalizer [sic]'.' This also is the case in the context of

occupational inheritance in STEM, suggesting that parental occupation plays a smaller role in the long-run than one may expect when looking at its effect at the point of labour market entry.

8. CONCLUSION

In this thesis, I set out to contribute to answering the question of 'who works in STEM?' Given the ever-increasing policy focus on the field among UK politicians, my aim was to shed light on a workforce that is much discussed but still under researched. STEM has long been considered as a meritocratic, universalist field (Merton 1973; J. S. Long and Fox 1995), a view which is also often reflected in the way contemporary UK politicians discuss STEM work. Political discourse surrounding the STEM workforce often assumes that any issues of underrepresentation in STEM are purely driven by the 'supply' in the form of a lack of (diverse) STEM students (for example, HC Deb 19 January 2016, HC Deb 27 October 2016, HC Deb 23 March 2017). The findings of this thesis draw this into question; not only does a STEM degree affect male and female graduates' likelihood of being in STEM differently, but social origin also plays an important role in determining STEM work, for STEM and non-STEM graduates alike. While STEM fields are often perceived as objective, their hiring practices may well not be.

This thesis was based on the experiences of the BCS70 cohort. This cohort entered the labour market in the early 1990s, and many of them continue to be active labour market participants to this day. Given some substantial changes in higher education and the labour market since the 1990s, is important to contextualise the findings of this thesis – especially those regarding the point of labour market entry – in the settings experienced by BCS70 respondents. Chapter 2 outlined these settings in detail, but broadly speaking the key changes that have taken place since the 1990s are (i) an increase in the number of people going to university, (ii) a shift away from manufacturing jobs and towards 'professional and technical services', including STEM jobs, (iii) increasing employer demand for university educated workers, and (iv) an increase in the number of women entering the labour market.

Therefore, while the findings of this thesis can shed light on the relationships studied, especially when investigating the work life course, it is important to bear in mind that my findings may not accurately reflect today's situation. For example, the graduates studied in this thesis entered the labour market at a time of a rapidly increasing supply of STEM jobs, with employers who did not yet require degree-level education in the way it is often required today. This suggests that I may be underestimating the strength of horizontal education-job matches in today's labour market. On the other hand, having obtained a STEM degree may have benefitted BCS70 labour market entrants more than it does today's labour market entrants, as it helped them stand out compared to non-degree educated applicants. The findings of this thesis should therefore be read with the historical context of the data in mind.

This does not undermine the value of these findings, however, especially given that important aspects of the BCS70 cohort's experiences were rather similar to those of today's graduates and labour market entrants. The UK government has actively encouraged students to go into STEM degrees for decades, and the share of STEM graduates (compared to non-STEM graduates) has remained relatively stable since the BCS70 respondents attended university. Similarly, women have remained underrepresented in STEM higher education, and the share of female Core STEM graduates has not changed substantially since the 1990s. The findings of this thesis therefore emerge from a similar political climate to today when it comes to STEM education, with similar higher educational outcomes.

✶

In what follows, I first summarise the findings of the three analytical chapters of this thesis, referring to the theoretical debates which I introduced in Chapter 3 and how I

contribute to them. This section is divided into the two domains I studied in regard to determinants of STEM work: the (gendered) role of higher education, and degree field of study specifically, and the role of social origin, and parental occupation in particular. Next, given that this thesis was inspired by political debates and policies surrounding STEM work, I discuss the policy implications of my findings. Finally, I discuss the limitations of my research and relatedly, areas of future research.

8.1. Summary of Findings

8.1.1. The (Gendered) Role of Higher Education

The thesis initially set out to investigate horizontal education-job (mis)matches (working in an occupation that corresponds to one's field of study) in the context of STEM. Because the prevalence of such matches has been covered by various studies in the UK context, and because much of UK policy surrounding STEM work focuses on women, I specifically focused on the role that gender plays in moderating the relationship between one's field of study and one's field of occupation. The results of Chapter 5 regarding the general pattern of matches (independent of gender) are in line with previous literature, as I also find that around half of all STEM graduates do not enter STEM work at the point of labour market entry (Bosworth, Lyonette, and Wilson 2013; Select Committee on Science and Technology 2012; E. Smith and White 2017, 2018a; DIUS 2009; E. Smith 2011a), reinforcing consensus in the literature regarding the prevalence of early horizontal education-job (mis)matches in STEM. It is clear that it is not the case that simply studying STEM at university will lead to STEM work.

Because horizontal education-job (mis)matches are relatively understudied compared to vertical matches (working in an occupation that corresponds to one's level of education) (Vecchia et al. 2023), the role gender plays in determining the relationship

between field of study and field of occupation continues to be disputed. Past literature has suggested that although men tend to be less likely to be in matching occupations in general, in the context of STEM, the opposite trend may be the case, with fewer women 'benefiting' from their STEM degree (Xu 2013). I too find that male STEM graduates are considerably more likely to work in STEM occupations than their female counterparts, although this observation varies by which STEM sub-fields are being studied. I only find substantial (and statistically significant) gender differences in the association between having a STEM degree and working in STEM when focusing on what I call 'Core STEM', computer science and IT, engineering, mathematics and the physical sciences, while I do not find differences in the likelihood of working in STEM when using the broader definition, which additionally includes biological sciences, medicine, dentistry, veterinary science, nursing, other health fields including psychology, planning and construction-related fields, agriculture, forestry and any not elsewhere categorised STEM fields. Looking at Core STEM fields, I show that at the point of labour market entry, the likelihood of entering STEM is around 50% for male STEM graduates, but only 35% for their female counterparts.

My findings furthermore highlight the importance of studying such patterns over the work life course, which has not commonly been done by past literature investigating horizontal education-job (mis)matches, both in general and in the context of STEM. I find that although both men and women's likelihood of working in STEM decreases as their careers progress, the careers of male and female STEM graduates vary quite considerably in their patterns. While male STEM graduates initially become increasingly likely to enter STEM work as time passes, with slight attrition only being observed after 10 years in the labour market, women drop out of STEM from the point of labour market entry, with most attrition being concentrated in the early years of their time in the labour market.

These patterns are once more substantially more pronounced when only examining Core STEM fields, and the gender differences across the work life course remain non-significant when using the broader definition. In the Core STEM fields, female STEM graduates' likelihood of working in STEM decreases by around 43% (14 percentage points), while that of their male peers drops by 13% (8 percentage points) over the 25 year time period I study. This points towards gender playing a vital role in how horizontal (mis)matches develop over the work life course.

These gendered patterns are likely driven by differences in occupational choices and constraints faced by male and female graduates. In line with Robst (2007a, 174), who concluded that: 'Men tend to report career-related reasons for mismatch while women are more likely to report amenity/constraint reasons for mismatch', I demonstrate that family obligations seem to play an important role in shaping women's decreasing likelihood of 'benefiting' from their STEM degree over the work life course, while pay and promotion opportunities (outside of STEM) seem to lead to male graduates leaving STEM work. Furthermore, career interests, which are a third reason that is used to explain (female) attrition from STEM work, also play a small role in the gender differences I observe. Together, these findings demonstrate that male and female STEM graduates have very different experiences in the (STEM) labour market, with women likely facing more constraints and having fewer opportunities.

The differences in findings across definitions of STEM demonstrate that horizontal education-job matches and their determinants indeed vary by field, as suggested by prior literature (for example, Boudarbat and Chernoff 2009; Salas-Velasco 2021). Past studies have hypothesised that such matches may be particularly prevalent in STEM work due to a higher supply of jobs (Robst 2007a) and strong education-work skill matches in those fields (M. C. Long, Goldhaber, and Huntington-Klein 2014; Salas-

Velasco 2021). However, the fact that the way in which graduates 'benefit' from their STEM degree varies by gender highlights that the prevalence of education-job matches in certain fields cannot simply be explained by the availability of jobs or education-work skill matches. Instead, individual choices, which are influenced by societal gender roles and stereotypes, and discrimination on part of employers (the extent to which may be informed by field-specific culture) are likely to contribute.

Hence, the findings of Chapter 5 highlight the importance of clearly defining what fields are being included when discussing STEM work, as results can vary substantially by included STEM sub-fields, and I only find pronounced gender differences when investigating the more stereotypically male-typed Core STEM fields. It is likely that the difference between my own findings and those of Smith and White (2018a; P. White and Smith 2022), who also use BCS70 data but show that gender differences between male and female STEM graduates in the UK remain relatively stable across the work life course, are due to differences in the operationalisation of STEM. While I take a categorisation approach to defining STEM, including fields based on whether they are commonly understood as belonging to the STEM category, Smith and White take a realised matches approach, defining the most common destinations of STEM graduates as STEM work. This results in occupations such as 'business and finance associate professionals' being defined as STEM work in their study, while I group those fields into the LEMB category, and understand people moving into these fields as leaving STEM. Definitional issues are particularly important when it comes to gender, as auxiliary analyses where I re-ran the results regarding the role of social origin only showed minor differences between the two definitions of STEM.

Overall, Chapter 5 reveals that gender gaps in STEM degree uptake, which have been the focus of much of the literature (for example, Friedman-Sokuler and Justman

2016; Morgan, Gelbgiser, and Weeden 2013), are not sufficient to explain gender gaps in the STEM labour market, as I find substantial gender differences among STEM degree holders, both at the point of labour market entry and across the work life course. Furthermore, finding oneself in STEM work more generally cannot sufficiently be explained through whether someone has obtained a STEM degree. Although having studied STEM at university is an important determinant of STEM work, a large proportion of STEM graduates never enter the field, and around 10% of non-STEM graduates do end up working in STEM. Therefore, studies investigating the STEM labour market need to look beyond university education and gender to get a 'fuller' picture of who works in STEM.

8.1.2. The Role of Social Origin

Given that Chapter 5 revealed that degree field of study and gender are not sufficient to explain who works in STEM, I next turned to an as yet understudied determinant of STEM work: the role of parents. Past literature investigating the direct effect of social origin (DESO), the association that remains between family background and occupational attainment after controlling for education, has increasingly suggested that parents have a direct influence on their children's labour market outcomes, although there is some debate on whether this relationship persists among the highly educated. My results show that DESO indeed remains among graduates when investigating occupational inheritance in STEM, and that parents play an important role in their children's likelihood of being found in STEM work.

Past studies of DESO have tended to focus on parental class /occupational status and income, and occupations have only recently become a focus of study in this regard (Bernardi and Gil-Hernandez 2021). Nonetheless, occupational inheritance continues to

be relatively understudied, both in the context of STEM and in general, despite prior research suggesting that it plays an important role in the intergenerational transmission of societal advantage (Jonsson et al. 2009). My results highlight that the intergenerational transfer of individual occupations is an important area of study, as I find a substantial, positive, association between having a parent who works in STEM and working in STEM oneself. At the point of labour market entry, having a 'STEM parent' increases graduates' likelihood of working in STEM by around 60% (18 percentage points) when looking at all STEM fields (the Broad definition of STEM). Auxiliary analyses using the more restrictive Core definition of STEM reveal similar, albeit somewhat less more pronounced, patterns. Therefore, while different definitions of STEM yielded substantially different results when studying gender, the way in which occupational inheritance operates seems to differ less by sub-field.

The initial DESO I observe in Chapter 6 remains after taking into account a variety of school, university and parental help mediators. Among the mediators I consider, the university decisions/experiences of graduates mediate the relationship between having a parent in STEM and working in STEM most strongly, with field of study choice being particularly instrumental. Including these mediators reduces the 'STEM parent' effect by around 22% (down to 14 percentage points, from 18 percentage points). Parents therefore have substantial influence on their children's occupations beyond shaping their education (and thus occupation-specific skills). This may be, for example, by passing down occupation-specific cultures and tastes (Jonsson et al. 2011), or, as Zuckerman (1996, 108) puts it, ensuring their children are socialised in the 'ways of science'.

Furthermore, I do not find a difference in how parental occupation shapes own occupation among STEM and non-STEM graduates. I find some non-significant evidence that degree field of study may moderate this relationship in the form of a slight 'boosting'

effect, with the 'STEM parent' effect being larger among STEM graduates. However, in addition to being statistically non-significant, this effect is also substantially relatively small, which is why the remainder of the thesis did not take it into account. Although degree field of study mediates the 'STEM parent' effect, this effect remains over and above people's university choices, and non-STEM graduates are also more likely to enter STEM work if they have at least one parent in STEM. Therefore, social origin does not seem to play a large role in shaping the likelihood of horizontal education-job (mis)matches in the context of STEM. This is perhaps unsurprising given that past research has similarly found a weak relationship between horizontal (mis)matches and family background (Boudarbat and Chernoff 2009; Xu 2013, 2017).

Occupational inheritance, and DESO more generally, have rarely been studied from a life course perspective. Past research investigating DESO in the context of occupational status or income has generally been inconclusive regarding the way in which it develops over the work life course. While some have demonstrated relative stability in DESO over the life course (Manzoni, Härkönen, and Mayer 2014; Passaretta et al. 2018; Ballarino, Cantalini, and Panichella 2021; Cantalini and Ballarino 2023), pointing towards 'permanence in occupational inequality' (Manzoni, Härkönen, and Mayer 2014, 1285), others have demonstrated that DESO dissipates in the first decade of people's careers (Jacob and Klein 2019; Byrne, Chandola, and Shlomo 2018; Kratz, Pettinger, and Grätz 2022). Gubler, Biemann and Herzog (2017), who explicitly studied occupational inheritance across the work life course, found that teachers whose mothers also worked as teachers were substantially more likely to leave the profession as their career progressed.

The results of my third analytical chapter (Chapter 7) are in line with the latter body of literature, as I show that the positive association between parental STEM

occupation and own STEM occupation persists beyond labour market entry, but steadily declines and disappears after 8 years in the labour market. This is driven by two patterns: while the likelihood of children of 'STEM parents' working in STEM *decreases* over the first decade of graduates' careers (similarly to Gubler, Biemann and Herzog's (2017) findings), the likelihood of children of 'non-STEM parents' working in STEM *increases.* These patterns point towards children of 'STEM parents' being more likely to become discontented with their STEM careers and eventually breaking from family traditions, while children of 'non-STEM parents' face more barriers to entry when it comes to STEM work, which seems to be the case for both STEM and non-STEM graduates. Having a 'STEM parent' therefore helps graduates navigate obstacles in the STEM labour market, especially early on in their career.

Looking at potential mediators of the 'STEM parent' effect over the first decade of graduates' careers reveals that DESO remains after taking into account education. While school-level factors mediate the relationship between parental STEM occupation and own STEM occupation in the early years of graduates' time in the labour market, the mediating effect of higher education factors subsumes the effect of school, and remains stable over the work life course. However, work specific factors quickly overtake the importance of higher education, and explain a relatively large proportion of the 'STEM parent' effect, and its decline, which I observe. Nonetheless, a substantial 'STEM parent' effect remains in the first years following labour market entry after taking into account all mediators. This highlights the importance of parental occupation at the point of transition from university to the labour market.

These results regarding occupational inheritance among STEM graduates make the case for the usefulness of the microclass approach in the context of STEM. While *parental STEM occupation* was consistently statistically and substantially significant in

my analyses, my 7-level parental social class variable was consistently non-significant. This does not mean I dismiss the usefulness of more traditional class schemes, as my findings could be driven by my exclusive focus on graduates, but rather, I believe my findings highlight that the micro-level should not be overlooked in settings where 'big class' schemes suggest a lack of importance of parental occupation. Furthermore, the results presented in this thesis make the case for a continued focus on parental occupation in DESO research. The strong 'STEM parent' effect, which remains after accounting for a variety of mediators, highlights that social origin certainly plays a role in determining who works in STEM.

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Taken together, the findings of this thesis highlight that the 'road into STEM work' is more complicated than often implied by political discourse in the UK. It is not a simple case of STEM education leading to STEM work, and other determinants such as graduates' gender and family background play an important role in their labour market outcomes. I demonstrate that women benefit less from obtaining a (Core) STEM degree, as they are less likely to enter (Core) STEM work and more likely to leave it across the work life course. My results also suggest that parents can play an important role in helping their children overcome barriers in the STEM labour market, as the children of 'STEM parents' are substantially more likely to start out in STEM work than those whose parents worked in non-STEM fields.

I addressed a variety of theoretical debates in this thesis. The results of Chapter 5 highlight the importance of taking gender into account when investigating horizontal education-job (mis)matches, as the underlying mechanisms that lead to someone being in a matching occupation differ for men and women. Furthermore, this chapter demonstrates

the importance of taking a work life course perspective when studying such matches, as their prevalence varies substantially at different points in people's time in the labour market. The results of Chapters 6 and 7 show that social origin, and parental occupation in particular, plays an important role in determining people's field of occupation, and should therefore be taken into account more in studies investigating determinants of STEM work. In the context of occupational inheritance, taking a work life course perspective again revealed patterns that would have been missed if only focusing on the point of labour market entry, highlighting the importance of a work life course approach when studying school-to-work links.

8.2. Policy Implications

Much of the policy focus regarding the STEM workforce has been centred around education and encouraging more students to study STEM to increase the STEM workforce. The findings of this thesis suggest that this approach may be misguided.

Firstly, my findings regarding the large proportion of STEM graduates who do not enter STEM work calls the need for more STEM graduates into question. This sentiment is echoed by other researchers who have studied the UK labour market (Bosworth, Lyonette, and Wilson 2013; E. Smith 2017; E. Smith and White 2018a), who conclude that there are more than sufficient numbers of STEM graduates to fill vacancies in the STEM labour market. Smith and White (2018a, 6) go so far as to say: 'employment in STEM shortage areas is either unattractive or unobtainable for the majority of STEM graduates.' The horizontal education-work mismatches I observe are not merely due to individual choice; both the underrepresentation of female STEM graduates and the role of parental STEM occupation in shaping graduates' likelihood of working in STEM suggest that there are, in fact, STEM graduates who might wish to work in STEM but

who are prevented from doing so by various barriers in the labour market. Therefore, the existence of a 'STEM shortage' needs to be confirmed to ensure efficient spending of public funds.

Secondly, should there indeed be a wish to grow the STEM workforce, more policy focus needs to be directed to inequality of opportunity and structural (and individual) discrimination in the STEM labour market. The fact that gender differences *increase* when examining the fields that are often presented as 'key shortage' areas (contained in the Core definition of STEM), which supposedly need workers most, highlights this. The barriers to entry to and persistence in STEM work therefore need to be examined further, both regarding gender, and regarding the less discussed importance of social origin.

In the case of gender, better accommodation for family responsibilities and more equal pay and promotion opportunities are likely to allow more women to enter and stay in STEM. Although STEM fields are generally perceived as less family friendly than non-STEM fields (Tan-Wilson and Stamp 2015), this applies to the 'Core' STEM fields in particular. These fields continue to be less family friendly than fields such as medicine (Lambert, Smith, and Goldacre 2017), which attract a higher proportion of female graduates. Making these 'Core' fields more attractive to parents, and mothers in particular, entails changes both in the marketing of STEM fields and in the real-life cultures of such jobs (Weisgram and Diekman 2017). More women may enter traditionally male-typed STEM fields through interventions that portray scientists as 'multidimensional individuals who are both scientists and parents' (Weisgram and Diekman 2017, 13), for example. This has been demonstrated by Tan-Wilson and Stamp (2015), whose respondents changed their view on the family friendliness of STEM fields following a conversation with dual-STEM career couples with children. In the workplace,

STEM fields could be made more family friendly through provision of child-care and more part-time contracts which allow parents to look after a family alongside their career (Fouad et al. 2017).

Regarding social origin, and occupational inheritance in particular, it seems that the children of 'non-STEM parents' face more barriers when attempting to enter STEM work in their initial years in the labour market, suggesting more needs to be done to support such graduates in their university-to-work transitions. Mentorship schemes, for example, might be a promising avenue in this regard. In general, initiatives focusing on encouraging more students into STEM may be more efficient if directed at 'first generation STEM workers', whose parents are less likely to shape their trajectories into STEM.

Finally, in addition to policy aimed at increasing the STEM workforce, it is also important to make policy aimed at *maintaining* the STEM workforce. I observe decreasing likelihood of working in STEM over the work life course both among female STEM graduates, and among children of 'STEM parents', with the former being particularly pronounced. If current STEM workers are encouraged to remain in their roles, there will be less of a need for new STEM workers. A lack of pay and promotion opportunities in STEM, when compared to fields such as law, economics, business, and management, seems to be particularly instrumental in shaping the decreasing likelihood of being found in STEM work among 'privileged' graduates in this context, namely male STEM graduates and children of 'STEM parents'. Hence, a re-evaluation of pay and promotion structures in the field may be necessary (for all STEM workers, of course). In the case of female STEM graduates, better family accommodations are going to be particularly helpful in increasing retention.

8.3. Limitations and Future Research

As is the case with all academic research, the analyses presented in this thesis and the conclusions that can be drawn from them are subject to a variety of limitations, which are necessary to highlight (again) at this point, to frame my findings within the scope of the thesis. Furthermore, the thesis identified a number of avenues for future research, which I was not able to address in this piece of work.

Perhaps the main 'issue' of my thesis is the relatively small sample size my work is based on. Although I believe the sample size to be large enough to establish the relationships I present in my analytical chapters, the fairly small number of respondents who obtained a degree and whose occupational information was known meant that I could not explore certain issues and potential research avenues in depth. For example, STEM occupations are not homogenous (although I do argue that they all have things in common given the policy discourse regarding STEM), and Smith and White's (2018a) work using descriptive statistics highlights variation within the fields I consider. I address this to some extent by creating the distinction between Core and Broad STEM and dropping individual STEM sub-fields as part of the auxiliary analyses of Chapter 7, but would have liked to investigate individual STEM fields in more detail. Furthermore, the small sample size prevented me from disaggregating the effect of parental occupation over the work life course by gender (both of the parents and of the children) in my third analytical chapter. I believe this to be an interesting premise for future research, as Schoon (2023, 252) emphasises the importance of taking into account the 'intersection of sex, social and cultural background, ethnicity, and gender identity.'

A possible limitation I have addressed throughout is my use of data that is based on people who were born in 1970, which means they attended university before the term STEM was popularised, and before science and mathematics were made compulsory

school subjects in 1989. As I argue in Chapter 4, I nonetheless believe that BCS70 is the best dataset available for my purposes. Not only does it offer a rich account of people's lives, including detailed information on their social origin and their schooling, which is often missing from alternative datasets, but it also allowed me to follow graduates over the work life course, which would not have been possible with any other UK dataset given my variables of interest. Moreover, while the term STEM may not have been used when BCS70 respondents made educational and labour market choices, they nonetheless did so in the context of a government whose desire was to increase the science and technology workforce (Mandler 2020). It is worth noting that my analyses focusing on a single cohort of people means that the patterns I observe might have been influenced by changes over time, as the demand for STEM graduates in the UK labour market developed, and as gender inequality in the labour market decreased. However, given that I find continued attrition of women and children of 'STEM parents' from STEM across the observed time, my findings are likely the result of work life course effects rather than period effects.

Furthermore, despite my interest in explaining the patterns I observe, my method of 'unpacking' effects using nested models does not allow me to make causal claims. Instead, I identify correlations, which may well be the result of causal mechanisms, but which cannot be concluded as such without further examination. Qualitative interviews are likely to be particularly fruitful in this regard, as demonstrated by Preston (2004) and Fouad et al. (2017) in the case of gender differences in STEM, and Devine (2010) in the context of occupational inheritance, for example. Such interviews could also help to identify mechanisms and concepts that are not easily quantifiable. For example, interest in STEM (work) and general STEM skills seem to be important mediators of the effects I observe which I was not able to fully investigate.

My analyses only concern active labour market participants, and do not take unemployment into account. Although unemployment is certainly an important topic when it comes to the destinations of (STEM) graduates, it is not the focus of this study. Instead, I am interested in matches, firstly those between degree field of study and field of occupation (Chapter 5), and secondly those between parental field of occupation and own field of occupation (Chapters 6 and 7). This approach is not uncommon; episodes of unemployment and inactivity are often removed from studies of occupational outcomes (Ballarino, Cantalini, and Panichella 2021). Furthermore, the vast majority of respondents (92%, which rises to 95% when examining the first decade of graduates' careers) did not spend any time over the period I studied in unemployment seeking work.[46] These proportions do not vary substantially by parental field of occupation or gender. Therefore, although certainly an important and interesting avenue for future research, unemployment among graduates was outside of the scope of this thesis.

Because occupational inheritance remains understudied, more research needs to investigate how it varies by field of occupation. It is likely that the occupational inheritance I observe in Chapters 6 and 7, and the underlying mechanisms that drive it, are not unique to STEM, as past research has demonstrated that the children of professionals are more likely to work in professional occupations themselves (Egerton 1997; Ruggera and Barone 2017). It may, however, be more pronounced than in other fields because of the (relatively) well-paid, stable, and prestigious nature of STEM fields, which Devine (2010) has identified as increasing the likelihood of parents encouraging their children to follow in their occupational footsteps. More research is needed in order to establish whether occupational inheritance in STEM is unique, but this was beyond the

[46] This does not take into account people who were out of work for further education, due to sickness or disability, due to family responsibilities or due to retirement.

scope of this thesis. Should these patterns not be unique to STEM, they are nonetheless important, as they highlight the vital role parents continue to play in shaping their children's occupational outcomes, which has important equality of opportunity implications.

This thesis largely focuses on the work lives of British graduates. The earlier experiences of graduates in school and at university are taken into account to some extent, as controls and mediators, but this approach leaves out many aspects of graduates' early lives. These early experiences of people are bound to shape their field of work. For example, past research has highlighted the importance of teachers and school friends in shaping interest in STEM fields (Weber 2011; Tey, Moses, and Cheah 2020). Taking a more comprehensive life course perspective when studying the STEM labour market outcomes of graduates, as opposed to focusing largely on the work life course – as I have done – is therefore a fruitful area for future research. Due to the focus of this thesis lying in explaining how degree field of study and parental occupation specifically shape field of occupation choices, and due to the small sample size, I was unable to do so in depth. Incorporating the early life course in more detail would help to address some of the unexplained variance in who does and does not enter (and remain in) STEM work which I find.

Finally, although not a limitation per-se given the research questions this thesis posed, it should be noted that I look at associations between key variables and how they shape graduates' likelihood of being found in STEM work, rather than explicitly studying career trajectories. My concern was less with individuals' movement in- and out- of STEM, and more with how much degree field of study, gender and parental occupation mattered in shaping the likelihood of entering STEM across the work life course among graduates. Given that my findings revealed some interesting and novel patterns over the

work life course, future research using a larger sample should certainly delve into these further by analysing trajectories explicitly.

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APPENDIX

Appendix A: Coding STEM

A1. Coding STEM Occupations

As mentioned in the Data and Methods chapter (Chapter 4), I used SOC codes to group people's occupations into fields. Ideally, I would have used the latest version available to have a classification that is as up to date and detailed as possible. However, because the Hancock (2017) Activity Histories file only contains SOC90 information on the age 26 sweep, and because SOC90 information is available for the largest number of sweeps (see table A1), I used SOC90 codes as a starting point.

Table A1: List of SOC Codes in BCS70

SOC Code Version	Sweeps	Age(s)	Variable
SOC90	S5, S6, S7, S8 (work activities)	26, 30, 34, 38	J90SOC
SOC2000	S7, S8, S9 (work activity)	34, 38, 42	J2KSOC
SOC2010	S9 (work activities)	(42)	J10SOC/ B9AS2000
		46	B10LSOC3

Note: The above table is based on the Activity Histories file compiled by Hancock (2017), with the exception of the age 46 sweep, which was not included in the former so is a variable taken from the age 46 sweep base file, current job only for age 26

Broad Field of Occupation

Using SOC90 codes, I initially grouped the occupations into broad fields of work, using categories I also used when working on the field of study categorisation (see section A2). In doing so I focused on nuance between STEM fields (table A2). I grouped all other fields into broader categories, which I used for descriptive analyses. These categories are based on work by Walker and Zhu (2011), and adapted slightly to suit my purposes: (i) LEMB (law, economics, management, and business), (ii) OSSAH (Other social sciences, arts, and humanities which includes languages), and (iii) Vocational Fields (or more

specifically, ‘Manufacturing, Service Industry, and occupations n.e.c.’). Additionally, I added a fourth category, (iv) Education Related, because it is likely that graduates from all kinds of fields of study will enter teaching/academia and grouping these jobs in with more vocational jobs did not seem accurate enough. If I had more specific information I would have grouped education-related occupations into their respective fields, but for example for SOC90, I simply have the group ‘Teaching and Educational Professionals’ instead of information such as ‘Science teacher’/’History teacher’.

When coding STEM fields, I dropped all occupations that I do not consider to be (highly) skilled occupations – those belonging to SOC Major groups 1 (‘Managers, Directors, and Senior Officials’), 2 (‘Professional Occupations’) and 3 (‘Associate Professionals and Technical Occupations’) – as STEM. Furthermore, restricting the definition of STEM to focus on skilled work is commonly done; the one aspect past studies seem to agree on is that STEM occupations require post-compulsory schooling or training. This is either explicitly stated (OECD 2016; Han 2015, 2016; O*NET OnLine 2018; Ulicna and Royale 2015; E. Smith and White 2018a) or implied through the kinds of occupations considered STEM (OECD 2013; Caprile et al. 2015).

Table A2: List of Broad Field Categories

Number	Broad Field Category
1	Computer science and IT
2	Engineering
3	Mathematics
4	Physical sciences
5	Biological sciences
6	Medicine, dentistry and veterinary science
7	Nursing and other subjects allied to medicine (including psychology)
8	Architecture, building and planning related
9	Agriculture, forestry and other
10	LEMB (Law, economics, management and business)
11	OSSAH (Other social sciences, arts, and humanities, which include languages)
12	Education-related
13	Vocational fields

Because my data contained different occupational schemes across time, I coded SOC90/SOC2000/SOC2010 codes into these broad field categories (table A2) using the most systematic and harmonised way I could:

SOC90

I started off the process of coding all the SOC codes into broad fields with the 3-digit SOC90 variable from the Activity Histories file (Hancock 2017), which is available for the first four sweeps I am interested in (Age 26, Age 30, Age 34 and Age 38).[47] In the case of SOC90 information, I manually coded each individual SOC code into the broad fields identified in table A2. I did this using both the research I had done while coding fields of study for my degree characteristics variables and researching new fields. In many cases this process was quite straight forward (for example, I classed 'Electronic engineers professional' (SOC90 code 213) as engineers). In cases where I was uncertain, I researched the occupation and allocated them into the broad fields based on how the occupations were described (for example, I found out a chiropodist treats those who suffer from foot problems, so I allocated these people to 'Nursing and other Subjects Allied to Medicine'), and how I had assigned corresponding degree fields earlier on in the data preparation process (see section A2).

When a job could fall into two fields, my general approach was to 'overestimate' occupations when they were related to one of the broad STEM fields I was interested in. For example, I coded 'Other Natural Scientists nec' (SOC90 code 209) as 'Physical Sciences' although some people with 'other natural scientist' jobs may be doing work that would fall into the 'Biological Sciences' category. My reasoning for overestimating

[47] Current job only for Age 26.

these (STEM) occupations was that I wanted to ensure that the Core STEM category included everyone who belonged there.

SOC2000

Once I had finished the SOC90 grouping, I moved onto SOC2000. This information was once more taken from the Activity Histories file (Hancock 2017). The file contains 4-digit SOC2000 codes for the sweeps at age 34, 38 and 42. Because both SOC90 and SOC2000 information was available for the Age 34 and Age 38 sweeps, I started off by using the SOC90 field information I had already coded to inform my coding of SOC2000. I did so by following a method similar to that Oesch (2013, 157) used to transform SOC2000 into SOC90 codes. Specifically, I compared individuals' jobs which I had both SOC90 and SOC2000 codes for. I did so by looking at each individual SOC2000 occupational code and seeing what SOC90 codes had been used to describe the identical jobs, and what broad work field I had assigned these SOC90 codes into. I then assigned that (those) broad work field(s) to the SOC2000 code. Once I had classified all SOC2000 codes in that way, I went over them to manually decide which of the broad fields was most applicable in instances where the SOC2000 code corresponded with several SOC90 codes. I also manually changed some categorisations in cases where I did not agree with the grouping my more data driven method had resulted in (for example, I changed 'Assemblers and routine operatives n.e.c.' (SOC2000 code 8139) from OSSAH, which my method had suggested, to Vocational Fields)

The above process can most easily be demonstrated using an example. Take nurses, for instance; those who were identified as nurses using SOC2000, were not necessarily coded into 'Nursing and other Subjects Allied to Medicine' using SOC90 (table A3). Some people's work was instead grouped into LEMB or OSSAH. Because

made most sense to classify nurses as 'Nursing and other Subjects Allied to Medicine' professionals, that's what I did.

Table A3: SOC2000 Coding Example

SOC2000	SOC90	Broad Field, SOC90	Broad Field, SOC2000
Nurses (3211)	340: Nurses	Nursing and other Subjects Allied to Medicine	Nursing and other Subjects Allied to Medicine
	640: Assistant nurses, nursing auxiliaries	Nursing and other Subjects Allied to Medicine	
	644: Care assistants and attendants old	Nursing and other Subjects Allied to Medicine	
	173: Hotel and accommodation managers	LEMB	
	293: Social workers, probation officers	OSSAH	
	371: Welfare, community and youth workers	OSSAH	

The two broad field classifications (SOC90 and SOC2000) I created using the steps above aligned well; the variables are highly correlated ($r = 0.84$), especially when only looking at graduates ($r = 0.94$), who are my population of interest.

SOC2010

Next, I turned to the Age 46 sweep, which is not included in the Activity Histories file. The Age 46 sweep contains 3-digit SOC2010 codes. Because I did not have overlapping information for this sweep, I could not use the method I used for my coding of SOC2000 (described above). Instead, I used an ONS (2016) crosswalk. I encountered some problems with this sweep because 3-digit SOC2010 codes give less detail than 3-digit SOC90 and 4-digit SOC2000 codes. While I had information on 371 unit groups for SOC90 and 353 unit groups for SOC2000, I only had information on 90 minor groups for SOC2010. Hence, when using the ONS crosswalk, I did so at the minor group level for both SOC2000 and SOC2010.

As a result, I had several SOC2000 codes (at unit group) level correspond to single SOC2010 minor groups at times. In such cases, I manually chose the broad field (table A2) that came up the most among the SOC2000 codes and/or made the most sense (for example, 'Engineering Professionals' (SOC2010 code 212) corresponded to SOC2000 codes that I had grouped as 'Engineering', 'Architecture, Building and Planning Related' and 'LEMB' – I coded it as 'Engineering'). When making these judgments I again classified occupations into broad fields by looking back at what I had done for the degree fields and for SOC90 and SOC2000 and researching fields further if unsure (for example, using the ONS Occupational Coding Tool (2020)).

Because of SOC2010 being measured at the minor group level, in some cases it was impossible to distinguish between STEM and non-STEM occupations. In those instances, I decided to once more 'overestimate' the occupations. The most noteworthy example of this 'Natural and Social Science Professionals' (211), which I classed as 'Physical Sciences' (it is also the only SOC2010 code that was grouped into the physical sciences). This way of assigning occupations into broad fields is therefore limited.

Overall Broad Field Variable

After all the steps described above, I had three separate broad field of occupation variables, one for SOC90, one for SOC2000 and one for SOC2010. I combined these into one variable to be able to use it in my analyses. In cases where I had information both on SOC90 and SOC2000, I prioritised SOC2000. This was done because SOC2000 is more detailed when it comes to STEM jobs, so more suited to my work.

This variable had a high extent of missingness. Hence, I imputed values using nearest neighbours. In cases where I had broad work field information on previous or future jobs which a respondent had no more than 3 years before or after the job with missing information, I imputed the broad work field using the 'closest' information

available (for example, if I had missing information on job 3, but I had information for jobs 2 and 5, I would use the broad work field of job 2 for job 3 as well). In cases where there were ties, I again prioritised previous jobs (for example, if I had missing information on job 3, but I had information for jobs 2 and 4, I would use the broad work field of job 2 for job 3 as well).

STEM versus Non-STEM Occupations

Next, I used the broad categories shown in table A2 to create STEM variables. I created variables using two STEM definitions which collapse into each other, as shown in table A4. All fields that did not fall under a given definition of STEM were collapsed to be 'non-STEM'.

Table A4: STEM Measure Compositions

Broad Field Category	Broad STEM	Core STEM
Computer science and IT	✓	✓
Engineering	✓	✓
Mathematics	✓	✓
Physical sciences	✓	✓
Biological sciences	✓	
Medicine, dentistry and veterinary Science	✓	
Nursing and other subjects allied to medicine	✓	
Architecture, building and planning-related	✓	
Agriculture, forestry and other	✓	

I consulted previous classifications when classifying the SOC codes into broader categories and subsequently into STEM variables (E. Smith and White 2018b; Langdon et al. 2011; Beede et al. 2011), but I did not necessarily follow what they had done. Some of these past studies defined 'STEM jobs' based on the fields STEM graduates tend to

enter, rather than coding fields into STEM versus non-STEM based on their 'STEM-ness' so to speak, without taking graduates' behaviour into account (as was done by Melguizo and Wolniak (2012), for example). The former approach, which was taken by Bol et al. (2019) and Smith and White (2018b) for instance, leads to occupational groups such as 'Business and Finance Associate Professionals' being defined as STEM jobs (E. Smith and White 2018b, 27). Hence, this approach to defining STEM jobs and subsequently looking at congruence leads to a broader definition of STEM jobs which would subsequently affect the conclusions these past papers draw about horizontal education-job (mis)matches.

Because of my research interest, I chose to follow a different approach. Instead of defining STEM jobs based on STEM graduates' (however defined) trajectories, I thought it was important to have independent STEM degree and STEM job variables, to be able to see how they relate. Hence, unlike some past authors, I used a categorisation approach and labelled jobs as belonging to STEM based on their 'STEM-ness' – by which I mean I did so based on to what extent they seemed to truly fall into the different broad fields I identified, which inevitably involved judgment calls. Using my way of defining STEM jobs (and field of occupation more broadly), 'Business and Finance Associate Professionals' - which I use as an example above - would be grouped as 'non-STEM'. Of course, this difference in approaches is likely to also lead to differences in findings and conclusions between their studies and mine.

Table A5: SOC codes included in STEM Definitions

Core STEM	Broad STEM	Broad STEM Field	Subject (SOC Codes)		
			SOC90	SOC2000	SOC2010
✓	✓	Computer science and IT	- Computer systems and data processing managers (126) - Software engineers professional (214) - Computer analyst/programmers (320)	- IT strategy and planning professionals (2131) - Software professionals (2132) - IT operations technicians (3131) - Computer engineers, installation - Information and communication technology managers (1136) - IT user support technicians (3132)	- Information technology and telecommunications professionals (213) - Information technology technicians (313)
✓	✓	Engineering	- Civil, structural, municipal, mining and quarrying engineers (210) - Mechanical engineers general naval (211) - Electrical engineers professional meter (212) - Electronic engineers professional (213) - Chemical engineers (215) - Design and development engineers (216) - Process and production engineers (217) - Planning and quality control engineers (218) - Other engineers and technologists n.e.c. (219) - Engineering technicians (301) - Building and civil engineering technicians (304)	- Building and civil engineering technicians (3114) - Civil engineers (2121) - Mechanical engineers (2122) - Electrical engineers (2123) - Electronics engineers (2124) - Chemical engineers (2125) - Design and development engineers (2126) - Production and process engineers (2127) - Planning and quality control engineers (2128) - Engineering professionals n.e.c. (2129) - Electrical/electronics technicians (3112) - Engineering technicians (3113) - Quality assurance technicians (3115) - Quality assurance managers (1141)	- Engineering professionals (212) - Science, engineering and production technicians (311) - Quality and regulatory professionals (246)

✓	✓	Mathematics	- Actuaries, economists and statisticians (252)		
✓	✓	Physical sciences	- Chemists research (200) - Physicists, geologists and meteorologists (202) - Other natural scientists n.e.c. (209) - Laboratory technicians (300) - Other scientific technicians n.e.c. (309)	- Science and engineering technicians n.e.c. (3119) - Physicists, geologists and meteorologists (2113) - Chemists (2111) - Laboratory technicians (3111) - Scientific researchers (2321) - Research and development managers (1137)	- Natural and social science professionals (211)
✗	✓	Biological sciences	- Biological scientists and biochemists (201)	- Biological scientists and biochemists (2112) - Conservation and environmental protection (3551)	- Conservation and environment professionals (214) - Conservation and environment associate professionals (355)
✗	✓	Medicine, dentistry and veterinary science	- Medical practitioners (220) - Dental practitioners (223) - Veterinarians (224) - Medical technicians, dental auxiliaries (346)	- Paramedics (3213) - Pharmaceutical dispensers (3217) - Medical and dental technicians (3218) - Dental practitioners (2215) - Veterinarians (2216) - Medical practitioners (2211)	- Health professionals (221)
✗	✓	Agriculture, forestry and other	- Farm owners and managers, horticulturists (160) - Other managers in farming, forestry, and fishing n.e.c. (169)	- Natural environment and conservation managers (1212) - Managers in animal husbandry, forestry and fishing (1219) - Farm managers (1211)	- Managers and proprietors in agricultural related services (121)
✗	✓	Architecture, building and planning	- Architects landscape (260) - Town planners control (261) - Building, land, mining and 'general practice' surveyors (262) - Architectural and town planning technicians (303)	- Draughtspersons (3122) - Chartered surveyors (not quantity surveyors) (2434) - Production, works and maintenance managers (1121) - Architectural tech. and town planning technic (3121)	- Architects, town planners and surveyors (243) - Draughtspersons and related architectural technicians (312)

			- Building inspectors (311) - Quantity surveyors (312) - Marine, insurance and other surveyors (313) - Production, works and maintenance managers (110) - Managers in building contracting (111) - Draughtspersons (310)	- Building inspectors (3123) - Managers in construction (1122) - Architects (2431) - Town planners (2432) - Quantity surveyors (2433)	
✗	✓	Nursing and other subjects allied to medicine (including psychology)	- Pharmacists/ pharmacologists (221) - Nurses (340) - Midwives (341) - Medical radiographers (342) - Physiotherapists (343) - Chiropodists (344) - Ophthalmic opticians (222) - Environmental health officers (348) - Other health associate professionals animals (349) - Occupational hygienists and safety officers (health and safety) (396) - Psychologists (290) - Dispensing opticians (345) - Occupational and speech therapists, psychotherapists, therapists n.e.c. (347)	- Hospital and health service managers (1181) - Dispensing opticians (3216) - Therapists n.e.c. (3229) - Occupational hygienist and safety officers (3567) - Nurses (3211) - Midwives (3212) - Medical radiographers (3214) - Chiropodists (3215) - Physiotherapists (3221) - Occupational therapists (3222) - Pharmacy managers (1182) - Residential and day care managers (1185) - Psychologists (2212) - Pharmacists/ pharmacologists (2213) - Ophthalmic opticians (2214) - Environmental health officers (3568) - Speech and language therapists (3223) - Healthcare practice managers (1183)	- Therapy professionals (222) - Nursing and midwifery professionals (223) - Health associate professionals (321) - Health and social services managers and directors (118) - Managers and proprietors in health and care services (124)

A2. Coding Field of Study

Degree Field of Study

BCS70 has asked respondents about their degree field of study several time. The Age 30 answers were not coded by BCS70, so I manually coded the responses into the Age 34 codes. People were also asked about their field of study in the Age 38 sweep, but these responses do not seem to be publicly available, so were not used in this thesis. In the Age 42 sweeps, people were again asked about the field of study of their first degree, but their responses were recoded using substantially less detailed coding scheme. Hence, I created the field of degree variable(s) using the age 30, 34 sweeps, and 42 sweeps. In cases where I had different information on the first degree (from the Age 30/34 versus 42 surveys) I relied on the earlier surveys as these are likely to be more accurate as less time had passed between respondents' time in higher education and the interview.

Firstly, I categorised specific fields into 'STEM subfields' (table A6). The exact fields contained in each subfield category can be seen in table A7 below. If I was unsure what field a specific subject belonged to, I researched them. Most of my grouping of fields I was unsure about relied on university websites, and which departments universities grouped these subjects into. Using variables from all three sweeps, I created a separate STEM subfield variable for first/second/third/fourth undergraduate degree, and first/second postgraduate degree. Because BCS70 asks respondents about past degrees if they missed a sweep, I did this by counting the first time someone mentioned their degree field of study as the subject of their first degree, the second time as the subject of their second degree etc. Then, I created two different STEM variables (Core and Broad) using the definitions in table A6. I did this once more for first/second/third/fourth undergraduate degree, and first/second postgraduate degree.

To create an overall STEM variable to use in my analyses, I coded a variable that held the value of 0 if a respondent had not yet obtained any degree, a value of 1 if they

had not obtained a STEM degree of any kind, and a value of 2 if they had obtained any STEM degree (at undergraduate or postgraduate level). In my analyses, I dropped the 0 level, as I follow people from the point of labour market onwards, so they have obtained a degree by definition.

Table A6: STEM Measure Compositions

Broad Field Category	(1) CORE STEM	(2) BROAD STEM
Computer science and IT	✓	✓
Engineering	✓	✓
Mathematics	✓	✓
Physical Sciences	✓	✓
Biological Sciences	✗	✓
Medicine, Dentistry and Veterinary Science	✗	✓
Nursing and other Subjects Allied to Medicine	✗	✓
Architecture, Building and Planning Related	✗	✓
Agriculture, Forestry and Other	✗	✓

School Field(s) of Study

School subject information was available for the Age 30 sweep, but was not collected at Age 26. BCS70 did not code the subject variables at Age 30, instead simply reporting what interviewers had recorded. Hence, I manually coded these variables into the field of study variables I used for Degree Field of Study (which were based on those used by BCS70 in Sweep 34). In total, I did so for 13 CSE subject variables, 15 O-Level variables, 13 GCSE variables and 10 A-Level variables. Once I had coded these variables into broad field codes, I once more grouped each of them into STEM (defined in 3 different ways, see table A6), and non-STEM.

Other Field of Study Variables

To be able to get an in-depth idea of what I am comparing STEM graduates' trajectories, I also grouped non-STEM subjects into a few categories. I did so by slightly adapting Walker and Zhu's (2011) approach. Unlike them, I know what subjects people studied if they did combined degrees. Hence, instead of COMB, I have a category called 'vocational fields'. Furthermore, because Shauman (2017) highlights the earning advantage of Business graduates, I included this field into what Walker and Zhu call LEM.[48] This leaves me with three non-STEM categories: (i) LEMB (law, economics, management, and business), (ii) OSSAH (Other social sciences, arts, and humanities which includes languages), and (iii) Vocational.

[48] Walker and Zhu (2011) may have counted business as management, but whether they did is unclear from their text.

Table A7: Degree Subjects included in STEM Definitions

Core STEM	Broad STEM	Broad STEM Field	Subject (BCS70 Codes)	
			Age 30 and 34	Age 42
✓	✓	Computer science and IT	Computer Science and IT - Computer studies (mathematical bias) (6034) - Computer science (6044) - Computer systems analysis (7046) - Computer languages (7081) - Computer operation (7082) - Computer programming (7083) - Computing (7097) - Cybernetics (industrial) (4100) - Other technology (including IT) (4123) - Combinations with Technology (including IT)	- Computer science and IT (B9SBDG15)
✓	✓	Engineering	- Aeronautical engineering (3001) - Aero engineering and space technology (3005) - Agricultural engineering (3011) - Automobile engineering (3014) - Motor vehicle engineering (3017) - Chemical engineering and technology (3024) - Gas engineering (3028) - Civil engineering (3030) - Civil engineering (gas) (3031) - Municipal engineering (3032) - Traffic engineering (3033) - Electrical engineering (3035) - Electronic engineering (3040) - Illuminating engineering (3042) - Marine engineering (3048) - Mechanical engineering (3049) - Mechanical engineering craft practice (3052) - Mechanical engineering technicians (3053) - Mechanical engineering inspection (3054)	- Chemical engineering (B9SBDG11) - Civil engineering (B9SBDG13) - Electronics and electrical engineering (B9SBDG21) - Engineering general (B9SBDG22) - Materials and mineral engineering (B9SBDG27) - Mechanical engineering (B9SBDG29)

			- Refrigeration engineering (3056) - Production engineering (3063) - Precision engineering (3064) - General engineering (3068) - Combined engineering (3069) - Control engineering (3070) - Corrosion engineering (3074) - Engineering drawing (3075) - Engineering planning, estimating and costing (3076) - Engineering science (3077) - Fire engineering (3078) - Heating and ventilating engineering (3079) - Industrial engineering (3080) - Mill engineering and services (3082) - Instrument engineering and maintenance (3083) - Miscellaneous engineering (3087) - Nuclear engineering (3088) - Pipework engineering (3089) - Textile engineering (3094) - General and other engineering (3097) - Engineering combinations (3098) - Engineering & technology combinations (3099) - Engineering in combination with other groups (3100) - Plumbing and sanitary engineering (4023) - Structural engineering (4027) - Mineral engineering (4057) - Mining engineering (4058) - Offshore engineering and technology (4061) - Combinations of engineering-technology (4125) - Hydraulics (3051) - Aeronautics (3002) - Astronautics (3008)	
✓	✓	Mathematics	- Mathematics (6031)	- Mathematics (B9SBDG28)

			- Applied mathematics (6032) - Arithmetic including numeracy (6033) - Decimalisation (6035) - Numerical analysis (6036) - Probability theory (6039) - Statistics (6040) - Technological mathematics (6042) - Mathematics / physics (6058) - Mathematics / other sciences (6059) - Advanced / Additional Maths (6063) - Combinations with Mathematics	
✓	✓	Physical sciences	Physics - Physics (6045) - Applied physics (6046) - Mathematical physics (6048) - Nuclear physics (6049) - Astrophysics (6050) - Geophysics (6029) - Mathematics/physics (6058) - Elasticity (6037) Chemistry - Soil chemistry (5022) - Physiological chemistry (6017) - Chemistry (6018) - Analytical chemistry (6019) - Applied chemistry (6020) - Cosmetic chemistry (6021) - Chemistry as applied to textile industry (6023) - Polymer chemistry (6025) - Colour chemistry (6026) - Technical chemistry (6027) - Metal finishing and electro-chemistry (3084)	- Physics (B9SBDG37) - Chemistry (B9SBDG12) - Earth and marine sciences (B9SBDG18)

			- Agricultural chemistry (5001) - Combinations with Chemistry Astronomy and Other - Mineralogy (6030) - Geology (6028) - Soil science (5023) - Applied astronomy (6047) - Radio astronomy (6051) - Radiation protection (6052) - Oceanography (6054) - Meteorology (6055) - Combinations of physical sciences (6060) - Spectroscopy (6022) - Theoretical astronomy (6041) - Mining geology (4060) - Metrology (3086) (?) - Industrial radiography (3081) - Aerodynamics (3003)	
✗	✓	Biological sciences	- Biological sciences (6001) - Applied biology (6002) - Applied microbiology (6003) - Biology (6004) - Bacteriology (6005) - Biological chemistry (6006) - Botany (6007) - Genetics (6008) - Microbiology (6009) - Microscopy (6010) - Physiology and anatomy (6011) - Pathology (6012) - Zoology (6013) - Biochemistry (6014)	- Anatomy and physiology (B9SBDG03) - Biosciences (B9SBDG08)

			- Applied biochemistry (6015) - Medical biochemistry (6016) - Combinations of biological sciences (6061) - Human biology (6064) - Agricultural biology (5015) - Agricultural biochemistry (5016) - Agricultural botany (5017) - Animal genetics (5020) - Plant taxonomy (5021) - Combinations with Biological Sciences	
✗	✓	Medicine, dentistry and veterinary science	- Medicine (2003) - Medical certificate (2017) - Dentistry (2004) - Veterinary sciences (5031)	- Medicine (B9SBDG31) - Dentistry (B9SBDG16) - Veterinary science (B9SBDG46)
✗	✓	Agriculture, forestry and other	Agriculture and Forestry - Agricultural chemistry (5001) - Agriculture (5002) - Agricultural economics (5003) - Agricultural biology (5015) - Agricultural biochemistry (5016) - Agricultural botany (5017) - Agricultural science including rural science (5018) - Agricultural zoology (5019) - Animal technicians (5033) - Agricultural combinations (5034) - Agricultural and other group combinations (5035) - Animal nursing (5032) - Other animal care (5036) - Forestry (5024) - Arboriculture (5025) - Sylviculture (5026) - Forestry management (5027) - Timber felling and sawmilling (5028)	Agriculture and Forestry - Agriculture and forestry (B9SBDG01) Other - Geography and environment studies (B9SBDG24)

			- Timber merchanting (5029) - Tree nursery work (5030) Other - Geography (7006) - Environmental sciences (6053) - Air Pollution (2005) - Hydrodynamics (6038) - Science laboratory technician (6057) - General Science (6056) - Combinations of Science with other subjects (6062)	
✗	✓	Architecture, building and planning	Architecture - Architecture (11001) - Landscape architecture (11002) - Naval architecture and shipbuilding (3058) Town and Country Planning - Land use (11003) - Town and country Planning (11004) - Rural and regional resources planning (11006) Building - Building (4001) - Conservation (of buildings) (11005) - Building technology (4006) Surveying - Surveying / Valuation (4082) - Mine surveying (4083) Quantity surveying (4084)	- Architecture (B9SBDG06) Building and town and country planning (B9SBDG09)
✗	✓	Nursing and other subjects allied to	- Nursing (medical) (2019) - Nursery nursing (2020) - Pre-nursing (2025)	- Nursing (B9SBDG34) - Pharmacy and pharmacology (B9SBDG35) - Sports science (B9SBDG44)

		medicine (including psychology)	- Health visitors (2014) - Public-Health inspection (2026) - Other health subjects (2032) - Health and safety (2033) - Health combinations (2034) - Health combined with other groups (2035) - First Aid (2038) - Chiropody (2007) - Dental nurse and assistants (2009) - Dental technicians (2010) - Dietetics (2011) - Dispensing assistants-opticians-technicians (2012) - Medic laboratory technicians (2018) - Nutrition (2021) - Ophthalmic opticians (2022) - Physiological Measurement technician (2023) - Physiotherapy (2024) - Radiography (2028) - Speech therapy (2030) - Surgical laboratory technicians (2031) - Pharmacy (2001) - Pharmacology (2002) - Cardiography (2006) - Psychology (7018) - Physiological Measurement technician (2023) - Occupational therapy (2036)	- Psychology (B9SBDG39)

Appendix B: Supplementary Appendix, Chapter 5

Table B1: The effects of field of study, gender, and the control variables on the likelihood of being found in STEM work at labour market entry (AMEs)

	Core STEM		*Broad STEM*	
Dependent Variable: STEM Work	**Model 1**	**Model 2**	**Model 1**	**Model 2**
STEM degree	0.35***	0.41***	0.41***	0.40***
	(0.03)	(0.04)	(0.02)	(0.03)
Female	-0.11***	-0.08***	-0.09***	-0.10***
	(0.02)	(0.02)	(0.02)	(0.02)
STEM degree*Female		-0.10*		0.04
		(0.06)		(0.05)
Number of good A-Levels (A-C)	-0.00	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Has STEM A-Level	0.01	0.01	-0.01	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)
Type of University (Ref: Russel Group)				
Other University	-0.00	-0.00	0.01	0.02
	(0.02)	(0.02)	(0.03)	(0.03)
Post92 University	0.04	0.04	0.05*	0.06*
	(0.03)	(0.03)	(0.03)	(0.03)
Degree Class (Ref: Pass)				
First	0.11**	0.10**	-0.00	-0.01
	(0.05)	(0.05)	(0.05)	(0.05)
Upper Second	0.05	0.05	-0.04	-0.04
	(0.04)	(0.04)	(0.04)	(0.04)
Lower Second	0.02	0.02	-0.10**	-0.10**
	(0.04)	(0.04)	(0.04)	(0.04)
Third	0.01	0.01	-0.14***	-0.14***
	(0.05)	(0.05)	(0.05)	(0.05)
Has postgraduate degree	0.09***	0.09***	0.08***	0.08***
	(0.03)	(0.03)	(0.03)	(0.03)
Parent in STEM	0.11***	0.11***	0.14***	0.14***
	(0.04)	(0.04)	(0.04)	(0.03)
Parental Education (Ref: Neither has any qualifications)				
One secondary or lower qualification, one no qualification	0.03	0.03	0.05	0.04
	(0.04)	(0.04)	(0.04)	(0.04)
Both secondary or lower qualification	-0.00	-0.00	0.01	0.00
	(0.03)	(0.03)	(0.04)	(0.04)
One higher secondary or lower tertiary qualification, one lower qualification	0.03	0.02	0.03	0.02
	(0.04)	(0.04)	(0.04)	(0.04)
Both higher secondary or lower tertiary	-0.01	-0.01	-0.02	-0.02
	(0.05)	(0.05)	(0.05)	(0.05)
One degree-level qualification, one lower qualification	0.03	0.03	0.00	0.00
	(0.04)	(0.04)	(0.04)	(0.04)
Both degree-level qualification	-0.04	-0.04	0.00	0.00
	(0.05)	(0.05)	(0.05)	(0.05)

Parental Class (Ref: Routine Occupations)				
Higher managerial and professional occupations	-0.07	-0.07	-0.05	-0.05
	(0.06)	(0.06)	(0.06)	(0.06)
Lower managerial and professional occupations	-0.03	-0.03	0.01	0.01
	(0.06)	(0.06)	(0.06)	(0.06)
Intermediate occupations	-0.03	-0.04	0.01	0.00
	(0.05)	(0.05)	(0.05)	(0.05)
Small Employers and Own account workers	-0.05	-0.05	-0.03	-0.03
	(0.06)	(0.06)	(0.06)	(0.06)
Lower technical and supervisory occupations	0.00	0.00	0.01	0.00
	(0.06)	(0.06)	(0.06)	(0.06)
Semi-routine occupations	-0.05	-0.04	-0.04	-0.04
	(0.05)	(0.05)	(0.06)	(0.06)
Parental Income	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Migration Status	0.03	0.03	0.10*	0.10
	(0.06)	(0.06)	(0.06)	(0.06)
Person of Colour	0.00	0.00	0.02	0.02
	(0.04)	(0.04)	(0.04)	(0.04)
Age at Labour Market Entry	0.00	0.00	0.01	0.01
	(0.00)	(0.00)	(0.00)	(0.00)
Full-Time Work	0.08*	0.08*	0.10**	0.10**
	(0.05)	(0.05)	(0.04)	(0.04)
Number of Observations	1,373	1,373	1,819	1,819

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table B2: The effects of field of study, gender, and the control variables on the likelihood of being found in STEM work across the work life course (log-odds)

	Core STEM			*Broad STEM*		
Dependent Variable: STEM Work	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
STEM degree	11.11***	12.38***	12.56***	10.78***	11.19***	11.60***
	(0.99)	(0.93)	(0.78)	(0.49)	(0.65)	(0.68)
Female	-4.32***	-2.32***	-3.18***	-2.48***	-2.29***	-3.35***
	(1.46)	(0.55)	(0.63)	(0.40)	(0.43)	(0.52)
Time Elapsed since LM Entry	0.07***	0.07***	0.05	0.06***	0.06***	0.08**
	(0.02)	(0.02)	(0.06)	(0.02)	(0.02)	(0.04)
Time Elapsed since LM Entry^2	-0.00***	-0.00***	-0.00	-0.00***	-0.00***	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
STEM degree*Female		-5.17***	-2.87**		-0.87	1.43
		(1.34)	(1.13)		(1.25)	(1.62)
STEM degree *Time Elapsed since LM Entry			0.06			0.01
			(0.07)			(0.05)
STEM degree*Time Elapsed since LM Entry^2			-0.01			-0.00
			(0.00)			(0.00)
Female*Time Elapsed since LM Entry			0.17*			0.14**
			(0.09)			(0.06)
Female*Time Elapsed since LM Entry^2			-0.01			-0.00
			(0.00)			(0.00)
STEM degree*Female*Time Elapsed since LM Entry			-0.53***			-0.38***
			(0.15)			(0.10)
STEM degree*Female*Time Elapsed since LM Entry^2			0.02**			0.01***
			(0.01)			(0.00)
Number of good A-Levels (A-C)	-0.22	-0.21	-0.21	0.01	0.01	0.03
	(0.25)	(0.22)	(0.22)	(0.19)	(0.19)	(0.19)
Has STEM A-Level	0.00	0.12	0.13	-0.83*	-0.76*	-0.72
	(0.49)	(0.45)	(0.46)	(0.43)	(0.44)	(0.44)
Type of University (Ref: Russel Group)						
Other University	0.10	-0.08	-0.09	0.47	0.46	0.47

	(0.71)	(0.61)	(0.62)	(0.56)	(0.54)	(0.54)
Post92 University	1.65**	1.22*	1.25*	1.30**	1.30**	1.26**
	(0.83)	(0.69)	(0.69)	(0.57)	(0.57)	(0.57)
Degree Class (Ref: Pass)						
First	2.69*	2.04	2.07*	-1.82**	-1.76**	-1.71**
	(1.62)	(1.37)	(1.19)	(0.90)	(0.89)	(0.87)
Upper Second	2.05	1.51	1.53	-2.50***	-2.43***	-2.33***
	(1.45)	(1.21)	(0.97)	(0.65)	(0.66)	(0.66)
Lower Second	1.62	1.12	1.17	-3.14***	-3.04***	-2.91***
	(1.42)	(1.20)	(0.96)	(0.71)	(0.73)	(0.75)
Third	2.83	1.81	1.78	-2.76**	-2.68**	-2.52**
	(1.77)	(1.51)	(1.32)	(1.20)	(1.24)	(1.22)
Has postgraduate degree	1.14***	1.00**	1.03**	0.20	0.20	0.17
	(0.41)	(0.40)	(0.40)	(0.29)	(0.30)	(0.31)
Parent in STEM	1.85**	1.58**	1.54**	1.73**	1.73**	1.70**
	(0.79)	(0.76)	(0.75)	(0.72)	(0.72)	(0.72)
Parental Education (Ref: Neither has any qualifications)						
One secondary or lower qualification, one no qualification	0.03	0.25	0.25	1.07	1.04	0.99
	(1.01)	(0.89)	(0.91)	(0.81)	(0.80)	(0.80)
Both secondary or lower qualification	-0.83	-0.43	-0.43	0.44	0.41	0.42
	(0.95)	(0.81)	(0.82)	(0.76)	(0.75)	(0.74)
One higher secondary or lower tertiary qualification, one lower qualification	-0.61	-0.26	-0.24	-0.14	-0.16	-0.10
	(1.09)	(0.95)	(0.96)	(0.84)	(0.83)	(0.81)
Both higher secondary or lower tertiary	0.12	0.43	0.47	0.44	0.43	0.47
	(1.48)	(1.28)	(1.28)	(1.22)	(1.20)	(1.17)
One degree-level qualification, one lower qualification	-0.06	0.18	0.23	-0.18	-0.20	-0.16
	(1.05)	(0.89)	(0.91)	(0.84)	(0.82)	(0.80)
Both degree-level qualification	-1.45	-1.06	-1.05	-0.04	-0.10	-0.09
	(1.33)	(1.18)	(1.17)	(1.05)	(1.04)	(1.07)
Parental Class (Ref: Routine Occupations)						
Higher managerial and professional occupations	-0.72	-0.61	-0.61	1.07	-0.36	-0.29
	(1.40)	(1.31)	(1.32)	(0.81)	(1.18)	(1.15)

Lower managerial and professional occupations	-0.19	-0.04	-0.01	0.44	0.37	0.44
	(1.30)	(1.20)	(1.22)	(0.76)	(1.09)	(1.05)
Intermediate occupations	-0.47	-0.46	-0.47	-0.14	0.31	0.33
	(1.20)	(1.13)	(1.16)	(0.84)	(0.95)	(0.95)
Small Employers and Own account workers	-1.08	-0.88	-0.85	0.44	-0.66	-0.59
	(1.43)	(1.29)	(1.29)	(1.22)	(1.28)	(1.29)
Lower technical and supervisory occupations	1.38	1.26	1.25	-0.18	0.84	0.87
	(1.39)	(1.23)	(1.28)	(0.84)	(1.08)	(1.08)
Semi-routine occupations	-0.32	-0.37	-0.34	-0.04	-0.61	-0.57
	(1.33)	(1.23)	(1.26)	(1.05)	(1.09)	(1.08)
Parental Income	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age at LM entry	-0.00	0.03	0.03	0.26***	0.26***	0.25***
	(0.11)	(0.10)	(0.11)	(0.08)	(0.09)	(0.09)
Migration Status	0.90	0.82	0.79	1.85	2.02	1.98
	(1.87)	(1.56)	(1.57)	(1.51)	(1.30)	(1.29)
Person of Colour	0.09	0.14	0.14	0.62	0.63	0.64
	(0.96)	(0.85)	(0.87)	(0.87)	(0.84)	(0.86)
Full-Time Work	2.62***	2.61***	2.32***	0.87***	0.88***	0.96***
	(0.32)	(0.32)	(0.33)	(0.16)	(0.16)	(0.17)
Intercept	-15.98***	-16.74***	-16.27***	-14.45***	-14.52***	-14.98***
	(3.42)	(3.14)	(3.27)	(2.45)	(2.44)	(2.50)
Number of Observations	23,017	23,017	23,017	30,906	30,906	30,906
Number of Groups	1,470	1,470	1,470	1,859	1,859	1,859

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table B3: The effects of field of study, gender, family factors, pay and promotion and teenage career aspirations on the likelihood of being found in Core STEM work over the work life course (log-odds)

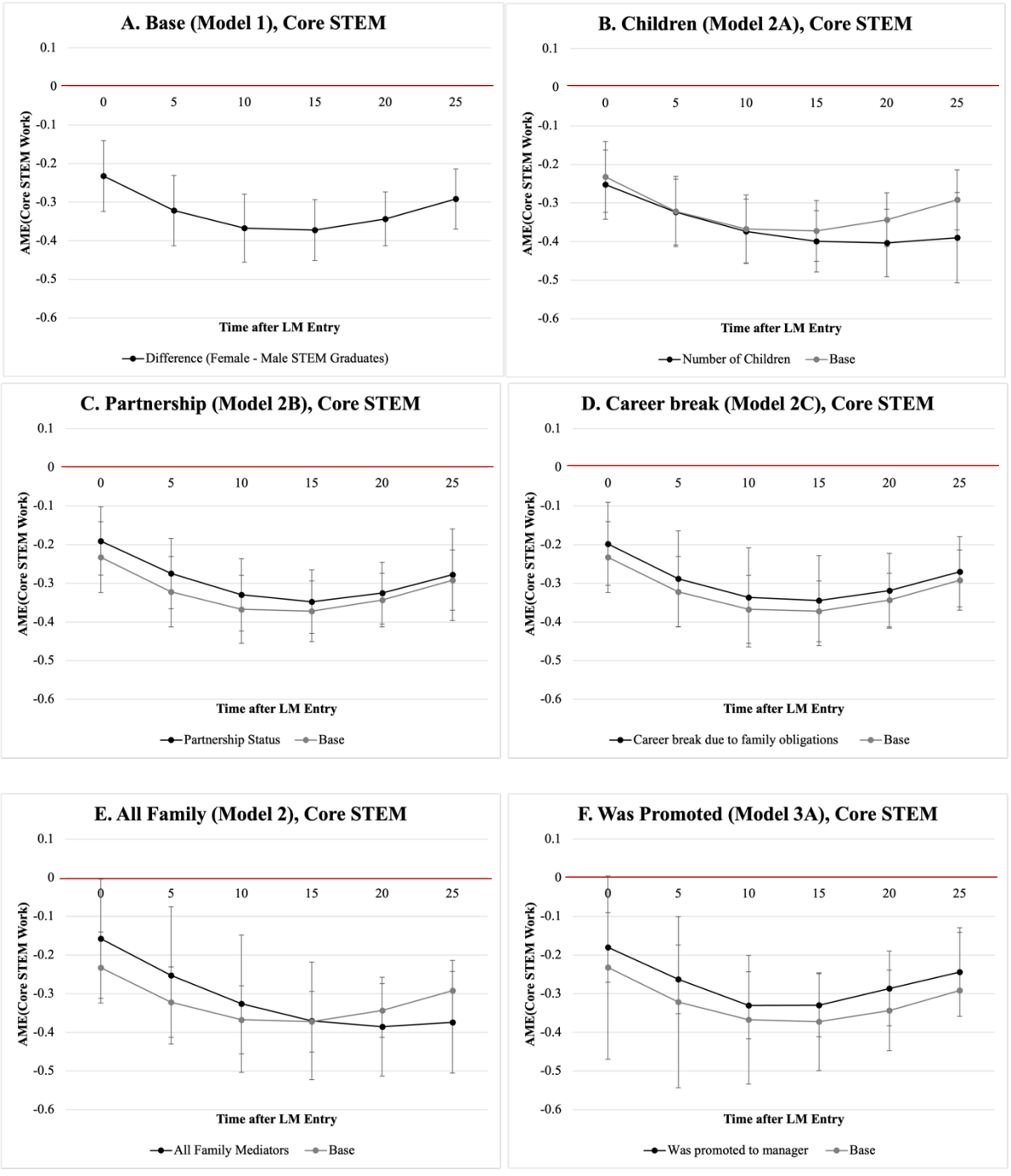
Dependent Variable: Core STEM Work	Model 1	Model 2A	Model 2B	Model 2C	Model 2	Model 3A	Model 3B	Model 3	Model 4A	Model 4B	Model 4	Model 5
STEM degree	12.56***	12.44***	12.41***	12.28***	13.03***	16.06***	12.89***	14.55***	12.30***	12.16***	12.04***	17.53***
	(0.78)	(0.92)	(0.74)	(0.70)	(0.79)	(2.58)	(2.87)	(1.92)	(0.74)	(0.79)	(0.80)	(3.90)
Female	-3.18***	-3.20***	-3.87***	-3.15***	-3.33***	-8.74***	-3.69***	-9.36***	-3.22***	-3.05***	-3.11***	-15.65***
	(0.63)	(0.69)	(0.67)	(0.64)	(0.74)	(2.78)	(1.33)	(3.41)	(0.65)	(0.66)	(0.71)	(5.32)
STEM degree*Female	-2.87**	-2.94**	-1.39	-2.22*	-1.10	0.15	-1.52	0.63	-2.66**	-2.62**	-2.48*	8.08
	(1.13)	(1.31)	(1.17)	(1.24)	(1.97)	(4.46)	(2.63)	(3.99)	(1.13)	(1.28)	(1.35)	(5.61)
Time Elapsed since LM Entry	0.05	0.11*	0.06	0.05	0.15**	-0.15	0.11	0.01	0.05	0.05	0.05	0.19
	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.21)	(0.12)	(0.21)	(0.06)	(0.06)	(0.06)	(0.34)
Time Elapsed since LM Entry2	-0.00	-0.00	-0.00	-0.00	-0.00	0.01	-0.00	0.00	-0.00	-0.00	-0.00	-0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)
STEM degree *Time Elapsed since LM Entry	0.06	-0.00	0.10	0.06	-0.01	0.33	-0.08	0.02	0.06	0.06	0.05	-0.17
	(0.07)	(0.08)	(0.08)	(0.07)	(0.09)	(0.24)	(0.16)	(0.28)	(0.07)	(0.07)	(0.07)	(0.44)
STEM degree*Time Elapsed since LM Entry2	-0.01	-0.00	-0.01*	-0.01	-0.00	-0.02**	0.00	-0.01	-0.01	-0.00	-0.00	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.02)
Female*Time Elapsed since LM Entry	0.17*	0.12	0.22**	0.16*	0.16	0.82***	0.31	0.53	0.17*	0.17*	0.17*	1.63**
	(0.09)	(0.10)	(0.10)	(0.09)	(0.11)	(0.29)	(0.23)	(0.35)	(0.09)	(0.09)	(0.09)	(0.67)
Female*Time Elapsed since LM Entry2	-0.01	-0.01	-0.01	-0.01	-0.01	-0.03***	-0.01	-0.02	-0.01	-0.01	-0.01	-0.06**
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.03)
STEM degree*Female*Time Elapsed since LM Entry	-0.53***	-0.43**	-0.63***	-0.53***	-0.59***	-1.35**	-0.71**	-0.75	-0.53***	-0.52***	-0.52***	-1.93**
	(0.15)	(0.18)	(0.17)	(0.15)	(0.20)	(0.53)	(0.34)	(0.56)	(0.15)	(0.15)	(0.15)	(0.86)
STEM degree*Female*Time Elapsed since LM Entry2	0.02**	0.01	0.02***	0.02**	0.01	0.05**	0.03*	0.03	0.02**	0.02**	0.02**	0.06*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.04)
Number of children (T-1)		-0.59***			-0.55***							-0.50
		(0.09)			(0.10)							(0.34)
Partnership Status (T-1, Ref: Not in partnership)												
Cohabiting			-0.28*		-0.46***							-1.06
			(0.16)		(0.17)							(0.80)
Married			-0.71***		-0.62***							-1.46**
			(0.15)		(0.18)							(0.70)
Career break due to family obligations				-1.35*	-1.93*							-4.10*
				(1.33)	(1.31)							(2.27)
Was promoted to manager						-0.66		-0.62				-0.32

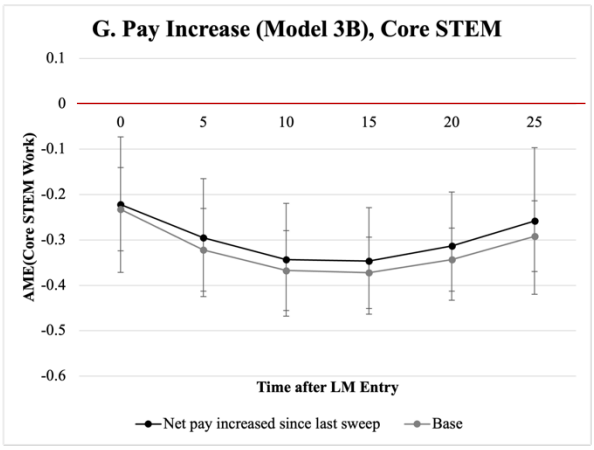
						(0.49)		(2.03)				(2.71)
Substantial pay increase since last sweep							-1.05***	-1.28***				-1.81*
							(0.38)	(0.47)				(0.94)
Health Career Aspiration									0.15		0.20	1.06
									(0.78)		(0.84)	(1.73)
Technology Career Aspiration										1.56**	1.60**	2.60*
										(0.62)	(0.63)	(1.53)
Number of good A-Levels (A-C)	-0.21	-0.20	-0.24	-0.22	-0.26	-0.17	-0.19	-0.18	-0.21	-0.22	-0.23	-0.39
	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)	(0.28)	(0.24)	(0.24)	(0.22)	(0.23)	(0.23)	(0.44)
Has STEM A-Level	0.13	0.37	0.08	0.14	0.37	-0.69	-0.36	-0.59	0.13	0.09	0.08	-0.44
	(0.46)	(0.48)	(0.47)	(0.44)	(0.50)	(0.70)	(0.54)	(0.61)	(0.46)	(0.47)	(0.47)	(0.96)
Type of University (Ref: Russel Group)												
Other University	-0.09	-0.21	-0.18	-0.11	-0.38	-0.15	-0.10	-0.57	-0.11	-0.08	-0.08	-0.43
	(0.62)	(0.62)	(0.64)	(0.59)	(0.67)	(0.89)	(0.73)	(0.80)	(0.63)	(0.64)	(0.65)	(1.20)
Post92 University	1.25*	1.55**	1.38*	1.28*	1.55**	2.00	1.37*	1.41*	1.23*	1.35*	1.36*	3.06**
	(0.70)	(0.62)	(0.75)	(0.67)	(0.68)	(1.25)	(0.78)	(0.86)	(0.71)	(0.74)	(0.78)	(1.49)
Degree Class (Ref: Pass)												
First	2.06*	3.14**	2.65**	2.15*	2.57**	0.32	0.65	0.63	1.98	2.02	2.07	1.58
	(1.19)	(1.54)	(1.22)	(1.23)	(1.20)	(1.67)	(1.65)	(1.38)	(1.28)	(1.55)	(1.39)	(2.33)
Upper Second	1.53	1.69	1.49	1.60	1.10	0.82	0.81	0.30	1.49	1.58	1.64	0.31
	(0.97)	(1.42)	(1.04)	(1.08)	(1.03)	(1.43)	(1.44)	(1.22)	(1.05)	(1.44)	(1.25)	(1.74)
Lower Second	1.17	1.48	1.28	1.27	0.89	1.05	0.94	0.80	1.12	1.17	1.21	0.81
	(0.96)	(1.40)	(1.04)	(1.05)	(1.04)	(1.46)	(1.44)	(1.21)	(1.04)	(1.43)	(1.24)	(1.77)
Third	1.78	2.43	0.90	1.85	0.97	3.27	2.17	2.47	1.75	1.96	2.06	2.58
	(1.33)	(1.76)	(1.48)	(1.33)	(1.53)	(2.01)	(2.01)	(1.62)	(1.40)	(1.76)	(1.60)	(2.54)
Has postgraduate degree	1.03**	1.02**	1.10***	1.02***	0.91*	1.48*	1.50**	1.11	1.04**	1.07***	1.10***	1.87
	(0.40)	(0.43)	(0.41)	(0.39)	(0.47)	(0.87)	(0.59)	(0.69)	(0.40)	(0.40)	(0.41)	(1.32)
Parent in STEM	1.54**	1.64**	1.78**	1.50**	1.69**	0.81	0.54	0.15	1.53**	1.60**	1.65**	-0.64
	(0.75)	(0.81)	(0.75)	(0.72)	(0.85)	(0.97)	(0.84)	(0.97)	(0.75)	(0.78)	(0.75)	(1.69)
Parental Education (Ref: Neither has any qualifications)												
One secondary or lower qualification, one no qualification	0.25	0.63	0.77	0.20	0.93	-0.77	-0.71	-1.10	0.25	0.05	0.03	-1.70
	(0.92)	(1.06)	(1.00)	(0.89)	(1.12)	(1.23)	(1.02)	(1.24)	(0.91)	(0.98)	(0.99)	(2.13)
Both secondary or lower qualification	-0.42	-0.17	-0.08	-0.48	-0.10	-0.80	-1.00	-1.16	-0.43	-0.44	-0.47	-1.08
	(0.83)	(1.02)	(0.91)	(0.83)	(1.10)	(1.27)	(0.94)	(1.10)	(0.82)	(0.88)	(0.90)	(2.29)
One higher secondary or lower tertiary qualification, one lower qualification	-0.23	0.08	0.31	-0.27	0.19	-1.52	-1.29	-1.69	-0.25	-0.25	-0.30	-1.85
	(0.97)	(1.08)	(1.04)	(0.94)	(1.19)	(1.43)	(1.06)	(1.30)	(0.97)	(1.03)	(1.07)	(2.42)
Both higher secondary or lower tertiary	0.49	1.34	0.64	0.48	1.67	0.56	0.30	0.35	0.47	0.56	0.54	1.64

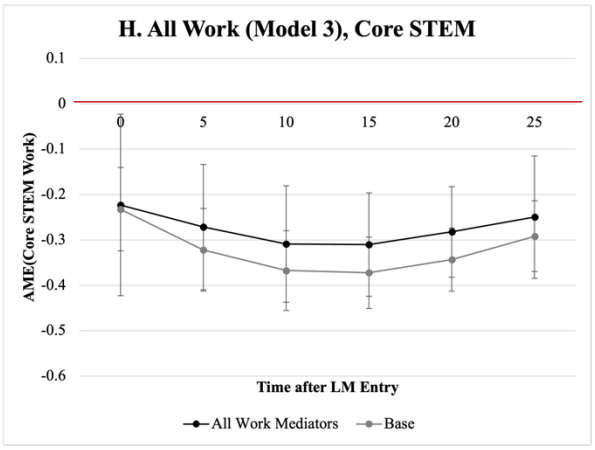
	(1.29)	(1.47)	(1.33)	(1.25)	(1.57)	(1.60)	(1.48)	(1.55)	(1.30)	(1.32)	(1.36)	(2.71)
One degree-level qualification, one lower qualification	0.24	0.81	0.46	0.26	0.86	-0.29	-0.75	-0.72	0.22	0.18	0.15	-0.14
	(0.92)	(1.15)	(1.02)	(0.92)	(1.27)	(1.22)	(1.03)	(1.18)	(0.92)	(0.97)	(0.99)	(2.67)
Both degree-level qualification	-1.04	-0.54	-0.71	-1.02	-0.50	-1.93	-1.92	-1.48	-1.04	-1.19	-1.22	-1.96
	(1.17)	(1.42)	(1.28)	(1.19)	(1.55)	(2.05)	(1.42)	(1.50)	(1.18)	(1.23)	(1.24)	(3.26)
Parental Class (Ref: Routine Occupations)												
Higher managerial and professional occupations	-0.62	0.11	-0.86	-0.60	-0.04	1.82	0.58	1.59	-0.59	-0.57	-0.55	2.89
	(1.31)	(1.57)	(1.46)	(1.35)	(1.56)	(2.25)	(1.46)	(1.84)	(1.29)	(1.32)	(1.37)	(2.96)
Lower managerial and professional occupations	-0.02	0.23	-0.56	0.01	-0.04	1.73	0.34	1.50	0.00	-0.00	0.03	0.86
	(1.21)	(1.38)	(1.38)	(1.26)	(1.41)	(2.19)	(1.38)	(1.65)	(1.20)	(1.23)	(1.25)	(2.61)
Intermediate occupations	-0.47	0.13	-1.27	-0.52	-0.77	1.74	0.56	1.27	-0.44	-0.44	-0.39	1.33
	(1.15)	(1.36)	(1.31)	(1.15)	(1.40)	(2.22)	(1.31)	(1.64)	(1.14)	(1.16)	(1.20)	(2.71)
Small Employers and Own account workers	-0.87	0.08	-1.07	-0.83	-0.30	2.19	0.01	1.65	-0.85	-0.94	-0.97	3.41
	(1.30)	(1.50)	(1.45)	(1.32)	(1.51)	(2.46)	(1.51)	(1.84)	(1.29)	(1.28)	(1.32)	(2.68)
Lower technical and supervisory occupations	1.24	2.52*	1.12	1.20	2.16	4.41*	2.41*	3.97**	1.26	1.35	1.40	5.86*
	(1.28)	(1.52)	(1.42)	(1.29)	(1.50)	(2.65)	(1.39)	(1.81)	(1.28)	(1.34)	(1.36)	(3.10)
Semi-routine occupations	-0.35	0.55	-1.14	-0.40	-0.18	2.47	0.59	1.74	-0.34	-0.24	-0.23	2.29
	(1.26)	(1.52)	(1.38)	(1.26)	(1.49)	(2.09)	(1.37)	(1.72)	(1.24)	(1.27)	(1.30)	(2.84)
Parental Income	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Age at LM entry	0.03	0.12	0.03	0.01	0.14	-0.04	0.08	0.06	0.03	0.05	0.05	0.28
	(0.11)	(0.11)	(0.11)	(0.11)	(0.12)	(0.15)	(0.11)	(0.14)	(0.11)	(0.11)	(0.11)	(0.25)
Migration Status	0.74	1.39	0.62	0.69	0.57	2.70	1.05	1.84	0.68	0.74	0.72	0.64
	(1.65)	(1.83)	(1.65)	(1.60)	(1.92)	(1.97)	(1.68)	(1.80)	(1.65)	(1.73)	(1.68)	(3.67)
Person of Colour	0.14	-0.48	0.08	0.13	-0.49	-0.31	-0.34	-0.58	0.14	0.21	0.24	-0.96
	(0.87)	(1.04)	(0.97)	(0.85)	(1.09)	(1.04)	(0.99)	(1.16)	(0.88)	(0.88)	(0.88)	(2.04)
Full-Time Work	2.32***	1.86***	3.20***	2.32***	2.93***	-0.97	1.63**	0.35	2.32***	2.32***	2.32***	1.98
	(0.33)	(0.35)	(0.42)	(0.33)	(0.44)	(0.66)	(0.71)	(0.78)	(0.33)	(0.33)	(0.33)	(1.54)
Intercept	-16.26***	-19.09***	-17.72***	-15.73***	-20.93***	-11.66**	-15.51***	-12.57***	-16.05***	-17.28***	-17.41***	-22.63***
	(3.29)	(3.27)	(3.26)	(3.19)	(3.43)	(4.65)	(4.27)	(4.59)	(3.40)	(3.39)	(3.29)	(6.56)
Number of Observations	23,017	17,929	20,830	23,017	17,111	15,919	5,221	4,005	23,017	23,017	23,017	3,085
Number of Groups	1,470	1,185	1,342	1,470	1,131	1,261	1,333	1,194	1,470	1,470	1,470	991

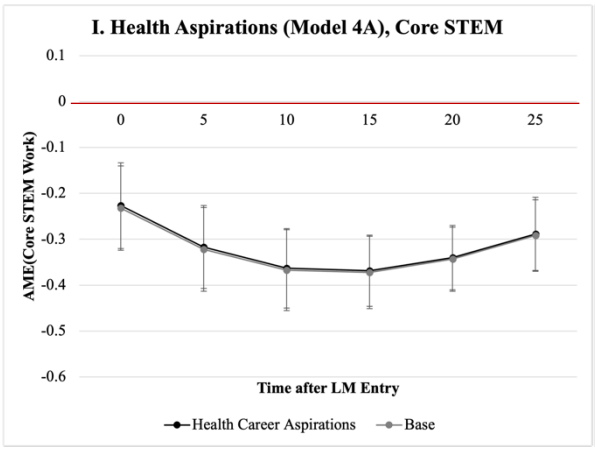
Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10

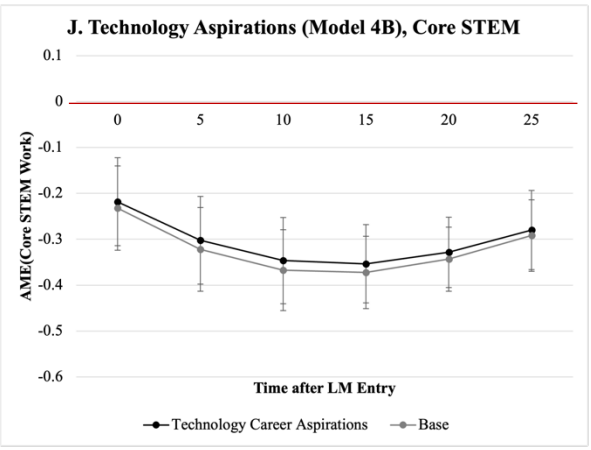
Figure B1: The gender difference in the average marginal effect of having a STEM degree on working in STEM across the work life course by included mediator(s) (based on models shown in table B3)

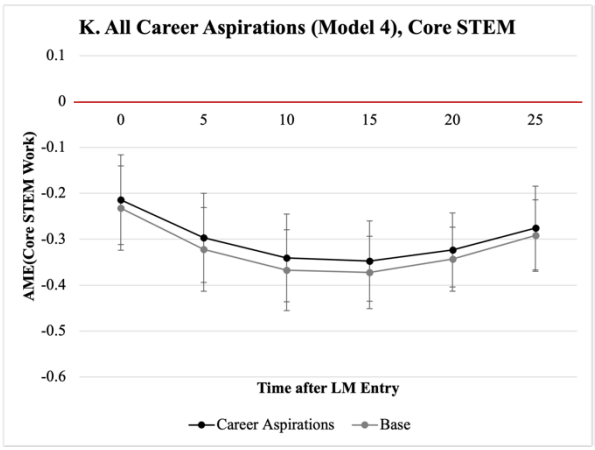



G. Pay Increase (Model 3B), Core STEM
AME(Core STEM Work)
Time after LM Entry
Net pay increased since last sweep
Base


H. All Work (Model 3), Core STEM
AME(Core STEM Work)
Time after LM Entry
All Work Mediators
Base


I. Health Aspirations (Model 4A), Core STEM
AME(Core STEM Work)
Time after LM Entry
Health Career Aspirations
Base


J. Technology Aspirations (Model 4B), Core STEM
AME(Core STEM Work)
Time after LM Entry
Technology Career Aspirations
Base


K. All Career Aspirations (Model 4), Core STEM
AME(Core STEM Work)
Time after LM Entry
Career Aspirations
Base

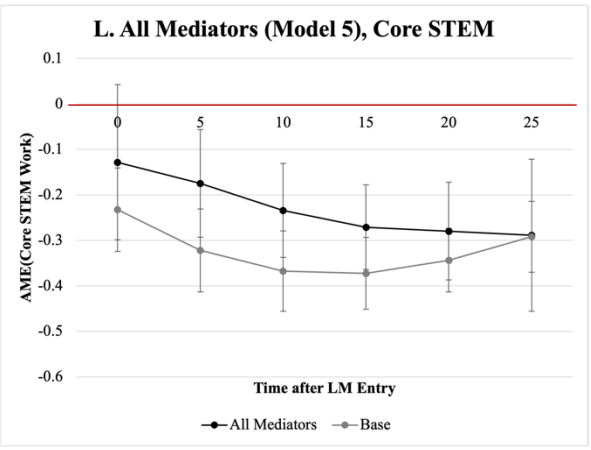
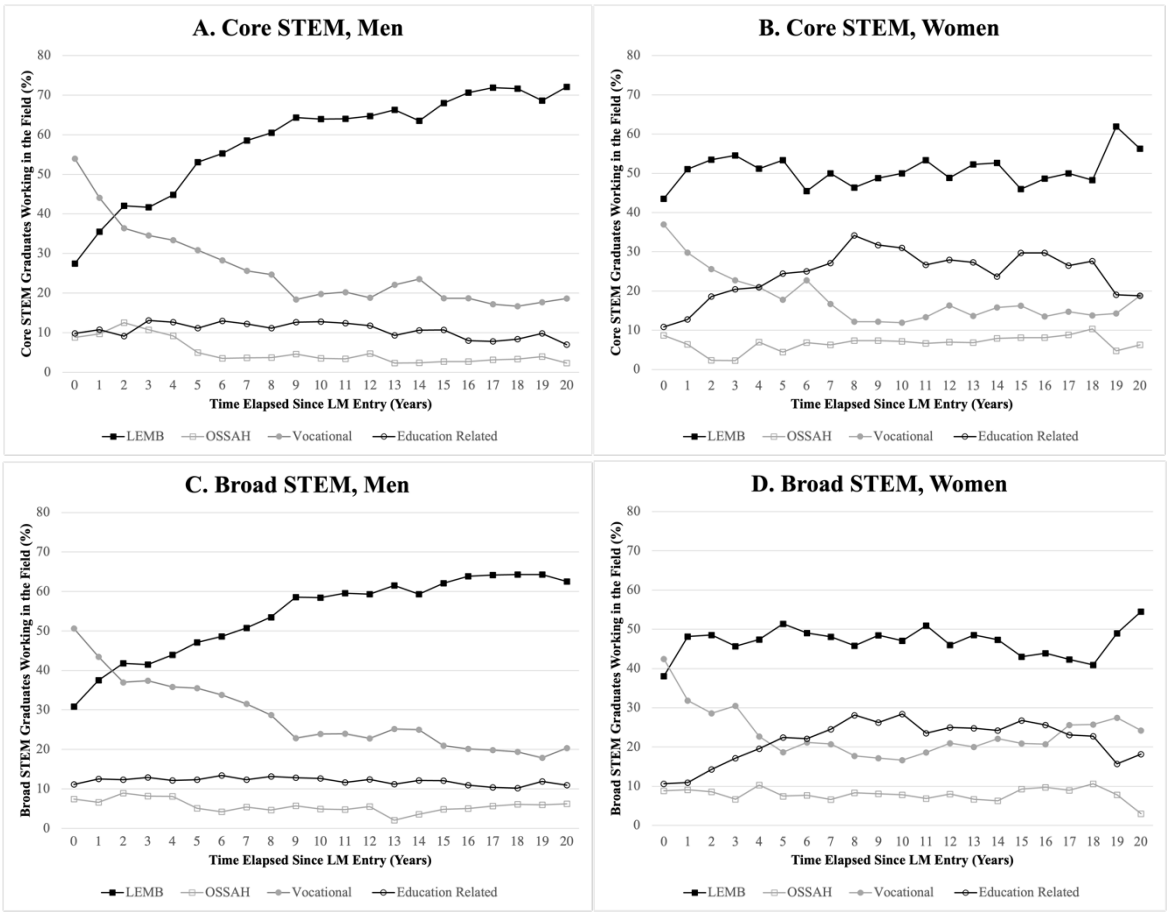

L. All Mediators (Model 5), Core STEM
AME(Core STEM Work)
Time after LM Entry
All Mediators
Base

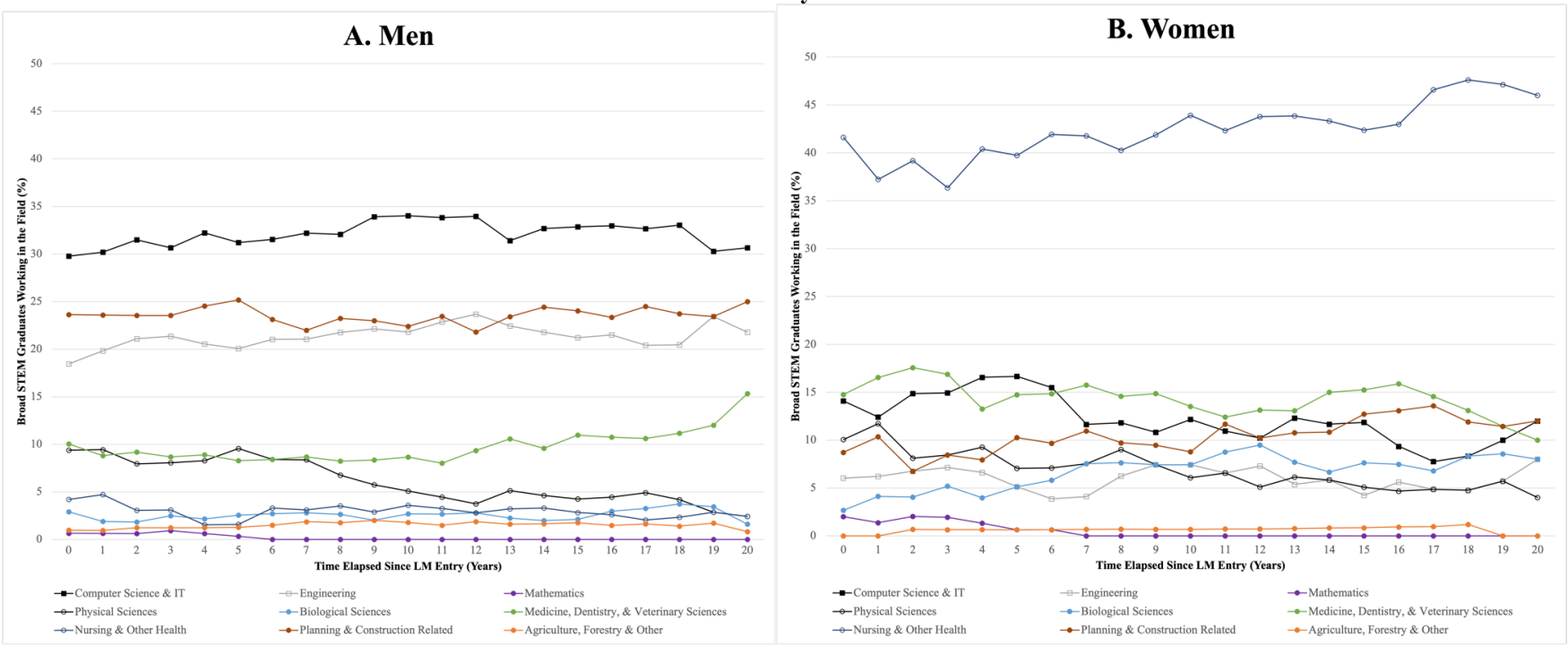
Figure B2: The destinations of STEM graduates in non-STEM fields based on descriptive statistics by gender, time elapsed since labour market entry and definition of STEM



Note: The first two categories are based on work by Walker and Zhu (2011): (i) LEMB (Law, Economics, Management, and Business)[49] and (ii) OSSAH (Other social sciences, arts, and humanities which includes languages). Additionally, I present (iii) Vocational Fields and (iv) Education-related Fields (i.e., teaching / academia). Core STEM: n= 180 for men, n=80 for women. Broad STEM: n= 283 for men, n=185 for women. Although some respondents are observed for longer, I only present information up to T20 here due to small sample size.

[49] The LEMB category is adapted from Walker and Zhu's (2011) 'LEM' category and includes other subjects associated with Business and Management such as Administration and Finance

Figure B3: The destinations of graduates in individual STEM fields based on descriptive statistics by gender and time elapsed since labour market entry



Note: Due to small sample sizes, this figure shows the STEM destinations of *all* graduates, STEM and non-STEM alike; n= 492 for men, n=291 for women. Although some respondents are observed for longer, I only present information up to T20 here due to small sample size.

Appendix C: Supplementary Appendix, Chapter 6

C1. Full Regression Results

Table C1: The average marginal effects of parental field of occupation, field of study, school level factors, university level factors, parental help factors and control variables on the likelihood of being found in Broad STEM work at labour market entry

Dependent Variable: Broad STEM Work	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
STEM Parent	0.18***	0.14***	0.13***	0.17***	0.18***	0.14***	0.18***	0.14***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Childhood Maths Test Score				0.00*				0.00
				(0.00)				(0.00)
Number of good A-Levels (A-C)				-0.01				-0.00
				(0.01)				(0.01)
Has STEM A-Level				0.12***				-0.01
				(0.02)				(0.02)
Health Career Aspiration					0.13***			0.07**
					(0.04)			(0.03)
Technology Career Aspiration					0.10***			0.04*
					(0.03)			(0.03)
STEM Degree		0.34***	0.40***			0.34***		0.33***
		(0.01)	(0.02)			(0.01)		(0.02)
STEM Parent*STEM Degree			0.04					
			(0.06)					
Type of University (Ref: Russel Group)								
Other University						0.02		0.01
						(0.03)		(0.02)
Post92 University						0.05**		0.05*
						(0.03)		(0.03)
Degree Class (Ref: Pass)								
First						-0.01		-0.01
						(0.05)		(0.05)
Upper Second						-0.04		-0.05

						(0.04)		(0.04)
Lower Second						-0.10***		-0.10***
						(0.04)		(0.04)
Third						-0.15***		-0.15***
						(0.05)		(0.05)
Has postgraduate degree						0.08***		0.09***
						(0.03)		(0.03)
Parental Advice							0.04	0.02
							(0.03)	(0.03)
Parental Recommendation							0.00	0.04
							(0.06)	(0.05)
Parental Direct Employment							0.01	0.01
							(0.05)	(0.04)
Parental Contacts							-0.01	-0.03
							(0.04)	(0.03)
Parental Education (Ref: Neither has any qualifications)								
One secondary or lower qualification, one no qualification	0.04	0.05	0.05	0.02	0.03	0.05	0.04	0.04
	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)
Both secondary or lower qualification	0.01	0.00	0.00	-0.01	-0.00	0.01	0.01	-0.00
	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
One higher secondary or lower tertiary qualification, one lower qualification	0.05	0.02	0.02	0.03	0.04	0.02	0.05	0.02
	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)
Both higher secondary or lower tertiary	0.00	-0.02	-0.02	-0.01	0.00	-0.02	0.00	-0.02
	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)	(0.05)
One degree-level qualification, one lower qualification	0.01	-0.01	-0.01	-0.02	0.01	0.00	0.01	-0.00
	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)
Both degree-level qualification	0.01	-0.01	-0.01	-0.03	0.00	-0.00	0.01	-0.00
	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)	(0.05)
Parental Class (Ref: Routine Occupations)								
Higher managerial and professional	-0.03	-0.03	-0.03	-0.05	-0.01	-0.05	-0.03	-0.04

occupations								
	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)
Lower managerial and professional occupations	0.01	0.02	0.02	-0.01	0.04	0.01	0.01	0.02
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Intermediate occupations	0.03	0.02	0.02	0.01	0.06	0.00	0.03	0.02
	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)	(0.05)
Small Employers and Own account workers	-0.02	-0.01	-0.01	-0.03	-0.01	-0.03	-0.02	-0.02
	(0.07)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.07)	(0.06)
Lower technical and supervisory occupations	0.01	0.02	0.02	-0.00	0.03	0.01	0.00	0.02
	(0.07)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.07)	(0.06)
Semi-routine occupations	-0.03	-0.03	-0.03	-0.05	-0.01	-0.04	-0.03	-0.03
	(0.07)	(0.06)	(0.06)	(0.07)	(0.07)	(0.06)	(0.07)	(0.06)
Parental Income	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Female	-0.16***	-0.08***	-0.08***	-0.15***	-0.17***	-0.09***	-0.16***	-0.09***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Migration Status	0.21***	0.11*	0.11*	0.17**	0.19**	0.10*	0.20***	0.09
	(0.07)	(0.06)	(0.06)	(0.07)	(0.07)	(0.06)	(0.07)	(0.06)
Person of Colour	0.00	0.02	0.02	0.02	0.01	0.02	0.00	0.03
	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)
Age	0.01**	0.01***	0.01***	0.02***	0.01**	0.01*	0.01***	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Full-Time Work	0.17***	0.12*	0.12*	0.16***	0.17***	0.10**	0.17***	0.10**
	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)
Number of Observations	1,819	1,819	1,819	1,819	1,819	1,819	1,819	1,819

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

C2. Isolating the Effect of Individual Mediators

Table C2: The average marginal effects of parental field of occupation on the likelihood of being found in Broad STEM work at labour market entry as mediated by school-level factors

Dependent Variable: Broad STEM Work	**Model 1** No School Mediators	**Model 4A** Childhood Maths Test Score	**Model 4B** Good A-Levels	**Model 4C** STEM A-Level	**Model 4** Full Model
STEM Parent	0.18***	0.18***	0.18***	0.17***	0.17***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Childhood Maths Test Score		0.00***			0.00*
		(0.00)			(0.00)
Number of good A-Levels (A-C)			0.01		-0.01
			(0.01)		(0.01)
Has STEM A-Level				0.12***	0.12***
				(0.02)	(0.02)
Number of Observations	1,819	1,819	1,819	1,819	1,819

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. All models sex, migration status, ethnicity, age, parental class, parental education and parental income, the results of which do not differ substantially to those shown in table C1

Table C3: The average marginal effects of parental field of occupation on the likelihood of being found in Broad STEM work at labour market entry as mediated by teenage career aspirations

Dependent Variable: Broad STEM Work	**Model 1** No Aspiration Mediators	**Model 5A** Health Career Aspiration	**Model 5B** Tech Career Aspiration	**Model 5** Full Model
STEM Parent	0.18***	0.18***	0.18***	0.18***
	(0.04)	(0.04)	(0.04)	(0.04)
Health Career Aspiration		0.14***		0.13***
		(0.04)		(0.04)
Technology Career Aspiration			0.10***	0.10***
			(0.03)	(0.03)
Number of Observations	1,819	1,819	1,819	1,819

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. All models control for sex, migration status, ethnicity, age, parental class, parental education, parental income and full-time work, the results of which do not differ substantially to those shown in table C1

Table C4: The average marginal effects of parental field of occupation on the likelihood of being found in Broad STEM work at labour market entry as mediated by university level factors

Dependent Variable: Broad STEM Work	**Model 1** No HE Mediators	**Model 6A** Field of Study	**Model 6B** Type of University	**Model 6C** Degree Class	**Model 6D** Has Postgrad	**Model 6** Full Model
STEM Parent	0.18***	0.14***	0.18***	0.17***	0.17***	0.14***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
STEM Degree		0.34***				0.34***
		(0.01)				(0.01)
Type of University (Ref: Russel Group)						
Other University			-0.03			0.02
			(0.03)			(0.03)
Post92 University			-0.02			0.05**
			(0.03)			(0.03)
Degree Class (Ref: Pass)						
First				0.00		-0.01
				(0.06)		(0.05)
Upper Second				-0.14***		-0.04
				(0.05)		(0.04)
Lower Second				-0.19***		-0.10***
				(0.04)		(0.04)
Third				-0.15**		-0.15***
				(0.06)		(0.05)
Has postgraduate degree					0.16***	0.08***
					(0.03)	(0.03)
Number of Observations	1,819	1,819	1,819	1,819	1,819	1,819

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. All models control for sex, migration status, ethnicity, age, parental class, parental education, parental income and full-time work, the results of which do not differ substantially to those shown in table C1

Table C5: The average marginal effects of parental field of occupation on the likelihood of being found in Broad STEM work at labour market entry as mediated by parental help in the labour market

Dependent Variable: Broad STEM Work	**Model 1** No Parent Help Mediators	**Model 7A** Parental Advice	**Model 7B** Parental Recommendation	**Model 7C** Parental Direct Employment	**Model 7D** Parental Contacts	**Model 7** Full Model
STEM Parent	0.18***	0.18***	0.18***	0.18***	0.18***	0.18***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Parental Advice		0.04				0.04
		(0.03)				(0.03)
Parental Recommendation			0.00			0.00
			(0.05)			(0.06)
Parental Direct Employment				0.00		0.01
				(0.05)		(0.05)
Parental Contacts					-0.00	-0.01
					(0.04)	(0.04)
Number of Observations	1,819	1,819	1,819	1,819	1,819	1,819

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. All models control for sex, migration status, ethnicity, age, parental class, parental education, parental income and full-time work, the results of which do not differ substantially to those shown in table C1

C3. Mechanisms Results including Interaction

Table C6: The average marginal effects of parental field of occupation as moderated by field of study, school level factors, university level factors, parental help factors and control variables on the likelihood of being found in Broad STEM work at labour market entry

Dependent Variable: Broad STEM Work	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
STEM Parent	0.13***	0.13***	0.14***	0.13***	0.13***	0.14***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
STEM Degree	0.40***	0.41***	0.39***	0.40***	0.40***	0.38***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
STEM Parent*STEM Degree	0.04	0.04	0.05	0.03	0.04	0.04
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Childhood Maths Test Score		0.00				0.00
		(0.00)				(0.00)
Number of good A-Levels (A-C)		0.00				-0.00
		(0.01)				(0.01)
Has STEM A-Level		-0.02				-0.01
		(0.02)				(0.02)
Health Career Aspiration			0.07**			0.07**
			(0.03)			(0.03)
Technology Career Aspiration			0.04*			0.04*
			(0.03)			(0.03)
Type of University (Ref: Russel Group)						
Other University				0.02		0.01
				(0.03)		(0.03)
Post92 University				0.05**		0.05*
				(0.03)		(0.03)
Degree Class (Ref: Pass)						
First				-0.01		-0.01
				(0.05)		(0.05)
Upper Second				-0.04		-0.05
				(0.04)		(0.04)
Lower Second				-0.10***		-0.10***
				(0.04)		(0.04)

Third				-0.15***		-0.15***
				(0.05)		(0.05)
Has postgraduate degree				0.08***		0.09***
				(0.03)		(0.03)
Parental Advice					0.02	0.02
					(0.03)	(0.03)
Parental Recommendation					0.03	0.04
					(0.05)	(0.05)
Parental Direct Employment					0.01	0.02
					(0.04)	(0.04)
Parental Contacts					-0.04	-0.03
					(0.03)	(0.03)
Number of Observations	1,819	1,819	1,819	1,819	1,819	1,819

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. All models control for sex, migration status, ethnicity, age, parental class, parental education, parental income and full-time work, the results of which do not differ substantially to those shown in table C1

Table C7: The distribution of the sample by degree field, degree level, parental field of occupation and own field of occupation at labour market entry

Degree Field	Highest Degree Level	Parental field of occupation	Field of occupation (%)							*N*
			Core STEM	Other STEM	LEMB	OSSAH	Education Related	Vocational	Total	
All	Undergraduate	Core STEM	17.3	18.7	34.6	7.6	3.5	18.3	100.00	80
		Broad STEM	12.7	24.6	30.0	8.8	5.8	18.1	100.00	234
		Non-STEM	13.0	13.2	23.0	9.0	12.1	29.7	100.00	1,274
	Postgraduate	Core STEM	48.0	14.1	16.4	10.8	0.4	10.3	100.00	22
		Broad STEM	42.6	16.7	13.8	6.2	5.5	15.2	100.00	42
		Non-STEM	28.6	17.5	15.2	14.6	10.1	14.0	100.00	126
Core STEM	Undergraduate	Core STEM	45.2	11.6	29.4	0.6	1.1	12.1	100.00	19
		Broad STEM	38.0	18.9	25.0	2.7	0.5	15.0	100.00	44
		Non-STEM	41.7	6.3	15.4	4.0	6.3	26.4	100.00	267
	Postgraduate	Core STEM	76.0	10.6	0.0	0.0	1.0	12.4	100.00	10
		Broad STEM	76.9	10.4	0.5	0.0	2.0	10.4	100.00	19
		Non-STEM	56.6	12.1	5.8	4.0	11.5	9.9	100.00	50
Broad STEM	Undergraduate	Core STEM	23.9	32.7	23.9	0.3	0.5	18.7	100.00	36
		Broad STEM	16.9	43.5	19.3	3.1	2.1	14.9	100.00	105
		Non-STEM	25.9	25.3	15.0	3.5	5.5	24.9	100.00	499
	Postgraduate	Core STEM	60.7	25.4	1.5	3.1	0.0	9.2	100.00	12
		Broad STEM	55.2	26.0	5.1	1.1	1.1	11.5	100.00	27
		Non-STEM	41.8	23.6	9.2	5.1	12.1	8.2	100.00	72
Non-STEM	Undergraduate	Core STEM	11.9	7.1	43.5	13.6	5.9	17.9	100.00	44
		Broad STEM	9.3	9.2	38.6	13.4	8.8	20.6	100.00	129
		Non-STEM	4.6	5.4	28.2	12.5	16.5	32.8	100.00	775
	Postgraduate	Core STEM	31.4	0.0	34.3	22.8	0.0	11.5	100.00	10
		Broad STEM	20.0	0.0	29.3	15.3	13.4	22.0	100.00	15
		Non-STEM	11.1	9.3	23.3	27.2	7.4	21.7	100.00	54

Note: This table displays averages values across all imputed datasets. 'Core STEM' work refers to computer science and IT, engineering, mathematics, and physical sciences, while 'Other STEM' work here refers to fields that fall under the Broad, but not the Core definition of STEM, namely, medicine, dentistry and veterinary science, nursing and other subjects allied to medicine (including psychology), planning and construction related, and agriculture, forestry and other fields allied to STEM. This table does not distinguish between whether someone has a STEM undergraduate or postgraduate degree, rather, the degree field column refers to people with *any* or *no* STEM degree.

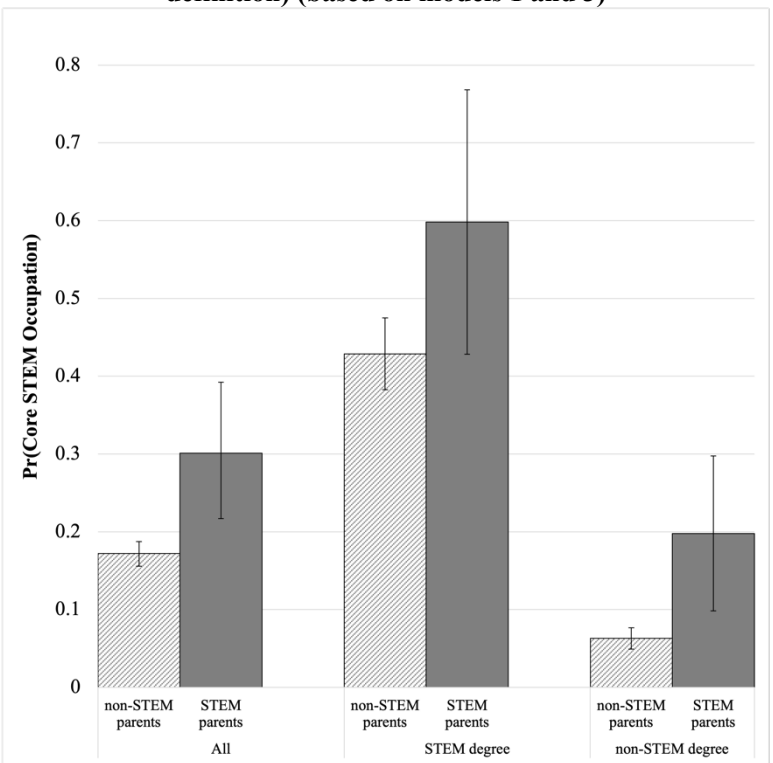
C4. Auxiliary Analyses using the Core Definition of STEM

Table C8: The distribution of the sample by degree field, parental field of occupation and own field of occupation at labour market entry (Core definition of STEM)

Degree Field	Parental field of occupation	Field of occupation (%)			*N*
		Core STEM	Non-STEM	Total	
All	Core STEM	27.0	70.0	100.00	92
	Non-STEM	17.3	82.7	100.00	1,454
Core STEM	Core STEM	62.6	37.4	100.00	25
	Non-STEM	49.3	50.7	100.00	346
Non-STEM	Core STEM	16.7	83.3	100.00	55
	Non-STEM	5.7	94.3	100.00	948

Note: This table displays averages values across all imputed datasets.

Figure C1: The predicted probability of working in a Core STEM occupation at labour market entry by parental field of occupation and degree field of study field of study (Core definition) (based on models 1 and 3)



Note: Overall, having a 'STEM parent' increases the likelihood of working in STEM by 13 percentage points (CI: 0.04 – 0.22). The difference between the likelihood of entering STEM work among people with 'STEM' and 'non-STEM parents' is statistically significant for non-STEM graduates (difference=13 percentage points, CI: 0.03 – 0.24), but not STEM graduates (difference=17 percentage points, CI: -0.01 – 0.35).

Table C9: The average marginal effects of parental field of occupation, field of study (Core Definition), school level factors, university level factors, parental help factors and control variables on the likelihood of being found in Core STEM work at labour market entry

Dependent Variable: Core STEM Work	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
STEM Parent	0.13**	0.13**	0.13**	0.12**	0.13**	0.11**	0.13**	0.11**
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Childhood Maths Test Score				0.00*				0.00
				(0.00)				(0.00)
Number of good A-Levels (A-C)				-0.01				-0.01
				(0.01)				(0.01)
Has STEM A-Level				0.09***				0.01
				(0.02)				(0.02)
Health Career Aspiration					0.04			0.02
					(0.03)			(0.03)
Technology Career Aspiration					0.12***			0.05**
					(0.02)			(0.02)
STEM Degree		0.26***	0.37***			0.25***		0.23***
		(0.01)	(0.03)			(0.01)		(0.02)
STEM Parent*STEM Degree			0.03					
			(0.12)					
Type of University (Ref: Russel Group)								
Other University						-0.00		-0.00
						(0.02)		(0.02)
Post92 University						0.04*		0.04
						(0.02)		(0.03)
Degree Class (Ref: Pass)								
First						0.10**		0.10**
						(0.04)		(0.05)
Upper Second						0.05		0.05
						(0.04)		(0.04)
Lower Second						0.02		0.01
						(0.04)		(0.04)
Third						0.02		0.01
						(0.05)		(0.05)

Has postgraduate degree						0.09***		0.09***
						(0.02)		(0.03)
Parental Advice							0.02	0.02
							(0.03)	(0.03)
Parental Recommendation							-0.02	-0.01
							(0.06)	(0.05)
Parental Direct Employment							-0.01	0.00
							(0.05)	(0.04)
Parental Contacts							-0.00	-0.02
							(0.03)	(0.03)
Parental Education (Ref: Neither has any qualifications)								
One secondary or lower qualification, one no qualification	0.05	0.03	0.03	0.03	0.03	0.03	0.05	0.01
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Both secondary or lower qualification	-0.01	-0.01	-0.01	-0.03	-0.02	-0.00	-0.01	-0.01
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)
One higher secondary or lower tertiary qualification, one lower qualification	0.04	0.03	0.03	0.03	0.04	0.02	0.04	0.02
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Both higher secondary or lower tertiary	-0.00	-0.00	-0.00	-0.01	0.01	-0.01	-0.00	-0.01
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)	(0.06)	(0.05)
One degree-level qualification, one lower qualification	0.03	0.03	0.03	0.00	0.03	0.03	0.03	0.02
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Both degree-level qualification	-0.02	-0.04	-0.04	-0.04	-0.02	-0.04	-0.02	-0.04
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Parental Class (Ref: Routine Occupations)								
Higher managerial and professional occupations	-0.04	-0.03	-0.02	-0.05	-0.02	-0.04	-0.04	-0.04
	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Lower managerial and professional occupations	-0.03	-0.01	-0.01	-0.05	-0.02	-0.02	-0.04	-0.02

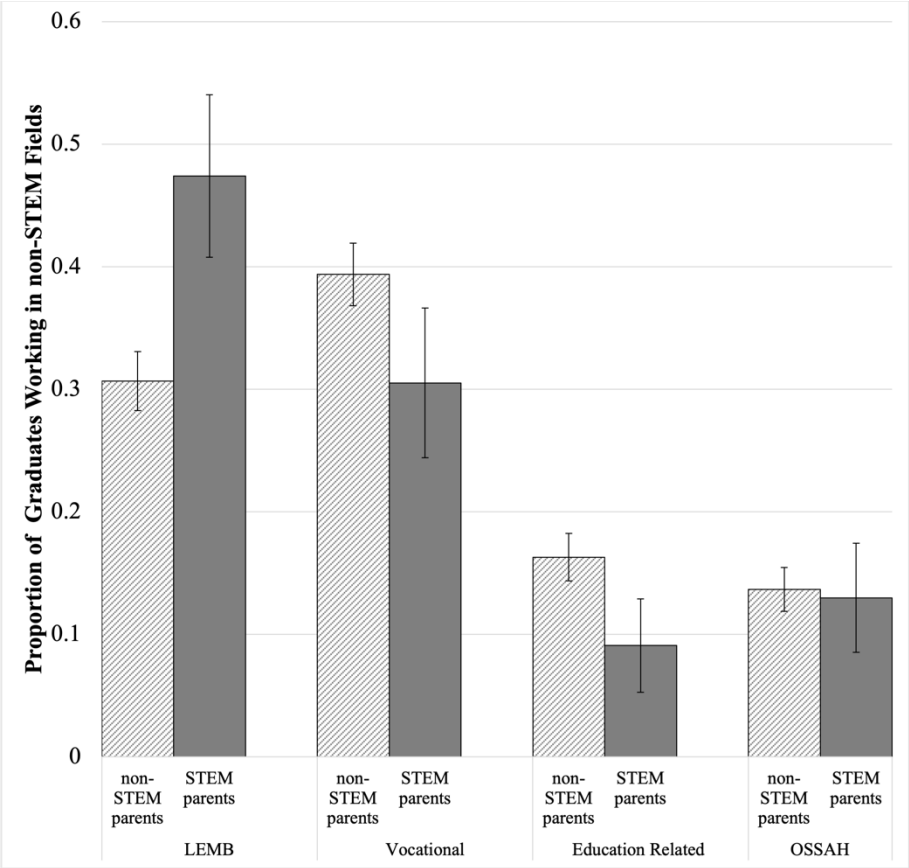
	(0.06)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.06)	(0.05)
Intermediate occupations	-0.01	-0.02	-0.02	-0.03	-0.00	-0.03	-0.01	-0.03
	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.06)	(0.05)
Small Employers and Own account workers	-0.02	-0.03	-0.03	-0.04	-0.02	-0.03	-0.03	-0.04
	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)	(0.05)
Lower technical and supervisory occupations	-0.01	0.01	0.02	-0.01	0.00	0.01	-0.01	0.01
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Semi-routine occupations	-0.02	-0.04	-0.04	-0.03	-0.00	-0.04	-0.02	-0.04
	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)	(0.05)
Parental Income	-0.00*	-0.00	-0.00	-0.00*	-0.00	-0.00	-0.00*	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Female	-0.19***	-0.11***	-0.11***	-0.17***	-0.17***	-0.11***	-0.19***	-0.10***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Migration Status	0.09	0.05	0.05	0.06	0.09	0.04	0.08	0.04
	(0.07)	(0.06)	(0.06)	(0.07)	(0.07)	(0.06)	(0.07)	(0.06)
Person of Colour	0.04	0.01	0.01	0.05	0.05	0.00	0.04	0.01
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Age	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Full-Time Work	0.18***	0.10**	0.10**	0.17***	0.17***	0.08*	0.18***	0.08*
	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)	(0.05)
Number of Observations	1,545	1,373	1,373	1,545	1,545	1,373	1,545	1,373

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

C5. The Non-STEM Destinations of STEM Graduates

Figure C2: The non-STEM destinations of graduates at labour market entry based on descriptive statistics by parental field of occupation



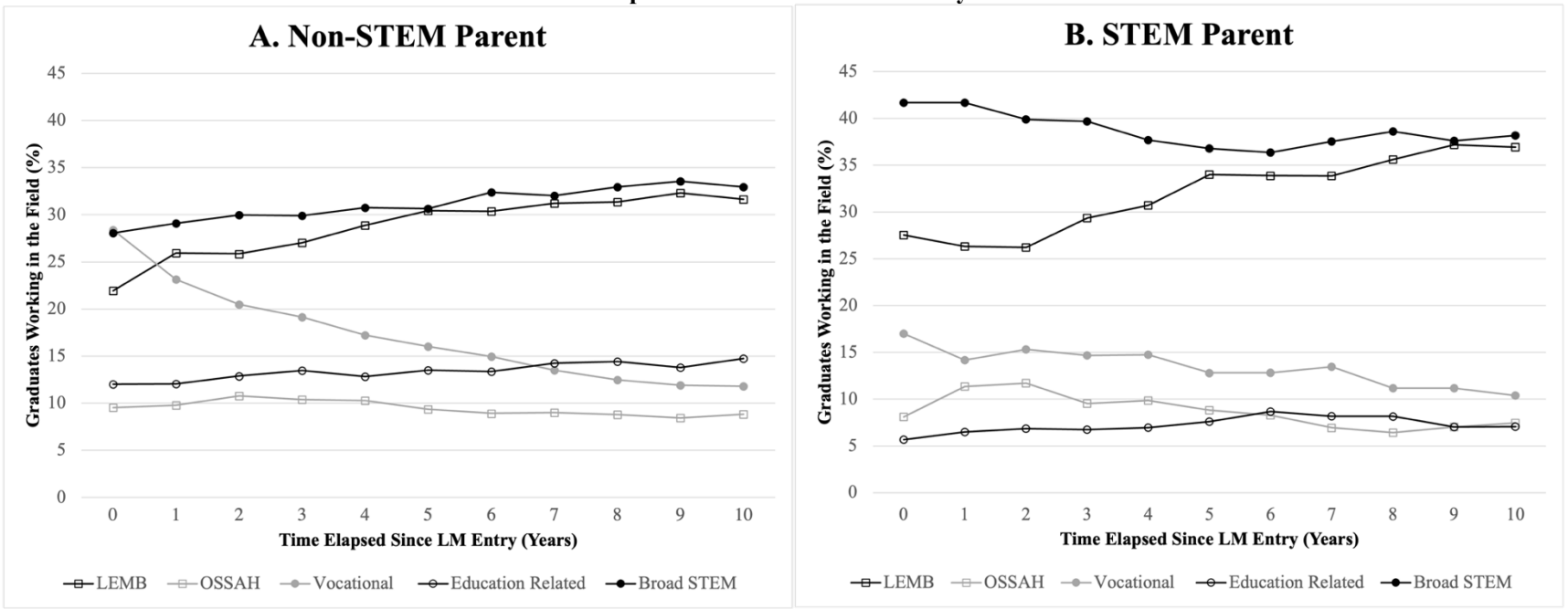
Note: Two of these categories are based on work by Walker and Zhu (2011): (i) LEMB (Law, Economics, Management, and Business)[50] and (ii) OSSAH (Other social sciences, arts, and humanities which includes languages). Additionally, I present (iii) Vocational Fields and (iv) Education-related Fields (i.e., teaching / academia) / This table displays averages values across all imputed datasets, n= 982 for people with non-STEM parents, n=160 for people with Broad STEM parents

[50] The LEMB category is adapted from Walker and Zhu's (2011) 'LEM' category and includes other subjects associated with Business and Management such as Administration and Finance

Appendix D: Supplementary Appendix, Chapter 7

D1. The Destinations of Graduates by Parental Field of Occupation

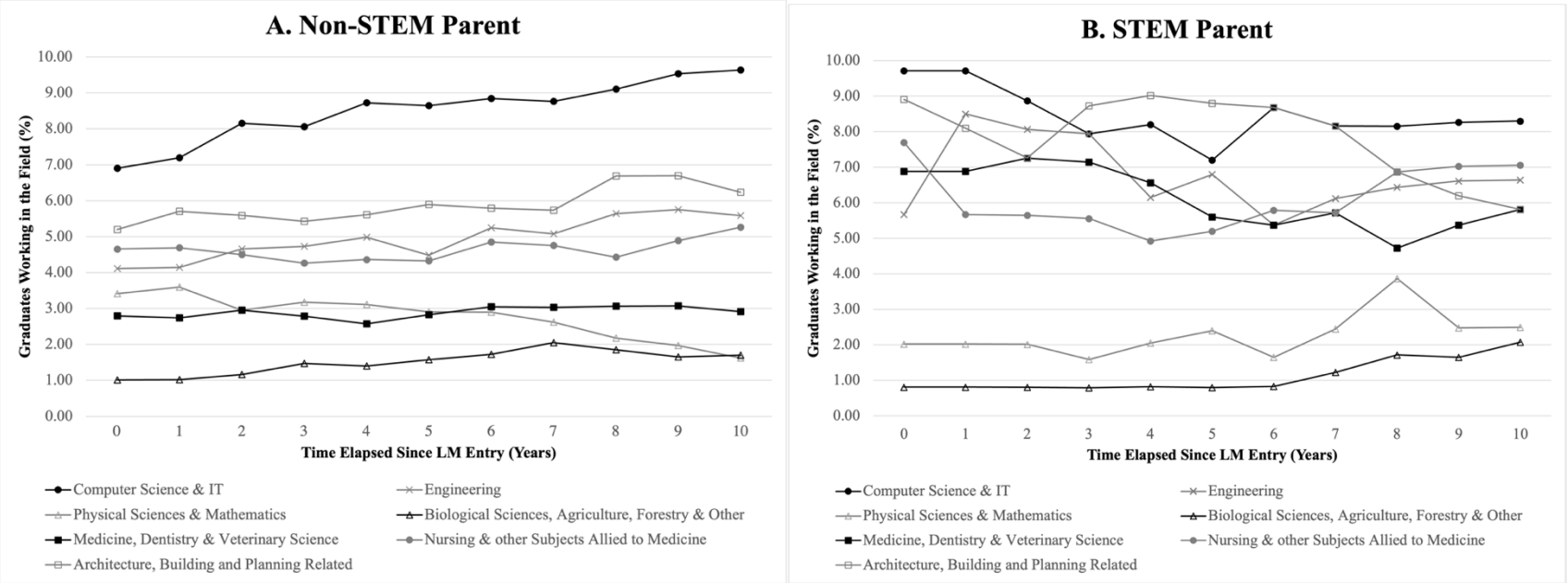
Figure D1: The STEM and non-STEM labour market destinations of graduates based on descriptive statistics by parental occupation and time elapsed since labour market entry



Note: Two of these categories are based on work by Walker and Zhu (2011): (i) LEMB (Law, Economics, Management, and Business)[51] and (ii) OSSAH (Other social sciences, arts, and humanities which includes languages). Additionally, I present (iii) Vocational Fields and (iv) Education-related Fields (i.e., teaching / academia). These graphs are based on 1,366 people with 'non-STEM parents' and 271 people with STEM parents.

[51] The LEMB category is adapted from Walker and Zhu's (2011) 'LEM' category and includes other subjects associated with Business and Management such as Administration and Finance

Figure D2: The STEM labour market destinations of graduates based on descriptive statistics by parental occupation and time elapsed since labour market entry



Note: This figure builds on figure D1 by further breaking down the 'Broad STEM' category. Some sub-categories have been collapsed due to low category sizes. The percentages are calculated based on the total of all graduates, including those working in non-STEM fields. Hence, as was the case for figure D1, the percentages are based on 1,366 people with 'non-STEM parents' and 271 people with STEM parents. In total, 440 people with 'non-STEM parents' and 111 people with 'STEM parents' work in STEM.

D2. Full Regression Results

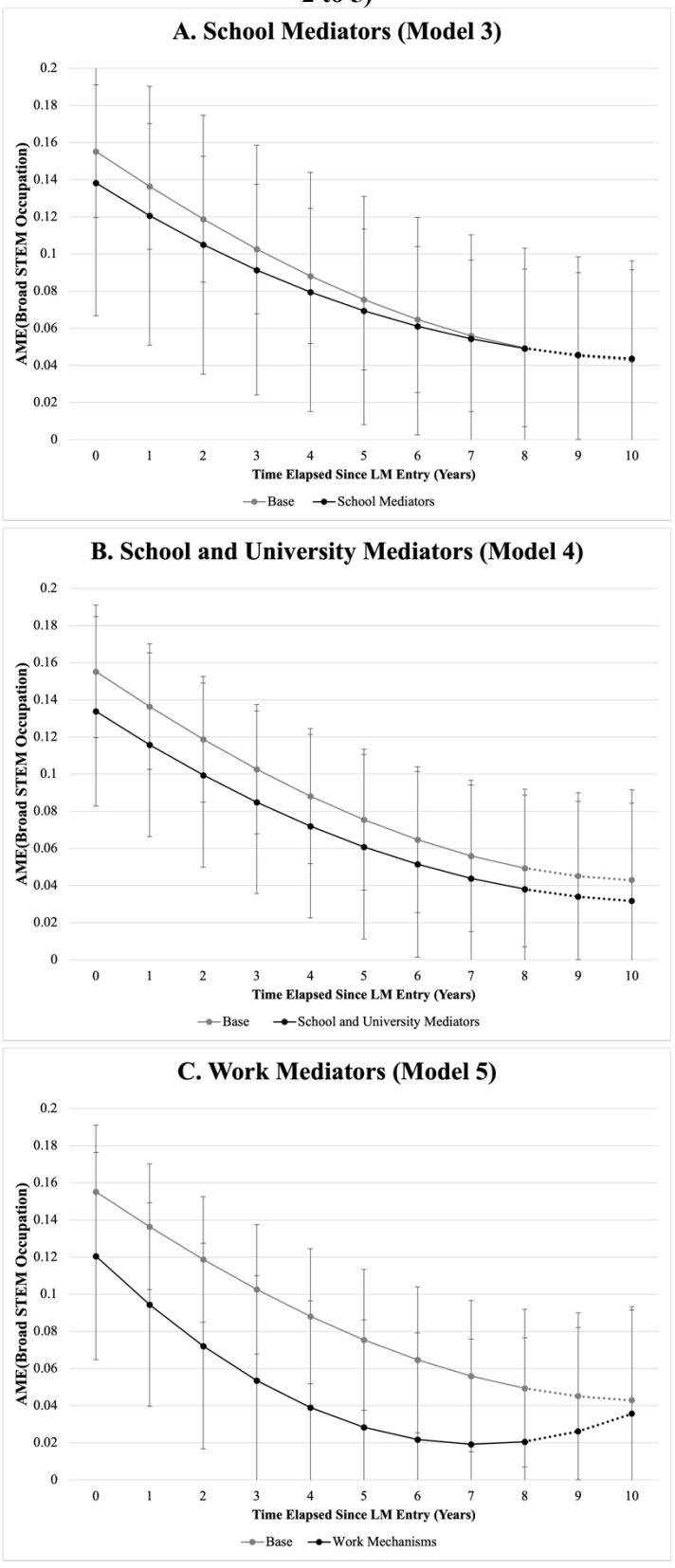
Table D1: The effects of parental field of occupation, school level factors, university level factors, and work-level factors and the control variables on the likelihood of being found in Broad STEM work over the first decade following labour market entry (log-odds)

Dependent Variable: Broad STEM Work	Model 1	Model 2	Model 3	Model 4	Model 5
STEM Parent	2.76***	4.29***	4.71***	3.73***	3.28***
	(0.64)	(0.80)	(0.79)	(0.84)	(0.91)
Time Elapsed since LM Entry	0.18***	0.30***	0.30***	0.24***	0.38***
	(0.05)	(0.06)	(0.06)	(0.06)	(0.08)
Time Elapsed since LM Entry^2	-0.01	-0.01*	-0.01*	-0.01	-0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
STEM Parent*Time Elapsed since LM Entry		-0.60***	-0.61***	-0.53***	-0.78***
		(0.15)	(0.15)	(0.13)	(0.21)
STEM Parent*Time Elapsed since LM Entry^2		0.03**	0.03**	0.02*	0.05***
		(0.01)	(0.01)	(0.01)	(0.02)
Childhood Maths Test Score			0.07***	0.05*	0.02
			(0.03)	(0.03)	(0.03)
Number of good A-Levels (A-C)			-0.09	0.10	0.14
			(0.17)	(0.20)	(0.22)
Has STEM A-Level			2.03***	-0.65	-1.05
			(0.43)	(0.49)	(0.52)
STEM Degree				10.33***	10.60***
				(0.54)	(0.60)
Has postgraduate degree				0.35	0.73
				(0.36)	(0.49)
Type of University (Ref: Russel Group)					
Other University				0.51	0.72
				(0.58)	(0.64)
Post92 University				1.92***	2.08***
				(0.61)	(0.70)
Degree Class (Ref: Pass)					
First				-1.52	-1.38
				(1.00)	(1.00)
Upper Second				-3.39***	-3.44***
				(0.77)	(0.78)
Lower Second				-4.31***	-4.42***
				(0.84)	(0.85)
Third				-3.45**	-3.74***
				(1.42)	(1.41)
Was promoted to manager					-0.78*
					(0.45)
Total number of LM activities					0.22
					(0.15)
Parental Education (Ref: Neither has any qualifications)					
One secondary or lower qualification, one no qualification	1.72**	1.56*	1.23	1.94*	0.87
	(0.85)	(0.93)	(0.84)	(1.00)	(1.03)
Both secondary or lower qualification	0.98	0.80	0.38	0.94	0.23
	(0.81)	(0.86)	(0.84)	(1.01)	(1.04)
One higher secondary or lower tertiary	1.14	0.98	0.73	0.56	-0.42

qualification, one lower qualification					
	(0.85)	(0.88)	(0.89)	(1.12)	(1.18)
Both higher secondary or lower tertiary	2.18**	1.87	1.66	1.66	1.09
	(1.09)	(1.21)	(1.12)	(1.40)	(1.41)
One degree-level qualification, one lower qualification	1.16	1.02	0.30	0.64	0.23
	(0.87)	(0.89)	(0.92)	(1.09)	(1.13)
Both degree-level qualification	0.76	0.75	-0.06	0.27	-0.29
	(1.13)	(1.11)	(1.18)	(1.31)	(1.38)
Parental Class (Ref: Routine Occupations)					
Higher managerial and professional occupations	-0.36	-0.21	-0.66	-0.79	-0.28
	(1.10)	(1.12)	(1.14)	(1.44)	(1.45)
Lower managerial and professional occupations	-0.20	-0.11	-0.60	-0.11	0.44
	(1.04)	(1.05)	(1.07)	(1.31)	(1.27)
Intermediate occupations	-0.06	0.06	-0.37	-0.29	0.02
	(0.95)	(0.96)	(0.97)	(1.20)	(1.21)
Small Employers and Own account workers	-0.66	-0.57	-0.93	-0.96	-0.09
	(1.19)	(1.22)	(1.19)	(1.46)	(1.41)
Lower technical and supervisory occupations	0.84	0.96	0.76	1.31	1.62
	(1.14)	(1.19)	(1.11)	(1.30)	(1.36)
Semi-routine occupations	-0.59	-0.45	-0.65	-1.01	-0.49
	(1.07)	(1.08)	(1.09)	(1.39)	(1.39)
Parental Income	-0.00*	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Female		-4.00***	-5.26***	-2.79***	-2.74***
		(0.57)	(1.64)	(0.47)	(0.49)
Age at LM entry		0.34***	0.51***	0.41***	0.23**
		(0.09)	(0.11)	(0.10)	(0.10)
Migration Status		6.61**	5.67*	1.60	1.58
		(3.10)	(2.93)	(1.65)	(1.77)
Person of Colour		-0.92	-0.54	0.17	-0.03
		(0.87)	(0.86)	(1.07)	(1.12)
Full-Time Work	0.62**	0.62**	0.62**	0.39	-0.21
	(0.25)	(0.26)	(0.26)	(0.26)	(0.37)
Partnership Status (T-1, Ref: Not in partnership)					
Cohabiting	0.11	0.20	0.20	0.18	-0.06
	(0.15)	(0.15)	(0.15)	(0.14)	(0.23)
Married	-0.41**	-0.34**	-0.34**	-0.26	-0.29
	(0.16)	(0.17)	(0.17)	(0.16)	(0.23)
Number of children (T-1)	-0.53***	-0.59***	-0.59***	-0.48***	-0.35**
	(0.11)	(0.12)	(0.12)	(0.11)	(0.15)
Intercept	-16.11***	-15.36***	-22.17***	-19.54***	-13.20***
	(2.36)	(2.49)	(4.95)	(3.34)	(3.54)
Number of Observations	14,057	14,057	14,057	14,057	8,402
Number of Groups	1,434	1,434	1,434	1,434	1,343

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10

Figure D3: The average marginal effect of having a 'STEM parent' on working in a Broad STEM occupation across the first decade in the labour market by included mediators (models 2 to 5)



Note: Statistical significance of changes across different time points are indicated through solid lines (non-significant changes are indicated using dotted lines)

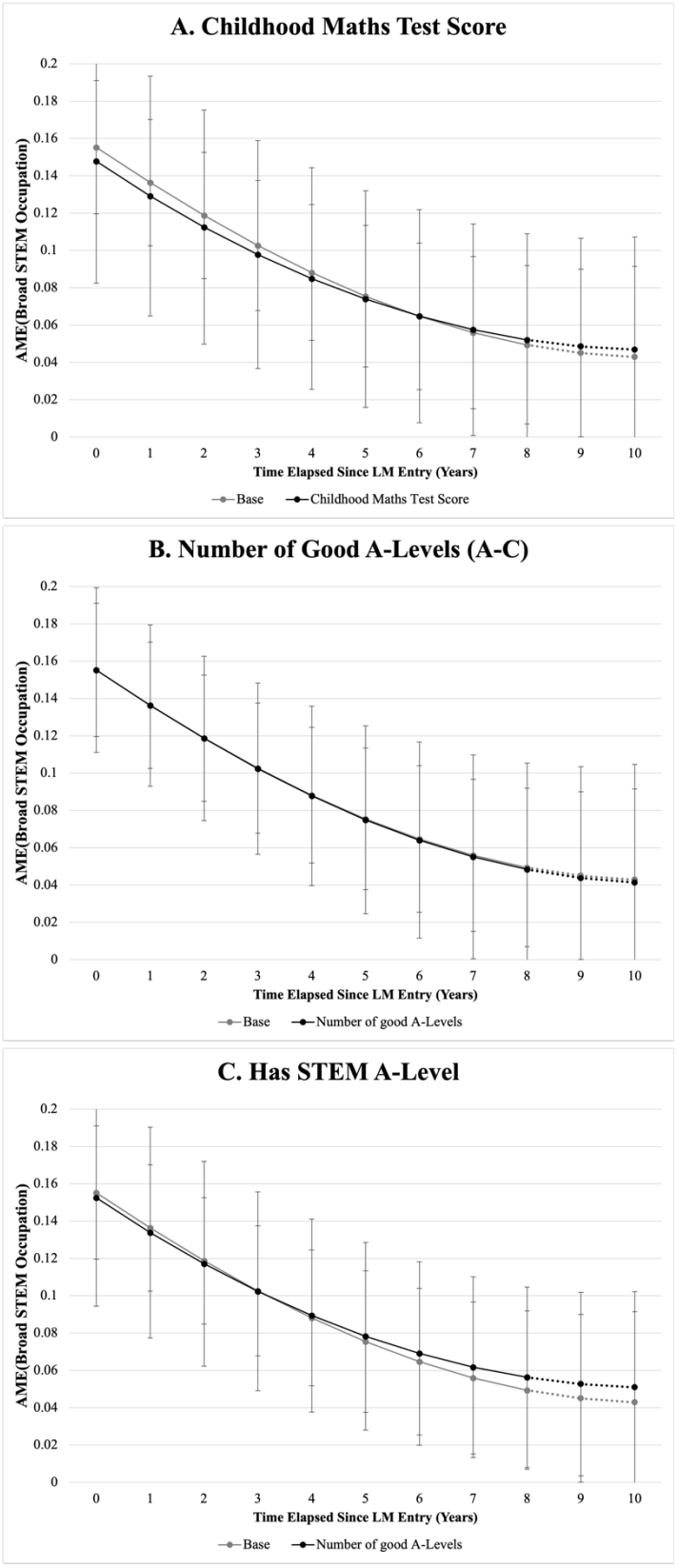
D3. Isolating the Effect of Individual Mediators

Table D2: The effect of parental field of occupation on the likelihood of being found in Broad STEM work over the work life course as mediated by school-level factors (log-odds)

Dependent Variable: Broad STEM Work	**Model 1** No School Mediators	**Model 2** Childhood Maths Test Score	**Model 3** Good A-Levels	**Model 4** STEM A-Level	**Model 5** All School Mediators
STEM Parent	4.36***	4.65***	4.35***	4.74***	4.77***
	(0.89)	(0.79)	(0.92)	(0.76)	(0.81)
Time Elapsed since LM Entry	0.31***	0.31***	0.31***	0.31***	0.31***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Time Elapsed since LM Entry^2	-0.01**	-0.01**	-0.01**	-0.01**	-0.01**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
STEM Parent*Time Elapsed since LM Entry	-0.61***	-0.61***	-0.61***	-0.61***	-0.62***
	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
STEM Parent*Time Elapsed since LM Entry^2	0.03**	0.03**	0.03**	0.03**	0.03**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Childhood Maths Test Score		0.08***			0.07***
		(0.03)			(0.02)
Number of good A-Levels (A-C)			0.13		-0.08
			(0.15)		(0.16)
Has STEM A-Level				2.29***	2.02***
				(0.40)	(0.42)
Number of Observations	14,057	14,057	14,057	14,057	14,057
Number of Groups	1,434	1,434	1,434	1,434	1,434

Note: The models control for respondents' sex, number of children (t_{-1}), partnership status (t_{-1}), migration status, ethnicity, age at labour market entry, parental class, parental education, parental income and full-time work, the results of which do not differ substantially to those shown in table D1

Figure D4: The average marginal effect of having a 'STEM parent' on working in a Broad STEM occupation across the first decade in the labour market by included school-level mediators



Note: Statistical significance of changes across different time points are indicated through solid lines (non-significant changes are indicated using dotted lines)

Figure D5: A comparison of how individual school-level variables mediate the average marginal effect of having a 'STEM parent' on working in a Broad STEM occupation across the first decade in the labour market

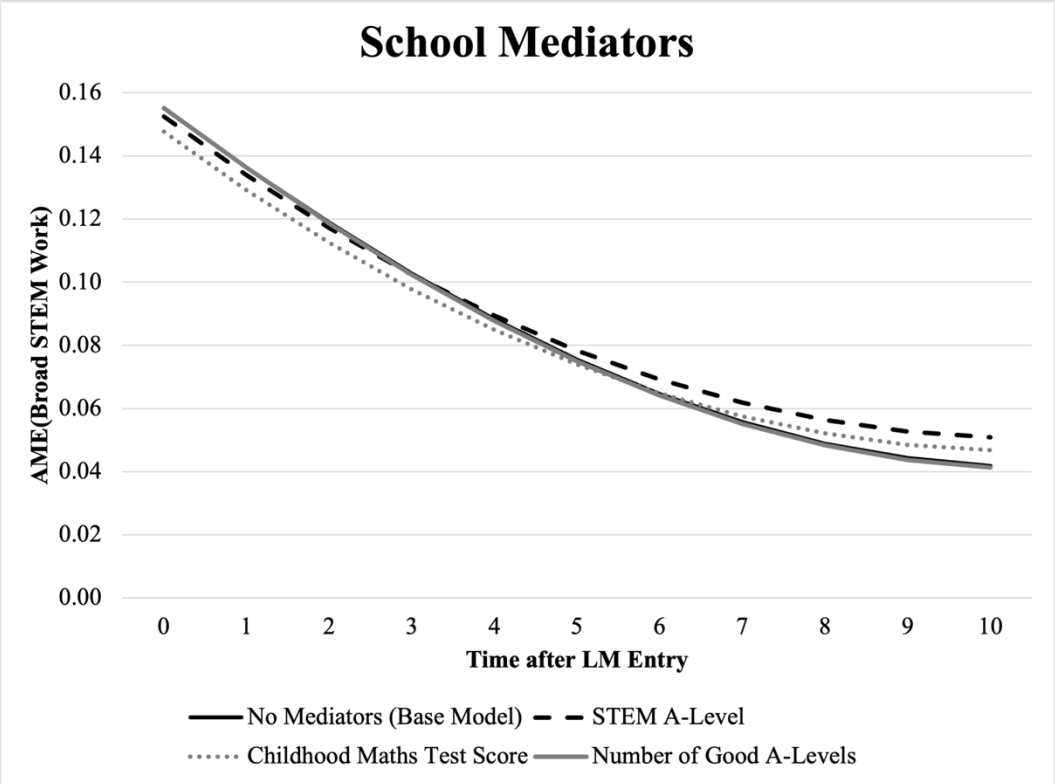


Table D3: The effect of parental field of occupation on the likelihood of being found in Broad STEM work over the work life course as mediated by university level factors (log-odds)

Dependent Variable: Broad STEM Work	**Model 1** No HE Mediators	**Model 2** STEM Degree	**Model 3** Has Postgrad degree	**Model 4** Type of Uni	**Model 5** Degree Class	**Model 6** All HE Mediators
STEM Parent	4.36***	3.94***	4.32***	4.34***	4.40***	3.73***
	(0.89)	(0.88)	(0.85)	(0.89)	(0.88)	(0.83)
Time Elapsed since LM Entry	0.31***	0.26***	0.29***	0.31***	0.31***	0.25***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Time Elapsed since LM Entry^2	-0.01**	-0.01*	-0.01*	-0.01**	-0.01*	-0.01*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
STEM Parent*Time Elapsed since LM Entry	-0.61***	-0.54***	-0.61***	-0.61***	-0.60***	-0.54***
	(0.15)	(0.13)	(0.15)	(0.15)	(0.15)	(0.13)
STEM Parent*Time Elapsed since LM Entry^2	0.03**	0.03**	0.03**	0.03**	0.03**	0.03**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
STEM Degree		10.59***				10.19***
		(0.53)				(0.52)
Has postgraduate degree			0.96***			0.36*
			(0.34)			(0.36)
Type of University (Ref: Russel Group)						
Other University				-0.54		0.43
				(0.45)		(0.54)
Post92 University				0.05		1.69***
				(0.46)		(0.54)
Degree Class (Ref: Pass)						
First					-2.95	-1.49
					(2.37)	(0.98)
Upper Second					-7.65***	-3.46***
					(2.16)	(0.76)
Lower Second					-8.30***	-4.40***
					(2.12)	(0.82)
Third					-4.47	-3.59***
					(2.81)	(1.39)
Number of Observations	14,057	14,057	14,057	14,057	14,057	14,057
Number of Groups	1,434	1,434	1,434	1,434	1,434	1,434

Note: The models control for respondents' sex, number of children (t_{-1}), partnership status (t_{-1}), migration status, ethnicity, age at labour market entry, parental class, parental education, parental income and full-time work, the results of which do not differ substantially to those shown in table D1

Figure D6: A comparison of how individual university-level variables mediate the average marginal effect of having a 'STEM parent' on working in a Broad STEM occupation across the first decade in the labour market

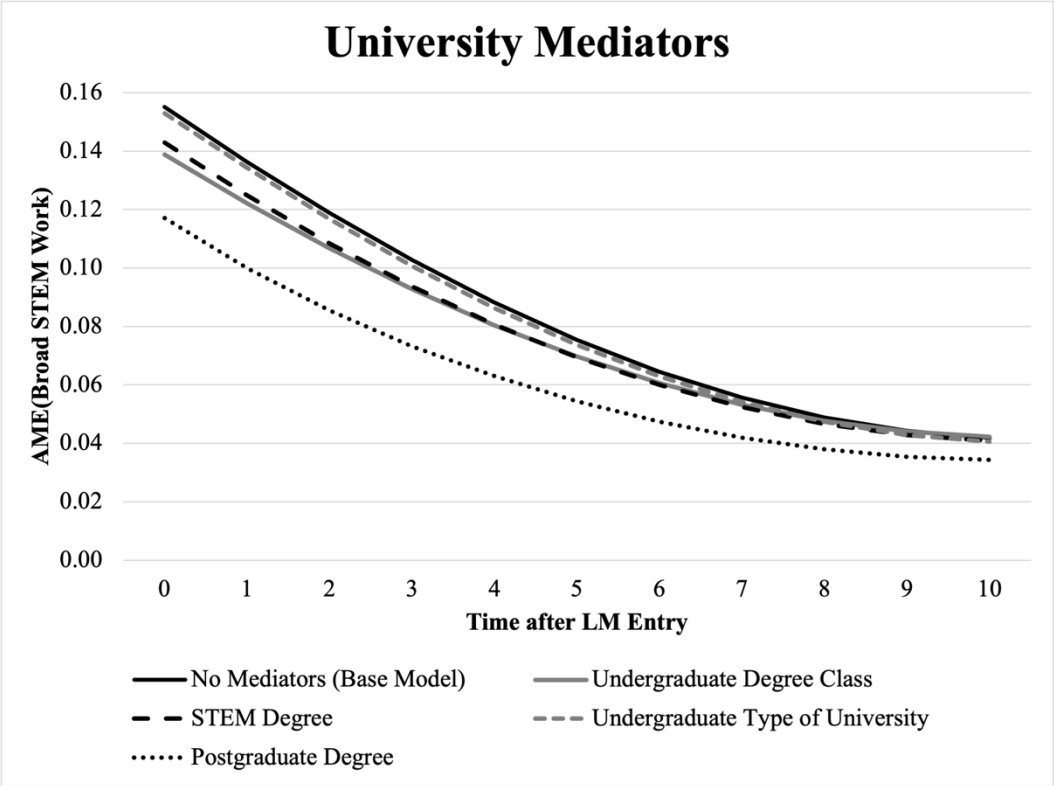
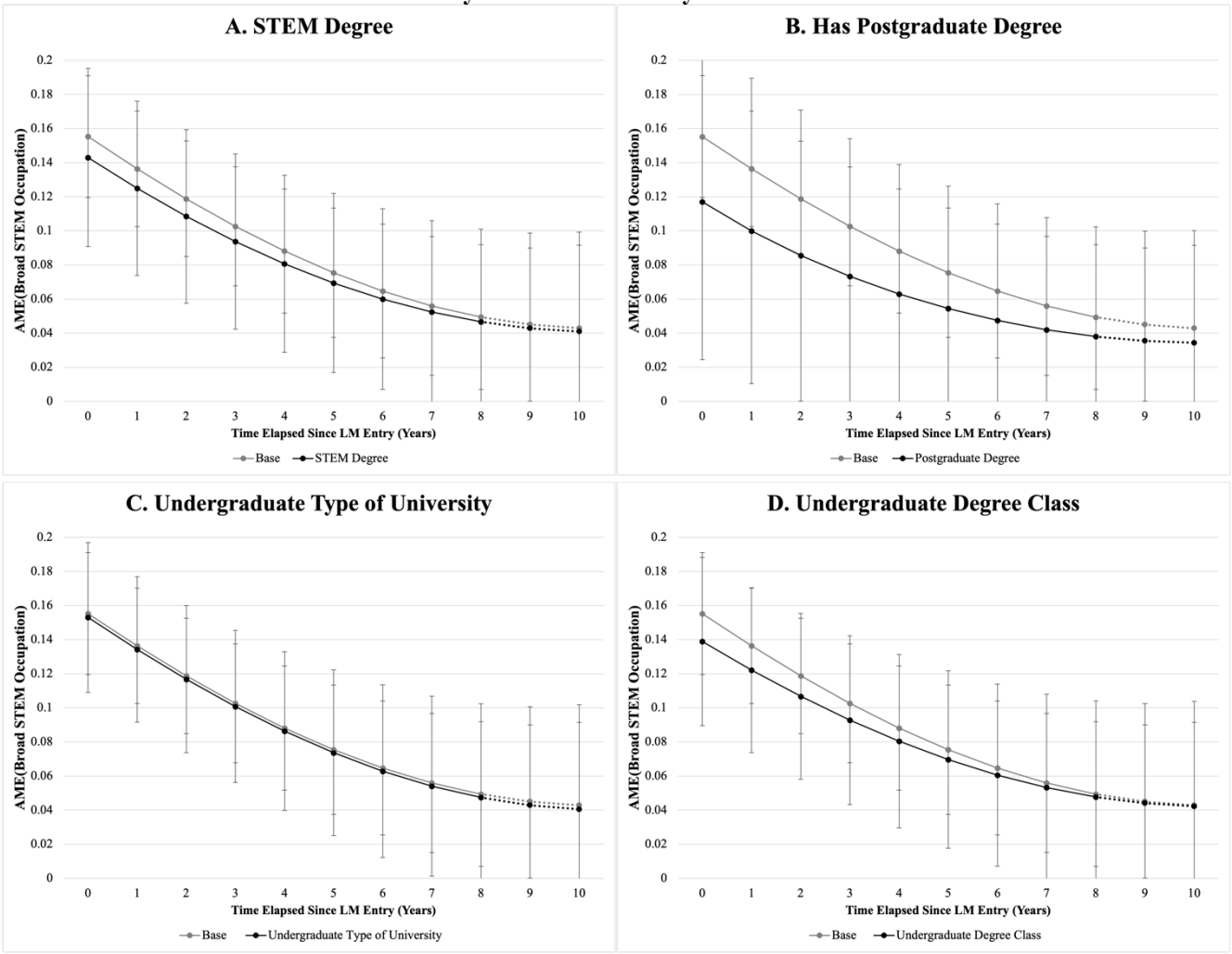


Figure D7: The average marginal effect of having a 'STEM parent' on working in a Broad STEM occupation across the first decade in the labour market by included university-level mediators



Note: Statistical significance of changes across different time points are indicated through solid lines (non-significant changes are indicated using dotted lines)

Table D4: The effect of parental field of occupation on the likelihood of being found in Broad STEM work over the work life course as mediated by work-level factors (log-odds)

Dependent Variable: Broad STEM Work	**Model 1** No Work Mediators	**Model 2** Was promoted	**Model 3** Total number of LM activities	**Model 4** All Work Mediators
STEM Parent	4.36***	4.03***	4.39***	3.91***
	(0.89)	(0.71)	(0.83)	(0.70)
Time Elapsed since LM Entry	0.31***	0.47***	0.30***	0.48***
	(0.06)	(0.09)	(0.06)	(0.09)
Time Elapsed since LM Entry^2	-0.01**	-0.03***	-0.01*	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
STEM Parent*Time Elapsed since LM Entry	-0.61***	-0.93***	-0.60***	-0.93***
	(0.15)	(0.23)	(0.15)	(0.22)
STEM Parent*Time Elapsed since LM Entry^2	0.03**	0.07***	0.03**	0.07***
	(0.01)	(0.02)	(0.01)	(0.02)
Was promoted to manager		-0.79*		-0.76*
		(0.46)		(0.45)
Total number of LM activities			0.25*	0.16
			(0.14)	(0.14)
Number of Observations	14,057	8,402	14,057	8,402
Number of Groups	1,434	1,343	1,434	1,343

Note: The models control for respondents' sex, number of children (t_{-1}), partnership status (t_{-1}), migration status, ethnicity, age at labour market entry, parental class, parental education, parental income and full-time work, the results of which do not differ substantially to those shown in table D1

Figure D8: A comparison of how individual work-level variables mediate the average marginal effect of having a 'STEM parent' on working in a Broad STEM occupation across the first decade in the labour market

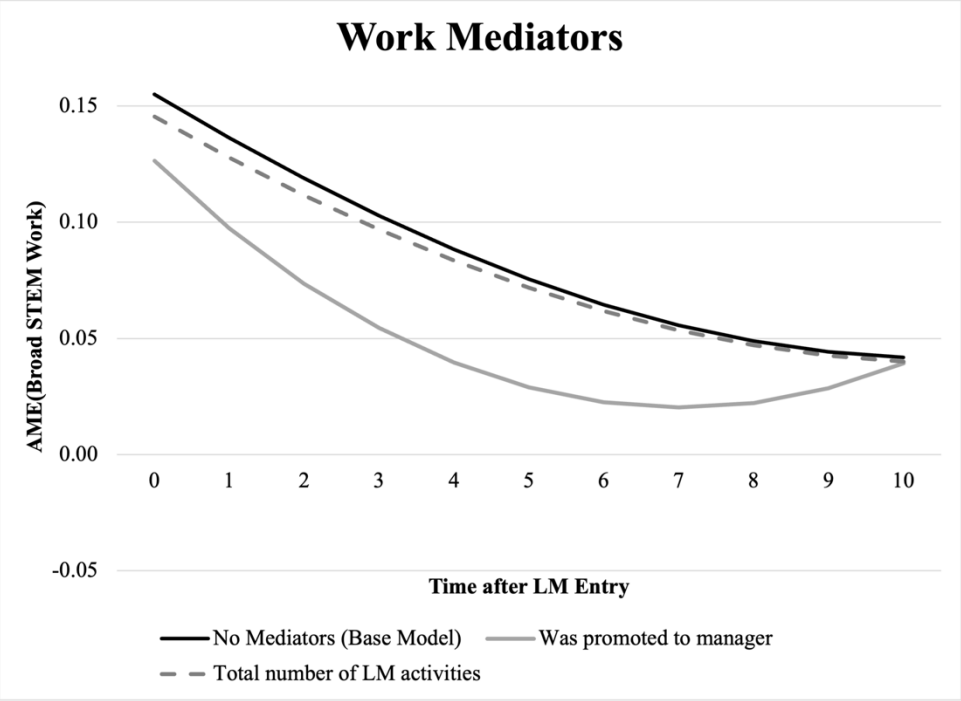
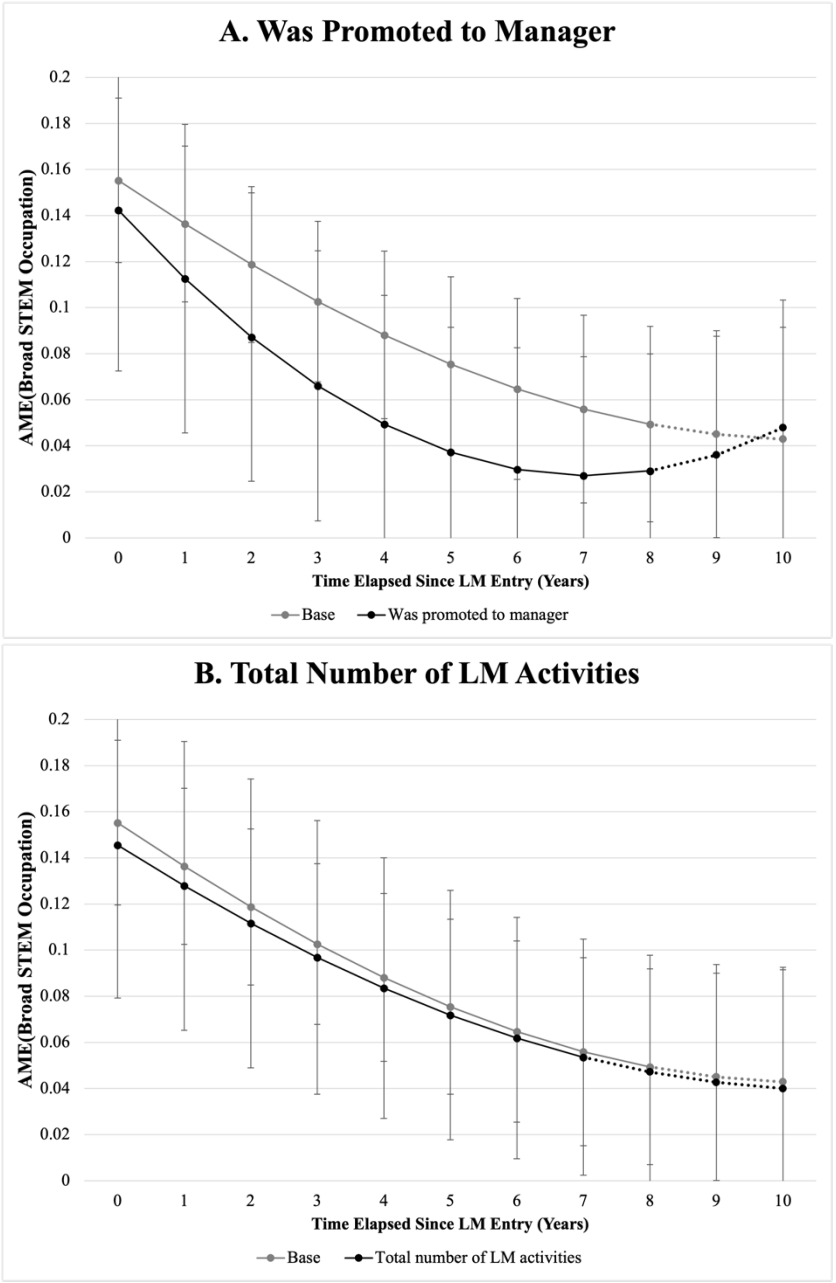


Figure D9: The average marginal effect of having a 'STEM parent' on working in a Broad STEM occupation across the first decade in the labour market by included work-level mediators



Note: Statistical significance of changes across different time points are indicated through solid lines (non-significant changes are indicated using dotted lines)

D4. Dropping Individual STEM-Subfields

Table D5: The effect of parental field of occupation on the likelihood of being found in Broad STEM work over the work life course by dropped STEM sub-field (log-odds)

Dependent Variable: Broad STEM Work	*Excluded STEM Work Field(s):*							
	None (Base Model)	**Computer science and IT**	**Engineering**	**Maths and physical sciences**	**Biological sciences, agriculture, forestry and other**	**Medicine, dentistry & veterinary science**	**Nursing & other subjects allied to medicine**	**Architecture, building & planning related fields**
STEM Parent	4.36***	3.78***	4.13***	4.41***	4.58***	4.28***	4.42***	3.48***
	(0.89)	(1.01)	(0.70)	(1.01)	(0.84)	(0.70)	(0.79)	(0.74)
Time Elapsed since LM Entry	0.31***	0.33***	0.34***	0.36***	0.30***	0.31***	0.30***	0.34***
	(0.06)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.07)	(0.07)
Time Elapsed since LM Entry^2	-0.01**	-0.02**	-0.01**	-0.01*	-0.01*	-0.01**	-0.01*	-0.01**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
STEM Parent*Time Elapsed since LM Entry	-0.61***	-0.61***	-0.70***	-0.63***	-0.59***	-0.56***	-0.53***	-0.74***
	(0.15)	(0.16)	(0.16)	(0.15)	(0.15)	(0.15)	(0.16)	(0.17)
STEM Parent*Time Elapsed since LM Entry^2	0.03**	0.03**	0.04***	0.02*	0.03*	0.02*	0.02	0.05***
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Number of Observations	14,057	12,994	13,352	13,650	13,873	13,531	13,423	13,259
Number of Groups	1,434	1,405	1,421	1,424	1,428	1,411	1,405	1,410

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. All models control for sex, migration status, ethnicity, age, number of children, partnership status, parental class, parental education. parental income and full-time work, the results of which do not differ substantially to those shown in table D1

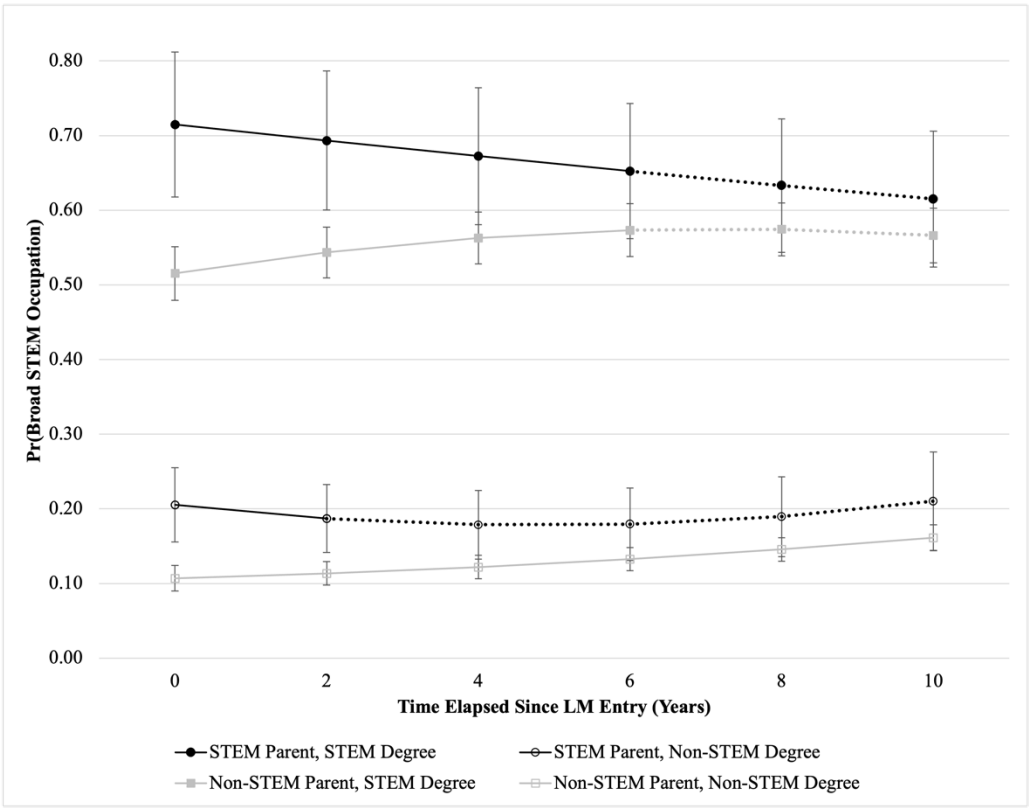
D5. Degree Field of Study as a Moderator

Table D6: The effect of parental field of occupation as moderated by degree field of study on the likelihood of being found in Broad STEM work over the work life course (log-odds)

Dependent Variable Broad STEM Work:	Model 1	Model 2	Model 3
STEM Parent	2.16***	2.20**	3.72***
	(0.81)	(0.97)	(1.02)
STEM Degree	10.43***	10.43***	10.73***
	(0.50)	(0.54)	(0.63)
Time Elapsed since LM Entry	0.15***	0.15***	0.12
	(0.05)	(0.05)	(0.09)
Time Elapsed since LM Entry^2	-0.01	-0.01	0.01
	(0.00)	(0.00)	(0.01)
STEM Parent*STEM Degree		-0.10	0.62
		(1.21)	(1.49)
STEM Parent*Time Elapsed since LM Entry			-0.50**
			(0.21)
STEM Parent*Time Elapsed since LM Entry^2			0.03
			(0.02)
STEM Degree*Time Elapsed since LM Entry			0.25**
			(0.12)
STEM Degree*Time Elapsed since LM Entry^2			-0.04***
			(0.01)
STEM Parent*STEM Degree*Time Elapsed since LM Entry			-0.12
			(0.28)
STEM Parent *STEM Degree*Time Elapsed since LM Entry^2			0.00
			(0.03)
Intercept	-20.16***	-20.16***	-21.58***
	(2.58)	(2.58)	(2.73)
Number of Observations	14,057	14,057	14,057
Number of Groups	1,434	1,434	1,434

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. All models control for sex, migration status, ethnicity, age, number of children, partnership status, parental class, parental education. parental income and full-time work, the results of which do not differ substantially to those shown in table D1

Figure D10: The predicted probability of working in a STEM occupation for children of 'STEM' and 'non-STEM parents' by degree field of study and time elapsed since labour market entry (based on model 3 in table E6)



Note: Statistical significance of changes across different time points are indicated through solid lines (non-significant changes are indicated using dotted lines)

Figure D11: The average marginal effect of having a 'STEM parent' on working in a Broad STEM occupation across the first decade in the labour market by degree field of study (based on model 3 in table D6)

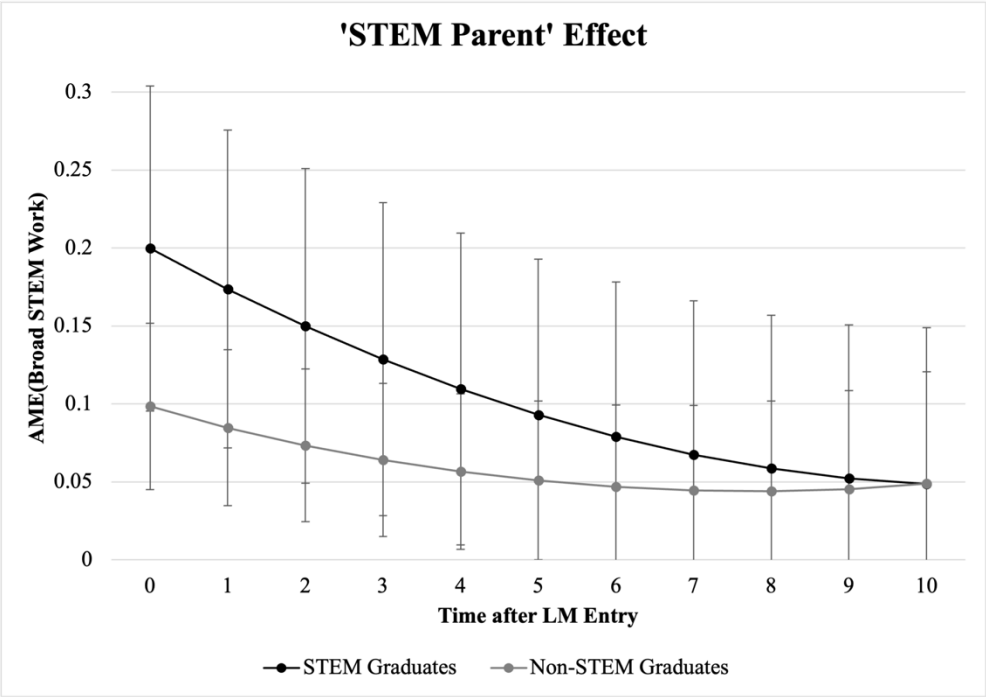


Table D7: The change in the predicted probabilities of working in STEM over the work life course by parental occupation and degree field of study (based on model 3 in table D6)

Change in Time Elapsed since LM Entry (years)	$PP(STEM\ Work)_{Ti+5}$ - $PP(STEM\ Work)_{Ti}$			
	STEM Parent		**Non-STEM Parent**	
	STEM Degree	**Non-STEM Degree**	**STEM Degree**	**Non-STEM Degree**
T0 → T2	-0.02* (0.01)	-0.02* (0.01)	0.03* (0.01)	0.01* (0.00)
T2 → T4	-0.02* (0.01)	-0.01 (0.01)	0.02* (0.00)	0.01* (0.00)
T4 → T6	-0.02* (0.00)	0.00 (0.00)	0.01* (0.00)	0.01* (0.00)
T6 → T8	-0.02* (0.01)	0.01 (0.01)	0.00 (0.00)	0.01* (0.00)
T8 → T10	-0.02 (0.01)	0.02 (0.01)	-0.01 (0.01)	0.02* (0.00)
Average: $T_i + 5$	-0.02	0.00	0.01	0.01

Note: Standard errors in parentheses, $*p < 0.10$, two-tailed tests, table format adapted from table 2 in Mize (2019, 90).

Table D8: Differences in the predicted probability of working in STEM by parental occupation and degree field of study, across the work life course (based on model 3 in table D6)

Time	$PP(STEM\ Parent, STEM\ Work)_{Ti}$ – $PP(Non\text{-}STEM\ Parent, STEM\ Work)_{Ti}$	
	STEM Degree	**Non-STEM Degree**
T0	0.20* (0.06)	0.10* (0.03)
T2	0.15* (0.06)	0.07* (0.03)
T4	0.11* (0.06)	0.06* (0.03)
T6	0.08 (0.06)	0.05 (0.03)
T8	0.06 (0.06)	0.04 (0.03)
T10	0.05 (0.06)	0.05 (0.04)
Average	0.11	0.06

Note: Standard errors in parentheses, $*p < 0.10$, two-tailed tests, table format adapted from table 2 in Mize (2019, 90)

Appendix E: Additional Descriptive Statistics

All tables in this section are based on unimputed data.

Table E1: Distribution of sample by degree field of study and time elapsed since LM entry

Time Elapsed Since Labour Market Entry	Non-STEM Degree		Core-STEM Degree		Broad STEM Degree		Total
	N	%	N	%	N	%	
0	1,092	58.0	427	22.7	792	42.0	1,884
1	1,090	57.9	429	22.8	793	42.1	1,883
2	1,085	57.8	430	22.9	793	42.2	1,878
3	1,087	57.7	432	22.9	796	42.3	1,883
4	1,081	57.4	433	23.0	801	42.6	1,882
5	1,080	57.4	433	23.0	802	42.6	1,882
6	1,080	57.3	434	23.0	804	42.7	1,884
7	1,079	57.3	434	23.1	803	42.7	1,882
8	1,080	57.4	434	23.1	803	42.6	1,883
9	1,079	57.3	434	23.1	804	42.7	1,883
10	1,079	57.3	434	23.1	804	42.7	1,883
11	1,080	57.4	434	23.1	803	42.6	1,883
12	1,080	57.4	433	23.0	803	42.6	1,883
13	1,080	57.4	433	23.0	801	42.6	1,881
14	1,077	57.4	432	23.0	800	42.6	1,877
15	1,073	57.3	431	23.0	799	42.7	1,872
16	1,061	57.3	428	23.1	790	42.7	1,851
17	1,018	56.7	420	23.4	776	43.3	1,794
18	988	57.1	405	23.4	741	42.9	1,729
19	951	57.6	383	23.2	700	42.4	1,651
20	867	56.9	364	23.9	657	43.1	1,524
21	788	57.6	323	23.6	580	42.4	1,368
22	660	58.4	262	23.2	470	41.6	1,130
23	414	56.1	176	23.9	324	43.9	738
24	142	52.0	64	23.4	131	48.0	273
25	10	62.5	5	31.3	6	37.5	16
26	3	60.0	1	20.0	2	40.0	5
27	1	50.0	1	50.0	1	50.0	2
Total	24,205	/	9,749	/	17,979	/	42,184

Note: The percentages in the Non-STEM and Core STEM columns are calculated based on the Broad STEM totals, as the Broad STEM definition contains Core STEM fields.

Table E2: Distribution of sample by field of occupation and time elapsed since labour market entry

Time Elapsed Since Labour Market Entry	Non-STEM Work		Core-STEM Work		Broad STEM Work		Total
	N	%	N	%	N	%	
0	1,269	69.7	277	15.2	551	30.3	1,820
1	1,193	67.9	280	15.9	546	31.1	1,756
2	1,161	68.1	288	16.9	544	31.9	1,705
3	1,132	68.0	283	17.0	532	32.0	1,664
4	1,137	67.9	287	17.1	538	32.1	1,675
5	1,115	67.8	280	17.0	530	32.2	1,645
6	1,073	66.0	288	17.7	553	34.0	1,626
7	1,069	66.3	279	17.3	544	33.7	1,613
8	1,037	65.3	283	17.8	552	34.7	1,589
9	1,033	65.5	279	17.7	544	34.5	1,577
10	1,022	65.5	273	17.5	538	34.5	1,560
11	1,013	65.7	272	17.6	529	34.3	1,542
12	996	66.3	256	17.0	506	33.7	1,502
13	978	66.7	242	16.5	488	33.3	1,466
14	926	66.7	228	16.4	463	33.3	1,389
15	830	65.3	213	16.8	441	34.7	1,271
16	773	65.3	199	16.8	411	34.7	1,184
17	711	65.4	175	16.1	376	34.6	1,087
18	612	65.5	150	16.1	322	34.5	934
19	495	65.2	122	16.1	264	34.8	759
20	353	65.2	86	15.9	188	34.8	541
21	273	64.5	70	16.5	150	35.5	423
22	214	64.8	54	16.4	116	35.2	330
23	128	66.3	32	16.6	65	33.7	193
24	50	64.9	9	11.7	27	35.1	77
25	4	66.7	0	0.0	2	33.3	6
26	1	50.0	0	0.0	1	50.0	2
Total	20,613	/	5,204	/	10,323	/	30,936

Note: The percentages in the Non-STEM and Core STEM columns are calculated based on the Broad STEM totals, as the Broad STEM definition contains Core STEM fields.

Note: The values displayed in tables A3 to A6 refer to the number/proportion of respondents who held a given degree or degree-work combination *at any time point* in the data.

Table E3: Distribution of sample by degree field of study and gender, 'between frequencies', using the Core definition of STEM

	All		Men		Women	
	N	%	N	%	N	%
Non-STEM Degree	1,091	71.9	420	58.8	585	87.2
Core STEM Degree	425	28.3	295	41.3	87	13.0
Total	1,512	/	714	/	671	/

Table E4: Distribution of sample by degree field of study and gender, 'between frequencies', using the Broad definition of STEM

	All		Men		Women	
	N	%	N	%	N	%
Non-STEM Degree	1,079	58.0	417	48.0	578	68.9
Broad STEM Degree	792	42.6	455	52.4	267	31.8
Total	1,859	/	869	/	839	/

Table E5: Distribution of sample by degree field of study, field of occupation, and gender, 'between frequencies', using the Core definition of STEM

Degree Field of Study	Field of occupation	All		Men		Women	
		N	%	N	%	N	%
Core STEM Graduates	Non-STEM Work	260	63.4	161	56.5	71	84.52
	Core STEM Work	277	67.6	215	75.4	37	44.05
	Total	410	/	285	/	84	/
Non-STEM Graduates	Non-STEM Work	1,027	96.5	375	92.4	568	97.9
	Core STEM Work	133	12.5	81	20.0	41	7.2
	Total	1,064	/	406	/	572	/
Total		1,474	/	691	/	656	/

Table E6: Distribution of sample by degree field of study, field of occupation, and gender, 'between frequencies', using the Broad definition of STEM

Degree Field of Study	Field of occupation	All		Men		Women	
		N	%	N	%	N	%
Broad STEM Graduates	Non-STEM Work	468	59.1	257	56.5	167	62.6
	Broad STEM Work	569	71.8	358	78.7	165	61.8
	Total	792	/	455	/	267	/
Non-STEM Graduates	Non-STEM Work	1,016	94.2	372	89.2	562	97.2
	Broad STEM Work	250	23.2	135	32.4	95	16.4
	Total	1,079	/	417	/	578	/
Total		1,871	/	872	/	845	/

Table E7: Distribution of sample by parental occupation and degree field of study at labour market entry, using the Broad definition of STEM

	All		Non-STEM Degree		Broad STEM Degree	
	N	%	N	%	N	%
Non-STEM Parent	1,406	84.0	838	85.9	568	81.5
Broad STEM Parent	267	16.0	138	14.1	129	18.5
Total	1,673	100.0	976	100.0	697	100.0

Table E8: Distribution of sample by parental occupation, field of occupation, and gender at labour market entry, using the Broad definition of STEM

Parental field of occupation	Field of occupation	All		Men		Women	
		N	%	N	%	N	%
Non-STEM Parent	Non-STEM Work	1,008	71.7	448	62.7	560	81.0
	Broad STEM Work	398	28.31	267	37.3	131	19.0
	Total	1,406	100.0	715	100.0	691	100.0
Broad STEM Parent	Non-STEM Work	156	58.4	68	47.6	88	71.0
	Broad STEM Work	111	42.6	75	52.5	36	29.0
	Total	267	100.0	417	100.0	124	100.0
Total		1,673	/	1,132	/	815	/