

SCHEDULED AT THE MARGINS:
ANTECEDENTS AND CONSEQUENCES OF
NONSTANDARD WORK SCHEDULES

Riley Taiji

Nuffield College



A thesis presented for the degree of
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THESIS ABSTRACT

The past 50 years have seen the erosion of working time regulations and transitions to service-based economies throughout most of Europe. This has led to, amongst other things, a growth in the proportion of the labour force employed in nonstandard work schedules. These are defined as work schedules falling outside of the traditional 9:00 am to 5:00 pm, Monday to Friday workweek. Given that such work arrangements can overlap with – and, in many cases, monopolize – the hours traditionally reserved for family life, the aim of this thesis is to provide a comprehensive investigation into the ways in which families use and are affected by nonstandard schedules, focusing on the previously understudied but highly relevant context of the UK.

Over the course of four empirical chapters, I explore the composition and occupational characteristics of nonstandard schedule workers, the effects that these schedules take on work-family balance, and the ways in which preferences and endowed traits play a large role in shaping which individuals select into and stay in these arrangements. The thesis is unique in the extensive scope with which nonstandard work schedules are studied: I move all the way from the molecular level to the individual level and then up to the country level to showcase the antecedents, consequences, and institutions relevant to the study of nonstandard work schedules and families in the UK and beyond.

This thesis makes several contributions to the existing body of knowledge on nonstandard work schedules and family life. First, I show the many channels of self-, socioeconomic, and occupational selection underlying employment in nonstandard schedules, and present ways to account for these selection mechanisms when studying outcomes relating to work-family balance. Second, I highlight that the consequences of nonstandard schedules on family life are not necessarily universal, but instead depend partially on the country and institutional context in which they are studied. Third, I integrate molecular genetic data to show how the timing of one's circadian rhythm influences preferences for nonstandard work hours, suggesting that such arrangements can be advantageous – and even optimal – for certain individuals.

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LIST OF ABBREVIATIONS

ATE – Average Treatment Effect
BIC – Bayesian Information Criterion
CBC – Collective Bargaining Coverage
EFA – Exploratory Factor Analysis
ESeC – European Socio-Economic Classification
ESS – European Social Survey
EU – European Union
GCSE – General Certificate of Secondary Education
GDP – Per Capita Gross Domestic Product
GWAS – Genome-Wide Association Study
 H_n – Hypothesis
ILO – International Labour Organization
ISCO – International Standard Classification of Occupation
ISEI – International Socio-Economic Index of Occupational Status
IV – Instrumental Variable
LATE – Local Average Treatment Effect
MDM – Mahalanobis Distance Matching
MLM – Multi-Level Model
MR – Mendelian Randomized
NACE – Statistical Classification of Economic Activities (Sector)
NHS – National Health Service
NS-SEC – National Statistics Socio-Economic Classification
OECD – Organization for Economic Co-operation and Development
OLS – Ordinary Least Squares (Regression)
PC – Principal Component
PGS – Polygenic Risk Score
PQ – Partnership Quality
SES – Socio-Economic Status
SNP – Single Nucleotide Polymorphism
UK – United Kingdom (England, Northern Ireland, Scotland, and Wales)
UKBB – United Kingdom Biobank
UKHLS – United Kingdom Household Longitudinal Study
WFC – Work-Family Conflict

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CHAPTER 1

INTRODUCTION

1. THE RISE OF THE 24/7 ECONOMY

On January 12th, 2016, nearly 4,000 operations across the UK were cancelled as more than 30,000 junior doctors took part in the first 24-hour strike within the NHS in 40 years (O. Wright, 2016). This was to be the first of many walkouts over the next few months by junior doctors, with two nine-hour strikes of over 21,000 doctors on April 27th and 28th coming as the latest blows to the NHS (Triggle, 2016). The impetus for the striking? Junior doctors were protesting proposed amendments to employment contracts put forward by the Ministry of Health that would, amongst other things, curtail what constitute unsocial working hours: basic pay rates on weekdays (Monday – Friday) would be extended from 7:00 pm to 9:00 pm, and daytime work hours (7:00 am – 5:00 pm) on Saturdays would be reclassified as basic pay rate hours. In a public statement released on the same day, The British Medical Association – the union representing over 153,000 doctors – cited growing levels of exhaustion and burnout amongst its junior doctors brought on by overwork during nonstandard hours and days, issues that would only be exacerbated by the proposed changes. As one representative put it, “In part, this dispute is a symptom of frustration and low morale that has been building for decades and the strain that a career in medicine can place on your work-life balance” (O. Wright, 2016).

The proposed changes to what constitute unsocial work hours put forward by the Ministry of Health are reflective of broader efforts being made in many industries throughout the UK and the rest of Europe to extend the range of services offered 24 hours a day and 7 days a week. Indeed, firms throughout most post-industrial societies are increasingly expanding their hours of operation outside of the traditional Monday to Friday, 9:00 am to 5:00 pm workweek

to increase competitiveness and provide continuous operation. Such trends, as Delsen, Bauer, Cette, and Smith (2009) observe, are part of a broader decoupling between individual working hours and firm operating hours as more people are being employed at staggered times to cover greater expanses of the day. While jobs entailing night, evening, and weekend hours were once primarily concentrated in the industrial and health sectors, we have witnessed an expansion of these schedules to a growing number of subsectors and occupational categories. Recent Labour Force Survey estimates indicate that now around 17% of employed Europeans work regular evenings (6:00 pm to 10:00 pm), 6% work regular nights (10:00 pm to 6:00 am), and between 14-25% work regularly on Saturdays and/or Sundays (Eurostat, 2016).

How did these high levels of nonstandard work schedules come about? Paid employment during nights, evenings, and at weekends is no new phenomenon. As Presser (2003) notes, it has been around at least as long as midwives have been employed for childbirth, an event that can occur at any hour. Similarly, policies promoting work during nights and evenings date back to Roman times, when Augustus Caesar restricted city deliveries of goods by horse-drawn vehicles to night hours to reduce daytime congestion (Scherrer, 1981). More recently, the industrial revolution of the 19th century saw the growth of large urban centers, a shift to more complex divisions of labour under Fordism, as well as the advent of artificial lighting; these factors both facilitated and necessitated the shift to round-the-clock economic activity (Presser, 2003; Scherrer, 1981). Since then, employment in night, evening, and weekend hours have been core features of many occupations, including nursing, protective services, transport, and manufacturing.

However, a confluence of interconnected secular economic, demographic, and technological trends occurring since around the 1950s have led to the spread of these schedules to a more varied array of jobs. Perhaps the most prominent of these factors has been the staggering growth of the service sector – what Presser (2003) calls, the *24/7 economy* – which

now accounts for roughly 72% of all jobs in Europe and explains much of the rise in nonstandard schedules (ILO, 2018; Presser, Gornick, & Parasher, 2008). A core feature of the service sector that distinguishes it from other sectors is the absence of a physical product that can be stockpiled. For this reason, the production of services is inextricably linked to their consumption, and in many cases, the two processes must occur contemporaneously (Bauer & Groß, 2009). As consumer demand for services increasingly spills outside of the traditional 9:00 am to 5:00 pm, Monday to Friday workweek, this means that more and more workers are required to sell their labour during nonstandard hours and days.

The growing demand for services during nonstandard hours and days is in part driven by the increased labour force participation of women during daytime hours and the concomitant decline in full-time homemaking; this has led to, amongst other things, an increased desire for restaurant and other food services in the evenings as well as the need to extend shop opening hours (Presser, 2003). It is also, as Wight, Raley, and Bianchi (2008) note, in part driven by the delaying of marriage and parenthood, which has increased the numbers of young adults without parental and spousal obligations who seek recreation and entertainment opportunities later in the evening and at weekends. On top of this, the growth in real wages over the past few decades has increased the amount of disposable income individuals and families can spend on services outside of work (Mills, 2004). Employers in the service sector are increasingly forced to meet this new demand by staffing more workers during evenings, nights, and at weekends. This is compounded by the proliferation of information and communication technologies, which has meant that workers can, in theory, be “on call” at all hours of the day (Winkler, Mason, Laska, Christoph, & Neumark-Sztainer, 2018).

While one could argue that firms have always been incentivized to extend their hours of operation to maximize productivity, it is also important to note that they have never been as free as they are now to do so. Over the past 30 years, countries throughout most of Europe have

made large pushes towards the deregulation of labour markets to combat unemployment and keep up with global competition (Philp, Slater, & Wheatley, 2014; Rubery, Smith, & Fagan, 1998). A new emphasis on promoting functional and temporal flexibility for firms means that employers have growing power to adjust not only the number of hours individuals work in accordance with demand but also when these hours are worked (Mills, 2004; Presser, 1998). Moreover, as Chatzitheochari and Arber (2009) note, the continuing erosion of working time regulations and declining representation from unions in the negotiation of working conditions have turned working time into a private arrangement made between employees and employers rather than a matter to be settled through governmental policies or collective agreements. This has meant that throughout Europe the primary determinant of the duration and location of paid work hours is increasingly the market rather than a State-defined workweek.

It should be noted, however, that nonstandard work schedules can also represent a choice on the part of the employee. Indeed, an important supply-side factor in the rise of the 24/7 economy has been the growing labour force participation of women and increase in dual-earner households, who increasingly turn to nonstandard schedules as a means of work-care reconciliation (Begall, Mills, & Ganzeboom, 2015; Carriero, Ghysels, & van Klaveren, 2009; Mills & Täht, 2012). For example, in what's been termed, *tag-team parenting* (Presser, 2003) or *off-scheduling* (Lesnard, 2008), nonstandard work schedules can allow parents to desynchronize their work hours to be able to each cover caregiving responsibilities during different periods of the day. Nonstandard schedules also tend to concentrate amongst the rising numbers of self-employed workers like freelancers and independent contractors, especially those in the so-called, *gig economy*. Freed from managerial constraints, this growing segment of the labour force typically benefits from greater time sovereignty and flexibility, making it relatively free to align the quantity and timing of paid work hours with personal preference rather than a normatively-defined work week (Gold & Mustafa, 2013; Kunda & Barley, 2004;

Lombard, 2001; Osnowitz & Henson, 2016; Shevchuk, Strebkov, & Davis, 2018). It has even been suggested that the desire for flexible, atypical working times may influence the decision to enter into self-employment in the first place, particularly for those with dependent care responsibilities (Lombard, 2001).

2. NONSTANDARD SCHEDULES AND FAMILY LIFE

This thesis will not focus on the macro-level trends of or antecedents underlying the spread of nonstandard schedules. Not only is historical, cross-country data scarce, but such patterns have already been well-covered (e.g., Hamermesh, 1996, 1999; Presser, 2003; Scherrer, 1981). Instead, I seek to explore nonstandard schedules at the micro-level, focusing on the ways in which workers use and are affected by these arrangements and paying special attention to the relatively unexplored context of the UK. Why are the individual-level effects of nonstandard schedules important? As illustrated by the recent junior doctor's dispute, work during nonstandard work hours and days has important implications for the health and well-being of individuals as well as the implementation of social policy. Indeed, there has been a wide body of literature documenting both physiological and social consequences of nonstandard work schedules, and suggesting that these arrangements may not always be in the best interest of employees. Physiologically, nonstandard work hours, especially night shift hours, disturb the body's circadian rhythms and alter its biological functions (J. Li et al., 2014); these arrangements have been linked to, amongst other things, an increased risk of depression and sleep deprivation (Özdemir et al., 2013; Ramadan & Al-Saleh, 2014; Sanches, Teixeira, Moutinho Dos Santos, & Ferreira, 2015) as well as a higher incidence of workplace incidents (Costa, 2010).

Of interest to the current thesis, however, are the social consequences of nonstandard schedules, particularly those relating to family life. A wide body of research has shown that, by

engaging the worker in paid labor outside of the normative Monday-Friday diurnal workweek, nonstandard schedules have the potential to put individuals “out of sync” with their family and the rest of society in general (Täht, 2011). For example, as several studies have shown, night, evening, and weekend work schedules constrain the time that a worker can spend at home during the hours traditionally reserved for family life, which can increase the risk of work-family conflict. Evidence supporting this notion comes from studies linking nonstandard schedules to an increased risk of marital dissolution and conflict (Kalil, Ziol-Guest, & Epstein, 2010; Maume & Sebastian, 2012; Presser, 2000; White & Keith, 1990), and greater levels of negative work-to-family spillover (Davis, Benjamin Goodman, Pirretti, & Almeida, 2008; Grosswald, 2003; Maume & Sebastian, 2012).

These time constraints can also affect the children of workers, as evening, night, and weekend work limits the number of afterschool hours parents have available to support children’s cognitive and social development (Heymann & Earle, 2001). Research from the US, for example, has linked nonstandard schedules to several adverse outcomes for the children of workers, including an increased risk of emotional instability (Han, 2005; J. Li et al., 2014; Strazdins, Clements, Korda, Broom, & D’Souza, 2006), increased incidence of substance abuse and risky behavior (Han, Miller, & Waldfogel, 2010; Hendrix & Parcel, 2014), and decreased academic performance (Gennetian, Lopoo, & London, 2008; Han, 2005; Han & Fox, 2011; Heymann & Earle, 2001).

However, it is important to note that findings on the effects of nonstandard schedules on family life have not always been so negative. A second strand of research has also documented that nonstandard schedules can be beneficial to families if they represent a strategic choice by the household. Such was found, for example, in the case of dual-earner parents selecting into desynchronized work schedules where one partner works nights or evenings while the other works days to more equally distribute caregiving and household responsibilities

(e.g., Begall, Mills, & Ganzeboom, 2015; Deutsch, 1999; Mills & Täht, 2012; Presser, 2003). These arrangements not only cater to a preference for familial caregiving but also allow parents to avoid the high costs and long waiting lists typical of public and private child care institutions. Other studies have also highlighted that nonstandard schedules can promote work-family balance if they come with a relatively high degree of flexibility and predictability, one of the reasons individuals – particularly working mothers – often self-select into such arrangements (Deutsch, 1999; Fenwick & Tausig, 2001; Lombard, 2001; Lozano, Hamplová, & Le Bourdais, 2016; Staines & Pleck, 1986). These findings point to the important channels of self-selection that often underlie employment in nonstandard schedules. More broadly, they also highlight the difficulty in generalizing on the effects that nonstandard schedules can take on family life.

Another important point worth noting is that much of the existing research into the social consequences of nonstandard schedules has taken a distinctly US-based focus. Indeed, with the exception of a handful of recent works (e.g., Hook & Wolfe, 2013; Lesnard, 2008; Täht & Mills, 2016; Tammelin, Malinen, Rönkä, & Verhoef, 2017), research into the social consequences of nonstandard schedules has in general lagged in the European context, largely falling behind the rate at which such work schedules have spread. As Presser et al. (2008) note, while much attention within recent sociological work in Europe and the UK has been paid to the changing number of hours spouses and parents are working, relatively little attention has been paid to important shifts in when these hours are being worked. The social consequences of nonstandard schedules have gone particularly overlooked in the UK; this is despite it having not only amongst the highest rates of nonstandard schedule work in Europe (Presser et al., 2008) but also some of the weakest regulations for jobs involving these schedules (Gornick & Meyers, 2003; Philp et al., 2014).

Whether the negative effects of nonstandard schedules on family life found in the US can be extended to the UK context largely remains to be seen. There is good reason to expect that the ways in which the nonstandard schedules affect family life might in part depend on the context in which they are studied. On the one hand, welfare and labour institutions aimed at promoting work-family reconciliation vary considerably across most industrialized nations (Gershuny & Sullivan, 2003; Gornick & Heron, 2006; Mosher & Trubek, 2003). On the other hand, there is substantial between-country variation in the ways in which nonstandard schedules are organized and regulated (Gornick & Meyers, 2003), which in turn might limit the representativeness of conclusions drawn from any single context. A handful of recent cross-national studies underscore the importance of country context, and indicate that the effects of nonstandard schedules on outcomes relating to work-family balance are highly sensitive to national context (Anttila, Oinas, Tammelin, & Nätti, 2015; Hook & Wolfe, 2013; Täht & Mills, 2016; Tammelin et al., 2017). When studying the social consequences of nonstandard schedules, such research highlights the need to situate these arrangements in the broader contexts in which they are organized and regulated.

3. AREAS FOR FURTHER RESEARCH

As exemplified by the recent saga of the junior doctor's dispute, the UK presents an especially important case for further study in Europe. Following the guidelines of the European Employment Strategy, the UK has made large pushes toward the flexibilization of its labor market in order to decrease unemployment, which has ultimately led to lower levels of protections for workers – especially those in nonstandard employment (Casey, 2004; Gornick & Meyers, 2003). The UK has also taken a notoriously minimalist approach to the regulation of working time, avoiding any strong incorporation of the European Working Time Directive into national law. A vivid example of this is that today, the UK remains one of the only national

entities in Europe that allows workers to opt-out of the EU mandated 48-hour maximum workweek (Philp et al., 2014). The low coverage of collective bargaining agreements, weak regulation of working time, and the presence of a long and late hours work culture create an atmosphere where overwork and unhealthy work schedules are increasingly the norm (Chatzitheochari & Arber, 2009). Yet despite this, relatively little is known about the ways in which UK families utilize and are affected by nonstandard work schedules.

Along with exploring the social consequences of nonstandard schedules in the previously understudied but highly relevant context of the UK, this thesis will focus on addressing three main gaps in the existing literature. First, I attempt to characterize and correct for the complex patterns of self- and structural selection underlying employment in nonstandard schedules. Work schedule arrangements like nights, rotating shifts, and weekend work are far from randomly distributed across the population. Rather, entrance into these schedules is influenced by complex and competing preferences and constraints tied to characteristics of an individual's household situation and employment relationship – factors that are likely not independent of outcomes relating to family cohesion (Grzywacz, Daniel, Tucker, Walls, & Leerkes, 2011; Presser, 2003). Moreover, a distinction must be made between those who choose for a variety of reasons to work nonstandard schedules and those on whom these arrangements are imposed by the employer or the nature of the job. Despite this, few existing studies have attempted to characterize these selection processes, which may have contributed to inconsistent findings across previous research on the effects such schedules take on family life.

A second relatively underexplored area for research is the extent to which the effects of nonstandard schedules on family life might vary by country or be buffered by institutional context. With the exception of a few recent studies (Anttila et al., 2015; Hook & Wolfe, 2013; Täht & Mills, 2016; Tammelin et al., 2017), previous research on the social consequences of nonstandard schedules has largely been confined to the study of single – and generally quite

specific – country contexts, therefore overlooking the ways in which the effects of these arrangements on family life might depend on the context in which they are studied. As discussed earlier, there is little reason to expect that the effects of nonstandard schedules on families would be the same across different country contexts given the substantial heterogeneity in how these jobs are organized and regulated (Gornick & Meyers, 2003), as well as the considerable between-country variation in welfare and labour institutions aimed at promoting work-family balance (Gershuny & Sullivan, 2003; Gornick & Heron, 2006; Mosher & Trubek, 2003). Despite this, the extent to which the effects of nonstandard schedules on outcomes relating to work-family balance vary by country and institutional context remains surprisingly overlooked.

A final avenue of research that I look at is the question of whether endowed and biological characteristics might affect preferences surrounding the timing of paid work. While previous research has alluded to the possibility that certain individuals – due to a host of unobservable factors – may prefer or be better equipped to tolerate work during nonstandard hours than others, few studies have attempted to unpack or test this claim. What remains surprisingly underexplored is the question of whether the timing of an individual’s endogenous circadian clock – or *chronotype* – influences his or her preferences surrounding the timing of paid work. Indeed, we still know relatively little about whether individuals with later circadian rhythms – often referred to as “owls” or “evening people” – are also those most likely to be observed in nonstandard work hours. A strong association between eveningness and night shift work selection, if observed, would suggest that individuals choose the work schedule that best suits their internal biological clock. Perhaps more interesting, however, a weak association would indicate that there is often a mismatch between individuals’ actual and optimal work schedules in the labour market, such that those best suited to daytime work hours instead select into night shift work schedules and vice versa. This latter trend, if observed, might shed light

on some of the well-documented social and physical consequences of night shift work discussed above.

4. OVERVIEW OF THESIS

In this thesis, I seek to fill these gaps and build on the extant knowledge of the individual-level antecedents and consequences of nonstandard work schedules. I will contribute to the existing literature on the relationship between nonstandard work schedules and family life in three ways: (1) through methodological improvements in assessing causality between nonstandard schedules and family cohesion by addressing selection biases into these arrangements, (2) by exploring the moderating effects of country and institutional context, and (3) by looking at the ways in which chronotype influences an individual's preferences for nonstandard work hours. This thesis includes a collection of one descriptive and three empirical chapters that together work towards addressing these objectives. These chapters are described in the following discussion and are summarized in Table 1-1.

In Chapter 2, I present a detailed descriptive analysis of who works nonstandard schedules and in which jobs these schedules tend to concentrate in the UK and the rest of Europe. Emphasis in this chapter is placed on answering three main questions: (1) how common is nonstandard hour and day work in the UK and the rest of Europe?; (2) what are the salient demographic, household, and socioeconomic characteristics of the individuals who work these arrangements?; and (3) what are the characteristics of the occupations where these schedules are most common? More broadly, this chapter is meant to showcase the size and composition of the sample that will be of interest to subsequent empirical chapters. Results show wide variation in the rates of nonstandard hour and day work across Europe, which appear to be highest in the UK, Turkey, and Scandinavian countries, and lowest in Austria, the Czech Republic, and Italy. To the extent that there is the emergence of a 24/7 economy in Europe,

findings suggest it is clearly developing at different rates between countries. Crucially, findings from this chapter also show that individuals working regular nonstandard hours and days are a relatively selective population: they tend on average to be younger, have lower levels of educational attainment, and are more likely to be self-employed and have a partner who also works a nonstandard schedule. Related to this, findings also suggest that nonstandard schedules appear to be a symptom of a lower position in the occupational hierarchy: they tend to concentrate in relatively low-status occupations as well as amongst those individuals employed on nonstandard contracts and who have most recently joined a company.

In Chapter 3, I move on to explore the relationship between nonstandard work schedules and partnership quality using 2010-2016 data from UK Household Longitudinal Study. This chapter builds on previous research on the effects of nonstandard schedules on partnership quality by attempting to characterize and correct for the complex process of selection underlying employment in these arrangements through a matching-based quasi-experiment. To do so, Mahalanobis Distance Matching and propensity score stratification techniques are used to simulate blocked randomization and identify patterns of positive and negative selection. Results indicate that after correcting for baseline selection biases through matching, nonstandard schedules only take negative effects on partnership quality when worked by women. Crucially, however, it appears that women's nonstandard work hours and days appear to take the largest tolls on the partner of the worker rather than the worker herself. This could be tied to a third major finding of this chapter: it appears that women positively select into nonstandard schedules on the basis of their own but not their partner's perceived partnership quality. Such findings highlight the importance of a nuanced approach to the study of the relationship between nonstandard schedules and outcomes relating to family cohesion that takes into account the complex processes of selection into these arrangements as well as the diverging actor and partner effects.

In Chapter 4 (co-authored with Melinda Mills¹), we use multi-level modeling techniques on 2004 and 2010 European Social Survey data to explore whether the effects of nonstandard schedules on work-family conflict (WFC) vary across 32 countries in Europe, and if so, whether this contextual variation can be explained by labour regulations and industrial relations characteristics measured at the country level. Findings show that while nonstandard work hours and days are associated with increased WFC across all but two of the 32 sampled countries, the strength of this association varies significantly between countries. The strongest factor shaping the social consequences of nonstandard schedules is the degree to which workers are covered under collective bargaining agreements in a country, which explains as much as 24% of the observed between-country variation in the effects of nonstandard schedules on WFC. These findings highlight collective agreements as the central mechanism through which family-friendly regulations on working times and conditions are generated for nonstandard schedule workers across Europe. More broadly, findings suggest that when studying the social consequences of nonstandard schedules, these arrangements must be contextualized in the broader institutional frameworks within which they are organized and regulated.

In Chapter 5, I explore whether the timing of an individual's circadian rhythm – or their chronotype – predicts selection into nonstandard work hours. Previous research has documented a strong association between eveningness chronotypes and selection into and tolerance of night shift work, suggesting that the ability to thrive in nonsocial hours may be partially dependent on a circadian clock optimized for these times of the day. However, the use of cross-sectional data and self-reports of chronotype in these studies raises concerns surrounding the direction of causality: it is unclear whether eveningness influences shift work selection, or whether prolonged shift work increases the likelihood of self-reported eveningness. In this study, I address these concerns by proposing a novel framework in which

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to view and operationalize chronotype that takes into account the relative contributions of genes, measurement error, and cumulative social environment. Under this framework, I utilize Mendelian Randomization techniques on genetic and work history data from the UK Biobank to study the causal association between eveningness and selection into night shift schedules. Results indicate that eveningness significantly increases the probability of being observed in a night shift work schedule, an effect that appears to be causal. However, findings also suggest that the strength of this association in part depends on the level of information individuals have on their true chronotype as well as their position in the occupational hierarchy. Taken together, such results broadly suggest that individuals do indeed have a tendency to select into the work hours best suiting their endogenous circadian clock, even if these hours are nonstandard in nature. Results also suggest, however, that factors like imperfect information and occupational position can often result in individual's selecting into sub-optimal work hours.

Table 1-1. *Thesis Outline*

Chapter	Research Questions	Core Variables Studied	Data and Methods	Contributions
Chapter 2. Who Works Nonstandard Schedules?	1. How prevalent are nonstandard schedules in the UK and Europe? 2. What are the salient demographic, socioeconomic, and occupational characteristics of nonstandard schedule workers?	<u>Dependent variables</u> : Nonstandard work hours and days. <u>Independent variables</u> : Education, occupation, family structure, ethnicity, employment relationship, gender.	<u>Data</u> : 2004 and 2010 European Social Survey Data. <u>Methods</u> : Descriptive statistics, logistic and OLS regression.	1. First comprehensive investigation of dominant characteristics of nonstandard schedule workers in the UK.
Chapter 3. Gender, Nonstandard Schedules and Partnership Quality: Exploring Heterogeneous Actor and Partner Effects through a Quasi-Experiment	1. Do nonstandard work schedules affect levels of partnership quality for the worker and/or her partner? 2. Is there evidence of positive or negative selection into these arrangements?	<u>Dependent variables</u> : Self-reported partnership stability, self-reported partnership cohesion. <u>Independent variables</u> : Work schedule timing, treatment selection covariates.	<u>Data</u> : 2010-2016 UK Household Longitudinal Study. <u>Methods</u> : Mahalanobis distance matching and propensity score stratification.	1. Methodological improvements in assessing causality between nonstandard schedules and family cohesion. 2. Disentangling of gendered differences in actor and partner effects.
Chapter 4. Nonstandard Schedules, Work-Family Conflict, and the Moderating Effect of Country Context: Evidence from 32 European Countries	1. Do the effects of nonstandard schedules on work-family conflict vary across countries in Europe? 2. Do country-level labour relations characteristics moderate the effect of nonstandard schedules on work-family conflict?	<u>Dependent variables</u> : Self-reported work-family conflict. <u>Independent variables</u> : Work schedule timing, collective bargaining coverage, union membership density, quality of the national working environment.	<u>Data</u> : 2004 and 2010 European Social Survey Data. <u>Methods</u> : Cross-classified random effects multi-level models.	1. Cross-country analysis of social consequences of nonstandard schedules. 2. Exploration of the potential of labour institutions to buffer social consequences of nonstandard schedules.
Chapter 5. Do Owls Work at Night? Using Genetic Data to Explore the Causal Link Between Eveningness and Night Shift Work	1. Does eveningness increase the probability of being observed in night shift work schedule? 2. To what extent does this relationship depend on the level of information and bargaining power of the worker?	<u>Dependent variables</u> : Night shift work. <u>Independent variables</u> : Self-reported eveningness, genetic propensity for eveningness (polygenic risk score), employment duration, age, sex, genetic principal components.	<u>Data</u> : 2017 UK Biobank. <u>Methods</u> : Mendelian randomized probit regression.	1. Methodological improvements in assessing causality between chronotype and work schedule timing. 2. Exploration of how genetics influence labour market decisions.

5. METHODOLOGY

The four empirical chapters in this thesis each utilize different analytic techniques to address their respective research questions. For this reason, methods are described in detail in each chapter separately. I present below a brief summary of the data and terminology that will be used throughout the thesis.

5.1. DATA

This study addresses several research questions with differing needs surrounding geographic and analytic scope. The three datasets used in this thesis are: (1) the UK Household Longitudinal Study (UKHLS), (2) the European Social Survey (ESS), and (3) the UK Biobank (UKBB). The UKHLS (used in Chapter 3) is the largest household panel dataset in Europe, providing a nationally representative probability sample of over 40,000 households in the UK (University of Essex, Institute for Social and Economic Research, NatCen Social Research, & Kantar Public, 2017). The UKHLS currently has 7 available waves of data spanning from 2009-2016; the current thesis will employ Waves 2 to 7 (2010-2016). The ESS (used in Chapters 2 and 4) is a cross-national survey which conducts face-to-face interviews every two years for newly selected, cross-sectional samples (Norwegian Centre for Research Data, 2016). These interviews measure the attitudes, beliefs, and behaviour patterns of diverse populations in more than thirty nations. The ESS currently has 8 rounds of available data spanning from 2002-2016; the current thesis will employ Rounds 2 and 5 (2004 and 2010) as these contain measures of nonstandard work schedules and work-family conflict. The UKBB (used in Chapter 5) provides genetic, demographic, and socioeconomic information on roughly 500,000 British respondents between the ages of 40-69 (UK Biobank, 2018). Data collection for the latest cross-sectional release occurred over the period of 2006-2018.

5.2. SAMPLE

The working sample for the analyses done in this thesis will include individuals in regular paid employment between the ages of 18-59. This upper-bound age restriction of 59 is consistent with previous research on the relationship between paid work and family dynamics (e.g., Kan, Sullivan, & Gershuny, 2011). For the purposes of the current thesis, it removes from the sample those individuals who might be winding down labour market activity leading up to retirement and/or those individuals who may have reached an age where family dynamics may be less sensitive to work schedule timing. In Chapters 3 and 4 (where I focus on the impacts of nonstandard schedules on outcomes relating to work-family balance), I further restrict the sample to include only individuals in co-resident partnerships and those in paid employment in excess of 11 hours per week. The choice of setting a minimum of 12 working hours per week as a sample restriction is consistent with similar research done in the Netherlands (Täht & Mills, 2016). For the purposes of the current thesis, it removes those individuals from the sample who may be in a nonstandard schedule but are working too few hours to experience any negative social consequences from such arrangements.

Within these two chapters, I also exclude individuals in self-employment. This choice was due to not only to the contention that self-employed workers are in general a relatively selective population, but also to the fact that nonstandard schedules will likely mean different things for employed and self-employed workers. For self-employed individuals, work during nonstandard hours or days will largely reflect the workers' preferences. In contrast, for employees, such work is usually set by the employers and can often be viewed as contrary to employees' interests. That said, the social consequences of nonstandard schedule work amongst the self-employed is an important and under-studied area; I return to this in Chapter 6 and discuss areas for future research. It should also be noted that self-employed individuals will be included in the samples analyzed in Chapters 2 and 5: in Chapter 2, I explore rates of

nonstandard schedule work amongst the self-employed; and in Chapter 5, I explore how chronotype affects preferences surrounding work schedule timing amongst the self-employed.

5.3. TERMINOLOGY

5.3.1. NONSTANDARD WORK SCHEDULES

In this thesis, a nonstandard schedule is defined broadly as any work schedule where the majority of hours in paid employment occur outside of the traditional Monday-Friday, 9:00 am to 5:00 pm diurnal workweek. This definition can be separated into two forms of nonstandard work times: nonstandard work hours, or those schedules involving regular work between the hours of 5:00 pm and 6:00 am (i.e., during evenings or at night); and nonstandard work days, or those schedules involving regular work between Friday and Monday (i.e., on Saturdays and/or Sundays). Overlapping these categories, one can further differentiate non-fixed work schedule variants like rotating shift work and variable-hour schedules, which both include some combination of evening, night, and day work hours; I define these work schedule variants in Table 1-2 using a typology adapted from Presser (2003).

Surveys differ widely in the measurement of nonstandard work schedules: where some surveys ask respondents to choose whether they work nonstandard or standard times, others allow respondents to indicate that their jobs involve work during both standard and nonstandard times. A hybrid of these two strategies and perhaps the most common measurement strategy is to ask respondents to report the frequency with which they work nonstandard hours or days. As Dunifon, Kalil, Crosby, Su, and Deleire (2013) note, these cross-survey inconsistencies in nonstandard schedule measurement make it challenging to compare findings across studies that relate to family life outcomes. The current thesis will, unfortunately, be no exception to this as I will be employing three different datasets, which each differ slightly in the measurement of nonstandard work schedules. For example, the latter strategy of measuring the regularity of

nonstandard work hours and days is used in two datasets that will be employed in the present thesis (UKBB and ESS). It is also used in the UKHLS's measurement of nonstandard work days, where respondents are asked to report their frequency of weekend work. However, the UKHLS's measurement of nonstandard work hours, in contrast, asks respondents to choose a single category best describing at what times of the day their work hours most often occur.

Given these differences in measurement strategies across the surveys employed in the current thesis, it is profitless to attempt to provide a single overarching operationalization of nonstandard work schedules in the present discussion. That said, in subsequent chapters any reference to nonstandard work times will generally be to any work occurring during evenings, nights, or at weekends. It should also be noted that for the purposes of the current thesis, the distinction between non-day and day work is more important than distinctions between different types of non-day work. Therefore, when discussing nonstandard work hours, I will focus broadly on the effects of employment during evenings and/or nights rather than the effects of specific variants of nonstandard hours like variable and rotating hours. While this choice will inevitably obscure important differences between specific variants of nonstandard work hours (like the differing levels of flexibility and predictability), it will also facilitate a more coherent discussion and analytical simplicity. Moreover, it will allow for greater comparability of nonstandard work schedules across several institutionally diverse European countries for which the definitions and arrangements of specific work schedule variants like shift work and variable-hour schedules differ widely. Techniques to measure nonstandard schedule work will be elaborated on further within each respective chapter.

Table 1-2. *Typology of Nonstandard Work Schedules*

Work Schedule	Designation	Definition
Work Hours		
Day	Standard	Majority of regular work hours occur between 9:00 am - 5:00 pm
Evening	Nonstandard	Majority of regular work hours occur between 5:00 pm - 10:00 pm
Night	Nonstandard	Majority of regular work hours occur between 10:00 pm - 6:00 am
Rotating	Nonstandard	Schedule changes periodically from days to evenings or nights with a high degree of regularity
Variable	Nonstandard	Schedule changes periodically from days to evenings or nights with a low degree of regularity
Work Days		
Weekday	Standard	All work hours occur between Monday and Friday
Weekend	Nonstandard	Work regularly occurs on Saturday and/or Sunday

Notes: Typology adapted from Presser (2003).

5.3.2. WORK-FAMILY CONFLICT

Chapters 3 and 4 of this thesis will focus on modeling the effects of nonstandard work schedules on work-family conflict or related outcomes. Work-family conflict (WFC) captures the simultaneous pressures of work and family demands that are incompatible in some respect (Baltes, Clark, & Chakrabarti, 2010). Demands in both family and job roles broadly refer to structural or psychological claims relating to role requirements, expectations, and norms to which individuals must attend to by exerting physical or mental effort (Voydanoff, 2004). This thesis will focus on one type of WFC, *work-to-family interference*, which occurs when participation in one's work roles inhibits full participation in family roles (Greenhaus & Beutell, 1985). I distinguish between two types of work-to-family interference that are of interest to the current thesis: (1) *strain-based conflict*, which arises when the physical and/or mental pressures associated with one's work roles make it difficult to meet the demands of one's family roles; and (2) *time-based conflict*, which arises when time spent on one's work roles makes it difficult to dedicate sufficient time to one's roles in the family and household.

Chapter 4 of this thesis focuses on modeling the effects of nonstandard work schedules on a direct measurement of WFC; specifically, a three-item index capturing the degree of time- and strain-based WFC. In contrast, Chapter 3 focuses on modeling the effects of nonstandard work schedules on a proximate measure of WFC; specifically, a 9-item index capturing the subjective levels of cohesion and stability within a romantic partnership. Generally speaking, both chapters focus on the extent to which the timing of one's work schedule gives rise to practical difficulties surrounding participation in family and household roles. However, where Chapter 4 focuses broadly on all family roles, Chapter 3 takes a more narrow focus by looking at whether nonstandard schedules restrict the worker's ability to participate fully in the roles and rhythms of a conjugal relationship. These differences in the measurement of work-family conflict are discussed in further detail within each respective chapter.

CHAPTER 2

WHO WORKS NONSTANDARD SCHEDULES?

1. BACKGROUND AND MEASURES

In this chapter, I present an overview of the salient characteristics of the nonstandard schedule labour force in the United Kingdom. Surprisingly little descriptive analysis on the socioeconomic and demographic characteristics of nonstandard schedule workers has been done in the UK context. Moreover, few attempts have been made to describe the occupations where these schedules are most common. This chapter will be descriptive in nature and is intended primarily to illustrate the size and composition of the sample that will be of interest to subsequent empirical chapters. To contextualize these findings, descriptive statistics on nonstandard schedule workers will also be presented for the rest of Europe.² Emphasis will be placed on answering three main questions: (1) how common is nonstandard hour and day work in the UK and the rest of Europe?; (2) what are the salient demographic, household and socioeconomic characteristics of the individuals who work these arrangements?; and (3) what are the characteristics of the occupations where these schedules are most common?

The sample for this analysis includes individuals in regular paid employment (including self-employment) who are between the ages of 18 and 59. All estimates will be derived from 2004 and 2010 data (Rounds 2 and 5) of the European Social Survey.³ In the interest of maximizing sample size and as the focus of this chapter is not on period effects, these rounds will be collapsed into a single period. In subsequent discussions, the primary dependent

² Countries included in the rest of Europe are Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Lithuania, Luxembourg, the Netherlands, Norway, Poland, Portugal, Russia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, Ukraine.

³ These are the only Rounds of the European Social Survey that measure whether an individual works nonstandard hours and days.

variables of interest will be two different forms of nonstandard schedules: (1) nonstandard hours (i.e., evening and/or night work), and (2) nonstandard days (i.e., Saturday and/or Sunday work). The measure of nonstandard hours will be derived from a question asking respondents to report, “How often [their] work involve[s]... working evenings or nights” in their primary job. The measure of nonstandard days is derived from a question asking respondents, “How often [their] work involve[s] working at weekends?” The core focus in this chapter is on describing the salient characteristics of individuals for whom work hours regularly occur during evenings, nights, or at weekends. As most work today involves some degree of evening, night, or weekend work, I focus here on the extreme cases who work nonstandard hours most days or every day and those who work nonstandard days every week. Therefore, both measures will be dichotomized such that respondents are coded as nonstandard hour workers if they report having to work evenings or nights “every day” or “several times a week”, and are coded as nonstandard day workers if they report working at weekends “every week”.⁴

2. PREVALENCE OF NONSTANDARD SCHEDULE WORK

I start first by exploring how common nonstandard schedules are in the UK and across the rest of Europe. Figures 2-1 and 2-2 show the proportions of individuals working regular nonstandard hours and days by country. A first notable finding is that the UK ranks amongst the top countries in rates of nonstandard work hours and days for both men and women. Between 2004 and 2010 in the UK, around 22% of women and 31% of men reported working nights and/or evenings every day or several times a week. Turning to nonstandard work days, around 17% of women and 21% of men report working at weekends every week. Comparing

⁴ While it would be ideal to only include those individuals who report working nights and/or evenings every day as nonstandard hour workers, the small n for this group would not provide sufficient power to be able to perform any meaningful statistical tests; in the UK, only 77 men and 52 women were in this category. Moreover, sensitivity analyses (results available upon request) suggest that trends remain largely consistent regardless of whether individuals who work nights/evenings several times a week are included or not. I return to limitations of this operationalization in subsequent discussions.

these rates to the rest of Europe (Appendix 2-1) shows that the proportions of the UK workforce working regular nonstandard hours is around 0.07 higher than the European average for women and 0.12 higher for men ($p < 0.001$). Similarly, the proportion of the UK workforce engaged in regular weekend work is around 0.07 higher than the European average for women and 0.09 higher for men ($p < 0.001$). These gaps remain significant when looking at rates of nonstandard day and hour work amongst part- and full-time workers. Such findings are largely consistent with estimates derived from the EU Labour Force Surveys from Presser et al. (2008) that highlighted the UK as a particularly important case for study with regards to the spread of nonstandard work schedules in Europe.

Similarly high rates of nonstandard work hours can also be seen in Scandinavian countries like Sweden, Finland, Norway, and Iceland, while rates of nonstandard day work appear highest in Mediterranean countries like Turkey, Greece and Cyprus. In contrast, rates of both nonstandard work hours and days appear to be lowest in Austria, the Czech Republic, and Italy. Italy stands out, in particular, for having extremely low rates of nonstandard schedule work: rates of nonstandard hour work range from 8% for men to around 1% for women, while rates of nonstandard day work range from 6% for women to around 5% for men. Taken together, these findings highlight the large variation with which nonstandard schedule work has spread across countries in Europe; to the extent that there is the emergence of a 24/7 economy in Europe, it is clearly developing at different rates between countries. Such variation in the rates of nonstandard schedule work between countries reflects both differences in the stringency of working time regulations as well as structural differences in the labour market, for example, in the prevalence of certain occupations requiring round-the-clock production (e.g., services and manufacturing). Findings on the prevalence of nonstandard work hours and days also show interesting patterns by gender: across the UK and the rest Europe, night and evening work

WHO WORKS NONSTANDARD SCHEDULES?

appears to be particularly common for men, while weekend work appears to be more common for women.

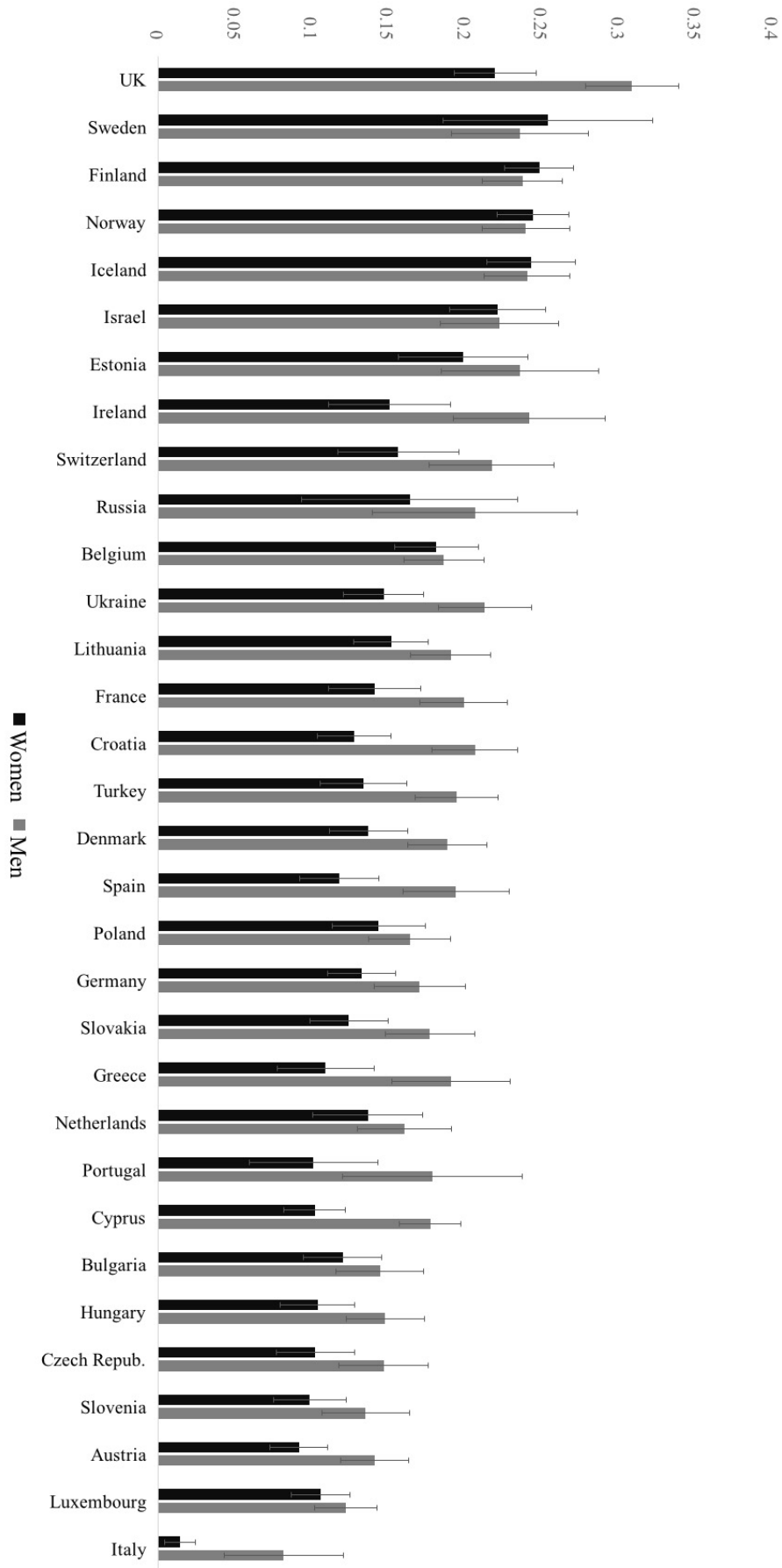


Figure 2-1. *Proportion of Individuals Working Regular Nonstandard Hours, by Gender and Country*

Data Sources: 2004 and 2010 European Social Survey (Rounds 2 and 5)
Notes: Sample includes respondents in paid employment between the ages of 18-59. Error bars indicate 95% confidence intervals around estimate.

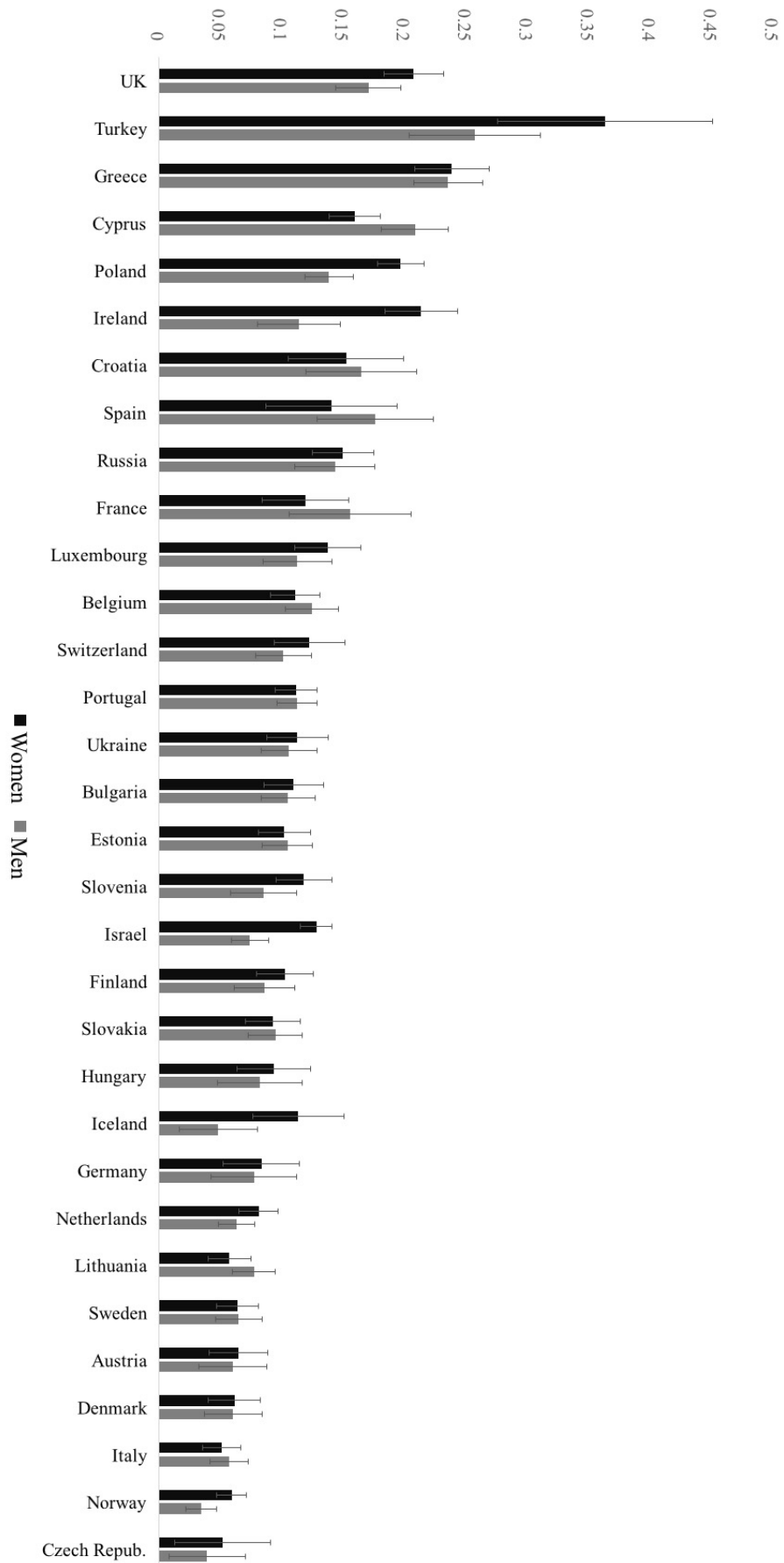


Figure 2-2. *Proportion of Individuals Working Regular Nonstandard Days, by Gender and Country*

Data Sources: 2004 and 2010 European Social Survey (Rounds 2 and 5)

Notes: Sample includes respondents in paid employment between the ages of 18-59. Error bars indicate 95% confidence intervals around estimate.

3. BACKGROUND CHARACTERISTICS OF NONSTANDARD SCHEDULE WORKERS

I turn now to describing some of the salient demographic, household, and socioeconomic characteristics of nonstandard schedule workers in the UK and the rest of Europe. Eight covariates will be analyzed in this section. I firstly look at differences in (1) age (measured in years) between individuals regularly working nonstandard hours/days and those not who do not regularly work these times. Along with this, two measures of education are included: (2) years of education, and (3) whether the respondent has a tertiary degree. I also look at three binary variables indicating whether: (4) the respondent identifies as an ethnic minority in their country, (5) the respondent has at least one dependent child under 16 living at home, and (6) the respondent is in a co-resident partnership (either married or cohabiting). For those respondents in co-resident partnerships, I also look at whether (7) the partner is also in paid employment, and if so, (8) whether he or she also works nonstandard hours/days.

Table 2-1 shows the means or proportions (depicted as alpha term, α) of covariates by for nonstandard schedule workers by gender. For continuous covariates (age and years of education), the beta term b denotes the raw difference in observed means between individuals working regular nonstandard schedules and those not regularly working these schedules. For binary variables (all other covariates), the beta term b denotes the odds ratio of nonstandard schedule workers relative to those not in these arrangements. All standard errors have been clustered around the country-period ID to account for multiple rounds of data collection.

Looking first to the characteristics of women, it appears that those regularly working nonstandard hours and days are in general significantly younger than control subjects. This seems particularly true for women working regular weekends, where age differences range from -2.55 years in the UK to -2.20 years in the rest of Europe ($p < 0.001$). The exception to this trend is for female nonstandard hour workers in the rest of Europe, where no significant age differences are observed. Another clear trend for female nonstandard schedule workers seen

both in the UK and the rest of Europe is to be more likely to be childless as well as have no spouse or partner present in the household. This seems particularly true for female nonstandard hour workers in the UK, for whom the odds of being in a co-resident partnership are 0.69 times as large as for those not in these arrangements ($p < 0.05$) and the odds of having dependent children in the household are 0.60 times as large ($p < 0.001$). However, as these are merely associations, it is unclear what the direction of causality is here. For example, one cannot be certain whether single, childless women are more likely to work nonsocial hours due to fewer family responsibilities during these hours, or, conversely, whether nonsocial work hours constrain the opportunity to meet a partner and have children. It should also be noted that, as these are unconditional bivariate associations, differences in household composition for female nonstandard schedule workers are likely at least in part tied to the younger ages of these workers.

Looking to male nonstandard schedule workers, no clear trends emerge when looking at average age or the presence of children. In the rest of Europe, however, it does appear that men in nonstandard days and hours are slightly more likely to be single; although this trend is not observed in the UK. A clear trend that does emerge across both the UK and the rest of Europe for men with partners is to be on average the sole earner in the household. As can be seen in the UK, for example, men in co-resident partnerships who work nonstandard hours are 0.65 times as likely to have a partner in paid employment than men in co-resident partnerships who do not work these hours ($p < 0.05$). Similarly, men working nonstandard days in the UK are 0.58 times as likely to have a partner in paid employment than men in co-resident partnerships who do not work regularly work these days ($p < 0.001$). These trends are for the most part also seen in the rest of Europe; the exception is for male nonstandard hours where no significant differences are observed. It is again unclear what the direction of causality is here. However, this association could highlight that fact that for couples, nonstandard schedules

present particularly dire time constraints on shared couple time when both partners are in paid employment.

Turning now to socioeconomic characteristics, a clear trend for men working regular nonstandard days is to have on average lower levels of educational attainment. In the UK, for example, men working regular weekends have on average 1 year less education and are 0.46 times as likely to have a college degree than men who do not regularly work these days ($p < 0.001$). Similar – if slightly smaller – gaps are also seen throughout the rest of Europe. This educational gap for weekend workers is also observed for women in the rest of Europe but does not reach significance in the UK. Interestingly, no significant gaps are observed in the levels of educational attainment for male and female nonstandard hour workers in the UK. However, looking at the rest of Europe shows that both men and women in nonstandard hours have on average higher levels of educational attainment. For example, women working regular nights or evenings throughout the rest of Europe have on average 0.53 years more education and are 1.25 more likely to have a college degree ($p < 0.001$). Similar trends are also seen for male nonstandard hour workers in the rest of Europe.

That regular nonstandard hour workers would have higher levels of educational attainment is somewhat surprising when one reflects on previous literature from the US and France that has shown that nonstandard work hours are often concentrated amongst those with the least bargaining power and human capital in the labour market (Grzywacz et al., 2011; Hamermesh, 2002; Lesnard, 2008; Presser, 1987). In the present case, the higher levels of educational attainment amongst nonstandard hour workers could be an artifact of the way in which nonstandard work hours are operationalized. As I can only measure the regularity of night and evening work hours within the current data, I cannot determine whether the majority of work hours actually occur during nights or evenings. Therefore, I cannot differentiate, for example, between individuals who only work nights and evenings and those individuals in

white collar occupations who might regularly work long hours that spill into evenings and nights. I return to this issue in subsequent discussions.

For both women and men in the rest of Europe, regular nonstandard work days appear to be concentrated amongst those identifying as an ethnic minority in their country ($b = 1.34$ - 1.39 , $p < 0.01$). However, no significant differences in ethnic minority status are observed for nonstandard work hours. A clearer trend that can be observed across genders for those working regular nonstandard work hours and days is to have a partner who works a synchronized nonstandard schedule. In the UK, for example, men working regular nonstandard days are 3.65 more likely to have a partner who also works nonstandard hours ($p < 0.001$). Similarly, women working regular nonstandard days are 2.85 times more likely to have a partner who also works regular nonstandard days ($p < 0.001$). These same patterns are also seen for nonstandard day and hour work throughout the rest of Europe. This tendency for dual-earner partnerships to synchronize working times is consistent with previous research from other European countries (Carriero et al., 2009; Lesnard, 2008; Mills & Täht, 2010). As has been suggested, work schedule synchronization allows partners to maximize shared couple time by enabling them to both be at work and at home during the same times. Such patterns allude to the possibility that, within dual-earner partnerships, work schedule timing is often a couple-level rather than an individual-level decision.

Table 2-1. *Socioeconomic and Demographic Characteristics of Nonstandard Schedule Workers, by Gender*

Variable	Range	The UK							Rest of Europe						
		Nonstandard Hour Workers			Nonstandard Day Workers			<i>n</i>	Nonstandard Hour Workers			Nonstandard Day Workers			<i>n</i>
		<i>a</i> ^a	<i>b</i> ^b	<i>SE</i> ^c	<i>a</i>	<i>b</i>	<i>SE</i>		<i>a</i>	<i>b</i>	<i>SE</i>	<i>a</i>	<i>b</i>	<i>SE</i>	
Women															
Age	18-59	38.67	-1.73*	0.85	37.91	-2.55**	0.93	924	40.45	-0.39	0.85	38.81	-2.20***	0.25	19,569
Years of Education	0-42	14.02	0.32	0.26	13.76	-0.02	0.29	922	14.03	0.53***	0.07	13.00	-0.65***	0.08	19,442
Tertiary Degree	0-1	0.38	1.06	0.18	0.94	-0.01	0.17	896	0.45	1.25***	0.05	0.32	0.67***	0.03	19,012
Ethnic Minority	0-1	0.06	0.94	0.30	0.06	0.93	0.33	919	0.05	1.11	0.10	0.06	1.39**	0.14	19,076
Dependent child(ren) in HH	0-1	0.44	0.60**	0.10	0.49	0.76	0.13	924	0.54	0.90**	0.04	0.54	0.91*	0.04	19,549
Spouse or partner present	0-1	0.54	0.69*	0.11	0.59	0.94	0.17	924	0.62	0.78***	0.03	0.64	0.87**	0.04	19,296
Partner employed	0-1	0.87	0.62	0.21	0.82	0.37**	0.12	562	0.87	0.97	0.07	0.85	0.85*	0.07	12,927
Partner in NS schedule	0-1	0.29	1.88*	0.49	0.36	2.85***	0.77	508	0.32	2.68***	0.16	0.36	6.61***	0.49	11,160
Men															
Age	18-59	39.33	-0.77	0.78	39.17	-0.88	0.88	890	40.00	-0.16	0.19	39.62	-0.57*	0.23	20,747
Years of Education	0-42	13.31	-0.23	0.26	12.63	-1.05***	0.29	887	13.27	0.20**	0.06	12.43	-0.76***	0.08	20,631
Tertiary Degree	0-1	0.35	0.96	0.15	0.23	0.46***	0.09	852	0.33	1.08*	0.04	0.24	0.67***	0.03	20,169
Ethnic Minority	0-1	0.12	1.53	0.37	0.12	1.48	0.39	884	0.05	0.94	0.07	0.07	1.34**	0.11	20,315
Dependent child(ren) in HH	0-1	0.46	1.12	0.16	0.46	1.12	0.19	890	0.52	1.02	0.04	0.51	0.98	0.04	20,708
Spouse or partner present	0-1	0.67	1.05	0.16	0.65	0.93	0.16	890	0.68	0.88**	0.03	0.65	0.76***	0.04	20,450
Partner employed	0-1	0.64	0.65*	0.12	0.61	0.58**	0.12	589	0.68	0.96	0.04	0.63	0.74***	0.04	14,285
Partner in NS schedule	0-1	0.30	2.62***	0.69	0.26	3.65***	1.20	414	0.23	3.07***	0.21	0.33	9.18***	0.77	9,719

Data Sources: 2004 and 2010 European Social Survey (Rounds 2 and 5). *Notes:* ^a Alpha term denotes mean/proportion for nonstandard hour/day workers. ^b The beta term denotes the difference in alpha term between nonstandard hour/day workers and those who do not regularly work these hours/days. For continuous variables, beta is a raw difference in means; for binary variables, beta is an odds ratio. ^c Refers to the standard error around beta term; these are clustered around the country-period ID to account for nested data. * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

4. EMPLOYMENT CHARACTERISTICS OF NONSTANDARD SCHEDULE WORKERS

In the following discussion, I present a brief overview of the salient employment characteristics of individuals working regular nonstandard hours and days. Five covariates will be analyzed in this section. To approximate the occupational status of the worker, I use (1) the International Socio-Economic Index of Occupational Status (ISEI).⁵ Secondly, (2) employment duration captures the length of the worker's tenure with his or her current employer in years. Thirdly, (3) work hours captures the average number of work hours per week, including overtime. There are also two dichotomous variables capturing the characteristics of the worker's employment relationship: (4) fixed or no contract captures whether the worker has a limited duration contract or works under no contract at all, and (5) self-employed captures whether the worker is her or his own employer.

Table 2-2 shows employment characteristics of nonstandard hour and day workers in the UK and the rest of Europe, by gender. A first notable observation is that women's and men's nonstandard schedule work is strongly associated with a higher number of weekly working hours in both the UK and the rest of Europe. For example, women engaged in regular nonstandard hours in the UK work on average 5.84 hours more per week than women who do not regularly work these schedules ($p < 0.05$). Similarly, men in regular nonstandard hours in the UK work an average of 5.75 hours more per week ($p < 0.001$). These trends of longer working hours are also seen for nonstandard work days in the UK, as well as for nonstandard work hours and days in the rest of Europe. It is, however, unclear as to whether long working hours are a symptom of a nonstandard schedule, or whether long working hours often mean having to work during evenings, nights, or at weekends. Indeed, such findings likely highlight

⁵ The ISEI is derived from the optimal scaling of occupation groups to maximize the indirect effect of education on income through occupation and to minimize the direct effect of education on income, net of occupation (both effects being net of age) (Ganzeboom, De Graaf, & Treiman, 1992)

the limitations of the current measures of nonstandard work hours and days. That is, by operationalizing nonstandard schedules as the regularity with which work occurs during evenings, nights, or at weekends, it is difficult to distinguish between those individuals who only work nonstandard hours or days and those individuals whose long working hours or overtime regularly spill into these times (i.e., core vs. fringe nonstandard schedule workers; Hamermesh, 1996).

Another consistent trend for nonstandard schedule workers across the UK and the rest of Europe is to be in occupations of on average lower socioeconomic status. As can be seen, average values of ISEI are significantly lower for women in nonstandard hours and days across both the UK and the rest of Europe; the same patterns hold for men working regular nonstandard days across both the UK and the rest of Europe. This trend is consistent with previous research from the US and France, for instance, that has shown that employment in nonstandard schedules is strongly tied to the workers' relative position in the labour market, as those in lower-status routine and non-professional occupations are disproportionately represented in these arrangements (Hamermesh, 2002; Lesnard, 2008; Presser, 1987). This trend is also consistent with the overall shorter employment durations with current employers that can be observed for workers in nonstandard schedules in Table 2-2, which serves as another important indicator of bargaining power. Similarly, it appears that those in nonstandard schedules are also more likely to be employed under a fixed contract or no contract at all.

A notable exception to this trend is for male nonstandard hour work. Interestingly, no significant gaps are observed for male nonstandard hour workers across the UK or the rest of Europe in either occupational status, employment duration, or the likelihood of a nonstandard contract. This discrepancy between the status positions of male and female nonstandard hour workers could again be tied to how nonstandard hours are operationalized here. It is also likely

partially tied to the differences between genders in the jobs where these nonstandard work hours are typically concentrated; I explore this contention later.

Looking at employment relationship characteristics, it appears that both men and women working regular nonstandard hours and days are much more likely to be self-employed. This seems particularly true for those working regular nonstandard work days. In Europe, for example, women working regularly weekends are 4.73 times as likely to be in self-employment than those not regularly working these days ($p < 0.001$); for men in nonstandard days, this figure jumps to 5.41. That self-employment and the regularity of nonstandard hour and day work would be strongly associated is consistent with findings from the US (Edwards & Field-Hendrey, 1996). As has been noted, self-employment generally affords a greater amount of temporal flexibility in the setting of work hours as individuals are freed from managerial constraints; this means that work hours can often be aligned to personal preference rather than to a normatively-defined workweek. It has also been suggested that the desire for flexible, nonstandard working times may influence the decision to enter into self-employment in the first place (Lombard, 2001).

Table 2-2. *Employment Characteristics of Nonstandard Schedule Workers, by Gender*

Variable	Range	The UK							Rest of Europe						
		Nonstandard Hour Workers			Nonstandard Day Workers			<i>n</i>	Nonstandard Hour Workers			Nonstandard Day Workers			<i>n</i>
		<i>a</i> ^a	<i>b</i> ^b	<i>SE</i> ^c	<i>a</i>	<i>b</i>	<i>SE</i>		<i>a</i>	<i>b</i>	<i>SE</i>	<i>a</i>	<i>b</i>	<i>SE</i>	
Women															
Occupational Status (ISEI)	16-90	42.77	-3.61**	1.36	42.80	-3.37*	1.49	919	44.42	-1.65***	0.35	42.79	-3.38***	0.41	18,419
Employment Duration (Yrs.)	0-47	6.70	-1.12	0.69	5.93	-1.96*	0.77	843	8.84	-0.48*	0.20	7.38	-2.04***	0.25	17,445
Work Hours (OT included)	1-96	37.68	5.84*	1.05	35.89	3.34**	1.17	921	40.70	3.36***	0.23	42.44	5.11***	0.27	19,074
Fixed or No Contract	0-1	0.17	0.91	0.20	0.30	2.29***	0.49	849	0.22	1.24***	0.07	0.27	1.74***	0.11	17,519
Self-Employed	0-1	0.08	1.06	0.31	0.12	1.77*	0.50	924	0.13	1.89***	0.12	0.25	4.73***	0.29	18,834
Men															
Occupational Status (ISEI)	16-90	44.01	-2.46	1.31	38.42	-9.22***	1.45	877	44.02	0.00	0.30	39.93	-4.64***	0.37	19,445
Employment Duration (Yrs.)	0-49	7.06	-1.10	0.75	7.74	-0.12	0.89	720	8.77	-0.86***	0.19	7.76	-1.88***	0.26	17,269
Work Hours (OT included)	1-105	47.95	5.75***	0.89	46.66	3.37**	1.03	884	49.35	6.21***	0.21	51.06	7.62***	0.26	20,214
Fixed or No Contract	0-1	0.22	1.19	0.23	0.25	1.39	0.31	729	0.19	1.08	0.06	0.31	2.20***	0.13	17,362
Self-Employed	0-1	0.24	1.58*	0.28	0.29	2.18***	0.42	890	0.25	2.31***	0.10	0.41	5.41***	0.26	20,056

Data Sources: 2004 and 2010 European Social Survey (Rounds 2 and 5). *Notes:* ^a Alpha term denotes mean/proportion for nonstandard hour/day workers. ^b The beta term denotes difference in alpha between nonstandard hour/day workers and those who do not regularly work these hours/days. For continuous variables, beta is a raw difference in means; for binary variables, beta is an odds ratio. ^c Refers to the standard error around beta term; these are clustered around the country-period ID to account for nested data. * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

5. COMMON OCCUPATIONS FOR NONSTANDARD SCHEDULE WORK

I now turn to exploring the occupations where nonstandard schedules are most common. Using International Standard Classification of Occupations (ISCO-88) codes, I have compiled a list of the ten occupations that account for the highest proportions of nonstandard hour and day work across the UK and the rest of Europe. To illustrate broader trends, I also classify these occupations into sectors using Statistical Classification of Economic Activity (NACE, revision 2) codes. Table 2-3 shows results for the women in the UK and the rest of Europe and Table 2-4 shows results for men. Looking first to women in nonstandard schedules, a notable observation is that the ten most common occupations for both nonstandard hours and days account for nearly half of all regular nonstandard schedule work in the UK and the rest of Europe. This suggests that female nonstandard schedule work is highly clustered in a handful of occupations.

The most prominent of these occupations for women appear to be shop salespersons and demonstrators, or those selling goods and services directly to the public on behalf of retail or wholesale establishments. These jobs account for between 7-8% of regular night and evening work in the UK and the rest of Europe, and a staggering 18-19% of regular weekend work. Other prominent occupations in the retail and trade sector for women in nonstandard schedules are managers (both small and large enterprise) as well as cashiers. Worth noting here is the fact that regular nonstandard work hours and days are so common for managers in retail and trade; this suggests that unsocial working times may not only be a symptom of a low position in the occupational hierarchy within this sector. Expanding to all jobs in retail and trade across the UK and the rest of Europe (including those not shown in the current table; results available upon request) shows that this sector accounts for around 13% of all regular female nonstandard hour work and 26% of female nonstandard day work. If I further include jobs in the

accommodation and food services sectors (e.g., cooks, waiters, hotel workers, etc.), these figures jump to 23% for nonstandard hour work and 40% for nonstandard day work. Such findings are consistent with Presser's (2003) work in the US, which found that service sector jobs – especially those jobs serving the local community rather than the global economy – account for much of the growth in women's nonstandard schedule work; this seems particularly true for weekend work.

Another prominent sector for women's nonstandard schedule work – particularly nonstandard hour work – is human health and social work. In the UK, the most prominent occupations within this sector appear to be home- and institution-based personal care work, or those jobs involving the provision of care, supervision, and assistance for children, patients, elderly or disabled persons. These jobs account for 16% of female nonstandard hour work and 11% of female nonstandard day work in the UK. However, in the rest of Europe, these jobs account for just 6% of female nonstandard hour work and less than 2% of female nonstandard day work. Other prominent jobs in the human health and social work sector across the UK and Europe are nursing, midwifery, hairdressing, and other beauty-related work. Looking at all jobs within health-related sectors (results available upon request) shows that human health and social work accounts for around 26% of all female nonstandard hour work and around 9% of female nonstandard day work across both the UK and the rest of Europe.

Helpers and cleaners also appear to be common occupations for women working regular nonstandard hours and days. In the education sector, pre-primary, primary, and secondary teaching jobs also account for a large portion of women's regular nonstandard hour and day work. However, this latter trend is likely tied to the fact that during term-time teaching often involves overtime hours linked to marking and other-extracurricular responsibilities that may spill into evenings and weekends. Teachers may be compensated for this regular weekend and evening work by having their summers free.

Table 2-3. *Top-Ten Occupations for Women in Nonstandard Schedules in the UK and the Rest of Europe*

Female Nonstandard Hour Workers			Female Nonstandard Day Workers		
Job	Industry	Proportion ^a	Job	Industry	Proportion
<i>The UK</i>					
Home-based personal care workers	Health & Social Work	0.10	Shop salespersons & demonstrators	Retail & Trade	0.18
Shop salespersons & demonstrators	Retail & Trade	0.07	Home-based personal care workers	Health & Social Work	0.07
Nursing associate professionals	Health & Social Work	0.06	Institution-based personal care workers	Health & Social Work	0.04
Institution-based personal care workers	Health & Social Work	0.06	Helpers & cleaners	Misc.	0.04
Helpers & cleaners	Misc.	0.05	Mngrs (small ent.) in retail trade	Retail & Trade	0.04
Secondary education teachers	Education	0.04	Secondary education teachers	Education	0.04
Social work associate professionals	Health & Social Work	0.03	Primary & pre-primary teachers	Education	0.03
Primary & pre-primary teachers	Education	0.03	Primary education teachers	Education	0.03
Mngrs in wholesale & retail trade	Retail & Trade	0.02	Mngrs in wholesale & retail trade	Retail & Trade	0.03
Mngrs in restaurants & hotels	Accomm. & Food	0.02	Mngrs in restaurants & hotels	Accomm. & Food	0.03
<i>Cumulative Proportion</i>		0.50	<i>Cumulative Proportion</i>		0.53
<i>Rest of Europe</i>					
Shop salespersons & demonstrators	Retail & Trade	0.08	Shop salespersons & demonstrators	Retail & Trade	0.19
Nursing associate professionals	Health & Social Work	0.05	Hairdressers, barbers & related	Health & Social Work	0.06
Waiters, waitresses & bartenders	Accomm. & Food	0.04	Waiters, waitresses & bartenders	Accomm. & Food	0.06
Institution-based personal care workers	Health & Social Work	0.04	Mngrs (small ent.) in retail trade	Retail & Trade	0.04
Primary education teachers	Education	0.04	Primary education teachers	Education	0.03
Secondary education teachers	Education	0.04	Cooks	Accomm. & Food	0.03
Nursing & midwifery professionals	Health & Social Work	0.03	Secondary education teachers	Education	0.03
Helpers & cleaners	Misc.	0.03	Helpers & cleaners	Misc.	0.03
Home-based personal care workers	Health & Social Work	0.02	Crop & animal producers	Agriculture	0.03
Hairdressers, barbers & related	Health & Social Work	0.02	Cashiers	Retail & Trade	0.02
<i>Cumulative Proportion</i>		0.40	<i>Cumulative Proportion</i>		0.51

Data Sources: 2004 and 2010 European Social Survey (Rounds 2 and 5). *Notes:* Sample includes respondents between the ages of 18-59 who are in regular paid employment. Job categories are derived from ISCO88 coding. Sector categories are derived from NACE Rev. 2 coding. ^a Refers to the proportion of all nonstandard hour/day workers that are in the corresponding ISCO job category.

I turn now to the common occupations for men working regular nonstandard hours and days (Table 2-4). A first notable observation is that relative to women, the top-ten most common occupations appear to account for a far smaller proportion of total nonstandard hour and day work for men. This is particularly true for nonstandard hour work, where the top-ten most common occupations account for only around a quarter of all jobs involving these hours; this is compared to nearly half for the top-ten occupations for women. This suggests that male nonstandard schedule work is far more diffuse throughout the UK and Europe than for women.

As was observed for women, however, it appears that for men jobs in retail, accommodations, and food sectors account for a large proportion of nonstandard schedule work; the most prominent of these jobs is again shop salespersons and demonstrators. Other common service-sector jobs for male nonstandard schedule work are waiting and bartending, managing a hotel or restaurant, as well as cooking. Taken together, all jobs in retail, food, and accommodation sectors (including those not in Table 2-4; results available upon request) account for around 20% of nonstandard hour work for men across the UK and the rest of Europe and 28% of nonstandard day work.

Other common occupations for men's nonstandard hour and day work are in the transport sector. The most prominent of which, particularly in the UK, are car, taxi, and van driving; these jobs accounts for 6% of regular night and evening work, and 9% of regular weekend work. In the rest of Europe, truck and lorry driving is another prominent job for male nonstandard schedule work in the transport sector. Looking across all forms of transport sector work in the UK and rest of Europe (including those not listed), these jobs account for 15% of all male nonstandard hour work and 11% of male nonstandard day work. This high concentration of nonstandard schedule work in transport amongst males is perhaps not surprising. Transport jobs, particularly taxi and lorry driving, are generally male-dominated occupations (T. Wright, 2014). Crucially, work hours in these jobs are often not synchronized

to normal business hours. For example, taxi drivers often become busiest when the rest of the workforce finishes their work day and requires transit options home or elsewhere. Similarly, van, long-haul truck, and lorry drivers increasingly must cater to demands for expedited and overnight shipping options. The growing centrality of online retailers like Amazon and their emphasis on next day shipping may only further increase the reliance on nonstandard hour and day workers within the transport sector.

Table 2-4. *Top-Ten Occupations for Men in Nonstandard Schedules in the UK and the Rest of Europe*

Male Nonstandard Hour Workers			Male Nonstandard Day Workers		
Job	Industry	Proportion ^a	Job	Industry	Proportion
<i>The UK</i>					
Car, taxi & van drivers	Transport	0.06	Car, taxi & van drivers	Transport	0.09
Shop salespersons & demonstrators	Retail & Trade	0.04	Shop salespersons & demonstrators	Retail & Trade	0.07
Finance & administration mngrs	Misc.	0.03	Mngrs (small ent.) in retail trade	Retail & Trade	0.05
Mngrs (small ent.) in retail trade	Retail & Trade	0.03	Mngrs (small ent.) in restaurants & hotels	Accomm. & Food	0.03
Mngrs (small ent.) in restaurants & hotels	Accomm. & Food	0.02	Waiters, waitresses & bartenders	Accomm. & Food	0.03
Waiters, waitresses & bartenders	Accomm. & Food	0.02	Mngrs in restaurants & hotels	Accomm. & Food	0.02
Doorkeepers, watchpersons, related workers	Misc.	0.02	Secondary education teachers	Education	0.02
Transport laborers & freight handlers	Transport	0.02	Cooks	Accomm. & Food	0.02
Mngrs in manufacturing	Manufacturing	0.02	Carpenters & joiners	Construction	0.02
Mngrs in restaurants & hotels	Accomm. & Food	0.02	Doorkeepers, watchpersons, related workers	Misc.	0.02
<i>Cumulative Proportion</i>		0.28	<i>Cumulative Proportion</i>		0.39
<i>Rest of Europe</i>					
Heavy truck & lorry drivers	Transport	0.04	Shop salespersons & demonstrators	Retail & Trade	0.06
Shop salespersons & demonstrators	Retail & Trade	0.03	Crop & animal producers	Agriculture	0.06
Waiters, waitresses & bartenders	Accomm. & Food	0.03	Mngrs (small ent.) in retail trade	Retail & Trade	0.05
Mngrs (small ent.) in retail trade	Retail & Trade	0.03	Waiters, waitresses & bartenders	Accomm. & Food	0.04
Car, taxi & van drivers	Transport	0.03	Field crop & vegetable growers	Agriculture	0.04
Protective services workers	Public Administration	0.02	Dairy & livestock producers	Agriculture	0.03
Cooks	Accomm. & Food	0.02	Mngrs (small ent.) in restaurants & hotels	Accomm. & Food	0.03
Mngrs (small ent.) in restaurants & hotels	Accomm. & Food	0.02	Cooks	Accomm. & Food	0.03
Crop & animal producers	Agriculture	0.02	Car, taxi & van drivers	Transport	0.03
Technical & commercial sales	Misc.	0.02	Heavy truck & lorry drivers	Transport	0.02
<i>Cumulative Proportion</i>		0.25	<i>Cumulative Proportion</i>		0.38

Data Sources: 2004 and 2010 European Social Survey (Rounds 2 and 5). *Notes:* Sample includes respondents between the ages of 18-59 who are in regular paid employment. Job categories are derived from ISCO88 coding. Sector categories are derived from NACE Rev. 2 coding. ^a Refers to the proportion of all nonstandard hour/day workers that are in the corresponding ISCO job category.

6. DISCUSSION

In this chapter, I explored the size and characteristics of the nonstandard schedule labour force in the UK and the rest of Europe. Surprisingly, a comprehensive investigation of the demographic, socioeconomic, and employment characteristics of nonstandard schedule workers in the UK has yet to be undertaken. Emphasis in this chapter was therefore placed on answering three main questions: (1) how common is nonstandard hour and day work in the UK and the rest of Europe?; (2) what are the salient demographic, household and socioeconomic characteristics of the individuals who work these arrangements?; and (3) what are the characteristics of the occupations where these schedules are most common? More broadly, this chapter was meant to showcase the size and composition of the sample that will be of interest to subsequent empirical chapters.

Results show wide variation in the rates of nonstandard hour and day work across Europe, which appear to be highest in the UK, Turkey, and Scandinavian countries, and lowest in Austria, the Czech Republic, and Italy. This variation is most pronounced in the case of regular nonstandard hour work, the rates of which range from 30% of men and 23% of women in the UK to 9% of men and 1% of women in Italy. To the extent that there is the emergence of a 24/7 economy in Europe, these findings suggest it is clearly developing at different rates between countries. Such variation in the rates of nonstandard schedule work between countries reflects both differences in the stringency of working time regulations as well as structural differences in the labour market, for example, in the prevalence of certain occupations requiring round-the-clock production (e.g., services and manufacturing jobs). As the primary aims of this chapter were descriptive in nature, factors underlying between-country variation in nonstandard schedule work were not explored or tested. Future research could attempt to explain these

between-country differences by looking at, for instance, between-country variation in the prevalence of manufacturing work or in the regulation of working times.

The significantly higher rates of both nonstandard hour and day work in the UK relative to the rest of Europe highlight it as a particularly important case for study with regards to the spread of nonstandard work schedules in Europe. These high rates of nonstandard hour and day work reflect the UK's notoriously minimalist approach to the regulation of working time as well as its long-and-late-hours work culture (Chatzitheochari & Arber, 2009; Philp et al., 2014). Findings on the prevalence of nonstandard work hours and days also show interesting patterns by gender: across the UK and the rest Europe, night and evening work appears to be particularly common for men, while weekend work appears to be more common for women.

Results from this chapter also show that individuals working regular nonstandard hours and days are a relatively selective population: they tend on average to be younger, have lower levels of educational attainment, and are more likely to be self-employed and have a partner who also works a nonstandard schedule. In terms of occupational characteristics, nonstandard schedules appear to be highly clustered in a handful of jobs in the health, personal care, retail, food, and accommodation sectors. Crucially, findings suggest that nonstandard schedules appear to be a symptom of a lower position in the occupational hierarchy: they tend to concentrate in relatively low-status occupations amongst those individuals employed on nonstandard contracts and who have most recently joined a company. These findings are in general consistent with previous literature from the US and France that has shown that nonstandard work schedules are often concentrated amongst those with the least bargaining power in the labour market (Grzywacz et al., 2011; Hamermesh, 2002; Lesnard, 2008; Presser, 1987).

It should be noted that an important limitation to this analysis is the way in which nonstandard work hours and days have been operationalized. As discussed earlier, by

operationalizing nonstandard schedules as the regularity with which work hours occur during evenings, nights, or at weekends, it is difficult to distinguish between those individuals who only work nonstandard hours or days and those individuals whose long working hours or overtime regularly spill into these times. Indeed, the robust finding that nonstandard hours and days were associated with significantly higher weekly work hours for both men and women highlights the limitations of this operationalization of nonstandard work schedules. For this reason, estimates on the prevalence of nonstandard hour and day work should be taken with a grain of salt.

Related to this, the current operationalization of nonstandard schedule work as the regularity of work during night, evening, or weekend hours will have likely obscured important between-country differences in the structure and arrangement of nonstandard hours and days as well as the work cultures these differences represent. For example, the relatively high rates of evening and night work in Spain, Portugal and Greece – seen particularly for men – may reflect that in several locales within these countries, midday siestas are still a common practice (Huberman, 2004). Similarly, the high rates of evening work in Scandinavian countries may in part reflect the high degree of flexibility workers have within these countries to structure their working day according to personal preference rather than a pre-defined workweek (Gallie & Russell, 2009). In both examples, nonstandard hours will likely represent a completely different phenomenon (both in terms of the antecedents and social consequences) than in contexts like the UK or France where such hours are largely imposed on the worker. Future research could use finer-grained measures of nonstandard work hours and days that take into account the structure and characteristics of these arrangements to better understand the reasons underlying country-level variation the rates of nonstandard schedule work.

That said, results from this chapter highlight the large variation across the UK and the rest of European in the rates of regular nonstandard hour and day work. They also suggest that

such arrangements are far from randomly distributed across any given population: they appear to be highly concentrated amongst certain groups within the labour market and within certain jobs. When studying nonstandard schedules, such findings highlight the need to acknowledge the important channels of occupational, household, and socioeconomic selection underlying employment in these arrangements. Accordingly, the following chapter will attempt to characterize and correct for these processes of selection in studying the effects nonstandard schedules take on partnership quality.

CHAPTER 3

GENDER, NONSTANDARD SCHEDULES, AND PARTNERSHIP QUALITY: EXPLORING HETEROGENEOUS ACTOR AND PARTNER EFFECTS THROUGH A QUASI-EXPERIMENT

1. INTRODUCTION

Though it varies by country and sector, the standard workweek is usually defined as being fixed somewhere between the hours of 8:00 am to 6:00 pm, Monday through Friday. This workweek was not only a core feature of the traditional employment relationship of the 1950s and 1960s, but also guided much of how social and family life was organized over the day and week (Hamermesh, 1999). However, in what's been referred to as the rise of the 24/7 economy (Presser, 2003), participation rates in nonstandard work schedules (i.e., employment during nights, evenings, and at weekends) have increased over the past few decades throughout most of Europe as more people are being employed during atypical times to cover greater expanses of the day and week (Gornick & Meyers, 2003; Kümmertling & Lehdorff, 2007; Messenger, 2011). Given that such work schedules have the potential to overlap with – and even monopolize – the times of the day and week traditionally reserved for family life, considerable research conducted over the past few decades has explored the negative effects nonstandard schedules have on work-family balance (e.g., Craig & Powell, 2011; Heymann & Earle, 2001; Hosking & Western, 2008).

One strand of this research has focused on the ways in which nonstandard schedules negatively affect partnership quality (i.e., the underlying degree of cohesion and stability within a romantic union; hereafter, PQ) by constraining a worker's ability to participate fully in the roles and rhythms of a conjugal relationship. As Presser (2003) observes, by engaging the

worker in paid labor during nights, evenings, or at weekends, nonstandard schedules can restrict his or her ability to participate in the activities necessary to maintain stable relations with their partner, be it sleep, shared time, or household responsibilities. Compelling evidence of this comes from studies linking nonstandard schedules to a higher risk of union dissolution and conflict (Davis, Benjamin Goodman, Pirretti, & Almeida, 2008; Kalil, Ziol-Guest, & Epstein, 2010; Presser, 2000, 2003; White & Keith, 1990) and decreased partnership satisfaction (Davis et al., 2008; Maume & Sebastian, 2012; Presser, 2003; Strazdins, Clements, Korda, Broom, & D'Souza, 2006; White & Keith, 1990).

Several explanations have been put forward for the destabilizing effects nonstandard work schedules can have on partnerships. Some have focused, for example, on the physical tolls these schedules can take on workers. Nonstandard schedules, especially night shift hours, disturb the body's circadian rhythms and alter its physiological functions (J. Li et al., 2014), and have been linked to an increased risk of depression and sleep deprivation (Özdemir et al., 2013; Ramadan & Al-Saleh, 2014; Sanches et al., 2015). As has been argued (e.g., Fenwick and Tausig, 2001; Han 2005), the heightened physical and mental demands associated with such schedules have the potential to carry over into couple dynamics, leading to more irritable partners and fostering greater conflict within romantic unions.

In line with Hill's (1988) attachment theory, others have suggested that these schedules decrease PQ via the temporal restrictions they place on shared couple time, which is a partnership-specific capital crucial for stability and intimacy (Kalil et al., 2010; Presser, 2000). Indeed, as time-use research from France and the US indicates, by taking the worker out of the household during afterschool, dinner, and leisure hours, nonstandard schedules like weekend and evening work hours often do not allow the worker to participate fully in joint leisure time and family activities (Lesnard, 2008; Wight, Raley, & Bianchi, 2008). Several researchers have also noted that such schedules can restrict the workers' ability to attend fully to domestic

responsibilities such as care or household work, which can lead to frustration and role-overload amongst partners (Craig & Powell, 2011; Presser, 2003; Presser & Cain, 1983; Wight et al., 2008). This has been put forward as an explanation for why women's nonstandard work schedules are often observed to be particularly destabilizing to partnerships, as they may be the ones typically more responsible for homemaking, caretaking, and cultivating shared couple time (Kalil et al., 2010; Lozano et al., 2016; Maume & Sebastian, 2012; Mills & Täht, 2010; Presser et al., 2008).

However, despite their discordancy with the traditional organization of family life, findings on the effects of nonstandard schedules on PQ have not always been so negative. A second strand of research has also documented that nonstandard schedules can be beneficial to families in general – and partnerships, in particular – if they represent a strategic choice by the household. Such was found, for example, in the case of dual-earner parents selecting into desynchronized work schedule arrangements as a means of spending more time with children and more equally distributing childcare between both partners (e.g., Begall, Mills, & Ganzeboom, 2015; Deutsch, 1999; Mills & Täht, 2012; Presser, 2003). Other studies have also highlighted that nonstandard schedules can promote work-family balance if they also come with a relatively high degree of flexibility and predictability, one of the reasons individuals often self-select into these arrangements (Deutsch, 1999; Fenwick & Tausig, 2001; Lombard, 2001; Lozano et al., 2016; Staines & Pleck, 1986).

In attempting to reconcile these two conflicting strands of previous findings – one highlighting the negative effects of nonstandard schedules on PQ, the other highlighting the positive impacts of these arrangements – it is important to acknowledge the many channels of selection underlying employment in nonstandard schedules. Work schedule arrangements like night, evening, and weekend work are far from randomly distributed across the population. Rather, entrance into these schedules is influenced by complex and competing preferences and

constraints tied to characteristics of an individual's household situation and employment relationship – factors that are likely not independent of outcomes relating to family cohesion (Grzywacz et al., 2011; Presser, 2003). Moreover, a distinction must be made between those who choose for a variety of reasons to work nonstandard schedules and those on whom these arrangements are imposed by the employer or the nature of the job. Failing to adequately account for these treatment assignment mechanisms will likely produce biased and/or inconsistent findings, and undermine the ability to draw any sort of conclusions on the causal effect of nonstandard work schedules on PQ.

2. CURRENT STUDY

This chapter builds on previous research on the effects of nonstandard schedules on PQ by attempting to characterize and correct for these selection processes. Competing theories of positive and negative selection are proposed based on the contention that there will be heterogeneous returns to partnerships from nonstandard schedules (in terms of penalties and benefits) that will depend on how and why partners have selected into these arrangements. Premised on principles of rational choice theory (e.g., Becker, 1965; Elster, 1989), a *positive selection* thesis is that individuals choose the work schedule arrangement that will maximize their own and their household's expected well-being. Therefore, the couples most often observed in nonstandard schedules are selective of those who stand to benefit the most from these arrangements. A competing *negative selection* hypothesis consistent with theories of labour market segmentation (Loveridge & Mok, 1979) is that the individuals most often observed in nonstandard schedules are those in low-SES households and low-amenity jobs where the destabilizing effects of these arrangements on partnerships are most acute. In contrast to positive selection, entrance into a nonstandard schedule is assumed here to be tied less to personal preference than to employer mandate. Such patterns of selection, if they are to be

observed for men or women, would help reconcile contradictory previous findings on the effects of nonstandard schedules on PQ, and shed new light on the complex and reciprocal relationship between work schedule timing and family functioning.

To account and test for baseline selection biases and heterogeneous treatment effects, this chapter employs Mahalanobis Distance Matching and propensity score stratification techniques on 2010-2016 UK Household Longitudinal Study data. In comparison to the regression adjustment techniques typical in previous studies on the topic, the use of distance matching in the present study will allow for conditioning on a greater number of relevant pre-treatment confounders (overcoming the so-called, “curse of dimensionality”; Rosenbaum & Rubin, 1983), while propensity score stratification techniques will help identify how treatment effects on PQ might vary depending on the likelihood of entrance into a nonstandard schedule. Rather than identifying heterogeneous effects through discrete interactions on factors like gender and parental status, this study explores the ways in which overlapping social categories grounded in class, ethnicity, gender, family structure, and preference interact in a multivariate space to shape and confound the relationship between work schedule timing and partnership quality.

The richness of the UKHLS’ self-completion partnership quality questionnaire will also help disentangle two distinct forms of partnership effects tied to a nonstandard work schedule: (1) *actor effects*, or the effect of an individual’s work schedule on her own subjective PQ; and (2) *partner effects*, or the effect of an individual’s work schedule on her partner’s subjective PQ. Analysis will be oriented around two main questions. First, net of baseline selection biases, are nonstandard schedules associated with lower PQ for the worker and/or her partner as previous research would suggest? Second, is there evidence of positive or negative selection into these arrangements amongst men or women that could have biased previous results?

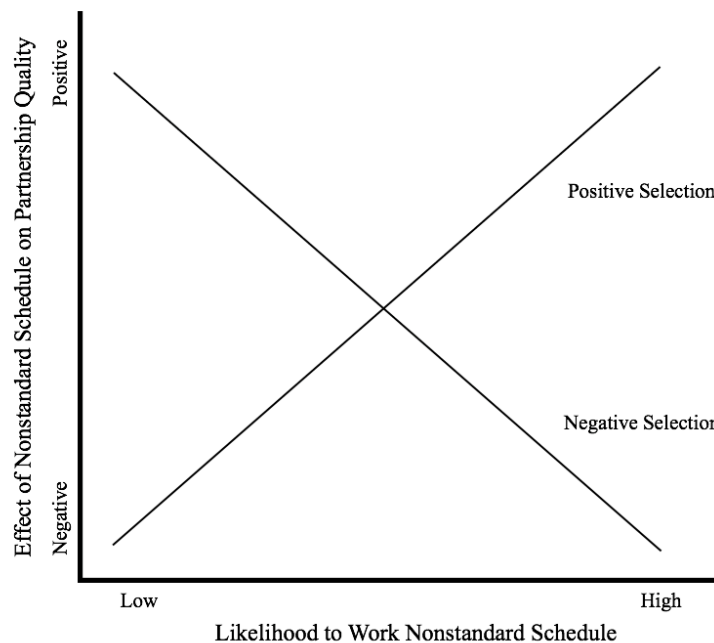
3. THEORETICAL AND METHODOLOGICAL FOUNDATIONS

One can generally distinguish two types of selection bias present in observational data. The first derives from heterogeneity in pre-existing conditions or attributes that are related to both the treatment condition and the outcome (Brand and Xie, 2010). This is what is commonly referred to as, *baseline bias*, and alludes to the possibility that observed differences in outcomes between treatment and control groups may simply reflect the underlying differences between the groups rather than the effects caused by the treatment per se. The second type of selection bias – what is often called, *heterogeneous treatment effects bias* – is due to heterogeneity in the size and/or direction of treatment effects that is associated with one's likelihood of receiving the treatment. In the present case, this would occur if respondents who are most likely to select or be selected into nonstandard work schedules are also those who will experience the greatest partnership penalties or benefits from these arrangements.

Typically, the traditional regression adjustment approaches common in previous studies have – to varying degrees of efficiency – aimed to reduce baseline biases by conditioning on a handful of covariates hypothesized a priori to confound the relationship between nonstandard work schedules and partnership quality (e.g., age, education, the presence of children, etc.). A limitation of such methods, however, is it that they are often less adept at identifying heterogeneous treatment effects as they essentially produce a weighted average of varying treatment effects across the sample, some of which will be higher and some lower than the population average (Brand & Xie, 2010). While researchers have done well to test interactions with factors such as age, gender, and parental status independently, their analyses have been grounded on the underlying assumption that – net of observed background characteristics and modelled interactions – the effects of a nonstandard work schedule should be relatively homogenous across members of a population.

This study breaks from this assumption of effect homogeneity and proposes that the individuals most likely to select into nonstandard work schedules will differ not only in their baseline partnership quality but also in the size and direction of the partnership returns they are likely to experience from working these arrangements. In the following discussion, two competing directions of heterogeneous treatment effects are hypothesized (depicted in Figure 3-1): (1) positive selection, occurring if the individuals or couples most likely to select into schedules involving nonstandard hours or days are those most likely to be positively affected by these arrangements; and (2) negative selection, occurring if the individuals or couples most likely to select into schedules involving nonstandard hours or days are those most likely to be negatively affected by these arrangements.

Figure 3-1. *Theorized Heterogeneous Treatment Effects*



3.1. POSITIVE SELECTION

Following principles of the rational choice framework, one thesis is that individuals choose to enter a nonstandard schedule only when the expected utility is greater than the expected cost.

This is consistent with Becker's (1965) theory of the allocation of time, where decisions within the home surrounding the timing of paid work are grounded in rational deliberations of utility maximization for the actor. Through this lens, individuals choose to engage in paid employment during times of the day and week when the value of non-work activities like leisure or household labor is less than the value of work (Täht & Mills, 2016). Therefore, barring imperfect information and constraints on autonomy, one should expect that only the individuals who stand to benefit most – or suffer the least – from these arrangements will select into and stay in them.

One example of positive selection would be parents selecting into split-shifts where one partner works nights or evenings while the other works days to more equally distribute caregiving and household responsibilities (Bünning & Pollmann-Schult, 2016; Lesnard, 2008; Mills & Täht, 2012; Presser, 1988). Such arrangements not only cater to a preference for familial caregiving but also allow parents to avoid the high costs and long waiting lists typical of public and private child care institutions. A lack of decreased partnership quality for parents in desynchronized schedules, as has been found in the US and the Netherlands (Chait Barnett, Gareis, & Brennan, 2008; Han et al., 2010; Kalil et al., 2010; H. Liu, Wang, Keesler, & Schneider, 2011; Mills & Täht, 2010), may simply reflect the fact that these arrangements are part of a conscious shared strategy by partners to maintain stability in other areas of the household. This may be especially true for women working nonstandard hours or days, as previous literature suggests that women, more so than men, take family considerations into account when making labour force decisions (Bielby & Bielby, 1989; Duncan & Perrucci, 1976; Presser, 1995).

A complementary explanation is that it might be only the most objectively stable partnerships that are better able to endure the strain associated with nonstandard schedules that are most often observed in these arrangements. For example, Presser (2000) suggested

that parents selecting into split-shift arrangements to more equally distribute care work may also tend towards more progressive ideologies surrounding the gendered division of labor in the household, a factor which might make maternal employment in general and nonstandard schedules, in particular, less disruptive to partnership quality. Indeed, for parents, it may be that women's employment at nonstandard times reflects their male partners' willingness to assume caregiving responsibilities while their female partners are at the workplace (Presser et al., 2008). Along the same vein, Presser (2000) also showed that only in the early years of a partnership were nonstandard schedules associated with a greater risk of partnership instability. This suggests that nonstandard schedule workers in older partnerships – who have likely worked these arrangements longer – may be representative of those who are better able to adapt, with the others having already selected out of these schedules. As Harrington (2001) put it, those that remain shift workers for years are a survivor population representative of those best able to cope with nonsocial hours.

Evidence of individuals self-selecting into nonstandard schedules based on expectations of greater job satisfaction and well-being has also been documented. For instance, literature from the fields of organizational psychology and human resource management has provided evidence that many workers have an innate preference for work during nonstandard hours and days, a preference which has been linked to various personality factors like introversion and neuroticism, as well as the timing of one's circadian rhythm (i.e., their chronotype)⁶ (Costa, Lievore, Casaletti, Gaffuri, & Folkard, 1989; Popp, Laursen, Kerr, Stattin, & Burk, 2008; Willis, O'Connor, & Smith, 2008). Likewise, certain workers have been shown to actively seek out nonstandard schedules for the indirect benefits they can sometimes afford, like greater freedom during the day, being able to avoid busy shops and traffic, as well as the generally

⁶ Chronotype will be out of the purview of the current chapter as it is not measured in the UKHLS. However, it is relevant to the thesis as in Chapter 5 I look at the ways in which chronotype influences an individual's likelihood to select into and stay in nonstandard work hours.

more relaxed and social working conditions (seen particularly on weekends) (Täht & Mills, 2016).

Taken together, such findings allude to the possibility that the individuals and couples most often observed in nonstandard schedules are selective of those best suited to thrive in these arrangements. If such were the case, then previous estimates of the effect of nonstandard work schedules on partnership quality will have been biased upwards. I therefore make the following positive selection hypothesis: *H_{1a}* The positive effects of nonstandard schedule work on partnership quality will be largest for those individuals with the highest probability of working these arrangements.

3.2. NEGATIVE SELECTION

While the preceding discussion may give the impression that most nonstandard schedule workers self-select into these arrangements voluntarily, the available evidence overwhelmingly suggests that entrance into these arrangements is primarily linked to job constraints imposed by the employer rather than to personal preference. Research from the US and France, for instance, shows that nonstandard schedule use is strongly tied to the workers' relative position in the labour market, as those in routine and non-professional occupations are overrepresented in these schedules (Hamermesh, 2002; Lesnard, 2008; Presser, 1987). As noted by Grzywacz et al. (2011), those with low education, little formal training, and few labor market prospects are often pushed into these schedules simply for a lack of better options.

Consistent with theories of occupational sorting (Blau, Duncan, & Tyree, 1978; DiPrete & Eirich, 2006) and labour market segmentation (Loveridge & Mok, 1979), such findings suggest that there is a high degree of structural selection occurring whereby individuals from marginalized groups within the labor market are disproportionately channeled into nonstandard work schedules. Through this lens, standard work hours and days can be viewed as a job

amenity for which employees with superior bargaining power can buy and for which those with the least bargaining power may not always be able to afford (Hamermesh, 1996); this ultimately leads to a high concentration of nonstandard work hours and days in already disadvantaged labour market segments. This may be particularly true in the UK context, given the UK's *laissez faire* approach to the regulation work times and conditions as well as its increasingly diminishing labour union and collective bargaining presence (Casey, 2004; Gornick & Meyers, 2003; Philp et al., 2014); in such a context, entrance into nonstandard schedules will may most often represent a forced choice rather than personal preference. As I will argue below, these processes of structural selection have the potential to generate a negative selection bias whereby the individuals most likely to be observed in nonstandard schedules are also those who may have their partnership quality suffer the most from these arrangements.

With regards to the modal occupational situation of nonstandard schedule workers, it appears that those individuals most likely to be selected into these arrangements are also in jobs where the destabilizing effects of these schedules on partnerships might be exacerbated. Indeed, while nonstandard schedules can in some instances come with buffer mechanisms against the unhealthy effects of these arrangements, like the ability to reduce working hours or to adjust start and end times flexibly (e.g., Hosking and Western, 2008), these amenities appear to be concentrated in a small proportion of jobs at the top of the occupational ladder (Golden, 2001; Henly, Shaefer, & Waxman, 2006). The majority of nonstandard schedules occur in occupations that have higher exposure rates to occupational stressors like low job security, physical strain, low job control, and low influence on working hours (Bøggild, Burr, Tüchsen, & Jeppesen, 2001; Mohren et al., 2002; Nabe-Nielsen, Jørgensen, Garde, & Clausen, 2016; Nabe-Nielsen, Tüchsen, Christensen, Garde, & Diderichsen, 2009; Vanroelen, Levecque, Moors, & Louckx, 2010). The lack of buffer mechanisms and increased workplace stressors

within jobs where nonstandard schedules are most common may then overinflate the negative effects these arrangements exercise on partnerships.

With regards to the modal household situation of nonstandard schedule workers, it appears that the individuals disproportionately channeled into these work schedules are in low-SES households that may have an already high pre-existing risk of family discord (Presser, 2003; Presser & Cox, 1997). Research from the past two decades clearly supports a positive gradient between socioeconomic status and various indicators of partnership quality and stability (Amato, 2009; Dakin & Wampler, 2008; Karney & Bradbury, 2005; Rauer, Karney, Garvan, & Hou, 2008). The dominant explanation for these findings is that the greater economic strain faced by low-SES households has the potential to generate intrapersonal distress and interpersonal conflict within partnerships (Conger et al., 1992). In households where the potential for family conflict is already high, it is possible that the negative effects of a nonstandard work schedule on partnership quality may be particularly acute. This is due not only to the potentially already high levels of economic strain within the household but also to the scarcity of resources that might otherwise mitigate the negative effects these schedules have on work-family balance. For example, the income security and bargaining power that might allow one to alter the number and organization of work hours in the face of partnership strain (Bianchi, 2011), or, for parents, the resources required to find quality substitute care when their work keeps them away from their children in the evenings, nights, or at weekends (Heymann & Earle, 2001).

If it is indeed true that the individuals most likely to be selected into nonstandard schedules are also those in jobs or households where the social consequences of these arrangements might be exacerbated, then previous estimates of the true causal effect of nonstandard schedules on partnership quality will have been biased downwards. I therefore make the following competing hypothesis surrounding negative selection into nonstandard

work schedules: H_{1b} The negative effects of nonstandard work schedules on partnership quality will be largest for those individuals with the highest probability of working these arrangements.

4. METHODS

4.1. DATA

To test these hypotheses, this study uses Waves 2 to 7 (2010-2016) of the UK Household Longitudinal Study (UKHLS). The UKHLS is the largest household panel dataset in Europe, providing a nationally representative probability sample of over 40,000 households in the UK. Data collection for each wave occurs over a period of two years, with the second year of collection overlapping with the first year of collection for the subsequent wave. Given the extensive scope of the information collected within the UKHLS questionnaire, several variables (including those of interest to the current study) are only measured every other wave of data collection. Consequently, Waves 2, 4, and 6 (collected between 2009-2010, 2012-2013, and 2015-2016, respectively) contain measures for the independent and selection variables, and Waves 3, 5, and 7 (collected between 2010-2011, 2013-2014, and 2015-2017, respectively) contain the measures of partnership quality. Methods to account for the non-contemporaneous measurement of predictor and outcome variables are discussed later. To maximize statistical power, these waves are collapsed and stacked into person-period format such that Period 1 is comprised of Waves 2 and 3 (spanning 2009 to 2011), Period 2 is comprised of Waves 4 and 5 (spanning 2012 to 2014), and Period 3 is comprised of Waves 6 and 7 (spanning 2015 to 2017). Table 3-1 illustrates this data structure in further detail.

Table 3-1. *Outline of UKHLS Data Structure*

Cross-Period Total Analytic Sample, $n = 20,647$						
	Period 1, $n = 8,234$		Period 2, $n = 6,945$		Period 3, $n = 5,468$	
	Wave 2	Wave 3	Wave 4	Wave 5	Wave 6	Wave 7
Years	2010-2011	2011-2012	2012-2013	2013-2014	2014-2015	2015-2016
Measures Included	Work Schedule Selection Covariates	Partnership Quality	Work Schedule Selection Covariates	Partnership Quality	Work Schedule Selection Covariates	Partnership Quality

Data Source: 2010-2016 UKHLS (Waves 2-7)

Notes: Sample includes individuals in co-resident partnerships between the ages of 18-59 who are in regular paid employment.

The working sample for this study is individuals between the ages of 18-59 in co-resident, heterosexual married or cohabiting unions who are in regular paid employment (excluding self-employment) of at least 12 hours per week.⁷ To account for the fact that independent and dependent variables used in this analysis are not measured contemporaneously within each period of observation (a lag of between 1 to 2 years), individuals were only included if they were in paid employment and a married or cohabiting union across both waves of each period; issues related to this choice are addressed in subsequent discussions. Individuals were also excluded if they changed jobs ($n = 1,285$) or partners ($n = 361$) between the two constituent waves of each period. List-wise deletion was used to enable matching procedures.⁸ After

⁷ The choice of setting a minimum of 12 working hours per week as a sample restriction is consistent with similar research done in the Netherlands (Täht & Mills, 2016). For the purposes of the current analysis, it removes those individuals from the sample who may be in a nonstandard schedule but are working too few hours to experience any negative social consequences from such arrangements.

⁸ The matching procedures used in this analysis (elaborated on in subsequent discussions) require there to be no missing values on any of the selection covariates. This led to a large sample loss due to high missingness on partner's employment information, as well as on the Big 5 Personality Indicators. The sample loss on the former is due to several cases having incomplete partner information, while the sample loss on the latter is tied to the fact that these measures were only taken at Wave 3; therefore, respondents who were not sampled in this wave were removed. These sample restrictions are outlined in detail in Appendix 3-1. To determine whether nonrandom missingness might be an issue, I regressed both the treatment and outcome variables on binary missing flag variables for each of these selection covariates. This revealed no significant effects (results available upon request): Those in nonstandard schedules were equally as likely to have missing values on these selection covariates. Similarly, there were no significant differences in reports of partnership quality for those with missing values on these covariates. This suggests that list-wise deletion does not pose any immediately visible threats surrounding nonrandom missingness biases.

removing missing values on the treatment, selection, and outcome variables, this amounted to a total sample of 20,647 person-period observations nested within 10,098 individuals. For detailed information on how each sample restriction affected the overall sample size, please see Appendix 3-1.

In the case of households where both partners are in regular paid employment, information will be used on both partners in the household. This created a three-level data structure where up to three person-period observations are nested within individuals which are further nested within couples ($n = 6,350$); techniques to account for this clustering are addressed in subsequent discussions. All estimates derived from this sample will use the recommended household weights for national representativeness and to account for selective attrition between waves.

4.2. PARTNERSHIP QUALITY

The outcome variable for this analysis is partnership quality (PQ). Attempting to operationalize PQ into a single measure is somewhat controversial due to how complex and multidimensional in nature the quality of a partnership is. That said, it has been argued that an accurate evaluative depiction of PQ should attempt to capture the underlying degree of cohesion, intimacy, and stability within a romantic partnership (Spanier, 1979). The primary criteria for selecting measures of PQ and constructing an evaluative index, as Norton (1983) notes, should be whether each item: (1) has sufficiently similar semantic values to the other items; (2) intrinsically reflects some component of “goodness”, even if it is skewed; and (3) contributes to an overall evaluative gestalt that is greater than the sum of its parts.

Bearing these considerations in mind, PQ is measured in this study using nine items taken from the UKHLS self-completion Partnership Module that together attempt to evaluate the presence of positive aspects of a partnership and the accompanying absence of negative

aspects. These questions ask respondents to report on a six-point ordinal scale how often they and their partner: (1) “calmly discuss something”, (2) “consider divorce”, (3) “regret getting married”, (4) “quarrel”, (5) “get on each other’s nerves”, (6) “engage in a stimulating exchange of ideas”, (7) “work together on a project”, and (8) “engage in outside interests”. Lastly, respondents are asked to report on a 7-point scale their overall, (9) “degree of happiness with the relationship”.

As no a priori assumptions are made on the relative importance of each of these items for the overall quality of a partnership, a data-driven approach through exploratory factor analysis (EFA) was used to reduce these items into indexes. This revealed two underlying factors consistent across males and females (results shown in Table 3-2), which will be modelled separately. Factor 1, defined as *Partnership Cohesion*, captures the degree of intimacy, positive communication, and support between partners. The factor includes four items measuring how often the respondent and her partner, “engage in a stimulating exchange of ideas”, “engage in outside interests”, “calmly discuss something”, and “work together on a project”. Factor 2, defined as *Partnership Stability*, captures the degree of durability of and conflict within a given partnership as well as the partner’s overall satisfaction with the relationship. The factor includes four items measuring how often the respondent and her partner, “consider divorce”, “regret getting married”, “quarrel”, and “get on each other’s nerves”, as well as a fifth item asking the respondent to rate her overall, “degree of happiness with the relationship”. The two indexes are constructed by first summing each item, weighted by its respective (oblique) rotated factor loading score⁹, and then standardizing to a cross-

⁹ Oblique rotation was opted for over orthogonal rotation for three reasons. First, there is no clear evidence suggesting how the two factors would be related to one another; thus, there is no reason to assume they are completely independent (Preacher & MacCallum, 2003). Second, oblique rotation in the present context allows one to see how these factors are correlated with one another between- and within-partnerships. Third, given that these factors are to be modelled separately as outcomes, the correlations between the two are not as problematic as if they were to be included in the same model as independent variables; in such a case, orthogonal rotation would be the better solution.

gender mean of 0. Referring to Table 3-2, the final indexes have high reliability for both women and men, with Cronbach Alpha scores between 0.73 to 0.75. Moreover, while moderately correlated with one another ($r = 0.42-0.48$, $p < 0.001$), the components do diverge sufficiently to be modelled separately.

Table 3-2. *Exploratory Factor Analysis of Partnership Quality Items, by Gender*

Item	Range	Women, <i>n</i> = 10,190		Men, <i>n</i> = 10,457	
		Factor 1	Factor 2	Factor 1	Factor 2
		Promax Rotated EFA Loading Scores ^a			
<i>Partnership Cohesion</i>					
Engage in a stimulating exchange of ideas	1-6	0.58		0.56	
Calmly discuss something	1-6	0.54		0.53	
Work together on a project	1-6	0.54		0.55	
Engage in outside interests	1-6	0.27		0.28	
<i>Partnership Stability</i>					
Consider divorce	1-6		0.48		0.46
Regret marriage	1-6		0.46		0.46
Quarrel	1-6		0.46		0.49
Get on each other's nerves	1-6		0.46		0.48
Degree of overall happiness	1-7		0.34		0.31
Cronbach's Alpha (<i>a</i>)		0.75	0.77	0.73	0.73
Mean (Raw)		5.75	10.63	5.85	10.76
<i>SE</i>		0.02	0.01	0.02	0.01
Correlation (<i>r</i>) Between Partners		0.34***	0.50***	0.33***	0.49***
Correlation (<i>r</i>) Between Components		0.48***		0.42***	

Data Source: 2010-2016 UKHLS

Notes: Sample includes individuals in co-resident partnerships between the ages of 18-59 who are in regular paid employment. ^a Rotated loading scores below 0.20 have been omitted.

+ $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

As both partners within a union are asked to complete the partnership questionnaire separately, there is a unique opportunity to exploit within-partnership variability in reported PQ by modeling both actor effects (i.e., the effect of an individual's work schedule on her own subjective PQ) as well as partner effects (i.e., the effect of an individual's work schedule on her partner's subjective PQ). Looking at correlations within partnerships in Table 3-2, reports of Partnership Stability appear, on average, to be relatively consistent between partners within the

same union ($r = 0.49-0.50$, $p < 0.001$), while reports of Partnership Cohesion appear to diverge more strongly ($r = 0.33-0.34$, $p < 0.001$). This is an interesting finding, in its own right, and highlights the complex and subjective nature of partnership quality; what is a cohesive partnership for one individual may be less so for her or his partner. This intra-partnership variation in reported PQ is explored further in subsequent discussions.

4.3. NONSTANDARD WORK SCHEDULES

The independent – or treatment – variables for this analysis are: (1) nonstandard work hours and (2) nonstandard work days. Nonstandard work hours are defined as work occurring outside of traditional 9:00 am to 5:00 pm diurnal work day. The measure is derived from a question asking respondents to report, “Which times of day [they] usually work?” In the interest of maximizing statistical power and enabling a binary treatment/non-treatment matching design, this measure is dichotomized such that respondents are coded as nonstandard hour workers if they listed their regular working time as occurring during: “evenings only”, “at night”, or “rotating shifts”.

A limitation of this operationalization is that it neglects important differences between rotating and fixed nonstandard hours, like the differing levels of flexibility and predictability. However, for the purposes of the current analysis, the distinction between non-day and day work is more important than distinctions between different types of non-day work. Another important point is that variable-hour and flexi-time schedules are not included in the current classification of nonstandard work hours. As Presser (1995) notes, the issue of working during nonstandard hours is distinct from that of having flexible work hours. Schedules involving nonday shifts are usually set by the employers and can often be viewed as contrary to employees’ interests. In contrast, the practice of flexibility in work hours (i.e., the option of changing the starting and ending hours of employment by a few hours) largely reflects

employees' preference. Crucially, there is also a great deal of ambiguity in classifying at what times of day the majority of hours in a flexi-time or variable-hour schedule actually occur. That said, sensitivity analyses that include variable-hour schedules in the classification of nonstandard work hours are presented at the end of this chapter.

Table 3-3. *Descriptive Statistics on Nonstandard Schedule Work, by Gender and Period*

Sample	Time Span	Nonstandard Work Hours				Nonstandard Work Days				
		Control		Treatment		Control		Treatment		
		Freq.	Prop.	Freq.	Prop.	Freq.	Prop.	Freq.	Prop.	
Women, $n = 10,190$										
Period 1	2010-12	3,553	0.89	419	0.11	3,353	0.84	630	0.16	
Period 2	2012-14	3,005	0.89	371	0.11	2,883	0.85	510	0.15	
Period 3	2014-16	2,457	0.91	249	0.09	2,335	0.86	381	0.14	
Cross-Period	2010-16	9,015	0.90	1,039	0.10	8,571	0.85	1,521	0.15	
Men, $n = 10,457$										
Period 1	2010-12	3,472	0.85	615	0.15	3,311	0.81	787	0.19	
Period 2	2012-14	2,889	0.84	547	0.16	2,820	0.82	621	0.18	
Period 3	2014-16	2,297	0.86	361	0.14	2,206	0.83	454	0.17	
Cross-Period	2010-16	8,658	0.85	1,523	0.15	8,337	0.82	1,862	0.18	

Data Source: 2010-2016 UKHLS

Notes: Sample includes individuals in co-resident partnerships between the ages of 18-59 who are in regular paid employment.

Nonstandard work days are defined as work occurring outside of the traditional Monday-Friday workweek (i.e., on Saturdays and/or Sundays). The measure is derived from a question asking respondents, “Do you ever work at weekends?” To enable matching procedures, this measure is again dichotomized such that respondents are coded as nonstandard day workers if they responded having to work “most or every weekend”. In contrast, respondents are coded into the control group if they reported having to work no or only occasional weekends; the inclusion of occasional weekend work was due to the contention that most work today involves some degree of weekend work. Sensitivity analyses that include occasional weekend work in the classification of nonstandard work days are presented at the

end of this chapter. Descriptive statistics for nonstandard work hours and days are shown by period and gender in Table 3-3. Note that the cross-period figure represents the total analytic sample.

4.4. MATCHING COVARIATES

This chapter employs Mahalanobis Distance Matching techniques (elaborated on later) to simulate a blocked randomized experiment. In choosing covariates to include in the distance matching matrix, it was essential to include factors that plausibly predicted both the treatment and outcome as well as being correlated with unmeasured confounding variables. Covariates were also included if they were thought to be related to the outcome but only indirectly related to the treatment as such factors have been shown through simulations to reduce bias with sufficient sample size (Garrido et al., 2014). Several theoretically relevant factors (most notably, income and the number of working hours) were omitted as they were hypothesized to lie along the causal pathway between nonstandard schedules and partnership quality; therefore, their inclusion could obscure a non-trivial portion of the treatment effect. Included covariates can be roughly broken into three categories: (1) *structural selection*, (2) *self-selection*, and (3) *occupational selection*.

Structural selection covariates include socioeconomic and demographic characteristics shown to affect both the likelihood of being selected into a nonstandard schedule as well as the risk of partnership instability (age, education, race or ethnicity, migrant status, and rural dwelling; Hamermesh, 1996; Hoem, 1997; Jalovaara, 2001; Maslauskaitė, Jasilionienė, Jasilionis, Stankunienė, & Shkolnikov, 2015; Presser, 2003; Presser & Cox, 1997). Self-selection covariates include characteristics of the individual or household shown to affect preferences for and perceived returns from work in a nonstandard schedule. These include: family structure characteristics (presence, number, and age of children); characteristics of the

partnership (whether partners are cohabiting or married and the age difference between partners¹⁰; Presser, 1995; Presser & Cain, 1983; Wight, Raley, & Bianchi, 2008); characteristics of the partner's employment situation (employment status, full-time work, and use of a nonstandard work schedule¹¹; Carriero, Ghysels, & van Klaveren, 2009; Hamermesh, 2002; Lesnard, 2008; Mills & Täht, 2010; Presser, 2000); and time-invariant individual characteristics (Big 5 Personality Inventory; Foldal, Langvik, & Saksvik-Lehouillier, 2016; Larsgård & Saksvik-Lehouillier, 2016; Storemark et al., 2013). Lastly, occupational selection covariates include characteristics of the individual's occupation affecting the likelihood of being channeled into a nonstandard schedule as well as the levels of job demands and resources that might moderate the effect of such schedules on PQ (occupational role, occupational status, and the level of autonomy the respondent has in the timing of work hours¹²; Burgard & Lin, 2013; Daw & Hardie, 2012; Golden, 2001; Gornick & Meyers, 2003; Hamermesh, 1996). Covariates included in the matching matrix are summarized in further detail in Table 3-4.

¹⁰ The age difference between partners has been used in similar studies (e.g., Presser, 2000) as a predictor of partnership stability. To this end, I also experimented with the inclusion of partnership duration. However, the variable had high multicollinearity with age, and more importantly, had little effect on partnership quality after controlling for age. The measure was also highly unreliable for cohabiting partnerships, for whom reports of partnership duration often differed drastically between partners.

¹¹ The choice to include the partner's work schedule timing as a selection covariate is contentious as it is unclear whether the respondent's work schedule is a consequence or a cause of her partner's schedule (i.e., the schedules are likely jointly determined at the couple level). I return to this issue in later discussions.

¹² Occupational role is measured using four NS-SEC (National Statistics Socio-Economic Classification) categories included as dummy variables, while occupational status is measured using the continuous ISEI scale. Although both indicators are in general meant to capture an employee's social position within the occupational hierarchy, they differ greatly in their approaches to measure this: NS-SEC captures characteristics of employment relations and conditions of employment, while ISEI groups individuals based on the income and educational qualifications profiles of incumbents. For a review of these differences, see Connelly, Vernon, and Lambert (2016). Crucially, the inclusion of ISEI (as a continuous scale) will also help capture the large degree of variation in social position occurring within the discrete NS-SEC categories included in the matching matrix.

Table 3-4. *Variables Used in Mahalanobis Matching Procedures*

Variable	Description	Type
Age	Respondent's age at the time of data collection	Continuous
Time Period	Period of data collection (1 = 2010-12, 2 = 2012-14, 3 = 2014-16)	Continuous
Rural	Respondent lives in a rural area	Binary
Race/Ethnicity	White British, Black or Black British, Middle Eastern, East Asian, Mixed Background (included as dummies)	Categorical
Born in UK	Respondent is born in the UK	Binary
Household		
Parent	Child under age 16 present in the household	Binary
Number of Children	Number of children under age 16 in the household	Continuous
Young Child Present	Child under age 4 present in the household	Binary
Partnership		
Cohabiting	Respondent is in a cohabiting partnership	Binary
Age Difference	Difference in age between partners (0 = ≤ 5 years, 1 = > 5 years)	Binary
Partner is Employed	Partner is in regular paid employment	Binary
Partner Full-Time	Partner works full-time (≥ 35 hours/week)	Binary
Partner Works Nights ^a	Partner works nights, evenings, or rotating shifts	Binary
Partner Works Weekends ^b	Partner works weekends every week	Binary
Education		
Highest Qual. is GCSE	Highest qualification is secondary education	Binary
Highest Qual. is Degree	Highest qualification is a tertiary degree	Binary
Occupation		
Professional Occupation	Respondent works in a professional or higher technical grade occupation (NS-SEC coding)	Binary
Lower-Management	Respondent works in a lower-management role (NS-SEC coding)	Binary
Intermediate	Respondent works in an intermediate-grade (clerical, sales, technical, or engineering) occupation (NS-SEC coding)	Binary
Routine Occupation	Respondent works in a routine or semi-routine grade occupation (NS-SEC coding)	Binary
ISEI Index ^c	International Socio-Economic Index of respondent's occupation	Continuous
Low Autonomy	Respondent has little to no influence over start and end of work day (1 = "a little", "none"; 0 = "some", "a lot")	Binary
Personality		
Big 5 Personality Items	Agreeableness, Conscientiousness, Neuroticism, Openness, and Extroversion (included separately)	Continuous

Notes: ^a Variable is included only in nonstandard work hours matching matrix; ^b Variable is included only in nonstandard work days matching matrix; ^c The ISEI index is derived by the optimal scaling of occupation groups to maximize the indirect effect of education on income through occupation and to minimize the direct effect of education on income, net of occupation (Ganzeboom et al., 1992).

4.5. MAHALANOBIS DISTANCE MATCHING

To evaluate the impact of nonstandard work hours and days on partnership quality, Mahalanobis Distance Matching (MDM) techniques are used to reduce baseline selection biases. MDM is grounded in the idea finding for each observation in the treatment group a statistical twin in the control group with the same (or at least very similar) values on a host of pre-treatment confounding variables (Jann, 2017). MDM does so by matching on a distance metric that measures the proximity between observations in the multivariate space of X . Mahalanobis distance can be formally expressed as

$$MD(X_i, X_j) = \sqrt{(X_i - X_j)' \Sigma^{-1} (X_i - X_j)}$$

where X_i denotes the vector of observed covariates for an individual with work schedule (i) and X_j denotes the vector of observed covariates for an individual with work schedule (j). Σ represents a scaling matrix, in this case, the sample variance-covariance matrix of X . The promise of MDM is to simulate a blocked randomized experiment where the distributions of measured confounders are equalized between treatment and control groups, allowing one to better delineate the true effect of a treatment, in this case, a nonstandard work schedule.¹³

Gender-specific MDM analyses are performed with one-to-two matching with replacement that selects the closest two control subjects for each treated individual. As three-level clustered data is used (20,297 person-period observations nested within 10,098 individuals which are further nested within 6,350 couples), an exclusion restriction matrix¹⁴

¹³ Mahalanobis Distance Matching simulates a fully blocked random experiment where treated and control subjects are matched at the start on observed covariates. This approximation of blocked randomization means that MDM has the ability to achieve lower levels of imbalance, model dependence, and bias than the more commonly used method of propensity score matching, which simulates a completely randomized experimental design (King & Nielsen, 2016).

¹⁴ A matching exclusion restriction matrix lists all possible observation pairs that should be excluded from matching procedures. The matrix has one row for each restriction and three columns: the first two columns contain the observation numbers that are to be restricted, and the third column contains the restriction imposed on the observation-pair. More information can be found in the R “Matching” package documentation (Sekhon, 2015).

was created that ensured that an individual surveyed during period j could never be matched to her future or earlier self surveyed during period $j + 1$ or $j - 1$. Note that as gender-specific models are run and as only heterosexual couples are included in the sample, individuals were automatically restricted from being matched to their partners.¹⁵ After fitting initial matching models for men and women, balance was checked across all covariates between the treatment and control groups. If any of the covariates remained unbalanced after matching ($a \geq 0.1$ standardized mean difference between treatment and control groups; Austin, 2001), the matching matrix was re-specified with further two- and three-way interaction terms to improve balance (Morgan & Todd, 2008). All matching procedures were performed in R using the “Matching” package created by Sekhon (2015).

The ignorability assumption is invoked in this stage of analysis, or that balancing on the rich set of selection covariates (Table 3-4), there are no additional confounders between standard and nonstandard schedule workers. This assumption is technically untestable and generally tenuous when using observational data as there are plausibly many unobserved confounders. However, as Brand and Xie (2010) argue, the inclusion of known meaningful confounders renders the assumption more plausible, if not necessarily true. Moreover, this same tenuous ignorability assumption plagues the regression adjustment methods typical in most other studies on the relationship between nonstandard schedules and partnership quality. The use of distance matching in the current study, however, allows for the adjustment of a greater number of covariates while avoiding inferences based on sparse data at certain values of covariates; the so-called, “curse of dimensionality” (Rosenbaum & Rubin, 1983). This dimensionality issue is particularly problematic in the case of nonstandard schedule workers (particularly night workers), for whom sample sizes in survey data are often quite low.

¹⁵ Analyzing male and female partners separately is crucial to fulfilling the SUTVA assumption of causal inference, or that one unit’s outcomes are unaffected by another unit’s treatment assignment. If male and female partners were included in the same analysis, it is likely that there would be interference (a treatment applied to one partner would likely affect the outcome of the other partner).

While other approaches to approximate causal effects may not rest so heavily on the ignorability assumption, they also come with their own shortcomings. For example, the use of instrumental variables comes with the difficulty of finding an instrument that strongly predicts employment in a nonstandard schedule directly but affects PQ only indirectly through a nonstandard schedule. Similarly, a differencing technique like fixed effects that requires at least two periods of observation and a change in work schedule timing for each individual would purge from the sample those individuals in nonstandard schedules whose partnerships dissolved before a change in work schedule could be observed; this, in turn, could overestimate the true effect of a nonstandard schedule on PQ by only including objectively stable partnerships in the analysis. Though not without its limitations, the current application of MDM avoids such issues and allows for an intuitive way to simulate blocked randomization on measured confounders.

4.6. HETEROGENEOUS TREATMENT EFFECTS

To identify patterns of positive and negative selection, heterogeneous treatment effects are estimated across strata of estimated propensity scores and the trend across strata is summarized in a hierarchical linear model (Brand & Xie, 2010; Tumin & Zheng, 2018; Xie, Brand, & Jann, 2012). The general process – performed on nonstandard work hour and days separately – is as follows. Propensity scores capturing an individual’s likelihood of working in nonstandard work days and hours are first constructed separately on the total unmatched sample using the final specifications of the Mahalanobis matching matrix earlier.¹⁶ Propensity scores are expressed as

$$e_i = \Pr (Z_i = 1|X_i)$$

¹⁶ As discussed earlier, the matrixes used in the Mahalanobis Distance Matching analysis included several two- and three-way interactions between covariates to improve balance between the treatment and control groups. For consistency, the same covariates and interactions between covariates were used in the construction of the propensities scores used in the current analysis; as with the Mahalanobis Distance Matching, these interactions improved balance between the treated and control groups when matching on the propensity score.

where e_i denotes the probability (probit) of selection into a nonstandard work schedule ($Z_i = 1$) conditional on observed pre-treatment covariates (X_i).¹⁷ Using a stratification algorithm (S. Becker & Ichino, 2002), these propensity scores are then divided into the minimum number of strata that ensures that within each stratum there are no significant mean differences (calculated through t -tests) in any of the covariates between treated and control groups. To ensure sufficient sample sizes within each stratum, strata with less than 20 cases were combined with the next-highest or next-lowest stratum. Cases outside the area of common support (where the propensity scores of standard and nonstandard schedule workers overlap) are also excluded.

Stratum-specific treatment effects are then estimated in the following hierarchical model

$$Y_{ij} = \alpha_j + \beta_j Z_{ij} + \epsilon_{ij}$$

$$\beta_j = \delta_0 + \sigma_j + \eta_j$$

where i indexes the individual and j indexes the propensity score stratum. β_j represents the stratum-specific treatment effect and σ_j denotes the linear slope of the treatment effects across strata (Tumin & Zheng, 2018). σ_j is estimated using a variance-weighted least squares regression across strata and is the primary parameter of interest in this analysis. A significant positive σ_j across strata would indicate positive selection, or that individuals with the highest likelihood to work in a nonstandard work schedule are also those whose partnerships benefit the most from these arrangements. In contrast, a significant negative σ_j across strata would indicate negative selection, or that individuals with the highest likelihood to work a nonstandard work schedule are also those whose partnerships suffer the most from these arrangements. As three-level clustered data is used, standard errors are clustered around the partnership ID within each stratum-specific regression to correct for case dependence. To account for any residual

¹⁷ It was necessary to switch from the Mahalanobis distance to a propensity score as a balancing metric in this stage of analysis. To identify heterogeneous treatment effects, it was important to have a single scalar variable capturing the probability of X for each respondent along which to examine heterogeneity in the effect of X on Y.

confounding within propensity score strata, covariates from the matching matrix were controlled for within a given level-one stratum-specific regression if they had standardized mean differences of > 0.1 within that respective stratum.

5. RESULTS

Table 3-5 summarizes the characteristics of women and men according to whether they work nonstandard hours and nonstandard days respectively. Across the total sample, 10% of women and 15% of men reported working regular nonstandard hours, and 15% of women and 18% of men reported working regular nonstandard days. For men and women working regular nonstandard hours, the largest differences relative to control groups are seen primarily in the proportions identifying as an ethnicity other than White British and being born outside of the UK, having a GCSE rather than a degree qualification, being in an occupation with low to no work schedule autonomy, and working in a routine or semi-routine occupation relative to a professional occupation. Similar (if less drastic) trends are also observed for men and women working regular nonstandard days. Other clear trends for both nonstandard day and hour workers are to be on average younger, live predominantly in urban areas, have lower overall occupational status, be in a partnership with an age difference greater than 5 years, and have a partner who works a synchronized (either in days or hours) nonstandard schedule. No clear trends emerge for household composition. However, nonstandard schedule workers appear on average to have slightly higher numbers of children present in the household and are more likely to be parents in general. The notable exception is women working nonstandard work days, who are less likely to have dependent children present. For statistical tests of these differences, see Appendix 3-2. These covariate imbalances were successfully eliminated after matching treatment and control groups on a Mahalanobis Distance matrix, where standardized mean

differences of < 0.1 were achieved for all covariates (Appendix 3-3). I now restrict focus to this matched sample to estimate the effects of nonstandard schedules on partnership quality.

Table 3-5. Means or Proportions of Pre-Treatment Covariates, by Gender and Work Schedule

Variable	Nonstandard Work Hours				Nonstandard Work Days			
	Women, <i>n</i> = 10,054		Men, <i>n</i> = 10,181		Women, <i>n</i> = 10,092		Men, <i>n</i> = 10,199	
	Control	Treat.	Control	Treat.	Control	Treat.	Control	Treat.
	Mean							
Age	42.93	42.42	42.75	41.81	43.06	41.82	42.88	41.41
Time Period	1.87	1.81	1.84	1.81	1.87	1.82	1.85	1.80
Rural	0.27	0.22	0.24	0.22	0.27	0.25	0.24	0.24
<i>Race/Ethnicity</i>								
White British	0.90	0.83	0.88	0.85	0.89	0.90	0.88	0.87
Black	0.01	0.03	0.02	0.02	0.02	0.02	0.02	0.01
Middle Eastern	0.04	0.09	0.05	0.08	0.04	0.04	0.05	0.08
East Asian	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00
Mixed Background	0.04	0.04	0.04	0.05	0.05	0.04	0.04	0.04
Born in UK	0.91	0.84	0.90	0.86	0.90	0.90	0.90	0.88
<i>Household</i>								
Parent	0.48	0.49	0.56	0.59	0.48	0.46	0.56	0.57
Number of Children	0.81	0.89	0.99	1.05	0.82	0.80	1.00	1.01
Young Child Present	0.14	0.15	0.21	0.24	0.14	0.16	0.21	0.24
<i>Partnership</i>								
Cohabiting	0.18	0.19	0.18	0.18	0.17	0.22	0.18	0.19
Age Difference	0.24	0.30	0.21	0.26	0.24	0.29	0.21	0.25
Partner is Employed	0.91	0.88	0.80	0.77	0.91	0.89	0.79	0.78
Partner Full-Time	0.71	0.69	0.30	0.30	0.71	0.70	0.30	0.29
Partner Works Nights	0.26	0.35	0.21	0.28				
Partner Work Weekends					0.15	0.25	0.10	0.19
<i>Education</i>								
Highest Qual. GCSE	0.29	0.36	0.28	0.42	0.28	0.41	0.27	0.41
Highest Qual. Degree	0.38	0.18	0.38	0.14	0.38	0.26	0.37	0.22
<i>Occupation</i>								
Professional Occupation	0.12	0.04	0.25	0.05	0.13	0.03	0.25	0.09
Lower MGMT	0.40	0.34	0.33	0.15	0.40	0.36	0.32	0.25
Intermediate	0.21	0.13	0.10	0.16	0.22	0.10	0.11	0.10
Routine Occupation	0.23	0.39	0.20	0.42	0.22	0.41	0.19	0.38
ISEI Index	48.68	37.68	50.73	38.05	48.14	44.39	50.19	42.83
Low Autonomy	0.54	0.79	0.41	0.79	0.54	0.70	0.44	0.60
<i>Personality</i>								
Agreeableness	4.73	4.84	4.18	4.07	4.73	4.77	4.17	4.15
Conscientiousness	6.01	6.02	5.57	5.48	6.00	6.06	5.54	5.60
Neuroticism	2.47	2.42	1.44	1.40	2.47	2.40	1.44	1.39
Openness	6.98	6.79	7.31	6.99	6.95	7.01	7.29	7.13
Extroversion	3.20	3.21	2.65	2.76	3.19	3.29	2.63	2.84

Data Source: 2010-2016 UKHLS

Notes: Sample includes individuals in co-resident partnerships between the ages of 18-59 who are in regular paid employment.

Gender-specific average treatment effects – obtained on the Mahalanobis distance matched sample – representing the effect of nonstandard work hours and days respectively are shown in Table 3-6. Looking first to the effects of nonstandard work hours, it appears that, consistent with previous research (Kalil et al., 2010; Lozano et al., 2016; Maume & Sebastian, 2012; Mills & Täht, 2010; Presser et al., 2008), night and evening schedules are most destabilizing to partnerships when worked by women. A novel finding, however, is that it appears that for women these arrangements take the biggest toll on the partner of the worker. As can be seen, women's nonstandard hour work is associated with significantly lower levels of Partnership Stability ($b = -0.14, p < 0.01$) for her partner but only marginally lower levels for the worker herself ($b = -0.09, p < 0.10$). Similarly, such work is associated with borderline significant lower levels of reported Partnership Cohesion for the partner ($b = -0.09, p < 0.10$) but has no significant effect on the female worker's reported levels of Partnership Cohesion. Men's nonstandard hour work, on the other hand, appears to have no significant effects on either his own or his partner's reported levels of Partnership Cohesion or Stability.

A similar pattern emerges when looking at the effects of nonstandard work days. Men's weekend work appears to have no significant effects on his own and his partner's reported levels of Partnership Cohesion and Stability. In contrast, women's weekend work is associated with significantly lower reported levels of both Partnership Stability ($b = -0.08, p < 0.05$) and Cohesion ($b = -0.10, p < 0.01$) for the partner. As with women's night and evening work, it appears that the women's absence from the household and partnership during weekends is particularly destabilizing to their male partner's perceptions of partnership quality. A notable finding is that not only does women's weekend work have no significant negative actor effects on reported Partnership Stability, but actually appears to marginally (but not significantly) improve subjective levels of Partnership Cohesion for the worker herself ($b = 0.07, p < 0.10$).

Table 3-6. *Mahalanobis Distance Matching Estimates of Nonstandard Schedule Treatment Effects*

		Average Treatment Effect on Partnership Stability		Average Treatment Effect on Partnership Cohesion	
Treatment	<i>n</i> ^a	<i>b</i>	<i>SE</i> ^b	<i>b</i>	<i>SE</i>
Women					
Nonstandard Hours					
Actor Effect	3,424	-0.09+	0.05	-0.04	0.05
Partner Effect	3,424	-0.14**	0.05	-0.09+	0.05
Nonstandard Days					
Actor Effect	5,152	-0.03	0.04	0.07+	0.04
Partner Effect	5,152	-0.08*	0.04	-0.10**	0.04
Men					
Nonstandard Hours					
Actor Effect	5,232	0.04	0.04	-0.02	0.04
Partner Effect	5,232	0.02	0.04	-0.03	0.04
Nonstandard Days					
Actor Effect	6,392	0.01	0.03	0.04	0.03
Partner Effect	6,392	-0.05	0.04	0.00	0.04

Data Source: 2010-2016 UKHLS

Notes: Sample includes individuals in co-resident partnerships between the ages of 18-59 who are in regular paid employment. ^a Pruned sample includes only treated and untreated cases matched 1-to-2 on Mahalanobis Distance. ^b Abadie-Imbens standard errors are used that take into account the uncertainty of the matching procedure.

+ $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

That women's weekend could have negative partner effects on Partnership Cohesion and positive actor effects is a surprising finding. As matching did not take into account the number of work hours (as is was posited to lie along the causal pathway), a possible explanation consistent with research from the Netherlands (Mills & Täht, 2010) would be that women's weekend work is tied to fewer and/or more flexible work hours arranged around the family. However, if fewer or more flexible work hours were the explanation in the present case, one should expect that the partners of women working weekends would also benefit from such arrangements; instead, the opposite pattern emerges. Indeed, post-hoc analyses revealed no significant differences in the number of weekly work hours between women working regular nonstandard days and those not working these schedules in the matched sample (results available upon request). In addition, nonstandard day work for women was shown to be

associated with lower average levels of flexibility in setting the start and end of the work day, suggesting there is likely something else behind this paradox.

Further scrutinizing the data through sub-index analyses (Appendix 3-4 and Appendix 3-5) reveals some important insights into the diverging actor and partner effects of women's weekend work on partnership quality. Looking to Appendix 3-4, women working weekends are on average significantly more likely to report engaging in a stimulating exchange of ideas ($b = 0.08, p < 0.05$) and calmly discussing something with their partner ($b = 0.09, p < 0.05$). In contrast, the partners of women in such arrangements show conflicting trends: they are on average significantly less likely to report both engaging in a stimulating exchange of ideas ($b = -0.07, p < 0.05$) and calmly discussing something with their partner ($b = -0.12, p < 0.01$). This divergence is not inconsistent with the relatively weak intra-partnership correlations between these items across the total sample shown in Appendix 3-6 ($r = 0.23$ and $r = 0.25$, respectively). As mentioned earlier, these items leave room for a large degree of subjectivity on the part of each partner, and what is a cohesive partnership for one individual may not always be perceived as such for her or his partner.

An alternative explanation for these diverging trends in the actor and partner effects of women's nonstandard schedule work would be that women may be positively selecting into such arrangements on the basis of their own well-being but not their partner's. This could be either to arrange their employment around other activities outside of work (household-related or otherwise) or to engage in the more social services-based work often concentrated on weekends and during evenings. Indeed, looking at the most common occupations for nonstandard schedule work in the current sample (Appendix 3-7) shows that for women around 35% of nonstandard day and hour work is clustered in shop salesperson and personal care jobs, which generally have more social and relaxed working conditions. To the extent that such

working conditions are conducive to overall job satisfaction and well-being for women, this might have positive spillover effects on outcomes relating to perceived work-family balance.

One way to test for patterns of positive selection in the present case is to look at how treatment effects of women's and men's nonstandard work schedules vary depending on the likelihood of working these arrangements. To do so, separate propensity scores capturing the likelihood of working in nonstandard hours and days are first constructed for men and women using the same selection covariates and their interactions included in the construction of the Mahalanobis Distance Matching matrixes earlier. These scores are then broken down into balanced strata, and hierarchical linear models are fit to estimate stratum-specific treatment effects as well as the linear trend of these effects across strata. Recall that a significant positive slope across strata indicates positive selection, or that individuals with the highest likelihood to work in a nonstandard schedule are also those whose partnerships benefit the most from these arrangements. In contrast, a significant negative slope indicates that those with the highest likelihood to work a nonstandard schedule are also those whose partnerships suffer the most from these arrangements. Tables 3-7 and 3-8 show stratum-specific actor effects of women's and men's nonstandard hour and day work and the corresponding linear slope across strata; Tables 3-9 and 3-10 show stratum-specific partner effects of women's and men's nonstandard hour and day work and the corresponding linear slope across strata.

Table 3-7. *Propensity Stratum Actor Effects of Nonstandard Work Hours and Linear Relationship Between Propensity Stratum and Estimated Treatment Effect*

Nonstandard Hours Stratum	Propensity Score Range	Average Actor Effect on Partnership Stability		Average Actor Effect on Partnership Cohesion	
		<i>b</i>	<i>SE</i> ^{<i>a</i>}	<i>b</i>	<i>SE</i>
Women, <i>n</i> = 10,031					
1, <i>n</i> = 2,384	0.01 - 0.02	-0.17	0.23	-0.03	0.26
2, <i>n</i> = 1,400	0.03 - 0.05	0.01	0.15	-0.25	0.14
3, <i>n</i> = 1,692	0.05 - 0.10	0.02	0.10	0.13 +	0.14
4, <i>n</i> = 788	0.10 - 0.12	-0.06	0.13	-0.21	0.12
5, <i>n</i> = 870	0.13 - 0.15	-0.23 *	0.10	-0.16 +	0.11
6, <i>n</i> = 1,226	0.15 - 0.20	-0.04	0.09	-0.07	0.08
7, <i>n</i> = 1,330	0.20 - 0.40	-0.03	0.08	0.14	0.08
8, <i>n</i> = 78	0.40 - 0.58	0.01	0.36	0.30	0.35
Slope across strata		0.00	0.02	0.05 *	0.02
Men, <i>n</i> = 10,144					
1, <i>n</i> = 1,839	0.01 - 0.02	0.50 *	0.16	-0.04	0.19
2, <i>n</i> = 1,213	0.03 - 0.05	-0.22	0.15	-0.29 +	0.17
3, <i>n</i> = 1,231	0.05 - 0.10	-0.10	0.10	-0.04	0.10
4, <i>n</i> = 465	0.10 - 0.12	0.44 *	0.13	0.35 *	0.14
5, <i>n</i> = 391	0.13 - 0.15	0.06	0.14	0.18	0.12
6, <i>n</i> = 983	0.15 - 0.20	-0.08	0.08	-0.12	0.09
7, <i>n</i> = 2,626	0.20 - 0.30	0.04	0.05	-0.02	0.05
8, <i>n</i> = 862	0.30 - 0.40	-0.07	0.09	0.04	0.08
9, <i>n</i> = 153	0.40 - 0.56	-0.05	0.24	0.21	0.22
Slope across strata		-0.02	0.02	0.01	0.02

Data Source: 2010-2016 UKHLS

Notes: Sample includes individuals in co-resident partnerships between the ages of 18-59 who are in regular paid employment. ^a Standard errors in stratum-specific regressions are clustered around unique partnership ID's to account for nested data.

+ $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

Table 3-8. *Propensity Stratum Actor Effects of Nonstandard Work Days and Linear Relationship Between Propensity Stratum and Estimated Treatment Effect*

Nonstandard Days Stratum	Propensity Score Range	Average Actor Effect on Partnership Stability		Average Actor Effect on Partnership Cohesion	
		<i>b</i>	<i>SE</i> ^{<i>a</i>}	<i>b</i>	<i>SE</i>
Women, <i>n</i> = 10,091					
1, <i>n</i> = 1,195	0.01 - 0.05	-0.05	0.16	-0.06	0.13
2, <i>n</i> = 2,260	0.05 - 0.10	0.01	0.09	-0.06	0.09
3, <i>n</i> = 2,328	0.10 - 0.15	-0.16 *	0.07	-0.07	0.07
4, <i>n</i> = 1,639	0.15 - 0.20	-0.02	0.07	0.01	0.07
5, <i>n</i> = 1,539	0.20 - 0.30	0.04	0.07	0.00	0.07
6, <i>n</i> = 601	0.30 - 0.40	0.15	0.10	0.03	0.10
7, <i>n</i> = 263	0.40 - 0.72	0.16	0.14	0.45 **	0.15
Slope across strata		0.05 *	0.02	0.06 *	0.02
Men, <i>n</i> = 10,197					
1, <i>n</i> = 744	0.02 - 0.05	0.05	0.23	0.08	0.20
2, <i>n</i> = 1,719	0.05 - 0.10	0.01	0.10	0.16	0.10
3, <i>n</i> = 1,699	0.10 - 0.15	0.01	0.07	0.03	0.07
4, <i>n</i> = 1,853	0.15 - 0.20	-0.12 *	0.06	-0.03	0.06
5, <i>n</i> = 756	0.20 - 0.23	-0.06	0.09	-0.04	0.08
6, <i>n</i> = 665	0.23 - 0.25	0.11	0.08	-0.05	0.09
7, <i>n</i> = 1,093	0.25 - 0.30	0.02	0.08	0.01	0.08
8, <i>n</i> = 676	0.30 - 0.35	-0.01	0.10	0.16 +	0.09
9, <i>n</i> = 310	0.35 - 0.40	0.27 *	0.14	0.38 **	0.14
10, <i>n</i> = 300	0.40 - 0.72	0.06	0.12	0.15	0.13
Slope across strata		0.02	0.01	0.02	0.01

Data Source: 2010-2016 UKHLS

Notes: Sample includes individuals in co-resident partnerships between the ages of 18-59 who are in regular paid employment. ^a Standard errors in stratum-specific regressions are clustered around unique partnership ID's to account for nested data.

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

For women's nonstandard hour work (Table 3-7), no significant positive or negative trends are observed across strata for Partnership Cohesion, where treatment effects appear relatively stable. In contrast, there is a significant positive slope ($b = 0.05$, $p < 0.05$) in the effects on Partnership Cohesion across strata, indicating that the women with the highest likelihood of working nonstandard hours are those who receive the largest gains in perceived Cohesion with partners. Similarly, for women's nonstandard day work (Table 3-8), significant positive slopes in actor effects across propensity score strata are observed for both Partnership Cohesion ($b = 0.06$, $p < 0.05$) and Stability ($b = 0.05$, $p < 0.05$). Crucially, however, when

looking at how the partner effects of women's nonstandard hour (Table 3-9) and day (Table 3-10) work on Partnership Cohesion and Stability vary across propensity score strata, no discernible positive slopes are observed. Taken together, these findings support a thesis of positive rather than negative selection into nonstandard work schedules for women: it appears that those most likely to enter into these arrangements are also those who receive the largest perceived benefits to partnership quality. However, in line with earlier contentions, it appears that any positive selection into these arrangements by women is likely occurring on the basis of their own and not their partner's perceived partnership quality.

For men working nonstandard hours or days, on the other hand, no clear patterns of positive or negative selection are observed for the actor and partner effects on partnership quality. The actor (Table 3-7) and partner effects (Table 3-9) of men's nonstandard hours on Partnership Cohesion appear relatively stable across strata. For Partnership Stability, there is slight evidence of a negative trend in actor effects across strata, where treatment effects appear most positive for men with the lowest probability of working these arrangements; however, the overall slope does not reach significance. These relatively flat slopes in treatment effects are also seen for both the actor (Table 3-8) and partner effects (Table 3-10) of men's nonstandard day work, where all slopes are slightly positive but not significant. Therefore, for men, there is insufficient evidence to support a hypothesis of positive or negative selection into either nonstandard day or -hour work schedules. That positive selection was not observed for men could perhaps be explained by the possibility that family considerations may be less relevant to men's entry into a nonstandard work schedule than for women; as has been suggested, men more so than women work nonstandard hours out of necessity than preference (Presser, 1995). Broader interpretations and implications for these findings are discussed below.

Table 3-9. *Propensity Stratum Partner Effects of Nonstandard Work Hours and Linear Relationship Between Propensity Stratum and Estimated Treatment Effect*

Nonstandard Hours Stratum	Propensity Score Range	Average Partner Effect on Partnership Cohesion		Average Partner Effect on Partnership Closeness	
		<i>b</i>	<i>SE</i> ^{<i>a</i>}	<i>b</i>	<i>SE</i>
Women, <i>n</i> = 10,031					
1, <i>n</i> = 2,384	0.01 - 0.02	0.24 +	0.13	-0.09	0.19
2, <i>n</i> = 1,400	0.03 - 0.05	0.03	0.11	0.13	0.12
3, <i>n</i> = 1,692	0.05 - 0.10	-0.21	0.13	-0.14	0.15
4, <i>n</i> = 788	0.10 - 0.12	-0.08	0.10	-0.05	0.11
5, <i>n</i> = 870	0.13 - 0.15	-0.06	0.10	0.11	0.10
6, <i>n</i> = 1,226	0.15 - 0.20	-0.14 +	0.08	-0.18 *	0.08
7, <i>n</i> = 1,330	0.20 - 0.40	-0.08	0.08	-0.05	0.08
8, <i>n</i> = 78	0.40 - 0.58	0.53	0.33	-0.02	0.40
Slope across strata		-0.03	0.02	-0.02	0.02
Men, <i>n</i> = 10,144					
1, <i>n</i> = 1,839	0.01 - 0.02	0.13	0.13	0.42 *	0.19
2, <i>n</i> = 1,213	0.03 - 0.05	-0.28	0.21	-0.30	0.20
3, <i>n</i> = 1,231	0.05 - 0.10	0.00	0.12	0.01	0.14
4, <i>n</i> = 465	0.10 - 0.12	0.36 *	0.18	0.19	0.18
5, <i>n</i> = 391	0.13 - 0.15	0.01	0.19	0.03	0.16
6, <i>n</i> = 983	0.15 - 0.20	-0.03	0.09	-0.14	0.09
7, <i>n</i> = 2,626	0.20 - 0.30	-0.01	0.06	-0.04	0.06
8, <i>n</i> = 862	0.30 - 0.40	-0.13	0.09	-0.04	0.09
9, <i>n</i> = 153	0.40 - 0.56	0.10	0.21	-0.09	0.26
Slope across strata		-0.02	0.02	-0.03	0.02

Data Source: 2010-2016 UKHLS

Notes: Sample includes individuals in co-resident partnerships between the ages of 18-59 who are in regular paid employment. ^a Standard errors in stratum-specific regressions are clustered around unique partnership ID's to account for nested data.

+ $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

Table 3-10. *Propensity Stratum Partner Effects of Nonstandard Work Days and Linear Relationship Between Propensity Stratum and Estimated Treatment Effect*

Nonstandard Days Stratum	Propensity Score Range	Average Partner Effect on Partnership Cohesion		Average Partner Effect on Partnership Closeness	
		<i>b</i>	<i>SE</i> ^{<i>a</i>}	<i>b</i>	<i>SE</i>
Women, <i>n</i> = 10,091					
1, <i>n</i> = 1,195	0.01 - 0.05	-0.04	0.14	0.07	0.14
2, <i>n</i> = 2,260	0.05 - 0.10	-0.04	0.08	-0.04	0.09
3, <i>n</i> = 2,328	0.10 - 0.15	-0.10	0.06	-0.13 +	0.08
4, <i>n</i> = 1,639	0.15 - 0.20	-0.06	0.07	-0.10	0.07
5, <i>n</i> = 1,539	0.20 - 0.30	-0.02	0.07	-0.17 *	0.07
6, <i>n</i> = 601	0.30 - 0.40	-0.02	0.10	-0.08	0.10
7, <i>n</i> = 263	0.40 - 0.72	0.23 +	0.13	0.13	0.16
Slope across strata		0.03	0.02	-0.01	0.02
Men, <i>n</i> = 10,197					
1, <i>n</i> = 744	0.02 - 0.05	0.10	0.19	-0.15	0.17
2, <i>n</i> = 1,719	0.05 - 0.10	0.09	0.10	0.06	0.10
3, <i>n</i> = 1,699	0.10 - 0.15	-0.10	0.08	-0.03	0.08
4, <i>n</i> = 1,853	0.15 - 0.20	-0.10	0.07	-0.04	0.07
5, <i>n</i> = 756	0.20 - 0.23	-0.20 +	0.11	-0.06	0.10
6, <i>n</i> = 665	0.23 - 0.25	-0.01	0.11	0.10	0.10
7, <i>n</i> = 1,093	0.25 - 0.30	0.08	0.08	-0.02	0.08
8, <i>n</i> = 676	0.30 - 0.35	-0.08	0.10	-0.13	0.10
9, <i>n</i> = 310	0.35 - 0.40	0.12	0.15	0.13	0.14
10, <i>n</i> = 300	0.40 - 0.72	0.00	0.13	0.08	0.13
Slope across strata		0.01	0.01	0.01	0.01

Data Source: 2010-2016 UKHLS

Notes: Sample includes individuals in co-resident partnerships between the ages of 18-59 who are in regular paid employment. ^a Standard errors in stratum-specific regressions are clustered around unique partnership ID's to account for nested data.

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6. SUPPLEMENTARY ANALYSES

As discussed, the current operationalization of nonstandard work hours excluded variable-hour schedules. This was due to the contention that the issue of working during nonstandard hours is distinct from that of having flexible work hours: schedules involving nonday shifts are usually set by the employers, while the practice of flexibility in work hours (i.e., the option of changing the starting and ending hours of employment by a few hours) largely reflects employees' preferences (Presser, 1995). Crucially, there is also a great deal of ambiguity in

classifying at what times of day the majority of hours in a flexi-time or variable-hour schedule actually occur. Another important note is that the current operationalization of nonstandard work days excluded those who report working occasional weekends; this was due to the contention that most work today involves some amount of weekend work – especially for those working long hours.

To determine whether these choices substantially altered results, sensitivity analyses were run that included variable-hour schedules in the classification of nonstandard work hours, and that included occasional weekend work in the classification of nonstandard work days. Results (shown in Appendix 3-8) indicate that including variable-hour schedules in the classification of nonstandard work hours makes no major changes to the actor or partner effects of men's nonstandard hour work. Similarly, for men, the inclusion of occasional weekend work in the classification of nonstandard days does not alter the actor or partner effects of these arrangements. For women, however, the inclusion of variable-hour schedules attenuates the negative partner effects of women's nonstandard hour work to non-significance; this could be due to the benefits that flexibility in work hours generally affords. Similarly, the inclusion of occasional weekend work in the nonstandard day measure reduces negative partner effects to non-significance. This latter finding is likely due to the fact that nearly half of the women in the sample reported working occasional weekends, which likely diluted any observable adverse effects of regular weekend work on partnership quality.

Patterns of heterogeneous treatment effects in this sensitivity analysis are also largely consistent with results seen in original analyses (shown in Appendix 3-9). As in the original analysis, for women, significant positive slopes are observed across propensity strata in the actor effects of nonstandard hours and days, while there are no significant slopes in the partner effects of these arrangements. Trends consistent with original analyses are also largely observed for men. One particularly interesting departure seen in this analysis is that for men, the inclusion

of variable-hour schedules in the classification of nonstandard hours results in a significant negative slope in the partner effects of nonstandard work hours across propensity score strata. This suggests that the men most likely to select into variable-hour schedules are also those most likely to have their partner negatively affected by such arrangements. It is difficult to say what might be driving this trend. However, this finding could suggest that variable-hour schedules for men are highly concentrated in households with an already high pre-existing risk of partnership discord. Future research could attempt to unpack this finding further.

An important limitation to the current analysis was that work schedule timing and partnership quality were not measured in the same waves of each period (a lag of between 1 to 2 years). To account for this, it was necessary to exclude any individuals in partnerships that ended between these waves (e.g., between Waves 2 and 3, or between Waves 4 and 5); the specific sample restrictions used are outlined in detail in Appendix 3-1. An issue with this choice is that it is possible that by only including objectively stable partnerships over each observation period, I may have overestimated the true effect of nonstandard schedules on partnership quality that might be observed if independent and dependent variables were measured contemporaneously. To determine whether this might be the case, I regressed a binary indicator of whether the individual was in a partnership that dissolved between the two waves of each period (i.e., a within-period partnership dissolution) on work schedule timing. Results (shown in Appendix 3-10) reveal that both men and women working regular nonstandard days were significantly more likely to have their partnership dissolve between the waves of a given period. However, no significant effects were found for nonstandard hours. This suggests that selective attrition might be generating an upwards bias on estimates of the effects of nonstandard days on partnership quality. Future research could try to replicate the current findings using contemporaneous measures of work schedule timing and partnership quality to determine the extent of this bias.

7. DISCUSSION

This study presented evidence on the links between nonstandard work schedules and partnership quality for men and women. Aside from exploring this relationship in the previously unstudied context of the UK, a major aim of this paper was to characterize and correct for the complex processes of selection underlying employment in nonstandard schedules. Prior studies on the relationship between nonstandard schedules and partnership quality have long acknowledged that such arrangements are far from a randomly distributed treatment. For example, by controlling for factors like age, education, and occupational class, many studies (e.g., Davis, Benjamin Goodman, Piretti, & Almeida, 2008; Maume & Sebastian, 2012; Presser, 2000) have attempted to account for the tendency of nonstandard work hours and days to concentrate in segments of the labour market with the least bargaining power. Similarly, by modeling interactions on characteristics like gender, parental status, and the employment characteristics of an individual's partner, several studies (e.g., Kalil et al., 2010; Mills & Täht, 2010; White & Keith, 1990) have also acknowledged that the effect of a nonstandard schedule on partnership quality will likely not be homogeneous across members of a given population.

A relatively unexplored avenue of research, however, is the extent to which these interdependent characteristics and social categories might interact in a multivariate space to shape and confound the relationship between nonstandard work schedules and partnership quality. The antecedents of selection into a nonstandard schedule are not univariate or bivariate. To wit, a mother does not work during weekends solely because she is a woman with children. Similarly, a man in a routine occupation does not necessarily work nights because he is in a routine occupation. Rather, one's likelihood to be observed in a nonstandard schedule depends on the interaction of the individual's age, gender, family structure, occupational class, human capital, partner's employment situation, as well as preferences surrounding the organization of work and non-work hours. Attempting to study these antecedents in isolation will likely reveal

only fragments of the ways in which they interact with one another to shape the effects that nonstandard schedules have on partnership quality.

Building off this premise, the current study tested whether the individuals most likely to select into nonstandard work schedules – based on their relative position within the multivariate space of measured confounders – differ not only in their baseline partnership quality but also in the size and direction of the partnership returns they receive from working these arrangements. Net of the confounding effects of occupational, self-, and socioeconomic selection, I explored first whether nonstandard work hours and days predicted levels of subjective partnership quality for the worker or her partner through a matching-based quasi-experiment. Second, I tested for competing patterns of positive or negative selection by looking at whether the men and women most likely to work nonstandard schedules were also those who stood to have their partnership quality benefit (suffer) the most from these arrangements.

Findings include three major patterns. First, it appears that women's nonstandard schedule work is, by and large, more detrimental to partnership quality than men's. These results are consistent with previous studies (Kalil et al., 2010; Lozano et al., 2016; Maume & Sebastian, 2012; Mills & Täht, 2010; Presser et al., 2008), which have found that women's night, evening, and weekend work hours create greater discord within partnerships than men's. As has been suggested, women's work during nonstandard hours or days often means that men have to take a greater responsibility for female-typed household tasks like dependent care work, cooking, and cleaning, which can lead to feelings of frustration and role-overload. As Kalil et al. (2010) also note, it could be that female partners, more so than male partners, cultivate the pleasurable shared time and attend to the emotional maintenance activities necessary for forming the strong bonds that solidify a partnership. Thus, a woman's absence from the household during nights, evenings, or weekends – times of the day and week traditionally reserved for family life – may have particularly dire effects on perceptions of cohesion and

stability.

However, a second major finding of this study was that, after correcting for baseline selection biases through matching, women's nonstandard work hours and days only appear to take a negative toll on the partner of the worker rather than the worker herself. This was most apparent in the case of women's weekend work, which had significant negative effects on the male partners' subjective levels of partnership cohesion and stability but appeared to marginally (but not significantly) improve subjective levels of cohesion for the worker. That women working nonstandard hours and days do not share the same lower evaluations of partnership cohesion and stability as their male partners is a novel finding. One explanation consistent with findings from Kingston and Nock (1987) is that male and female partners might have differing conceptions of what constitutes quality time together and when this should occur. Similarly, it could be that male partners, particularly those of women working nonstandard hours, might be suffering disproportionately from the added household and care responsibilities they must shoulder when their partner is away from the home during these times (Kalil et al., 2010). Through this lens, women's work during nonstandard hours and days could be revealing mismatched gender-role expectations between the women who choose to work these arrangements and their male partners. Applying Ogburn's cultural lag theory (1923), men's more traditional expectations of when their partners should be at home may be lagging behind the material conditions working women must now navigate in the UK: in particular, limited or expensive childcare options during the day, a crowded labour market, and a high demand for services-based labour in the evenings and at weekends.

Interestingly, after matching, men's nonstandard day and hour work were found to have no negative effects on the female partner's perceived levels of partnership cohesion or stability. One explanation for this divergence between the partner effects of men's and women's nonstandard schedule work could be differences in social network formation between genders.

As Cristobal and Chaeyoon (2014) argue, free time – like that often concentrated at weekends or during evening and night hours – is a network good, the value of which depends on the number of social others who share the same schedule of time available. For the male partners of women working nights, evenings, or at weekends, the value of non-work leisure time is diminished as their significant other is not available during these hours; this, in turn, could have negative spillover effects on well-being and relationship satisfaction. The female partners of men working nights, evenings, or at weekends, on the other hand, may cope better with their partner's absence during non-work hours as they have richer networks of social others outside of the relationship. Previous research, for example, indicates that women not only have larger social networks than do men in general (Antonucci & Akiyama, 1987; Antonucci, Akiyama, & Lansford, 1998; Turner & Marino, 1994), but are also more likely to have a confidant outside of a conjugal relationship (while men have more formal associations) (Booth, 1972) and report receiving more social support from coworkers, relatives, and friends than do men (Turner & Marino, 1994; Umberson, Chen, House, Hopkins, & Slaten, 1996). Therefore, to the extent that nonstandard work hours and days reduce the time the worker can spend with his or her partner (as time-use research indicates they do; Lesnard, 2008; Wight, Raley, & Bianchi, 2008), it would follow that male partners might suffer from this diminished partner interaction the most.

The lack of significant negative actor effects of women's nonstandard work hours and days on her own subjective levels of partnership quality is also a novel finding. This could be tied to a third major finding of this study: it appears that women positively select into nonstandard schedules on the basis of their own (but not their partner's) perceived partnership quality. As was found, the women with the highest likelihood of working nonstandard hours and days were also those who received the largest gains in perceived cohesion and stability with partners. These trends of positive selection were, however, not observed for the partner effects of women's nonstandard schedule work, nor were they observed for the actor or partner effects

of men's nonstandard hour and day work. It is also important to note is that no patterns of negative selection into nonstandard schedules were observed for men or women. This lack of observed negative selection is particularly interesting when one reflects on previous findings that nonstandard schedules, especially nonstandard hours, are often an employer-driven job disamenity largely concentrated amongst largely marginalized groups within the labour market (Grzywacz et al., 2011; Hamermesh, 2002; Lesnard, 2008; Presser, 1987).

That positive selection was only observed for females is also surprising. One explanation would be that women, more so than men, engage in these schedules to arrange their work around other household activities during weekdays, for example, caring for children. Indeed, there is some evidence from the US that family considerations are more relevant for female non-day than male non-day employment (Presser, 1984, 1987, 1988, 1995). This would, however, not explain why the male partners of such women do not also benefit from these arrangements. It could be that, regardless of the female worker's intentions, men still experience feelings of frustration that partners are at work during the hours and days typically reserved for domestic life. A complementary explanation would be that women's positive selection into nonstandard schedules has more to do with the benefits of the jobs where these schedules are most common rather than the benefits of the schedules per se. For example, supplementary analyses (Appendix 3-7) revealed that nonstandard work hour and days for women are highly clustered in shop salesperson and personal care jobs, which have generally more relaxed and social working conditions. To the extent that such working conditions are conducive to overall job satisfaction and well-being for women, this could have positive trickle-down effects on outcomes relating to perceived work-family balance.

Further research is still needed to identify in greater detail the mechanisms through which women positively select into nonstandard schedules. Similarly, it is also important to understand better why such patterns of positive selection were not also observed for men. For

example, is it that, as Presser (1995) originally suggested, men more so than women work nonstandard schedules out of necessity rather than preference? Another important avenue for further research would be to unpack why women's nonstandard schedule work negatively affects the partner but not the worker herself. For example, is it that such arrangements are indeed pushing men to engage more in household labour and childcare tasks? Alternatively, do these diverging trends have more to do with differing responses between genders to the time-constraints these arrangements place on shared couple time? Lastly, another important question that could be explored is whether and how patterns of positive selection might replicate in other country contexts. As discussed earlier, the UK labour market is characterized by relatively weak working time regulations and employee protections as well as an increasingly diminished influence of social partners in the negotiation of working conditions. Given this, it would be interesting to see whether patterns of positive selection by men or women into nonstandard schedules are even stronger in labour contexts like Sweden, the Netherlands and Denmark where family-friendly labour regulations are common and where entrance into nonstandard schedules may more often represent personal preference.

There are also several limitations to the current study that could suggest further opportunities for future research. A first limitation is that, as this analysis uses independent variables measured during Waves 2, 4, and 6 and dependent variables measured during Waves 3, 5, and 7, I was forced to exclude any individuals in partnerships that ended between the constituent waves of each observation period (e.g., between Waves 2 and 3, or between Waves 4 and 5). Therefore, it is possible that by only including objectively stable partnerships over each observation period, I have overestimated the true effect of nonstandard schedules on partnership quality that might be observed if independent and dependent variables were measured contemporaneously. Sensitivity analyses (Appendix 3-10) supported this contention, revealing that individuals in nonstandard days were significantly more likely to have their

partnerships dissolve between waves, indicating the presence of a selective attrition bias. Future research could explore the use of contemporaneous measures of work schedule timing and partnership quality to determine the extent of this bias or utilize a quasi-experimental design with partnership dissolution as the outcome.

A second limitation of this analysis is that due to limited sample sizes, I grouped parents and non-parents together. This could be problematic as it is likely that the channels of selection into nonstandard schedules will differ greatly depending on whether there are children present in the household. Moreover, the presence of children within a household is, itself, a highly endogenous characteristic of a partnership affected by factors theoretically related to both preferences surrounding work schedule timing and partnership quality; therefore, conditioning on this in the matching matrix might have, in fact, introduced bias (Elwert & Winship, 2014). Future research could stratify analysis by parental status to determine whether selection into nonstandard schedules operates differently depending on the presence of children. A third limitation to this analysis surrounds the validity of the ignorability assumption invoked in the construction of the matching matrix. I assumed that conditioning on the rich set of selection covariates, there were no additional confounders between nonstandard schedules and partnership quality. While this assumption is technically untestable, one could rightly argue that it is tenuous when using observational data as there are plausibly many unobserved confounders. Given that results do suggest that positive selection biases might be at play, particularly for women, future research could try to tease out the causal effects of nonstandard schedules on family cohesion through the use of an instrumental variable technique or fixed effects.

A final limitation worth noting here is with regards to the inclusion of the partner's work scheduling timing (i.e., whether he or she also works a nonstandard schedule) as a treatment selection covariate in the current study. Several studies have documented that dual-earner

couples tend to synchronize work schedules: when one partner works nonstandard hours or days it significantly increases the odds that the other partner will also work such an arrangement (Carriero et al., 2009; Hamermesh, 2002; Lesnard, 2008; Mills & Täht, 2012). As discussed earlier, this coordination of work schedules can, in turn, have positive effects on outcomes relating to partnership quality as it facilitates more shared couple time. However, such patterns of synchronization also naturally raise concerns surrounding simultaneity: it is unclear whether the respondent working a nonstandard schedule is a response to or cause of her partner also working a nonstandard schedule. Indeed, in the context of the current research design, it is difficult to say whether partners' nonstandard schedule work is, in fact, a pre-treatment confounder (as it was treated here) or whether it is instead a mediating variable; if the latter, its inclusion in the Mahalanobis matching matrix would have obscured a portion of the treatment effect.

This joint-determination problem may partly explain why some studies (e.g., Lesnard, 2008; Mills & Täht, 2010) have used couple-level measures of work schedules that look at the combination of the male and female partners' work schedule timing. While this couple-level approach would help circumvent simultaneity bias in the present case, it would also come with the drawback of obfuscating some of the individual-level selection mechanisms underlying employment in nonstandard schedules. Though not without its limitations, the current study's inclusion of partners' work schedule timing as a selection covariate (using an individual-level data structure) identified the effect of the respondent's work schedule on her own and her partner's subjective partnership quality holding constant the timing of the partner's work schedule. That said, work schedule synchronization between partners is an important component of conjugal life, especially when studying outcomes relating to partnership quality. Rather than simply controlling for this tendency for between-partner work schedule coordination (as the current study has done), future research could explore ways to exploit it

using a quasi-experimental design. A particularly interesting avenue that could be explored is whether and how positive selection into nonstandard schedules operates at the couple level.

Partnership quality is an important determinant of adult identity, life satisfaction, and physical and mental health. Moreover, there is a vast literature documenting the short- and long-term negative social and economic consequences of partnership dissolution for adults and their children (Amato, 2014; Chase-Lansdale, Cherlin, & Kiernan, 1995; Fergusson, McLeod, & John Horwood, 2014; Kim, 2011; Kitson & Morgan, 1990; Lorenz, Wickrama, Conger, & Elder, 2006). As such, the relationship between partnership quality and a known risk factor for partnership dissolution and discord such as nonstandard schedules warrants serious examination. Findings from this study broadly suggest that after correcting for baseline selection biases, nonstandard schedules are associated with lower levels of partnership quality in the UK, but only for the male partners of women working these arrangements. They also suggest, somewhat more optimistically, that the women most tolerant of nonstandard schedules are also those most likely to select into these arrangements. Indeed, the patterns of positive selection observed for women indicate that those who become nonstandard schedule workers may be acting rationally given their characteristics and preferences, selecting into the work schedule arrangement that maximizes their own well-being and utility. Such findings are not only informative, in their own right, but also highlight the importance of a nuanced approach to the study of the relationship between nonstandard schedules and outcomes relating to family cohesion that takes into account the complex processes of selection into these arrangements as well as the heterogeneous actor and partner effects.

CHAPTER 4

NONSTANDARD SCHEDULES, WORK-FAMILY CONFLICT, AND
THE MODERATING EFFECT OF COUNTRY CONTEXT: EVIDENCE
FROM 32 EUROPEAN COUNTRIES

Author's Note: In the preceding chapter, focus was restricted to the UK, where I looked at the ways in which nonstandard work hours and days affected romantic partnerships. This chapter expands the lens of focus to include the rest of Europe as well as by studying the myriad other ways in which nonstandard schedules can harm work-family balance. This chapter was co-authored with Professor Melinda Mills.¹⁸

1. INTRODUCTION

Across Europe, heightened international competition and movements towards flexible labor markets have exposed large numbers of individuals to work schedules that are for the most part incompatible with the typical rhythms of family life. Not only are individuals working more hours on average than ever before but there is also growing complexity in how their work schedules are arranged over the day and week, with the traditional 9:00 am to 5:00 pm, Monday to Friday workweek becoming less and less common (Presser et al., 2008). Consequently, issues surrounding work-family balance have been given prominence by European policymakers over the past 25 years, resulting in considerable efforts within recent comparative sociological research to better understand in which national contexts workers are most prone to experience conflict between their employment and family domains (e.g., Gallie & Russell, 2009; McGinnity & Calvert, 2009; Steiber, 2009; Stier, Lewin-Epstein & Braun, 2012). However, while much attention within this body of work has been paid to the changing number of hours

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spouses and parents are working, relatively little attention has been paid to important shifts in when these hours are being worked. What has trailed behind, in particular, is comparative empirical research on the conflicting work and family spheres for the growing number of individuals employed during nonstandard hours and days.

As discussed in the previous chapter, the individual-level effects of nonstandard schedules on family life have been well-studied over the past 40 years. The overwhelming consensus within this literature is that, by removing workers from the household during these key family times, nonstandard schedules have the potential to constrain the ability to fully participate in the roles and rhythms of family life. In turn, this can increase the risk of work-family conflict. Evidence supporting this notion comes from studies linking nonstandard schedules to an increased risk of marital dissolution and conflict (Kalil et al., 2010; Maume & Sebastian, 2012; Presser, 2000; White & Keith, 1990), greater levels of negative work-to-family spillover (Davis et al., 2008; Grosswald, 2003; Maume & Sebastian, 2012), and adverse developmental outcomes for the children of workers (Han, 2005; Han et al., 2010; Hendrix & Parcel, 2014; Heymann & Earle, 2001; J. Li et al., 2014).

Though such research has successfully highlighted how nonstandard schedules can harm work-family balance, it has, with the exception of a few recent studies (Anttila et al., 2015; Hook & Wolfe, 2013; Täht & Mills, 2016; Tammelin et al., 2017), largely been confined to the study of single country contexts, therefore overlooking the ways in which the effects of these arrangements on family life might depend on the context in which they are studied. On the one hand, welfare and labour institutions aimed at promoting work-family reconciliation vary considerably across industrialized nations (Gershuny & Sullivan, 2003; Gornick & Heron, 2006; Mosher & Trubek, 2003). On the other hand, there is substantial between-country variation in the ways in which nonstandard schedules are organized and regulated (Gornick & Meyers, 2003), which, in turn, might limit the representativeness of conclusions drawn from

any single context. Despite this, relatively little is known about how the effects of nonstandard schedules on work-family balance vary across countries.

The current chapter fills this gap in the literature by exploring whether and how country context moderates the effects of work schedule timing on work-family conflict. Using multi-level modeling techniques on 2004 and 2010 data from the European Social Survey, we test: (1) whether nonstandard work hours and days are associated with increased work-family conflict across 32 European countries; (2) whether the effects of these arrangements on work-family conflict vary by country; and, if so, (3) whether between-country variation can be explained by characteristics of labour regulations and industrial relations measured at the country level. In short, we explore the contexts in which Europeans in nonstandard work schedules are most prone to experience conflict between their work and family domains, and the potential of labour institutions to buffer the negative effects of these arrangements.

In the next section, we present an overview of theories on work-family conflict and discuss these in the context of previous research on the social consequences of nonstandard schedules. We then elaborate on some contextual factors that may explain or moderate the degree of work-family conflict experienced by individuals in nonstandard schedules. Following this, we discuss the data and methods that will be used in the current study, and then go on to present analyses and results. The chapter will finish with broader conclusions and a discussion of possible policy implications as well as areas for further research.

2. BACKGROUND

2.1. DEFINING WORK-FAMILY CONFLICT

We take as the definition of work-family conflict (hereafter, WFC) that proposed by Greenhaus and Beutell (1985), which sees WFC as stemming from the opposing pressures of work and family roles. WFC arises when the demands associated with one's work roles are incompatible

with the demands associated with his or her family roles. Demands in both family and job roles broadly refer to structural or psychological claims relating to role requirements, expectations, and norms to which individuals must attend by exerting physical or mental effort (Voydanoff, 2004). Job demands can include not only the degree of insecurity within one's employment arrangement, but also the amount of pressure caused by factors such as demanding work, tight deadlines, and long or unsocial work hours. Demands within one's family roles, on the other hand, can include overt responsibilities surrounding household or care work as well as more tacit expectations and norms surrounding, for example, conjugal or parent-child time.

Through this lens, WFC refers to the degree of discordance between the demands associated with one's family and work roles, and subsequent cognitive appraisals of how this friction hinders participation in either of these roles. This study will focus on one type of WFC, *work-to-family interference*, which occurs when participation in one's work roles inhibits full participation in family roles (Greenhaus & Beutell, 1985). We distinguish between two types of work-to-family interference: (1) *strain-based conflict*, which arises when the physical and/or mental pressures associated with one's work roles make it difficult to meet the demands of one's family roles; and (2) *time-based conflict*, which arises when time spent on one's work roles makes it difficult to dedicate sufficient time to one's roles in the family and household.

2.2. DEFINING NONSTANDARD WORK SCHEDULES

Nonstandard work schedules refer to those schedules taking place outside of the traditional Monday-Friday, 9:00 am to 5:00 pm workweek. We distinguish broadly between three categories of nonstandard working times of paid employment occurring as: (1) *evening work*, between the hours of 5:00 pm and 10:00 pm; (2) *night work*, between the hours of 10:00 pm and 6:00 am; and (3) *weekend work*, on Saturday and/or Sunday. Overlapping these categories, one can further differentiate non-fixed work schedule variants like rotating shift work, variable

hours, and flexi-time, which all include some combination of evening, night, day and even weekend work hours.

In this paper, we focus broadly on the effects of employment during nonstandard hours and days rather than the effects of specific nonstandard schedule variants. As such, we will utilize a broad definition of nonstandard work times as any work occurring during evenings, nights, or at weekends in subsequent discussions. While this definition will inevitably obscure important differences between fixed and non-fixed nonstandard hours (like the differing levels of flexibility and predictability), it will also facilitate a more coherent discussion and analytical simplicity. Moreover, it will allow for greater comparability of nonstandard work schedules across several institutionally diverse European countries for which the definitions and arrangements of specific work schedule variants like flexi-time and variable-hour schedules differ widely. For a review of different approaches to the measurement of nonstandard work and their associated tradeoffs, see Dunifon et al. (2013).

2.3. NONSTANDARD SCHEDULES AND WORK-FAMILY CONFLICT

For the growing numbers of individuals earning some or all their wages during nonstandard hours or days, it appears that the borders and linkages between work and family spheres may be especially difficult to manage, making the risk of time- and strain-based conflict particularly dire (Davis et al., 2008; Lozano et al., 2016). Indeed, by engaging the worker in labor outside of the normative 9:00 am to 5:00 pm, Monday to Friday workweek, nonstandard schedules can place temporal barriers on his or her ability to participate fully in family life. However, the specific pathways through which nonstandard work schedules can lead to WFC are myriad and will likely vary depending on the type of schedule worked.

Evening and weekend work is often a symptom of long or overtime hours typical in white-collar occupations (Hamermesh, 1996; Presser, 2003). Evidence suggests that evening

and weekend hours can lead to time-based conflict as they take the worker out of the household during the afterschool, dinner, and leisure hours typically reserved for family life (Presser, 2000; Steiber, 2009; Täht & Mills, 2016). Indeed, time-use research from the US and France indicates that work during evenings and at weekends inhibits full participation in family activities and joint leisure time (Lesnard, 2008; Wight et al., 2008), and can decrease the worker's participation in care and household work (Craig & Powell, 2011; Lesnard, 2008; Presser, 2003; Presser & Cain, 1983). This time-strain penalty appears to be especially acute for women – and, in particular, mothers – working evenings and weekends, as they may be typically more responsible for homemaking, caretaking, and cultivating shared family time (Kalil et al., 2010; Lozano et al., 2016; Maume & Sebastian, 2012; Mills & Täht, 2010; Presser et al., 2008). We therefore test whether and how gender moderates the WFC penalty associated with nonstandard schedules.

Night work, particularly rotating shift work, often clusters in relatively low-status manufacturing and routine jobs or medical and service occupations (Hamermesh, 1996; Presser et al., 2008). Time-based conflict may be less of an issue for night work, as for most households, the majority of family activities occur during mornings, evenings, and at weekends (Wight et al., 2008). These schedules may instead lead to more strain-based conflict as they typically disrupt workers' sleep patterns. As previous research has highlighted, night work can disturb the body's circadian rhythms and alter its physiological functions (J. Li et al., 2014), and has been linked to an increased risk of sleep deprivation and depression (Özdemir et al., 2013; Ramadan & Al-Saleh, 2014; Sanches et al., 2015). It has therefore been argued that the heightened physical and mental demands associated with night hours may make it difficult to meet the demands of one's household or family roles (e.g., Fenwick & Tausig, 2001; Han, 2005).

It is important to note that weekend and evening work can also lead to a high degree of strain-based conflict if they are coupled with long working hours or noxious and intense working conditions. Similarly, night work can lead to time-based conflict if it overlaps with household or family obligations or induces the worker to reallocate sleep hours to times where family and leisure activities occur. As this study focuses broadly on the experience of WFC rather than specific experiences of time- or strain-based conflict¹⁹, we make the following general hypothesis surrounding the effects of nonstandard schedules: *H₁* Across all countries, nonstandard hours and days will be associated with greater levels of WFC.

3. THE MODERATING EFFECT OF COUNTRY CONTEXT

Much of the research cited above has involved studying single and rather specific country contexts, therefore neglecting the ways in which the effects of these arrangements might partially depend on how they have been institutionally filtered at the country level. Indeed, there is little reason to expect that the effects of nonstandard schedules on families would be the same across different country contexts given the substantial heterogeneity in how these jobs are organized and regulated (Gornick & Meyers, 2003), as well as the considerable between-country variation in welfare and labour institutions aimed at promoting work-family balance (Gershuny & Sullivan, 2003; Gornick & Heron, 2006; Mosher & Trubek, 2003). Despite this, the extent to which the effects of nonstandard schedules on outcomes relating to WFC vary by country and institutional context remains surprisingly overlooked.

Although comparative research on the social consequences of nonstandard schedules is scarce, several recent studies that have used a handful of country cases suggest that the effects

¹⁹ We give analytical justification for this choice in our methods section. More generally, the choice not to differentiate between time- and strain-based conflict in our hypotheses was grounded in the fact that we have little empirical evidence to suggest why institutional factors would moderate the experience of these forms of WFC differently. Therefore, building separate hypotheses for time- and strain-based conflict would simply increase the complexity of our discussion and analysis with little empirical justification to do so.

of these arrangements on family life may be highly sensitive to national context. For example, Täht and Mills (2016) compared the effects of nonstandard schedules on families in the US and the Netherlands and observed notable differences between countries in the extent to which these arrangements affected partnership quality and work-care reconciliation. Similarly, Hook and Wolfe (2013) saw a wide variation in the relationship between nonstandard schedules and parental involvement across Germany, the US, Norway, and the UK. Anttila et al. (2015) also found that the negative effects of unsocial work hours on work-life balance were largest in working time regimes in Europe where such work hours were the least common. More recently, in a comparison of the Netherlands, the UK, and Finland, Tammelin et al. (2017) found that rates of strain- and time-based conflict amongst nonstandard schedule workers varied widely across countries. Building on this research, we use data from 32 countries across two time points to determine whether the effects of nonstandard schedules on WFC do indeed vary significantly by country context.²⁰ To this end, we propose the following hypothesis: H_2 There will be significant variation across European countries in the extent to which nonstandard schedules are associated with WFC.

If there is significant between-country variation in the effects of nonstandard schedules on WFC, another empirically-open question is which factors might explain why workers in some countries are buffered from potentially negative effects compared to those in other countries. A further aim of this paper is, therefore, to explore whether the national labour market context predicts the extent to which nonstandard schedules lead to WFC. To test this, we will focus on two aspects of a country's industrial relations and regulatory context suggested to moderate experiences of WFC (Anttila et al., 2015; Gallie & Russell, 2009; Gornick & Heron, 2006; Gornick & Meyers, 2003; Täht & Mills, 2016): (1) the extent to which regulations on

²⁰ Despite their innovation, previous studies cited above have largely relied on a select handful of country cases ($n < 5$). As such, there is a small n problem at level two (the country level), which constrains the ability to determine if indeed the effects of nonstandard schedules vary significantly by country or instead whether the observed variation is simply an artifact of the (non-random) selection of countries under study.

working conditions are influenced by labour unions and collective agreements, and (2) the quality of the national working environment. Before expanding on and building hypotheses around these indicators, we make note of three important points.

First, in the current paper, we focus on testing the moderating effects of labour market institutions. We do acknowledge that cultural factors within a given context are no doubt highly important in dictating experiences of work-family conflict for nonstandard schedule workers. For example, it may be that due to normative factors relating to the centrality of work relative to family life, gender expectations around the household division of labor, and the ubiquity and cultural acceptance of non-social working hours in general, the meaning and consequences of these arrangements will vary by country; put simply, these arrangements may be more nonstandard in some contexts than in others. However, given the difficulty in accurately measuring such constructs and in the interest of a more focused study, we restrict focus to institutional factors for which historically- and internationally-comparable measures are available. We will, however, inevitably refer to such cultural factors in later discussions as they will likely figure prominently in the error terms of any cross-country model of work-family conflict.

A second point is that an institutional factor that will be out of the purview of the current analysis is the role of family supports, or those social provisions designed and implemented at the national level to ease burdens faced by working families. Though research suggests that institutional arrangements surrounding, for example, the provision of public childcare and parental leave schemes are important in dictating experiences of WFC (Crompton & Lyonette, 2006; Lippe, Jager, & Kops, 2006; Scherer & Steiber, 2007; Steiber, 2009; Tang & Cousins, 2005), it is difficult to conceive of how such policies and provisions would ease the unique day-to-day challenges faced by nonstandard schedule workers. This is especially true when one considers that such institutions are most often tailored to the needs of standard daytime schedule

workers (Gornick & Meyers, 2003). For example, the public provision of caring services is largely constrained to daytime hours (hence the name, “daycare”) and so mainly helps those parents working daytime hours (Presser, 1988, 2003; Rachidi, 2016; Verhoef, Roeters, & Lippe, 2016).²¹ In the tradition of comparative research done by Gornick and Heron (2006), we focus instead on the regulation of working time and working conditions as a form of family reconciliation policy with more direct implications for nonstandard schedule workers’ ability to balance work and family demands. For example, regulations on the duration and/or frequency of nonsocial hours, or the mandated availability of flexible or part-time work hours for nonstandard schedule workers if and when they require it.

A final general point worth noting is that an alternative and somewhat more common approach to measuring country-specific orientations towards labour market institutions (as opposed to the current indicator-based approach) would be to differentiate countries based on some accepted welfare state or labor market regime typology (e.g., Esping-Andersen, 1990). While typology-based groupings would provide perhaps the simplest way to approximate labour-related contextual factors, such an approach would also no doubt obscure a lot of important and testable variation occurring within groups. Moreover, such typologies often struggle to adequately categorize the many hybrid countries in Europe (e.g., the Netherlands, France, and Post-Communist countries), which increasingly blur the lines between traditional typological groupings. For a comprehensive review of these issues, see for example: Bambra (2007); Scruggs and Allan (2006). Perhaps most importantly, a typology-based approach would not allow one to disentangle the impacts of specific institutional characteristics, thus leaving

²¹ An earlier version of this chapter included the proportion of the national GDP dedicated to family spending; following an approach used by Chung (2012), this was meant to serve as a proxy measure for the general emphasis a country places on providing support to working families. However, the indicator was shown to play no significant moderating role on the effect of nonstandard schedules on work-family conflict. More importantly and as was rightly pointed out by reviewers, it was difficult to conceive of the pathway through which such an indicator would buffer the social consequences of nonstandard schedules given that family supports are most often tailored to the needs of standard schedule workers.

the mechanisms through which country context affects the strength and direction of our individual-level relationship as something of a black box. That said, we will ground much of the following discussion through the lens of such typologies, as – despite their limitations – they do provide intuitive heuristics through which to understand observable patterns of institutional regularities across countries. We return to the country-level institutional buffers that will be tested in this chapter in the following discussion.

3.1. REPRESENTATION FROM UNIONS AND COLLECTIVE AGREEMENTS

National and sectoral regulations on working times and conditions and their enforcement at the company level have often been central concerns of labour unions and collective agreements across Europe. While more general regulations on working conditions have been the domain of national legislation, there is often a great deal of decentralization in the negotiation and enforcement of more specific regulations. For instance, regulations surrounding the length of the working day, the right to rest periods, and remuneration for overtime and nonstandard working hours or days are most often negotiated at the sectoral or company level with substantial involvement from unions and collective agreements (Gornick & Heron, 2006; Lee, McCann, & Messenger, 2007; Messenger, 2011).

That said, there exists a great deal of variation across European countries in the extent to which unions and collective agreements exert influence on regulations surrounding working times and conditions. The most obvious distinction can be drawn between coordinated and liberal market economies. Following the guidelines of the European Employment Strategy, liberal market economies like the UK and Ireland have made large pushes towards the deregulation and flexibilization of their labor markets to decrease unemployment (Mosher & Trubek, 2003). This has led to, amongst other things, lower levels of union and collective agreement coverage as well as a *laissez-faire* approach to the regulation of working times and

working conditions (Glassner, Keune, & Marginson, 2011; Gornick & Meyers, 2003). Coordinated markets, in contrast, still maintain relatively rigid labour regulations with high levels of involvement from social partners in the negotiation of collective agreements around working conditions and even nonstandard working times (Berg, Appelbaum, Bailey, & Kalleberg, 2004). For example, within many of these countries, the enforcement of Sunday work schedules by an employer is prohibited by law, and others law specifically ban employers from assigning night time work to women with children under the age of fourteen who lack adequate care arrangements (Gornick & Meyers, 2003).

Between these poles, there is large variation across Europe in the degree of representation from unions and collective agreements. Figure 4-1 plots the relationship between union membership and collective bargaining coverage (as well as the quality of the working environment) across sampled countries. The figure depicts a generally positive association between union membership and collective bargaining, while also showing the considerable spread in the rates of each across sampled countries: the former ranging from 10% in Estonia to 96% in Iceland; the latter ranging from 11% in Turkey to 98% in Austria and France. The direct effects of this variation on WFC remain unstudied in comparative research.²² However, we posit that countries with greater union presence and coverage under collective agreements will have more favourable regulations on working times and conditions for jobs involving nonstandard hours and days. These more favourable employment settings, we argue, will have the potential to mitigate the negative effects nonstandard schedules can take on family life. Crucially, we expect that stronger union and collective bargaining presence at the country level will have cascading positive effects on working conditions even for those nonstandard schedule workers not directly represented by unions or under collective agreements.

²² A similar study was done by Pichler and Wallace (2009), which found that the degree of unionization within a country predicted job satisfaction across 27 European countries.

We also posit that the degree of union presence and collective bargaining coverage within a country will indirectly reduce the negative effects of these arrangements by altering the selectivity of nonstandard schedule workers. That is, in contexts where workers have better representation and therefore more leverage in the labor market, entrance into nonstandard schedules may not necessarily represent a forced choice as much as a matter of personal preference. Therefore, within these contexts, the workers most often observed in nonstandard schedules will be those that stand to benefit the most – or suffer the least – from these arrangements. We thus make the following hypothesis: H_3 The negative effects of nonstandard schedules on WFC will be smaller in contexts with stronger union presence and greater coverage under collective agreements.

3.2. QUALITY OF THE WORKING ENVIRONMENT

Another crucial factor dictating the extent to which nonstandard schedules will lead to WFC is the objective quality of the working environment in which individuals earn their living. The quality of the working environment captures non-economic characteristics of the job, including factors that relate to the nature and content of work performed, working-time arrangements, and workplace relationships. Despite the recognition that good working conditions are a major component of worker well-being and productivity, there remains considerable variation between European countries in the quality of working environments, as job quantity rather than quality appears to be given most prominence in policy practice (Holman, Holtgrewe, Rafferty, Ramioul, & Vandekerckhove, 2015). Evidence suggests that features of the working environment that individuals face – for example, the degree of time pressure relating to long, inflexible working hours, high work intensity, or physical health risk factors – vary widely across European countries (OECD, 2014). This variation is tied to structural differences in the

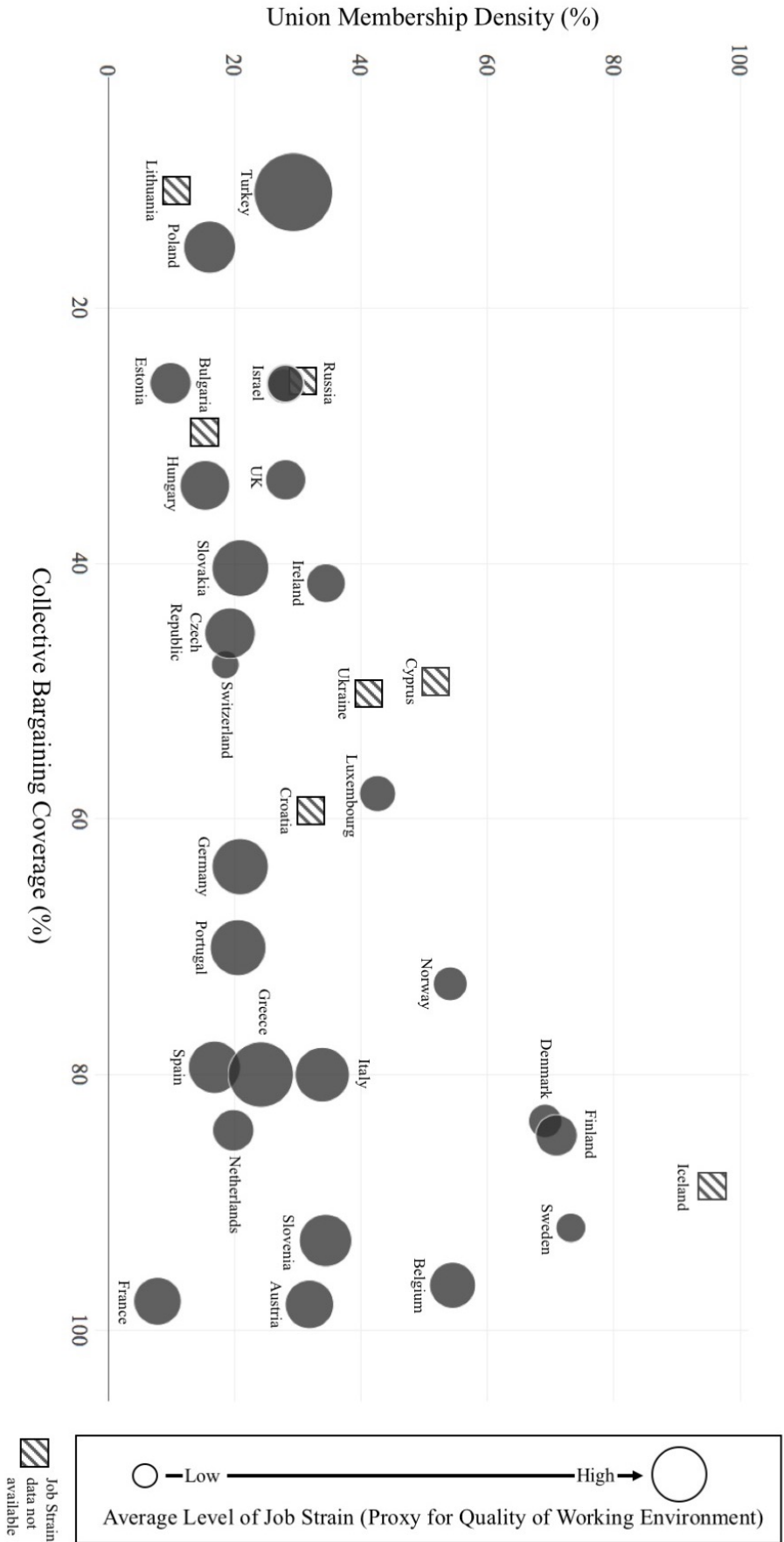
prevalence of certain occupations (e.g., services versus manufacturing), as well institutional factors like the strength of labor regulations, unions, and collective agreements (J. Kelly, 2014).

In line with research done by the OECD (2014), we use the incidence of job strain within a given country as a proxy measure for the quality of the national working environment. Job strain is defined here as employment conditions in which workers face more job demands (e.g., demanding work hours, noxious conditions, etc.) than the number of resources (e.g., autonomy, social support, etc.) they have at their disposal; we expand on this measure in subsequent discussions. Referring to Figure 4-1, one can see wide variation in the incidence of job strain across European countries, which appears to be highest in Mediterranean countries like Turkey, Greece, and Portugal, and lowest in Nordic countries such as Sweden, Denmark, and Norway.

While nonstandard schedules may be tied to higher levels of WFC in general, we posit that this baseline effect will be magnified in contexts where there is less emphasis placed on occupational well-being at the national level. Given earlier arguments that unions and collective agreements play a crucial role in generating favourable working conditions, one could argue that the quality of the working environment as we conceive it here would be endogenous to union and collective agreement influence. However, we argue that the quality of the working environment within a given country will also capture the stringency of national regulations on working times and conditions as well as the efficiency of their implementation at lower levels.²³ We therefore present the following hypothesis: H_4 The negative effects of nonstandard schedules on WFC will be larger in contexts with poorer quality working environments.

²³ Through this lens, the quality of the national working environment also serves as a proxy measure for the stringency and efficacy of national labour regulations. Measuring such a construct directly is difficult: one could either attempt to amalgamate a series of different policy indicators (often categorical in nature) into a single, linear indicator, or rely on the often highly subjective and opaque labour regulations indexes currently available.

Figure 4-1. Relationship Between Collective Bargaining Coverage ^a, Union Membership Density ^a, and Quality of the National Working Environment ^b

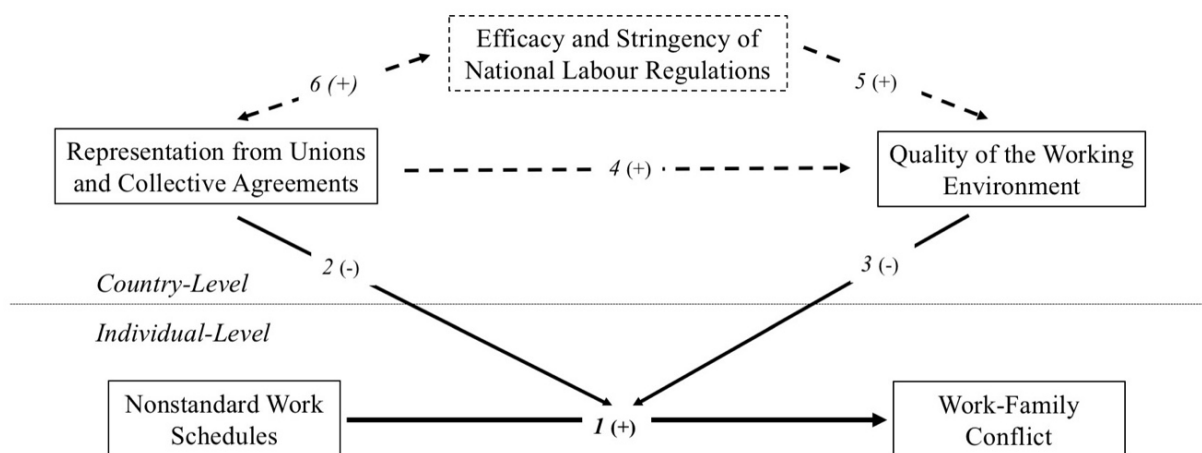


Data Sources: ^a ILO Database of Labour Statistics (ILO, 2017); ^b OECD Job Quality Database (OECD, 2017).

3.3. SUMMARIZING HYPOTHESIZED RELATIONSHIPS

We present a stylized account of the hypothesized relationships of interest in the directed acyclic graph shown in Figure 4-2. Path 1 depicts the main relationship of interest, showing a tendency for nonstandard work schedules to increase WFC across all countries. Paths 2 and 3 show the hypothesized cross-level interactions that will be modelled for union and collective bargaining representation and the quality of the working environment, with each path indicating a buffering effect of the contextual variable on the main relationship of interest. Paths 4 to 6 depict theorized unmeasured relationships: path 4 shows that greater representation from social partners will likely improve the quality of the working environment, thus indicating that the latter partially mediates the cross-level effect of the former on the main relationship of interest; path 5 shows that more stringent and effectively implemented national regulations surrounding working times and conditions (unmeasured) will also improve the quality of the working environment; path 6 accounts for the likelihood that there will be a reciprocal positive relationship between the influence of unions and collective agreements and the strength of national labor regulations.

Figure 4-2. *Directed Acyclic Graph of National Labour Relations Characteristics*



Notes: Representation from unions and collective agreements refers to the degree of influence these institutions have in negotiating working conditions and regulations at the national level. The quality of the working environment refers to the objective quality of working conditions in which employees earn

their living in a country. Efficacy and stringency of national labour regulations refer to the ability of national labour laws to promote quality working conditions for workers.

4. METHODS

4.1. DATA

To test these hypotheses, we will utilize Rounds 2 and 5 (2004 and 2010) of the European Social Survey (ESS). The ESS is a cross-national survey which conducts face-to-face interviews every two years for newly selected, cross-sectional samples. These interviews measure the attitudes, beliefs, and behaviour patterns of diverse populations in more than thirty nations. Using both Rounds 2 and 5 as a repeated cross-section will maximize statistical power, while also providing between- and within-country variation in factors relating to national labor and welfare institutions. In total, this leaves 51 country-period observations nested within 32 countries. Information on country-wave availability and sample sizes from the ESS is available in Appendix 4-1.

The primary aim of this study is to understand how the timing of one's work schedule can impact his or her ability to balance work and family life. As such, we restrict the analytical sample to individuals who, at the times of the data collection: (1) reported working at least 12 hours of paid employment in the past 7 days, (2) reported their employment relationship as "employed" and not "self-employed", (3) were between the ages of 18 to 59, and (4) were in a co-resident partnership. After removing missing values on variables of interest, this amounted to a sample of 21,361 individuals across all countries and both waves. For details on the how each sample restriction affected the overall sample size, please see Appendix 4-2.

4.2. WORK-FAMILY CONFLICT

The dependent variable is the subjective level of WFC, which is measured using a four-item index capturing the extent to which one's employment relationship gives rise to practical difficulties around the family and home. The questions, measured on a five-point scale ranging from "Never" to "Always", ask the respondent how often he or she: (1) "...feel[s] too tired after work to enjoy the things you would like to do at home"; (2) "...find[s] that your job prevents you from giving the time you want to your partner or family"; (3) "...feels that their "partner or family is fed up with the pressures of your job"; and (4) "...worr[ies] about work problems when not working". Together, these items have high reliability, with a Cronbach's Alpha of 0.743. Performing exploratory factor analysis (EFA) on the three items also revealed a single underlying factor consistent across males and females, and parents and non-parents. To construct the final index, we use the promax (oblique) rotated loadings from this EFA to weight each item. Following this, the index is standardized to a cross-country mean of 0 to aid interpretability. More information on the construction of this index can be found in Appendix 4-3.

4.3. NONSTANDARD WORK SCHEDULES

The primary independent variables of interest in this study will be two different forms of nonstandard schedules of work: (1) nonstandard hours (i.e., evenings and/or nights) and (2) nonstandard days (i.e., Saturdays and/or Sundays). The measure of nonstandard hours will be derived from a question asking respondents to report, "How often [their] work involve[s]... working evenings or nights" in their primary job. The measure of nonstandard days is derived from asking respondents, "How often [their] work involve[s] working at weekends?" Table 4-1 shows the regularity of nonstandard hour and day work across the total sample and by gender. Both measures are included as ordinal variables, where coefficients represent the change in

WFC associated with a one unit increase in the regularity of working nonstandard hours or days. Sensitivity analyses with different specifications of nonstandard hours and days indicate that the effects of these arrangements on WFC are largely consistent regardless of whether an ordinal, categorical, or dichotomous classification is used (results available upon request). In the end, an ordinal specification is adopted, as log-likelihood ratio tests reveal it to explain significantly more variation in the dependent variable than other specifications.

Table 4-1. *Descriptive Statistics on Regularity of Nonstandard Schedule Work, by Gender*

		Pooled		Women		Men	
	Coding	<i>n</i>	<i>Prop.</i>	<i>n</i>	<i>Prop.</i>	<i>n</i>	<i>Prop.</i>
Nonstandard Work Hours							
Never	1	9,600	0.45	5,605	0.54	3,995	0.36
Less than once a month	2	2,851	0.13	1,155	0.11	1,696	0.15
Once a month	3	1,464	0.07	602	0.06	862	0.08
Several times a month	4	3,230	0.15	1,177	0.11	2,053	0.19
Once a week	5	927	0.04	445	0.04	482	0.04
Several times a week	6	2,614	0.12	1,149	0.11	1,465	0.13
Every day	7	675	0.03	268	0.03	407	0.04
Nonstandard Work Days							
Never	1	8,585	0.40	4,924	0.47	3,661	0.33
Less than once a month	2	3,958	0.19	1,563	0.15	2,395	0.22
Once a month	3	2,498	0.12	1,009	0.10	1,489	0.14
Several times a month	4	4,660	0.22	2,084	0.20	2,576	0.24
Every week	5	1,660	0.08	821	0.08	839	0.08

Data Source: European Social Survey Rounds 2 and 5 (2004 and 2010)

Notes: ^a Depicted categories are in response to the question, “How often [respondent’s] work involves regular work during nights and/or evenings?” ^b Depicted categories are in response to the question, “How often [respondent’s] work involves regular work during weekends?” Sample includes respondents between the ages of 18-59 in paid employment and living in a co-residential union. Individuals were removed if they had missing values on work work-family conflict indicators, education (ISCED-97), work hours, presence of children, partner’s employment status, age, or occupational status (ESeC).

4.4. COUNTRY-LEVEL PREDICTORS

Other independent variables of interest in this study will be a series of macro-level variables capturing variation in labour market characteristics between countries. To approximate the influence of trade unions and collective agreements, we use three-year averaged estimates of

the trade union membership density rate and the collective bargaining coverage rate taken from the International Labor Organization (ILO, 2017).²⁴ The former represents the number of workers who are members of workers' organizations as a percentage of the total number of workers in a country. The latter denotes the number of workers whose pay and/or conditions of employment are determined by one or more collective agreements as a percentage of the total number of employees. We include these as separate measures due to the lack of sufficient correlations between them in most European countries (apart from Scandinavia). However, there is a relatively strong association between these factors ($r = 0.46$, $p < 0.01$), raising issues of multicollinearity that will be addressed in subsequent discussions. Mean values and data availability by country for all macro indicators are shown in Table 4-2, with a full correlation matrix showing associations between macro indicators in Table 4-3.

To approximate the quality of the national working environment, we use the Job Strain Index created by the OECD (2014). This is an additive measure of the overall level of job demands that workers in a given country experience to meet their job requirements, and the amount of buffering job resources they have at their disposal. Two types of job demands are identified: (1) time pressure, which encompasses long working hours, high work intensity, and working time inflexibility; and, (2) physical health risk factors, such as dangerous work (i.e., being exposed to noise, vibrations, extreme temperatures) or hard work (i.e., carrying and moving heavy loads, painful and tiring positions). Similarly, two types of job resources are considered: (1) work autonomy and learning opportunities, which include workers' freedom to choose or change their work tasks and methods, as well as formal (i.e., training) and informal learning opportunities at work; and (2) social support at work, which measures the amount of social support that workers receive from colleagues and supervisors. The resultant Job Strain Index refers to those jobs where the workers face one demand but have no resources, or face

²⁴ We use three-year averages here to ensure that we are capturing a country's longer-term rates rather than a random fluctuation within a given year.

two demands but have one or no resource. The construction of the Job Strain Index is described further in Appendix 4-4.

Table 4-2. *Means and Data Availability of Macro-Level Variables, by Country*

	Job Strain Index ^a		Union Membership ^b		CBC Coverage ^b		GDP per Capita ^c	
	2004	2010	2002-04	2008-10	2003-04	2007-08	2003-04	2007-08
Austria	45.10	51.89	34.97	28.73	98.00	98.00	39984	43296
Belgium	36.87	54.75	54.57	54.37	97.00	96.00	38416	41039
Bulgaria	+	+	22.50	16.60	40.00	33.00	10997	15400
Croatia	+	+	38.00	33.47	%	60.00	17966	20849
Cyprus	+	+	63.50	51.77	%	50.45	32118	34763
Czech Republic	47.62	53.48	21.63	16.93	44.10	46.80	23184	28446
Denmark	27.55	39.47	71.20	67.00	85.00	82.25	42971	44416
Estonia	40.37	42.39	12.23	7.47	28.00	23.75	19354	23633
Finland	26.86	56.01	72.63	69.13	91.00	78.50	37086	40430
France	48.56	46.74	7.90	7.67	97.40	98.10	35723	36949
Germany	55.20	57.33	22.90	18.87	66.70	60.75	37219	40068
Greece	65.73	64.66	25.10	23.23	85.00	75.00	28077	30346
Hungary	52.04	47.51	17.40	13.23	40.75	27.05	20352	22649
Iceland	%	%	95.60	82.37	%	88.00	35980	40781
Ireland	27.34	49.87	36.33	32.57	44.85	38.25	45535	46096
Israel	34.38	%	%	27.80	40.00	26.10	25183	29021
Italy	54.35	42.51	33.87	34.53	80.00	80.00	37241	36622
Lithuania	+	+	13.87	10.00	14.55	11.25	15570	21645
Luxembourg	36.09	51.35	42.60	35.87	58.00	59.00	85116	91539
Netherlands	26.85	56.04	20.77	18.83	82.55	86.15	42244	45928
Norway	28.80	38.90	54.87	53.30	74.80	71.00	60301	63151
Poland	52.85	51.42	17.30	14.77	15.70	14.80	15874	21038
Portugal	58.95	52.58	21.10	19.97	64.75	75.40	26283	27191
Russia	+	+	%	31.57	%	25.90	16840	23079
Slovak Republic	48.07	65.47	25.70	16.13	42.00	38.75	17820	24838
Slovenia	46.80	58.10	42.83	25.97	100.00	86.00	25027	29423
Spain	52.74	51.26	16.00	17.60	78.25	80.60	31824	33107
Sweden	24.82	34.62	78.03	68.30	94.00	90.00	38994	42424
Switzerland	27.97	%	19.77	17.30	48.00	47.85	50535	55485
Turkey	78.56	75.53	29.30	%	10.95	7.35	13666	16616
Ukraine	+	+	42.10	42.10	55.00	54.75	6276	8015
United Kingdom	35.94	44.46	29.27	26.87	35.10	31.80	35307	36563
<i>n</i>	9,502	9,021	9,961	11,400	9,961	11,400	9,961	11,400

Data Sources: ^a OECD Job Quality Database (OECD, 2017); ^b International Labour Organization Database of Labour Statistics (ILO, 2017); ^c World Bank International Program Comparison Database (World Bank, 2017).

Notes: Grey cells indicate country-periods where no ESS data was collected. Therefore, information within these cells will go unused. + Data missing – Not an OECD country; % Data missing – reason otherwise or unstated. GDP is shown in US \$ 2011 Prices

Table 4-3. *Macro-Level Variable Pearson Correlation Matrix*

	Collective Bargaining Coverage ^a	Union Membership Density ^a	Job Strain Index ^b	GDP ^c
Collective Bargaining Coverage	1			
Union Membership Density	0.46***	1		
Job Strain Index	-0.14	-0.46**	1	
GDP	0.41**	0.33*	-0.48***	1

Data Sources: ^a International Labour Organization Database of Labour Statistics (ILO, 2017); ^b OECD Job Quality Database (OECD, 2017); ^c World Bank International Program Comparison Database (World Bank, 2017).

* $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

4.5. CONTROL VARIABLES

The focus in this analysis is not on establishing a causal effect of nonstandard hours or days on work-family conflict. Rather, we are interested in investigating the degree to which the gross effect of these arrangements is moderated by factors measured at the country level. That said, we will condition on a limited selection of individual-level demographic, socioeconomic, and household characteristics to address important between-country compositional differences. Control variables include firstly the respondent's age (18-24, 25-35, 36-50, 50-59), gender, and educational level (ISCED 97). To account for varying degrees of job demands, we include working hours (12-34, 35-50, and 50+ hours/week), as well as occupational class using the European Socio-Economic Classification (ESeC). To account for household demands, we control for the presence of children under age 13 (as a binary variable) and the employment situation of the spouse (employed, non-employed, or unemployed). Finally, to account for the possibility that more favorable working conditions concentrate in the most economically

prosperous countries, we will control for GDP per capita at the country-level using standardized three-year averages collected by the World Bank (2017). Since multi-level models with random intercepts are used, all covariates are centered around their mean or modal positions to ensure that the intercept variance refers to a representative part of the population under study.

4.6. ANALYTIC TECHNIQUE

To examine the impact of both contextual- and individual-level factors on WFC, we use restricted maximum likelihood multi-level modeling techniques (MLM). Briefly, by allowing residual components at the individual-, country-, and year-level, MLM accounts for clustering of individuals in higher-order units, in this case, countries and periods of observations. As we are utilizing repeated cross-sections for multiple countries, there is a data structure where individuals are nested within the cells of the cross-classification of countries and survey years (both conceptually at level two). To account for this, we apply the cross-classified modeling approach proposed by H. Goldstein (1994). Here, countries are treated as the level-two units with a random intercept specified for each. The survey year is then treated as the level-three unit, where we introduce a dummy variable for each year (-1) in the fixed part of the model and a random coefficient for each of these dummies in the random part; we expand on this technique in Appendix 4-5. Practically, the main assumptions of any restricted maximum likelihood multi-level modeling technique remain the same.

As a preliminary diagnostic step, we ran variance components models to determine whether there was a non-negligible proportion of the variance in WFC explained at the country level (and thus sufficient justification to proceed with a multilevel modeling approach). The parameters in these null models (shown in Table 4-4) include a fixed effect for the overall intercept across all countries, and in the random part of the models, a set of variance parameters that indicate the extent to which the total variance in WFC is due to within- and between-

country factors. This analysis revealed that non-negligible inter-dependency by country was present in WFC, as shown in the significant country-year random effects. The findings, however, suggest that only between 3-5% (shown in the variance partitioning coefficients) of the variance in WFC across the sample is located at the country level. It thus appears that countries appear to be relatively unimportant for explaining WFC.

Table 4-4. *Multi-Level Variance Components Models for WFC*

Parameters	Pooled	Women	Men
Fixed Effects			
Intercept	0.05	-0.05	0.02
Random Effects			
Country-Year-Level Variance	0.03**	0.03**	0.04**
Individual-Level Variance	0.94***	0.95***	0.92***
Variance Partitioning Coefficient ^a	0.03	0.03	0.05
AIC	58845.71	28929.42	29917.03
BIC	58885.52	28958.41	29946.19
<i>n</i>	21,361	10,401	10,960

Data Source: European Social Survey Rounds 2 and 5 (2004 and 2010)

Notes: Respondents were included if there were in paid employment and living in a co-residential union. Dependent variable is WFC index. ^a The Variance Partitioning Coefficient (or intra-class correlation), in this case, shows how much of the total variance in WFC is located at the country-year level.

* $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

This relatively small intra-class correlation is consistent with findings derived from Steiber's (2009) analysis of cross-national variation in time- and strain-based WFC using 2004 ESS data. While some argue that MLM is not necessary when the ICC is sufficiently close to zero (as this would imply that level-one units are statistically independent), evidence suggests that values of ICC as small as 0.05 can invalidate statistical tests and confidence intervals when MLM is not used (Kreft & Leeuw, 1998). We thus chose to proceed with the application of a MLM technique, the process of which is outlined below.

In the first step, we include individual-level covariates in a random intercepts model to test the effects of nonstandard schedules across all countries. Following this, we introduce

random slopes into the model, allowing the coefficients of nonstandard work days and hours to vary randomly across countries. If this step reveals that the effects of nonstandard schedules do vary significantly across countries, we will then include macro-level predictors and cross-level interactions in an attempt to explain this between-country slope variance and draw interpretations about the moderating effects of country-level institutional factors. The full model is expressed as

$$\begin{aligned} WFC_{ijk} = & \beta_0 + \beta_1 Work\ Schedule_{ijk}^{(1)} + \beta_2 Controls_{ijk}^{(1)} + \beta_3 Institutions_{jk}^{(2)} \\ & + \beta_4 Work\ Schedule_{ijk}^{(1)} * Institutions_{jk}^{(2)} \\ & + u_{0country(j)}^{(2)} + u_{1country(j)}^{(2)} Work\ Schedule_{ijk} + u_{year(k)}^{(3)} + e_{ijk} \end{aligned}$$

where WFC_{ijk} is the level of work-family conflict of individual i who lives in country j and was surveyed during year k , $Work\ Schedule_{ijk}^{(1)}$ represents work schedule timing, and $Institutions_{jk}^{(2)}$ refers to the country-level predictor variables. Within this model, β_1 is interpreted as the effect of $Work\ Schedule_{ijk}^{(1)}$ in an average country ($u_{1country(j)}^{(2)} = 0$) when $Institutions_{jk}^{(2)} = 0$. With each one standard deviation increase in $Institutions_{jk}^{(2)}$, the effect of $Work\ Schedule_{ijk}^{(1)}$ changes by β_4 . Should β_4 be statistically significant and should the addition of this cross-level interaction significantly improve model fit and explain slope variance between countries, we will have sufficient evidence to support hypotheses surrounding the moderating effects of country-level institutional factors.

In the random part of the model, $u_{country(j)}^{(2)}$ refers to country-level effects, $u_{year(k)}^{(3)}$ refers to period effects, and e_{ijk} is the individual-level residual error term. The $u_{1country(j)}^{(2)} Work\ Schedule_{ijk}$ term refers to the fact that we allow the effect of work schedule timing to vary across countries. These random effects and residual errors are assumed to be independent of one another and normally distributed with zero means and constant variances.

For ease, superscripts have been added to denote the level of measurement. To aid in interpretability, $u_{country(j)}^{(2)}$ and $u_{year(k)}^{(3)}$ are given different superscripts, even though in this cross-classified model they are conceptually both at level two.

Before proceeding to results, we note that an important limitation to the current multilevel modeling approach surrounds the small number of countries available ($n = 32$). While multilevel modeling naturally suits the current paper's aims of modeling country-level effects, the relatively small number of units at level-two may mean that country-level effects and variances will be estimated imprecisely; imprecision that will not adequately be reflected in test statistics. While simulations have shown that between 25-30 country units can be sufficient for the estimation of country-effects in multilevel linear models (Bryan & Jenkins, 2016; Maas & Hox, 2004), the applicability of these rules of thumb will largely depend on the complexity of the models being estimated. We do note that the potential imprecision of country-level effects should at least be reduced in the present case as we use the cross-classification of countries and survey rounds at level two, which effectively creates 51 level-two units. That said, we will proceed with caution when drawing conclusions from estimated country-level interaction effects and their test statistics. We return to this issue in the Discussion section.

Sensitivity analyses will also be presented where we use an adaptation of the two-step estimation procedure proposed by Bryan and Jenkins (2016) to test the robustness of cross-level interactions. In step one, country-period-specific OLS regressions with individual-level parameters are run to infer country-period-specific slopes (i.e., the nonstandard hours and days coefficients, respectively). In step two, these country-period-specific slopes are then regressed on country-period-level predictor variables. Following Bryan and Jenkins, we also perform a pooled OLS model with country-period fixed-effects in step 1, average the predicted values for each country-period ($\widehat{y}_{ct}$), and then in step two regress $\widehat{y}_{ct}$ on country-period-level variables. We describe these techniques further in the Sensitivity Analyses section.

5. RESULTS

The first hypothesis predicts that across all countries, nonstandard schedules will be associated with increased WFC. Table 4-5 shows the results from pooled and gender-specific random intercepts models including individual-level predictors only; full results including estimates for control variables can be found in Appendix 4-6. Looking first to the fixed effects in Table 4-5, across all countries, nonstandard work hours and days are both significantly and monotonically associated with increased WFC. The pooled models show that a one-unit increase in the regularity of nonstandard hours and days increases WFC by around 0.09 and 0.08 standard deviations respectively across all countries ($p < 0.001$).

Looking at the full range of this effect, it appears that on average, those who work nonstandard hours everyday experience levels of WFC nearly one standard deviation (0.88) higher than counterparts who never work these hours. Similarly, those who work nonstandard days every week experienced levels of WFC nearly three-quarters of a standard deviation (0.73) higher than those who never work these days. From looking at the gender-specific models, these effects appear relatively consistent across males and females. Moreover, interactions with gender revealed no significant variation in effects between groups and no improvements in model fit. Findings support the first hypothesis that nonstandard work hours and days are associated with greater levels of WFC; these effects do not depend upon gender.

The lack of significant gender interactions is surprising when one reflects on previous research that found that these schedules lead to greater WFC when worked by women (e.g., Kalil et al., 2010; Lozano et al., 2016; Maume & Sebastian, 2012; Mills & Täht, 2010). This could be tied to the fact that we include nonstandard work hours and days as ordinal variables capturing the unit-change in the regularity of such work schedules. This is a departure from previous studies where nonstandard hour/day work are often dichotomized such that only those who usually or only work such hours/days are in the treatment group. This could suggest that

gender differences in the social consequences of nonstandard schedules only emerge when looking at the more extreme cases that only or very regularly work such arrangements.

Testing interactions with parental status (whether the respondent has a child under 5 and 13; Appendixes 4-7) shows no significant interactions and indicates that the effects of the regularity of nonstandard hour and day work are relatively consistent regardless of whether dependent children are present in the household. One interesting finding in Column 4 of Appendix 4-7-1 (a three-way interaction between gender, parental status and nonstandard hours) is that for mothers with children under 13, the effect of nonstandard hours on WFC is 0.026 standard deviations smaller ($p < 0.05$) than their male parent counterparts in such arrangements. This could be tied to the fact that for women more so than men, non-day work is often used as a work-care reconciliation strategy (Presser, 1995, 2003).

Turning now to model fit diagnostics, included predictors appear to perform reasonably well in reducing individual-level residual variance, with level-one R^2 's of ~14%. Log-likelihood ratio tests comparing our random intercepts model to the null model also suggest that the inclusion of individual-level predictors significantly improves model fit. One particularly interesting finding is that for women, the inclusion of individual-level predictors explains about 33% of the between-country intercept variance in WFC. This suggests that nearly half of the variance in WFC that was located at the country level for females was due to compositional differences between countries, for example, in age, working hours, or the presence of children. We do not observe such a precipitous drop for males in between-country intercept variance (10%) after the inclusion of individual-level covariates, which suggests that country-level factors may still play a significant role in explaining WFC for this group.

Table 4-5. *Random Intercepts Models of the Effects of Work Schedule Timing on WFC*

	Pooled			Women	Men
	1	2	3	4	5
Fixed Effects					
Nonstandard Days	0.094*** (0.005)	0.082*** (0.015)	0.094*** (0.005)	0.098*** (0.008)	0.090*** (0.008)
Nonstandard Hours	0.086*** (0.004)	0.086*** (0.004)	0.079*** (0.010)	0.088*** (0.006)	0.084*** (0.005)
Woman	0.149*** (0.015)	0.128*** (0.026)	0.136*** (0.023)		
NS Days * Woman		0.008 (0.009)			
NS Hours * Woman			0.005 (0.007)		
Random Effects					
Year	0.003***	0.003***	0.003***	0.002***	0.004***
Variance	[0.001, 0.026]	[0.001, 0.026]	[0.001, 0.026]	[0.000, 0.017]	[0.001, 0.036]
Country Variance	0.027*** [0.016, 0.046]	0.027*** [0.016, 0.046]	0.027*** [0.016, 0.046]	0.018*** [0.010, 0.032]	0.038*** [0.022, 0.065]
Individual Variance	0.829*** [0.814, 0.845]	0.829*** [0.814, 0.845]	0.829*** [0.814, 0.845]	0.833*** [0.809, 0.854]	0.822*** [0.800, 0.844]
Model Fit					
Change in Country-Year Intercept Variance ^a	-13%	0%	0%	-33%	-10%
Change in Individual Variance ^a	-14%	0%	0%	-14%	-14%
LL Ratio Test ^b	2010***	0.9	0.5	1572***	1651***
Change in BIC ^c	-3020	9	10	-1387	-1465
<i>n</i>		21361		10401	10960

Data Source: European Social Survey Rounds 2 and 5 (2004 and 2010)

Note: Sample includes individuals between the ages of 18-59 in paid employment and living in a co-residential union. Control variables are gender, education, age, working hours, occupational class, presence of children under 13 in household, and partner's employment status. ^a Calculated as the proportional reduction in variance from null model; for columns 2 and 3, this is change from column 1. ^b Results of log likelihood ratio tests are calculated against the null model; for columns 2 and 3, this is test against column 1. ^c Change in BIC from null model; for columns 2 and 3, this is change from column 1. Reductions in BIC values of about 4 or more suggest a strong improvement in model fit.

+ $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

In the preceding analysis, the slopes of nonstandard hours and days were fixed across countries, meaning that the effects of these arrangements were assumed to be invariant across the 32 countries in the sample. However, as argued earlier, due to substantial heterogeneity in the organization and regulation of nonstandard schedules across countries, it is possible that the strength of the effects these arrangements have on WFC may differ by country. We test this claim by introducing random slopes into the models, allowing the coefficients of nonstandard work hours and days to vary randomly at the country level. Note that random slopes are added for nonstandard hours and days in separate models to isolate the degree of cross-country variation for each arrangement respectively.

Results of the models are shown in Table 4-6. We draw attention first to the country slope variance terms, which denote the degree to which the effects of nonstandard work hours and days vary by country. In the pooled models, while these slope variance terms appear quite small (~ 0.001), they are highly significant ($p \leq .0001$). Moreover, the results of log likelihood ratio tests and reduction in BIC values against random intercepts models indicate that including random slope terms for both nonstandard days and hours significantly improves model fit. Thus, findings support the second hypothesis that the effects of nonstandard work days and hours do vary significantly (if only marginally) across countries; this variability is the most pronounced for the effects of nonstandard day work.

The gender-specific models present a more ambiguous picture. Log-likelihood tests indicate that the inclusion of a random slope term marginally improves model fit for both men's and women's nonstandard hour work. However, for nonstandard work days, the inclusion of a random slope term only improves model fit for women but not men. We also see that for both nonstandard hours and days, the inclusion of random slopes terms in the gender-specific models increases BIC values and therefore worsens model fit. This lack of significant between-country variation in the gender-specific models is likely tied to a loss of statistical power when the

sample was cut in half. For this reason, later analyses including country-level institutional factors will be restricted to the pooled sample with sufficient statistical power; within these pooled models, gender interactions will be tested.

Table 4-6. *Random Slopes Models of the Effects of Work Schedule Timing on WFC*

	Pooled		Women		Men	
	NS Days	NS Hours	NS Days	NS Hours	NS Days	NS Hours
Fixed Effects						
β_1	0.094*** (0.008)	0.087*** (0.006)	0.098*** (0.011)	0.088*** (0.008)	0.090*** (0.009)	0.086*** (0.007)
Random Effects						
Year Intercept Variance	0.003*** [0.0004, 0.026]	0.003*** [0.0004, 0.026]	0.002*** [0.0002, 0.018]	0.002*** [0.0002, 0.018]	0.004*** [0.001, 0.037]	0.004*** [0.001, 0.036]
Country Intercept Variance	0.030*** [0.016, 0.054]	0.034*** [0.019, 0.060]	0.026*** [0.013, 0.052]	0.027*** [0.014, 0.050]	0.045*** [0.024, 0.085]	0.054*** [0.030, 0.096]
Country Slope Variance	0.001*** [0.001, 0.003]	0.001*** [0.0002, 0.026]	0.002*** [0.001, 0.004]	0.001*** [0.0002, 0.002]	0.001*** [0.0001, 0.003]	0.001*** [0.0002, 0.002]
Individual Variance	0.827*** [0.812, 0.843]	0.827*** [0.812, 0.843]	0.829*** [0.806, 0.852]	0.830*** [0.807, 0.853]	0.821*** [0.799, 0.843]	0.820*** [0.798, 0.842]
Model Fit						
LR Test (against RI Model)	25.84***	21.15***	15.86***	8.29*	2.48	11.14**
Change in BIC from RI Model	-5.90	-1.21	2.64	10.31	16.12	7.46
N	21361		10401		10960	

Data Source: European Social Survey Rounds 2 and 5 (2004 and 2010)

Notes: Sample includes respondents between the ages of 18-59 in paid employment and living in a co-residential union. Control variables are gender, education, age, working hours, occupational class, presence of children under 13 in household, and partner's employment status. Random slopes are added for nonstandard hours and days in separate models to isolate the degree of cross-country variation for each arrangement respectively.

* $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

The above analyses are meant only to depict the degree of variability in slopes between countries, and thus do not show country-level differences in the effects of nonstandard work schedules on WFC. For further illustration of the variability in the effects of nonstandard work

schedules on WFC across countries, we also present estimates derived from country-specific OLS regressions in Figures 4-3 and 4-4. Note that WFC is now standardized to the country-specific mean so that each regression coefficient indicates the change in country-standardized WFC associated with a one unit increase in the regularity of nonstandard schedule work.

Notably, in the pooled models, the vast majority of countries show significant positive effects of nonstandard work hours (with the exceptions of Bulgaria and Italy) and days (with the exception of Italy) on WFC. Despite this commonly shared positive coefficient, there is substantial variation in effect sizes across countries. For nonstandard work days, coefficients in the pooled models range from a 0.29 standard deviation increase in WFC (in Iceland) to a less than 0.08 standard deviation increase in WFC (in Israel). For nonstandard work hours, coefficients range from a 0.21 standard deviation increase in WFC (in Iceland) to a 0.05 and non-significant standard deviation increase (in Bulgaria).

Another interesting finding is that there are no immediately visible patterns of effects across countries that would conform to traditional welfare state typological groupings. For example, for nonstandard work hours, we see that the countries where the effects are on average strongest (Iceland, Turkey, Norway, and Russia) are ones that would be grouped into entirely different regimes in most welfare state typologies. A similar incompatibility with most welfare state typologies can be seen when looking at countries with the strongest effects for nonstandard work days (Iceland, Norway, Czech Republic, and Hungary). Such findings reinforce the need for a more nuanced indicator-based approach to understanding the moderating effects of country-level institutions on the relationship between nonstandard schedules and WFC rather than a broad-strokes typology-based approach. Clearly, there are country-level differences (institutional or otherwise) shaping the social consequences of nonstandard work schedules that do not conform entirely to traditional typological groupings.

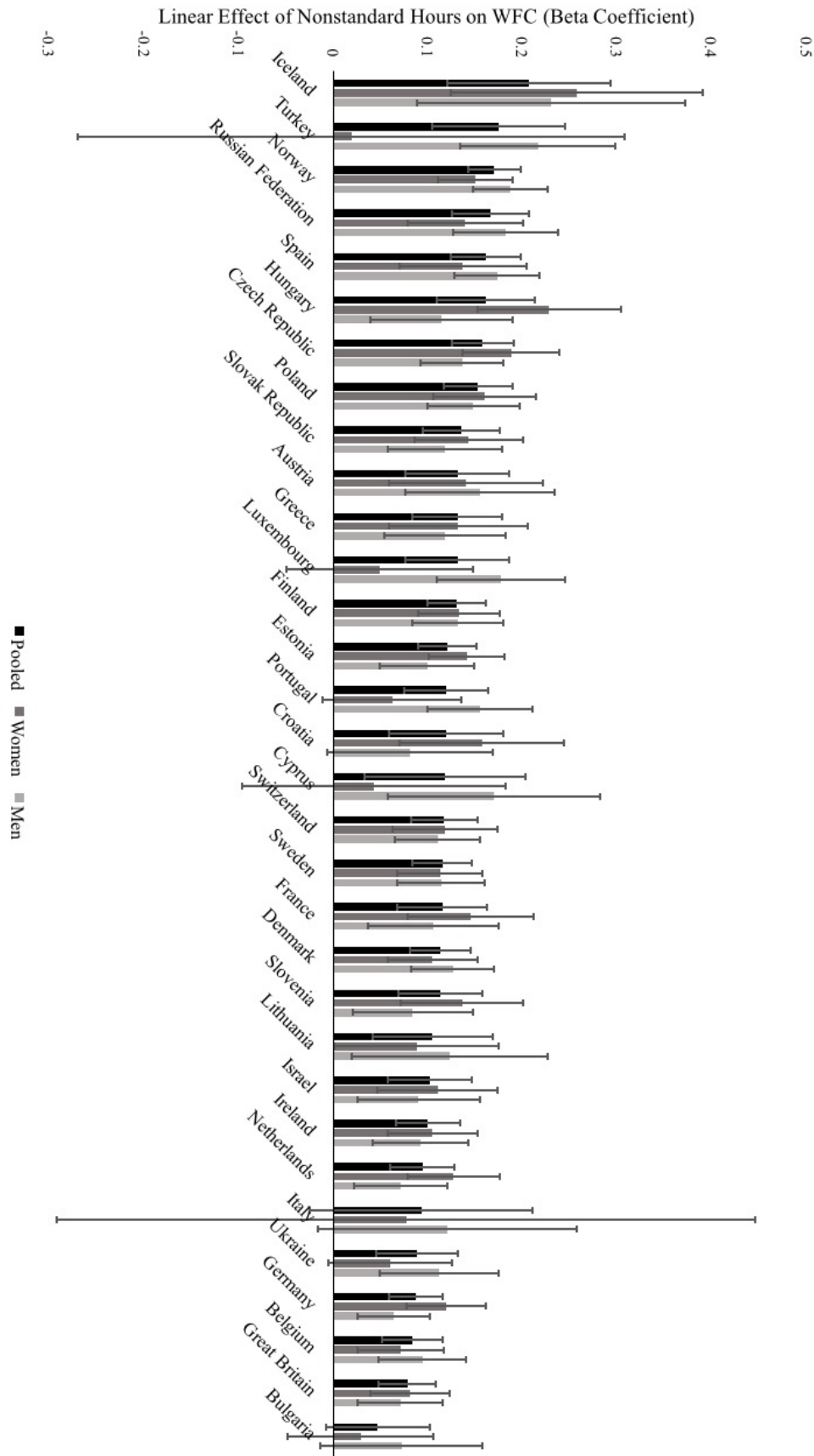
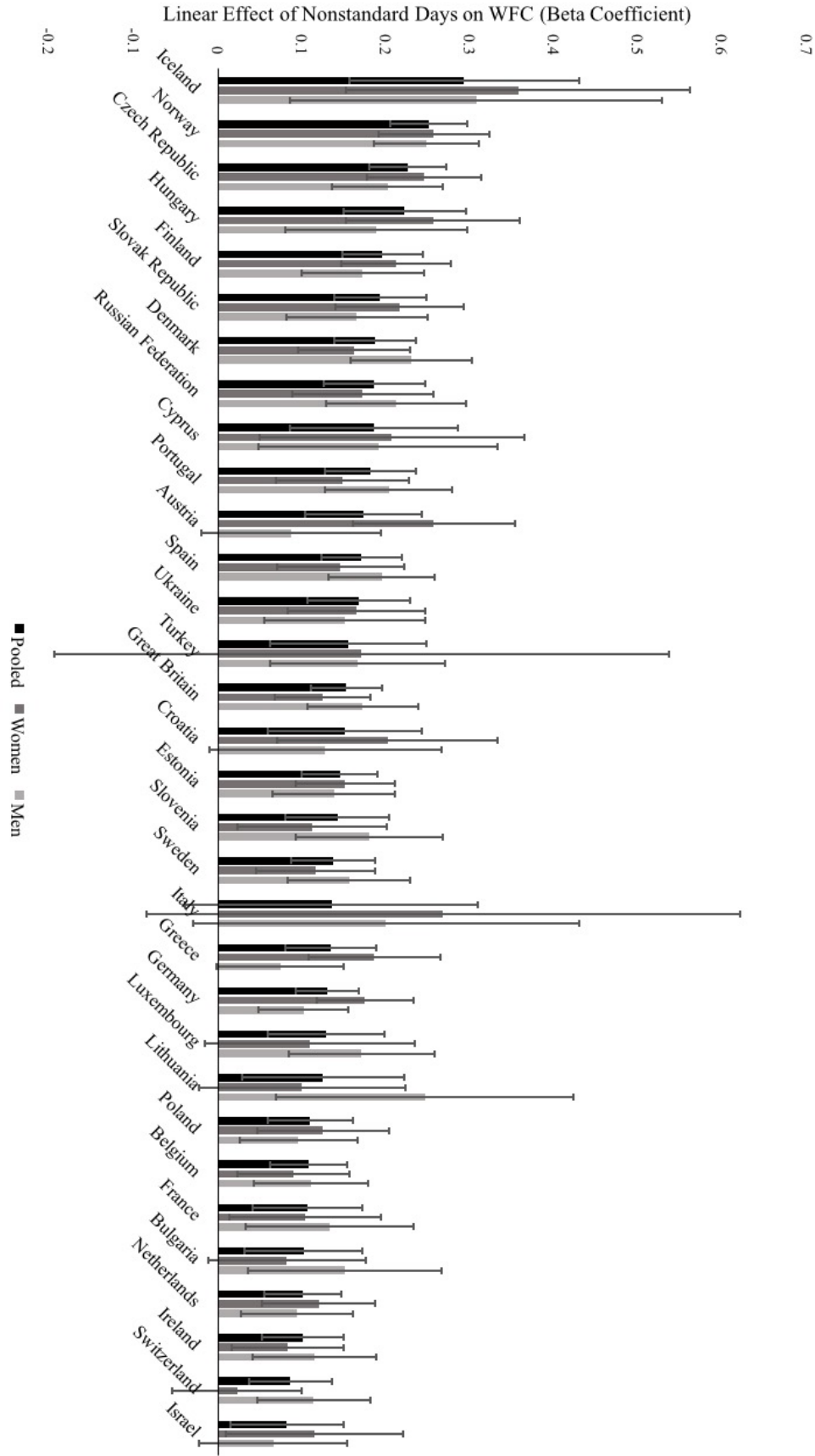


Figure 4-3. Country-Specific Regressions of WFC on Nonstandard Work Hours

Data Source: European Social Survey Rounds 2 and 5 (2004 and 2010)
Notes: Sample includes respondents between the ages of 18-59 in paid employment and living in a co-residential union. Control variables include age, gender (pooled model), work hours, education, occupational class, presence of children under 13, and employment situation of the partner. Dependent variable is the WFC index. Predictor variable is the regularity of nonstandard work hours. Error bars indicate 95% confidence intervals.

Figure 4-4. Country-Specific Regressions of WFC on Nonstandard Work Days



Data Source: European Social Survey Rounds 2 and 5 (2004 and 2010)

Notes: Sample includes respondents between the ages of 18-59 in paid employment and living in a co-residential union. Control variables include age, gender (pooled model), work hours, education, occupational class, presence of children under 13, and employment situation of the partner. Dependent variable is the WFC index. Predictor variable is the regularity of nonstandard work days. Error bars indicate 95% confidence intervals.

To explain between-country variation in the effects of nonstandard work hours and days on WFC, we now include country-level predictors capturing variation in the quality of the working environment (via the Job Strain Index) as well as trade union and collective bargaining influence. The Job Strain Index was not available in seven countries (Bulgaria, Croatia, Cyprus, Iceland, Lithuania, Russia, Iceland, and Ukraine); these were either not OECD countries or had data missing (as was the case in Iceland).²⁵ Data availability by country for macro-indicators can be found in Table 4-2. To account for this, we restrict this stage of analysis to countries where all three institutional indicators were available. While this reduces the number of level-two country-year units from 51 to 41, it also prevents cross-level interactions being modelled on different samples and thus not being comparable.

The results for nonstandard work hours, as shown in Table 4-7, indicate that the density of coverage under collective agreements is the labour relations characteristic that best explains between-country variation in the effects of nonstandard hours. The inclusion of this factor explains about 24% of the between-country slope variance and substantially improves model fit. In the fixed effects section, the negative interaction coefficient, while small, is statistically significant, indicating that with a one SD increase in the coverage under collective agreements, the effect of nonstandard work hours on WFC decreases by -0.008 SDs ($p < 0.05$). Looking at how these moderating effects vary by gender (Appendix 4-8) shows that the buffering effect of collective bargaining on WFC is about 0.016 SDs ($p > 0.05$) larger for women working nonstandard hours. In contrast, results indicate that these buffering effects do not vary significantly depending on whether there are children in the household under 13 or under 5 (Appendix 4-9).

²⁵ Analyses were run to determine whether this missingness on the macro-indicators was selective, or whether these countries differed systematically with regards to average experiences of work-family conflict as well as the effect of work-schedule timing on work-family conflict (results available upon request). This revealed that in countries missing data on the quality of the working environment, WFC was on average higher for females and the effect of nonstandard work hours on WFC was significantly lower. We return to this issue in subsequent discussions.

Table 4-7. *Nonstandard Work Hours Cross-Level Interactions in Random Slopes Pooled Models*

	Pooled Models - Nonstandard Hours				
	A	B	C	D	E
Fixed Effects					
Nonstandard Hours	0.085*** (0.004)	0.087*** (0.004)	0.086*** (0.004)	0.086*** (0.004)	0.086*** (0.004)
Union Coverage		-0.013 (0.036)			-0.049 (0.040)
Union Coverage * Nonstandard Hours		-0.006* (0.003)			-0.003 (0.004)
CBC			-0.052 (0.035)		0.047 (0.039)
CBC * Nonstandard Hours			-0.008* (0.004)		-0.007* (0.004)
Job Strain Index				0.070*** (0.019)	0.064** (0.020)
Job Strain Index * Nonstandard Hours				0.003 (0.004)	-0.001 (0.004)
Model Fit					
Change in Country Slope Variance ^a		-18%	-24%	-4%	-28%
Change in Country Intercept Variance ^a		3%	-3%	-1%	-1%
LR Test		4.53	6.29*	15.850***	24.200***
Change in BIC from RS Baseline Model		15.076	13.313	3.755	34.603
N	18044	18044	18044	18044	18044

Data Source: European Social Survey Rounds 2 and 5 (2004 and 2010)

Notes: Sample includes respondents between the ages of 18-59 in paid employment and living in a co-residential union. Predictor variable is regularity of nonstandard work hours. Control variables are gender, education, age, working hours, occupational class, presence of children under 13 in household, partner's employment status, and country GDP. ^aProportional reduction in the variance values calculated against a baseline random slopes model with only individual-level predictors and country- and individual-level control variables.

* $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

The significant negative interaction coefficient for union membership density ($b = -0.006$, $p < 0.05$) explains a large degree of between-country variation in the effects of nonstandard hours (18%). As with collective bargaining, the buffering effects of union coverage are significantly stronger for women working nonstandard hours, with a 0.02 SD difference in effects ($p < 0.01$) (Appendix 4-8). However, log-likelihood ratio tests indicate that adding this

factor to the model does not significantly improve model fit. Moreover, when all cross-level interactions are included in one model (column 5), the only significant moderator is collective bargaining coverage. Referring to the correlation matrix (Table 4-3), it appears that the non-significant interaction effect for union density is likely due to high multicollinearity with collective bargaining coverage across countries ($r = 0.46$). This alludes to the possibility that collective bargaining coverage might be a more important buffering mechanism than union strength in shaping experiences of WFC for nonstandard hour workers.

A somewhat surprising finding is that the quality of the national working environment appears to have no significant moderating effect on the nonstandard hour WFC penalty, and explains little to no between-country slope variance. While the quality of the working environment in a given country seems to be a strong predictor of the level of WFC in general (as seen in its highly significant coefficient of 0.07, $p < 0.001$), it appears to do little to impact the degree to which nonstandard hours affect WFC. Appendix 4-8 shows that this weak moderating effect is consistent across men and women, and Appendix 4-9 indicates a consistent trend regardless of the presence of children. This is, itself, an interesting finding that warrants further study and might suggest that collective agreements exert their buffering effect via means other than the regulation of the working environment. Alternatively, the measure could be picking up the effects of some unmeasured country-level factor, or somewhat more likely, it is more important to measure working conditions at the organization or company level rather than at the national level. In any case, the inclusion of all three macro-level institutional predictors and cross-level interactions explains about 28% of the total between-country variation in the effects of nonstandard hours (column 5). Taken together, this suggests that country-level labour market characteristics do indeed play an important role in shaping the individual-level social consequences of nonstandard hours.

The pooled model for nonstandard work days (see Table 4-8) presents a slightly different picture. As with nonstandard hours, collective bargaining coverage density has a statistically significant buffering influence on the effects of nonstandard days on WFC. This factor, however, appears to explain a considerably smaller proportion of between-country variation in the effects of nonstandard work days than nonstandard hours (7% as opposed to 24%). Moreover, including this term does not improve model fit. As with nonstandard hours, union membership density and quality of the working environment appear to have little buffering influence on the negative effects of nonstandard days and do not explain much between-country variation in the effects of these arrangements.

The inclusion of all three labour relations characteristics in the full model (column 5) explains only about 13% of the between-country variation in the effects of nonstandard days on WFC. It appears, therefore, that national-level institutions explain relatively little of the between-country variation in the effects of nonstandard work days on WFC. This suggests that there may be other unmeasured factors – cultural, workplace-specific, or otherwise – that are more important in dictating the effects of nonstandard days on work-family balance.

Looking at how these moderating effects vary by gender (Appendix 4-10) suggests that the buffering effects of union coverage and the quality of the working environment appear to be particularly strong for women. For union coverage, the buffering effect on the nonstandard day WFC penalty is about 0.018 SDs larger for women ($p < 0.05$), and the buffering effect of working conditions is about 0.027 SDs larger ($p < 0.01$). This suggests that labour-related institutions may be more relevant to the experience of WFC for women working nonstandard days than for men. In contrast, Appendix 4-11 indicates that the moderating effects of country-level labour-related factors on the nonstandard day WFC penalty do not vary significantly depending on whether there are children under 5 or 13 present.

Table 4-8. *Nonstandard Work Days Cross-Level Interactions in Random Slopes Pooled Models*

	Pooled Models - Nonstandard Days				
	1	2	3	4	5
Fixed Effects					
Nonstandard Days	0.095*** (0.006)	0.095*** (0.006)	0.096*** (0.006)	0.095*** (0.006)	0.095*** (0.006)
Union Coverage		-0.018 (0.036)			-0.066 (0.040)
Union Coverage * Nonstandard Days		-0.005 (0.004)			0.003 (0.006)
CBC			-0.052 (0.036)		0.055 (0.040)
CBC * Nonstandard Days			-0.009+ (0.005)		-0.010+ (0.006)
Job Strain Index				0.079*** (0.019)	0.081*** (0.021)
Job Strain Index * Nonstandard Days				0.007 (0.005)	0.007 (0.005)
Model Fit					
Change in Country Slope Variance ^a		-3%	-7%	-6%	-13%
Change in Country Intercept Variance ^a		3%	-3%	-2%	-3%
LR Test		1.880	4.170	17.360***	22.880***
Change in BIC from RS Baseline Model		17.720	15.430	2.244	35.926
N	18044	18044	18044	18044	18044

Data Source: European Social Survey Rounds 2 and 5 (2004 and 2010)

Notes: Sample includes respondents between the ages of 18-59 in paid employment and living in a co-residential union. Predictor variable is regularity of nonstandard work days. Control variables are gender, education, age, working hours, occupational class, presence of children under 13 in household, partner's employment status, and country GDP. ^a Proportional reduction in the variance values calculated against a baseline random slopes model with only individual-level predictors and country- and individual-level control variables.

* $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

6. SENSITIVITY ANALYSES

As discussed, a limitation of these analyses surrounds the relatively small number of country units. This small n at level two may mean that country variances have been underestimated and country-level effects estimated unreliably. As a sensitivity analysis, we perform an adaptation of the two-step estimation procedure advocated by Bryan and Jenkins (2016). In step one,

country-period-specific OLS regressions ($n = 41$)²⁶ are run with individual-level parameters to infer country-period-specific slopes (i.e., the nonstandard hours/days coefficients, respectively). In step two, these country-period-specific slopes are then regressed on country-period-level predictor variables (i.e., CBC, Union Coverage, GDP, and Job Strain) in a variance-weighted least squares regression.²⁷ Following Bryan and Jenkins, we also perform a pooled OLS model with country-period fixed-effects in step 1, average the predicted values for each country-period ($\widehat{y}_{ct}$), and then in step two regress $\widehat{y}_{ct}$ on country-period-level variables. This approach is informative as a sensitivity analysis not only because it provides a more intuitive way to estimate cross-level interactions, but – as Bryan and Jenkin (2016) note – it also depicts the sources of variation at the country level in the data and highlights how a small number of countries can affect the reliability of estimates.

Results of these analyses are presented in Appendix 4-12. Figure 4-12-1 plots country-period-averaged predicted values ($\widehat{y}_{ct}$) and Figures 4-12-3 and 4-12-4 plot the country-period-specific slopes of nonstandard hours and days, respectively. Table 4-12-1 shows results of step 2 when these country-period predicted values and slopes are regressed on country-period-level predictor variables. Consistent with findings from the multilevel analysis (Table 4-7), collective bargaining appears to be the strongest predictor of the effect of nonstandard hours across countries: a one standard deviation increase in collective bargaining decreases the country-period slope of nonstandard hours on WFC by 0.009. However, this effect only reaches significance at $p < 0.1$. Similar trends are also observed for nonstandard work days, where collective bargaining coverage plays the strongest buffering role ($b = -0.012$, $p < 0.1$). CBC is

²⁶ For several countries, we have observations for 2004 and 2010. We therefore perform separate regressions for each country-period observation that has non-missing values on country-level predictor variables. Figures 4-12-1 to 4-12-3 in Appendix 4-12 provide details on the country-period observations included.

²⁷ The technique applied in step 1 is discussed in the Bryan and Jenkins (2016) as ‘Approach 2’, where separate models are fitted to the data for each country. While they originally propose running a pooled model with country fixed effects in their paper, estimating country-specific models in the present case allows us to acquire more easily-interpretable country-specific slopes (which are not estimated in the Bryan and Jenkins paper); in a fixed-effects model, slopes would always be measured against some arbitrary reference country-period.

also associated with significantly lower average levels of predicted WFC ($b = -0.0324$, $p < 0.01$). Similarly, union coverage is associated with significantly lower average levels of predicted WFC ($b = -0.0376$, $p < 0.001$). That estimated cross-level interactions no longer reach significance at $\alpha = 0.05$ in this two-step approach is an interesting finding and could highlight limitations surrounding the small n at level two. It could also suggest that cross-level interactions derived from random effects multilevel models may have imprecisely estimated country-level variance. I return to this issue in the Discussion section.

7. DISCUSSION

The current chapter explored whether nonstandard work hours and days were associated with higher levels of work-family conflict (WFC) across Europe. While this relationship has been examined in the past, it has largely been confined to single and generally quite specific country contexts, particularly the US (e.g., Presser, 2003; White & Keith, 1990; Maume & Sebastian, 2012). This single-country approach not only raises concerns surrounding the generalizability of findings but also limits one's ability to understand the ways in which contextual factors might affect the strength and/or direction of this relationship. Building on previous research, the contributions made by this study were to test whether the effects of nonstandard schedules on WFC varied across 32 diverse national contexts in Europe, and if so, whether this between-country variation could be explained by factors relating to labour regulations and industrial relations measured at the country level.

Findings include three major patterns. First, all 32 countries showed a positive and monotonic association between the regularity of nonstandard hours and days and WFC. On average across all countries, those working nonstandard hours every day experienced levels of WFC nearly one standard deviation higher than counterparts who never worked these hours. Similarly, those working nonstandard days every week experienced levels of WFC nearly three-

quarters of a standard deviation higher than those who never worked these days. Country-specific analyses revealed that these effects were statistically significant in all but two countries (Italy and Bulgaria). In contrast to previous findings (Craig & Powell, 2011; Lozano et al., 2016; Maume & Sebastian, 2012; Mills & Täht, 2010; Presser, 2003; Presser & Cain, 1983), these effects did not depend on the gender of the worker or whether there were children present in the household.

Despite a commonly-shared positive association between nonstandard schedules and WFC across nearly all countries, a second major finding of this study was that the strength of this association varied significantly by national context. For both nonstandard hours and days, results from random effects models indicated slight but significant between-country variation in the extent to which these arrangements were associated with WFC. Moreover, country-specific analyses revealed a wide range in the magnitude of the effects of nonstandard work schedules on WFC across countries. The effects of nonstandard hours were nearly four times larger in Iceland than in Bulgaria, and the effects of nonstandard days were more than four times larger in Iceland than in Israel. These findings are consistent with previous comparative research indicating that the effects of these arrangements on work-family balance are highly sensitive to national context (Hook & Wolfe, 2013; Mills & Täht, 2010; Tammelin et al., 2017).

Crucially, findings from this study suggest that when studying the social consequences of nonstandard schedules, these arrangements must be contextualized in the broader institutional frameworks within which they are organized and regulated. A third major finding was that characteristics of a country's system of industrial labour relations play an important role in dictating the extent to which these arrangements lead to WFC, particularly for nonstandard work hours. The most important factor was the degree to which workers are covered under collective bargaining agreements: this explained over 24% of the between-country variation in the effects of nonstandard work hours on WFC and 7% of the variation in

the effects of nonstandard work days. Interestingly, this factor proved to be a much stronger moderator of the WFC penalty than union membership density, suggesting that collective agreements may be the central mechanism through which family-friendly regulations on working conditions are generated for nonstandard schedule workers across Europe.

Such a finding is perhaps not surprising when one considers that the regulation of working time has been a central focus for collective bargaining in Europe historically (Keune, 2006). For example, in many Western European countries, collective bargaining, particularly at local or company levels, has focused on promoting a range of flexible working time measures for workers (Thorntwaite, 2004). As has been shown, the ability to adjust nonstandard schedules flexibly is an important buffering mechanism against their negative side-effects relating to family cohesion (Deutsch, 1999; Fenwick & Tausig, 2001; Lozano et al., 2016; Staines & Pleck, 1986). Bargaining at the country level is also important in generating policy measures tailored uniquely to nonstandard work hours and days. For example, in Germany and certain Nordic countries, collective agreements have produced regulations prohibiting the enforcement of Sunday work by an employer, as well as the assignment of night work to women with children under the age of fourteen and who lack adequate care arrangements (Gornick & Meyers, 2003). Interestingly, our analyses revealed that the buffering effects of collective bargaining coverage on WFC are significantly stronger for women working nonstandard hours and days than for men. This suggests that labour-related institutions – and the family-friendly regulations on working times and conditions they can promote – may be more relevant to the experience of WFC for women working nonstandard schedules than men.

A surprising finding was that the quality of the working environment appeared to have no significant moderating effect on the nonstandard schedule WFC penalty. This might suggest that collective agreements exert their buffering effect via means other than the regulation of the working environment. Alternatively, it could highlight the importance of measuring the quality

of the working environment at the organization or company level rather than at the national level. A complementary explanation alluded to earlier would be that better collective bargaining coverage within a country may indirectly reduce the WFC penalty by altering the selectivity of nonstandard schedule workers. Put simply, in contexts where workers have better representation, entrance into nonstandard schedules may not necessarily represent a forced choice as much as a matter of personal preference. Future research could explore in greater detail the specific mechanisms through which collective bargaining buffers the negative effects of nonstandard schedules on families. Another important area for future research would be to look at whether and how these moderating effects might vary depending on whether the worker has children present in the household.

We make note of several limitations of this study that point to other directions for further research. First, we used rather blunt measures of nonstandard hours and days that only looked at the regularity of work during the evenings, nights, and at weekends. Such measures undoubtedly obscured important nuances of different types of nonstandard schedules, for example, the differing levels of autonomy and flexibility afforded to workers in rotating, variable, and fixed nonstandard schedules. Related to this point, we only studied the effects of nonstandard work schedules on partnerships at the individual level, neglecting the fact that work schedules are often jointly constructed at the couple-level (Täht & Mills, 2016). Future research could explore more detailed measures of nonstandard schedule arrangements constructed at the couple level.

Along with this and as alluded to earlier, the Job Strain Index was not available in seven countries (Bulgaria, Croatia, Cyprus, Iceland, Lithuania, Russia, Iceland, and Ukraine); these were either not OECD countries or had data missing (as was the case in Iceland). To account for this, we restricted this stage of analysis to countries where all three institutional indicators were available to ensure that estimates were comparable. Supplementary analyses, however,

revealed that in countries with no information on the Job Strain Index, female WFC was higher and the effect of nonstandard work hours on WFC was lower; this indicates that selective missingness might be partially biasing results. Further research exploring the moderating impacts of country-level institutional characteristics would do well to utilize or construct new indicators with more expansive availability across all European countries.

Another point is that several country-level indicators that are likely highly important moderators of the relationship between nonstandard work schedules and WFC were not considered in this study. This includes measures of family-related institutions as well as indicators of work, gender, and family norms. One particularly important indicator that was not measured is the overall prevalence of nonstandard schedules in a country, which may affect the meaning of these arrangements and the extent to they generate perceptions of WFC. Indeed, it may be that in contexts where nonstandard work hours and days are more common, these arrangements may not only be better regulated but also less discordant with the normative temporal organization of family life (i.e., these arrangements may be *less nonstandard* in some contexts than in others). However, to adequately control for the prevalence of nonstandard schedules in the present case, estimates would need to have been generated from a secondary dataset external to the one currently being used. To our knowledge, no cross-national datasets are available that cover the years and countries currently being studied in the present analyses.

Another limitation to the current analyses is that as we are using cross-sectional data, findings on the buffering effects of country-level institutional characteristics are merely associational at this point. This is due to that fact that we cannot reliably partial out the effects of the many unobserved country-level factors that are likely collinear with observed institutional factors. Future research could utilize a longitudinal or quasi-experimental research design to determine whether the moderating effects of collective bargaining coverage on the relationship between nonstandard schedules and WFC are in fact causal.

A final limitation to the current analyses surrounds the use of random effects multilevel modeling with a small number of countries ($n = 32$). While multilevel modeling naturally suits the current paper's aims of modeling country-level effects and decomposing country-level variation, the relatively small number of units at level-two may undermine the robustness of these estimates. Indeed, as Bryan and Jenkins (2016) note, with a large number of units per country but only a small number of countries, one might be able to reliably estimate individual-level effects (in this case, the effect of a nonstandard work schedule on WFC) but country-level variances will be estimated imprecisely; this imprecision will not be adequately reflected in test statistics. While simulations have shown that between 25-50 country units can be sufficient for the estimation of country-effects in multilevel linear models (Bryan & Jenkins, 2016; Maas & Hox, 2004), the applicability of these rules of thumb will largely depend on the complexity of the models being estimated. We do note that the potential imprecision of country-level effects should at least be reduced in the present case as we use the cross-classification of countries and survey rounds at level two, which effectively creates 51 level-two units (or 41 when including only those countries with country-level predictor variables available). That said, the relatively small number of level-two units remains a core limitation of these analyses. Indeed, sensitivity analyses revealed that the buffering effects of collective bargaining no longer reached significance when using the two-step estimation procedure advocated by Bryan and Jenkins (2016). Future research could attempt to replicate these findings by using, for example, regions within a country as the level-two unit; in such a case, issues surrounding a small n at level two will not be so problematic.

In the face of rising nonstandard schedule rates across Europe (Presser et al., 2008), it is essential for policymakers and researchers to better understand the potential of institutions to insulate workers from the harmful side-effects these arrangements can have on family life. Findings from this study indicate that while on average, nonstandard hours and days are

associated with higher levels of WFC across Europe, these negative side-effects are mitigated in contexts with greater coverage under collective agreements. This suggests that countries seeking to improve work-family balance for workers in nonsocial hours should perhaps focus first on creating and sustaining successful platforms – either at the national, company, or sectoral level – for collective bargaining on working times and conditions.

CHAPTER 5

DO OWLS WORK AT NIGHT? USING GENETIC DATA TO EXPLORE THE CAUSAL LINK BETWEEN EVENINGNESS AND NIGHT SHIFT WORK

1. INTRODUCTION

In the preceding two chapters, nonstandard work schedules were treated as an independent variable, with the aim of studying the effects of these arrangements on outcomes relating to family cohesion. In contrast, this chapter treats nonstandard schedules – and, in particular, nonstandard work hours – as the dependent variable to investigate how individual characteristics might affect the likelihood of entrance into and survival within these arrangements. As discussed in Chapter 3, nonstandard schedules are not randomly distributed: individuals select or are selected into these arrangements based on interactions between a host demographic, socioeconomic, and occupational characteristics. Crucially, individual preferences and endowed traits are also likely to play a role in dictating who selects into and stays in nonstandard schedules. This chapter focuses on one such set of individual characteristics: the timing of an individual's *circadian rhythm*. I explore how individual differences in circadian rhythms might affect the times of day people engage in paid labour.

The term circadian rhythm refers to an underlying 24-hour physiological cycle that occurs in most living organisms. It is, amongst other things, particularly important for regulating sleep patterns (Roenneberg, Wirz-Justice, & Mellow, 2003). Every individual possesses an endogenous circadian clock – or *chronotype* – that, at least in part, dictates at what times of day he or she functions best. Individuals with later rhythms – often referred to as “owls” or “evening people” – tend to do best with a late bedtime and a late rising time. In

contrast, individuals with earlier rhythms – so-called, “morning people” or “larks” – tend to feel tired earlier in the evening and wake up earlier in the morning. The majority of the population (~60-80%) exists on a continuum somewhere between these poles; this well-established Gaussian distribution has been found in most Western populations (Achari, Pati, & Parganiha, 2012; Adan et al., 2012; Ashkenazi, Reinberg, & Motohashi, 1997; Benedito-Silva et al., 1998; Natale & Adan, 1999; Natale & Cicogna, 2002; Natale & Danesi, 2002; Roenneberg et al., 2003).

A wide body of literature has linked eveningness chronotype with adaptation to and long-term tolerance of night shift work schedules, or those involving regular work between the hours of 10:00 pm and 6:00 am (Blok & De Looze, 2011; Costa et al., 1989; Furnham & Hughes, 1999; Khaleque, 1999; McLaughlin, Bowman, Bradley, & Mistlberger, 2008; Ognianova, Dalbokova, & Stanchev, 1998; Saksvik, Bjorvatn, Hetland, Sandal, & Pallesen, 2011; Seo, Matsumoto, Moon, & Hayasaka, 2005; Seo, Matsumoto, Park, Shinkoda, & Noh, 2000; Steele Mark, Ma, Watson William, & Thomas Harold, 2008; Storemark et al., 2013; Takahashi et al., 2005; Willis et al., 2008). These studies have found that morning types tend to have more adjustment difficulties related to night shifts than evening types, as evidenced by higher self-reported levels of drowsiness on the job as well as greater incidence of deleterious health outcomes including digestive problems, persistent fatigue, and adverse sleep alterations. Such research broadly alludes to the idea that the ability to adapt to and thrive in employment occurring outside of the traditional diurnal work period may partially depend upon having a circadian clock optimized for these times.

A related but relatively underexplored question, however, is the extent to which evening types are more likely to select into and stay in night shift work schedules. From a rational choice perspective, one would expect that individuals will on average prefer work hours that are aligned with their endogenous circadian clock. This preference would be rational given: (1) that

cognitive and physical performance are highest when one's external clock is synchronized with her endogenous clock (e.g., May & Hasher, 1998; Hasher, Zacks, & May, 1999), and (2) the short- and long-term health consequences of working hours that are out of sync with one's circadian rhythm discussed above. Therefore, it would follow that a strong association between eveningness and night work is indicative of people rationally selecting into the work schedule best suiting their own unique chronotype; I return to the application of rational choice in subsequent discussions. Perhaps more interesting, however, a weak or even negative association would indicate that there is often a mismatch between individuals' actual and optimal work schedules in the labour market, such that those best suited to daytime work hours instead select into night shift work schedules and vice versa. This latter trend, if observed, might shed light on some of the well-documented social and physical consequences of night shift work discussed in previous chapters. Despite these important insights, we still know relatively little about how chronotype affects preferences for night work hours.

Some studies, most commonly in the field of chronobiology, have shown that night shift workers on average tend to be more likely to report having eveningness chronotypes. For example, Achari et al. (2012) found that rates of morningness were significantly lower amongst shift workers in India than for those not regularly working such hours. Similarly, Paine, Gander, and Travier (2006) found that night workers in New Zealand were 1.49 times more likely to be evening types than those not regularly working these hours. However, such research has focused largely on elucidating bi-directional associations between eveningness and night shift work using self-reports of chronotype drawn from cross-sectional datasets. In the absence of longitudinal evidence (which recent meta-reviews suggest is rare; Härmä, 1993; Saksvik et al., 2011), this naturally raises concerns surrounding the direction of causality between eveningness and night shift work.

A key property of circadian rhythms is their ability to be synchronized – or *entrained* – to environmental cues (or *zeitgebers*), such as natural and synthetic light-dark cycles: if a shift in external cues occurs (e.g., following daylight savings, travel across time zones, or a change from a day to night work schedule), rhythms will eventually be aligned to the new cues (Roenneberg et al., 2003). Therefore, in the present case, it is unclear whether eveningness drives selection into a night shift work schedule, or whether prolonged exposure to night shift work hours increases the likelihood for self-identified eveningness. Indeed, as Saksvik et al. (2011) note, it may be that greater self-reported eveningness amongst night shift workers simply reflects a form of adaptation – and thus a treatment response – rather than a true and stable personality trait.

However, while the timing of an individual's circadian rhythm can be influenced over time by his or her cumulative social environment, these rhythms can also persist in the absence of external time cues (Roenneberg, Kuehnle, et al., 2007). This suggests that human preferences in the timing of sleep and wake are at least in part genetic and thus fixed over the life course. Indeed, both family and twin studies suggest that sleep-wake preferences are highly heritable, with heritability estimates ranging between 23-50% (Barclay, Eley, Buysse, Archer, & Gregory, 2010; Heath, Kendler, Eaves, & Martin, 1990; Klei et al., 2005; Koskenvuo, Hublin, Partinen, Heikkila, & Kaprio, 2007; Vink, Groot, Kerkhof, & Boomsma, 2001). Three recent Genome-Wide Association Studies (GWAS)²⁸ further support that chronotype has a strong genetic basis, with the latest study identifying a total of 351 genetic loci associated with being an evening person at $p < 5 \times 10^{-8}$ (Hu et al., 2016; S. E. Jones et al., 2018; Lane et al., 2016).²⁹

It appears then that, whether they are aware of it or not, individuals do indeed possess a time-invariant predisposition towards working best at certain times of the day – or their optimal

²⁸ A GWAS is a hypothesis-free survey across the entire genome that tests associations between millions of SNPs (usually through some form of logit or probit model) and a given phenotype (Belsky & Israel, 2014).

²⁹ $p < 5 \times 10^{-8}$ is the commonly used threshold for genome-wide significance in GWA studies.

work schedule. However, determining whether the previously documented association between eveningness and night shift work is reflective of individuals selecting into their optimal work schedules requires the use of an exogenous and time-invariant measure of chronotype. The recent advent of large-scale molecular genetic datasets – the same types used in the GWA studies cited above – might provide such a solution.

In this chapter, I blend concepts from chronobiology and rational choice theories to study the ways in which chronotype influences preferences surrounding the timing of paid work. I start by proposing a novel framework in which to view and operationalize chronotype that takes into account the relative contributions of genes, measurement error, and cumulative social environment. Under this framework, I utilize Mendelian Randomization (MR) techniques on genetic and work history data from the UK Biobank to study the causal association between eveningness and selection into night shift work hours. Briefly, MR is a form of instrumental variable regression where information on a variety of genes known to be associated with eveningness is used to instrument self-reports of eveningness. The key benefits of MR for the current study are twofold: first, as genetic variants are randomly assigned at conception, their effect on a phenotype³⁰ of interest (in this case, self-reported eveningness) is random with respect to potential confounders; second, as one's genetic code is fixed at birth, estimates produced by MR are not subject to reverse causation. Therefore, such an approach will allow one to better delineate the true effect of eveningness on the probability of night shift work. Accordingly, this chapter will seek to identify whether individuals with eveningness chronotypes are more likely to be observed in night shift work schedules. More broadly, I explore whether there is evidence of individuals selecting into their optimal work hours, and if not, why this might be the case.

³⁰ A phenotype refers to an observable characteristic of an individual resulting from the interaction of her genotype with the environment.

2. THEORETICAL AND METHODOLOGICAL FOUNDATIONS

2.1. OPERATIONALIZING CHRONOTYPE

I distinguish broadly between three ways in which to view and operationalize chronotype, which are displayed in Table 5-1. The first is one's *true chronotype*. This is influenced by an individual's genetic makeup and his or her cumulative social environment. It is the most accurate indicator of at what times of day that person is best suited to work (i.e., their optimal work schedule), but is technically unmeasurable. That is, one assumes in theory that every individual possesses a true chronotype, which exists on a normally-distributed continuum somewhere between morningness and eveningness, but this cannot ever be observed directly.³¹ *Self-identified* and *predisposed chronotype* then both refer to different ways in which to approximate this true chronotype.

Self-identified chronotype refers to our best guess of an individual's true chronotype based on his or her self-reports. This is measured, as the name suggests, through various survey instruments designed to associate individuals with temporal preferences of mornings or evenings; the Horne-Östberg (1976) Morning-Eveningness Questionnaire being the most widely used. These survey instruments are mostly subjective, relating an individual's chronotype to factors like preferred wake-up and/or sleep times, or in relation to the habits of others (e.g., "I get up later than most people") (Roenneberg, Kuehnle, et al., 2007). While self-reports of chronotype may be the best predictors of behavior (like for instance, selection into night shift work), such measures are also endogenous to one's social environment. As discussed

³¹ Non-invasive, ambulatory monitoring techniques like actigraphy are continually developing that might one day provide an objective measure of true chronotype (Çaliyurt, 2017). However, like self-reports, patterns of activity during night and day hours will likely in part be endogenous to one's cumulative social environment. To measure one's true chronotype (purged of the effects of one's cumulative social environment), such measures would likely need to be collected at birth. Saliva, blood, or urine samples capturing levels of the pineal hormone melatonin (or the melatonin rhythm) can also provide an optimal marker of circadian phase in humans under certain conditions. However, melatonin assays are not yet a rapid or easily available method for everyday diagnostic use (Wirz-Justice, 2007). Moreover, it is difficult to determine their validity in large samples.

earlier, a key property of circadian rhythms is their ability to be entrained over time by zeitgebers, or cues in one's natural and social environment.³² Therefore, survey instruments measuring morning-evening preferences are not strictly capturing an innate circadian clock as much as they are capturing the interaction of this innate clock with an individual's cumulative social environment. Indeed, what such forms of survey instruments are not so adept at measuring is the timing of the biological clock shielded from the social and natural environment (or in *constant conditions*; Roenneberg, Kuehnle, et al., 2007).

This is of course not only problematic in the sense of reverse causality (i.e., work schedule timing will likely affect self-reports of chronotype), but also when one considers the ways in which broader patterns of socialization might condition how individuals will respond to such questionnaires. We live in a society where the normative temporal organization of social life heavily favors morningness chronotypes. Indeed, the various social clocks we are socialized under throughout the life course (e.g., school start times, meal timing, shop opening hours, the diurnal workday, etc.) reward morningness and implicitly penalize eveningness. These patterns of morningness-oriented socialization are perhaps best evidenced by the robust finding that humans tend to show greater morningness with advancing age (Achari et al., 2012; Adan et al., 2012; Baehr, Revelle, & Eastman, 2000; Natale & Danesi, 2002; Paine et al., 2006; Roenneberg, Kuehnle, et al., 2007; Roenneberg et al., 2003; Tankova, Adan, & Buela-Casal, 1994).³³ Such patterns of socialization then allude to the possibility that the reliance on self-reports of chronotype may underestimate the true proportion of evening types in the population and overestimate the true proportion of morning types. Moreover, given that there is a well-

³² The molecular mechanisms underpinning the timing of the circadian period are tamed by the master clock in the brain (the suprachiasmatic nucleus, SCN), which coordinates tissue-specific rhythms according to light input it receives from the outside world (Reppert & Weaver, 2002).

³³ There is some evidence that these age differences in chronotype are also in part linked to age-dependent changes in the concentration and timing of certain hormones, including cortisol and growth hormones, which influence the timing and quality of sleep (Biss & Hasher, 2012; Roenneberg, Kuehnle, et al., 2007; Van Cauter, Leproult, & Plat, 2000).

established Gaussian distribution where between 60-80% of people have an intermediary chronotype somewhere between morning and evening type, the potential for measurement error in self-reports is high (Achari et al., 2012; Natale & Cicogna, 2002).

Predisposed chronotype refers to our best guess of an individual's true chronotype based on his or her time-invariant genetic makeup. While circadian rhythms are in part influenced by one's cumulative social environment, they also have a strong genetic basis and are thus partially fixed over the life course; as mentioned, twin and family studies suggest the proportion is between 23-50%. Candidate gene and GWA studies have revealed that circadian rhythms are in part determined by a core set of clock genes and proteins that interact in a transcriptional/translational feedback loop to influence the circadian period (Adan et al., 2012; Ko & Takahashi, 2006); many of these same clock genes also play important roles in sleep regulation and homeostasis (Franken & Dijk, 2009). These clock genes take their effect on chronotype via the suprachiasmatic nuclei (SCN) region of the hypothalamus, which is the master circadian clock that drives many rhythms in behavior and physiology (Verwey & Amir, 2016). Oscillations in clock gene expression within the SCN over the course of the 24-hour day are a key determinant of the overt circadian rhythm period: they provide the daily rhythm to the central clock and regulate downstream physiological and metabolic processes via direct signalling from the SCN and via signalling of peripheral clocks residing in bodily tissues (Hu et al., 2016; Ingram et al., 2016; Ralph, Foster, Davis, & Menaker, 1990; Reppert & Weaver, 2002; Verwey & Amir, 2016).

The growing availability of large-scale molecular genetic datasets provides a unique opportunity to utilize variation in these clock genes as an instrument for chronotype that is exogenous to one's social environment. Unlike one's self-reports of morning or evening preferences, genetically predisposed chronotype is fixed at birth³⁴ and will thus be unaffected

³⁴ While an individual's genetic code is fixed at birth, gene expression can change over the life course through various epigenetic mechanisms (M. J. Jones, Goodman, & Kobor, 2015). Although some recent research has

by socialization over the life course and – more importantly – the timing of one’s work schedule. Moreover, whether an individual possesses one or more eveningness-inducing clock genotypes³⁵ is determined randomly at meiosis; this natural experiment at conception means that any association between genetically predisposed chronotype and work schedule timing is not biased by confounding or reverse causation (Davey Smith & Ebrahim, 2003). Accordingly, one can aggregate variation in these clock genes to measure an individual’s genetic propensity for eveningness using a so-called, Polygenic Risk Score (PGS). A PGS can be thought of as a linear predictor score of a given phenotype – in this case, eveningness – based on variation in multiple genetic loci (or single nucleotide polymorphisms, SNPs³⁶) and their associated weights derived from GWA Studies. For the purposes of the current analysis, a PGS will provide an exogenous predictor of true eveningness based on an individual’s time-invariant genetic makeup; I return to the theory and construction of a PGS in the Methods section.

In subsequent discussions, any reference to eveningness (including in hypotheses) will be to one’s true level of eveningness. I approximate this true level of eveningness through Mendelian Randomization techniques where I instrument an individual’s self-identified eveningness with her PGS for eveningness; I elaborate on this technique further in the Methods section. Such an operationalization of eveningness will help address the issues relating to non-random measurement error and reverse causation discussed above.

shown that epigenetic alterations in the suprachiasmatic nucleus and hippocampus may lead to age-related changes in overt circadian rhythms (Bukowska-Damska et al., 2017; Deibel, Zelinski, Keeley, Kovalchuk, & McDonald, 2015; C. Liu & Chung, 2015), the epigenetic regulation of the circadian rhythm has not yet been thoroughly explored. Given the lack of concrete understanding of the nature of epigenetic changes in clock gene expression and in the interest of a more concise analysis, I treat the genetic predisposition to a given chronotype as fixed at birth and omit the possibility of epigenetic changes in this predisposition over the life course. I return to this issue in subsequent discussions.

³⁵ A genotype of an individual refers to the two alleles (variant gene forms) inherited at a specific locus (or, position in a DNA sequence). Individuals inherit one allele from each parent; if alleles are the same, the genotype is homozygous; if the alleles are different, the genotype is heterozygous (Davey Smith & Ebrahim, 2003).

³⁶ SNPs (colloquially referred to as, “snips”) are positions along a chromosome where the genetic code varies between individuals by a single base pair (Davey Smith & Ebrahim, 2003). SNPs are the most common type of genetic variation among people, occurring once in every 300 nucleotides on average, with roughly 10 million existing in the human genome (Shah, 2008). For the purposes of the current study, SNPs act as categorical markers identifying genetic variation associated with a given phenotype.

Table 5-1. *Operationalizing Individual Chronotype*

	True Chronotype	Self-Identified Chronotype	Predisposed Chronotype
	• Social environment	• Social environment	• Genetic makeup
<i>Influenced by:</i>	• Genetic makeup	• Measurement error • Genetic makeup	
<i>Measurement:</i>	• Unmeasurable	• Self-reports of morning or evening preferences	• Polygenic Risk Score

Notes: True chronotype here refers to a theoretical construct that is assumed to be unmeasurable.

2.2. CHRONOTYPE AND OPTIMAL PERFORMANCE WINDOWS

The recent GWA, twin, and family studies cited earlier suggest that individuals possess an innate optimal work schedule, or a window of time occurring somewhere throughout the 24-hour day during which they will function best. By extension, these studies also allude to the possibility that individuals (particularly those at the extreme ends of the chronotype spectrum, so-called, larks and owls) have a pessimal work schedule, or a window of time during which they will function sub-optimally. Such a framework would be consistent with a wide body of research documenting peak cognitive functioning and performance when an individual's external (or social) clock is synchronized with his or her endogenous circadian clock; a phenomenon May and Hasher (1998) termed, *synchrony effect*. For example, studies have found that when individuals are observed during times of the day optimized to their circadian period, inhibitory control³⁷ is greater (May & Hasher, 1998), cognitive performance and executive functioning are higher (D. Goldstein, Hahn, Hasher, Wiprzycka, & Zelazo, 2007; Hahn et al., 2012; Hasher, Zacks, & May, 1999; Lara, Madrid, & Correa, 2014), decision-making is more analytical (Bodenhausen, 1990), detection of faults and targets is better (Horne, Brass, & Petitt, 1980), and working memory is more accurate (May, Hasher, & Stoltzfus, 1993; Petros,

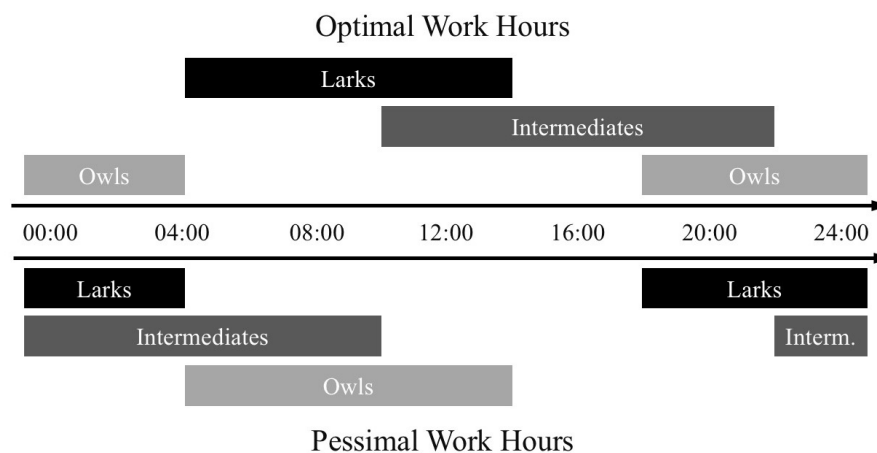
³⁷ Inhibitory control refers to the ability to suppress pre-potent responses in favour of goal-directed behavior.

Beckwith, & Anderson, 1990; Schmidt et al., 2015). Broadly, this research suggests that an individual's optimal performance timing will often mirror his or her phases of circadian arousal (Ingram et al., 2016).³⁸

Building on this notion of synchrony effect, Figure 5-1 presents a simplified theoretical model of optimal and pessimal performance times by chronotype. In this model, morning larks' optimal period of performance occurs somewhere between the hours of 04:00 to 14:00, and their pessimal period of performance occurs somewhere between 18:00 to 04:00; these optimal and pessimal periods of performance are reversed for night owls. Intermediate types, representing between 60-80% of the population, have a wider optimal performance window falling somewhere between these poles (between 10:00 and 22:00). Likewise, they have a relatively wide pessimal performance window, somewhere between 22:00 and 10:00. Larks, owls, and intermediate-types induced to work during pessimal windows are assumed to be prevented from expressing their true performance potential that might otherwise be expressed during optimal windows (Walker, 2018).

In reality, it is unlikely that optimal and pessimal performance periods will align entirely with chronotype. This is particularly true for intermediate types, for whom the location and width of optimal and pessimal performance windows will likely vary widely. For the purposes of the current discussion, this model serves to show a simplified framework by which to understand daily peaks and troughs in arousal by chronotype. More broadly, it shows how our endogenous circadian clocks might influence when we function best. In the following discussion, I apply these concepts of optimal and pessimal work hours to form hypotheses related to the potential influence of chronotype on preferences for night shift work.

³⁸ In his recent book, *Why We Sleep*, Walker (2018) suggests these synchrony effects may be linked to activity in the prefrontal cortex, the region at the front of the forebrain that controls high-level thought and logical reasoning. He argues, for example, that, "...when an owl is forced to wake up too early, their prefrontal cortex remains in a disabled, "offline" state. Like a cold engine after an early-morning start, it takes a long time before [the prefrontal cortex] warms up to operating temperature, and before that, it will not function efficiently" (p. 21).

Figure 5-1. *Theoretical Optimal and Pessimial Work Schedules, by Chronotype*

Notes: These hypothetical windows of optimal and pessimal performance are consistent with previous research documenting peaks and troughs in circadian arousal by chronotype (e.g., Hasher, Zacks, & May, 1999; May & Hasher, 1998).

2.3. WORK SCHEDULE TIMING AND RATIONAL CHOICE

The adoption of a rational choice model is particularly useful for understanding how chronotype might affect one's preferences for night shift work. A dynamic rational choice (or rational actor) model is one that helps us to understand how individuals make decisions under circumstances of uncertainty and incomplete information.³⁹ As Elster (1989) notes, the central explananda of rational choice theory are actions, which are assumed to stand in an optimizing relationship with the preferences and beliefs of the agent. That is, the action should provide the best means of satisfying the agent's preferences, given her beliefs and given the constraints imposed on her. Elster (1989) further argues that rational action can be thought of as the product of three separate but related optimization processes: (1) finding the best action, for given preferences, beliefs and constraints; (2) developing the most appropriate belief given the evidence at hand; and (3) collecting the correct amount of evidence while taking into account given preferences

³⁹ Following Huber (1997), when referring to rational choice theory, I refer not to the typical formulation in economics (i.e., the formal elaboration of decision-making constraints on utility maximization), but to the less restrictive model based on the assumption of purposive and conscious choice behavior. Such a model assumes that human action is goal-directed and is guided by a core set of values and beliefs.

and prior beliefs. The core assumption of this framework (and others like it) is that typical actors will on average try to act rationally to achieve an optimal outcome given an array of possible options and given a set of beliefs, preferences, and constraints (Green & Shapiro, 1994). For the purposes of this chapter, I illustrate rational choice using an exemplar optimal outcome: selecting into the work schedule that best suits one's true chronotype.⁴⁰

Consider a fictitious scenario where fully autonomous individuals with perfect information on their true chronotype can choose freely the location of paid work hours over the 24-hour day. If we assume that these individuals will on average prefer the work hours that will maximize cognitive and physiological performance and that will minimize deleterious health consequences, one would expect that, holding all other things constant, they will most often select into the work hours that are best aligned with peaks in their circadian arousal. Such a scenario would suggest that, given perfect information, unconstrained autonomy, and rational preferences, individuals will on average choose the work schedule best suiting their own unique chronotype.⁴¹ By extension, this would suggest that individuals with the highest propensity for eveningness should on average have the highest probability of being observed in night shift work hours; similarly, those with the highest propensity for morningness should have the lowest probability of being observed in night shift work hours. I therefore propose the following naïve

⁴⁰ There are of course many other factors that would contribute to the perceived utility of a given work schedule (e.g., compensation rate, the sociability of working hours, working conditions, etc.). However, in the interest of a more concise framework, I focus here only on the utility derived from work hours that align to one's endogenous circadian clock. This utility could come through increased physiological or cognitive performance on the job as well as the through the avoidance of deleterious health outcomes that might come from working hours that are incongruent with one's chronotype.

⁴¹ For theoretical simplicity, I have assumed here that individuals will on average prefer to reserve their chronotypically optimal hours for work. However, it is possible that many individuals might prefer to instead reserve their chronotypically optimal hours for activities or responsibilities outside of work. For example, for mothers or fathers with dependent children living in the household, a core priority may be to arrange work hours such that one has sufficient energy and cognitive resources to be able to tend to their children's cognitive and social development outside of work. Such a scenario would suggest that the relationship between eveningness and night work will partially depend on one's household structure and life course stage. However, due to insufficient measures of household structure and also largely owing to the older ages of the UK Biobank sample (the youngest of which are 40), I lack the data to test these assertions. I will return to these ideas in the Discussion section when presenting areas for further research.

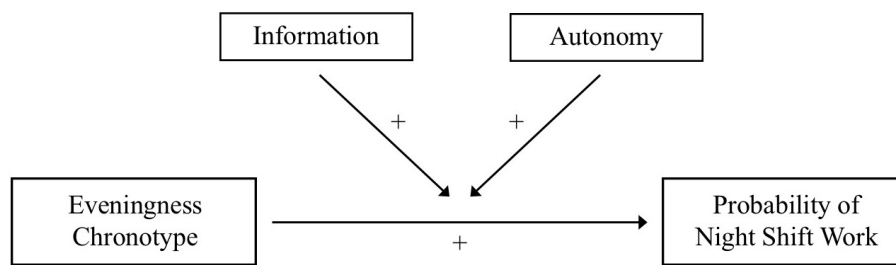
hypothesis: H_1 Eveningness will increase the probability of being observed in a night shift work schedule.

However, decisions surrounding the timing of paid work are rarely so straightforward. Indeed, choosing whether to enter into night shift work hours in the first instance comes with several decision-making problems where rational choice can further aid us. First, individuals have incomplete information about what times of day constitute their chronotypically optimal work hours. Related to this, those who have never worked a night shift schedule before will be uncertain about the consequences of these work hours for their own, and indeed their family's health. Therefore, without direct experience working in these shifts, actors are less able to reliably assign subjective probabilities to the various outcomes of their choice to work night shifts. Third, it is hard for actors to know how much evidence is needed to inform a rational decision of working night shifts; moreover, it is often too costly and time-consuming to gather this evidence. Fourth, even in the presence of complete information, individuals rarely have full autonomy to select work hours freely: rational deliberations of what constitute optimal work hours are bounded by the constraints imposed upon them by their employers, the nature of their jobs, and other household and non-work obligations.

For these reasons, it is unlikely that the perfect synchrony between actual and optimal work hours idealized in Hypothesis 1 will always occur. Indeed, while one can assume that individuals will on average prefer their chronotypically optimal work hours, they may have incomplete information on what constitute optimal work hours and imperfect autonomy to then select into these hours. Therefore, there will likely often be a mismatch between individuals' actual and optimal work schedules such that those best suited to daytime work hours will instead select into night shift work schedules and vice versa. Returning to Elster's (1989) model of rational action, I expect the strength of this mismatch to be a function of: (1) the amount of information individuals possess on their true chronotype (i.e., the amount of evidence upon

which beliefs are based), and (2) the amount of autonomy individuals possess to select into their optimal work hours (i.e., the level of constraints on action). This simple model is presented in Figure 5-2 and elaborated on in the following discussion.

Figure 5-2. *Directed Acyclic Graph of Eveningness and Nonstandard Work Hours*



Notes: Eveningness chronotype refers to an individual's true level of eveningness. Information refers to the amount of evidence an individual has acquired on her true chronotype. Autonomy refers to the degree to which an individual is able to freely select the timing of her work hours.

2.3.1. INFORMATION AS A MODERATOR

An individual's ability to select into her optimal work hours (and select out of her pessimal work hours) will depend in part on the level of awareness she has on her true chronotype. It is, however, unlikely that any individual will have an innate awareness of her true chronotype without gathering evidence over time through exposure to environments that are either concordant or discordant with her true chronotype. For example, an individual with a high predisposition towards morningness might only be made aware of such a predisposition by being placed in a context where she is induced to stay up late at night over an extended period. Over time, this discordance between the actual and optimal organization of waking and non-waking hours would provide evidence for the times of day at which functioning is sub-optimal: in the short-term, such evidence could come in the form of the fatigue and/or decreased performance she experiences; in the long-term, such evidence could come in the form of more distal social or physiological consequences. In a process akin to operant learning (Skinner, 1937), individuals experience rewards and penalties from contexts that are discordant or

concordant with their true chronotype. These penalties and rewards then provide the evidence that informs subsequent actions, such as the decision to select into or out of a night shift work schedule.

While it is difficult to measure directly the level of evidence an individual has gathered on her true chronotype, one way to roughly approximate this would be to look at the amount of time she has had to gather such evidence, or more simply, her chronological age. If we assume that individuals acquire evidence over time on their true chronotype through processes of operant learning, then it would follow that the amount of evidence an individual has acquired on her endogenous clock should be roughly collinear with the number of years she has had to acquire such information. Such a contention would be consistent with tenets of experiential learning theory (Kolb, 1984), which posits that the accumulation of direct experience with chronological age leads to greater quantity and quality of information; over time, this information is then organized and refined into theories and beliefs that serve as vehicles for decision-making (Kuhn et al., 1995; Salthouse, 2003). If in the present case information acquisition operates as a function of chronological age, it would follow that older individuals, *ceteris paribus*, will possess more evidence of their true chronotype. If we further assume that individuals will utilize this evidence to inform decisions surrounding the timing of paid work, one would expect that the link between eveningness and night shift work will be stronger for older individuals and weaker for younger individuals. I therefore propose the following hypothesis: H_2 The effect of eveningness on the probability of being observed in a night shift work schedule will increase with chronological age.

2.3.2. AUTONOMY AS A MODERATOR

The preceding hypothesis is premised in a somewhat fictitious labour market where, after gathering information on her true chronotype, an individual then faces no constraints in

selecting into her optimal work schedule or out of her pessimal work schedule. However, knowledge of one's true chronotype is only valuable if that individual has the autonomy to act on this information. Indeed, one's ability to select into her optimal work schedule will in part also depend on the level of job constraints she faces. From a labour supply perspective, workers' decisions surrounding the number and arrangement of work hours are based not only on their preferences and compensation rate but also on the constraints imposed on them by their employer and the nature of their job (Golden, 2001).⁴² These occupational constraints will partially determine the extent to which individuals are able to align their actual and optimal work hours.

A crucial form of occupational constraint is the level of autonomy one has over the timing of his or her work hours. Indeed, one's ability to select particular working hours in a job should depend on the degree of flexibility and control she has over the hours she works (Nadler, Voyles, Cocke, & Lowery, 2016). This flexibility and control can come in the form of institutionalized work-schemes like flexi-time or variable-hour schedules, or more informal company-specific arrangements that allow workers to vary the start and end of work times flexibly. Much research has shown that these forms of work schedule autonomy are highly valued by employees as they can help reduce conflicts between work and non-work responsibilities such as family obligations (Deutsch, 1999; Fenwick & Tausig, 2001; E. Kelly, Moen, & Tranby, 2011; Lombard, 2001; Lozano et al., 2016; Staines & Pleck, 1986). Less is known about how scheduling autonomy might reduce conflicts between the timing of an individual's optimal and actual work hours. Nonetheless, if we assume that individuals will on average prefer their optimal work hours, we would expect that the relationship between actual

⁴² Constraints tied to an individual's household situation (for example, the presence of young children) as well as her health status will likely also condition the amount of autonomy that individual has to freely select work hours. However, due to a lack of adequate measures within the currently-used UK Biobank release and in the interest of a more focused framework, these factors will be out of the purview of the current chapter. That said, I will return to them later when discussing areas for further research.

and optimal work hours to be strongest for those individuals with the most autonomy to schedule their work hours freely.

The dataset used in the current analysis does not include a direct measure of scheduling autonomy; indeed, such a construct can often be difficult to measure in general. However, one way to approximate scheduling autonomy would be to look at an individual's level of bargaining power with her current employer. Research from the US has found that access to work schedule autonomy and flexibility, particularly on an informal basis or agreement, is not evenly distributed across the labour market; it is an amenity afforded most often to those in jobs at the top of the occupational ladder as well as to those with the most bargaining power (Golden, 2001; Henly et al., 2006). To the extent that such patterns hold in the UK, one would then expect any positive relationship between eveningness and night work hours to be strongest for those with the most bargaining power. These individuals should, *ceteris paribus*, face the fewest constraints in selecting work schedules best suited to their chronotypes. I test this contention by using the duration of time an individual has spent with her current employer as a proxy measure for bargaining power. Employment tenure should roughly capture the amount of seniority a worker has accrued with her current employer as well as the level of job-specific skills and competitive advantage that worker has acquired (Abraham & Farber, 1987). These factors should, in part, determine the amount of leverage a worker has in negotiating working conditions, such as the number and timing of work hours.⁴³ I thus propose the following

⁴³ It is plausible that employment duration will also capture the amount of evidence an individual has acquired on her true chronotype. Indeed, to the extent that (1) night shift work should over time reveal the underlying compatibility of the worker's true chronotype with such work hours, and that (2) individuals have the autonomy to act on this information, it would follow that night shift workers who have worked these arrangements the longest will be selective of those with chronotypes best suited to these hours. Therefore, if employment duration does positively moderate the relationship between eveningness and night shift work, it is possible that this reflects processes of operant learning rather than the effect of increased bargaining power. However, this issue should be minimized in the present case as the measure of employment duration being utilized only captures the amount of time an individual has worked for her current employer, rather than the duration of time she has spent in her current work schedule. This issue could be further minimized by looking at occupational class as a measure of bargaining power instead of or in conjunction with employment duration. However, job codes are not available in the release of UK Biobank data currently used. I return to this issue in the Discussion section.

hypothesis: H_3 The effect of eveningness on the probability of being observed in a night shift work schedule will increase with employment duration.

3. METHODS

3.1. DATA

To test these hypotheses, I use genetic and employment data from the UK Biobank (UKBB). The UKBB provides genetic, demographic, employment, and socioeconomic information on roughly 502,599 British respondents between the ages of 40-69. Data collection for the latest cross-sectional release occurred over the period of 2005-2018. The analytic sample for this analysis will be individuals of European ancestry⁴⁴ who at the time of data collection were in regular paid or self-employment of at least 12 hours per week and were between the ages of 40 to 59.⁴⁵ This amounted to a sample of 212,595 individuals. After removing cases with missing values on work schedule timing and/or self-reported chronotype, the sample was further reduced to 190,631 individuals. As I will be using genotype data as an instrument, it was necessary to further restrict the sample to only those individuals who had genotype data collected. Of the total sample of employed individuals between the age of 40-59, genotype data was available for 186,171 individuals. When including indicators of current employment duration in later stages of analysis, this sample is further reduced to 185,910. Details on sample restrictions can be found in Appendix 5-1.

⁴⁴ The UK Biobank only includes genotype data for individuals of European ancestry. While this may constrain the representativeness of estimates, restricting analysis to ethnically homogenous groups is necessary to avoid spurious genetic associations brought on by population stratification (Davey Smith & Hemani, 2014). For the purposes of the current analysis, it is also necessary to restrict the sample to individuals of European ancestry as this is also the sample on which the 23andMe GWAS was run.

⁴⁵ The UK Biobank does not distinguish between individuals in paid employment and those in self-employment in their measure of current employment situation. For this reason, employees and self-employed workers will be grouped into a single category. I return to this issue later.

3.2. CHRONOTYPE

In this and subsequent discussions, chronotype is conceptualized as a continuum that moves from extreme morningness on the left all the way to extreme eveningness on the right; focus will be on the extent to which a one-unit movement right along this continuum (i.e., an increase in eveningness) increases the probability of being observed in a night shift work schedule. As I will be utilizing a two-stage instrumental variable design (elaborated on later), this chronotype continuum will be measured in two ways: (1) through an individual's self-reports of his or her chronotype (the endogenous regressor), and (2) through an individual's genetically predisposed chronotype (the instrument). These measures and the techniques through which they are modelled are discussed in the following sections.

3.2.1. SELF-REPORTED CHRONOTYPE

The instrumented variable (or endogenous regressor) in this analysis will be self-reported chronotype. This will be derived from a survey item asking respondents to report whether they, "...consider [themselves] to be": (1) "definitely a morning person", (2) "more a morning than evening person", (3) "more an evening than a morning person", (4) "definitely an evening person", or (5) "do not know".⁴⁶ To aid in interpretability, I will construct a binary eveningness score from these responses by coding them as follows: "definitely a morning person" = 0, "more a morning than evening person" = 0, "more an evening than a morning person" = 1, and "definitely an evening person" = 1. Effect sizes reported for this binary eveningness score will then refer to the change in the probability of night shift work associated with being an evening rather than a morning person. Sensitivity analyses will be presented where the raw eveningness scale is treated as linear. Frequencies by response category can be found in Table 5-2.

⁴⁶ Individuals had the option not to respond to this question ($n=1,575$); these cases were coded as missing.

Table 5-2. *Coding and Frequencies of Chronotype Responses, by Gender*

Variable	Coding	Total		Women		Men	
		Freq.	Prop.	Freq.	Prop.	Freq.	Prop.
<i>Raw Eveningness Scale</i>							
Definitely a morning person	1	46,268	0.25	25,440	0.25	20,828	0.25
More a morning than an evening person	2	65,726	0.35	36,682	0.36	29,044	0.34
More an evening than a morning person	3	56,046	0.30	29,913	0.30	26,133	0.31
Definitely an evening person	4	17,870	0.10	9,122	0.09	8,748	0.10
<i>Binary Eveningness</i>							
Morning Person	0	111,994	0.60	62,122	0.61	49,872	0.59
Evening Person	1	73,916	0.40	39,035	0.39	34,881	0.41

Data Source: 2016 UK Biobank Data

Notes: Sample includes respondents between the ages of 40-59 in paid employment (including self-employment) of at least 12 hours per week who were genotyped and who had non-missing values on self-reported chronotype, employment duration, and work hours.

3.2.2. GENETIC PROPENSITY FOR EVENINGNESS

The instrumental variable (or exogenous regressor) for this analysis will be an individual's genetic propensity for eveningness, which is measured using a polygenic risk score (PGS). A PGS is an index that linearly aggregates the estimated effects of individual single nucleotide polymorphisms (SNPs) on a trait of interest derived from an association study across the genome (a so-called, Genome-Wide Association Study, GWAS). The score can be thought of as a measure of an individual's predisposition towards a given trait based on his or her unique genetic make-up. A PGS for individual i is defined as a weighted sum of that person's genotypes at J loci. The score can be expressed as

$$PGS_i = \sum_{j=1}^J x_{ij} w_j$$

where x is individual i 's genotype (0, 1, 2) at variant j and w is a weight constructed from coefficients derived from a GWA study. As discussed earlier, a PGS and its constituent SNPs can be used as instrumental variables to test for a causal relationship between two traits because

genotypes are randomly assigned at meiosis, therefore genetic association is not biased by confounding or reverse causation (Belsky & Israel, 2014; Davey Smith & Ebrahim, 2003; Katikireddi, Green, Taylor, Davey Smith, & Munafò, 2018).

The current PGS will be constructed using UK Biobank genotype data containing 784,256 directly-assayed SNPs across chromosomes 1 to 22.⁴⁷ On these SNPs, I utilize association results from a recent GWAS on self-reported morningness conducted on 89,283 23andMe participants across a total of roughly 8 million genotyped sites (Hu et al., 2016).⁴⁸ Morningness was measured in this GWAS dichotomously using two highly concordant online surveys that asked individuals to report if they were naturally a morning or night person.⁴⁹ The study identified 15 loci significantly associated with morningness at $p < 5 \times 10^{-8}$ or less, including seven near established circadian genes; these loci are summarized in Appendix 5-4.⁵⁰ To maximize power the current PGS will be constructed by summing the top-ranked 480 SNPs (weighted by their respective effect sizes) that overlapped with the directly-assayed SNPs present in the UK Biobank genotype data.⁵¹ In contrast to a top-hit approach where only those SNPs reaching genome-wide significance are used, this whole-genome approach assumes that a very large number of SNPs will make infinitesimal contributions to phenotypic variation (Purcell et al., 2007). Genotype data will be merged and cleaned using the PLINK toolset in Linux (Purcell et al., 2007), and the final PGS will be constructed using the PRSice package in

⁴⁷ Only a fraction of total SNPs in the human genome are measured on genotype chips. To account for this, the UK Biobank also provides ~9 million imputed SNPs based on a reference panel of haplotypes at a dense set of SNPs, indels and structural variants. However, due to storage constraints, I was at this stage constrained to using only the handful of total SNPs that were directly assayed. Issues related to this choice will be addressed later.

⁴⁸ More recent meta-analyses conducted on larger samples have identified more loci than the 15 identified using the 23andMe cohort; the most recent identifying a total of 351 at $p < 5 \times 10^{-8}$ (S. E. Jones et al., 2018). However, these analyses have included the UK Biobank cohort that will be used in the current analysis. As Wray et al. (2013) notes, using association results on the same genotype data that was used in the estimation of those association results will inevitably distort findings and lead to an overfitting bias.

⁴⁹ Among the 135,447 individuals who answered at least one survey, 75.5% were scored as morning or night persons. Individuals who provided neutral ($n = 32,842$) or discordant responses across the two surveys ($n = 309$) were removed. The authors report finding no significant differences in age, gender, or principal components when looking at the respondents who provided discordant responses across the two surveys.

⁵⁰ 13 of these loci were replicated in a more recent GWAS on the UK Biobank cohort (S. E. Jones et al., 2016).

⁵¹ 23andMe only allows authors using their data to release association results for the top-ranked 10,000 SNPs. Of these 10,000 SNPs, ~ 5% (480) were also present in the directly assayed UK Biobank genotype data.

R (Euesdon, Lewis, & O'Reilly, 2015). To aid in interpretability, PG scores will be standardized to a cross-sample mean of 0.

One issue with this whole-genome approach (and with the use of genes as instruments in general) is that of horizontal pleiotropy, or the tendency of single genes to contribute to many phenotypic traits. Broadly, horizontal pleiotropy reflects the fact that most proteins have multiple roles in distinct cell types; thus, any genetic change that alters gene expression or function can potentially have wide-ranging effects in a variety of tissues (Hodgkin, 1998; Lobo, 2008). Therefore, in the present case, if a PGS for eveningness positively affects night shift work selection, it is unclear whether this association derives from an eveningness-inducing effect of the constituent SNPs (as hypothesized) or instead from some unmeasured biological pathway. If the latter, this could call to question the validity of the exclusion restriction criterion necessary for instrumental variable approaches.⁵² I return to the issue of horizontal pleiotropy in subsequent discussions and elaborate further on forms of pleiotropy in Appendix 5-5.

A final more general issue worth noting here is that the 23andMe GWAS on morningness – and other GWA studies like it (S. E. Jones et al., 2018; S. E. Jones et al., 2016; Lane et al., 2016) – have relied on self-reports of morningness/eveningness as the phenotype of interest. As I have argued earlier, self-reports of chronotype as a measure of one's true chronotype will likely be highly susceptible to non-random measurement error; patterns of socialization and – more importantly – the timing of one's work schedule over time will likely affect how individuals will respond to such questionnaires. However, biases relating to measurement error should be reduced in the present context as I will be instrumenting these self-reports with genotypic variation. As Lane et al. (2016) argue, since individuals do not know their genotype, any phenotypic misclassification (i.e., misreported self-identified chronotype)

⁵² The exclusion restriction criterion requires there to be no causal pathway between an instrument and an outcome except through the instrumented variable (Katikireddi et al., 2018)

will be random with respect to genotype. I return to the validity of this contention in the subsequent discussions.

3.3. NIGHT SHIFT WORK

The dependent variable for this analysis will be a binary indicator capturing whether the respondent reports working regular night shifts in his or her main job at the time of data collection. This measure will be derived from a two-part question asked to individuals in paid or self-employment at the time of data collection. Respondents were first asked whether their main job involves shift work, or "...a schedule that falls outside of the normal daytime hours". Individuals who responded "sometimes", "usually", or "always" were then asked whether their "...work involve[s] night shifts." Night shifts are defined in the UK Biobank questionnaire as, "...a work schedule that involves working through the normal sleeping hours, for instance working through the hours of 12:00 am and 6:00 am." If respondents had more than one job, they were advised to answer this question regarding their main job only. Using responses from this second question, I code individuals as night shift workers if they reported working night shifts either "sometimes" ($n = 10,039$), "usually" ($n = 2,698$), or "always" ($n = 4,802$). I then code respondents as non-night shift workers if they reported working night shifts "never/rarely" ($n = 16,673$), or if they reported "never/rarely" working shifts ($n = 168,371$) in the first part of the question. This amounted to a total sample of 17,539 night shift workers and 168,371 non-night shift workers. Sensitivity analyses will be presented where the uncollapsed continuous measure of the regularity of night shift work measure used. Frequencies for raw and recoded responses can be found in Table 5-3.

Table 5-3. *Coding and Frequencies of Night Shift Work Responses, by Gender*

Variable	Coding	Total		Women		Men	
		Freq.	Prop.	Freq.	Prop.	Freq.	Prop.
<i>Job involves night shift work</i>							
Never/rarely ^a	1	168,371	0.91	94,187	0.93	74,184	0.88
Sometimes	2	10,039	0.05	4,019	0.04	6,020	0.07
Usually	3	2,698	0.01	1,041	0.01	1,657	0.02
Always	4	4,802	0.03	1,910	0.02	2,892	0.03
<i>Final Coding</i>							
Non-night shift worker	0	168,371	0.91	94,187	0.93	74,184	0.88
Night shift worker	1	17,539	0.09	6,970	0.07	10,569	0.12

Data Source: 2016 UK Biobank Data

Notes: Sample includes respondents between the ages of 40-59 in paid employment (including self-employment) of at least 12 hours per week who were genotyped and who had non-missing values on self-reported chronotype, employment duration, and work hours. ^a Category includes individuals who responded that job “never/rarely” involved shift work in the first part of the question (Total = 152,325; Women = 85,426; Men = 66,899).

3.4. OTHER COVARIATES

Along with testing the direct effects of eveningness on night shift work selection, I am also interested in exploring the extent to which this relationship might depend on the level of information one has on her true chronotype as well as the level of autonomy she has to freely select into her optimal work hours. To approximate the level of information one has on her true chronotype, I use the respondent’s chronological age (in years) at the time of data collection. To approximate the level of autonomy one has to freely select into her optimal work hours, I use the duration (in years) that the respondent reports having worked in their current job at the time of data collection. As discussed earlier, such a measure should on average be roughly collinear with the level of bargaining power an individual can use to negotiate the organization of working hours. To test for interaction effects over age and employment duration, both covariates will be broken into quantiles and separate models will be run per quantile.⁵³ The

⁵³ Quantiles were generated automatically using the ‘xtile’ function in Stata.

criteria for selecting the number of quantiles was to choose the maximum number of quantiles that would: (1) produce relatively equal sample sizes per quantile; (2) ensure sufficient sample sizes within each quantile; and (3) produce substantively meaningful differences in age or employment tenure between quantiles. For employment duration, 6 quantiles were constructed, and for age, 5 quantiles were constructed (summarized in Table 5-4). Sensitivity analyses are presented later with different quantile-specifications.

Table 5-4. *Descriptive Statistics of Age and Employment Duration Quantiles*

Quantile	Age (years)			Employment Duration (years)		
	Range	Freq.	Prop.	Range	Freq.	Prop.
1	40-45	41,846	0.23	0-2	31,258	0.17
2	46-49	38,517	0.21	3-5	31,889	0.17
3	50-54	41,871	0.23	6-9	29,991	0.16
4	55-56	32,731	0.18	10-15	31,697	0.17
5	57-59	30,945	0.17	16-23	30,826	0.17
6				24-46	30,249	0.16

Data Source: 2016 UK Biobank Data

Notes: Sample includes respondents between the ages of 40-59 in paid employment (including self-employment) of at least 12 hours per week who were genotyped and who had non-missing values on self-reported chronotype, employment duration, and work hours.

I control for the age and sex of the respondent, which are assumed to be independent of the error terms. Given that the instrument being utilized is in theory highly exogenous, the potential of confounding is limited.⁵⁴ However, one source of potential confounding in genetic associations is population stratification, or the presence of systematic differences in allele frequencies between subpopulations in a study due to ancestry differences between study subjects (M. Li, Reilly, Rader, & Wang, 2010). To account for this, I adjust for genome-wide principal components (PCs) that function as ancestry markers (Price et al., 2006). Here, PCs are generated on the genotype data to infer continuous axes of genetic variation by ancestry;

⁵⁴ This, of course, excludes potential confounding tied to horizontal pleiotropy. I discuss this issue in further detail in Appendix 5-3.

for ease, the UK Biobank provides the top-ranking 20 PCs in their phenotypic data release. I then control for the first five PCs in all analyses that include polygenic risk scores.

3.5. ANALYTIC TECHNIQUE

The primary aim of this chapter is to explore whether eveningness increases the probability of being observed in a night shift work schedule. To test this, I utilize Mendelian Randomization techniques in a two-stage structural model where, in the first-stage, self-reported eveningness is regressed on the polygenic score for eveningness. In the second-stage, this Mendelian Randomized measure of eveningness (the predicted values from the stage-one model) is then used to assess the causal effect of eveningness on the probability of night shift work. This two-stage estimation can be expressed as

$$\hat{Y} = \delta_0 + \delta_1 z + \delta_2 PC_1 \dots \delta_6 PC_5 + \delta_7 Age + \delta_8 Sex + v$$

$$Y = \beta_0 + \beta_1 \hat{Y} + \beta_2 PC_1 \dots \beta_6 PC_5 + \beta_7 Age + \beta_8 Sex + u$$

where, in the first-stage equation, $\hat{Y}$ represents Mendelian Randomized eveningness and z represents the polygenic score for eveningness (the instrument). In the second-stage equation, Y represents the linear probability of being observed in a night shift schedule at the time of data collection. $PC_1 \dots PC_5$ (the first five genetic principal components), Age , and Sex are controlled for in both stages and are assumed to independent of error terms, v and u . Models are run using the ‘ivreg2’ package in Stata (Baum, Schaffer, & Stillman, 2002), and both the stage-one and stage-two outcomes are treated as linear.⁵⁵ Coefficients from stage two will therefore represent

⁵⁵ Stage one and two equations are estimated using linear probability models (LPM). A well-recognized flaw of a LPM is that its fitted values are not constrained to lie within the unit interval; therefore, it's possible that probabilities of > 0 or < 1 may be encountered. However, focus here is on estimating the marginal effects for a limited range of X values. Therefore, it makes little substantive difference to use an LPM, with its constant marginal effects, rather than the more complex marginal effects derived from a conditional distribution function such as a probit model where results are largely indistinguishable (Angrist & Pischke, 2008; Baum, Dong, Lewbel, & Yang, 2012; Wooldridge, 2013). That said, sensitivity analyses will be presented where the stage one and

the change in the linear probability of working a night shift associated with a one unit change in Mendelian Randomized eveningness. Sensitivity analyses will be presented where bivariate probit models are estimated instead of 2SLS linear probability models as well as where the uncollapsed continuous self-reported eveningness scale is used in stage one and the uncollapsed regularity of night shift work scale is used in stage two; both outcomes will again be treated as linear.⁵⁶

An important point general to the use of instrumental variable estimation is that such models will only provide estimates of local average treatment effects (LATEs), or the effects of eveningness on the probability of night shift work for those individuals induced to eveningness by their genetic make-up (so-called, compliers). Given that chronotype is a complex phenotype with many contributing non-genetic factors, such estimates will inevitably obscure some of the picture of how chronotype affects preferences surrounding work schedule timing. I return to this point in subsequent discussions.

To test whether and how the effects of eveningness on the probability of night work might depend on the level of information and autonomy an individual has (Hypotheses 2 and 3, respectively), I run separate 2SLS regressions of night work on Mendelian Randomized eveningness over quantiles of age and employment duration; for an outline of these quantiles, see Table 5-4. Coefficients and confidence intervals will then be compared across quantiles to draw interpretations on the moderating effects of age and employment duration. I opted for quantile-specific regressions rather than the inclusion of interaction terms into models for two

reduced form models are run using probit regression; for the two-stage structural model, the ‘biprobit’ Stata package will be used.

⁵⁶ The choice to primarily use the dichotomized measures of eveningness and night shift work was made in the interest of interpretability. Despite sacrificing variation in predictor and outcome variables, these operationalizations will allow one to depict how being an evening (rather than a morning) person changes the probability of being observed in a night shift work schedule. In contrast, drawing substantive meaning from the uncollapsed measures of eveningness and night shift work is slightly more difficult. Such operationalizations will show how a one-unit change in self-reported eveningness (for which there are only four values that are not necessarily equidistant) changes the regularity of night shift work (for which there are again only four non-equidistant values). That said, every estimate from a binary specification of eveningness and/or night work will be accompanied by sensitivity analyses which model uncollapsed continuous specifications of either variable.

reasons. First, such an approach is non-parametric, making no assumptions on the shape of interaction effects. Second, and perhaps most importantly, employment duration is likely endogenous with respect to the likelihood to work night shifts (i.e. one's willingness to work night shifts may affect his or her ability to stay with a given firm or in a given job). Therefore, without a separate instrument for employment duration, it is not viable to model its interaction with instrumented eveningness without invalidating the assumptions of instrumental variable regression.

4. RESULTS

Before testing this study's hypotheses, I first assess the strength of the current eveningness PGS as an instrument by estimating: (1) the first stage equation (i.e., the effect of the PGS on self-reported eveningness); and (2) the reduced form equation (i.e., the effect of the PGS on the probability of night shift work). For a full discussion of the satisfaction of the conditions necessary for the use of IV estimation, please see Appendix 5-4.

Table 5-5 presents results of the first-stage equation where self-reported eveningness is regressed on the PGS for eveningness. As can be seen, PG scores for eveningness positively and significantly predict self-reported eveningness. A one standard deviation increase in polygenic risk for eveningness increases the linear probability of self-reported binary eveningness by 2.5% ($p < 0.001$). Marginal effects estimated from a probit regression (Appendix 5-5) produce largely indistinguishable results ($b = 2.5\%$, $p < 0.001$). Sensitivity analyses that model the raw continuous eveningness scale (Appendix 5-6) indicate that a one standard deviation increase in polygenic risk for eveningness increases self-reported eveningness by 0.05 units ($p < 0.001$). Such findings suggest that the genetic propensity for eveningness is indeed a strong predictor of self-reported eveningness.

Table 5-5. *OLS Regressions of Self-Reported Eveningness (Binary) on PGS for Eveningness*

	Self-Reported Eveningness (Binary)	
	<i>Linear Probability</i>	
	1	2
Eveningness PGS (Std.)	0.0250*** (0.0011)	0.0247*** (0.0011)
Age		-0.0073*** (0.0002)
Male		0.0252*** (0.0023)
PC 1		-0.0001*** (0.00002)
PC 2		0.0001* (0.00004)
PC 3		-0.0006*** (0.0001)
PC 4		-0.00004 (0.0001)
PC 5		0.0021*** (0.0001)
N	185910	185910
F-Statistic	486.45***	262.01***
Adj. R-Squared	0.0026	0.0111

Data Source: 2016 UK Biobank Data

Notes: Sample includes respondents between the ages of 40-59 in paid employment (including self-employment) of at least 12 hours per week who were genotyped and who had non-missing values on self-reported chronotype, employment duration, and work hours. Robust standard errors are shown in parentheses. Coefficients represent the change in the linear probability of self-reporting as an evening person (rather than a morning person) associated with a one-unit increase in the corresponding variable. + $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

An important note here is the relatively weak predictive power of the PG scores on self-reported eveningness. In the unconditional model (column 1), PG scores for eveningness explain only around 0.3% of the variation in whether an individual self-identifies as an evening person or not. This small predictive power is also seen when using the uncollapsed measure of self-reported eveningness (Appendix 5-6). Although a highly significant F-statistic is observed (F-stat = 486.45, $p < 0.001$), this could point to the weakness of the current genetic instruments being utilized and highlight the need to integrate imputed SNPs in future research to capture

more of the genetic underpinnings of chronotype (the current PGS only includes 480 directly-assayed SNPs). Such findings also likely highlight the fact that chronotype is a complex phenotype that has many non-genetic contributing factors. For this reason, estimates derived from Mendelian Randomization procedures should be taken with a grain a salt when making conclusions on the total effect of chronotype on working schedule timing. As discussed earlier, such estimates will only show the change in the marginal probability of night shift work attributed to the relatively small proportion of the total variance in self-reported eveningness caused by the SNPs included in the current PG scores.

I now assess the predictive power of the genetic instrument for eveningness on the probability of night shift work in a reduced form model; here, night work is regressed on the PG score for eveningness in a linear probability model. Results are shown in Table 5-6. As can be seen, a one-unit increase in polygenic risk for eveningness increases the probability of night shift work by 0.2% ($p < 0.001$). Marginal effects computed from a probit regression (Appendix 5-5) again produce largely indistinguishable results ($b = 0.2\%$, $p < 0.001$). Sensitivity analyses reveal that this effect remains significant ($b = 0.004$, $p < 0.01$) when using uncollapsed continuous measures of both eveningness and the regularity of night shift work (Appendix 5-6). While these effects are small, they are highly significant and indicate that the genetic propensity for eveningness increases the likelihood of night shift work. I now proceed to testing the hypotheses presented in this study.

Table 5-6. *Reduced Form OLS Regression of Night Shift Work (Binary) on PGS for Eveningness*

	Night Shift Work (Binary)	
	Linear Probability	
	1	2
Eveningness PGS (Std.)	0.0024*** (0.0007)	0.0021*** (0.0007)
Age		-0.0021*** (0.0001)
Male		0.0559*** (0.0013)
PC 1		0.0001* (0.00004)
PC 2		-0.00001 (0.00002)
PC 3		0.0001** (0.0001)
PC 4		0.00004* (0.0001)
PC 5		0.00003* (0.00001)
N	185910	185910
F-Statistic	12.52***	474.61***
Adj. R-Squared	0.0001	0.0200

Data Source: 2016 UK Biobank Data

Notes: Sample includes respondents between the ages of 40-59 in paid employment (including self-employment) of at least 12 hours per week who were genotyped and who had non-missing values on self-reported chronotype, employment duration, and work hours. Robust standard errors are shown in parentheses. Coefficients represent the change in the linear probability of night shift work associated with a one-unit increase in the corresponding variable. + $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

In Hypothesis 1, I predicted that eveningness would increase the probability of night shift work. Table 5-7 shows results of linear probability models where night shift work (binary) is regressed on a binary (Column 1) and continuous (Column 2) specification of self-reported eveningness. As can be seen, self-reporting as an evening rather than a morning person increases the linear probability of being observed in a night shift work by 2% ($p < 0.001$). Similarly, a one-unit increase in self-reported eveningness increases the probability of night shift work by 1% ($p < 0.001$). These estimates provide initial evidence that eveningness is positively associated with night shift work. However, as discussed earlier, given that cross-

sectional data is in use, the direction of this effect is at this stage tenuous. As circadian rhythms entrain to one's environment, it is highly plausible – and indeed, very likely – that night shift work will increase the likelihood of self-reported eveningness. This reverse causation issue provides the justification for the use of Mendelian Randomization techniques that will be used in the subsequent stage of analysis.

Table 5-7. *OLS Regression of Night Shift Work (Binary) on Self-Reported Eveningness*

	Night Shift Work (Binary)			
	Linear Probability			
	1	2	3	4
Self-Reported Eveningness (Binary)	0.0260*** (0.0014)	0.0225*** (0.0014)		
Self-Reported Eveningness (Continuous)			0.0120*** (0.0007)	0.0102*** (0.0007)
Age		-0.0023*** (0.0001)		-0.0023*** (0.0014)
Male		0.0548*** (0.0014)		0.0549*** (0.0014)
N	185910	185910	185910	185910
Adj. R-Squared	0.0019	0.0125	0.0015	0.0121

Data Source: 2016 UK Biobank Data

Notes: Sample includes respondents between the ages of 40-59 in paid employment (including self-employment) of at least 12 hours per week who were genotyped and who had non-missing values on self-reported chronotype, employment duration, and work hours. Robust standard errors are shown in parentheses. Coefficients represent the change in the linear probability of night shift work associated with a one-unit increase in the corresponding variable. + $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

Table 5-8 shows the results of a 2SLS linear regression of night shift work (binary) on eveningness; here, self-reports of eveningness (binary) are instrumented with the polygenic score for eveningness. As can be seen, a one-unit increase in Mendelian Randomized eveningness increases the linear probability of being observed in a night shift schedule by 9.6% ($p < 0.001$); this effect decreases to 8.7% but remains significant when accounting for age, sex,

and population stratification⁵⁷. Crucially, significant Wald exogeneity test statistics⁵⁸ indicate that self-reported eveningness cannot be treated as exogenous in relation to night shift work, validating the need for a Mendelian Randomization approach. Significant Cragg-Donald F statistics⁵⁹ also indicate that the current analysis is not subject to a weak instrument bias. Sensitivity analyses reveal that when estimating through a bivariate probit model⁶⁰ rather than a linear probability model (Appendix 5-5), marginal effects attenuate but remain significant ($b = 0.0801$, $p < 0.01$). Moreover, when using uncollapsed continuous measures of both eveningness and the regularity of night shift work (Appendix 5-6), the effects of eveningness on the regularity of night shift work remain significant ($b = 0.0761$, $p < 0.001$).

Taken together these findings support the first hypothesis that an eveningness chronotype does indeed increase the probability of working at night, an effect that appears to be causal. This provides evidence that individuals tend to select into the optimal work hours best suiting their own unique circadian rhythm – even if these hours are nonstandard in nature. However, as discussed, these coefficients show the local average treatment effect (LATE) of eveningness, or the effect of eveningness attributed to the eveningness-inducing genotypes measured in the current polygenic score. That these LATEs are markedly higher than estimates shown when regressing the probability of night shift work on self-reports of eveningness (Table 5-6) is important to note. Indeed, plotting and comparing coefficients derived from self-reported

⁵⁷ Note that, as one would expect from a just identified model, the IV estimate is roughly equal to the ratio of the reduced form coefficient on the instrument to the first stage coefficient. The slight deviation is due to rounding.

⁵⁸ The Wald exogeneity test, included as part of the ‘ivreg2’ package in Stata, produces a test statistic similar to that produced by the Durbin-Wu-Hausman test. The test determines whether the error terms in the structural equation and the reduced-form equation for the endogenous variable are correlated. The null hypothesis being tested is that the specified endogenous regressor can be treated as exogenous; therefore, significant test statistics indicate the specified regressor is endogenous.

⁵⁹ To test for weak instrument bias, I compare the Cragg-Donald Wald F statistic to the Stock-Yoko weak ID test critical value at 10% (16.38). A test statistic larger than a critical value of 16.38 indicates that the instrument will lead to a rejection rate of $< 10\%$ when true rejection rate is 5% and is thus not a weak instrument.

⁶⁰ Bivariate probit regression – estimated using the ‘biprobit’ package in Stata – fits two seemingly unrelated probit models with correlated error terms. As with 2SLS regression, it aims to correct for the error correlation between self-reported eveningness and night shift work. In the present case, two models are fit simultaneously: (1) binary self-reported eveningness is regressed on the PGS for eveningness and the exogenous control variables; (2) binary night shift work is regressed on self-reported eveningness and the exogenous control variables.

eveningness and genetically-instrumented eveningness (Appendix 5-7) shows that coefficients from structural models are always significantly higher ($p < 0.05$), regardless of the modeling technique (i.e., 2SLS or bivariate probit) and regardless of the whether continuous or binary specifications of night work and eveningness are used. As can also be seen, estimates from structural models also have considerably wider confidence intervals, highlighting that standard estimates may be more efficient than IV estimates, even if biased.

Table 5-8. *Mendelian Randomization Regression of Night Shift Work (Binary) on Eveningness*

Variable	Night Shift Work (Binary)	
	2SLS Linear Probability Model	
	1	2
Mendelian Randomized Eveningness (Binary)	0.0959*** (0.0253)	0.0865*** (0.0251)
Age		-0.0018*** (0.0002)
Male		0.0549*** (0.0015)
PC 1		0.00010* (0.00004)
PC 2		-0.00002 (0.00002)
PC 3		0.0003** (0.0001)
PC 4		0.00003* (0.0001)
PC 5		0.00004* (0.00001)
N	185910	185910
Cragg-Donald F Statistic (H0: weak instrument)	486.45***	477.47***
Wald Test of Exogeneity ^a (H0: Regressor is exogenous)	6.69**	5.89**

Data Source: 2016 UK Biobank Data

Notes: Sample includes respondents between the ages of 40-59 in paid employment (including self-employment) of at least 12 hours per week who had non-missing values on self-reported chronotype and who had genotype data available. Robust standard errors are shown in parentheses. Modified version of Durbin-Wu-Hausman test statistic created by Baum, Schaffer, and Stillman (2003). + $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

As Angrist and Pischke (2008) note, LATEs can often be larger than the ATEs approximated by traditional regression adjustment estimates in the presence of violations to the

monotonicity assumption or heterogeneous treatment effects. This divergence may also suggest the presence of an omitted variable bias when regressing night work on self-reports of eveningness. For example, educational attainment has been shown to be positively associated with self-reported eveningness (Lane et al., 2016) and negatively associated with entrance into night shift work (Hamermesh, 1996; Presser, 1987; Presser & Cox, 1997); the latter trend reflects the fact that night shift work is often concentrated in lower-status occupations and amongst those with the least human capital. While I abstain from a more detailed comparison of standard and Mendelian Randomization estimates at this stage, such a stark divergence could also be tied to the considerably higher inefficiency of the IV estimates (as can be seen in Appendix 5-7). I return to this issue in the Discussion section.

The above findings provide evidence that eveningness has a causal effect on shift work selection, or more generally, that night owls tend on average to be more likely to work at night. However, it is possible that the strength of the association between eveningness and shift work selection might vary depending on the level of information one has on her true chronotype as well as the level of autonomy one has to freely select into her optimal work schedule. As discussed earlier, an individual's ability to select into her optimal work schedule will likely require her to first have an awareness of at what hours of the day she functions best, information that can only be acquired over time through processes of operant learning. This information on what times of day best suit one's true chronotype is then likely only valuable if that individual has sufficient autonomy to act on this information. To test these assertions (Hypotheses 2 and 3, respectively), I run separate 2SLS regressions of night shift work on Mendelian Randomized eveningness over quantiles of age and employment duration; the former serving as a proxy measure for the amount of information one has acquired on her chronotype through operant learning, and the latter serving as a proxy for the level of bargaining power one has to select into her optimal work hours. For an outline of these quantiles, see Table 5-4.

In Hypothesis 2, I predicted that the effect of eveningness on the probability of night shift work would increase with age. Figure 5-3 plots the coefficients of 2SLS linear probability models over age quantiles, with a full table of quantile-specific effects shown in Table 5-9. As can be seen, the effect of eveningness on the probability of night shift work is non-significant for the first three age quantiles representing individuals age 40 to 53. The effect then reaches significance for individuals age 54-56 ($b = 0.138, p < 0.05$) and is largest for individuals age 57-59 ($b = 0.142, p < 0.05$). Such trends suggest that the effect of eveningness on the probability of night shift work is strongest for the oldest individuals in the sample. However, as the 95% confidence intervals overlap for all groups, there is insufficient evidence to conclude whether the effects of eveningness on the probability of being observed in night shift work vary significantly with age. Moreover, results of variance-weighted least squares regression⁶¹ (Table 5-9) suggest that the slope in effects across quantiles – while positive – is not statistically significant. Sensitivity analyses reveal that these patterns are consistent when breaking age into a larger number of quantiles ($n = 9$; Appendix 5-8) as well as when using continuous measures of both eveningness and the regularity of night shift work (Appendix 5-9). Similar trends are also observed when quantile-specific bivariate probit models are estimated (Appendix 5-10); however, marginal effects no longer reach significance in the oldest two age quantiles.

These findings lend partial support to Hypothesis 2, where it was predicted that age would positively moderate the relationship between eveningness and the probability of being observed in a night shift work schedule. This hypothesis was based on the contention that eveningness should become a stronger predictor of selection into night shift work as individuals

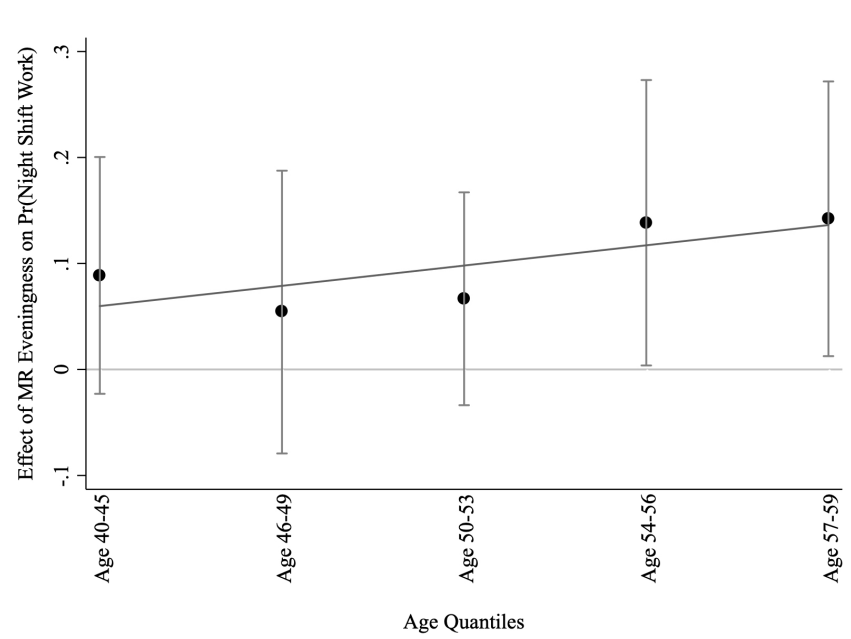
⁶¹ Variance-weighted least squares regression is performed using the in-built ‘vwls’ package in Stata. It treats each quantile as a single observation and summarizes the slope in effects across quantiles while accounting for heteroscedasticity. Slope estimation can be expressed as

$$b = (X'V^{-1}X)^{-1}X'V^{-1}y$$

where b represents the slope across quantiles, X represents quantile, y represents a vector of the quantile-specific coefficients, and V denotes the estimated variance of y . In the present case, the variance of y is simply the standard errors of y calculated in the quantile-specific 2SLS regressions.

grow older and gain more evidence on their true chronotype through processes of operant learning. Despite overlapping confidence intervals between quantiles and a non-significant positive slope across quantiles, the fact that effects are only significant for the oldest individuals in the sample does suggest that information may play a role in allowing individuals to select into optimal work hours (or select out of sub-optimal hours). Moreover, a key limitation to this analysis is the high ages of UK Biobank respondents, the youngest of which are age 40; this relatively narrow age bracket likely obscures a large portion of the moderating effect of age that might be observed had younger individuals been included in the sample.

Figure 5-3. *Linear Effects of Mendelian Randomized Eveningness (Binary) on the Probability of Night Shift Work, over Age Quantiles*⁶²



Notes: Results shown for quantile-specific 2SLS linear regression of night work (binary) on Mendelian Randomized eveningness (binary). Coefficients refer to the change in the linear probability of night shift work associated with a one-unit increase in eveningness. Control variables include sex, age, and the first five genetic principal components. Vertical capped lines indicate 95% confidence intervals.

⁶² Figures are produced by using the ‘*parmest*’ package in Stata to store coefficients and confidence intervals from 2SLS/bivariate probit models into a new dataset. After this, the in-built ‘two-way’ Stata plots are used.

Table 5-9. *Age and Employment Duration Quantile-Specific Mendelian Randomization Regressions of Night Shift Work (Binary) on Eveningness*

<i>2SLS Linear Probability Model</i>							
Age				Employment Duration			
Quantile	Range	Quantile-Specific Coefficient	<i>n</i>	Quantile	Range	Quantile-Specific Coefficient	<i>n</i>
1	Age 40-45	0.0887 (0.0570)	41846	1	0-2 yrs	0.1558*** (0.0591)	31258
2	Age 46-49	0.0541 (0.0681)	38517	2	3-5 yrs	0.1524** (0.0630)	31889
3	Age 50-54	0.0667 (0.0512)	41871	3	6-9 yrs	0.1886** (0.0783)	29991
4	Age 55-56	0.1384* (0.0687)	32731	4	10-15 yrs	0.1040 (0.0744)	31697
5	Age 57-59	0.1421* (0.0661)	30945	5	16-23 yrs	0.0037 (0.0634)	30826
				6	24-46 yrs	-0.0134 (0.0723)	30249
Slope Across Quantiles ^a		0.0169 (0.0198)	5	Slope Across Quantiles		-0.0378* (0.0155)	6

Data Source: 2016 UK Biobank Data

Notes: Sample includes respondents between the ages of 40-59 in paid employment (including self-employment) of at least 12 hours per week who had non-missing values on self-reported chronotype and who had genotype data available. Control variables include sex, age, and the first five genetic principal components. Results shown for linear regression of night shift work (binary) on Mendelian Randomized eveningness (binary). Coefficients refer to the change in the linear probability of night shift work associated with a one-unit increase in eveningness. Robust standard errors are shown in parentheses. ^a Calculated through variance-weighted least squares regression. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A competing explanation for the trends observed above would be that age is simply acting as a proxy for bargaining power rather than information. Therefore, it is not increased information that allows one to select into optimal work hours, but rather the increased autonomy and control one acquires over time on the hours in which they work. Indeed, in Hypothesis 3, I predicted that the effect of eveningness on the probability of night shift work would increase with employment duration and as one acquires more bargaining power. To test this contention, Figure 5-4 plots the coefficients of 2SLS linear probability models over employment duration quantiles, with a full table of quantile-specific effects shown in Table 5-9. In stark contrast to predicted trends, the effect of eveningness on the probability of night shift work is strongest for

those individuals with the shortest employment tenure. As can be seen in Table 5-9, the effect of eveningness is significant for individuals with employment tenures of 0-3 years ($b = 0.16$, $p < 0.001$), 3-5 years ($b = 0.15$, $p < 0.01$) and 6-9 years ($b = 0.19$, $p < 0.01$). However, the effects then decrease steadily across quantiles, becoming non-significant for individuals with 10-15 years of employment tenure and ultimately becoming negative (but not significant) for those with 24-27 years of tenure.

As confidence intervals overlap across all employment duration quantiles, there is insufficient evidence to infer whether the effects of eveningness on night work do indeed vary significantly by employment tenure. However, results of variance-weighted least squares regression (Table 5-9) suggest that the negative slope in effects across quantiles is statistically significant ($b = -0.04$, $p < 0.05$). Sensitivity analyses further reveal that these patterns are consistent when breaking employment duration into a larger number of quantiles ($n = 10$; Appendix 5-8) as well as when using continuous measures of both eveningness and the regularity of night shift work (Appendix 5-9). Similarly, consistent trends are also observed when quantile-specific bivariate probit models are estimated instead of 2SLS linear probability models (Appendix 5-10). The negative slope in effects across employment duration quantiles can also be seen when looking within age quantiles (Figure 5-5), suggesting this trend is consistent across the life course; the exception to this is for the youngest age quantile, where the trend appears relatively flat.

Figure 5-4. *Linear Effects of Mendelian Randomized Eveningness (Binary) on the Probability of Night Shift Work, over Employment Duration Quantiles*

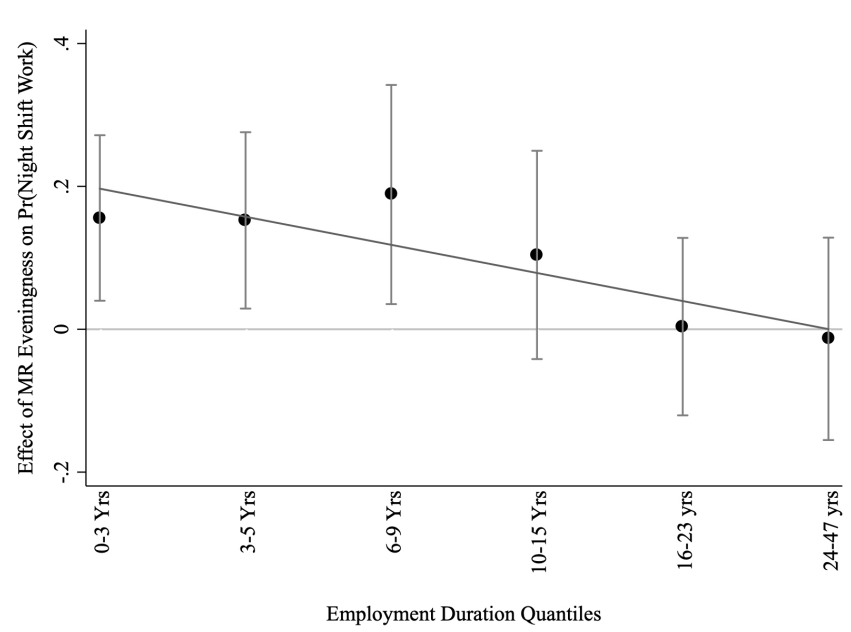
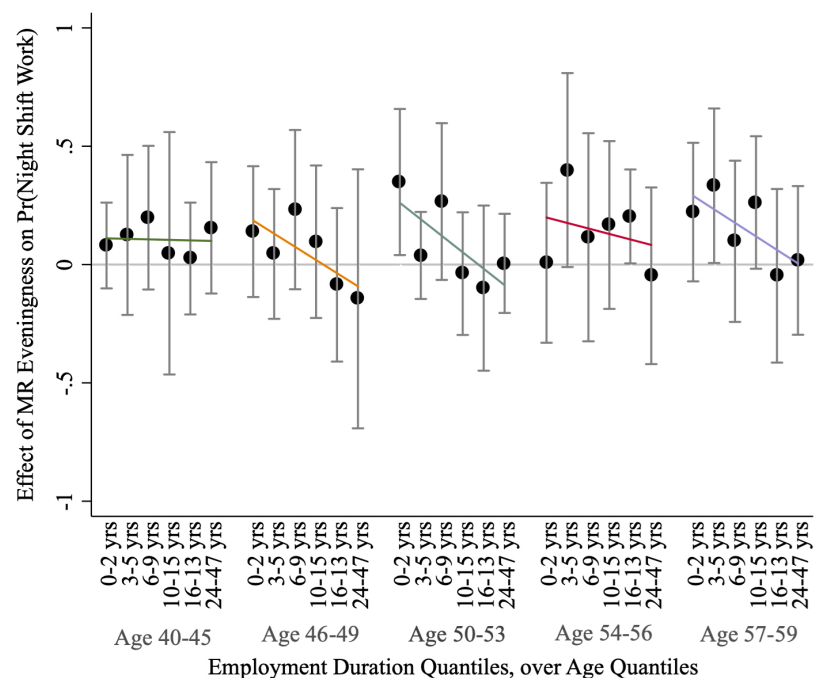


Figure 5-5. *Linear Effects of Mendelian Randomized Eveningness (Binary) on the Probability of Night Shift Work, over Employment Duration and Age Quantiles*



Notes (Figures 5-4 & 5-5): Results shown for quantile-specific 2SLS linear regression of night work (binary) on Mendelian Randomized eveningness (binary). Coefficients refer to the change in the linear probability of night shift work associated with a one-unit increase in eveningness. Control variables include sex, age, and the first five genetic principal components. Vertical capped lines indicate 95% confidence intervals.

Such results suggest that, in contrast to predictions made in Hypothesis 3, the effect of eveningness on the probability of being observed in night shift work is weakest for those individuals with the longest employment tenure. While these findings may highlight the limitations of employment tenure as a proxy for work schedule autonomy, they could also be tied to that fact that a longer employment tenure often comes with greater seniority as well as promotions to more managerial and supervisory roles within a company. Much research has shown that nonstandard work hours, like night shift work, tend to concentrate within lower positions in the occupational hierarchy, for example, in routine and manual jobs, and are much less common in managerial and supervisory roles (Hamermesh, 1996, 2002; Lesnard, 2008; Presser, 1984, 1987). Therefore, while longer employment tenure may provide eveningness-typed individuals more bargaining power to select into optimal work hours (i.e., night shifts), it also provides the opportunity to move up the occupational ladder within a company to positions where such work hours are no longer commonplace. Such an explanation would suggest that social forces can often override biological and genetic predispositions when it comes to work schedule timing.

5. DISCUSSION

The ways in which partially endowed traits like chronotype affect preferences surrounding the timing of paid work carries high sociological import. Studying such a relationship can provide insight into some of the hidden biological and genetic mechanisms underlying complex human preferences in the labour market, and can even inform human resource strategies to better match individuals with working conditions where performance might be optimized. Despite this, the relationship between chronotype and work schedule timing has gone surprisingly overlooked within the existing sociological literature. Such an omission could in part be due to data constraints: chronotype is scarcely measured within large-scale social surveys and is even rarer

in the longitudinal datasets necessary to study such a relationship. It could also in part be due to the relationship falling in a yet untouched gray area between the social and life sciences: studies in the social sciences have often tried to predict work schedule timing using demographic, household, and socioeconomic characteristics (e.g., Presser, 2003; Hamermesh, 1995), while relegating biological and endowed traits like chronotype to the error term as unobservable.

Much of the existing sociological research on night shift work schedules has painted such arrangements as a job disamenity and health risk factor concentrated amongst those in the labour market with the lowest occupational status and human capital. While previous research has alluded to the possibility that certain individuals – due to a host of unobservable factors – may prefer or be better suited to such work hours more than others, few studies have attempted to unpack or test this claim. What has received particularly little attention is the fact that night work hours may be advantageous – and, in fact, optimal – for individuals with chronotypes aligned to these times. From a rational choice perspective, one would expect that individuals should on average prefer work hours that are aligned with their chronotype; this is especially true when considering the vast evidence discussed earlier showing that performance is optimized and health consequences are minimized when an individual's external clock is synchronized with his or her endogenous circadian clock. Therefore, a strong congruity between chronotype and work schedule timing would indicate that people rationally select into the work schedule best suiting their own unique biology. This chapter sought to test these contentions by looking at whether an eveningness chronotype increased the probability of being observed in a night shift work schedule. More broadly, I explored whether there is evidence of individuals selecting into work schedules optimized for their endogenous circadian clock, and if not, why this might be the case. Findings include three major patterns.

First, results from Mendelian Randomization analyses suggest that eveningness does indeed increase the probability of being observed in night shift work schedules, an effect which appears to be causal. Findings show that being an evening rather than a morning person increases the probability of working night shifts by 8.7%. Sensitivity analyses revealed that these effects are robust to different specifications of night work and eveningness as well as different modeling techniques. These findings provide evidence that individuals have a tendency to select into the optimal work hours best suiting their own unique circadian rhythm, even if these hours are nonstandard in nature. In what May and Hasher (1998) termed, synchrony effect, cognitive functioning and physiological performance are at their peak when an individual's social clock is synchronized with his or her endogenous circadian clock. Findings from this study suggest that individuals may have an awareness of the benefits of synchrony, and in turn, tend to rationally select into the work hours that mirror the phases of their circadian arousal.

It appears, though, that this awareness is not necessarily innate. A second major finding of this study was that the strength of the relationship between eveningness and shift work tends to increase with age, becoming significant only for the oldest individuals in the sample. This was further evidenced by a positive (but non-significant) slope observed in the effects of eveningness on night work across age quantiles. Sensitivity analyses revealed these trends are robust to different modeling techniques and operationalizations of night work and eveningness. To the extent that individuals acquire information over time on their true chronotype, this trend suggests that older individuals use this information to select into their optimal work hours and out of their pessimal work hours. The finding that the effect of eveningness on the probability of night work grows weaker with employment duration provides indirect evidence that these age-related effects are not simply reflecting increased bargaining power. However, findings on the moderating effects of age are limited by the high ages of the individuals sampled by the UK

Biobank, the youngest of which are age 40. This relatively old sample composition likely obscures a large portion of the moderating effect of age (and by extension, information) that might occur over the life course. Future research could attempt to replicate these findings using data that provides a wider age range.

A third major finding of this study is that bargaining power appears to play a negligible role in the extent to which individuals are able to align their optimal and actual working hours. In contrast to as hypothesized, results show that the relationship between eveningness and the probability of night shift work becomes weaker as individuals gain tenure and seniority with their current employer. To the extent that increased tenure provides individuals more power to negotiate the terms of their working conditions, these findings suggest that individuals do not necessarily use this bargaining power to select into their optimal work hours. While this trend could partly reflect the imperfection of employment tenure as a proxy for work schedule autonomy, it could also be tied to the fact that, as individual's gain seniority with their employer, they get channeled into more managerial and supervisory positions within a company where night shift work is altogether less common. Through this lens, individuals may be trading optimal work hours for higher occupational status and the benefits this affords. Such an explanation would suggest that social preferences can often override biological and genetic predispositions when it comes to work schedule timing.

However, a core limitation to this stage of analysis is that the occupations where night shift work occurs are not measured; as discussed, job codes were not available in the UK Biobank data release currently being used. For this reason, theories surrounding the moderating effect of bargaining power are at this stage merely conjecture. Future research could try to test these claims by looking at how the relationship between eveningness and night shift work (or between chronotype and work scheduling timing in general) varies across different job groupings or across different occupational classes.

Similarly, and as mentioned earlier, another limitation to the current analysis was that the UK Biobank does not differentiate between employed and self-employed workers in their measure of current employment situation. An important question for future research would then be whether the relationship between chronotype and working timing differs amongst the self-employed. If the level of managerial constraints one faces conditions the amount of work schedule autonomy he or she has, one should also expect that self-employed individuals – who, by definition, face the fewest managerial constraints – would have comparatively high levels of work schedule autonomy. Indeed, as Lombard (2001) notes, self-employment generally affords a greater amount of temporal flexibility in the setting of work hours as individuals are freed from managerial oversight. It has even been suggested the desire for flexible working times may influence the decision to enter into self-employment in the first place (Edwards & Field-Hendrey, 1996). To the extent that work schedule autonomy facilitates the matching of actual and optimal work hours, it would follow that self-employed individuals should have the highest probability of being observed in schedules aligned with their true chronotype.

Another potential area for future research would be to look at how one's life course stage and family structure might shape an individual's ability to select into chronotypically optimal work hours – or even alter what constitute optimal work hours in general. Characteristics of a worker's family structure or life course stage, including the presence of dependent children or a co-resident partner, will inevitably influence decisions of at what times of day constitute optimal work hours. For example, an individual in a dual-earner partnership may try to coordinate her work hours with her partner's work hours to maximize the amount of shared time they have together outside of work; so-called, work-schedule synchronization (Lesnard, 2008; Mills & Täht, 2012). Similarly, a worker with children may try to concentrate his work hours during the day to allow him to be free in the evenings after his children are let out of school. These added layers of complexity in the scheduling of work hours should on

average constrain an individual's ability to freely select work hours based solely on chronotype; they may even redefine night shift works hours as sub-optimal regardless of one's chronotype given that such schedules can take the worker out of the household during the hours traditionally reserved for family life. Due to a lack of adequate measures and largely owing to the older ages of the UK Biobank sample (the youngest of which are age 40), such questions were out of the purview of the current analyses. Future research could try to explore how one's household structure and life course stage shape the relationship between chronotype and work schedule timing.

There are also two methodological limitations to the current analysis that could point to further areas for future research. First, a key limitation to this analysis is that the GWA results used in this study were derived from self-reports of chronotype. As discussed earlier, self-reports of chronotype as a measure of one's true chronotype will likely be highly susceptible to non-random measurement error; patterns of socialization and – more importantly – the timing of one's work schedule over time will likely affect how individuals will respond to such questionnaires. As mentioned, however, biases relating to non-random measurement error should be reduced in the current study as I instrumented self-reports with genotypic variation. As Lane et al. (2016) argue, since individuals do not know their genotype, any phenotypic misclassification (i.e., misreported self-identified chronotype) will be random with respect to genotype. That said, the reliance on self-reports of chronotype in available GWA studies may still call to question the validity of the current findings. New techniques are developing to assess more objective measures of chronotype across the genome. For example, a forthcoming publication by S. E. Jones et al. (2018) used activity monitor data from 85,760 UK Biobank participants to validate chronotype-associated SNPs derived from a GWAS on self-reports. Of the lead 292 lead SNPs reaching $p < 5 \times 10^{-8}$ found in the original GWAS, 258 had a consistent direction of effect for sleep midpoint, 262 with L5 timing (midpoint of the least active 5 hours

of the day), and 260 with M10 timing (midpoint of the most active 10 hours of the day). Future research could integrate these techniques to study the association between eveningness and night shift work using a less-error prone measure of true chronotype.

A second methodological limitation to the current analysis surrounds the construction of the current polygenic risk score for eveningness. As discussed earlier, the current PGS was constructed by summing the 480 directly assayed SNPs present in the UK Biobank genotype data that overlapped with the SNPs made available in the 23andMe chronotype GWAS association results (Hu et al., 2016). In contrast to a top-hit approach where only those SNPs reaching genome-wide significance are used, this whole-genome approach assumed that a very large number of SNPs will make infinitesimal contributions to phenotypic variation (Purcell et al., 2007). While such an approach increased the power of the genetic instrument, it also meant that I included SNPs with unknown or less clear circadian roles. This raises potential concerns surrounding horizontal pleiotropy, where one or more of the genetic variants used in the construction of the current PGS may in fact impact on an entirely separate biological pathway that affects shift work selection but is unrelated to chronotype (Katikireddi et al., 2018). Such a scenario would violate the exclusion restriction assumption necessary to the use of instrumental variables and call to question the validity of the current findings. While the issue of horizontal pleiotropy is in theory always present when using genetic instruments, it could at least be minimized in future research by using a weaker but more precise PGS that includes only those SNPs with well-established roles in the regulation of circadian rhythms.

As more and more firms continue to rely on shift work to expand hours of operation, it is essential to develop a better understanding of how to design these arrangements and to source workers such that negative health side-effects are minimized. As Phillips (2009) notes, working in a night schedule does not necessarily lead to adverse health consequences. Similarly, being a night owl should not in itself be a problem. Negative health effects instead come from having

to live and work in arrangements that are incongruent with one's own clock. Findings from this chapter optimistically suggest that individuals have a tendency to select into the work hours best suiting their endogenous circadian clock, even if these hours are nonstandard in nature. However, findings also suggest that the strength of this association in part depends on the level of information individuals have on their true chronotype as well as their position in the occupational hierarchy. Future research could explore further the pathways through which individuals are best able to align their actual and chronotypically optimal work schedules as well as the consequences of working pessimal schedules. Studying such questions could shed new light on some of the hidden mechanisms underlying health disparities in the labour market and could ultimately inform human resource strategies to optimize performance and reduce turnover amongst night shift workers.

CHAPTER 6

CONCLUSION

1. MAIN CONTRIBUTIONS

Social scientists have long focused on factors like unemployment, education, occupational class, and income when studying the health and well-being of workers and their families. A relatively underexplored dimension of social stratification, however, is when individuals participate in the labour market. Indeed, while much attention within recent sociological work in the UK has been paid to the changing number of hours spouses and parents are working, relatively little has been paid to important shifts in the location of these work hours. The past 50 years have seen the erosion of working time regulations and transitions to service-based economies throughout the UK. This has led to, amongst other things, a growth in the proportion of the labour force employed during times falling outside of the traditional 9:00 am to 5:00 pm, Monday to Friday workweek; so-called, nonstandard work schedules. As has been discussed, the timing of paid work hours has important implications not only for physical health but also for a worker's ability to remain connected with society and his or her family. This is perhaps most evident in the case of nonstandard work schedules, given that such arrangements have the potential to monopolize the times of day traditionally reserved for family and social life. As the UK continues to move towards a 24-7 economy where individuals are increasingly scheduled round-the-clock, it is essential to develop a better understanding of the effects that nonstandard schedules take on workers and their families.

The aim of this thesis was therefore to provide a comprehensive investigation of the ways in which families use and are affected by nonstandard schedules, focusing on the previously underexplored but highly relevant context of the UK. Over the course of four

empirical chapters, I looked at the composition and occupational characteristics of nonstandard schedule workers, the effects these schedules take on work-family balance, and the ways in which individual preferences and endowed traits play a large role in dictating which individuals select into and stay in nonstandard schedules. The thesis is unique in the extensive scope with which nonstandard work schedules were studied: I moved all the way from the molecular level to the individual level and then up to the country level to showcase the antecedents, consequences, and institutions relevant to the study of nonstandard work schedules and families in the UK and beyond.

This thesis makes several contributions to the existing body of knowledge on nonstandard work schedules and family life. First, I showed the many channels of self-, socioeconomic, and occupational selection underlying employment in nonstandard schedules, and presented ways to account for these selection mechanisms when studying the relationship between nonstandard schedules and work-family balance. Second, I highlighted that the consequences of nonstandard schedules on family life are not necessarily universal, but instead depend partially on the country and institutional context in which they are studied. Third, I integrated molecular genetic data to show how the timing of an individual's circadian rhythm influences preferences for nonstandard work hours, suggesting that such arrangements can be advantageous – and even optimal – for certain individuals. This latter approach is unique in that it is one of the first attempts to study how genes and their interaction with the environment influence how individuals engage in paid labour. The key findings of this thesis are summarized below.

2. SUMMARY OF MAIN FINDINGS

Throughout the course of this thesis, I sought to address five main research questions. The first of these questions were: Who works nonstandard schedules and in which types of jobs are these

schedules most common? To address these questions, I explored the salient occupational, socioeconomic, and demographic characteristics of the men and women working regular nonstandard hours and days in the UK and the rest of Europe. Findings broadly suggest that individuals working regular nonstandard hours and days are a highly selective population: they tend on average to be younger, have lower levels of educational attainment, and are more likely to be self-employed and have a partner who also works a nonstandard schedule. Findings also suggest that nonstandard schedules appear to be a symptom of a lower position in the occupational hierarchy: they tend to concentrate in relatively low-status occupations amongst those individuals employed on nonstandard contracts and who have most recently joined a company. Taken together, such patterns allude to the fact that nonstandard schedules are far from a randomly distributed treatment; employment in these arrangements is affected by complex and competing channels of occupational, household, and socioeconomic selection.

The third question this thesis sought to answer was: To what extent do nonstandard work schedules negatively affect romantic partnerships? While this question has been explored previously (e.g., Kalil et al., 2010; Mills & Täht, 2010; Presser, 2000; Wight et al., 2008), a major aim of the current thesis was to attempt to characterize and correct for the important channels of selection underlying employment in nonstandard schedules through a matching-based quasi-experiment. Results indicate that after correcting for baseline selection biases, nonstandard schedules only take negative effects on partnership quality when worked by women. Crucially, however, it appears that women's nonstandard work hours and days appear to only take a toll on the partner of the worker rather than the worker herself. This is likely in part tied to another major finding of this chapter: It appears that women positively select into nonstandard schedules on the basis of their own but not their partner's perceived partnership quality. Such findings highlight the importance of a nuanced approach to the study of the relationship between nonstandard schedules and outcomes relating to family cohesion that takes

into account the complex processes of selection into these arrangements as well as the diverging actor and partner effects.

The fourth research question this thesis sought to address was: To what extent do the destabilizing effects of nonstandard schedules on work-family balance depend on country and institutional context? To answer this question, this thesis used data from 32 countries in Europe across two time periods as well as a handful of macro-level indicators capturing the variation in working conditions and systems of industrial relations across countries. Findings showed that while nonstandard work hours and days are associated with increased work-family conflict across all but two of the 32 sampled countries, the strength of this association varied significantly between countries. The strongest factor shaping the social consequences of nonstandard schedules was the degree to which workers are covered under collective bargaining agreements in a country, which explained as much as 24% of the observed between-country variation in the effects of nonstandard schedules on WFC. These findings highlight collective agreements as the central mechanism through which family-friendly regulations on working times and conditions are generated for nonstandard schedule workers across Europe. More broadly, findings suggest that when studying the social consequences of nonstandard schedules, these arrangements must be contextualized in the broader institutional frameworks within which they are organized and regulated.

The final research question this thesis explored was: Does an individual's chronotype – or the timing of her circadian rhythm – influence the likelihood of selecting into nonstandard work hours? More broadly, this chapter sought to uncover whether there was evidence of individuals selecting into their optimal work hours. To address this question, I employed Mendelian Randomization techniques on genetic and work history data from the UK Biobank to study the causal association between chronotype and work schedule timing. Results indicate that eveningness significantly increases the probability of being observed in a night shift work

schedule, an effect that appears to be causal. However, findings also show that the strength of this association in part depends on the level of information individuals have on their true chronotype as well as on their position within the occupational hierarchy. Taken together, such results broadly suggest that individuals do indeed have a tendency to select into the work hours best suiting their endogenous circadian clock, even if these hours are nonstandard in nature. Results also indicate, however, that factors like low autonomy and occupation can often result in individual's selecting into sub-optimal work hours.

3. LIMITATIONS

I note several limitations to the analyses done in the current thesis. The first of these surround issues and inconsistencies in the measurement of nonstandard work hours. As discussed earlier, the current thesis employed three different datasets, which differed slightly in the measurement of nonstandard work hours. Chapter 3 employed the UKHLS, which measures nonstandard work hours by asking respondents to choose a single category best describing at what times of the day their work hours most often occur. In contrast, Chapters 2, 4, and 5 employed the ESS and UK Biobank datasets, which both measure nonstandard work hours by asking respondents to report the regularity with which work occurs during evening or night hours. These measurement inconsistencies are especially problematic in the case of Chapters 3 and 4 as both chapters focus on the effects that nonstandard schedules take on outcomes relating to work-family balance, but each employed different operationalizations of nonstandard hours. These cross-study inconsistencies naturally make it challenging to draw broader conclusions on the family effects of nonstandard work hours across chapters; as Dunifon et al. (2013) note, these inconsistencies are also a major limitation of the existing body of knowledge on the social consequences of nonstandard schedules. Future research is still needed to develop an internationally and historically comparable measure of nonstandard work hours.

A related measurement limitation specific to nonstandard work hours is that I operationalized such arrangements broadly as work hours occurring during evenings or nights. While this choice facilitated a more coherent discussion and analytical simplicity, it also inevitably obscured important differences between specific variants of nonstandard work hours, for example, the differing levels of autonomy and flexibility afforded to workers in rotating, variable, and fixed nonstandard hours. However, as discussed earlier, for the purposes of the current thesis, the distinction between non-day and day work was more important than distinctions between different types of non-day work. Moreover, this choice allowed for greater comparability of nonstandard work hours across several institutionally diverse European countries for which the definitions and arrangements of specific work schedule variants like shift work and variable-hour schedules differ widely. That said, nonstandard schedule variants like variable-hour and flexi-time schedules are becoming increasingly common, and pose unique opportunities and challenges for families. Future research could explore further how families in the UK use and are affected by such arrangements.

There are also several chapter-specific limitations that are worth noting and that could point to areas for further research. First, Chapter 3 utilized independent and dependent variables that were not measured contemporaneously in the UKHLS (a lag of between 1-2 years). I was therefore forced to exclude any individuals in partnerships that ended between these waves (e.g., between Waves 2 and 3, or between Waves 4 and 5). Sensitivity analyses revealed that by only including objectively stable partnerships over each observation period, I may have overestimated the true effect of nonstandard work days on partnership quality that might be observed if independent and dependent variables were measured contemporaneously. A second limitation to the analyses in Chapter 3 surrounds the validity of the ignorability assumption invoked in the construction of the matching matrix. While this assumption is technically untestable, one could rightly argue that it is tenuous when using observational data as there are

plausibly many unobserved confounders. Given that results do suggest that positive selection biases might be at play, particularly for women, future research could try to tease out the causal effects of nonstandard schedules on family cohesion through the use of an instrumental variable technique or fixed effects.

In Chapter 4, cross-sectional data was used to explore the moderating effects of labour-related institutions on the social consequences of nonstandard schedules. This naturally means that findings on the buffering effects of country-level institutional characteristics are merely associational at this point. This is due to that fact that I cannot reliably partial out the effects of the many unobserved country-level factors that are likely collinear with observed institutional factors. Future research could utilize a longitudinal or quasi-experimental research design to determine whether the observed moderating effects of collective bargaining coverage on the relationship between nonstandard schedules and WFC are in fact causal. Another limitation of the analyses of Chapter 4 is that the Job Strain Index was not available in seven countries, which were either not OECD countries or had data missing. To account for this, later stages of analysis that tested the moderating effects of labour-related factors were restricted to countries where all three institutional indicators were available to ensure that estimates were comparable. Supplementary analyses, however, revealed that in countries with no information on the Job Strain Index, female WFC was higher and the effect of nonstandard work hours on WFC was lower; this indicates that selective missingness might be partially biasing results.

Finally, in Chapter 5, I explored the relationship between eveningness and the probability of night shift work using Mendelian Randomization techniques. A limitation of this technique is that, as the biological pathways through which the SNPs used in the polygenic risk scores affect chronotype are still a black box, there are possible violations to the exclusion restriction assumption. That is, it is possible that the SNPs may affect night shift work selection via an entirely separate biological pathway than chronotype. Future research could address

these concerns by using a weaker but more precise genetic instrument that only includes SNPs with well-established roles in circadian rhythm regulation. Another important limitation of the analyses in this chapter is that the association results used to construct the PGS for eveningness were derived from self-reports of chronotype. As I have argued, self-reports are highly susceptible to non-random measurement error as the timing of an individual's work schedule will likely affect how individuals will respond to such questionnaires through entrainment. Future research could explore the use of more objective measures of chronotype to study its causal association with work schedule timing.

4. AREAS FOR FUTURE RESEARCH

This thesis could be extended in several ways. First, an important area for further research would be to integrate a couple-level approach to the study of nonstandard work schedules and their effects on partnership quality and family cohesion in general, as in the tradition of works such as Täht and Mills (2016) and Lesnard (2008). As discussed earlier, work schedules within dual-earner partnerships are often jointly determined at the couple-level; this is perhaps best evidenced by the robust finding that one partner working a nonstandard schedule significantly increases the odds that her partner will also work such an arrangement. A particularly interesting avenue for further research would then be to unpack whether and how patterns of positive and/or negative selection into nonstandard work schedules might operate at the couple-level. Similarly, it is also important to further test the mechanisms through which nonstandard schedules affect family life. Future research could, for example, explore whether nonstandard schedules exert their negative effects on family cohesion via reductions in family time, reductions in time spent in household and care-related responsibilities, or the physiological tolls on the worker; it would be particularly interesting to explore such mechanisms at the couple level.

Another important avenue for further research would be to utilize longitudinal data to explore whether the moderating effects of labour-related contextual factors like the regulation of union membership density and coverage under collective agreements found in the current thesis are in fact causal. Such research could provide invaluable insight for the development of policy that might reduce social externalities of round-the-clock scheduling. It is also important to explore how other contextual-level factors like family policy or norms surrounding, for example, the centrality of work and the gendered division of labour might also moderate the effects that nonstandard schedules take on family life. Similarly, and as discussed earlier, it would also be important to explore how sector- and company-level factors like working conditions and the availability of flexible work schemes might affect the destabilizing potential of nonstandard schedules on family life. Indeed, it is possible that the quality of the working environment, for example, may only exert a significant buffering effect when measured at the sector or company level rather than at the national level as the current thesis has done.

Along with this, findings from Chapter 5 point to some interesting areas for further research surrounding how chronotype might affect preferences surrounding the timing of paid work. One potential area for future research would be to look at how family structure might shape an individual's ability to select into chronotypically optimal work hours – or indeed, even alter what constitutes optimal work hours in general. Future research could also look at how the relationship between chronotype and work scheduling timing varies across different job groupings or across different occupational classes. Similarly, another important question for future research would be whether the relationship between chronotype and working timing differs amongst the self-employed, who should, in theory, have the most freedom to select into work hours aligned with their circadian rhythm. More broadly, the analyses done in Chapter 5 suggest that biological and genetic factors do indeed play a role in individuals' labour market decisions. As molecular and biological data becomes more widespread in social surveys, the

possibilities to build off these findings to further explore the mechanisms underlying complex human preferences in the labour market are endless.

A final area for future research is to explore the patterns and consequences of nonstandard work schedules amongst the growing numbers of self-employed workers like freelancers and independent contractors. As has been noted (Fenwick & Tausig, 2001; Shevchuk et al., 2018), much of the existing research on the social and physiological consequences of nonstandard schedules has relied almost exclusively on samples of employees while virtually ignoring self-employed individuals. Yet, there is good reason to expect that the size and even the direction of the effects of nonstandard schedules on family life might differ for the self-employed. Indeed, while nonstandard schedule work in organizations such as factories, call centers, and hospitals tends to reflect employer requirements and/or the nature of the job, nonstandard schedule use amongst the self-employed largely reflects personal preference. This naturally raises some interesting potential avenues for future research. For example, are patterns of positive selection into nonstandard schedules observed amongst women in the current thesis more pronounced for the self-employed? Another interesting avenue building off recent research from Shevchuk et al. (2018) would be whether and how unfettered access to work schedule autonomy and atypical working times amongst the self-employed might erode work-home boundaries; creating a so-called, “autonomy paradox”. Questions surrounding the uses and consequences of nonstandard schedules amongst the self-employed will become even more important as the highly unregulated gig economy (e.g., Deliveroo, Uber, Lyft, etc.) grows in prominence.

APPENDICES

APPENDIX 2-1. PREVALENCE OF NONSTANDARD WORK SCHEDULES IN THE UK
AND THE REST OF EUROPE

Table 2-1-1. *Proportion of Nonstandard Schedule Workers, by Gender and Work Hours*

	Women					Men				
	The UK, <i>n</i> = 924		Rest of Europe, <i>n</i> = 19,569		Diff. ^a	The UK, <i>n</i> = 890		Rest of Europe, <i>n</i> = 20,747		Diff.
	<i>b</i>	<i>SE</i>	<i>b</i>	<i>SE</i>		<i>b</i>	<i>SE</i>	<i>b</i>	<i>SE</i>	
Nonstandard Hour Workers										
Pooled	0.22	0.01	0.15	0.003	0.07***	0.31	0.02	0.19	0.003	0.12***
Part-Time	0.19	0.02	0.16	0.004	0.03	0.30	0.04	0.20	0.01	0.10**
Full-Time	0.26	0.02	0.15	0.003	0.11***	0.31	0.02	0.19	0.003	0.12***
Nonstandard Day Workers										
Pooled	0.17	0.01	0.10	0.002	0.07***	0.21	0.01	0.12	0.002	0.09***
Part-Time	0.16	0.02	0.10	0.004	0.06***	0.28	0.03	0.13	0.01	0.15***
Full-Time	0.19	0.02	0.10	0.003	0.08***	0.19	0.01	0.11	0.002	0.08***

Data Sources: 2004 and 2010 European Social Survey (Rounds 2 and 5)

Notes: Sample includes respondents in paid employment between the ages of 18-59. ^a Indicates the raw difference in proportions between the UK and the rest of Europe.

* $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

APPENDIX 3-1. OUTLINE OF SAMPLE SIZE RESTRICTIONS

Table 3-1-1. *Size of Sample Size Restriction by UKHLS Period*

Sample Restriction	UKHLS Period			
	Period 1 (Waves 2-3)	Period 2 (Waves 4-5)	Period 3 (Waves 6-7)	Cross-Period (Waves 2-7)
Baseline Sample (No restrictions)	54,597	47,157	45,290	147,044
1. Has marital or cohabiting partner in first wave	34,491	29,502	28,068	92,061
Sample Reduction	-20,106	-17,655	-17,222	-54,983
2. Has marital or cohabiting partner in second wave	27,930	25,497	23,279	76,706
Sample Reduction	-6,561	-4,005	-4,789	-15,355
3. ID of partner is the same across both waves	27,812	25,397	23,136	76,345
Sample Reduction	-118	-100	-143	-361
4. Living with spouse or partner in first wave	27,684	25,253	22,748	75,685
Sample Reduction	-128	-144	-388	-660
5. Living with spouse or partner in second wave	27,682	25,186	22,546	75,414
Sample Reduction	-2	-67	-202	-271
6. In paid employment in first wave	14,185	12,929	11,338	38,452
Sample Reduction	-13,497	-12,257	-11,208	-36,962
7. In paid employment in second wave	12,900	11,741	10,378	35,019
Sample Reduction	-1,285	-1,188	-960	-3,433
8. Reports no change in job between waves	12,446	11,297	9,991	33,734
Sample Reduction	-454	-444	-387	-1,285
9. Between the age of 18-59 in second wave	11,602	10,500	9,280	31,382
Sample Reduction	-844	-797	-711	-2,352
10. Non-missing values partnership quality indicators	10,110	8,754	8,603	27,467
Sample Reduction	-1,492	-1,746	-677	-3,915
11. Non-missing values on work schedule timing	9,909	8,616	7,924	26,449
Sample Reduction	-201	-138	-679	-1,018
12. Non-missing values on partner information ^a	8,378	7,306	6,675	22,359
Sample Reduction	-1,531	-1,310	-1,249	-4,090
13. Non-missing values on Big 5 Personality Indicators ^b	8,364	7,093	5,604	21,061
Sample Reduction	-14	-213	-1,071	-1,298
14. Non-missing values on other selection covariates	8,234	6,945	5,468	20,647
Sample Reduction	-130	-148	-136	-414

Data Source: 2010-2016 UKHLS

Notes: ^a High sample loss is due many cases where complete records on partner's employment situation being missing. ^b High sample loss in second and third period is due to the fact that Big 5 Personality Indicators were only measured in Wave 3; thus, cohorts added after this were removed.

APPENDIX 3-2. BALANCE DIAGNOSTICS FOR UNMATCHED RAW SAMPLE

Table 3-2-1. *Std. Mean Differences Between Treated and Control Groups in Unmatched Sample*

Variable	Nonstandard Work Hours		Nonstandard Work Days	
	Women, <i>n</i> = 10,054	Men, <i>n</i> = 10,081	Women, <i>n</i> = 10,092	Men, <i>n</i> = 10,199
	Standardized Mean Difference ^a			
Age	0.06	0.10 **	0.13 ***	0.16 ***
Time Period	0.07 +	0.04	0.07 ***	0.06 *
Rural	0.12 **	0.05 +	0.03	0.01
Race/Ethnicity				
White British	0.19 ***	0.10 ***	0.03	0.03
Black	0.12 ***	0.02	0.00	0.05 +
Middle Eastern	0.20 ***	0.10 ***	0.02	0.09 ***
East Asian	0.05	0.08 *	0.01	0.05
Mixed Background	0.00	0.06 *	0.04	0.02
Born in UK	0.22 ***	0.13 ***	0.01	0.06 *
Household				
Parent	0.03	0.06 *	0.05 +	0.02
Number of Children	0.08 *	0.05 +	0.02	0.01
Young Child Present	0.04	0.07 *	0.04	0.07 **
Partnership				
Cohabiting	0.02	0.01	0.13 ***	0.03
Age Difference	0.14 ***	0.10 ***	0.10 **	0.10 ***
Partner is Employed	0.11 **	0.06 +	0.09 **	0.03
Partner Full-Time	0.06 +	0.00	0.02	0.02
Partner Works Nights	0.19 ***	0.17 ***		
Partner Work Weekends			0.24 ***	0.25 ***
Education				
Highest Qual. is GCSE	0.15 ***	0.30 ***	0.28 ***	0.30 ***
Highest Qual. is Degree	0.47 ***	0.58 ***	0.25 ***	0.32 ***
Occupation				
Professional Occ.	0.33 ***	0.61 ***	0.35 ***	0.43 ***
Lower MGMT	0.13 ***	0.43 ***	0.08 *	0.14 ***
Intermediate	0.22 ***	0.18 ***	0.31 ***	0.03
Routine Occupation	0.35 ***	0.49 ***	0.42 ***	0.43 ***
ISEI Index	0.73 ***	0.83 ***	0.23 ***	0.44 ***
Low Autonomy	0.55 ***	0.84 ***	0.34 ***	0.33 ***
Personality				
Agreeableness	0.08 *	0.07 *	0.03	0.01
Conscientiousness	0.01	0.05 +	0.04	0.03
Neuroticism	0.02	0.02	0.03	0.02
Openness	0.10 **	0.19 ***	0.03	0.10 ***
Extroversion	0.00	0.06 +	0.05 +	0.11 ***

Data Source: 2010-2016 UKHLS

Notes: Sample includes individuals in co-resident partnerships between the ages of 18-59 who are in regular paid employment. ^a A SMD of > 0.1 indicates sufficient balance (Austin, 2001).

+ $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

APPENDIX 3-3. BALANCE DIAGNOSTICS FOR MAHALANOBIS MATCHED SAMPLE

Table 3-3-1. *Std. Mean Differences Between Treated and Control Groups in Matched Sample*

Variable	Nonstandard Work Hours		Nonstandard Work Days	
	Women, <i>n</i> = 3,424	Men, <i>n</i> = 5,232	Women, <i>n</i> = 5,152	Men, <i>n</i> = 6,392
	Standardized Mean Difference ^a			
Age	0.05	0.02	0.04	0.04
Time Period	0.03	0.06 *	0.04	0.04 +
Rural	0.03	0.05 +	0.05 +	0.03
Race/Ethnicity				
White British	0.02	0.05 +	0.02	0.04
Black	<0.001	<0.001	0.01	0.00
Middle Eastern	0.00	0.04	0.01	0.03
East Asian	<0.001	<0.001	<0.001	<0.001
Mixed Background	0.03	0.04	0.02	0.03
Born in UK	0.04	0.02	0.03	0.02
Household				
Parent	0.03	0.03	0.02	0.01
Number of Children	0.07 *	0.04	0.05 +	0.02
Young Child Present	0.06 +	0.03	0.06	0.05 +
Partnership				
Cohabiting	0.03	0.04	0.05	0.04
Age Difference	0.06 +	0.04	0.06	0.05 +
Partner is Employed	0.02	0.05 +	0.05	0.04
Partner Full-Time	0.03	0.03	0.06 *	0.01
Partner Works Nights	0.05	0.04		0.02
Partner Work Weekends			0.03	
Education				
Highest Qual. is GCSE	0.06 +	0.03	0.07 *	0.04
Highest Qual. is Degree	0.06 +	0.02	0.01	0.02
Occupation				
Professional Occupation	0.06 +	0.02	0.00	0.03
Lower MGMT	0.01	0.02	0.06	0.01
Intermediate	0.07 +	0.02	0.02	0.02
Routine Occupation	0.06 +	0.00	0.02	0.03
ISEI Index	0.03	0.01	0.72 *	0.05 *
Low Autonomy	0.04	0.05 +	0.03	0.00
Personality				
Agreeableness	0.01	0.04	0.06 +	0.03
Conscientiousness	0.03	0.04	0.00	0.01
Neuroticism	<0.001	0.01	0.01	0.04 +
Openness	0.02	0.05 +	0.06 +	0.02
Extroversion	0.01	0.01	0.02	0.04

Data Source: 2010-2016 UKHLS

Notes: Sample includes individuals in co-resident partnerships between the ages of 18-59 who are in regular paid employment. ^a A SMD of > 0.1 indicates sufficient balance (Austin, 2001).

+ $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

APPENDIX 3-4. SUB-INDEX ANALYSES OF THE EFFECT OF NONSTANDARD SCHEDULES ON PARTNERSHIP QUALITY FOR WOMEN

Table 3-4-1. *Mahalanobis Matching Estimates of Nonstandard Schedule Treatment Effects for Women*

Treatment	Female Actor Effect		Female Partner Effect	
	<i>b</i>	<i>SE</i>	<i>b</i>	<i>SE</i>
Nonstandard Hours, <i>n</i> = 3,424				
<i>Partnership Stability</i>				
Consider divorce	0.09+	0.05	0.12**	0.04
Regret marriage	0.06	0.05	0.10*	0.05
Quarrel	0.06	0.05	0.04	0.05
Get on each other's nerves	0.08+	0.05	0.09+	0.05
Overall happiness	-0.03	0.05	-0.10*	0.05
<i>Overall</i>	-0.09+	0.05	-0.14**	0.05
<i>Partnership Cohesion</i>				
Engage in stimulating exchange of ideas	-0.05	0.05	-0.06	0.04
Calmly discuss something	-0.03	0.05	-0.12**	0.05
Work together on a project	0.01	0.05	-0.02	0.05
Engage in outside interests	-0.09+	0.05	-0.04	0.05
<i>Overall</i>	-0.05	0.05	-0.09+	0.05
Nonstandard Days, <i>n</i> = 5,152				
<i>Partnership Stability</i>				
Consider divorce	0.05	0.04	0.04	0.04
Regret marriage	0.04	0.04	0.04	0.04
Quarrel	-0.01	0.04	0.09*	0.04
Get on each other's nerves	0.03	0.04	0.10**	0.04
Overall happiness	0.01	0.04	-0.02	0.04
<i>Overall</i>	-0.03	0.04	-0.08*	0.04
<i>Partnership Cohesion</i>				
Engage in stimulating exchange of ideas	0.08*	0.04	-0.07*	0.04
Calmly discuss something	0.09*	0.04	-0.12**	0.04
Work together on a project	0.05	0.04	-0.04	0.04
Engage in outside interests	-0.09*	0.04	-0.10**	0.04
<i>Overall</i>	0.07+	0.04	-0.10**	0.04

Data Source: 2010-2016 UKHLS

Notes: Sample includes individuals in co-resident partnerships between the ages of 18-59 who are in regular paid employment.

+ $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

APPENDIX 3-5. SUB-INDEX ANALYSES OF THE EFFECT OF NONSTANDARD SCHEDULES ON PARTNERSHIP QUALITY FOR MEN

Table 3-5-1. *Mahalanobis Matching Estimates of Nonstandard Schedule Treatment Effects for Men*

Treatment	Male Actor Effect		Male Partner Effect	
	<i>b</i>	<i>SE</i>	<i>b</i>	<i>SE</i>
Nonstandard Hours, <i>n</i> = 3,132				
Partnership Stability				
Consider divorce	-0.01	0.04	0.04	0.04
Regret marriage	-0.01	0.04	0.00	0.04
Quarrel	-0.03	0.04	-0.03	0.04
Get on each other's nerves	-0.04	0.04	-0.03	0.04
Overall happiness	0.09*	0.04	0.02	0.04
<i>Overall</i>	0.05	0.04	0.02	0.04
Partnership Cohesion				
Engage in stimulating exchange of ideas	0.01	0.04	-0.03	0.04
Calmly discuss something	-0.07+	0.04	-0.05	0.04
Work together on a project	0.00	0.04	0.00	0.04
Engage in outside interests	0.01	0.04	-0.04	0.04
<i>Overall</i>	-0.02	0.04	-0.03	0.04
Nonstandard Days, <i>n</i> = 6,392				
Partnership Stability				
Consider divorce	-0.01	0.03	0.04	0.04
Regret marriage	0.02	0.03	0.04	0.04
Quarrel	0.00	0.03	0.00	0.04
Get on each other's nerves	-0.04	0.03	0.02	0.04
Overall happiness	0.02	0.03	-0.05	0.04
<i>Overall</i>	0.01	0.03	-0.05	0.04
Partnership Cohesion				
Engage in stimulating exchange of ideas	0.06+	0.03	0.03	0.04
Calmly discuss something	0.00	0.03	-0.02	0.04
Work together on a project	0.02	0.03	0.03	0.04
Engage in outside interests	0.02	0.03	-0.09*	0.04
<i>Overall</i>	0.04	0.03	0.00	0.04

Data Source: 2010-2016 UKHLS

Notes: Sample includes individuals in co-resident partnerships between the ages of 18-59 who are in regular paid employment.

+ $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

APPENDIX 3-6. INTRA-PARTNERSHIP CORRELATIONS BETWEEN PARTNERSHIP QUALITY INDEX ITEMS

Table 3-6-1. *Intra-Partnership Correlations Between Partnership Quality Items*

	Women, <i>n</i> = 10,095	Men, <i>n</i> = 10,202
Item	<i>Intra-Partnership Pearson Correlation</i>	
<i>Partnership Cohesion</i>		
Stimulating Exchange of Ideas	0.23***	0.23***
Calmly Discuss Something	0.25***	0.26***
Work Together	0.26***	0.23***
Outside Interests	0.40***	0.39***
<i>Partnership Stability</i>		
Consider Divorce	0.44***	0.42***
Regret Marriage	0.28***	0.29***
Quarrel	0.45***	0.44***
Get on Each other's Nerves	0.36***	0.36***
Degree of Happiness	0.22***	0.22***

Data Source: 2010-2016 UKHLS

Notes: Sample includes individuals in co-resident partnerships between the ages of 18-59 who are in regular paid employment.

+ $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

APPENDIX 3-7. TOP-FIVE OCCUPATIONS FOR NONSTANDARD HOUR AND DAY WORKERS, BY GENDER

Table 3-7-1. *Frequencies and Proportions of Top-Five Most Common Occupations (ISCO-88) for
Nonstandard Hour and Day Workers, by Gender*

Treatment	Women		Men	
	Occupation	<i>n</i> Prop.	Occupation	<i>n</i> Prop.
<i>Nonstandard Work Hours</i>				
	Personal care and related workers	263 0.25	Protective services workers	160 0.11
	Nursing and midwifery associate professionals	221 0.21	Motor Vehicle drivers	114 0.07
	Shop salespersons and demonstrators	109 0.10	Messengers, porters, doorkeepers and related workers	99 0.07
	Client information clerks	64 0.06	Transport labourers and freight handlers	87 0.06
	Domestic and related helpers, cleaners and launderers	56 0.05	Machinery and fitters	67 0.04
	<i>Total</i>	713 0.69	<i>Total</i>	527 0.35
<i>Nonstandard Work Days</i>				
	Shop salespersons and demonstrators	286 0.19	Messengers, porters, doorkeepers and related workers	167 0.09
	Personal care and related workers	223 0.15	Production and operations department managers	165 0.09
	Nursing and midwifery associate professionals	103 0.07	Motor Vehicle drivers	137 0.07
	Production and operations department managers	88 0.06	Shop salespersons and demonstrators	110 0.06
	Primary and pre-primary education teaching professionals	88 0.06	Protective services workers	84 0.05
	<i>Total</i>	788 0.52	<i>Total</i>	663 0.36

Data Source: 2010-2016 UKHLS

Notes: Sample includes individuals in co-resident partnerships between the ages of 18-59 who are in regular paid employment.

APPENDIX 3-8. MAHALANOBIS MATCHING ANALYSIS INCLUDING VARIABLE-HOUR
SCHEDULES IN MEASURE OF NONSTANDARD HOURS, AND INCLUDING
OCCASIONAL WEEKEND WORK IN MEASURE OF NONSTANDARD DAYS

Table 3-8-1. *Mahalanobis Distance Matching Estimates of Nonstandard Schedule Treatment Effects*

		Average Treatment Effect on Partnership Stability		Average Treatment Effect on Partnership Cohesion	
Treatment	<i>n</i>	<i>b</i>	<i>SE</i>	<i>b</i>	<i>SE</i>
Women					
Nonstandard Hours					
Actor Effect	6,900	-0.03	0.03	0.02	0.03
Partner Effect	6,900	-0.05	0.03	-0.02	0.03
Nonstandard Days					
Actor Effect	14,688	-0.01	0.03	0.10***	0.03
Partner Effect	14,688	-0.01	0.03	0.01	0.03
Men					
Nonstandard Hours					
Actor Effect	9,576	0.03	0.03	0.02	0.03
Partner Effect	9,576	-0.04	0.03	-0.03	0.03
Nonstandard Days					
Actor Effect	21,356	0.01	0.02	-0.01	0.03
Partner Effect	21,356	-0.03	0.03	-0.01	0.03

Data Source: 2010-2016 UKHLS

Notes: Sample includes individuals in co-resident partnerships between the ages of 18-59 who are in regular paid employment.

+ $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

APPENDIX 3-9. HETEROGENEOUS TREATMENT EFFECTS ANALYSIS INCLUDING
VARIABLE-HOUR SCHEDULES IN MEASURE OF NONSTANDARD HOURS, AND
INCLUDING OCCASIONAL WEEKEND WORK IN MEASURE OF NONSTANDARD DAYS

Table 3-9-1. *Linear Relationship Between Propensity Stratum and Estimated Treatment Effect*

			Heterogeneous Treatment Effects on Partnership Stability		Heterogeneous Treatment Effects on Partnership Cohesion	
Treatment	# of Strata	<i>n</i>	Slope Across Strata	<i>SE</i>	Slope Across Strata	<i>SE</i>
Women						
Nonstandard Hours						
Actor Effect	7	10,031	0.01	0.02	0.04*	0.02
Partner Effect	7	10,031	0.02	0.02	0.01	0.02
Nonstandard Days						
Actor Effect	9	10,091	0.03*	0.02	0.02	0.02
Partner Effect	9	10,091	0.02	0.02	0.00	0.02
Men						
Nonstandard Hours						
Actor Effect	9	10,144	-0.01	0.01	-0.01	0.01
Partner Effect	9	10,144	-0.03**	0.01	-0.04*	0.01
Nonstandard Days						
Actor Effect	7	10,197	0.00	0.02	-0.03	0.02
Partner Effect	7	10,197	-0.03	0.03	0.03	0.03

Data Source: 2010-2016 UKHLS

Notes: Sample includes individuals in co-resident partnerships between the ages of 18-59 who are in regular paid employment.

+ $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

APPENDIX 3-10. SUPPLEMENTARY ANALYSES OF RELATIONSHIP BETWEEN WITHIN-PERIOD PARTNERSHIP DISSOLUTION AND WORK SCHEDULE TIMING

Table 3-10-1. *Proportions of Individuals in a Partnership that Dissolved Between Waves of Period*

Status	Women		Men	
	Freq.	Percent	Freq.	Percent
Remained in the Same Partnership Between Both Waves of Period	15,752	95.57	15,719	96.67
Partnership Dissolved Between Two Waves of Period ¹	731	4.43	542	3.33

Data Source: 2010-2016 UKHLS

Notes: Sample includes individuals in co-resident partnerships between the ages of 18-59 who are in regular paid employment. ¹ Individuals were coded as experiencing a within-period partnership dissolution if: (1) they reported being in a co-resident partnership in the first wave of a period, but not in the second wave of that period; or (2) the never-changing identifier number of his or her partner changed between the waves of a given period. These restrictions are outlined further in Appendix 3-1.

Table 3-10-2. *Logistic Regression of Within-Period Partnership Dissolution^a on Nonstandard Work Schedules*

		Likelihood of Partnership Dissolving Between Two Waves of a Period	
Treatment	<i>n</i>	<i>b</i> ^{<i>b</i>}	<i>SE</i>
Women			
Nonstandard Hours	15,680	1.25	0.14
Nonstandard Days	15,739	1.46***	0.14
Men			
Nonstandard Hours	14,293	1.12	0.14
Nonstandard Days	15,739	1.35**	0.14

Data Source: 2010-2016 UKHLS

Notes: Sample includes individuals in co-resident partnerships between the ages of 18-59 who are in regular paid employment. ^a Individuals were coded as experiencing a within-period partnership dissolution if: (1) they reported being in a co-resident partnership in the first wave of a period, but not in the second wave of that period; or (2) the never-changing identifier number of his or her partner changed between the waves of a given period. These restrictions are outlined further in Appendix 3-1. ^b Denotes odds ratio.

+ $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

APPENDIX 4-1. EUROPEAN SOCIAL SURVEY DATA AVAILABILITY

Table 4-1-1. *European Social Survey Sample Sizes, by Country and Round*

Country	ESS Round		
	2004	2010	Both Rounds
Austria	495	0	495
Belgium	457	471	928
Bulgaria	0	451	451
Croatia	0	287	287
Cyprus	0	188	188
Czech Republic	567	512	1,079
Denmark	502	493	995
Estonia	525	426	951
Finland	620	464	1,084
France	0	436	436
Germany	652	757	1,409
Great Britain	396	519	915
Greece	334	324	658
Hungary	0	400	400
Iceland	125	0	125
Ireland	398	387	785
Israel	0	479	479
Italy	114	0	114
Lithuania	0	231	231
Luxembourg	425	0	425
Netherlands	462	482	944
Norway	622	545	1,167
Poland	376	419	795
Portugal	348	353	701
Russian Federation	0	564	564
Slovak Republic	299	380	679
Slovenia	258	321	579
Spain	363	421	784
Sweden	633	432	1,065
Switzerland	474	395	869
Turkey	182	0	182
Ukraine	334	263	597
N	9,961	11,400	21,361

Data Source: European Social Survey Rounds 2 and 5 (2004 and 2010)

Notes: Cells with X indicate country-rounds where no data was collected. Country samples includes only respondents between the ages of 18 and 59 who are in paid employment and in a co-residential partnership. The sample also excludes respondents with missing values on any of our individual-level covariates: Work-family conflict, work schedule timing, weekly work hours, education, occupational class, presence of children, age, gender, and partner's work status.

APPENDIX 4-2. OUTLINE OF SAMPLE SIZE RESTRICTIONS FROM EUROPEAN SOCIAL SURVEY DATA

Table 4-2-1. *Sample Size and Reductions Following Each Sample Restriction*

Sample Restriction	ESS Round		
	2004	2010	Both Rounds
Baseline Sample (No restrictions)	49,066	57,011	106,077
Between age of 18 and 64	33,819	37,584	71,403
Sample Reduction	-15,247	-19,427	-34,674
Did paid work in the last 7 days	17,895	21,313	39,208
Sample Reduction	-15,924	-16,271	-32,195
Worked more than 11 hours per week	16,537	19,898	36,435
Sample Reduction	-1,358	-1,415	-2,773
Currently living with spouse or partner	11,039	13,072	24,111
Sample Reduction	-5,498	-6,826	-12,324
Missing values removed ^a	9,961	11,400	21,361
Sample Reduction	-1,078	-1,672	-2,750

Data Source: European Social Survey Rounds 2 and 5 (2004 and 2010)

^a The sample also excludes respondents with missing values on any of our individual-level covariates: Work-family conflict, work schedule timing, weekly work hours, education, occupational class, presence of children, age, gender, and partner's work status.

APPENDIX 4-3. OUTLINE OF WORK-FAMILY CONFLICT INDEX

In this paper, work-family conflict (WFC) refers to the extent to which participation in one's work role(s) inhibits full participation in one's family role(s). We measure this using 4 items collected during Rounds 2 and 5 of the European Social Survey that ask respondents to report how often they: (1) "...feel[s] too tired after work to enjoy the things you would like to do at home"; (2) "...find[s] that your job prevents you from giving the time you want to your partner or family"; (3) feels that their "partner or family is fed up with the pressures of your job"; and (4) "worr[ies] about work problems when not working". Exploratory Factor Analysis was performed on these items to reduce them into a more manageable index. Results of this analysis (shown below in Table B-1) revealed one underlying factor (with an eigenvalue of > 1) consistent across the pooled and gender-specific samples. These items were also shown to have high reliability, with Cronbach Alpha values ranging from 0.73-0.74. To construct the final index, we summed each of the four items weighted by their respective loading score. Following this, we standardized the resultant index to a cross-sample mean of 0; this process is done separately for the pooled and gender-specific samples. Coefficients will therefore represent that the change in standardized self-reported work-family conflict associated with a one-unit change in the independent variable.

Table 4-3-1. *Exploratory Factor Analysis of Work-Family Conflict Indicators*

Item	Range	Pooled, <i>n</i> = 21,361	Women, <i>n</i> = 10,401	Men, <i>n</i> = 10,960
		EFA Loading Score		
Too tired after work to enjoy things you like to do at home, how often	1-5	0.64	0.65	0.64
Job prevents you from giving time to partner/family, how often	1-5	0.72	0.73	0.72
Partner/family fed up with the pressure of your job, how often	1-5	0.64	0.64	0.63
Worry about work problems when not working, how often	1-5	0.48	0.49	0.48
Cronbach's Alpha (<i>a</i>)		0.73	0.74	0.73
Mean (Raw)		9.34	9.33	9.38
<i>SE</i>		0.02	0.02	0.02
Eigenvalues				
Factor 1		1.57	1.60	1.55
Factor 2		-0.05	-0.05	-0.05
Factor 3		-0.06	-0.07	-0.06

Data Source: European Social Survey Rounds 2 and 5 (2004 and 2010)

Notes: Sample includes individuals between the ages of 18-59 in paid employment of more than 11 hours per week and living in a co-residential union. Individuals were removed if they had missing values on work-family conflict indicators, education (ISCED-97), work schedule timing, work hours, presence of children, partner's employment status, age, or occupational status (ESeC).

APPENDIX 4-4. OVERVIEW OF OECD JOB STRAIN INDEX

Within this index, two types of job demands are identified: (1) Time pressure which encompasses long working hours, high work intensity and working time inflexibility; and (2) physical health risk factors, such as dangerous work (i.e., being exposed to noise, vibrations, high and low temperature) and hard work (i.e., carrying and moving heavy loads, painful and tiring positions). Similarly, two types of job resources are considered, namely: (1) Work autonomy and learning opportunities which include workers' freedom to choose and change their work tasks and methods, as well as formal (i.e., training) and informal learning opportunities at work; and (2) social support at work which measures the extent of which workers receive social support from colleagues and supervisors. The composite Job Strain index, therefore, refers to those jobs where the workers face one demand but have no resources, or face two demands but have one or no resource.

The Job Strain Index is obtained by combining two international surveys since there is no single data source that covers the OECD countries: the European Working Conditions Survey (for 2005, 2010 and 2015) and the Work Orientations modules of the International Social Survey Program (for 2005). Both surveys contain questions on the job demands and job resources discussed above; these questions differ in terms of question-wording, answer scales and questions order. This may result in differences in individuals' responses across countries. To overcome these problems, the OECD has conducted an extended analysis in order to assess the degree of comparability between the two surveys for the 169 common countries in 2005: it shows that choosing the most similar questions and applying certain thresholds yields a correlation coefficient of 0.89 between the job strain indices from the two surveys. The Job Quality Database thus presents the composite Job Strain Index (EWCS and rescaled ISSP indices), the proportion of workers who face time pressure, the proportion of workers who face

physical health risk factors, the proportion of workers who enjoy work autonomy and learning opportunities, and the proportion of workers who get social support at work.

APPENDIX 4-5. DESCRIPTION OF CROSS-CLASSIFIED MODELING APPROACH

As we are utilizing repeated cross-sections for multiple countries, we have a cross-classified data structure where countries belong to one or more higher level groups (the survey year). In contrast to a typical two-level multilevel model where individuals are nested within countries or where periods are nested within individuals, individuals here are nested within the cells of the cross-classification of countries and survey years (both conceptually at level 2). In this case, there is not repeated observations nested within individuals (like in panel data), but an overarching period level that shares variance with country. Another way of describing this data structure is to say that there are two separate two-level hierarchies, which cross on one another: (1) individuals-within-countries-hierarchy; and (2) individuals-within-survey-years-hierarchy.

To account for this, we apply the cross-classified modeling approach proposed by Goldstein (1994). We will treat countries as the level-2 units and specify a random intercept for each. The survey year will then be treated as the level three unit, where we will introduce a dummy variable for each year (-1) in the fixed part and a random coefficient for each of these dummies in the random part. Practically, the main assumptions of any multilevel model remain the same. Firstly, our random intercepts are assumed to have zero means and be independent of each other. Secondly, our random intercepts are assumed not to be correlated with the individual-level residual. The key difference is that the random intercept for a given country is shared across both survey years, and the random intercept for a given survey year is shared across all countries.

APPENDIX 4-6. FULL RESULTS FOR RANDOM INTERCEPTS MODELS, INCLUDING CONTROL VARIABLES

Table 4-6-1. *Random Intercepts Models of the Effects of Work Schedule Timing on WFC*

	Pooled			Women	Men
	1	2	3	4	5
Fixed Effects					
Nonstandard Days	0.094*** (0.005)	0.082*** (0.015)	0.094*** (0.005)	0.098*** (0.008)	0.090*** (0.008)
Nonstandard Hours	0.086*** (0.004)	0.086*** (0.004)	0.079*** (0.010)	0.088*** (0.006)	0.084*** (0.005)
Woman	0.149*** (0.015)	0.128*** (0.026)	0.136*** (0.023)		
Nonstandard Days * Woman		0.008 (0.009)			
Nonstandard Hours * Woman			0.005 (0.007)		
Education (Secondary degree ref.)					
> lower secondary (ISCED 0, 1)	-0.043 (0.034)	-0.043 (0.034)	-0.043 (0.034)	-0.059 (0.044)	-0.014 (0.052)
Lower secondary (ISCED 2)	-0.059** (0.022)	-0.058** (0.022)	-0.058** (0.022)	-0.038 (0.03)	-0.076* (0.032)
Post-second., non-tertiary (ISCED 4)	0.027 (0.031)	0.027 (0.031)	0.027 (0.031)	0.007 (0.043)	0.058 (0.043)
Tertiary education (ISCED 5, 6)	0.077*** (0.017)	0.077*** (0.017)	0.076*** (0.017)	0.067** (0.025)	0.080** (0.024)
ESeC (Routine ref.)					
Large employers, mgrs/professionals	0.218*** (0.027)	0.217*** (0.027)	0.218*** (0.027)	0.229*** (0.035)	0.212*** (0.041)
Lower mgrs, higher supervisors	0.206*** (0.023)	0.206*** (0.023)	0.206*** (0.023)	0.206*** (0.031)	0.214*** (0.033)
Intermediate occupations	0.057* (0.026)	0.059 (0.026)	0.058 (0.026)	0.017 (0.045)	0.084* (0.034)
Lower supervisors and technicians	0.120*** (0.025)	0.119*** (0.025)	0.119*** (0.025)	0.103*** (0.031)	0.157*** (0.043)
Lower sales and service	-0.027 (0.025)	-0.029 (0.025)	-0.027 (0.025)	-0.066 (0.041)	0.009 (0.033)
Lower technical	0.064* (0.026)	0.063* (0.026)	0.062 (0.026)	0.064 (0.03)	0.013 (0.056)
Age Group (36-50 ref.)					
18-24	-0.067	-0.067	-0.067	-0.029	-0.111*

	(0.041)	(0.041)	(0.041)	(0.062)	(0.054)
25-35	0.004	0.004	0.004	0.022	-0.021
	(0.015)	(0.015)	(0.015)	(0.022)	(0.022)
50-59	-0.049**	-0.049**	-0.049**	-0.059*	-0.040
	(0.018)	(0.018)	(0.018)	(0.024)	(0.026)
Parent	0.089***	0.089***	0.089***	0.087***	0.095***
	(0.014)	(0.014)	(0.014)	(0.02)	(0.021)
Work Hours (35-49 ref.)					
12-34	-0.266***	-0.265***	-0.266***	-0.151***	-0.308***
	(0.019)	(0.019)	(0.019)	(0.041)	(0.022)
50+	0.349***	0.351***	0.350***	0.368***	0.322***
	(0.018)	(0.018)	(0.018)	(0.022)	(0.033)
Partner's Work Status (Employed ref.)					
Non-Employed	0.152***	0.152***	0.152***	0.175***	0.119**
	(0.028)	(0.028)	(0.028)	(0.038)	(0.04)
Unemployed	0.102***	0.102***	0.102***	0.090***	0.137***
	(0.015)	(0.015)	(0.015)	(0.019)	(0.027)
Random Effects					
Year Variance	0.003***	0.003***	0.003***	0.002***	0.004***
	[0.001, 0.026]	[0.001, 0.026]	[0.001, 0.026]	[0.000, 0.017]	[0.001, 0.036]
Country Variance	0.027***	0.027***	0.027 ***	0.018***	0.038***
	[0.016, 0.046]	[0.016, 0.046]	[0.016, 0.046]	[0.010, 0.032]	[0.022, 0.065]
Individual Variance	0.829***	0.829***	0.829***	0.833***	0.822***
	[0.814, 0.845]	[0.814, 0.845]	[0.814, 0.845]	[0.809, 0.854]	[0.800, 0.844]
Model Fit					
Change in Residual Country- Year Intercept Variance ^a	-13%	0%	0%	-33%	-10%
Change in Residual Individual Variance ^a	-14%	0%	0%	-14%	-14%
LL Ratio Test ^b	2010***	0.9	0.5	1572***	1651***
Change in BIC ^c	-3020	9	10	-1387	-1465
N		21361		10401	10960

Data Source: European Social Survey Rounds 2 and 5 (2004 and 2010)

Notes: Sample includes individuals between the ages of 18-59 in paid employment and living in a co-residential union. ^a Calculated as the proportional reduction in variance from the values derived from the null model. ^b Results of log likelihood ratio tests are calculated against the null model. ^c Reductions in BIC values of about 4 or more suggest a strong improvement in model fit.

* $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

APPENDIX 4-7. RANDOM INTERCEPTS MODELS WITH PARENTAL STATUS INTERACTIONS

Table 4-7-1. *Random Intercepts Models with Interactions on Presence of Children Under Age 13*

	Pooled			
	1	2	3	4
Fixed Effects				
Nonstandard Days	0.093*** (0.007)	0.095*** (0.005)	0.079*** (0.022)	0.095*** (0.005)
Nonstandard Hours	0.086*** (0.004)	0.079*** (0.005)	0.086*** (0.004)	0.047** (0.016)
Woman	0.149*** (0.015)	0.148*** (0.015)	0.122*** (0.038)	0.085*** (0.033)
Child Under 13	0.083** (0.026)	0.055* (0.023)	0.065 (0.082)	-0.078 (0.071)
Nonstandard Days * Child Under 13	0.003 (0.009)		0.004 (0.029)	
Nonstandard Hours * Child Under 13		0.012 (0.006)		0.053* (0.021)
Nonstandard Days * Woman			0.009 (0.014)	
Nonstandard Hours * Woman				0.021* (0.010)
Child Under 13 * Woman			0.010 (0.050)	0.086* (0.043)
Nonstandard Days * Woman * Child Under 13			0.000 (0.018)	
Nonstandard Hours * Woman * Child Under 13				-0.026* (0.013)
Random Effects				
Year Variance	0.003*** [0.001, 0.026]	0.003*** [0.001, 0.026]	0.003*** [0.001, 0.026]	0.003*** [0.001, 0.026]
Country Variance	0.027*** [0.016, 0.046]	0.027*** [0.016, 0.046]	0.027*** [0.016, 0.046]	0.027*** [0.016, 0.046]
Individual Variance	0.829*** [0.814, 0.845]	0.829*** [0.814, 0.845]	0.829*** [0.814, 0.845]	0.829*** [0.814, 0.845]
Model Fit				
Change in Country-Year Intercept Variance ^a	0.0%	-0.1%	-0.2%	-0.1%
Change in Individual Variance ^a	0.0%	0.0%	0.0%	0.0%
LL Ratio Test ^b	0.1	3.7*	1.1	8.8*
Change in BIC from Model w/ No Interactions	9.9	6.3	38.8	31.1
N	21361			

Data Source: European Social Survey Rounds 2 and 5 (2004 and 2010)

Notes: Sample includes individuals between the ages of 18-59 in paid employment of more than 11 hours per week and living in a co-residential union. Sample size also reflects list-wise deletion done on all covariates. Control variables are gender, education, age, working hours, occupational class, presence

of children under 13, and partner's employment status. ^a Calculated as the proportional reduction in variance from the values derived from model with no interactions. ^b Results of log likelihood ratio tests are calculated against model with no interactions. * p<0.5, ** p<0.01, *** p<0.001

Table 4-7-2. *Random Intercepts Models with Interactions on Presence of Children Under Age 5*

	Pooled			
	1	2	3	4
Fixed Effects				
Nonstandard Days	0.092*** (0.007)	0.094*** (0.005)	0.087*** (0.021)	0.095*** (0.005)
Nonstandard Hours	0.086*** (0.004)	0.081*** (0.005)	0.086*** (0.004)	0.060*** (0.015)
Woman	0.147*** (0.015)	0.147*** (0.015)	0.136*** (0.036)	0.107*** (0.031)
Child Under 5	0.065* (0.025)	0.049* (0.022)	0.094 (0.081)	-0.032 (0.070)
Nonstandard Days *	0.004 (0.009)		-0.010 (0.029)	
Child Under 5				
Nonstandard Hours *		0.009 (0.009)		0.035 (0.020)
Child Under 5				
Nonstandard Days *			0.004 (0.013)	
Woman				
Nonstandard Hours *				0.014 (0.009)
Woman				
Child Under 5 *			-0.020 (0.050)	0.052 (0.043)
Woman				
Nonstandard Days *			0.010 (0.018)	
Woman * Child Under 5				
Nonstandard Hours *				-0.017 (0.013)
Woman * Child Under 5				
Random Effects				
Year Variance	0.003*** [0.001, 0.026]	0.003*** [0.001, 0.026]	0.003*** [0.001, 0.026]	0.003*** [0.001, 0.026]
Country Variance	0.027*** [0.016, 0.046]	0.027*** [0.016, 0.046]	0.027*** [0.016, 0.046]	0.027*** [0.016, 0.046]
Individual Variance	0.830*** [0.814, 0.846]	0.830*** [0.814, 0.846]	0.830*** [0.814, 0.846]	0.830*** [0.814, 0.846]
Model Fit				
Change in Country-Year Intercept Variance ^a	0.0%	-0.1%	-0.3%	0.0%
Change in Individual Variance ^a	0.0%	0.0%	0.0%	0.0%
LL Ratio Test ^b	0.1	2.1	1.4	4.5
Change in BIC from Model w/ No Interactions	9.8	7.9	38.5	35.4
N	21361			

Data Source: European Social Survey Rounds 2 and 5 (2004 and 2010)

Notes: Sample includes individuals between the ages of 18-59 in paid employment of more than 11 hours per week and living in a co-residential union. Sample size also reflects list-wise deletion done on all covariates. Control variables are gender, education, age, working hours, occupational class, presence of children under 13, and partner's employment status. ^a Calculated as the proportional reduction in

variance from the values derived from model with no interactions. ^b Results of log likelihood ratio tests are calculated against model with no interactions. * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

APPENDIX 4-8. NONSTANDARD HOURS CROSS-LEVEL GENDER INTERACTIONS IN RANDOM SLOPES MODELS

Table 4-8-1. *Nonstandard Hours Cross-Level & Gender Interactions in Random Slopes Models*

	Pooled			
	1	2	3	4
Fixed Effects				
Nonstandard Hours	0.070*** (0.011)	0.071*** (0.011)	0.070*** (0.012)	0.070*** (0.012)
Woman	0.145*** (0.016)	0.145*** (0.016)	0.145*** (0.016)	0.145*** (0.016)
Woman * Nonstandard Hours	0.011 (0.007)	0.011 (0.007)	0.011 (0.007)	0.013+ (0.007)
Union Coverage	-0.135** (0.049)			-0.167** (0.058)
NS Hours * Union Coverage	0.024* (0.01)			0.028* (0.013)
Woman * Union Coverage	0.079*** (0.021)			0.076** (0.028)
<i>NS Hours * Woman * Union Coverage</i>	-0.020** (0.006)			-0.021* (0.008)
CBC		-0.074 (0.051)		-0.021 (0.058)
NS Hours * CBC		0.016 (0.011)		0.000 (0.013)
Woman * CBC		0.082*** (0.024)		0.043 (0.028)
<i>NS Hours * Woman * CBC</i>		-0.016* (0.007)		-0.003 (0.009)
Job Strain			-0.056 (0.041)	-0.121** (0.046)
NS Hours * Job Strain			-0.007 (0.011)	0.008 (0.013)
Woman * Job Strain			-0.011 (0.024)	0.036 (0.027)
<i>NS Hours * Woman * Job Strain</i>			0.007 (0.007)	-0.005 (0.008)
Model Fit				
Change in Country Slope Variance ^a	4%	5%	4%	8%
Change in Country Intercept Variance ^a	1%	4%	1%	1%
LR Test	15.530**	14.030**	2.830	22.950**
Change in BIC from RS Baseline Model	13.871	15.376	26.566	46.651
N	18044	18044	18044	18044

Data Source: European Social Survey Rounds 2 and 5 (2004 and 2010)

Note: Sample includes respondents between the ages of 18-59 in paid employment and living in a co-residential union. Dependent variable is WFC Index. Predictor variable is regularity of nonstandard work hours. Control variables are gender, education, age, working hours, occupational class, presence of children under 13 in household, partner's employment status, and country GDP. ^aProportional change in variance from a model with no gender interactions. * p<0.5, ** p<0.01, *** p<0.001

APPENDIX 4-9. NONSTANDARD HOURS CROSS-LEVEL PARENTAL STATUS INTERACTIONS IN RANDOM SLOPES MODELS

Table 4-9-1. *Nonstandard Hours Cross-Level Parent (Child Under 13 present) Interactions in Random Slopes Models*

	Pooled			
	1	2	3	4
Fixed Effects				
Nonstandard Hours	0.079*** (0.006)	0.078*** (0.006)	0.078*** (0.006)	0.078*** (0.006)
Parent (child under 13 present)	0.085*** (0.015)	0.085*** (0.015)	0.086*** (0.015)	0.085*** (0.015)
Parent * Nonstandard Hours	0.013+ (0.007)	0.014+ (0.007)	0.013+ (0.007)	0.012+ (0.007)
Union Coverage	-0.011 (0.038)			-0.052 (0.043)
NS Hours * Union Coverage	-0.009* (0.005)			-0.007 (0.006)
Parent * Union Coverage	0.000 (0.021)			0.008 (0.028)
<i>NS Hours * Parent * Union Coverage</i>	<i>0.006 (0.006)</i>			<i>0.007 (0.008)</i>
CBC		0.065+ (0.038)		0.061 (0.043)
NS Hours * CBC		-0.011* (0.006)		-0.006 (0.007)
Parent * CBC		-0.022 (0.024)		-0.026 (0.028)
<i>NS Hours * Parent * CBC</i>		<i>0.005 (0.007)</i>		<i>-0.001 (0.009)</i>
Job Strain			-0.064** (0.023)	-0.057* (0.025)
NS Hours * Job Strain			0.004 (0.005)	-0.002 (0.006)
Parent * Job Strain			-0.011 (0.024)	-0.010 (0.028)
<i>NS Hours * Parent * Job Strain</i>			<i>-0.002 (0.007)</i>	<i>0.002 (0.008)</i>
Model Fit				
Change in Country Slope Variance ^a	-2%	-5%	-2%	-3%
Change in Country Intercept Variance ^a	-1%	0%	-1%	0%
LR Test	7.700+	5.200	5.810	9.900
Change in BIC from RS Baseline Model	22.333	24.197	23.590	58.705
N	18044	18044	18044	18044

Data Source: European Social Survey Rounds 2 and 5 (2004 and 2010)

Note: Sample includes respondents between the ages of 18-59 in paid employment and living in a co-residential union. Dependent variable is WFC Index. Predictor variable is regularity of nonstandard work hours. Control variables are gender, education, age, working hours, occupational class, presence of children under 13 in household, partner's employment status, and country GDP. ^a Proportional change in variance from a model with no parent interactions. * p<0.5, ** p<0.01, *** p<0.001

Table 4-9-2. *Nonstandard Hours Cross-Level Parent (Child Under 5 present) Interactions in Random Slopes Models*

	Pooled			
	1	2	3	4
Fixed Effects				
Nonstandard Hours	0.081*** (0.006)	0.081*** (0.006)	0.081*** (0.006)	0.081*** (0.006)
Parent (child under 5 present)	0.072*** (0.015)	0.072*** (0.015)	0.071*** (0.015)	0.071*** (0.015)
Parent * Nonstandard Hours	0.010 (0.007)	0.010 (0.007)	0.010 (0.007)	0.009 (0.007)
Union Coverage	-0.006 (0.037)			-0.044 (0.042)
NS Hours * Union Coverage	-0.009* (0.004)			-0.006 (0.006)
Parent * Union Coverage	-0.008 (0.021)			-0.007 (0.028)
<i>NS Hours * Parent * Union Coverage</i>	<i>0.006 (0.006)</i>			<i>0.005 (0.008)</i>
CBC		0.065+ (0.037)		0.057 (0.042)
NS Hours * CBC		-0.012* (0.005)		-0.008 (0.006)
Parent * CBC		-0.022 (0.024)		-0.019 (0.028)
<i>NS Hours * Parent * CBC</i>		<i>0.006 (0.007)</i>		<i>0.002 (0.009)</i>
Job Strain			-0.065** (0.022)	-0.055* (0.024)
NS Hours * Job Strain			0.004 (0.005)	0.000 (0.006)
Parent * Job Strain			-0.011 (0.024)	-0.017 (0.027)
<i>NS Hours * Parent * Job Strain</i>			<i>-0.003 (0.007)</i>	<i>0.000 (0.008)</i>
Model Fit				
Change in Country Slope Variance ^a	-2%	-3%	-1%	-1%
Change in Country Intercept Variance ^a	-1%	0%	-1%	-1%
LR Test	4.150	3.560	4.640	6.130
Change in BIC from RS Baseline Model	25.250	25.842	24.763	62.477
N	18044	18044	18044	18044

Data Source: European Social Survey Rounds 2 and 5 (2004 and 2010)

Note: Sample includes respondents between the ages of 18-59 in paid employment and living in a co-residential union. Dependent variable is WFC Index. Predictor variable is regularity of nonstandard work hours. Control variables are gender, education, age, working hours, occupational class, presence of children under 13 in household, partner's employment status, and country GDP. ^a Proportional change in variance from a model with no parent interactions. * p<0.5, ** p<0.01, *** p<0.001

APPENDIX 4-10. NONSTANDARD DAYS CROSS-LEVEL GENDER INTERACTIONS IN RANDOM SLOPES MODELS

Table 4-10-1. *Nonstandard Days Cross-Level & Gender Interactions in Random Slopes Models*

	Pooled			
	1	2	3	4
Fixed Effects				
Nonstandard Days	0.095*** (0.006)	0.096*** (0.006)	0.095*** (0.006)	0.095*** (0.006)
Woman	0.134*** (0.016)	0.132*** (0.016)	0.133*** (0.016)	0.133*** (0.016)
Woman * Nonstandard Days	0.012 (0.010)	0.015 (0.010)	0.013 (0.010)	0.018+ (0.010)
Union Coverage	-0.124* (0.052)			-0.103 (0.063)
NS Days * Union Coverage	0.024+ (0.015)			0.007 (0.019)
Woman * Union Coverage	0.068** (0.024)			0.022 (0.032)
<i>NS Days * Woman * Union Coverage</i>	-0.018* (0.009)			-0.002 (0.012)
CBC		-0.082 (0.057)		-0.051 (0.064)
NS Days * CBC		0.019 (0.016)		0.011 (0.018)
Woman * CBC		0.086** (0.028)		0.069* (0.033)
<i>NS Days * Woman * CBC</i>		-0.018+ (0.01)		-0.014 (0.012)
Job Strain			0.006 (0.045)	-0.030 (0.051)
NS Days * Job Strain			-0.033* (0.015)	-0.029 (0.017)
Woman * Job Strain			-0.057* (0.027)	-0.036 (0.031)
<i>NS Days * Woman * Job Strain</i>			0.027** (0.01)	0.025* (0.011)
Model Fit				
Change in Country Slope Variance ^a	-1%	-3%	-2%	-7%
Change in Country Intercept Variance ^a	1%	4%	1%	2%
LR Test	9.680*	13.170**	8.950*	22.750**
Change in BIC from RS Baseline Model	19.717	16.229	20.453	45.855
N	18044	18044	18044	18044

Data Source: European Social Survey Rounds 2 and 5 (2004 and 2010)

Note: Sample includes respondents between the ages of 18-59 in paid employment and living in a co-residential union. Dependent variable is WFC Index. Predictor variable is regularity of nonstandard work days. Control variables are gender, education, age, working hours, occupational class, presence of children under 13 in household, partner's employment status, and country GDP. ^aProportional change in variance from a model with no gender interactions. * p<0.5, ** p<0.01, *** p<0.001

APPENDIX 4-11. NONSTANDARD HOURS CROSS-LEVEL PARENTAL STATUS INTERACTIONS IN RANDOM SLOPES MODELS

Table 4-11-1. *Nonstandard Days Cross-Level Parent (Child Under 13 present) Interactions in Random Slopes Models*

	Pooled			
	1	2	3	4
Fixed Effects				
Nonstandard Days	0.094*** (0.008)	0.096*** (0.008)	0.095*** (0.008)	0.094*** (0.008)
Parent (child under 13 present)	0.086*** (0.015)	0.085*** (0.015)	0.085*** (0.015)	0.085*** (0.015)
Parent * Nonstandard Days	0.002 (0.01)	0.000 (0.01)	0.001 (0.01)	-0.001 (0.01)
Union Coverage	-0.006 (0.039)			-0.064 (0.044)
NS Days * Union Coverage	-0.015* (0.007)			-0.005 (0.009)
Parent * Union Coverage	-0.022 (0.024)			-0.002 (0.032)
<i>NS Days * Parent * Union Coverage</i>	<i>0.017+</i> <i>(0.009)</i>			<i>0.013</i> <i>(0.012)</i>
CBC		0.076+ (0.04)		0.079+ (0.045)
NS Days * CBC		-0.017* (0.008)		-0.013 (0.009)
Parent * CBC		-0.042 (0.028)		-0.042 (0.033)
<i>NS Days * Parent * CBC</i>		<i>0.013</i> <i>(0.01)</i>		<i>0.005</i> <i>(0.012)</i>
Job Strain			-0.085*** (0.025)	-0.084** (0.027)
NS Days * Job Strain			0.014+ (0.007)	0.010 (0.009)
Parent * Job Strain			0.009 (0.027)	0.005 (0.031)
<i>NS Days * Parent * Job Strain</i>			<i>-0.012</i> <i>(0.01)</i>	<i>-0.005</i> <i>(0.011)</i>
Model Fit				
Change in Country Slope Variance ^a	0%	-2%	-2%	0%
Change in Country Intercept Variance ^a	0%	1%	0%	0%
LR Test	6.050	2.270	3.460	10.000
Change in BIC from RS Baseline Model	23.355	27.137	25.944	58.603
N	18044	18044	18044	18044

Data Source: European Social Survey Rounds 2 and 5 (2004 and 2010)

Note: Sample includes respondents between the ages of 18-59 in paid employment and living in a co-residential union. Dependent variable is WFC Index. Predictor variable is regularity of nonstandard work days. Control variables are gender, education, age, working hours, occupational class, presence of children under 13 in household, partner's employment status, and country GDP. ^a Proportional change in variance from a model with no parent interactions. * p<0.5, ** p<0.01, *** p<0.001

Table 4-11-2. *Nonstandard Days Cross-Level Parent (Child Under 5 present) Interactions in Random Slopes Models*

	Pooled			
	1	2	3	4
Fixed Effects				
Nonstandard Days	0.093*** (0.008)	0.095*** (0.008)	0.094*** (0.008)	0.093*** (0.008)
Parent (child under 5 present)	0.072*** (0.015)	0.071*** (0.015)	0.071*** (0.015)	0.071*** (0.015)
Parent * Nonstandard Days	0.003 (0.01)	0.001 (0.01)	0.002 (0.01)	0.000 (0.01)
Union Coverage	-0.008 (0.038)			-0.064 (0.043)
NS Days * Union Coverage	-0.011+ (0.006)			0.000 (0.008)
Parent * Union Coverage	-0.017 (0.024)			-0.002 (0.032)
<i>NS Days * Parent * Union Coverage</i>	<i>0.012</i> <i>(0.009)</i>			<i>0.005</i> <i>(0.012)</i>
CBC		0.069+ (0.039)		0.070 (0.044)
NS Days * CBC		-0.014* (0.007)		-0.013 (0.008)
Parent * CBC		-0.030 (0.028)		-0.028 (0.033)
<i>NS Days * Parent * CBC</i>		<i>0.010</i> <i>(0.01)</i>		<i>0.005</i> <i>(0.011)</i>
Job Strain			-0.086*** (0.023)	-0.086*** (0.026)
NS Days * Job Strain			0.015* (0.007)	0.013+ (0.008)
Parent * Job Strain			0.014 (0.027)	0.011 (0.031)
<i>NS Days * Parent * Job Strain</i>			<i>-0.015</i> <i>(0.01)</i>	<i>-0.012</i> <i>(0.011)</i>
Model Fit				
Change in Country Slope Variance ^a	0%	-1%	-2%	-2%
Change in Country Intercept Variance ^a	0%	0%	0%	0%
LR Test	2.520	1.250	4.750	6.380
Change in BIC from RS Baseline Model	26.879	28.155	24.650	62.221
N	18044	18044	18044	18044

Data Source: European Social Survey Rounds 2 and 5 (2004 and 2010)

Note: Sample includes respondents between the ages of 18-59 in paid employment and living in a co-residential union. Dependent variable is WFC Index. Predictor variable is regularity of nonstandard work days. Control variables are gender, education, age, working hours, occupational class, presence of children under 5 in household, partner's employment status, and country GDP. ^a Proportional change in variance from a model with no parent interactions. * p<0.5, ** p<0.01, *** p<0.001

APPENDIX 4-12. SENSITIVITY ANALYSES PERFORMING TWO-STEP REGRESSION INSTEAD OF MULTI-LEVEL MODELING

Table 4-12-1. Variance-Weighted Least Squares *Regression of Country-Intercepts and –Slopes on Country-Level Predictors*

	Country-Period-Averaged WFC	Country-Period-Specific Slopes	
		Nonstandard Hours	Nonstandard Days
CBC (Std.)	-0.0324** (0.0105)	-0.0085+ (0.005)	-0.0119+ (0.0068)
Union Coverage (Std.)	-0.0376*** (0.0101)	0.0009 (0.0045)	-0.0091 (0.0063)
Job Strain (Std.)	0.0096 (0.0103)	0.0008 (0.0046)	0.0061 (0.0064)
GDP (Std.)	-0.0280** (0.0102)	-0.0003 (0.0048)	-0.0018 (0.0065)
<i>n</i>	41	41	41

Data Source: European Social Survey Rounds 2 and 5 (2004 and 2010)

Notes: In step one, sample includes respondents between the ages of 18-59 in paid employment and living in a co-residential union. Control variables are gender, education, age, working hours, occupational class, presence of children under 5 in household, partner's employment status, and country GDP. In step 2, sample includes countries where all four country-level indicators were available. + $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

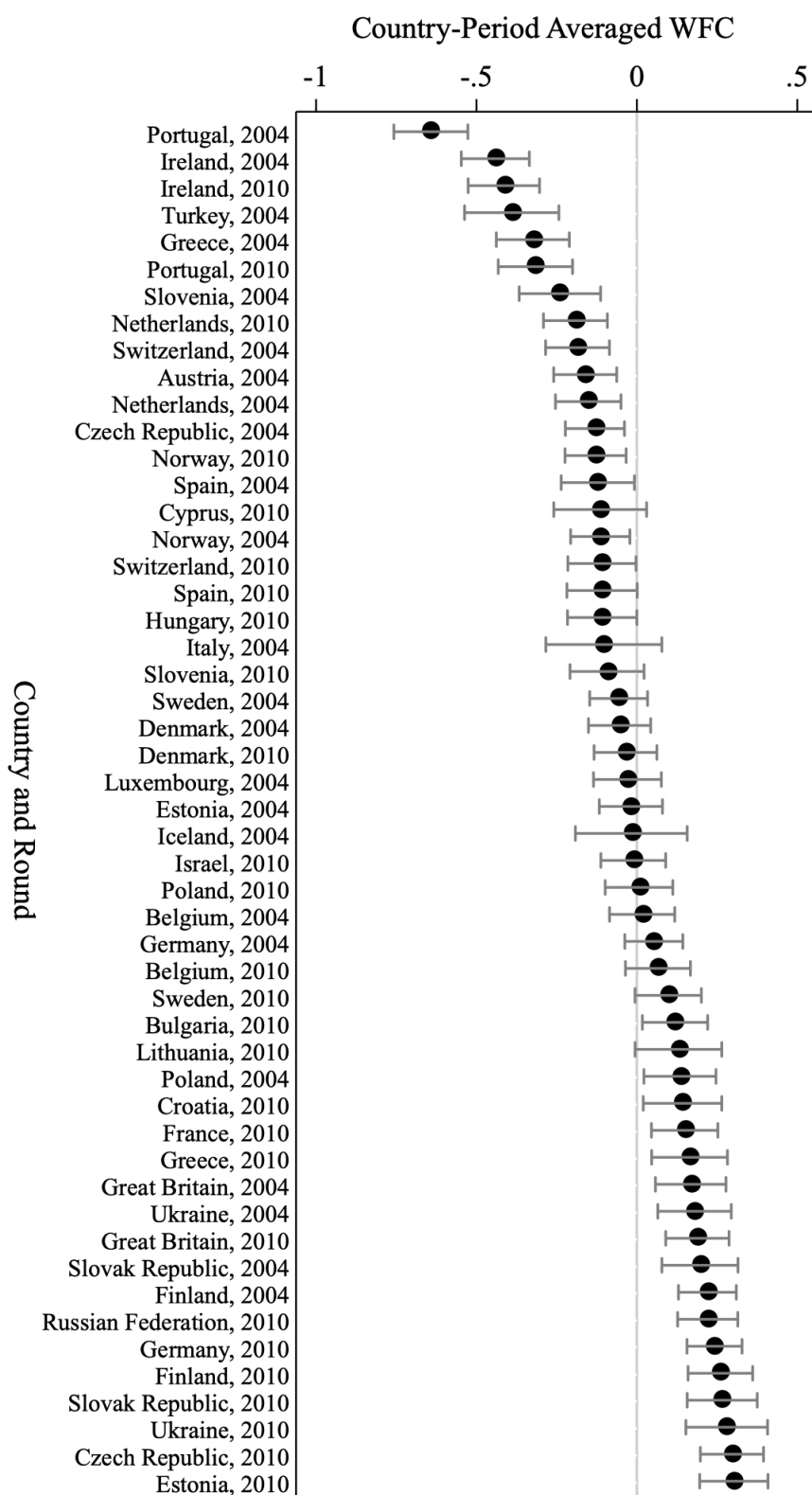


Figure 4-12-1. Country-Period-Averaged Predicted WFC

Data Source: European Social Survey Rounds 2 and 5 (2004 and 2010)

Notes: In step one, sample includes respondents between the ages of 18-59 in paid employment and living in a co-residential union. Control variables are gender, education, age, working hours, occupational class, presence of children under 5 in household, partner's employment status, and country GDP. In step 2, sample includes countries where all four country-level indicators were available. Dots indicate coefficients, and capped lines indicate 95% confidence intervals.

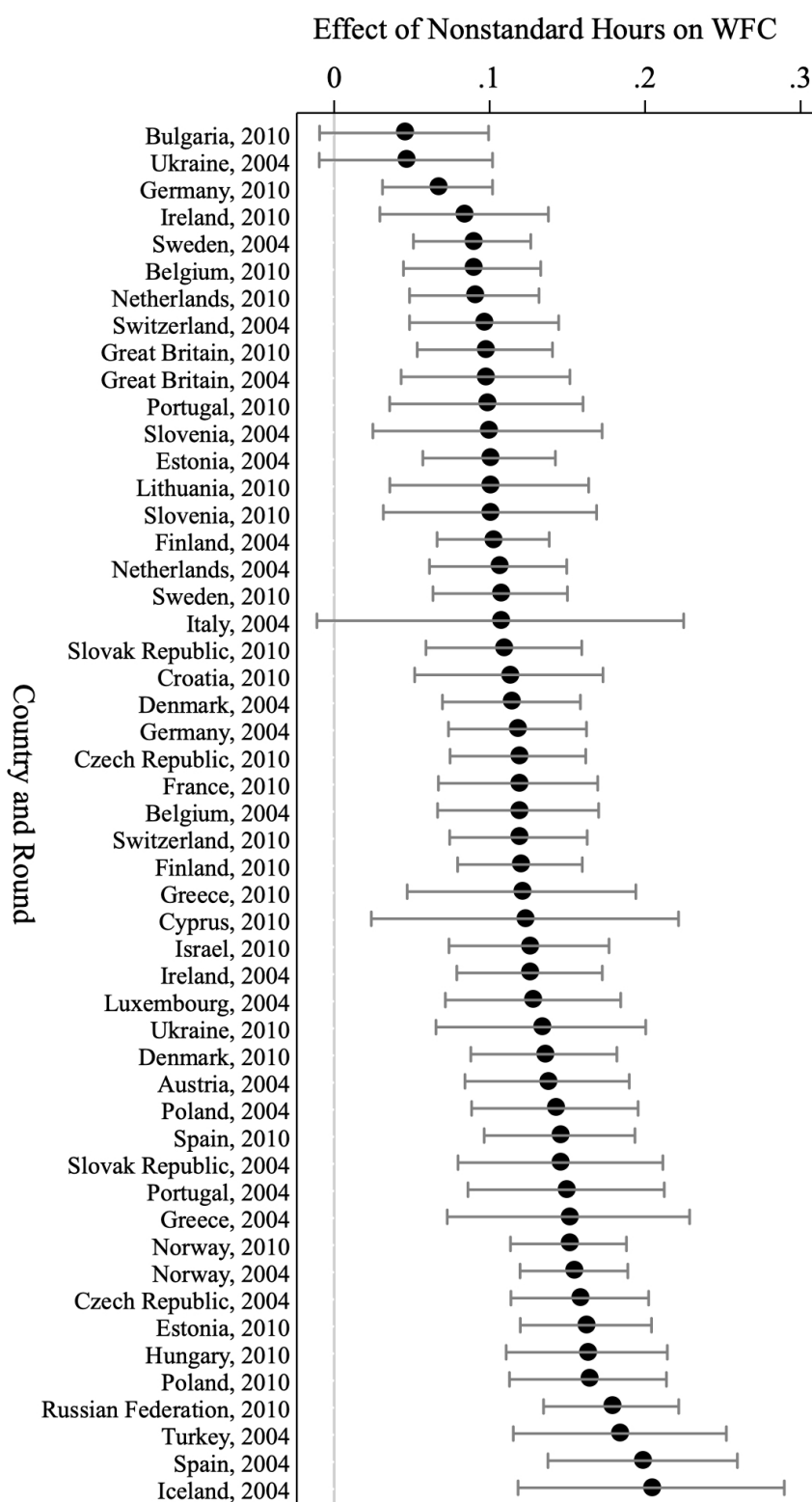


Figure 4-12-2. Country-Period-Specific Slopes of Nonstandard Work Hours

Data Source: European Social Survey Rounds 2 and 5 (2004 and 2010)

Notes: In step one, sample includes respondents between the ages of 18-59 in paid employment and living in a co-residential union. Control variables are gender, education, age, working hours, occupational class, presence of children under 5 in household, partner's employment status, and country GDP. In step 2, sample includes countries where all four country-level indicators were available. Dots indicate coefficients, and capped lines indicate 95% confidence intervals.

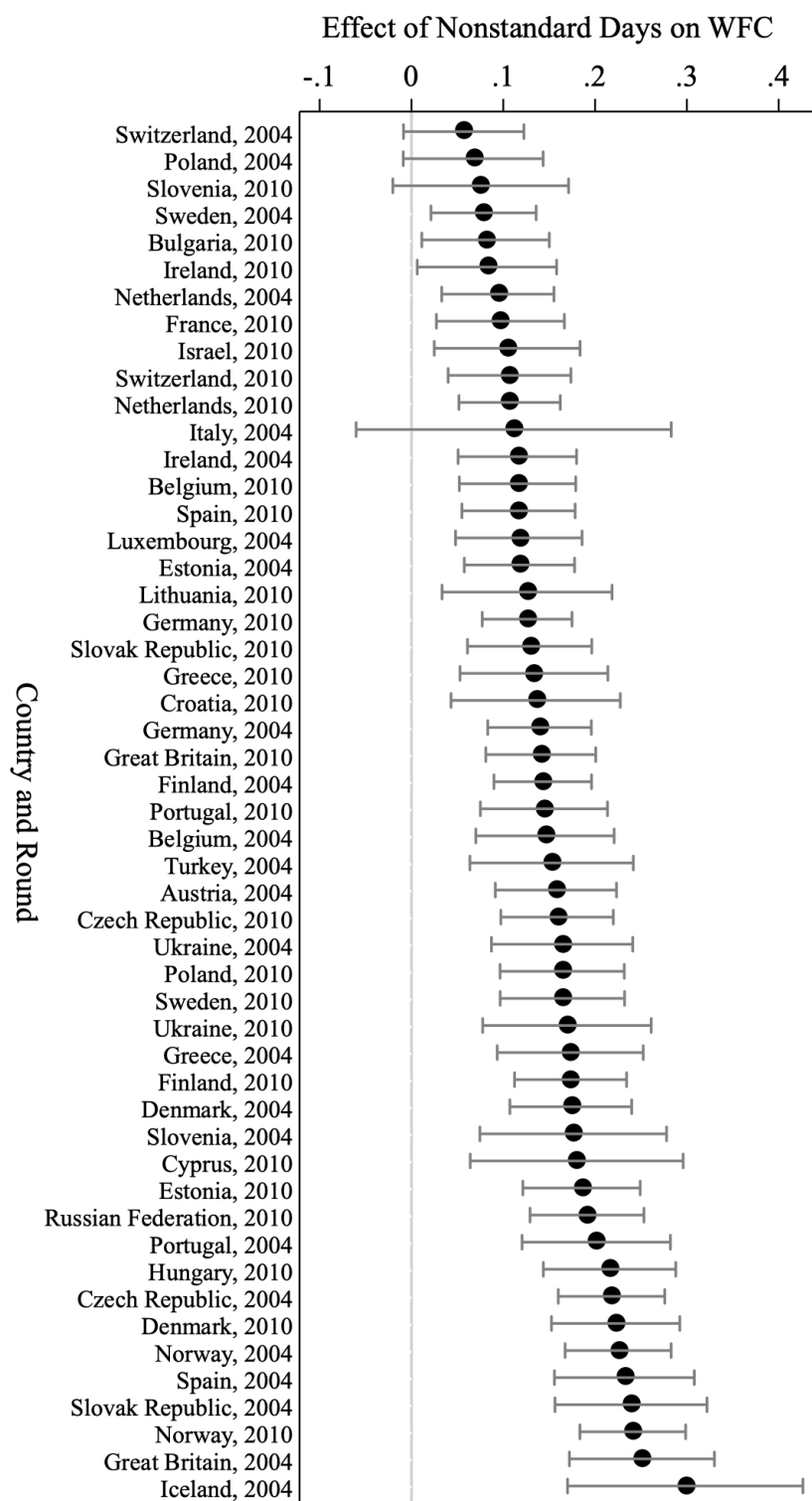


Figure 4-12-3. Country-Period-Specific Slopes of Nonstandard Work Days

Data Source: European Social Survey Rounds 2 and 5 (2004 and 2010)

Notes: In step one, sample includes respondents between the ages of 18-59 in paid employment and living in a co-residential union. Control variables are gender, education, age, working hours, occupational class, presence of children under 5 in household, partner's employment status, and country GDP. In step 2, sample includes countries where all four country-level indicators were available. Dots indicate coefficients, and capped lines indicate 95% confidence intervals.

APPENDIX 5-1. OUTLINE OF SAMPLE RESTRICTIONS FROM UK BIOBANK DATA

Table 5-1-1. *Size of Sample Size Restriction in UK Biobank*

Sample Restriction	<i>n</i>
Baseline Sample (No Restrictions)	502,999
1. Between Ages of 40 to 59	274,766
Sample Reduction	-228,233
2. In paid or self-employment	271,357
Sample Reduction	-3,409
3. Working at least 12 hours per week	212,595
Sample Reduction	-58,762
4. Non-missing night shift work indicator	212,464
Sample Reduction	-131
5. Non-missing eveningness measure	190,631
Sample Reduction	-21,833
6. Non-missing genotype data	186,171
Sample Reduction	-4,460
7. Non-missing values on employment duration	185,910
Sample Reduction	-261

Data Source: 2016 UK Biobank Data

APPENDIX 5-2. OUTLINE OF GENOME-WIDE SIGNIFICANT SNPs FROM 23ANDME COHORT

Table 5-2-1. *Index Significant SNPs Associated with Morningness (23andMe Cohort)*

Gene context	Marker name	Alleles (A/B)	OR for B allele	95% CI	<i>p</i> value
Genes with well-known circadian role					
RGS16 (<i>RNASEL</i>)	rs12736689	C/T	0.74	(0.69, 0.79)	7.0×10^{-18}
VIP	rs9479402	C/T	0.69	(0.62, 0.77)	3.9×10^{-11}
PER2	rs55694368	G/T	0.86	(0.81, 0.90)	2.6×10^{-9}
HCRT2 (aka <i>OX2R</i>)	rs35833281	C/G	0.92	(0.90, 0.95)	3.7×10^{-9}
RASD1	rs11545787	A/G	1.08	(1.05, 1.11)	1.4×10^{-8}
PER3 (<i>VAMP3</i>)	rs11121022	A/C	1.07	(1.04, 1.09)	2.0×10^{-8}
FBXL3 (<i>CLN5</i>)	rs9565309	C/T	1.19	(1.12, 1.26)	3.5×10^{-8}
Genes with plausible circadian role					
PLCL1	rs1595824	C/T	1.08	(1.05, 1.10)	1.2×10^{-10}
APH1A (<i>CA14</i>)	rs34714364	G/T	1.12	(1.08, 1.16)	2.0×10^{-10}
FBXL13 (<i>FAM185A</i>)	rs3972456	A/G	0.92	(0.89, 0.94)	6.0×10^{-9}
NOL4	rs12965577	A/G	0.94	(0.92, 0.96)	2.1×10^{-8}
Genes with less clear circadian role					
TOX3	rs12927162	A/G	0.91	(0.89, 0.94)	1.6×10^{-12}
AK5	rs10493596	C/T	1.09	(1.07, 1.12)	8.0×10^{-12}
DLX5 (<i>SHFMI</i>)	rs2948276	A/G	0.92	(0.89, 0.95)	1.1×10^{-8}
ALG10B	rs6582618	A/G	1.07	(1.04, 1.09)	1.5×10^{-8}

Source: 23andMe data (Hu et al., 2016).

APPENDIX 5-3. ISSUES SURROUNDING HORIZONTAL AND VERTICAL PLEIOTROPY

In general, two forms of pleiotropy can be distinguished. Vertical pleiotropy would occur if the genetic variants used in the PGS are associated with a factor(s) that lies along the pathway between chronotype and shift work selection (e.g., sleep duration requirements, sleep rigidity, etc.). This form of pleiotropy would, however, not violate the exclusion restriction as it is part of the pathway through which chronotype exerts an effect on shift work selection. In contrast, the second type of pleiotropy, so-called, horizontal pleiotropy, occurs when the genetic variants impact on an entirely separate biological pathway that affects shift work selection but is unrelated to chronotype and therefore violates the exclusion restriction (Katikireddi et al., 2018). One possible instance of horizontal pleiotropy would be via educational attainment. Lane et al. (2016), for example, found that many of the same genetic variants associated with eveningness are also associated with greater years of education (r_g (s.e.) 0.161 (0.041), $p > 8.96 \times 10^{-5}$). This genetic correlation alludes to the possibility that any association between eveningness and shift work may be acting via education (and its cognitive and non-cognitive antecedents) rather than via chronotype. However, in theory, there is an infinite and unknowable number of possible pathways through which horizontal pleiotropy could occur – this is a limitation that plagues most applications of Mendelian Randomization. One way future research could address this issue in the present case would be to use a weaker but more precise genetic instrument that only includes those SNPs with a well-established role in the regulation of circadian rhythms.

APPENDIX 5-4. IV ESTIMATION ASSUMPTIONS

IV estimation requires the use of four assumption: (1) the independence assumption, or that the instrument is random with respect to potential confounders; (2) there is a non-zero effect of the instrument on the endogenous regressor; (3) the exclusion restriction assumption, or that there is no causal pathway between an instrument and an outcome except through the instrumented variable; and (4) the monotonicity assumption, or that the instrument affects the instrumented variable in the same direction for all equivalent individuals. Of these, only assumption two can be tested. In the following discussion, I address each of these assumptions in the context of the current analysis.

With regards to assumption one (the independence assumption), it is generally accepted that genotypes are randomly assigned at meiosis, and thus the instrument should by extension be random with respect to potential confounders. As discussed earlier, one possible violation to the independence assumption could come via population stratification; I addressed this by controlling for the first five genetic principal components in all analyses that included PG scores and by restricting the analysis to the relatively genetically homogeneous sample of individuals from European ancestry.

Regarding assumption two (a non-zero effect of the instrument on the endogenous regressor), I tested this by regressing the self-reported eveningness on the PGS for eveningness (Table 5-2). As was found, a one standard deviation increase in polygenic risk for eveningness was associated with an 2.5% increase in the probability self-reported eveningness ($P < 0.001$). This effect held after controlling for the first 5 genetic principal components, suggesting that this relationship is not spuriously tied to population stratification.

Regarding assumption three (the exclusion restriction assumption), it is generally accepted that one can never prove that an instrument affects an outcome solely through the

endogenous regressor. In the context of genetic instruments, the exclusion restriction is particularly hard to prove given that most genetic loci are pleiotropic and contribute to many phenotypic traits. Compounding this is the fact that many of the biological pathways through which genetic loci affect phenotypic variation are still a black box. As discussed in Appendix 5-3, this issue of pleiotropy should only be problematic for the exclusion restriction if it is horizontal (i.e. the genetic variants impact on an entirely separate biological pathway that affects shift work selection but is unrelated to chronotype). As with most applications of genetic instruments, there are in theory an infinite and unknowable possible instances of horizontal pleiotropy that could call to question the validity of the exclusion restriction assumption. I discuss on such instance in Appendix 5-3 and outline this issue further in the Discussion section.

Regarding the monotonicity assumption (i.e., the instrument affects the instrumented variable in the same direction for all equivalent respondents), verifying this requires one to be able to observe counterfactuals for each individual; for this reason, it is generally thought to be untestable (Small, Tan, Ramsahai, Lorch, & Brookhart, 2017). While there is no available evidence documenting a violation to the monotonicity assumption in the present case, one plausible threat could come via gene-environment interactions where clock gene expression might vary depending on one's environment and life course. For example, there is some evidence of epigenetic changes in clock gene expression that occur as individuals grow older (Bukowska-Damska et al., 2017; Deibel et al., 2015; C. Liu & Chung, 2015). However, in the present case, such epigenetic alterations would likely only attenuate the predictive strength of the instrument as individuals age rather than reversing the direction of its effect. I return to this issue in subsequent discussions in the Results section.

APPENDIX 5-5. SENSITIVITY ANALYSES PERFORMING PROBIT RATHER THAN OLS REGRESSION ON BINARY OUTCOMES

Table 5-5-1. *Stage-One Probit Regressions of Self-Reported Eveningness (Binary) on Polygenic Risk for Eveningness*

	Self-Reported Eveningness (Binary)	
	Marginal Probability	
	1	2
Eveningness PGS (Std.)	0.0250*** (0.0011)	0.0247*** (0.0011)
Age		-0.0073*** (0.0002)
Sex		0.0251*** (0.0023)
PC 1		-0.0001*** (0.00002)
PC 2		0.0001* (0.00004)
PC 3		-0.0006*** (0.0001)
PC 4		-0.00004 (0.0001)
PC 5		0.0020*** (0.0001)
N	185910	185910
Pseudo R-Squared	0.0019	0.0083

Data Source: 2016 UK Biobank Data

Notes: Sample includes respondents between the ages of 40-59 in paid employment (including self-employment) of at least 12 hours per week who had non-missing values on self-reported chronotype and employment duration as well as having genotype data available. The dependent variable is night shift work (binary). Coefficients refer to the change in the marginal probability of self-reporting as an evening person associated with a one-unit change the corresponding variable.

+ $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

Table 5-5-2. *Reduced Form Probit Regressions of Night Shift Work (Binary) on Polygenic Risk for Eveningness*

	Night Shift Work (Binary)	
	Marginal Probability	
	1	2
Eveningness PGS (Std.)	0.0024*** (0.0007)	0.0021*** (0.0007)
Age		-0.0021*** (0.0001)
Male		0.0552*** (0.0014)
PC 1		0.0001* (0.00004)
PC 2		-0.00001 (0.00002)
PC 3		0.0001** (0.0001)
PC 4		0.00004* (0.0001)
PC 5		0.00003* (0.00001)
N	185910	185910
Pseudo R-Squared	0.0001	0.0002

Data Source: 2016 UK Biobank Data

Notes: Sample includes respondents between the ages of 40-59 in paid employment (including self-employment) of at least 12 hours per week who had non-missing values on self-reported chronotype and employment duration as well as having genotype data available. The dependent variable is night shift work (binary). Coefficients refer to the change in the marginal probability of night shift work associated with a one-unit change the corresponding variable.

+ $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

Table 5-5-3. *Bivariate Probit Regressions of Night Shift Work (Binary) on Eveningness*

Variable	Night Shift Work (Binary)	
	<i>Bivariate Probit Model</i>	
	1	2
Eveningness (Binary)	0.0855** (0.0282)	0.0801** (0.0283)
Age		-0.0019*** (0.0253)
Male		0.0545*** (0.0253)
PC 1		0.0002* (0.0001)
PC 2		-0.00004 (0.00003)
PC 3		0.0004** (0.0001)
PC 4		0.0001* (0.0001)
PC 5		0.0001* (0.0001)
N	185910	185910
Likelihood-Ratio Test of Rho ^a	5.12*	5.01*

Data Source: 2016 UK Biobank Data

Notes: Sample includes respondents between the ages of 40-59 in paid employment (including self-employment) of at least 12 hours per week who had non-missing values on self-reported chronotype and employment duration as well as having genotype data available. The dependent variable is night shift work (binary). Coefficients refer to the change in the marginal probability of night shift work associated with a one-unit change the corresponding variable. ^a The likelihood ratio test of rho indicates the strength of the correlation between the residuals of each of the two probit models. In this sense, it is analogous to the Wald test in linear 2SLS regression. + $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

APPENDIX 5-6. SENSITIVITY ANALYSES WITH UNCOLLAPSED CONTINUOUS MEASURES OF SELF-REPORTED EVENINGNESS AND REGULARITY OF NIGHT SHIFT WORK

Table 5-6-1. *Stage-One OLS Regressions of Self-Reported Eveningness (Continuous) on Polygenic Risk for Eveningness*

	Self-Reported Eveningness (Continuous)	
	<i>Linear Effect</i>	
	1	2
Eveningness PGS (Std.)	0.0497*** (0.0022)	0.0498*** (0.0022)
Age		-0.0153*** (0.0004)
Sex		0.0435*** (0.0043)
PC 1		-0.0003*** (0.00004)
PC 2		0.0003*** (0.0001)
PC 3		-0.0015*** (0.0001)
PC 4		-0.0006** (0.0002)
PC 5		0.0029*** (0.0021)
N	185910	185910
Adj. R-Squared	0.0028	0.0126

Data Source: 2016 UK Biobank Data

Notes: Sample includes respondents between the ages of 40-59 in paid employment (including self-employment) of at least 12 hours per week who had non-missing values on self-reported chronotype and employment duration as well as having genotype data available. The dependent variable is self-reported eveningness, for which there are four possible ordered values. Coefficients refer to the linear change in self-reported eveningness associated with a one-unit change the corresponding variable.

+ $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

Table 5-6-2. *Reduced Form OLS Regressions of Regularity of Night Shift Work (Continuous) on Polygenic Risk for Eveningness*

	Night Shift Work (Continuous)	
	<i>Linear Effect</i>	
	1	2
Eveningness PGS (Std.)	0.0044** (0.0013)	0.0038** (0.0013)
Age		-0.0035* (0.00004)
Male		0.0959* (0.00004)
PC 1		0.0011* (0.0001)
PC 2		-0.0002** (0.00004)
PC 3		0.0001 (0.0001)
PC 4		0.0002* (0.00003)
PC 5		0.0003** (0.0001)
N	185910	185910
Adj. R-Squared	0.0001	0.0016

Data Source: 2016 UK Biobank Data

Notes: Sample includes respondents between the ages of 40-59 in paid employment (including self-employment) of at least 12 hours per week who had non-missing values on self-reported chronotype and employment duration as well as having genotype data available. The dependent variable is the regularity of night shift work, for which there are four possible ordered values. Coefficients refer to the linear change in the regularity of night shift work associated with a one-unit change the corresponding variable. + $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

Table 5-6-3. *Mendelian Randomization Regression of Night Shift Work (Continuous) on Eveningness*

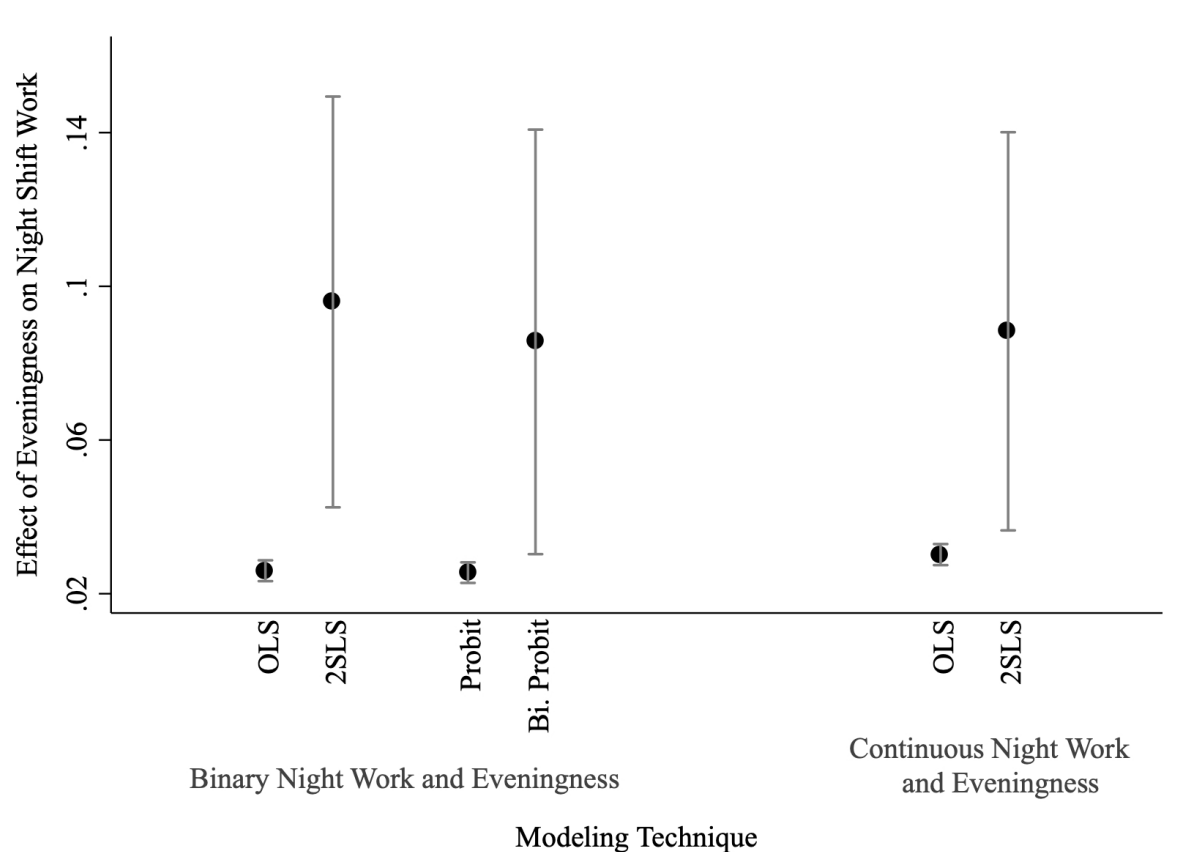
Variable	Night Shift Work (Continuous)	
	2SLS Linear Model	
	1	2
Mendelian Randomized Eveningness (Continuous)	0.0883*** (0.0264)	0.0761*** (0.0265)
Age		-0.0029*** (0.0005)
Male		0.0943*** (0.0028)
PC 1		0.0010* (0.0001)
PC 2		-0.0003** (0.00004)
PC 3		0.0001 (0.0001)
PC 4		0.0002* (0.00004)
PC 5		0.0004** (0.0001)
N	185910	185910
Cragg-Donald F Statistic (H0: weak instrument)	526.26***	529.48***
Wald Test of Exogeneity ^a (H0: Regressor is exogenous)	4.89*	4.39*

Data Source: 2016 UK Biobank Data

Notes: Sample includes respondents between the ages of 40-59 in paid employment (including self-employment) of at least 12 hours per week who had non-missing values on self-reported chronotype and who had genotype data available. Robust standard errors are shown in parentheses. The dependent variable is the regularity of night shift work, for which there are four possible ordered values. The endogenous variable is the continuous specification of eveningness, for which there are four possible ordered values. ^a Modified version of Durbin-Wu-Hausman test statistic created by Baum, Schaffer, and Stillman (2003). + $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

APPENDIX 5-7. COMPARING STANDARD AND IV ESTIMATES OF THE EFFECT OF EVENINGNESS ON NIGHT SHIFT WORK

Figure 5-7-1. *Coefficient Plot of the Effect of Eveningness on Night Work from Standard and IV Estimations*



Notes: Estimates from structural models (2SLS and bivariate probit) are derived from the exclusion of the eveningness PGS only; no control variables have been added. Sample includes respondents between the ages of 40-59 in paid employment (including self-employment) of at least 12 hours per week who had non-missing values on self-reported chronotype and employment duration as well as having genotype data available. The area around the line indicates 95% confidence intervals.

APPENDIX 5-8. SENSITIVITY ANALYSES OF QUANTILE-SPECIFIC 2SLS REGRESSION WITH 9 AGE QUANTILES AND 10 EMPLOYMENT DURATION QUANTILES

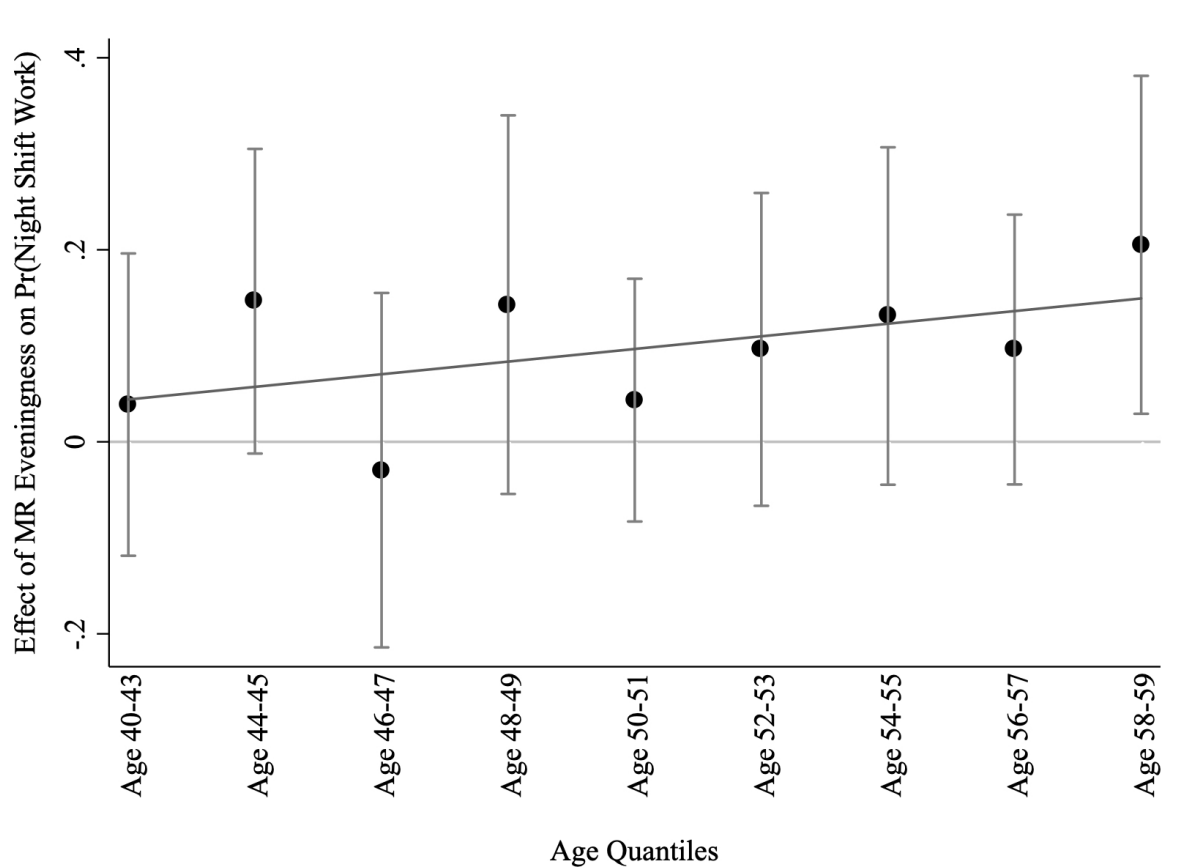
Table 5-8-1. *Age and Employment Duration Quantile-Specific Mendelian Randomization Regressions of Night Shift Work (Binary) on Eveningness*

<i>2SLS Linear Probability Model</i>							
Age				Employment Duration			
Quantile	Range	Quantile-Specific Coefficient	<i>n</i>	Quantile	Range	Quantile-Specific Coefficient	<i>n</i>
1	Age 40-43	0.0388 (0.0803)	24110	1	0-1 yrs	0.1947** (0.0699)	18762
2	Age 44-45	0.1464+ (0.0809)	17736	2	2-3 yrs	0.1588* (0.0734)	23787
3	Age 46-47	-0.0295 (0.0942)	18770	3	4-5 yrs	0.1017 (0.0818)	20598
4	Age 48-49	0.1429 (0.1006)	19747	4	6-7 yrs	0.1802 (0.1101)	16002
5	Age 50-51	0.0434 (0.0645)	20621	5	8-9 yrs	0.1988+ (0.1116)	13989
6	Age 52-53	0.0962 (0.0831)	21250	6	10-12 yrs	0.1374 (0.1219)	18770
7	Age 54-55	0.1310 (0.0897)	21791	7	13-17 yrs	0.0627 (0.0708)	19942
8	Age 56-57	0.0961 (0.0717)	21542	8	18-21 yrs	0.0088 (0.0834)	17575
9	Age 58-59	0.2052* (0.0898)	20343	9	22-28 yrs	0.0407 (0.088)	19076
				10	29-47 yrs	-0.0967 (0.1033)	17409
Slope Across Quantiles ^a		0.0113 (0.0348)	9	Slope Across Quantiles		-0.0240* (0.0091)	10

Data Source: 2016 UK Biobank Data

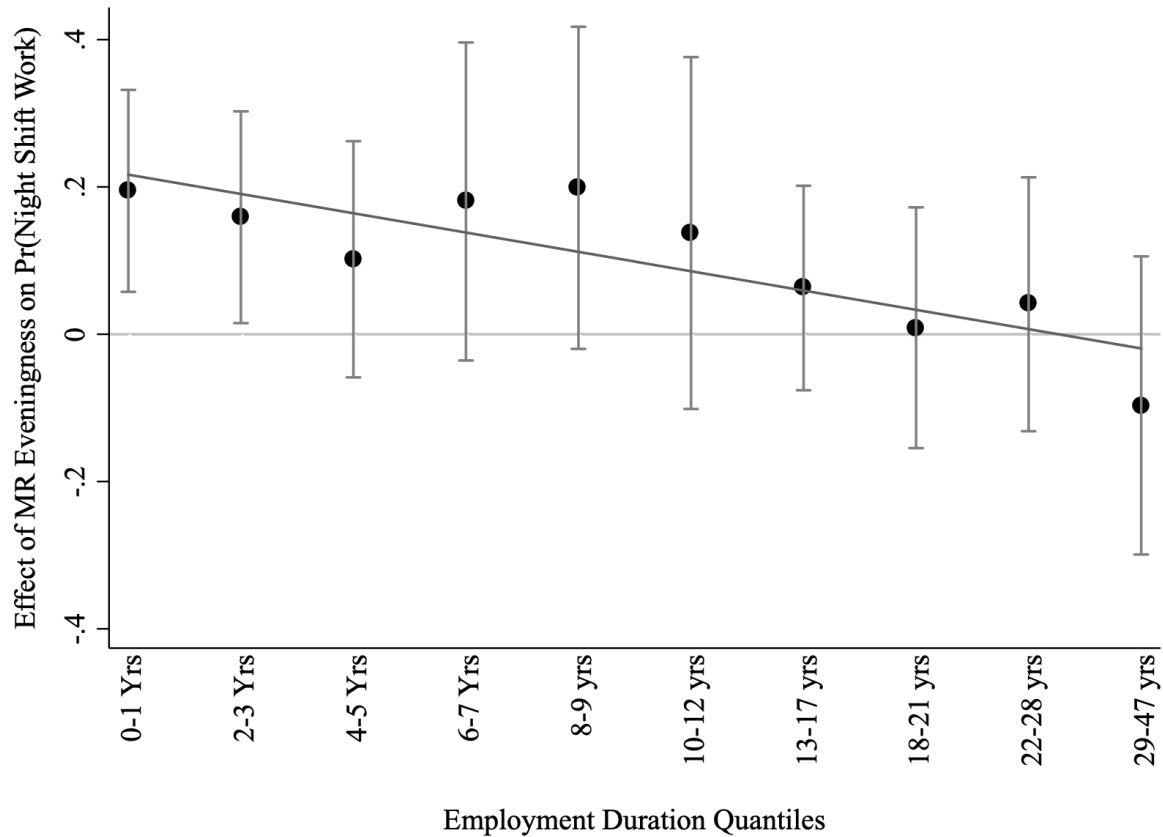
Notes: Sample includes respondents between the ages of 40-59 in paid employment (including self-employment) of at least 12 hours per week who had non-missing values on self-reported chronotype and who had genotype data available. Control variables include sex, age, and the first five genetic principal components. Results shown for linear regression of night shift work (binary) on Mendelian Randomized eveningness (binary). Coefficients refer to the change in the linear probability of night shift work associated with a one-unit increase in eveningness. Robust standard errors are shown in parentheses. ^a Calculated through variance-weighted least squares regression. + $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

Figure 5-8-1. *Linear Effects of Mendelian Randomized (Binary) Eveningness on the Probability of Night Shift Work, over Age Quantiles*



Notes: Results shown for linear regression of night shift work (binary) on Mendelian Randomized eveningness (binary). Coefficients refer to the change in the linear probability of night shift work associated with a one-unit increase in eveningness. Sample includes respondents between the ages of 40-59 in paid employment (including self-employment) of at least 12 hours per week who had non-missing values on self-reported chronotype and employment duration as well as having genotype data available. Control variables include sex, age, and the first five genetic principal components. The area around the line indicates 95% confidence intervals.

Figure 5-8-2. *Linear Effects of Mendelian Randomized (Binary) Eveningness on the Probability of Night Shift Work, over Employment Duration Quantiles*



Notes: Results shown for linear regression of night shift work (binary) on Mendelian Randomized eveningness (binary). Coefficients refer to the change in the linear probability of night shift work associated with a one-unit increase in eveningness. Sample includes respondents between the ages of 40-59 in paid employment (including self-employment) of at least 12 hours per week who had non-missing values on self-reported chronotype and employment duration as well as having genotype data available. Control variables include sex, age, and the first five genetic principal components. The area around the line indicates 95% confidence intervals.

APPENDIX 5-9. SENSITIVITY ANALYSES OF QUANTILE-SPECIFIC 2SLS REGRESSION WITH CONTINUOUS SPECIFICATIONS OF EVENINGNESS AND NIGHT SHIFT WORK

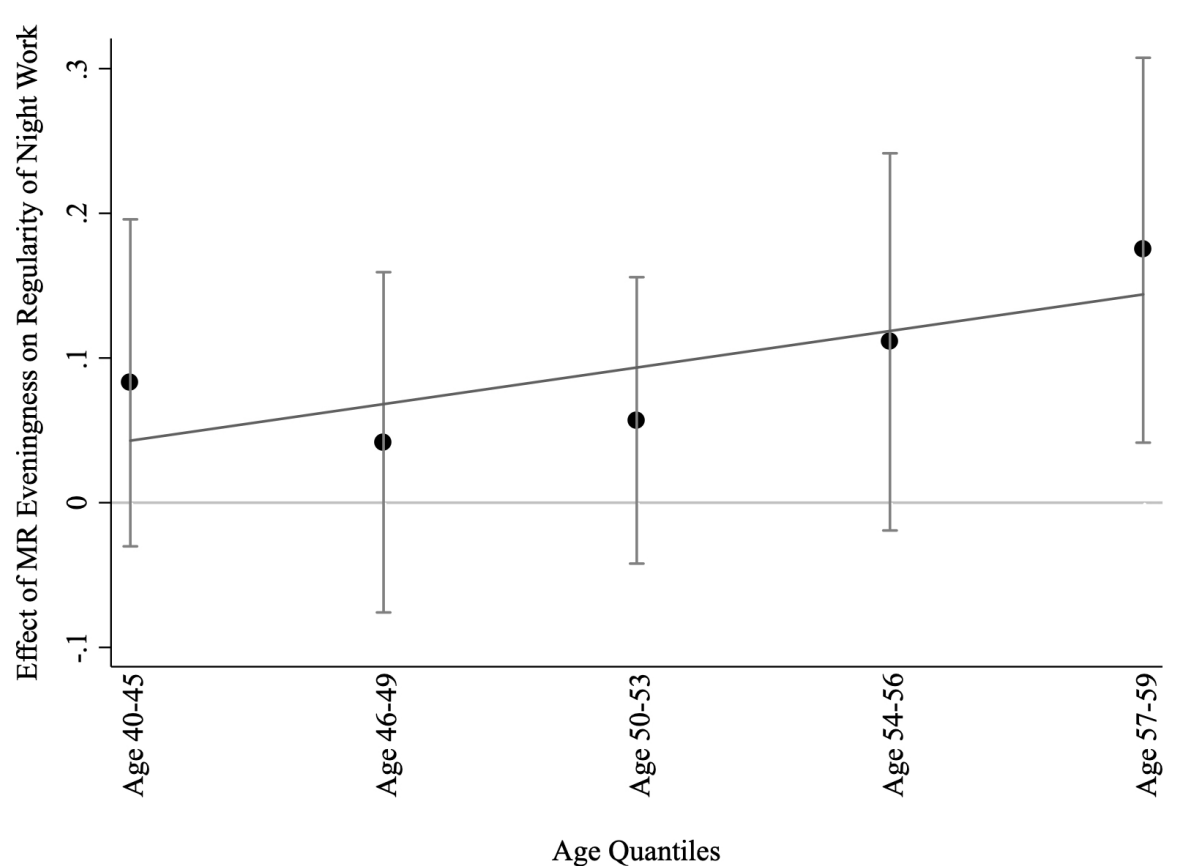
Table 5-9-1. *Age and Employment Duration Quantile-Specific Mendelian Randomization Regressions of Night Shift Work (Continuous) on Eveningness (Continuous)*

2SLS Linear Regression							
Age				Employment Duration			
Quantile	Range	Quantile-Specific Coefficient	<i>n</i>	Quantile	Range	Quantile-Specific Coefficient	<i>n</i>
1	Age 40-45	0.0828 (0.0577)	41846	1	0-2 yrs	0.1557* (0.0622)	31258
2	Age 46-49	0.0417 (0.0600)	38517	2	3-5 yrs	0.1003 (0.0623)	31889
3	Age 50-54	0.0569 (0.0505)	41871	3	6-9 yrs	0.1605* (0.0689)	29991
4	Age 55-56	0.1111+ (0.0665)	32731	4	10-15 yrs	0.1090 (0.0713)	31697
5	Age 57-59	0.1745* (0.0679)	30945	5	16-23 yrs	0.0336 (0.0611)	30826
				6	24-46 yrs	-0.0082 (0.0687)	30249
Slope Across Quantiles ^a		0.0230 (0.0198)	5	Slope Across Quantiles		-0.0300+ (0.0154)	6

Data Source: 2016 UK Biobank Data

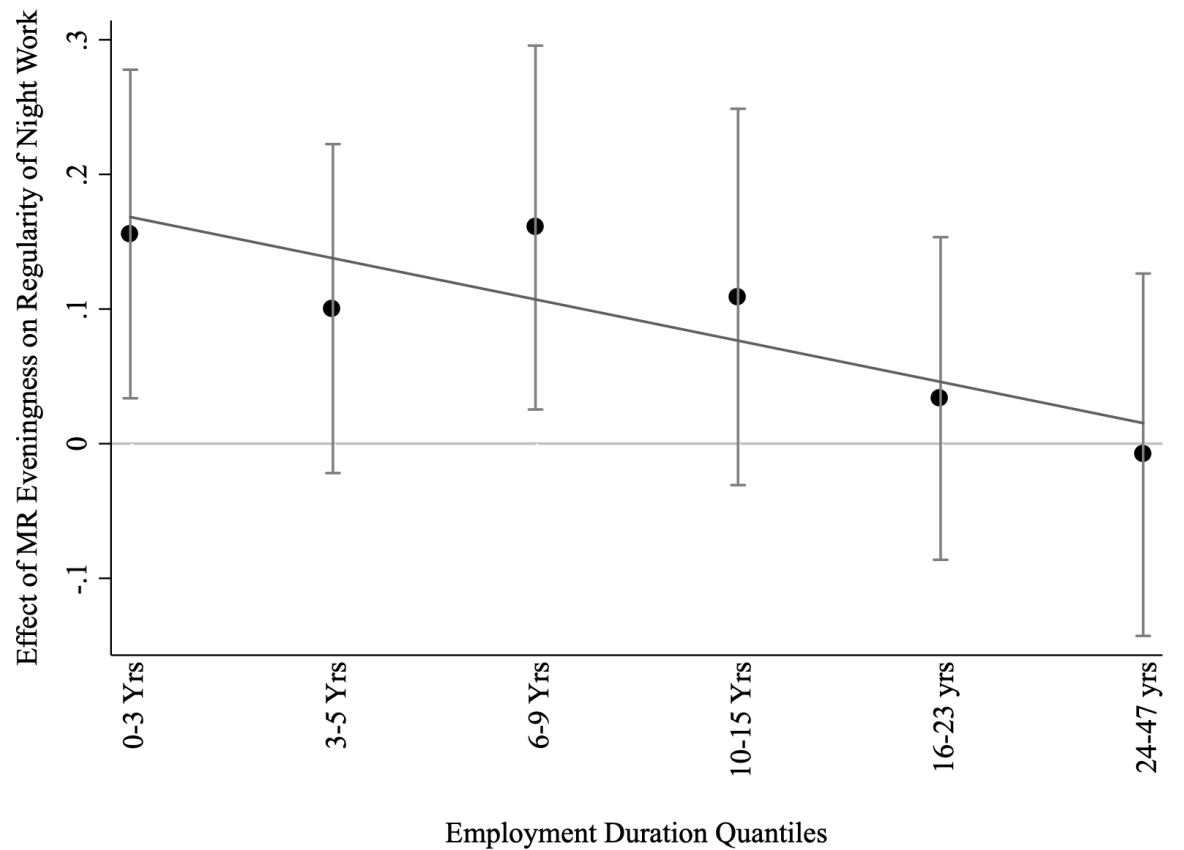
Notes: Sample includes respondents between the ages of 40-59 in paid employment (including self-employment) of at least 12 hours per week who had non-missing values on self-reported chronotype and who had genotype data available. Robust standard errors are shown in parentheses. The dependent variable is the regularity of night shift work, for which there are four possible ordered values. The endogenous variable is the continuous specification of eveningness, for which there are four possible ordered values. Coefficients refer to the change in the regularity of night shift work associated with a one-unit increase in eveningness. ^a Calculated through variance-weighted least squares regression. + $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

Figure 5-9-1. *Linear Effects of Mendelian Randomized (Continuous) Eveningness on the Regularity Night Shift Work, over Age Quantiles*



Notes: Results shown for linear regression of night shift work (binary) on Mendelian Randomized eveningness (binary). Coefficients refer to the change in the regularity of night shift work associated with a one-unit increase in eveningness. Sample includes respondents between the ages of 40-59 in paid employment (including self-employment) of at least 12 hours per week who had non-missing values on self-reported chronotype and employment duration as well as having genotype data available. Control variables include sex, age, and the first five genetic principal components. The area around the line indicates 95% confidence intervals.

Figure 5-9-2. *Linear Effects of Mendelian Randomized (Continuous) Eveningness on the Regularity Night Shift Work, over Employment Duration Quantiles*



Notes: Results shown for linear regression of night shift work (continuous) on Mendelian Randomized eveningness (continuous). Coefficients refer to the change in the regularity of night shift work associated with a one-unit increase in eveningness. Sample includes respondents between the ages of 40-59 in paid employment (including self-employment) of at least 12 hours per week who had non-missing values on self-reported chronotype and employment duration as well as having genotype data available. Control variables include sex, age, and the first five genetic principal components. The area around the line indicates 95% confidence intervals.

APPENDIX 5-10. SENSITIVITY ANALYSES OF QUANTILE-SPECIFIC REGRESSION USING BIVARIATE PROBIT ESTIMATION

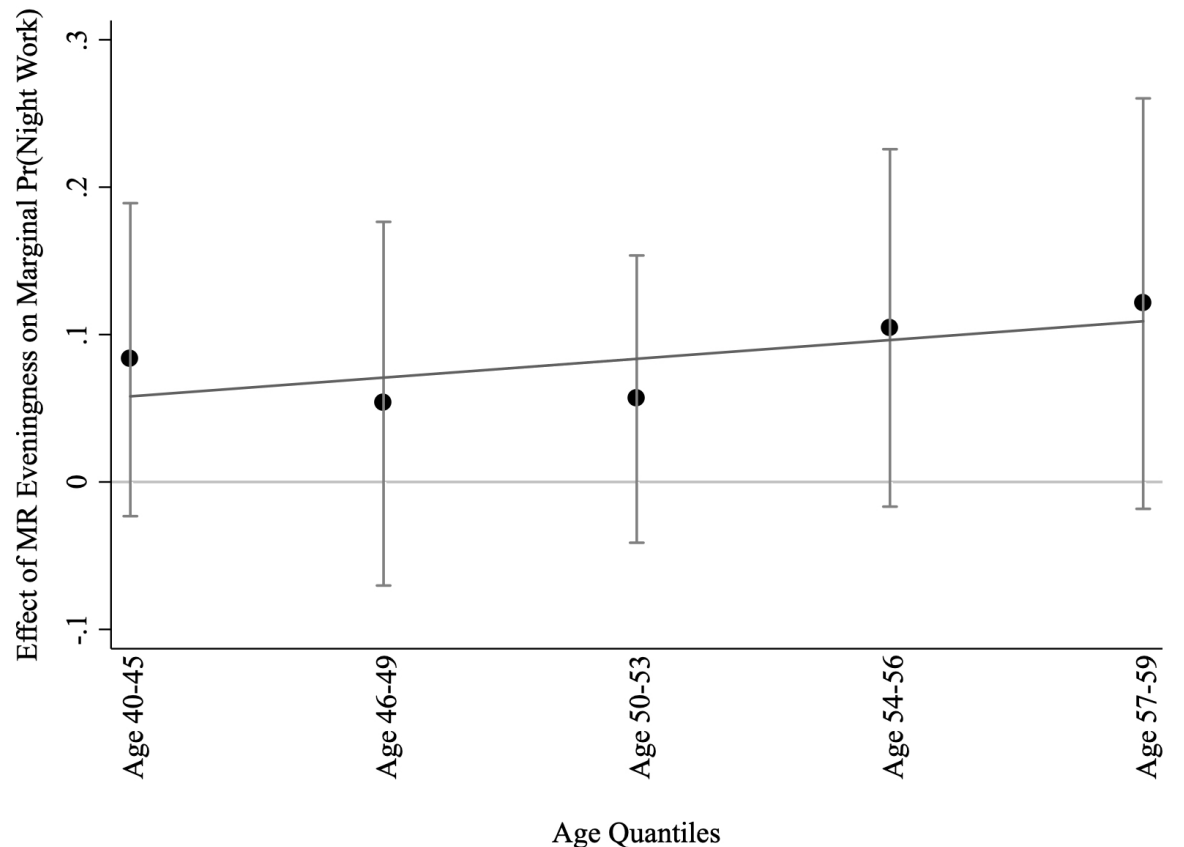
Table 5-10-1. *Age and Employment Duration Quantile-Specific Bivariate Probit Regressions of Night Shift Work (Binary) on Eveningness (Binary)*

<i>Bivariate Probit Model</i>							
Age				Employment Duration			
Quantile	Range	Quantile-Specific Marginal Effect	<i>n</i>	Quantile	Range	Quantile-Specific Marginal Effect	<i>n</i>
1	Age 40-45	0.0808 (0.0588)	41846	1	0-2 yrs	0.1298* (0.0614)	31258
2	Age 46-49	0.0393 (0.0626)	38517	2	3-5 yrs	0.1387* (0.0686)	31889
3	Age 50-54	0.0665 (0.0526)	41871	3	6-9 yrs	0.1710* (0.0831)	29991
4	Age 55-56	0.1296 (0.0792)	32731	4	10-15 yrs	0.0932 (0.0826)	31697
5	Age 57-59	0.1332+ (0.0802)	30945	5	16-23 yrs	0.0103 (0.0598)	30826
				6	24-46 yrs	-0.0111 (0.0679)	30249
Slope Across Quantiles ^a		0.0167 (0.0219)	5	Slope Across Quantiles		-0.0324* (0.0154)	6

Data Source: 2016 UK Biobank Data

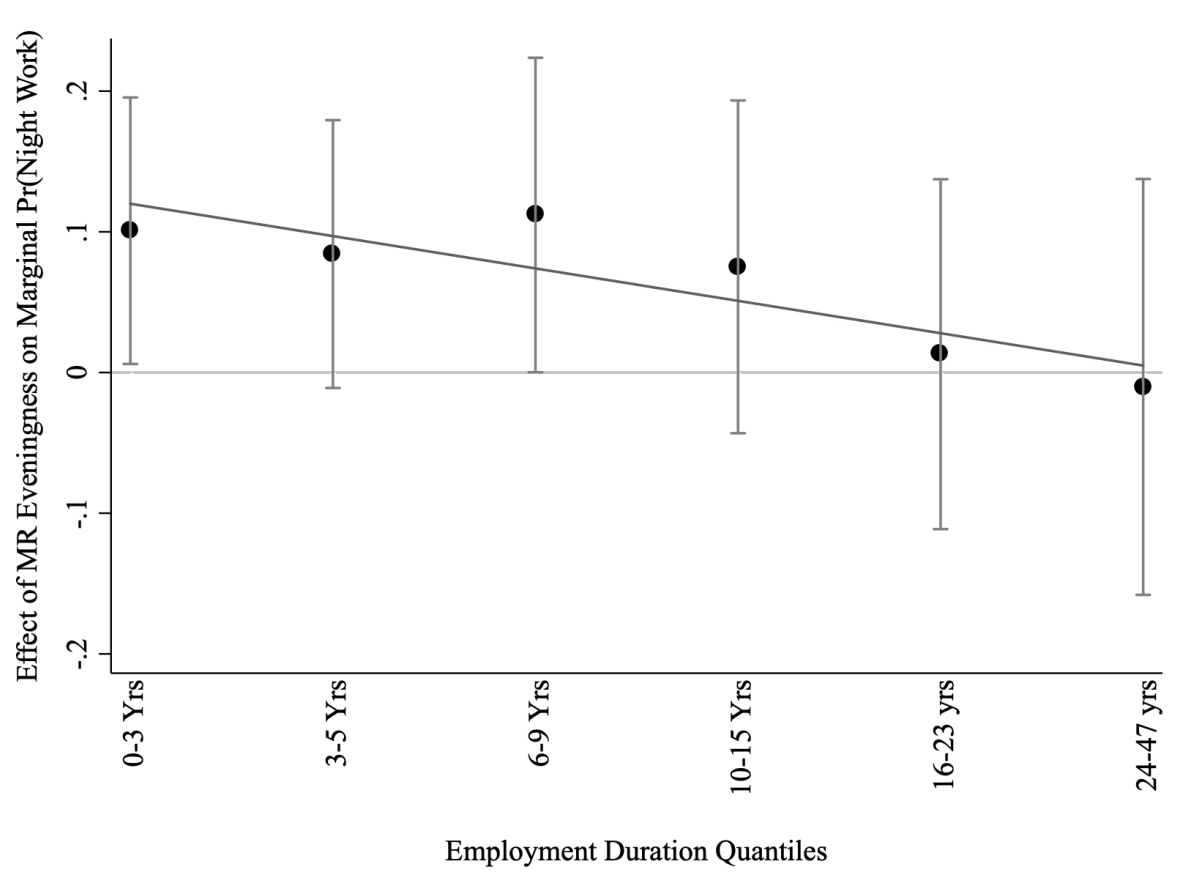
Notes: Sample includes respondents between the ages of 40-59 in paid employment (including self-employment) of at least 12 hours per week who had non-missing values on self-reported chronotype and employment duration as well as having genotype data available. The dependent variable is night shift work (binary). Coefficients refer to the change in the marginal probability of night shift work associated with a one-unit change in eveningness. ^aCalculated through variance-weighted least squares regression. + $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

Figure 5-10-1. *Marginal Effects of Mendelian Randomized (Binary) Eveningness on the Probability of Night Shift Work, over Age Quantiles*



Notes: Results shown for bivariate probit regression of night shift work (binary) on Mendelian Randomized eveningness (binary). Coefficients refer to the change in the marginal probability of night shift work associated with a one-unit increase in eveningness. Sample includes respondents between the ages of 40-59 in paid employment (including self-employment) of at least 12 hours per week who had non-missing values on self-reported chronotype and employment duration as well as having genotype data available. Control variables include sex, age, and the first five genetic principal components. The area around the line indicates 95% confidence intervals.

Figure 5-10-2. *Marginal Effects of Mendelian Randomized (Binary) Eveningness on the Probability of Night Shift Work, over Employment Duration Quantiles*



Notes: Results shown for bivariate probit regression of night shift work (binary) on Mendelian Randomized eveningness (binary). Coefficients refer to the change in the marginal probability of night shift work associated with a one-unit increase in eveningness. Sample includes respondents between the ages of 40-59 in paid employment (including self-employment) of at least 12 hours per week who had non-missing values on self-reported chronotype and employment duration as well as having genotype data available. Control variables include sex, age, and the first five genetic principal components. The area around the line indicates 95% confidence intervals.

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