Staying Healthy and Happy at Work

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How Job Flexibility Can Help

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How Job Flexibility Can Help

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Shuye Yu,
Groningen, 17 October 2022

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Chapter 1

Introduction

The health and well-being of the 3.5 billion working population, approximately half of the world population, has received significant attention from researchers and policy-makers. Many occupational characteristics such as job strains, job control and working hours are essential determinants of health. Some workplace problems have detrimental, even fatal, impacts on health. For example, a joint estimate by the World Health Organisation (WHO) and the International Labour Organization (ILO) indicates that 745,000 fatalities from stroke and ischemic heart disease were caused by long working hours in 2016, 26% higher than in 2000 (Pega et al., 2021). The high number of death is also documented by Goh et al. (2016). They find that 120,000 annual all-cause deaths are workplace-associated in the US, which accounts for 5%–8% of the healthcare costs per year. In addition, the growing workplace stress contributes to the feeling of 'time poverty', which is closely tied to poor individual and societal well-being (Giurge et al., 2020).

Health and well-being in the workplace are also of interest to policy-makers because of their relevance to workers' future labour market participation, income and wealth. Health is perceived as a crucial factor in the process of human capital formation (Grossman, 1972). People with poor health are less likely to be active in the labour market (García-Gómez et al., 2010), have shorter working hours (Jones et al., 2020) and retire earlier (Jones et al., 2010). The labour market consequences of ill-health further translate into a reduction in personal and household income (Lenhart, 2019), which generates an income gap between people with and without health disadvantages. Thus, there have been many discussions and practices on how to maintain workers' health and well-being and integrate workers with poor health into the labour market (Reeves et al., 2014; Weathers & Bailey, 2014).

One of the approaches that could improve health and well-being in the workplace is flexible employment, defined as the mutual agreement between employees and employers on when, where and how work is conducted with an emphasis on employees' control over some aspects of the job (Thompson & Kossek, 2016). Various measures of flexible employment can be generally classified into three patterns: *contractual flexibility*, *temporal flexibility* and *spatial flexibility* (Joyce et al., 2010). The first pattern enables workers to adjust their workload. For example, workers switch to part-time work from full-time work by reducing their total number of working hours. The latter two patterns empower workers' autonomy in deciding working hours and location. Typical examples of these patterns are self-scheduling and home-based work, respectively.

Flexible employment can be beneficial for health and well-being in at least two ways. First, control over when, where and how work is done is helpful for an employee to reconcile working and non-working tasks, which reduces workplace stress. This is particularly helpful for people in the phase with heavy home duties (e.g., early years of parenting) and a great demand for healthcare (e.g., after an adverse health event). Second, lengthy commuting is considered as one source of workplace stress (Kahneman et al., 2004). Moreover, the time spent on commuting has constantly been increasing for decades (Giménez-Nadal et al., 2021). In this case, spatial flexibility measures (e.g., working from home) are expected to promote workers' health and well-being by relieving their burden of commuting.

This thesis discusses the relationships between flexible employment and the health and well-being of different groups of the working population in three chapters. Chapter 2 evaluates the effects of various types of flexible working arrangements on parental life satisfaction during the transition into parenthood. Chapter 3 discusses the benefits of spatial flexibility for people with health disadvantages by examining the uptake of home-based work following a health shock. Chapter 4 turns attention to the detrimental effect of a lengthy commute on subjective well-being and self-rated health, which highlights the potential advantages of spatial flexibility in reducing the burden of commuting. Finally, Chapter 5, as the concluding chapter, summarises the findings in the preceding chapters and discusses the implications for policy and future research.

A more detailed summary of each main chapter is provided in Section 1.3. Before that, Section 1.1 and Section 1.2 introduce two fundamental concepts to this thesis: flexible employment and the measurement of health and well-being, respectively. Finally, Section 1.4 discusses the contributions of this thesis.

1.1 Trend toward Flexible Working

Flexible employment has been on the rise since the 1980s. The International Labour Organization's Workers with Family Responsibilities Convention, 1981 (No.156) advocated improving parents' accessibility to flexible jobs to reconcile their working and non-working responsibilities (Avendano & Panico, 2018). Since then, there has been a growing trend in adopting flexible jobs. For example, in Australia, the number of people having a flexible contract or working part-time in 1996 was 44% higher than a decade ago (Kramar, 1998).

However, to a large extent, flexible employment was an informal practice in the last century as its accessibility relies on the employer's discretion. It has become a formal practice in the new century since policies that guarantee the right to request flexible working were implemented in many countries. In the Netherlands, *Wet Aanpassing Arbeidsduur* in 2000 entitled workers in a company with over ten employees to the right to adjust the number of weekly working hours. In 2016, *Wet Flexibel Werken* further allowed adjusting the workplace and working time. In 2003, a similar policy, *Flexible Working Act*, was enacted in the UK. The initial policy allowed parents whose children are under the age of 6 to switch to flexible work. This entitlement was further granted to workers that need to care for other adults and to all workers after two reforms in 2007 and 2014, respectively. Note that to whom this policy applies differs by country. For example, all employees in Belgium, France, New Zealand and the Netherlands are eligible to apply for flexible employment, while this entitlement is only granted to workers with specific demands (e.g., childcare) in Australia, Finland, Norway and Sweden (OECD, 2016).

Although flexible employment has risen in popularity, the so-called *flexibility stigma* still persists. This term describes the view that flexible jobs are inferior to 'normal' jobs, and people with this view would impose penalties on flexible workers (Williams et al., 2013). While a typical flexibility stigma is related to part-time jobs, where part-time workers are considered not productive and not committed to work (Chung, 2020), workers with *flexplace* and *flextime* also suffer from similar discrimination (Chung & Van der Horst, 2020). As a result, flexible workers exposed to flexibility stigma feel less satisfied with their job and become less likely to stay in the current industry in the future (Cech & Blair-Loy, 2014). Further research argues that discrimination against flexible workers depends on gender and the purpose of flexibility. In terms of gender, female flexible workers are more worried about their future career development (e.g., promotion) than their male counterparts (Chung, 2020). In terms of the purpose of flexibility, men working at home for childcare reasons are less negatively perceived than those whose home-based work is unrelated to childcare (Munsch, 2016).

1.2 Measuring Health and Well-being

Subjective well-being (SWB) and *self-rated health* are used throughout this thesis to measure perceived happiness and general health. The former reflects people's cognitive and affective responses to life circumstances (Diener et al., 2009). In particular, the cognitive part of SWB emphasises one's cognitive assessment of life overall (Veenhoven, 2012). Thus, SWB is also referred to as *life satisfaction* in this context. In many surveys, SWB is elicited with the question, "All things considered, how satisfied are you with your life?" For an 11-point Likert scale, respondents choose an integer between 0 (totally unsatisfied) and 10 (totally satisfied) to indicate their SWB. In economic research, SWB is a useful tool for measuring welfare since it takes the non-monetary aspect of well-being into account (Graham, 2016). Moreover, it is recognised as a summary of one's satisfaction with multiple life domains according to the 'bottom-up' theory of life satisfaction (Brief et al., 1993).

Self-rated health captures people's assessment of their general health status. Typically, it is measured on a 5-point Likert scale. Respondents need to describe their current health as "bad", "less", good", "satisfactory", "good" and "very good". Each of the options represents an integer between 1 and 5, respectively. Despite being a subjective indicator, self-rated health is found to be strongly associated with objective health (Wu et al., 2013) and mortality (Kaplan et al., 1996).

While self-rated health takes a snapshot of one's health status at a given point, the transition from one status to another can be realised through a health shock. Although a health shock, in principle, can be positive or negative depending on health becoming better or worse, the one most observed in reality and most discussed by the health economics literature is negative. In contrast to a progressive health deterioration over time, a health shock emphasises a sudden decline in health, which is, to a large extent, unexpected. There are several ways to capture a health shock, for example, a sharp increase in medical expenses (Islam & Maitra, 2012) or the onset of a chronic disease (Duguet & Le Clainche, 2020). With rich medical data, some studies can focus on specific diseases, such as cancer (Jeon & Pohl, 2017) or cardiovascular diseases (Fadlon & Nielsen, 2019). However, due to the lack of medical data, this thesis defines health shocks as the occurrence of a severe injury or illness, which is also used by Cai et al. (2014).

1.3 Outline of the Thesis

1.3.1 Flexible Jobs Make Parents Happier: Evidence from Australia

A stylised fact shows that parental life satisfaction suddenly drops after the birth of a child and remains low for several years before it returns to the baseline level, typically the level of life satisfaction in the second or third year prior to childbirth (Clark & Georgellis, 2013). Previous research has attributed part of this decline to parents' time conflicts, especially when a parent needs to work (Pollmann-Schult, 2014).

Chapter 2 explores the effect of three forms of flexible employment (i.e., contractual flexibility, temporal flexibility and spatial flexibility) on alleviating this drop. This study relies on 16 waves of a longitudinal household survey in Australia, *The Household, Income and Labour Dynamics in Australia* (HILDA), from 2002 to 2017. To address the unobserved individual characteristics associated with the choice of working arrangements, we use an individual fixed-effects model in an event-study framework proposed by Clark et al. (2008). We also extend Clark et al.'s (2008) approach by interacting job flexibility with period dummies that indicate how long it is away from childbirth. The extended model captures trajectories of life satisfaction in the nine years around childbirth with respect to different forms of job flexibility.

We find that flexible employment can improve parental life satisfaction during the transition into parenthood. Yet, which type of job flexibility is effective and in which period a given type of job flexibility is effective depends on gender: mothers with short part-time jobs (0-20 hours per week) exhibit greater life satisfaction than mothers who work full-time, especially when their children are younger than four; among fathers, self-scheduling and home-based work yield a significant increase in perceived happiness compared to a fixed working scheme. This is especially true for fathers of one- and two-year-olds.

These findings are in line with a classical intra-household time allocation of parents in Australia: when a child is young, the mother reduces her working hours or does not work at all to take care of the child, while the father, typically having a full-time job, does not change his working hours (Baxter, 2013). Therefore, one possible explanation for our results is that part-time jobs reduce mothers' total weekly working hours, which mitigates their time conflicts between work and childcare. For fathers, the opportunity to adjust their workplace and working schedule enables them to undertake some domestic work with total working hours unchanged.

1.3.2 Uptake of Home-based Work Following a Health Shock: Evidence from Australia

The detrimental effect of health shocks on various labour market outcomes (e.g., labour market participation, working hours and productivity) has been well-documented (García-Gómez et al., 2010; Lenhart, 2019; Jones et al., 2020). However, how to integrate workers experiencing health shocks into the labour market and improve their labour market positions has not been extensively studied.

Chapter 3 documents how recent health shocks affect the extensive and intensive margins of the uptake of home-based work using eight waves of the HILDA survey between 2012 and 2019. Health shocks are defined as the occurrence of a serve injury or illness in the past 12 months. Taking the argument of revealed preference, this analysis examines whether home-based work is a favourable working arrangement that potentially accommodates the needs of workers with poor health.

As Jäckle and Himmler (2010) point out, labour market participation, as an endogenous choice, might be driven by health. Thus, estimating the effects of health shocks on labour market outcomes that are only observable for people active in the labour market is associated with the problem of non-random selection. In our context, this means that there are unobserved correlations between the decisions on labour market participation and the uptake of home-based work. To correct for the sample selection bias, we adopt a set of Heckman-type models that can jointly model the two decisions and allow them to be correlated in an unobserved way. We use a binary response panel data model with sample selection proposed by Semykina and Wooldridge (2018) for the extensive margin, where home-based work is treated as a binary outcome. Furthermore, we extend their work so that the model can fit partially observable panel data for the intensive margin as the home-based working hours are positive for home-based workers and censored at zero for workers without home-based work.

We find a negative correlation between the decisions on employment and home-based work, suggesting that people active in the labour market are less likely to choose home-based work. While the effect sizes of health shocks estimated from Heckman-type models are larger than those estimated from models without correcting for the non-random selection bias, the effects of health shocks on the uptake of home-based work appear gender-asymmetric. For women, health shocks can increase the likelihood of home-based work by 8.1 percentage points and home-based working hours by 0.65 weekly hours. These effects are sizeable as they represent an increase of around 37% relative to each sample mean. However, for men, health shocks do not significantly affect the uptake of home-based work for both extensive and intensive margins. These gender asymmetric results are in line with the fact that women typically undertake more domestic work than men in Australia. Home-based work could be helpful for women to reconcile working and non-working duties when their health is poor. Furthermore, a supplementary analysis shows that home-based work in an adverse health event is associated with women's labour market participation and household income over five years after a health shock but not men's. This finding could be another reason for the gender heterogeneous results in our analysis.

1.3.3 The Effect of Commuting on Subjective Well-being and Health: Evidence from Germany

Over recent decades, the time used for commuting has been increasing in many developed countries (Giménez-Nadal et al., 2021), whereas psychologists have shown that the journey to work imposes negative emotions on commuters, which is described as *commuting stress* (Kahneman et al., 2004).

Chapter 4 explores the impact of commuting on SWB and health using 15 waves of data from *The German Socio-Economic Panel* (GSOEP) between 2001 and 2017. The length of a commute is measured by the self-reported one-way commuting distance. The burden of commuting might be endogenous as it can be confounded by unobserved determinants of the place of residence and the workplace. We addressed this issue in an instrumental variable (IV) approach. Three regional characteristics from a governmental database (INKKAR) operated by the Federal Institute for Research on Building, Urban Affairs and Spatial Development are used to instrument for individual commuting distance: 1) the average commuting time at the state-year level, 2) the average price for building blocks at the county-year level and 3) the net number of commuters at the county-year level. To our knowledge, this is the first study that applies an IV estimation to evaluate the causal impact of commuting on SWB and health. Our results indicate that all the candidate instruments are predictive of individual commuting distance. Relying on a series of tests and falsification exercises, we show that these instruments also satisfy other fundamental assumptions of the IV strategy.

The IV estimation suggests that a lengthy commute is detrimental to SWB and health: A 10-kilometre increase in commuting distance can reduce SWB and health by around 15% and 7% of a standard deviation, respectively. The magnitude of the effect is considerable for people with a long commuting distance, e.g., over 25km, which accounts for 20% of the workers in Germany (Federal Statistical Office, 2020).

To uncover through which pathways the length of commutes affect SWB and health, we look at the effects of commuting distance on nine aspects of personal health and satisfaction with seven life domains. We conclude that long commuting distances are particularly harmful to mental health as people with a long journey to the workplace feel more depressed and less energetic compared to their counterparts with short distances. Moreover, we find that people commuting longer are less satisfied with their sleep, health, leisure time and family life.

1.4 Contributions

This thesis provides insights into the relationships between flexible employment and the health and well-being of different subgroups of the working population. Chapter 2 reveals that flexible employment can alleviate reductions in parental SWB in the early years of parenting. Chapter 3 indicates that a recent health shock boosts the uptake of home-based work, especially for women. Chapter 4 illustrates the potential advantages of home-based work by showing the detrimental effect of a lengthy commute on workers' SWB and health. Emphasis is placed on gender heterogeneity when we interpret the results in Chapters 2 and 3. We find that these gender asymmetric results align with the gender differences in labour market attachment and intra-household time and task allocations in the present context. In Chapter 4, we find that a lengthy commute impacts health through the pathway of mental health, reiterating the presence of workplace stress in the lack of proper flexible working arrangements.

This thesis also contributes to the econometric methods within health economics. First, we apply novel empirical models and propose candidate instrumental variables to account for the endogeneity issue in several labour market decisions. In Chapter 3, we extend a recently developed model by Semykina and Wooldridge (2018) for binary response panel data with sample selection. The extended model combines the Heckman selection model and a Tobit I model to fit partially observable panel data with sample selection. Future research can consider this model in the presence of sample selection and censored data. In Chapter 4, we instrument commuting distance with a set of regional characteristics to address the endogenous location choices of the workplace and the place of residence that determine the length of commutes. This study provides the first estimates of the health impact of commuting in an instrumental variable approach. Second, the results in Chapter 2 contribute to the discussion on the empirical framework to model categorical SWB. Classic econometrics textbooks recommend employing non-linear models (e.g., the ordered probit model) for the outcome variables with ordered categories. However, Ferrer-i Carbonell and Frijters (2004) argue that linear models generate highly similar results to non-linear models in the context of SWB as long as the individual fixed effect is controlled for. In Chapter 2, we compare the results estimated by the two types of models. The qualitatively unchanged results in our analyses are in favour of Ferrer-i Carbonell and Frijters (2004) and mitigate the concern of using a linear model in future research on SWB.

Chapter 2

Flexible Jobs Make Parents Happier: Evidence from Australia*

*This chapter is based on Yu and Postepska (2020). We are particularly grateful to Rob Alessie for his suggestions and his guidance on this project. We also thank Jochen Mierau, Peter Eibich, and Sarah See for their comments. We would also like to thank participants of the seminar series at the University of Groningen and the Max Plank Institute for Demographic Research for their valuable inputs. All errors and omissions are the sole responsibility of the authors.

2.1 Introduction

Numerous empirical studies have reached a counter-intuitive conclusion that parents feel less satisfied with their lives after parenthood compared to prenatal periods or non-parents (see Hansen (2012) for a review.) On the one hand, childbirth enhances parental life satisfaction through both psychological benefits (satisfying emotional needs) and utilitarian benefits (providing material support for the family) (Aycicegi-Dinn & Kagitcibasi, 2010). On the other hand, it often triggers financial difficulties (Stanca, 2012) and time pressure (Buddelmeyer et al., 2018), which negatively affects life satisfaction. The latter is particularly emphasised for working parents since reconciling work and family life often leads to a work-family conflict (Matysiak et al., 2016).

Labour market decisions may help to achieve a balance between work and family life and allow utility-maximising parents to optimally choose between work and leisure according to their preferences, which can result in higher life satisfaction. Some parents may exploit household specialisation: one partner participates in the labour market while the other one mainly undertakes domestic work, including childcare (Booth & Van Ours, 2009). In dual-earner families with children, parents seek to acquire an adjustable working schedule through either self-employment (mostly women) (Semykina, 2018) or directly through flexible employment in the wage sector (Minnotte et al., 2016).

The latter is at the centre of this study. Using a longitudinal household survey in Australia (HILDA), this paper investigates how flexible employment affects parental life satisfaction, also known as subjective well-being (SWB), during the early years of parenthood and whether there is gender heterogeneity in the effects.[1] The panel structure of HILDA benefits us in two aspects. Firstly, it helps to eliminate the endogeneity caused by time-invariant factors. Secondly, knowing how parental status changes over a relatively long period (16 years) enables us to capture the time profile of SWB around childbirth under different forms of flexibility with an event study framework. We find that flexible employment is associated with higher parental SWB during the transition into parenthood. Moreover, we find evidence

[1] SWB describes people's affective and cognitive assessments of their life circumstances (Diener et al., 2009). The cognitive assessment is also referred to as life satisfaction, which stresses one's evaluation of the overall quality of life (Veenhoven, 2012).

of substantial gender heterogeneity, showing that mothers' and fathers' SWB responds differently to different forms of flexible employment. Our results are in line with recent research on different labour market trajectories between men and women around childbirth and the classical household specialisation in Australia.

Diverse forms of flexible employment (see Hill et al. (2008) for a review) can be generally categorised into three types: *contractual flexibility*, *temporal flexibility* and *spatial flexibility* (Joyce et al., 2010). Contractual flexibility shortens total working hours and allows part-time jobs, normally defined as jobs shorter than 35 weekly working hours (Van Bastelaer et al., 1997). The other two types of flexibility do not necessarily shorten working hours but enable workers to decide the start and end of working hours (e.g., self-scheduling) and the place of work (e.g., work at home) (Hill et al., 2001).

Previous literature has typically focused on the role of contractual flexibility and found that women with part-time jobs report higher SWB than women working full-time (Booth & Van Ours, 2008; Álvarez & Miles-Touya, 2016). In addition, Pollmann-Schult (2018) finds that working time flexibility can mitigate the physiological stress raised by parenthood. To our best knowledge, our study is the first to provide comprehensive comparisons between various forms of flexible working schemes. We analyse all three types of flexible employment within the same population and empirical frameworks, which allows us to assess the relative importance of the different forms of flexible employment on parental SWB.

Our study also contributes to the literature by delivering convincing evidence for significant gender heterogeneity with respect to the effect of the different types of flexible employment on mothers' and fathers' SWB. Previous studies have documented the gender asymmetric effect of other factors on parental SWB (e.g., Balbo and Arpino (2016); Musick et al. (2016); Roeters et al. (2016); Le Moglie et al. (2019)). First of all, some factors may exclusively affect the SWB of one gender and have no impact on the SWB of the other gender. For example, mothers are more likely to report lower SWB after childbirth when they are well-paid (Le Moglie et al., 2019) and family-orientated (Balbo & Arpino, 2016), whereas the links between these two factors and father's SWB is absent. Second, even if one factor affects parental SWB for both genders, the magnitude of this effect differs between mothers and fathers. Both in Australia and Germany, childbirth results in a much larger time pressure among new mothers than among new fathers (Buddelmeyer et al., 2018). Similarly, mothers in the USA tend to evaluate time spent with children with less happiness, more stress and stronger fatigue than fathers (Musick et al., 2016). The division of labour within a couple can drive this heterogeneity. When household specialisation is gendered, some factors that are more related to one's responsibility can reasonably make one's SWB more responsive than the partner's (Matysiak et al., 2016). Therefore, we interpret our findings with some facts about the classical intra-household division of labour in Australia.

Labour market context is extremely important when we analyse flexible employment. In many countries, the presence of *flexibility stigma*, meaning that flexible employment (e.g., part-time contracts) is considered inferior to normal employment (e.g., full-time contracts), has decreased the productivity and competitiveness of flexible workers (Cech & Blair-Loy, 2014). Due to this stigma, many workers decline flexible working opportunities, even if they should have benefited from flexible employment. This leads to underestimating the effect of flexible employment in these countries. We believe this is not the case in Australia, where working parents have commonly used well-established flexible working schemes (Bardoel & Haar, 2018). Flexible employment has been developing in Australia for over 30 years. The fast growth of working flexibility began in the 1990s, during which the number of flexible workers had increased by 41% (Kramar, 1998). The growing trend continues in the new century. In 2008, around 56.4% of men and 50.3% of women reported high flexibility in terms of work scheduling (Skinner & Pocock, 2008). The right to a flexible working arrangement for parents was announced in 2009 and enacted in 2010 by a new labour market legislation, *Fair Work Act 2009*. The new regulation allows the parents who have worked for their current employer for more than one year and have a school-aged or younger child to adjust their working hours and physical workplace. Statistics show that 20.1% of employees (15.4% men and 25.1% women) had requested such an arrangement until 2014, and nearly 90% of those requests were fully or partially approved (Skinner & Pocock, 2014). Part-time work has also been widely used by Australian parents. Since 2001, the most common combination of labour force status for parents is such that one partner holds a full-time job and the other works part-time, which accounts for over 30% of parents in Australia, while only around 20% of parents decide to undertake full-time jobs at the same time (Baxter, 2013). Given the long history, the regulatory framework, and the prevalence of flexible employment, we consider setting this study in Australian society is desirable for our purpose.

The remaining paper is organised as follows: Section 2.2 discusses the sample and variables used in the empirical estimation; Section 2.3 describes the empirical strategy; Section 2.4 provides the estimation results; Section 2.5 presents robustness checks, and Section 2.6 concludes.

2.2 Data and Measurements

We use data from the Household Income and Labour Dynamics in Australia (HILDA) survey between 2002 and 2017. HILDA is a national representative longitudinal survey in Australia conducted annually since 2001. Our analysis employs data from wave two onward as some questions about working flexibility were not asked in the first wave. We restrict our sample to individuals who have at least one child born between 2002 and 2017 and whom we can observe in three waves prior to and in five waves after childbirth. Since we cannot distinguish between biological and adopted children in the data, assuming that adoption is more likely among older parents, we only include men and women who had a child before age 55 and 45, respectively. The *full sample* comprises 18,363 male-year and 22,215 female-year observations (3,159 men and 3,721 women).

Furthermore, we focus on parents who report having a heterosexual partner in the household as parenthood may affect single and partnered parents differently due to the cost of childbearing and childrearing in terms of psychological distress, time and financial burdens (Myrskylä & Margolis, 2014; Pollmann-Schult, 2014). Moreover, this allows us to incorporate the partners' information, as also done in Booth and Van Ours (2008). We refer to it as the *main sample*. The number of observations in the *main sample* reduces to 17,097 for male-year and 17,281 female-year observations corresponding to 3,057 men and 3,124 women.

Table 2.1 presents the descriptive statistics for the analytical sample by gender. The comparison between the main sample and the full sample shows that excluding single and non-heterosexual parents does not substantially alter the sample composition. The exception is the slightly higher reported SWB and health among women in the main sample, which is likely driven by the fact that most excluded observations are single parents (separated, divorced and widowed).[2]

SWB is elicited with a single question where respondents are asked to evaluate their overall life satisfaction with a number between 0 (totally dissatisfied) and 10 (totally satisfied). It can be interpreted as either a cardinal or an ordinal number based on different assumptions. However, Ferrer-i Carbonell and Frijters (2004) have pointed out that assuming the cardinality and ordinality of SWB generates similar results once individual fixed effects are added to the model. For simplicity, we assume cardinal SWB, which allows us to use a linear model in our analyses.[3]. Figure 2.1 illustrates the trajectory of SWB around the transition to parenthood (from 3 years ahead of childbirth to 5 years after it). T denotes the year of childbirth, and -/+ refers to a preceding/following period relative to childbirth. We can observe a sharp decrease in SWB for both men and women between T and $T+1$ from Figure 2.1, suggesting that parents feel less satisfied with their life after childbirth compared to the prenatal periods. Moreover, parental SWB remains below the prenatal levels until the 5^{th} year after childbirth, which is the end of the observation window.

We distinguish between three forms of flexible employment: *contractual*, *temporal* and *spatial*. Contractual flexibility is first broadly reflected by labour force status: full-time, part-time and non-employed.[4] We later define contractual flexibility more precisely using working hour intervals based on a question about usual weekly working hours. As presented in Table 2.1, men are much more likely to work (only 8% of men and 40% of women are not working), and they are also more likely to work more hours (85% of men report full-time employment versus 26% of women). These crude summary statistics confirm that part-time jobs are more prevalent among mothers in Australia, which aligns with the high ratio of part-time mothers with children younger than six documented by Baxter (2013).

Temporal flexibility is defined as the possibility of a flexible start and end time

[2] We re-estimate the model using the full sample in Section 2.5.4. The results reported in Appendix Tables 2.A.5 and 2.A.6 are highly similar to the results based on the main sample.

[3] A similar approach has been used in many studies concerning SWB (e.g., Stanca (2012); Clark and Georgellis (2013); Matysiak et al. (2016). Furthermore, we assume ordinal SWB and estimate a fixed-effects ordered response model in Section 2.5.1 The results presented in Tables 2.4 and 2.5 suggest that our findings are robust to an ordinal interpretation of SWB

[4] We combine unemployment and not in the labour force into the non-employment category. We use 35 hours per week as a threshold to distinguish full-time and part-time employment.

of a working day (self-scheduling), and spatial flexibility refers to the possibility of home-based work. No major differences with respect to these forms between men and women can be found in Table 2.1. Note that temporal flexibility seems more popular than spatial flexibility as 62% of working men and women are entitled to self-scheduling while only about 32% have access to home-based work.

Table 2.1. Descriptive Statistics by Gender

	Full Sample (n=40,578)				Main Sample (n=34,378)			
	Men		Women		Men		Women	
Variable	Mean	s.d.	Mean	s.d.	Mean	s.d.	Mean	s.d.
Individual information								
SWB	7.88	1.32	7.94	1.35	7.90	1.29	8.06	1.23
Health	7.45	1.70	7.43	1.80	7.44	1.69	7.50	1.73
Age	34.33	6.99	31.72	6.27	34.57	6.79	32.13	5.99
Household information								
Children under 18	1.69	1.20	1.73	1.21	1.74	1.18	1.75	1.19
- Resident	1.57	1.14	1.70	1.18	1.63	1.12	1.73	1.16
- Non-resident	0.12	0.46	0.03	0.25	0.11	0.45	0.02	0.21
Use of childcare	0.55	0.50	0.56	0.50	0.57	0.50	0.57	0.50
Household income (,000)	92.61	50.64	87.06	50.21	93.85	50.31	93.30	49.78
Labour market information								
Non-employed	0.09	0.29	0.42	0.49	0.08	0.28	0.40	0.49
Part-time (PT)	0.07	0.25	0.33	0.47	0.06	0.25	0.34	0.48
Full-time (FT)	0.84	0.37	0.25	0.43	0.85	0.35	0.26	0.44
within PT								
- 0-20 hours	0.39	0.49	0.57	0.50	0.37	0.48	0.58	0.49
- 21-34 hours	0.61	0.49	0.43	0.50	0.63	0.48	0.42	0.49
within FT								
- 35-40 hours	0.42	0.49	0.67	0.47	0.42	0.49	0.68	0.47
- 41-50 hours	0.37	0.48	0.25	0.43	0.37	0.48	0.25	0.43
- >50 hours	0.21	0.41	0.08	0.27	0.21	0.41	0.07	0.26
Given Employed								
- Temporally flexible	0.62	0.49	0.62	0.49	0.62	0.49	0.62	0.48
- Spatially flexible	0.30	0.46	0.33	0.47	0.30	0.46	0.35	0.48
Supervise others	0.53	0.50	0.25	0.43	0.54	0.50	0.26	0.44
Self-employment	0.17	0.37	0.07	0.26	0.17	0.38	0.08	0.26
Observations	18,363		22,215		17,097		17,281	

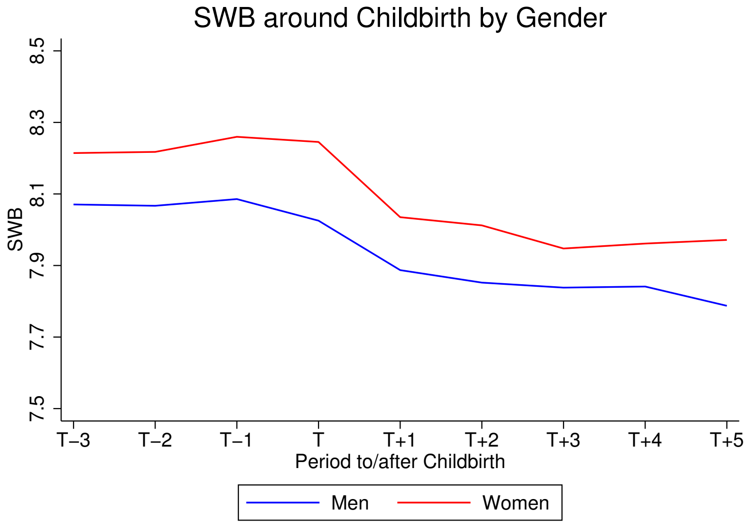


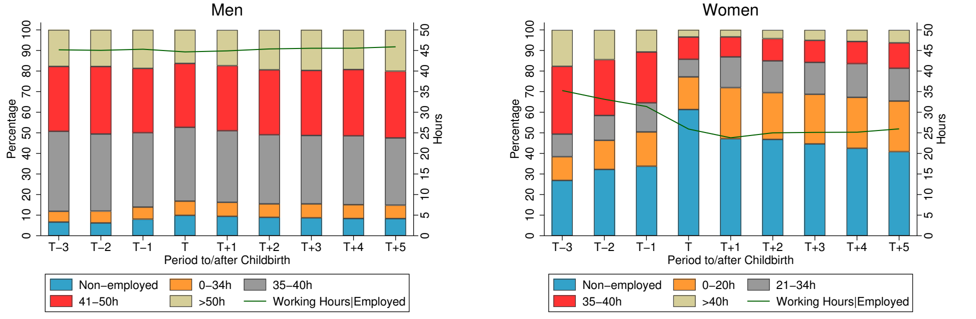
Figure 2.1. Trajectories of SWB at the stage of parenthood by gender

Note: T denotes the birth period (year) of a child. $T+/-s$ means s periods (years) before (-) or after (+) this childbirth.

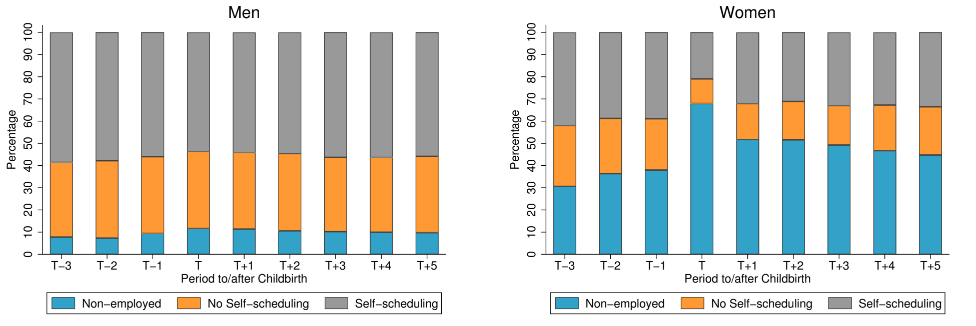
Figure 2.2 presents the distribution of different forms of flexible employment among fathers and mothers during the transition to parenthood. Each panel corresponds to a different type of flexibility. In each chart, a single bar represents the shares of different levels of flexibility in a specific period relative to childbirth, which adds up to 1. For Panel A, the green line corresponds to the secondary y-axis and shows the average working hours in each period for employed people. Among men, there is limited variation across periods for all types of flexibility and working hours: the majority of men work full-time (between 35-50 hours per week) throughout the transition to parenthood, and about 60% of men are entitled to self-scheduling, and 30% to home bases work. These facts are consistent with some findings in the literature: Baxter (2019) finds that most fathers in Australia hold full-time jobs even if they can switch to part-time jobs, and Baxter (2013) shows that fathers' use of flexible arrangements (including self-scheduling and home-based work) does not vary with the age of children. In contrast, mothers are more likely to adjust their working lives than fathers: nearly 70% of women do not work in the year of childbirth, which is 30% more than the previous year, as depicted on the right-hand-side graph in Panel A.[5] Despite some decreases in the following years, the proportion of non-working women remains high after childbirth. Moreover, the green line noting the average working hours shows that employed women spend 30-35 hours per week on their work before childbirth while the weekly hours are slightly over 25 after childbirth. This further confirms that women who stay in the labour market after childbirth tend to reduce weekly hours and opt for part-time jobs (Baxter, 2013).

Figure 2.3 summarises SWB during the transition into parenthood separately for men and women by job flexibility. In each graph, solid lines represent SWB among individuals in different types of flexible employment, and the dashed line denotes the overall SWB in each period. According to Panel A, men without jobs have much lower SWB than those with jobs, which may highlight the importance of employment for men. Among employed men, there is little difference between men in part-time and full-time jobs. Among women, labour force status appears to affect SWB mainly after childbirth. Part-time or non-employed mothers have much higher SWB than full-time mothers in postnatal periods. We also find that men's SWB is associated with temporal and spatial flexibility when their children are young (i.e., 1-2 years old). In Panel B, men with temporal flexibility have slightly higher SWB than those without it at $T+1$. Home-based work appears to have an even more pronounced effect in $T+1$ and $T+2$, as depicted in Panel C. However, both temporal and spatial flexibility does not seem to affect women's SWB, suggesting the presence of substantial gender heterogeneity. Mothers' SWB seems sensitive to contractual flexibility, while temporal and spatial flexibility appears to matter more for fathers' SWB.

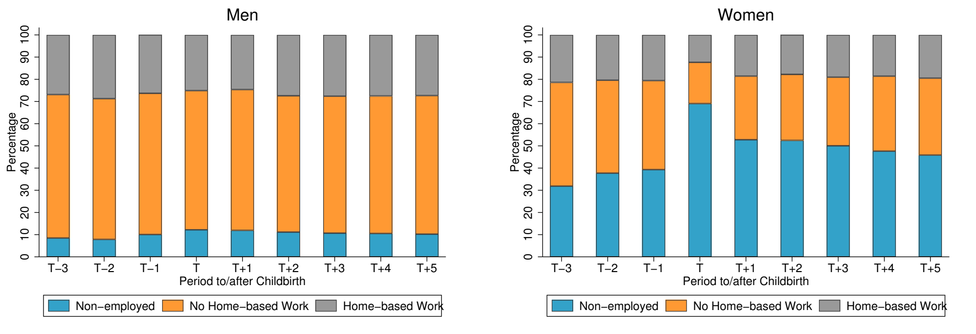
[5] The particularly high ratio of non-employment among women in period T can be partly attributed to parental leave. In Australia, there are generally three possibilities regarding parental leave for women: unpaid leave, government-funded paid leave and employer-funded paid leave. Employer-funded parental leave is contingent on the agreement or contract between an employer and an employee; government-funded leave is provided to the primary carer at the national minimum wage for 18 weeks; and unpaid leave for 12 months is guaranteed, which can also be extended for another 12 months by request. HILDA treats the latter two cases as not in the labour force.



Panel A: Contractual Flexibility



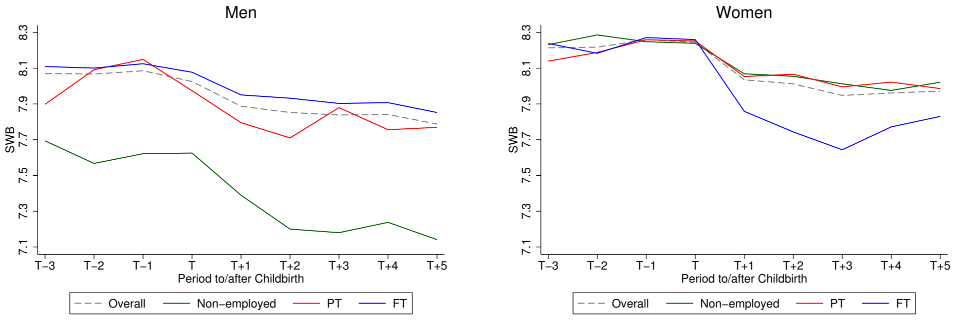
Panel B: Temporal Flexibility



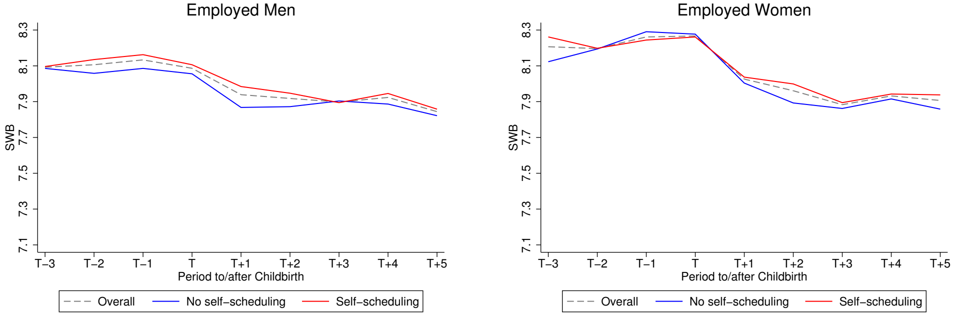
Panel C: Spatial Flexibility

Figure 2.2. Share of each level of job flexibility at the stage of parenthood by gender and flexibility types

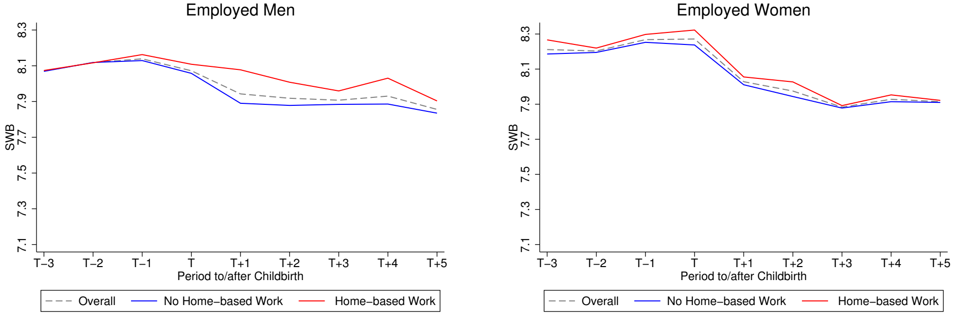
Note: T denotes the birth year of a child. $T + / - s$ means s periods (years) before (-) or after (+) this childbirth. In Panel A, the line subject to the secondary axis shows the average working hours of the employed people in each period.



Panel A: Contractual Flexibility



Panel B: Temporal Flexibility



Panel C: Spatial Flexibility

Figure 2.3. Trajectories of SWB at the stage of parenthood by gender and job flexibility

Note: T denotes the birth year of a child. $T+/-s$ means s periods (years) before (-) or after (+) this childbirth. The dashed line is the average trajectory for each gender.

2.3 Empirical Strategy

We employ an event-study framework with a linear fixed-effects model. This approach enables us to obtain the dynamic effect of parenthood on parental SWB. This is important for two reasons. First of all, according to the set-point theory of happiness, while SWB (from a life-course perspective) is relatively stable at a level predetermined by biological and social endowments, referred to as a *baseline level* (Matysiak et al., 2016), a life-changing event (e.g., parenting) can lead to transitory variation in SWB (Clark et al., 2008; Clark & Georgellis, 2013; Frijters et al., 2011). Moreover, the transitory variation may start prior to the event when someone forms exceptions about the event (Frijters et al., 2011). Thus, the time profile of SWB around a life-changing event has two phases. In each phase, the dynamic of SWB is characterised by a different effect: an *anticipation effect* represents the deviation of SWB from the baseline before an event, and an *adaptation effect* describes the recovery of SWB to the baseline after the event. Due to these leads and lags of SWB caused by these two effects, our empirical framework focuses on several periods during the transition into parenthood to capture the dynamics of SWB in each period. Second of all, a within-individual analysis accounts for all unobserved time-invariant factors that impact SWB, which may confound our estimates.[6]

Our basic specification is as follows:

$$SWB_{it} = \sum_{s=-2}^{5} \phi_s period_{s,it} + \mathbf{job}'_{\mathbf{it}}\boldsymbol{\beta} + \mathbf{x}'_{\mathbf{it}}\boldsymbol{\gamma} + \alpha_i + \mu_t + \epsilon_{it}, \tag{2.1}$$

where SWB_{it} represents the SWB of individual i in year t; $period_{s,it}$ is a period dummy variable indicating that it is the s^{th} year away from childbirth;[7] $\mathbf{job_{it}}$ is a vector of job characteristics including flexibility (e.g., part-time work), a dummy for self-employment, a dummy for supervision roles and partner's job character-

[6] For example, depending on the personality type, individuals may over- or under-estimate their SWB. Personality type might also correlate with the preference for full- and part-time employment (recall the flexibility stigma mentioned above). Under the assumption that personality is constant over time , the within-transformation with panel data removes the confounding factor of personality.

[7] As shown in Eq. (2.1), the observation window is from period $T-3$ to $T+5$ ($T-3$ is omitted as a reference period). The same observation window is also used by Le Moglie et al. (2019). In addition, previous studies have found that a significant anticipation effect generally begins at $T-2$ or $T-1$, and a significant adaptation effect ends before $T+5$ (Clark et al., 2008; Frijters et al., 2011; Clark & Georgellis, 2013; Le Moglie et al., 2019). Hence, the window used here should enable us to observe a complete time profile of SWB.

istics;[8] $\mathbf{x_{it}}$ is a vector of other control variables which can be broadly categorised into household and individual level controls. At the household level, we control for household income (in logarithm) which reflects the impact of financial situation on parental SWB; the number of resident and non-resident children under 18 as not only the transition into parenthood but the number of children also matters for SWB; use of childcare service as it can be an alternative solution for flexible employment. At the individual level, we control for respondents' health status and squared age. We also control for the partner's health, squared age and work flexibility to capture the spill-over effect from the partner. We also include individual and time (yearly) fixed effects with α_i and μ_t, respectively, and ϵ_{it} is an idiosyncratic error term. The model is estimated separately for men and women to account for gender heterogeneity in the effects of flexible employment on parental SWB.[9]

The period indicators, $period_{s,it}$, are essential elements in an event study analysis. We explain how they are formulated in detail with a hypothetical example in Table 2.2. Suppose we have information for an individual i for 7 consecutive years ($t \in [1,7]$). During these 7 years, individual i has two children: one in year 1 and the other in year 5 whose ages in each year t are also shown in Table 2.2. The right-hand side of Table 2.2 is the period indicators generated from the ages of these children, where T corresponds to the year of birth of a child.[10] In year t, a period indicator $period_{s,it}$ takes a value 1 if this year corresponds to the T+s period relative to the birth of a child born in T and 0 otherwise. The earliest period in our scope is $T-3$, three periods before childbirth while the latest period in our scope is $T+5$, five periods after childbirth. For individual i, as the first child is aged 0 in year 1, indicator T corresponding to the birth of this child equals to 1. Since the second childbirth will occur in year 5, year 1, the 4^{th} period before this childbirth, is outside of our observation window (earlier than $T-3$). Thus, in year 1, the remaining indicators are zero. However, this is not the case for year 2. Year 2 is the first period

[8] We do not exclude self-employed people in our analyses. Although they have strong control over when, where and how their work is conducted, some of them cannot work flexibly in our sample. For example, 23% of them have no access to self-scheduling, and 50% of them cannot work from home. However, we find that the results without the self-employed are not different from the main results.

[9] Due to an expectation that childbirth may affect mothers' and fathers' SWB differently, a separate estimation by gender is a common practice in literature (e.g., Myrskylä & Margolis, 2014; Matysiak et al., 2016; Le Moglie et al., 2019).

[10] We only generate indicators from the ages of resident children. Here we implicitly assume these two children live together with individual i.

after the first childbirth and the third period before the second birth, both of which are in our scope. Accordingly, $T+1$ and $T-3$ are equal to 1. Consequently, in each following year up to year 6, two corresponding indicators are equal to 1 to denote the period relative to the two childbirth in each year t. Finally, in year 7, only indicator $T+2$ equals to 1 for the second child as it has been the 6^{th} period after the birth of the first child, which is, again, out of the range of the period indicators in our model.

Table 2.2. A Hypothetical Example to Explain the Construction of Period Indicators

	Ages of Children		Period Indicators								
Year	Child 1	Child 2	T-3	T-2	T-1	T	T+1	T+2	T+3	T+4	T+5
1	0	.	0	0	0	1	0	0	0	0	0
2	1	.	1	0	0	0	1	0	0	0	0
3	2	.	0	1	0	0	0	1	0	0	0
4	3	.	0	0	1	0	0	0	1	0	0
5	4	0	0	0	0	1	0	0	0	1	0
6	5	1	0	0	0	0	1	0	0	0	1
7	6	2	0	0	0	0	0	1	0	0	0

Since $period_{s,it}$, shows the period relative to childbirth, its coefficient ϕ_s captures the variation of SWB when a respondent is in this period. Thereby, coefficients for all period indicators can jointly capture the dynamic effect of parenthood on parental SWB from 3 years before to 5 years after childbirth. Also, in Eq. (2.1), $\boldsymbol{\beta}$ represents an overall effect of job-related factors on parental SWB.

To capture the heterogeneity in the dynamic effect on SWB with respect to work flexibility, we extend the model by including interaction terms between the period indicators and the level of job flexibility included in vector $\mathbf{job_{it}}$, and we estimate the following model:

$$\begin{aligned} SWB_{it} = & \sum_{s=-2}^{5} (\phi_s period_{T+s,it} + \psi_s period_{T+s,it} \times flex_{it}) \\ & + \mathbf{job'_{it}}\boldsymbol{\beta} + \mathbf{x'_{it}}\gamma + \alpha_i + \mu_t + \epsilon_{it}, \end{aligned} \tag{2.2}$$

where $flex_{it}$ is the variable for a given type of flexible employment included in $\mathbf{job_{it}}$. ψ_s is the coefficient for the interaction term, which captures how the trajectories of SWB differ with respect to job flexibility in the s^{th} period relative to childbirth.

We assume that all time-varying regressors, conditional on the individual and time fixed effects, are orthogonal to the idiosyncratic error term, ϵ_{it}. This assumption is violated if, for example, parents' preferences towards work and leisure change in the event of childbirth. For example, parents who derive more utility from parenting might opt for more flexible jobs. Therefore, it is likely that the coefficients on $period_{T+s,it} \times flex_{it}$ capture the effect of changing preferences as well as the greater flexibility in accommodating work and family life. While this does not threaten our identification strategy, it limits our interpretation of the results, i.e., we cannot identify the mechanisms through which flexible employment affects parental SWB. We also acknowledge that the event of childbirth is not completely random. However, as argued by Kleven et al. (2019), the sharp changes in the outcomes (i.e., parental SWB) around childbirth should not be driven by the unobserved determinants of fertility, which are supposed to progressively affect the outcomes over time.

2.4 Results

We start by estimating the dynamic effect of parenthood on parental SWB (Eq. (2.1)), which is presented in Panel A of Table 2.3 and Figure 2.4.[11] Our results are in line with the literature and suggest a presence of both anticipation and adaptation effects (Clark et al., 2008; Clark & Georgellis, 2013). In the prenatal periods, the coefficients on $T-1$ and T are significantly higher than the reference level at $T-3$ for both men and women. This is suggestive of a positive anticipation effect. In the postnatal periods, men's SWB reverts to the reference level relatively quickly and remains stable at this level for the remaining periods. In contrast, it takes more time for women's SWB to recover to its baseline level as their SWB is significantly lower than the reference level up to $T+4$, suggesting a longer adaptation effect.

Panels B-E of Table 2.3 present the estimates corresponding to different forms

[11] Due to our interest in diverse forms of flexible employment, we estimate the model for multiple times with different flexible employment variables, which makes the estimated coefficients on period indicators slightly different each time. The coefficients presented here are from the estimation with different labour force status (non-employed/PT/FT).

of flexible employment. Panels B and C correspond to contractual flexibility measured with labour force status (Panel B) and weekly working hours (Panel C). Both sets of results reveal substantial gender heterogeneity with respect to the effect of contractual flexibility on SWB during the transition to parenthood. In Panel B, compared to part-time, full-time employment raises men's SWB by 0.09 but reduces women's SWB by 0.07. In contrast, women's SWB is not affected by non-employment, whereas this status could lead to a -0.14 decline in men's SWB.[12] Similar trends are found for working hours (Panel C). The intervals used in the estimation are 0-20 hours, 21-34 hours, 35-40 hours, 41-50 hours and more than 50 hours.[13] Although previous results in Panel B suggest full-time employment, as a whole, boosts men's SWB, results in Panel C show that this positive effect is mainly attributed to 35-50 weekly hours because jobs requiring longer weekly hours can hardly improve men's SWB. For women, in general, when working hours get longer, their impact on SWB becomes more negative. Therefore, even within part-time employment, working less than 20 hours a week yields higher SWB than working 21-35 hours a week.

The bottom two panels (Panels D and E) present the results concerning temporal and spatial flexibility.[14] The results once again confirm the presence of gender heterogeneity. However, in this case, the effects are more pronounced among men. The effectiveness of temporal and spatial flexibility in improving men's SWB is illustrated by some significantly positive coefficients in Panels D and E, although the coefficient of temporal flexibility is only significant at the 10% level. Men with temporal and spatial flexibility are 0.04 and 0.09 higher in their SWB than their inflexible counterparts. However, the control over working time and the workplace has a negligible and insignificant effect on women's SWB.

The presence of gender heterogeneity with respect to the forms of flexible employment among parents is in itself interesting, but it is not informative about the intermediary effect of job flexibility on the trajectory of SWB during the transition to parenthood. Therefore, we turn to Eq. (2.2) and extend the model to include interaction terms between period indicators and flexible employment. Figure 2.5

[12] Considering the standard deviation of SWB is around 1.3, the effect size around 0.1-0.2 is not insubstantial even if it seems small in a 0-10 scale of SWB.

[13] Due to small sample size, 1-20 hours and 21-34 hours are combined for men, and 41-50 hours and more than 50 hours are combined for women.

[14] Only the working sample is considered in this analysis.

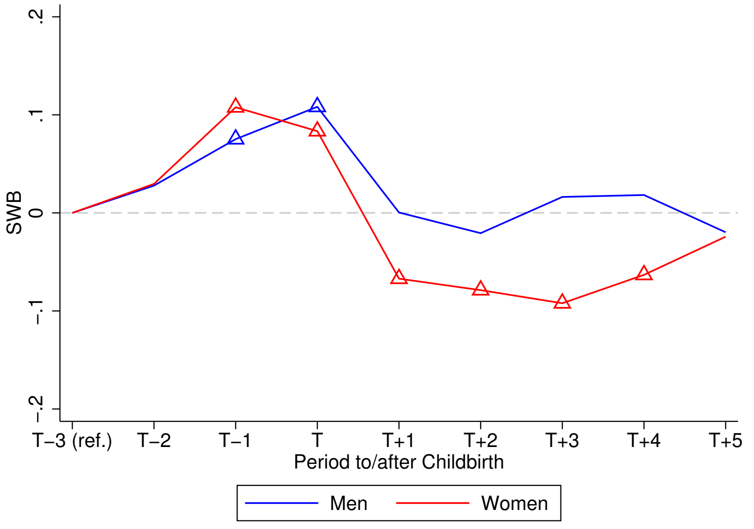


Figure 2.4. Dynamic effect of parenthood on SWB by gender

Note: T denotes the birth period (year) of a child. $T + / - s$ means s periods (years) before (-) or after (+) this childbirth. The SWB in $T - 3$ is set to be 0 as the reference level for each gender. ◯ □ and △ denote the effect is significant at the 10%, 5% and 1% level, respectively.

presents the estimated trajectories during the transition to parenthood for different forms of flexible employment, separately for men and women. The top two panels consider contractual flexibility (Panels A and B), while the bottom two panels present the results for spatial and temporal flexibility (Panels C and D, respectively), with graphs for fathers depicted on the left and for mothers on the right. In each graph, geometric shapes denote the significance level of the interaction terms between flexible employment and period indicators. A significant interaction term indicates the intermediary effect of job flexibility at a certain period. It means that in a given period, the difference between the SWB generated by a given level of flexible employment and by the reference level is significantly different from the one in the baseline period, $T - 3$. The output table used to create Figure 2.5 is available in Appendix Table 2.A.1.

It appears that contractual flexibility has little effect on men as none of the interaction terms between full-time jobs and period indicators is significant. The SWB of full-time and part-time workers progresses similarly: both exhibit a positive anticipation effect in the pre-birth periods, while SWB remains relatively stable around each respective baseline level after childbirth. However, the SWB of non-workers follows a different path because such a positive anticipation effect does not exist, and non-workers' SWB is significantly worse at children's age of 2-3. Using working hours to measure work flexibility confirms that men's SWB progresses in a similar way regardless of working hours (Panel B).[15] Moreover, as none of the interaction terms turns out to be significant, we conclude that contractual flexibility might not effectively alter men's SWB at the stage of parenthood.

A very different story unfolds when we consider mothers. Contractual flexibility appears to have a positive effect on mothers' SWB during the transition into parenthood. Part-time working women first experience a significant increase between $T-2$ and $T-1$, and then their SWB fluctuates around the baseline level in subsequent periods. The SWB of full-time and non-employed women also increases in the periods leading to the birth of a child, but then it sharply drops and remains at a lower level than each baseline level for at least three periods. In Panel A, the interaction terms for both non-employed and full-time working mothers are significantly negative at $T+2$, which implies some negative effects of these two labour force status on mothers' SWB at $T+2$. Moreover, as depicted in Panel B, such a negative intermediary effect exists in jobs requiring longer than 20 hours in some periods between $T+2$ and $T+4$ in contrast to women working under 20 hours.

Similar to baseline estimates (Eq. (2.1)), an opposite pattern is observed for temporal and spatial flexibility. While men entitled to self-scheduling and home-based work gain some additional SWB at children's early ages compared to their inflexible counterparts, women's SWB does not seem to be affected similarly. Both self-scheduling and home-based work do not make a significant difference in their SWB in any period compared to the situation at $T-3$. This of course can be driven by the types of occupations and industries. We explore this further in Section 2.5.3.

[15] We also treat 'non-employment' as a special category and interact it with period indicators. Since we mainly discuss the role of different working hours, they are not shown in Panel B

Table 2.3. Fixed-effects Estimation of Parental SWB

Dependent Variable	Men			Women	
SWB	coef.	s.e.		coef.	s.e.
Panel A: Dynamic Effect of Parenthood					
T-2	0.028	0.024		0.030	0.024
T-1	0.075***	0.023		0.108***	0.023
T	0.106***	0.027		0.086***	0.027
T+1	-0.001	0.025		-0.065**	0.025
T+2	-0.022	0.024		-0.077***	0.024
T+3	0.016	0.024		-0.090***	0.024
T+4	0.018	0.025		-0.062***	0.024
T+5	-0.020	0.025		-0.023	0.024
Observations	17,097			17,281	
Number of ID	3,057			3,124	
Panel B: Contractual Flexibility (Labour Force Status)					
non-employed	-0.142***	0.047		0.027	0.024
PT	ref.			ref.	
FT	0.092***	0.036		-0.067***	0.024
Observations	17,097			17,281	
Number of ID	3,057			3,124	
Panel C: Contractual Flexibility (Working Hour Intervals)					
non-employed	-0.142***	0.047	non-employed	0.000	0.026
0-34 h	ref.		0-20 h	ref.	
35-40 h	0.108***	0.037	21-34 h	-0.079***	0.028
41-50 h	0.092**	0.038	35-40 h	-0.086***	0.030
>50 h	0.015	0.042	>40 h	-0.179***	0.038
Observations	17,097			17,281	
Number of ID	3,057			3,124	
Panel D: Temporal Flexibility					
no self-scheduling	ref.			ref.	
self-scheduling	0.040*	0.022		0.028	0.028
Observations	12,449			8,447	
Number of ID	2,625			2,180	
Panel E: Spatial Flexibility					
no home-based work	ref.			ref.	
home-based work	0.085***	0.025		0.048	0.032
Observations	11,703			8,048	
Number of ID	2,603			2,135	

Notes: This table reports the estimates of period indicators and job flexibility. Results in Panels A and B are from the same estimation. In Panels B-E, other control variables are one's and partner's health, one's and partner's squared age (divided by 1,000), household income (in logarithm), use of childcare, the number of resident and non-resident children, self-employment, supervising others, period indicators, year dummies and partner's labour force status (in Panel B)/partner's working hour intervals (in Panel C)/one's and partner's working hour intervals (in Panels D and E). Significance levels are shown as *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Panel A: Contractual Flexibility (Labour Force Status)

Panel B: Contractual Flexibility (Working Hour Intervals)

Figure 2.5. Dynamic effect of parenthood on SWB by gender and job flexibility

Panel C: Temporal Flexibility

Panel D: Spatial Flexibility

Figure 2.5 (Cont.). Dynamic effect of parenthood on SWB by gender and job flexibility

Note: The SWB for the reference working status at $T-3$ is set to be 0. ◯ □ and △ indicate the interaction term between a period indicator and flexible employment is significant at the 10%, 5% and 1% level, respectively.

2.5 Robustness Checks

2.5.1 Non-linear Effects

Following previous studies, our primary analysis employs a linear fixed-effects model that implicitly assumes the cardinality of SWB. However, as SWB is typically measured with ordered categories, the distance between categories is unknown (Van Praag & Ferrer-i Carbonell, 2004). An alternative approach is to rely only on the ordinal nature of SWB and employ a non-linear model instead. Keeping in mind that Ferrer-i Carbonell and Frijters (2004) have shown that the cardinal or ordinal assumption of SWB hardly affects the estimation results, we perform a robustness check in which we accept the ordinal interpretation in this section. We re-estimate our model with a panel ordered response model to reassure that our results are not sensitive to the assumptions of the nature of SWB.

We consider a blow-up and cluster (BUC) estimator that allows us to implement a within-transformation in an ordered response panel data setting. Due to an incidental parameter problem, a non-linear panel data model is generally incompatible with a within-transformation. One exception is a fixed-effects binary logit model, which identifies model parameters using the individuals whose dependent variable varies across time. Based on this feature of the fixed-effects binary logit model, Baetschmann et al. (2015) propose the BUC estimator to perform a fixed-effects analysis on ordered response panel data. To apply the BUC estimator in our context, we first duplicate the observations of each individual 10 times as there are 10 cut-offs yielded by 11 possible values of SWB (from 0 to 10).[16] Then, every duplicate is collapsed into a binary variable at a different cut-off. Finally, the BUC estimator generates consistent results by fitting the expanded dataset using a fixed-effect logit model.[17] These steps can be easily achieved with a Stata command '*feologit*' programmed by Baetschmann et al. (2020).

The results from the fixed-effects ordered response model are displayed in Table 2.4 and Table 2.5. The estimated vector of coefficients ($\hat{\boldsymbol{\beta}}$) in this model does not have a natural interpretation as it describes the latent process. Instead, we present $exp(\hat{\beta}_j)$

[16] The BUC estimator implicitly assumes a homogeneous coefficient (β) at every cut-off (i.e., $\beta^1 = \beta^2 = ... = \beta^{10}$) where the superscript of β denotes a specific cut-off.

[17] Applying a fixed-effect logit model means we lose the observations whose dependent variable does not vary across time. However, there is not a substantial observation loss in practice because the dependent variable, parental SWB, typically fluctuates a lot during the transition into parenthood.

for each regressor, x_{itj}, which represents the marginal change in the odds ratio of $SWB \geq l$ against $SWB < l$ induced by a one-unit increase in a regressor x_{itj} (Baetschmann et al., 2020), where l is a possible value of SWB. It is critical to compare $exp(\hat{\beta}_j)$ with one. The situation of $exp(\hat{\beta}_j) > 1$ ($exp(\hat{\beta}_j) < 1$) suggests that the marginal increase in x_{itj} can make the odds of $SWB \geq l$ relative to $SWB < l$ higher (lower).

The estimates in both tables indicate our main results remain qualitatively unchanged in a non-linear setting that assumes ordinal SWB. Panel A of Table 2.4 shows the dynamic effect of parenthood. The results are similar to what Figure 2.4 depicts in the main analysis. Both men and women have a positive anticipation effect at $T-1$ and T as the odds ratios in these periods are significantly greater than one. A negative adaptation effect exclusively happens to women in postnatal periods from $T+1$ to $T+4$. Panels B-E show the overall effect of each type of flexible employment on parental SWB during the transition into parenthood. Similarly to the primary analysis, we find evidence of gender heterogeneity. Women's SWB benefits from short working hours while men's SWB improves with the entitlement of self-scheduling and home-based work. Note, however, that some point estimates lose statistical significance in the non-linear model, which can be explained with smaller sample size. For example, non-employment cannot significantly affect men's SWB compared to part-time work. Full-time work can only improve men's SWB at the 10% level, which is mainly attributed to jobs requiring 35-40 weekly hours.

The intermediary effect of job flexibility is examined by interacting job flexibility and period indicators and shown in Table 2.5. Our findings are in line with the findings from the linear model presented in the Results section. Part-time jobs, especially those between 0-20 weekly hours, improve women's SWB in postnatal periods because all other working hour intervals decrease the odds of reporting higher SWB in some periods. In contrast, flexible working time and workplace increase men's SWB in the early years of parenthood. The similarity of the results from the linear and non-linear models confirms the robustness of our analysis under different interpretations of SWB.

Table 2.4. Fixed-effects Ordered Response Estimation of Parental SWB

Dependent Variable	Men			Women	
SWB	odds ratio	s.e.		odds ratio	s.e.
Panel A: Dynamic Effect of Parenthood					
T-2	1.059	0.066		1.098	0.069
T-1	1.208***	0.076		1.305***	0.085
T	1.302***	0.106		1.274***	0.105
T+1	0.972	0.074		0.837**	0.062
T+2	0.901	0.062		0.809***	0.057
T+3	1.004	0.069		0.784***	0.053
T+4	1.037	0.071		0.836***	0.056
T+5	0.928	0.059		0.924	0.057
Observations	15,576			15,840	
Number of ID	2,362			2,411	
Panel B: Contractual Flexibility (Labour Force Status)					
non-employed	0.808	0.116		1.073	0.071
PT	ref.			ref.	
FT	1.191*	0.122		0.871**	0.056
Observations	15,576			15,840	
Number of ID	2,362			2,411	
Panel C: Contractual Flexibility (Working Hour Intervals)					
non-employed	0.813	0.116	non-employed	0.996	0.071
0-34 h	ref.		0-20 h	ref.	
35-40 h	1.250**	0.130	21-34 h	0.804***	0.060
41-50 h	1.183	0.130	35-40 h	0.823**	0.065
>50 h	0.979	0.117	>40 h	0.645***	0.067
Observations	15,576			15,840	
Number of ID	2,362			2,411	
Panel D: Temporal Flexibility					
no self-scheduling	ref.			ref.	
self-scheduling	1.119*	0.072		1.081	0.090
Observations	10,931			7,080	
Number of ID	1,872			1,394	
Panel E: Spatial Flexibility					
no home-based work	ref.			ref.	
home-based work	1.267***	0.101		1.142	0.108
Observations	10,162			6,700	
Number of ID	1,810			1,348	

Notes: This table reports the odds ratios of period indicators and job flexibility on SWB around childbirth. Results in Panels A and B are from the same estimation. In Panels B-E, other control variables are one's and partner's health, one's and partner's squared age (divided by 1,000), household income (in logarithm), use of childcare, the number of resident and non-resident children, self-employment, supervising others, period indicators, year dummies and partner's labour force status (in Panel B)/partner's working hour intervals (in Panel C)/one's and partner's working hour intervals (in Panels D and E). Significance levels are shown as *** p<0.01, ** p<0.05, * p<0.1.

Table 2.5. Intermediary Effect of Job Flexibility on Parental SWB

Dependent Variable	Men			Women	
SWB	odds ratio	s.e.		odds ratio	s.e.
Panel A: Contractual Flexibility (Labour Force Status)					
non-employed×					
T-2	0.783	0.254		1.016	0.148
T-1	0.584*	0.17		0.840	0.109
T	0.859	0.225		0.885	0.115
T+1	0.864	0.226		0.871	0.1
T+2	0.664	0.179		0.794**	0.09
T+3	0.720	0.22		0.908	0.105
T+4	0.792	0.266		0.842	0.103
T+5	0.690	0.204		1.019	0.119
FT×					
T-2	1.117	0.306		0.964	0.135
T-1	0.828	0.179		1.089	0.137
T	0.829	0.174		1.237	0.193
T+1	0.923	0.196		0.751*	0.111
T+2	0.962	0.196		0.714**	0.100
T+3	0.894	0.184		0.871	0.130
T+4	0.839	0.225		0.851	0.123
T+5	0.752	0.154		1.220	0.172
Observations	15,576			15,840	
Number of ID	2,362			2,411	
Panel B: Contractual Flexibility (Working Hour Intervals)					
35-40 h×			21-34 h×		
T-2	1.055	0.297	T-2	1.136	0.242
T-1	0.847	0.194	T-1	0.948	0.17
T	0.823	0.179	T	1.007	0.223
T+1	0.851	0.19	T+1	1.111	0.191
T+2	0.908	0.191	T+2	0.902	0.151
T+3	0.857	0.183	T+3	0.763	0.13
T+4	0.865	0.238	T+4	0.618***	0.109
T+5	0.737	0.158	T+5	0.909	0.158
41-50 h×			35-40 h×		
T-2	1.131	0.323	T-2	0.987	0.184
T-1	0.777	0.178	T-1	1.114	0.177
T	0.818	0.181	T	1.065	0.194
T+1	0.936	0.209	T+1	0.726*	0.133
T+2	1.063	0.230	T+2	0.619***	0.106
T+3	0.968	0.210	T+3	0.860	0.154
T+4	0.756	0.211	T+4	0.609***	0.107
T+5	0.731	0.159	T+5	1.118	0.190

Table 2.5 (Cont.). Intermediary Effect of Job Flexibility on Parental SWB

Dependent Variable	Men			Women	
SWB	odds ratio	s.e.		odds ratio	s.e.
>50 h×			>40 h×		
T-2	1.209	0.357	T-2	1.077	0.234
T-1	0.872	0.211	T-1	0.886	0.188
T	0.837	0.200	T	1.923**	0.541
T+1	1.067	0.245	T+1	0.933	0.222
T+2	0.948	0.214	T+2	0.852	0.187
T+3	0.881	0.205	T+3	0.623*	0.155
T+4	0.965	0.277	T+4	0.852	0.191
T+5	0.814	0.188	T+5	1.216	0.295
Observations	15,576			15,840	
Number of ID	2,362			2,411	
Panel C: Temporal Flexibility					
self-scheduling×					
T-2	1.077	0.148		0.874	0.150
T-1	1.019	0.131		0.910	0.153
T	1.120	0.140		1.093	0.222
T+1	1.407***	0.180		0.973	0.157
T+2	1.081	0.125		0.972	0.149
T+3	1.013	0.120		0.898	0.141
T+4	0.980	0.129		0.909	0.156
T+5	1.032	0.128		1.095	0.169
Observations	10,931			7,080	
Number of ID	1,872			1,394	
Panel D: Spatial Flexibility					
home-based work ×					
T-2	0.989	0.152		0.891	0.162
T-1	1.000	0.151		1.153	0.191
T	1.154	0.170		1.134	0.235
T+1	1.488***	0.210		0.890	0.141
T+2	1.339**	0.177		0.764*	0.116
T+3	1.032	0.141		0.814	0.136
T+4	1.190	0.171		0.858	0.141
T+5	1.142	0.164		0.889	0.143
Observations	10,162			6,700	
Number of ID	1,810			1,348	

Notes: This table reports the odds ratios of the intermediary effect of job flexibility in each period relative to childbirth. Other control variables are one's and partner's health, one's and partner's squared age (divided by 1,000), household income (in logarithm), use of childcare, the number of resident and non-resident children, self-employment, supervising others, period indicators, year dummies and partner's labour force status (in Panel A)/partner's working hour intervals (in Panel B)/one's and partner's working hour intervals (in Panels C and D). Significance levels are shown as *** p<0.01, ** p<0.05, * p<0.1.

2.5.2 An Alternative Specification

In Eq. (2.2), we use a set of interaction terms between period indicators and flexible employment to examine the effect of flexible employment in each period during the transition into parenthood. However, since the sample is divided by periods and job flexibility, some period-flexibility pairs only contain a small number of observations, which could result in a lack of precision in our estimates. To cope with this problem, we re-estimate the model with an alternative specification proposed by Berger (2013), where dummies for age categories of the youngest resident child are used instead of period indicators. We estimate the following models:

$$SWB_{it} = \mathbf{age}'_{\mathbf{it}}\boldsymbol{\beta}_1 + \mathbf{job}'_{\mathbf{it}}\boldsymbol{\beta}_2 + \mathbf{x}'_{\mathbf{it}}\gamma + \alpha_i + \mu_t + \epsilon_{it}, \tag{2.3}$$

$$SWB_{it} = \mathbf{age}'_{\mathbf{it}}\boldsymbol{\beta}_1 + \mathbf{job}'_{\mathbf{it}}\boldsymbol{\beta}_2 + (flex_{it} \times \mathbf{age}'_{\mathbf{it}})\boldsymbol{\theta} + \mathbf{x}'_{\mathbf{it}}\gamma + \alpha_i + \mu_t + \epsilon_{it} \tag{2.4}$$

where $\mathbf{age_{it}}$ is a vector of four age categories: not born, age 0, age 1-2, and age 3-5.[18] The remaining notation follows previous specifications. It is worth noting that we include an additional control variable, *expecting*, which takes on the value 1 if a child is born in the household in the following year and 0 otherwise.

The results of Eq. (2.3) presented in Table 2.6 are similar to the results in the main analysis (Table 2.3) in terms of both the magnitude and statistical significance of the coefficients. Compared to men with part-time jobs, non-employed men report lower SWB, while men with full-time jobs report higher SWB, especially among those working 35-50 hours a week. In contrast, full-time jobs harm women's SWB, and the negative impact becomes stronger as the weekly hours are longer. In terms of temporal and spatial flexibility, the positive effect on SWB is only significant for men.

Estimates from Eq. (2.4) are also qualitatively comparable with the results from the main analysis. Based on these estimates, Figure 2.6 depicts the trajectories of SWB for different forms of flexible employment depending on the age of the young-

[18] The group *not born* composes individuals who currently have no resident children but will have at least one within 3 years. This group is omitted in the regression as a reference group. In this estimation, the maximum age of the youngest child is 5. For this reason, we selected out 392 observations whose youngest child is older than 5.

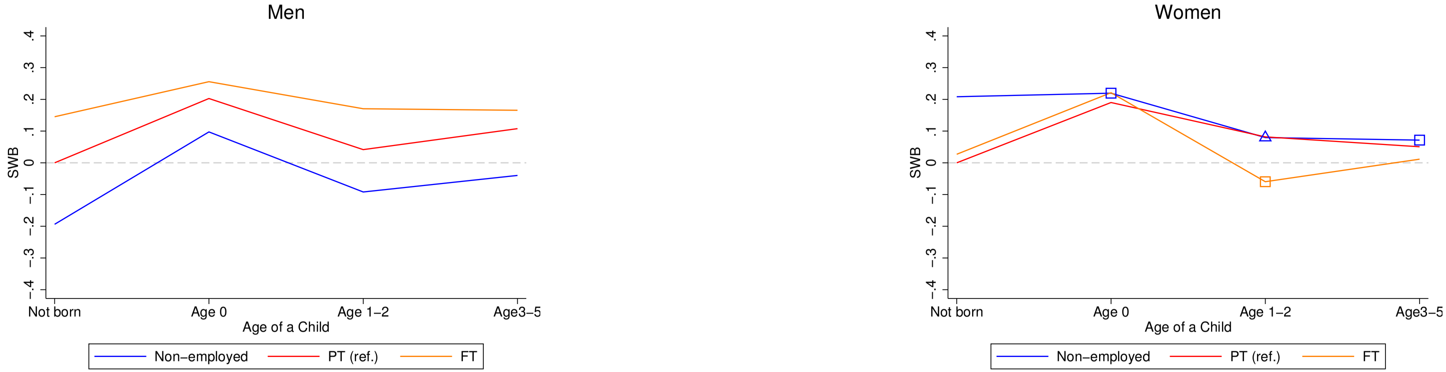
est resident child.[19] In the alternative specification, we still find contractual flexibility has no intermediary effect on men's SWB, as none of the interaction terms between the youngest child's age and full-time work (Panel A) or working hours (Panel B) is significant. However, the age-specific effects of contractual flexibility can be found among women. Compared to working up to 20 hours per week, working between 35 and 40 hours decreases the SWB of mothers with children aged 1-2. Furthermore, for mothers with the youngest child between 3-5 years old, working more than 20 hours negatively impacts their SWB (Panel B). In terms of temporal flexibility, we find the results in Panel C are slightly different from the main analysis. Although the difference in SWB between men with and without self-scheduling at children's age 1-2 appears to be larger than the difference at the baseline (childless periods), this difference is not statistically significant. This could be driven by the fact that self-scheduling is especially beneficial to fathers at $T+1$ (as shown in the primary analysis) and becomes less important afterwards. In terms of spatial flexibility, the results from the primary analysis and this one are similar. Since home-based work has a significantly positive effect on men's SWB at both $T+1$ and $T+2$ in the main analysis, a similar effect is also found in Panel D for the corresponding age group, aged 1-2.

[19] The output table for this estimation is available in Appendix Table 2.A.2.

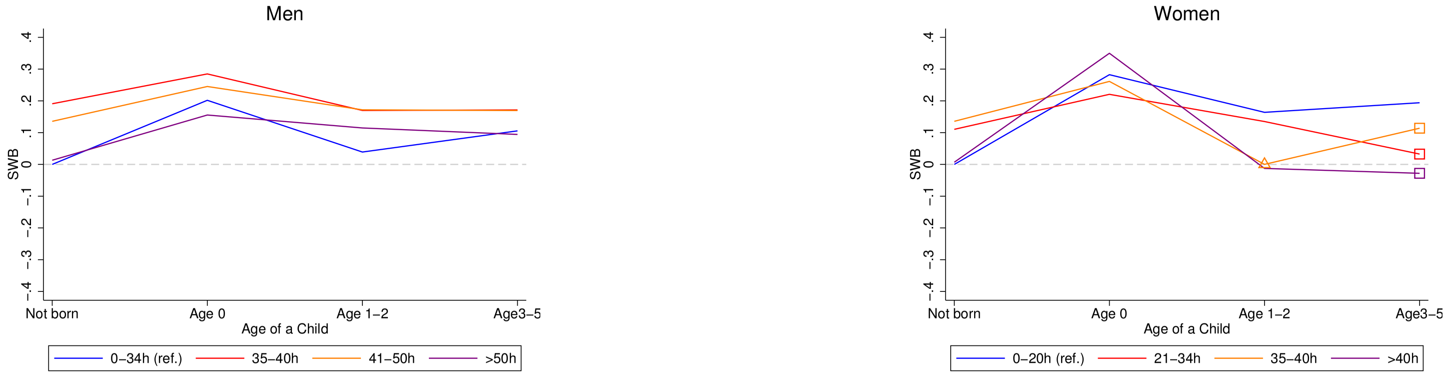
Table 2.6. Fixed-effects Estimation of Parental SWB by Children's Age Groups

Dependent Variable	Men			Women	
SWB	coef.	s.e.		coef.	s.e.
Panel A: Contractual Flexibility (Labour Force Status)					
non-employed	-0.144***	0.047		0.023	0.024
PT	ref.			ref.	
FT	0.091**	0.036		-0.059***	0.025
Observations	16,916			17,023	
Number of ID	3,057			3,124	
Panel B: Contractual Flexibility (Working Hour Intervals)					
non-employed	-0.144***	0.047	non-employed	-0.002	0.026
0-34 h	ref.		0-20 h	ref.	
35-40 h	0.107***	0.037	21-34 h	-0.077***	0.029
41-50 h	0.090**	0.039	35-40 h	-0.079***	0.031
>50 h	0.012	0.043	>40 h	-0.171***	0.039
Observations	16,916			17,023	
Number of ID	3,057			3,124	
Panel C: Temporal Flexibility					
no self-scheduling	ref.			ref.	
self-scheduling	0.045**	0.022		0.018	0.029
Observations	12,307			8,317	
Number of ID	2,621			2,171	
Panel D: Spatial Flexibility					
no home-based work	ref.			ref.	
home-based work	0.085***	0.026		0.050	0.032
Observations	11,568			7,923	
Number of ID	2,599			2,126	

Notes: This table reports the estimates of job flexibility on SWB around childbirth. Other control variables are one's and partner's health, one's and partner's squared age (divided by 1,000), household income (in logarithm), use of childcare, the number of resident and non-resident children, an indicator of childbirth in the next period, self-employment, supervising others, age of the youngest child (age 0, age 1-2 and age 3-5), year dummies and partner's labour force status (in Panel A)/partner's working hour intervals (in Panel B)/one's and partner's working hour intervals (in Panels C and D). Significance levels are shown as *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

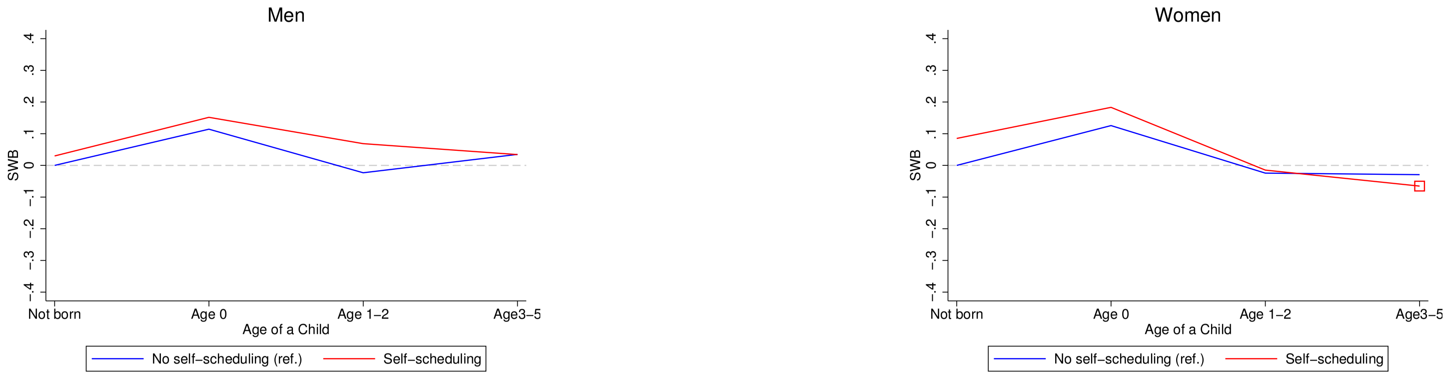


Panel A: Contractual Flexibility (Labour Force Status)

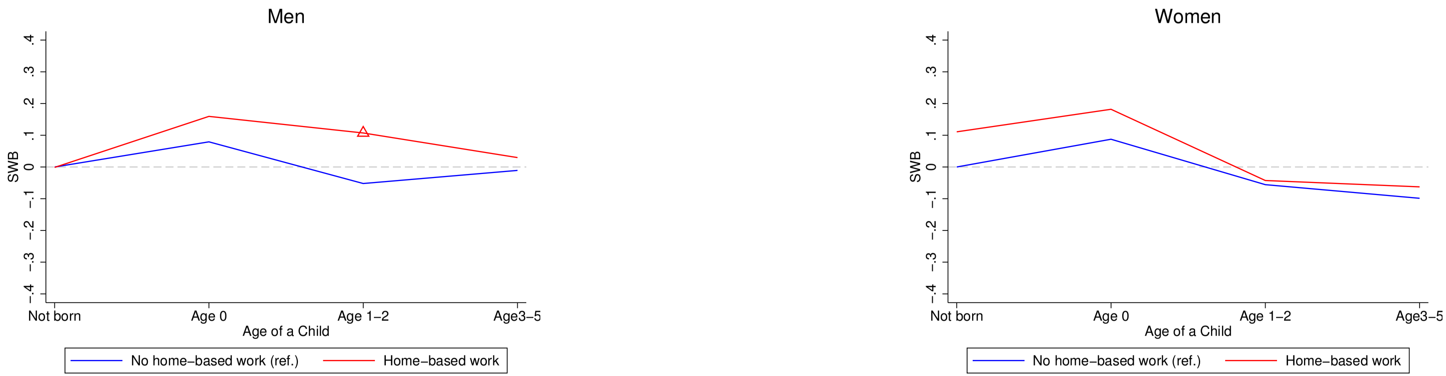


Panel B: Contractual Flexibility (Working Hour Intervals)

Figure 2.6. Dynamic effect of parenthood on SWB by gender and job flexibility



Panel C: Temporal Flexibility



Panel D: Spatial Flexibility

Figure 2.6 (Cont.). Dynamic effect of parenthood on SWB by gender and job flexibility

Note: The SWB for the reference working status at *not born* is set to be 0. ◯ □ and △ indicate the interaction term between a period indicator and flexible employment is significant at the 10%, 5% and 1% level, respectively.

2.5.3 Industry and Occupation

As mentioned in the Results section, we realise that the effect of flexible employment on SWB can be driven by industries and occupations due to unequal accessibility of flexible opportunities across industries and occupations. Our fixed-effects estimation should not be affected if individuals remain in the same industry and occupation through the observational period. However, industries and occupations could be confounding factors once the variation in job flexibility within an individual is driven by switching between industries and occupations. To address this concern, we add industry and occupation fixed effects into the model. By doing so, the coefficients on flexibility indicators can be interpreted as the effect of flexible employment on SWB given the industry and occupation. The results reported in Appendix Tables 2.A.3 (without interaction terms) and 2.A.4 (with interaction terms) are in line with the results from the main analysis, suggesting that industries or occupations do not confound the effect of flexible employment on parental SWB.

2.5.4 Alternative Sample

In addition to the checks above, we also consider three alternative samples to verify the external validity of our results for different population groups.

First, we re-estimate the model with the full sample mentioned in the Data section, i.e., we include single parents in the analysis. Different from the main analysis, we cannot control for the partner's information such as health, age and flexibility in this model as this information is missing for some single parents. Instead, we add a set of dummy variables indicating respondents' marital status: *single*, *cohabited*, *married* and *other status (separate, devoiced and widowed).* The statistical description of the full sample has been given in Table 2.1.

The results reported in Appendix Table 2.A.5 confirm that marital status appears to be a significant determinant of SWB (e.g., Panel A). Compared to being single (the reference status), cohabitation and marriage are positively related to SWB, and the marginal effects for women (0.29 and 0.38) are stronger than for men (0.11 and 0.22). Women's SWB decreases by -0.14 when they are separated, divorced or widowed, while these events seem not significantly related to men's SWB. Nevertheless, our main findings regarding the role of flexible employment on SWB during the transition to parenthood still hold. This is especially true in terms of the period-specific impact of flexible employment shown in Table 2.A.6. We also find evidence of gender heterogeneity based on the full sample. Working more than 20 hours a week negatively impacts women's SWB during certain postnatal periods while men's SWB is positively affected by the accessibility of self-scheduling and home-based work when children are young. Since all of these results do not differ from the main results, we could claim the results based on the partnered sample can be generalised to the population of all parents.

The second problem is the incompleteness of the period indicators in the last three waves. When period indicators are generated, whether one year is a preceding period relative to childbirth is informed by children's ages in future waves. For example, if a respondent reports having a 0-year-old in the following wave, we know the current wave is one period before this childbirth. This approach may cause difficulty in generating the indicators for upcoming childbirth (from $T-3$ to $T-1$) for the last three waves (2015-2017) as no further waves can provide information on future childbirth. As a result, some observations from 2015 to 2017, which are prenatal periods, are omitted. The reported SWB might be affected by the corresponding anticipation effect, which we cannot account for. To solve this problem, we re-estimate the model using observations from 2002 to 2014, in which we have full information. The estimated results are very similar to the main results in terms of magnitudes and significance, suggesting that our main results are not affected by this potential bias.[20]

Finally, contrary to our approach, some previous studies only consider how parental SWB progresses during the first childbirth (Roeters et al., 2016; Le Moglie et al., 2019). While we acknowledge that the effect of the first-born child is more pronounced than that of subsequent children, following this approach results in a significant information loss. The sample size reduces to 8,230 male-year and 8,517 female-year observations, less than half of the sample used in our main analysis. Due to this information loss, if we re-estimate the model using the specification in the primary analysis where periods are interacted with flexibility, some period-flexibility combinations would only contain limited observations and thus lead to

[20] Output tables are available on request.

imprecise estimation. Instead, we employ the alternative specification used in Section 5.2, which interacts children's age groups with job flexibility to enlarge the sample size of each combination. The results are reported in Appendix Tables 2.A.7 (without interaction terms) and 2.A.8 (with interaction terms). According to Appendix Table 2.A.7, the overall effect of temporal and spatial flexibility for first-time fathers is not significantly positive, which is different from the results for all childbirth. A possible reason is that the work-family conflict is still moderate for the first child, so the autonomy of work time and the workplace has not become an essential determinant for men's SWB. However, we find the estimated results in Appendix Table 2.A.8 are not qualitatively different from the all-childbirth case (Appendix Table 2.A.2), suggesting the intermediary effect of flexible employment also appears for the first-born child.

2.6 Conclusion

This paper provides clear evidence that flexible employment is an effective tool to alleviate the drop in parental SWB in the early years of parenthood. We also find evidence for gender heterogeneity regarding each form of flexible employment. Contractual flexibility, especially a part-time job between 0-20 weekly working hours, appears to be important for women's SWB, while spatial and temporal flexibility yields an increase in SWB among fathers of young children. However, it should be noted that involuntary part-time work is not negligible in the Australian labour market. For example, about 30% of workers would like to work more hours (Abhayaratna et al., 2008). This fact may also happen to the part-time working mothers in our sample, as more than 95% of them work part-time for childcare tasks. In this case, short part-time work (i.e., 0-20 weekly working hours) may not be an optimal choice for female workers. For this reason, our results represent a lower bound of the effect of flexible employment on parental SWB. However, looking at the ideal working hours for these part-time working mothers, we find only a small share of them (<5%) would rather have a full-time job. Therefore, we argue that the results for contractual flexibility divided by labour force status (part-time or full-time) are still, to a large extent, reliable.

Our main results are in line with the classical intra-household time allocation adopted by Australian households: most fathers are employed in full-time jobs, whereas mothers split their time between domestic work and part-time jobs or do not participate in the labour market at all (Baxter, 2015). Also, as Buddelmeyer et al. (2018) point out, mothers in Australia are under greater time stress than fathers in the first few years after childbirth. Therefore, contractual flexibility increases women's SWB as it could relieve the work-family conflict. Spatial and temporal flexibility does not have the same effect on women's SWB because these two arrangements are generally along with long working hours, which is considered less family-friendly by many mothers (Spreitzer et al., 2017).[21] In contrast, fathers benefit from spatial and temporal flexibility as the possibility of self-scheduling and home-based work allows them to maintain relatively long hours while undertaking some non-working responsibilities. These effects are significant when children are one and two years old, which typically corresponds with the mother's return to the labour market after maternity/parental leave.

Our findings also align with a recent study by Kleven et al. (2019) documenting the typical labour market trajectories for men and women around childbirth. They find that men's labour market outcomes are relatively stable regardless of fatherhood, suggesting that parenting does not substantially affect men's labour market attachment. This fact reinforces our argument that spatial and temporal flexibility facilitates childcare duties for fathers while not altering working hours. In contrast, Kleven et al. (2019) show that women's labour market participation rates sharply decline after motherhood compared to prenatal periods, which is referred to as a *child penalty*. Therefore, contractual flexibility can improve women's SWB by reintegrating mothers who would otherwise not work into the labour market, which partly resolves the child penalty.

The results of this paper are important for at least three reasons. Firstly, we believe that they can be generalised to parents in other developed countries where flexible employment is also prevalent. Flexible employment has also been a common practice in European countries with 75% of employees entitled to the flexibility of work scheduling (OECD, 2016). Similarly to Australia, some countries have announced policies to guarantee accessibility to job flexibility for working parents. For example, in the Netherlands, *Wet Aanpassing Arbeidsduur* in 2000 and *Wet Flex-*

[21] In our sample, the average weekly hours for jobs allowing home-based work is 30 hours for women.

ibel Werken in 2016 guarantee that the parents of young children are entitled to all three forms of flexibility discussed in this paper.

Secondly, by delivering convincing evidence that flexible employment can alleviate the loss in the SWB of parents in the transition to parenthood, our results further enhance the motivation for such policies. Our results show that the SWB of mothers with young children is higher in part-time jobs, suggesting that some women might opt out of the labour market if only full-time jobs are considered. However, access to contractual flexibility needs to be universal across all jobs to ensure that the gender gap does not widen. Hence, policies that make it more attractive to employers to offer part-time positions might help to close the gap. In addition, flexible jobs are often associated with social stigma (Chung, 2020). Improving the attractiveness of such jobs may help overcome the social stigma and result in higher uptake of flexible employment to alleviate the stress at work in the early years of parenting.

Lastly, through the inter-generational transmission of happiness within a family, our results suggest that flexible employment among parents may benefit the well-being of children. Powdthavee and Vignoles (2008) find that parental distress levels in the preceding year have a spill-over effect on children's current well-being. Additionally, flexible employment among parents also effectively promotes parent-child interactions during the first years of the child's life (Kim, 2020). Therefore, the impact of parental job flexibility on children's health and well-being in early childhood is clearly a question for further research.

2.A Appendix

Table 2.A.1. Intermediary Effect of Job Flexibility on Parental SWB

Dependent Variable	Men			Women	
SWB	coef.	s.e.		coef.	s.e.
Panel A: Contractual Flexibility (Labour Force Status)					
non-employed ×					
T-2	-0.094	0.122		0.015	0.055
T-1	-0.220**	0.112		-0.043	0.049
T	-0.017	0.100		-0.031	0.048
T+1	-0.024	0.098		-0.062	0.044
T+2	-0.206**	0.098		-0.103**	0.042
T+3	-0.196**	0.100		-0.051	0.043
T+4	-0.127	0.105		-0.087*	0.045
T+5	-0.254**	0.108		0.004	0.046
FT ×					
T-2	0.005	0.092		-0.012	0.055
T-1	-0.101	0.087		0.019	0.051
T	-0.088	0.078		0.081	0.060
T+1	0.006	0.076		-0.092	0.057
T+2	-0.001	0.076		-0.129**	0.055
T+3	-0.078	0.077		-0.056	0.055
T+4	-0.098	0.081		-0.067	0.058
T+5	-0.119	0.083		0.076	0.057
Observations	17,097			17,281	
Number of ID	3,057			3,124	
Panel B: Contractual Flexibility (Working Hour Intervals)					
35-40 h ×			21-34 h ×		
T-2	-0.011	0.096	T-2	0.049	0.081
T-1	-0.093	0.091	T-1	-0.032	0.071
T	-0.080	0.081	T	-0.003	0.078
T+1	-0.017	0.079	T+1	0.056	0.065
T+2	-0.017	0.080	T+2	-0.036	0.063
T+3	-0.095	0.081	T+3	-0.089	0.064
T+4	-0.093	0.086	T+4	-0.159**	0.067
T+5	-0.131	0.087	T+5	-0.029	0.068
41-50 h ×			35-40 h ×		
T-2	-0.003	0.097	T-2	-0.010	0.071
T-1	-0.125	0.092	T-1	0.018	0.065
T	-0.103	0.082	T	0.029	0.073
T+1	0.007	0.080	T+1	-0.095	0.069
T+2	0.032	0.080	T+2	-0.171**	0.067

Table 2.A.1 (Cont.). Intermediary Effect of Job Flexibility on Parental SWB

Dependent Variable	Men			Women	
SWB	coef.	s.e.		coef.	s.e.
T+3	-0.049	0.082	T+3	-0.052	0.068
T+4	-0.130	0.086	T+4	-0.183**	0.072
T+5	-0.124	0.088	T+5	0.049	0.072
>50h ×			>40 h ×		
T-2	0.050	0.103	T-2	0.046	0.084
T-1	-0.080	0.097	T-1	-0.054	0.081
T	-0.088	0.088	T	0.232**	0.105
T+1	0.061	0.085	T+1	-0.003	0.098
T+2	-0.008	0.085	T+2	-0.088	0.091
T+3	-0.088	0.086	T+3	-0.186**	0.090
T+4	-0.040	0.091	T+4	-0.046	0.090
T+5	-0.080	0.093	T+5	0.077	0.088
Observations	17,097			17,281	
Number of ID	3,057			3,124	
Panel C: Temporal Flexibility					
self-scheduling ×					
T-2	0.010	0.049		-0.046	0.059
T-1	-0.026	0.046		-0.062	0.056
T	0.015	0.044		0.016	0.066
T+1	0.115***	0.042		-0.018	0.054
T+2	0.023	0.042		-0.012	0.053
T+3	-0.018	0.043		-0.043	0.054
T+4	-0.020	0.045		-0.037	0.056
T+5	0.005	0.046		0.025	0.057
Observations	12,449			8,447	
Number of ID	2,625			2,180	
Panel D: Spatial Flexibility					
home-based work ×					
T-2	-0.012	0.054		-0.033	0.062
T-1	-0.017	0.051		0.033	0.058
T	0.022	0.048		0.042	0.066
T+1	0.122***	0.046		-0.034	0.054
T+2	0.099**	0.046		-0.080	0.054
T+3	-0.013	0.048		-0.060	0.056
T+4	0.049	0.050		-0.048	0.058
T+5	0.029	0.051		-0.031	0.058
Observations	11,703			8,048	
Number of ID	2,603			2,135	

Notes: This table reports the estimates of the intermediary effect of job flexibility in each period relative to childbirth. Other control variables are one's and partner's health, one's and partner's squared age (divided by 1,000), household income (in logarithm), use of childcare, the number of resident and non-resident children, self-employment, supervising others, period indicators (from $T-2$ to $T+5$), year dummies and partner's labour force status (in Panel A)/partner's working hour intervals (in Panel B)/one's and partner's working hour intervals (in Panels C and D). Significance levels are shown as *** p<0.01, ** p<0.05, * p<0.1.

Table 2.A.2. Intermediary Effect of Job Flexibility on Parental SWB by Children's Age Groups

Dependent Variable	Men			Women	
SWB	coef.	s.e.		coef.	s.e.
Panel A: Contractual Flexibility (Labour Force Status)					
non-employed ×					
Age 0	0.113	0.139		-0.177	0.085
Age 1-2	0.085	0.132		-0.209	0.081
Age 3-5	0.070	0.140		-0.186	0.083
FT ×					
Age 0	-0.073	0.105		0.005	0.076
Age 1-2	0.003	0.099		-0.168	0.068
Age 3-5	-0.067	0.105		-0.065	0.068
Observations	16,916			17,023	
Number of ID	3,057			3,124	
Panel B: Contractual Flexibility (Working Hour Intervals)					
35-40 h ×			21-34 h ×		
Age 0	-0.090	0.109	Age 0	-0.173	0.125
Age 1-2	-0.040	0.103	Age 1-2	-0.140	0.113
Age 3-5	-0.105	0.108	Age 3-5	-0.273**	0.115
41-50 h ×			35-40 h ×		
Age 0	-0.073	0.111	Age 0	-0.156	0.110
Age 1-2	0.017	0.104	Age 1-2	-0.299***	0.102
Age 3-5	-0.051	0.110	Age 3-5	-0.216**	0.104
>50h ×			>40 h ×		
Age 0	-0.039	0.117	Age 0	0.061	0.134
Age 1-2	0.082	0.110	Age 1-2	-0.183	0.115
Age 3-5	-0.004	0.116	Age 3-5	-0.228**	0.113
Observations	16,916			17,023	
Number of ID	3,057			3,124	

Table 2.A.2 (Cont.). Intermediary Effect of Job Flexibility on Parental SWB by Children's Age Groups

	(1)		(2)	
Dependent Variable	Men		Women	
SWB	coef.	s.e.	coef.	s.e.
Panel C: Temporal Flexibility				
self-scheduling ×				
Age 0	0.005	0.055	-0.021	0.072
Age 1-2	0.061	0.050	-0.074	0.056
Age 3-5	-0.032	0.054	-0.119**	0.060
Observations	12,307		8,317	
Number of ID	2,621		2,171	
Panel D: Spatial Flexibility				
home-based work ×				
Age 0	0.076	0.060	-0.012	0.075
Age 1-2	0.157***	0.055	-0.096	0.060
Age 3-5	0.039	0.059	-0.073	0.065
Observations	11,703		8,048	
Number of ID	2,603		2,135	

Notes: This table reports the estimates of the intermediary effect of job flexibility in each children's age group. Other control variables are one's and partner's health, one's and partner's squared age (divided by 1,000), household income (in logarithm), use of childcare, the number of resident and non-resident children, an indicator of childbirth in the next period, self-employment, supervising others, age of the youngest child (age 0, age 1-2 and age 3-5), year dummies and partner's labour force status (in Panel A)/partner's working hour intervals (in Panel B)/one's and partner's working hour intervals (in Panels C and D). Significance levels are shown as *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 2.A.3. Fixed-effects Estimation of Parental SWB with Industrial and Occupational Fixed Effects

Dependent Variable	Men			Women	
SWB	coef.	s.e.		coef.	s.e.
Panel A: Contractual Flexibility (Labour Force Status)					
non-employed	0.266	0.354		-0.265	0.409
PT	ref.			ref.	
FT	0.086**	0.036		-0.074***	0.025
Observations	17,097			17,281	
Number of ID	3,057			3,124	
Panel B: Contractual Flexibility (Working Hour Intervals)					
non-employed	0.275	0.354	non-employed	-0.283	0.409
0-34 h	ref.		0-20 h	ref.	
35-40 h	0.102***	0.037	21-34 h	-0.075***	0.028
41-50 h	0.085**	0.039	35-40 h	-0.092***	0.030
>50 h	0.007	0.043	>40 h	-0.189***	0.039
Observations	16,916			17,023	
Number of ID	3,057			3,124	
Panel C: Temporal Flexibility					
no self-scheduling	ref.			ref.	
self-scheduling	0.039*	0.022		0.029	0.029
Observations	12,449			8,447	
Number of ID	2,625			2,181	
Panel D: Spatial Flexibility					
no home-based work	ref.			ref.	
home-based work	0.082***	0.026		0.039	0.032
Observations	11,703			8,048	
Number of ID	2,603			2,135	

Notes: This table reports the estimates of period indicators and job flexibility on SWB during the transition into parenthood including industrial and occupational fixed-effects indicators. Other control variables are one's and partner's health, one's and partner's squared age (divided by 1,000), household income (in logarithm), use of childcare, the number of resident and non-resident children, self-employment, supervising others, period indicators (from $T-2$ to $T+5$), year dummies and partner's labour force status (in Panel A)/partner's working hour intervals (in Panel B)/one's and partner's working hour intervals (in Panels C and D). Significance levels are shown as *** p<0.01, ** p<0.05, * p<0.1.

Table 2.A.4. Intermediary Effect of Job Flexibility on Parental SWB with Industrial and Occupational Fixed Effects

Dependent Variable	Men			Women	
SWB	coef.	s.e.		coef.	s.e.
Panel A: Contractual Flexibility (Labour Force Status)					
non-employed ×					
T-2	-0.101	0.123		0.017	0.055
T-1	-0.221**	0.112		-0.041	0.049
T	-0.020	0.100		-0.024	0.048
T+1	-0.032	0.098		-0.057	0.044
T+2	-0.202**	0.098		-0.097**	0.042
T+3	-0.196**	0.100		-0.047	0.043
T+4	-0.121	0.105		-0.084*	0.045
T+5	-0.250**	0.108		0.014	0.046
FT ×					
T-2	-0.002	0.092		-0.010	0.055
T-1	-0.103	0.087		0.017	0.051
T	-0.094	0.078		0.086	0.060
T+1	0.000	0.076		-0.093	0.057
T+2	0.000	0.076		-0.129**	0.055
T+3	-0.082	0.077		-0.057	0.056
T+4	-0.095	0.082		-0.069	0.058
T+5	-0.122	0.083		0.078	0.057
Observations	17,097			17,281	
Number of ID	3,057			3,124	
Panel B: Contractual Flexibility (Working Hour Intervals)					
35-40 h ×			21-34 h ×		
T-2	-0.018	0.096	T-2	0.044	0.081
T-1	-0.097	0.091	T-1	-0.027	0.072
T	-0.088	0.081	T	0.005	0.078
T+1	-0.024	0.080	T+1	0.055	0.065
T+2	-0.018	0.080	T+2	-0.038	0.063
T+3	-0.097	0.081	T+3	-0.090	0.064
T+4	-0.090	0.086	T+4	-0.149**	0.067
T+5	-0.133	0.088	T+5	-0.027	0.068
41-50 h ×			35-40 h ×		
T-2	-0.009	0.097	T-2	-0.011	0.071
T-1	-0.126	0.092	T-1	0.017	0.065
T	-0.108	0.083	T	0.037	0.073
T+1	0.001	0.080	T+1	-0.099	0.069
T+2	0.035	0.080	T+2	-0.168**	0.067
T+3	-0.053	0.082	T+3	-0.055	0.068
T+4	-0.127	0.086	T+4	-0.186***	0.072
T+5	-0.127	0.088	T+5	0.047	0.072

Table 2.A.4 (Cont.). Intermediary Effect of Job Flexibility on Parental SWB with Industrial and Occupational Fixed Effects

Dependent Variable	Men			Women	
SWB	coef.	s.e.		coef.	s.e.
>50h ×			>40 h ×		
T-2	0.042	0.103	T-2	0.039	0.084
T-1	-0.080	0.097	T-1	-0.049	0.081
T	-0.091	0.088	T	0.236**	0.105
T+1	0.057	0.085	T+1	-0.003	0.098
T+2	-0.006	0.085	T+2	-0.096	0.092
T+3	-0.093	0.087	T+3	-0.185**	0.090
T+4	-0.040	0.092	T+4	-0.034	0.090
T+5	-0.085	0.093	T+5	0.090	0.088
Observations	17,097			17,281	
Number of ID	3,057			3,124	
Panel C: Temporal Flexibility					
self-scheduling ×					
T-2	0.015	0.049		-0.051	0.059
T-1	-0.026	0.046		-0.061	0.056
T	0.017	0.044		0.009	0.066
T+1	0.113***	0.042		-0.026	0.054
T+2	0.026	0.042		-0.013	0.053
T+3	-0.016	0.043		-0.040	0.054
T+4	-0.016	0.045		-0.034	0.056
T+5	0.006	0.046		0.030	0.057
Observations	12,449			8,447	
Number of ID	2,625			2,180	
Panel D: Spatial Flexibility					
home-based work ×					
T-2	-0.014	0.054		-0.038	0.062
T-1	-0.020	0.051		0.033	0.058
T	0.023	0.048		0.039	0.066
T+1	0.116**	0.046		-0.052	0.054
T+2	0.099**	0.046		-0.089*	0.054
T+3	-0.015	0.048		-0.069	0.055
T+4	0.047	0.050		-0.054	0.058
T+5	0.027	0.051		-0.036	0.059
Observations	11,703			8,048	
Number of ID	2,603			2,135	

Notes: This table reports the estimates of the intermediary effect of job flexibility in each period relative to childbirth with occupational and industrial fixed effect. Other control variables are one's and partner's health, one's and partner's squared age (divided by 1,000), household income (in logarithm), use of childcare, the number of resident and non-resident children, self-employment, supervising others, period indicators (from $T-2$ to $T+5$), year dummies and partner's labour force status (in Panel A)/partner's working hour intervals (in Panel B)/one's and partner's working hour intervals (in Panels C and D). Significance levels are shown as *** p<0.01, ** p<0.05, * p<0.1.

Table 2.A.5. Fixed-effects Estimation of Parental SWB with Full Sample

Dependent Variable	Men			Women	
SWB	coef.	s.e.		coef.	s.e.
Panel A: Marital Status					
single	ref.			ref.	
married	0.114**	0.056		0.289***	0.046
cohabited	0.217***	0.047		0.381***	0.036
other status	-0.046	0.086		-0.136**	0.062
Observations	18,363			22,215	
Number of ID	3,159			3,721	
Panel B: Contractual Flexibility (Labour Force Status)					
non-employed	-0.137***	0.044		-0.021	0.024
PT	ref.			ref.	
FT	0.098***	0.034		-0.050**	0.024
Observations	18,363			22,215	
Number of ID	3,159			3,721	
Panel C: Contractual Flexibility (Working Hour Intervals)					
non-employed	-0.136***	0.044	non-employed	-0.039	0.026
0-34 h	ref.		0-20 h	ref.	
35-40 h	0.115***	0.035	21-34 h	-0.057**	0.027
41-50 h	0.091**	0.037	35-40 h	-0.054*	0.029
>50 h	0.033	0.041	>40 h	-0.155***	0.037
Observations	18,363			22,215	
Number of ID	3,159			3,721	
Panel D: Temporal Flexibility					
no self-scheduling	ref.			ref.	
self-scheduling	0.029	0.021		0.035	0.026
Observations	13,242			10,224	
Number of ID	2,712			2,572	
Panel E: Spatial Flexibility					
no home-based work	ref.			ref.	
home-based work	0.066***	0.025		0.038	0.030
Observations	12,432			9,726	
Number of ID	2,685			2,518	

Notes: This table reports the estimates of marital status and job flexibility on SWB during the transition into parenthood using the full sample. Results in Panels A and B are from the same estimation. In Panel A, other status denote being separated, divorced and widowed. In Panels B-E, other control variables are one's health, one's squared age (divided by 1,000), household income (in logarithm), marital status, use of childcare, the number of resident and non-resident children, self-employment, supervising others, period indicators (from $T-2$ to $T+5$) and year dummies. In Panels C and D, one's working hour intervals are also included. Significance levels are shown as *** p<0.01, ** p<0.05, * p<0.1.

Table 2.A.6. Intermediary Effect of Job Flexibility on Parental SWB with Full Sample

Dependent Variable	Men			Women	
SWB	coef.	s.e.		coef.	s.e.
Panel A: Contractual Flexibility (Labour Force Status)					
non-employed ×					
T-2	-0.072	0.112		-0.056	0.053
T-1	-0.143	0.105		-0.067	0.048
T	0.057	0.096		0.022	0.047
T+1	0.020	0.093		-0.013	0.043
T+2	-0.170*	0.094		-0.074*	0.041
T+3	-0.112	0.096		-0.011	0.042
T+4	-0.028	0.101		-0.103**	0.044
T+5	-0.142	0.104		0.009	0.045
FT ×					
T-2	-0.035	0.086		-0.069	0.054
T-1	-0.054	0.082		-0.009	0.051
T	-0.047	0.076		0.059	0.061
T+1	0.037	0.073		-0.105*	0.057
T+2	-0.015	0.074		-0.133**	0.055
T+3	-0.061	0.075		-0.091*	0.055
T+4	-0.099	0.079		-0.087	0.056
T+5	-0.065	0.081		0.071	0.056
Observations	18,363			22,215	
Number of ID	3,159			3,721	
Panel B: Contractual Flexibility (Working Hour Intervals)					
35-40 h ×			21-34 h ×		
T-2	-0.064	0.090	T-2	0.109	0.080
T-1	-0.049	0.086	T-1	0.006	0.072
T	-0.038	0.079	T	-0.052	0.079
T+1	0.012	0.077	T+1	0.008	0.065
T+2	-0.035	0.078	T+2	-0.060	0.063
T+3	-0.083	0.079	T+3	-0.081	0.064
T+4	-0.093	0.083	T+4	-0.166**	0.066
T+5	-0.082	0.085	T+5	0.011	0.067
41-50 h ×			35-40 h ×		
T-2	-0.026	0.091	T-2	-0.054	0.071
T-1	-0.064	0.087	T-1	-0.003	0.065
T	-0.051	0.081	T	-0.013	0.074
T+1	0.055	0.078	T+1	-0.135*	0.070
T+2	0.030	0.079	T+2	-0.195***	0.067
T+3	-0.018	0.080	T+3	-0.079	0.067
T+4	-0.118	0.084	T+4	-0.207***	0.070
T+5	-0.058	0.086	T+5	0.045	0.070

Table 2.A.6 (Cont.). Intermediary Effect of Job Flexibility on Parental SWB with Full Sample

Dependent Variable	Men			Women	
SWB	coef.	s.e.		coef.	s.e.
>50h ×			>40 h ×		
T-2	0.009	0.097	T-2	0.054	0.083
T-1	-0.044	0.093	T-1	-0.035	0.082
T	-0.056	0.086	T	0.160	0.107
T+1	0.067	0.083	T+1	-0.044	0.099
T+2	-0.032	0.083	T+2	-0.096	0.091
T+3	-0.078	0.085	T+3	-0.236**	0.089
T+4	-0.057	0.089	T+4	-0.071	0.088
T+5	-0.034	0.091	T+5	0.114	0.087
Observations	18,363			22,215	
Number of ID	3,159			3,721	
Panel C: Temporal Flexibility					
self-scheduling ×					
T-2	-0.008	0.047		-0.007	0.056
T-1	-0.010	0.045		-0.023	0.053
T	0.010	0.043		0.001	0.064
T+1	0.105**	0.041		0.005	0.052
T+2	0.015	0.041		0.013	0.051
T+3	-0.014	0.043		-0.039	0.051
T+4	-0.019	0.044		-0.007	0.053
T+5	-0.003	0.046		0.062	0.054
Observations	13,242			10,244	
Number of ID	2,712			2,572	
Panel D: Spatial Flexibility					
home-based work ×					
T-2	-0.025	0.050		0.013	0.056
T-1	0.030	0.051		0.050	0.050
T	0.027	0.049		0.073	0.063
T+1	0.123***	0.048		0.025	0.052
T+2	0.096**	0.045		-0.036	0.047
T+3	0.004	0.048		-0.053	0.055
T+4	0.067	0.050		-0.016	0.053
T+5	0.041	0.050		0.009	0.053
Observations	12,432			9.726	
Number of ID	2,685			2,518	

Notes: This table reports the estimates of the intermediary effect of job flexibility in each period relative to childbirth using the full sample. Other control variables are one's health, one's squared age (divided by 1,000), household income (in logarithm), marital status, use of childcare, the number of resident and non-resident children, self-employment, supervising others, period indicators (from $T-2$ to $T+5$) and year dummies. In Panels C and D, one's working hour intervals are also included. Significance levels are shown as *** p<0.01, ** p<0.05, * p<0.1.

Table 2.A.7. Fixed-effects Estimation of Parental SWB for First-time Parents

Dependent Variable	Men			Women	
SWB	coef.	s.e.		coef.	s.e.
Panel A: Contractual Flexibility (Labour Force Status)					
non-employed	-0.081	0.069		0.051	0.034
PT	ref.			ref.	
FT	0.073	0.052		-0.088***	0.033
Observations	8,230			8,517	
Number of ID	1,819			1,878	
Panel B: Contractual Flexibility (Working Hour Intervals)					
non-employed	-0.077	0.069	non-employed	0.040	0.037
0-34 h	ref.		0-20 h	ref.	
35-40 h	0.106**	0.053	21-34 h	-0.035	0.040
41-50 h	0.043	0.056	35-40 h	-0.085**	0.041
>50 h	-0.026	0.062	>40 h	-0.177***	0.050
Observations	8,230			8,517	
Number of ID	1,819			1,878	
Panel C: Temporal Flexibility					
no self-scheduling	ref.			ref.	
self-scheduling	0.017	0.031		0.057	0.039
Observations	6,104			4,483	
Number of ID	1,566			1,322	
Panel D: Spatial Flexibility					
no home-based work	ref.			ref.	
home-based work	0.037	0.037		0.074	0.044
Observations	5,695			4,231	
Number of ID	1,543			1,294	

Notes: This table reports the estimates of job flexibility on SWB during the transition into parenthood for first-time parents. Other control variables are one's and partner's health, one's and partner's squared age (divided by 1,000), household income (in logarithm), use of childcare, the number of resident and non-resident children, an indicator of childbirth in the next period, self-employment, supervising others, age of the youngest child (age 0, age 1-2 and age 3-5), year dummies and partner's labour force status (in Panel A)/partner's working hour intervals (in Panel B)/one's and partner's working hour intervals (in Panels C and D). Significance levels are shown as *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 2.A.8. Intermediary Effect of Job Flexibility on Parental SWB for First-time Parents

Dependent Variable	Men			Women	
SWB	coef.	s.e.		coef.	s.e.
Panel A: Contractual Flexibility (Labour Force Status)					
non-employed ×					
Age 0	-0.020	0.187		-0.148	0.105
Age 1-2	0.118	0.170		-0.221**	0.093
Age 3-5	-0.058	0.169		-0.244***	0.093
FT ×					
Age 0	-0.030	0.136		-0.021	0.098
Age 1-2	0.059	0.123		-0.078	0.083
Age 3-5	-0.021	0.123		-0.053	0.080
Observations	8,230			8,517	
Number of ID	1,819			1,878	
Panel B: Contractual Flexibility (Working Hour Intervals)					
35-40 h ×			21-34 h ×		
Age 0	-0.113	0.141	Age 0	0.031	0.161
Age 1-2	0.030	0.127	Age 1-2	-0.103	0.127
Age 3-5	-0.029	0.127	Age 3-5	-0.283**	0.125
41-50 h ×			35-40 h ×		
Age 0	-0.023	0.144	Age 0	-0.084	0.132
Age 1-2	0.085	0.129	Age 1-2	-0.176	0.118
Age 3-5	-0.026	0.129	Age 3-5	-0.239**	0.115
>50h ×			>40 h ×		
Age 0	0.116	0.154	Age 0	0.046	0.170
Age 1-2	0.078	0.136	Age 1-2	-0.119	0.147
Age 3-5	0.002	0.135	Age 3-5	-0.137	0.129
Observations	8,230			8,517	
Number of ID	1,819			1,878	

Table 2.A.8 (Cont.). Intermediary Effect of Job Flexibility on Parental SWB for First-time Parents

Dependent Variable	Men		Women	
SWB	coef.	s.e.	coef.	s.e.
Panel C: Temporal Flexibility				
Age 0	-0.029	0.074	-0.017	0.100
Age 1-2	0.101	0.063	-0.085	0.071
Age 3-5	-0.008	0.062	-0.049	0.070
Observations	6,104		4,483	
Number of ID	1,566		1,322	
Panel D: Spatial Flexibility				
Age 0	0.178**	0.082	0.105	0.130
Age 1-2	0.187***	0.069	-0.023	0.074
Age 3-5	0.120*	0.069	-0.140*	0.074
Observations	5,695		4,231	
Number of ID	1,543		1,294	

Notes: This table reports the estimates of the intermediary effect of job flexibility in each children's age group. Other control variables are one's and partner's health, one's and partner's squared age (divided by 1,000), household income (in logarithm), use of childcare, the number of resident and non-resident children, an indicator of childbirth in the next period, self-employment, supervising others, age of the youngest child (age 0, age 1-2 and age 3-5), year dummies and partner's labour force status (in Panel A)/partner's working hour intervals (in Panel B)/one's and partner's working hour intervals (in Panels C and D). Significance levels are shown as *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Chapter 3

Uptake of Home-based Work Following a Health Shock: Evidence from Australia*

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3.1 Introduction

The occurrence of health shocks, defined as a sudden decline in one's health condition, can influence people's lives in various aspects. Many studies in labour economics have documented the detrimental effects of health shocks on labour market outcomes. García-Gómez (2011) finds that a sharp decrease in self-reported health or an emergence of a chronic disease reduces labour market participation in the following year by more than 6% in Denmark, the Netherlands, Spain and Ireland. A health limitation also hinders the non-employed from returning to employment (García-Gómez et al., 2010). Among employed people, a health shock leads to persistent reductions in working hours for at least three years (Jones et al., 2020) and increases in the probability of early retirement (Jones et al., 2010). Moreover, a health shock lowers workers' productivity and thus has an income effect (García-Gómez et al., 2013; Jeon & Pohl, 2017). For example, in the UK, the decline in productivity can last for nine years and reduce a worker's annual labour income by 21% relative to the average income level (Lenhart, 2019).[1]

The enormous and persistent gaps in labour market participation and income between people with and without health shocks have raised public concern. In response, policy-makers have been making a great effort to re-integrate people with ill health into the labour market to narrow these gaps, such as making employment protection policies (Reeves et al., 2014) or offering rehabilitation and counselling services (Weathers & Bailey, 2014). Besides these attempts, one option that has not been extensively documented is flexible employment, which empowers employees to decide when, where and how their work is conducted (Thompson & Kossek, 2016). A flexible working arrangement is expected to benefit people with health disadvantages by accommodating their rising and unpredictable healthcare demands resulting from a health shock. Among multiple types of flexible employment, home-based work can be particularly helpful as this working pattern is free of daily commuting, which is desirable for those with limited mobility after a health shock.

This paper investigates the effect of health shocks on the uptake of home-based

[1] The annual labour income loss for the nine-year sample is £4,432 in Lenhart (2019). This percentage is calculated by using the average annual income for this sample (£21,055) from the descriptive statistics in his paper. A health shock's impact can last longer, while the longest time range in Lenhart (2019) is up to the ninth years after a health shock.

work with respect to both the extensive and intensive margins of home-based work. The focus of the workplace decision following a health shock is indicative of whether home-based work is a preferable working pattern in response to a recent health shock. This is because the workplace chosen by workers should yield the highest level of utility among all feasible options according to the revealed preference theory.

This paper uses a longitudinal household survey in Australia (HILDA) between 2012 and 2019. Using Australian survey data provides two advantages for the purpose of my study. First, the Australian labour market features a high prevalence of flexible jobs. Flexible employment has been on the rise in Australia since the 1990s (Bardoel & Haar, 2018). In 2010, new legislation entitled workers to request flexible working arrangements, including home-based work. Workers in Australia actively react to this new policy. For example, around 20% of workers requested such an arrangement from 2013 to 2014 (Skinner & Pocock, 2014). Second, the survey used in this paper contains well-recorded information on home-based work. In HILDA, home-based work is not simply captured by an 'either-or' question. Once confirming the uptake of home-based work, respondents need to report regular hours working from home, which facilitates the study of both the extensive and the intensive margin of home-based work.

Gender plays an important role in interpreting the labour market impacts of health shocks, as men and women appear to be affected differently by health shocks (Jäckle & Himmler, 2010; Cai et al., 2014; García-Gómez et al., 2013). For example, Halla and Zweimüller (2013) argue that women exhibit weaker labour market attachment after a commuting accident by showing their higher laid-off probability than men's. The gender heterogeneous effects could stem from different responsibilities men and women undertake within a household (Duguet & Le Clainche, 2020; Jones et al., 2020). Due to this fundamental difference, the opportunities of working from home could be more useful for one gender than the other after health shocks. At the same time, the extent to which home-based work can alleviate the detrimental labour market effects of health shocks can also be different by gender in the long run. This long-term difference may also determine men's and women's decisions on the workplace after health shocks. Based on these reasons, all of the analyses in this paper are conducted separately for men and women.

As emphasised by Jäckle and Himmler (2010), estimating the causal impact of health-related variables on labour market outcomes is associated with many statistical problems. One of them is particularly relevant to my research question: non-random selection. After a health shock, people sequentially decide on their labour market participation and home-based work. The latter decision is only observable, conditional on individuals being active in the labour market. Non-random selection occurs when some unobserved factors affecting these two decisions are correlated. This sample selection can be either positive or negative. In the context of home-based work, positive selection means people deciding to work have a greater incentive to work from home than those opting not to work. An example is that some people only seek jobs allowing them to work from home and cease working otherwise. Conversely, negative selection implies that people deciding to work are less likely to choose home-based work. For example, resilient people may have a high probability of working due to their capability to handle difficulties at work. Nevertheless, these people may find home-based work not useful as some of them are able to handle the health disadvantages without this working pattern. In both cases, failing to address this selection issue leads to an inconsistent estimation.

The non-linear setting of my research question adds to the difficulty in solving non-random selection. While a conventional Heckman selection model can address the issue of non-random selection, this approach requires the decision on home-based work to be a linear equation. Unfortunately, the outcome variable for home-based work is either binary or partially observable and thus should be modelled with non-linear methods. Thus, I adopt a recently developed method proposed by Semykina and Wooldridge (2018), which could correct for non-random selection in a binary panel data setting. However, Semykina and Wooldridge's (2018) approach only solves the statistical problem for the extensive margin that reflects the 'either-or' outcome of home-based work. The situation becomes more complicated when I model home-based working hours. The data for working hours are continuous but only partially observable because they are left-censored at zero for the employees not working from home. Hence, I extend Semykina and Wooldridge's (2018) framework by implementing the Heckman correction in a Tobit I model, which applies to partially observable panel data with sample selection.

A good practice of a Heckman-type model requires imposing exclusion restrictions on the covariates for the participation decision (i.e., employment in this paper) to identify sample selection. Valid exclusion restrictions should include at least one variable only affecting the decision on employment but not on home-based work. In this paper, respondents' cognitive ability in the baseline year serves as an appropriate exclusion restriction. HILDA measured all participants' cognitive ability by three cognitive tests in 2012 and 2016 (Wooden, 2013). Relying on the longitudinal structure of HILDA, I use the first available cognitive test scores to model each individual's decision on employment in subsequent periods. This identification strategy implies that someone's cognitive ability has a prolonged effect on subsequent employment but is unrelated to the choice of workplace.

The paper contributes to the existing literature in three ways. First, this paper provides the first evidence on the effect of health shocks on home-based work and shows clear gender differences, adding to the small number of studies on how people adapt to the detrimental impacts of health shocks. It appears that health shocks can positively affect women's uptake of home-based work, while such an effect remains small and statistically insignificant on men's outcomes. This gender difference can be a result of household specialisation. Women who typically undertake a major part of home duties alongside their market work may find this working pattern helps to fulfil their responsibilities in these two aspects with ill health. In contrast, men focusing on their market work may not consider home-based work a useful entitlement regardless of their health condition. In addition, a supplementary analysis suggests that the heterogeneous results align with the gender difference in the long-term labour market performance associated with home-based work during a health shock.

Second, this paper addresses the non-random sample selection associated with employment using a Heckman-type panel data model. Recent studies have highlighted the importance of accounting for the sample selection when someone investigates the relationship between health-related variables and labour market outcomes (Trevisan & Zantomio, 2016; Jones et al., 2020). For example, Trevisan and Zantomio (2016) find that an acute health shock does not reduce women's working hours and even increases men's. They claim that these results could be attributed to a selection mechanism: the workers severely affected by health issues and strongly demanding shorter working hours may have selected themselves out of the labour market. My paper identifies the presence of sample selection and shows that it downward biases the estimate of health shocks.

Third, my study provides an empirical model that allows researchers to fit partially observable panel data with sample selection, which has not been studied extensively. This model is built upon a model proposed by Semykina and Wooldridge (2018) that tackles the sample selection bias arising in binary response panel data. Instead of a binary response, sometimes, the value of an outcome is partially observable. For example, the outcome variable can be home-based working hours (in this paper) or days spent on a job training programme (if there is an upper or lower bound on training days).[2] In these cases, researchers can use the partially observed value information to model the intensive margin of an outcome with the model derived in this paper.

The remainder of this paper proceeds as follows. Section 3.2 discusses the empirical strategy. Section 3.3 describes the data. Section 3.4 reports the empirical results. Section 3.5 presents the robustness checks. Section 3.6 reports the heterogeneity analysis, and Section 3.7 concludes.

3.2 Empirical Model

This section discusses the model used to analyse the impacts of health shocks on the extensive and intensive margins of home-based work. In spirit, my empirical framework is similar to a typical sample selection problem in labour economics. To address the issues of non-random selection in a non-linear setting, I employ a Heckman-type panel data model. Proposed by Semykina and Wooldridge (2018) and applied by Semykina (2018), this model is similar to a conventional Heckman selection model, except that the second-step equation is a binary response model (e.g., a Probit model) instead of a linear model. I adopt Semykina and Wooldridge's (2018) original framework when estimating the extensive margin of home-based work. Furthermore, I extend their framework in a way that the second-step equation is a Type I Tobit model to estimate the internal margin. In the rest of this paper, I will refer to the model for the extensive margin as a *Heckman-probit* model and the model for the intensive margin as a *Heckman-tobit* model.

[2] In the example of job training, the binary outcome is whether an employee attends this programme.

3.2.1 Modelling the Extensive Margin

For the extensive margin, I treat home-based work as a binary variable. The model for the home-based work decision can be written as

$$\begin{aligned} hw^*_{it} &= \mathbf{x}'_{it}\boldsymbol{\beta} + \gamma shock_{it} + c_{i1} + u_{it1}, \\ hw_{it} &= \mathbb{1}[hw^*_{it} \geq 0], \end{aligned} \tag{3.1}$$

where hw^*_{it} and hw_{it} are latent and observed variables of home-based work, respectively; $shock_{it}$ is an indicator of a health shock; $\mathbf{x}_{it}$ is a vector of other control variables; c_{i1} is unobserved individual heterogeneity; u_{it1} is an idiosyncratic error term.

However, home-based work status is not observable unless people are employed. Estimation solely based on Eq. (3.1) is potentially inconsistent due to non-random selection into work, which happens when some unobserved characteristics in the home-based work decision and the employment decision are correlated. Therefore, I also take the employment decision into account, which is

$$\begin{aligned} emp^*_{it} &= \mathbf{z}'_{it}\boldsymbol{\alpha} + \theta shock_{it} + c_{i2} + u_{it2}, \\ emp_{it} &= \mathbb{1}[emp^* \geq 0], \end{aligned} \tag{3.2}$$

where emp^*_{it} and emp_{it} are latent and observed variables of employment, respectively; $\mathbf{z}_{it}$ is a vector of other control variables; c_{i2} is unobserved individual heterogeneity; u_{it2} is an idiosyncratic error. In particular, $\mathbf{z}_{it}$ includes at least one variable not entering the home-based work decision as an exclusion restriction. In this paper, three cognitive ability test scores in a given year serve as exclusion restrictions. More details are available in Section 3.3.1. In the remainder of this paper, I will call Eq. (3.1) and Eq. (3.2) the main equation and the selection equation, respectively.

Besides non-random selection, another issue to be addressed is the correlation between observed variables and unobserved individual heterogeneity in both equations, which also causes inconsistent estimation. The unobserved heterogeneity cannot be eliminated through a within transformation in a non-linear setting due to a serious incidental parameter problem. Alternatively, I decompose c_{i1} and

c_{i2} in Mundlak's (1978) approach such that

$$\begin{aligned} c_{i1} &= \eta_1 + \bar{\mathbf{x}}_i' \zeta_1 + a_{i1}, \\ c_{i2} &= \eta_2 + \bar{\mathbf{z}}_i' \zeta_2 + a_{i2}, \end{aligned} \tag{3.3}$$

where η_1 and η_2 are constants; $\bar{\mathbf{x}}_i = \frac{1}{T}\sum_{t=1}^{T} \mathbf{x}_{it}$ and $\bar{\mathbf{z}}_i = \frac{1}{T}\sum_{t=1}^{T} \mathbf{z}_{it}$ are individual time means of the time-varying components in $\mathbf{x}_{it}$ and $\mathbf{z}_{it}$; and a_{i1} and a_{i2} are the time-constant error terms assumed to be independent of $shock_{it}$, x_{it} and z_{it}. Plugging Eq. (3.3) into Eq. (3.1) and (3.2), I can obtain the following model:

$$\begin{aligned} emp_{it} &= \mathbb{1}[\mathbf{z}_{it}'\boldsymbol{\alpha} + \theta shock_{it} + \eta_2 + \bar{\mathbf{z}}_i \boldsymbol{\zeta}_2 + \epsilon_{it2} \geq 0], \\ hw_{it} &= \begin{cases} - & \text{if } emp_{it} = 0 \\ \mathbb{1}[\mathbf{x}_{it}'\boldsymbol{\beta} + \gamma shock_{it} + \eta_1 + \bar{\mathbf{x}}_i \boldsymbol{\zeta}_1 + \epsilon_{it1} \geq 0] & \text{if } emp_{it} = 1 \end{cases}, \end{aligned} \tag{3.4}$$

where $\epsilon_{it1} = a_{i1} + u_{it1}$ and $\epsilon_{it2} = a_{i2} + u_{it2}$. For simplicity, I also define $\tilde{\mathbf{x}}_{it}'\tilde{\boldsymbol{\beta}} = \mathbf{x}_{it}'\boldsymbol{\beta} + \gamma shock_{it} + \eta_1 + \bar{\mathbf{x}}_i'\zeta_1$ and $\tilde{\mathbf{z}}_{it}'\tilde{\boldsymbol{\alpha}} = \mathbf{z}_{it}'\boldsymbol{\alpha} + \theta shock_{it} + \eta_2 + \bar{\mathbf{z}}_i'\zeta_2$.

Eq. (3.4) is a two-step model where someone sequentially makes employment and home-based work decisions. If an individual decides to work, the selection equation equals one, and a subsequent decision on home-based work is made. Otherwise, the selection equation equals zero, and home-based work takes a missing value. As mentioned, non-random selection occurs when the error terms in the selection equation and the main equation are correlated. In Eq. (3.4), it can be formally defined as a correlation between ϵ_{it1} and ϵ_{it2}. As discussed in the Introduction section, this correlation can be positive (e.g., deciding to work due to working from home is possible) or negative (e.g., resilience).

For the error terms, I adopt the assumption made by Semykina and Wooldridge (2018) such that $Var(\epsilon_{it1}) = Var(\epsilon_{it2}) = 1$ and $Corr(\epsilon_{it1}, \epsilon_{it2}) = Cov(\epsilon_{it1}, \epsilon_{it2}) = \rho$. Therefore, the joint distribution of the composite error term ϵ_{it1} and ϵ_{it2} conditional on $\tilde{\mathbf{x}}_{it}$ and $\tilde{\mathbf{z}}_{it}$ is

$$\begin{pmatrix} \epsilon_{it1} \\ \epsilon_{it2} \end{pmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \\ \rho & 1 \end{bmatrix} \right).$$

Assuming employment and home-based work decisions are correlated in some unobserved ways, I estimate Eq. (3.4) with a pooled maximum likelihood estimator (pooled MLE) and cluster the standard errors at the individual level.[3] The likelihood function is divided into three parts according to the possible combinations of the two decisions' results: non-employed, employed without home-based work and employed with home-based work. Thus, I derive the log-likelihood function respectively for each scenario:

If $emp_{it} = 0$,

$$\ell_{it} = \ln \int_{-\infty}^{-\tilde{\mathbf{z}}_{it}\tilde{\boldsymbol{\alpha}}} \phi(\epsilon_2) d\epsilon_2;$$

If $emp_{it} = 1$ and $hw_{it} = 0$,

$$\ell_{it} = \ln \int_{-\infty}^{\tilde{\mathbf{z}}_{it}\tilde{\boldsymbol{\alpha}}} \int_{-\infty}^{-\tilde{\mathbf{x}}_{it}\tilde{\boldsymbol{\beta}}} \phi_2(\epsilon_1, \epsilon_2; \rho) d\epsilon_1 d\epsilon_2;$$

If $emp_{it} = 1$ and $hw_{it} = 1$,

$$\ell_{it} = \ln \int_{-\infty}^{\tilde{\mathbf{z}}_{it}\tilde{\boldsymbol{\alpha}}} \int_{-\infty}^{\tilde{\mathbf{x}}_{it}\tilde{\boldsymbol{\beta}}} \phi_2(\epsilon_1, \epsilon_2; \rho) d\epsilon_1 d\epsilon_2,$$

where $\phi(\cdot)$ is the probability density function of a standard normal distribution, and $\phi_2(\cdot)$ is the probability density function of a bivariate standard normal distribution.

3.2.2 Modelling the Intensive Margin

Besides a binary outcome of using home-based work, I am also interested in the change in home-based working hours following a health shock. One challenge of modelling home-based working hours is the censored working hours. In my analytical sample, nearly 80% of the employed people do not choose home-based work and thus report their home-based working hours as zero. Unlike the conventional Heckman selection model where the dependent variable for the main equation is continuous or Semykina and Wooldridge's (2018) model where the dependent variable for the main equation is binary, the dependent variable in this case is partially observable and heavily censored at 0. To solve this problem, I extend Semykina and

[3] A simple way to implement a pooled MLE is to use a standard Stata command 'heckprobit' with clustered standard errors.

Wooldridge's (2018) model such that the main equation can fit partially observable data with a Type I Tobit model.[4]

Different from Eq. (3.1), the main equation for home-based working hours is written as

$$
\begin{aligned}
hour^*_{it} &= \mathbf{x}'_{it}\boldsymbol{\beta} + \gamma shock_{it} + c_{i1} + u_{it1}, \\
hour_{it} &= \begin{cases} 0 & \text{if } hour^*_{it} \leq 0 \\ hour^*_{it} & \text{if } hour^*_{it} > 0 \end{cases},
\end{aligned}
\tag{3.5}
$$

where $hour^*_{it}$ and $hour_{it}$ are the latent and observed home-based working hours. The observed hours are zero when the latent variable is non-positive (i.e., someone does not choose home-based work). Apart from the main equation, the selection equation and the decomposition of the unobserved heterogeneity for the intensive margin are the same as the extensive margin. Therefore, by combining Eq. (3.2) and Eq. (3.5) and plugging in Eq. (3.3), I obtain the following model for home-based working hours:

$$
\begin{aligned}
emp_{it} &= \mathbb{1}[\mathbf{z}'_{it}\boldsymbol{\alpha} + \theta shock_{it} + \eta_2 + \bar{\mathbf{z}}'_i\boldsymbol{\zeta}_2 + \epsilon_{it2} \geq 0], \\
hour_{it} &= \begin{cases} - & \text{if } emp_{it} = 0 \\ Max[0,\ \mathbf{x}'_{it}\beta + \gamma shock_{it} + \eta_1 + \bar{\mathbf{x}}'_i\boldsymbol{\zeta}_1 + \epsilon_{it1}] & \text{if } emp_{it} = 1 \end{cases}.
\end{aligned}
\tag{3.6}
$$

Note that Eq. (3.6) is different from the model for the extensive margin in terms of in terms of the covariance matrix of error terms because $Var(\epsilon_1) = \sigma$ in the Tobit model. Therefore, the joint distribution of ϵ_{it1} and ϵ_{it2} given $\tilde{\mathbf{x}}_{it}$ and $\tilde{\mathbf{z}}_{it}$ can be written as

$$
\begin{pmatrix} \epsilon_{it1} \\ \epsilon_{it2} \end{pmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma^2 & \\ \rho\sigma & 1 \end{bmatrix} \right).
$$

Eq. (3.6) denotes three sequential decisions on employment, home-based work and home-based working hours. One first makes the employment decision. If an

[4] An alternative approach is to use the conventional Heckman model with two-level selection equations. The employment decision is modelled in the first level, while the home-based work is modelled in the second level. In this case, home-based working hours are continuous and only observable when these two selection equations both equal to one. I do not use this framework as it requires at least one additional exclusion restriction only affecting home-based work status but not home-based working hours, which is difficult to find.

individual decides not to work, the selection equation equals zero, and the main equation has a missing value. If one decides to work, the next decision is about the uptake of home-based work. If one chooses not to work from home, the hour is censored at zero. Otherwise, positive home-based working hours are determined. Accordingly, I divide the log-likelihood function into three parts:

If $emp_{it} = 0$,

$$\ell_{it} == \ln \int_{-\infty}^{-\tilde{\mathbf{z}}_{it}\tilde{\boldsymbol{\alpha}}} \phi(\epsilon_2) d\epsilon_2.$$

If $emp_{it} = 1$ and $hour_{it} = 0$,

$$\ell_{it} = \ln \int_{-\infty}^{\tilde{\mathbf{z}}_{it}\tilde{\boldsymbol{\alpha}}} \int_{-\infty}^{-\tilde{\mathbf{x}}_{it}\tilde{\boldsymbol{\beta}}} binormal(\epsilon_1, \epsilon_2; \sigma, \rho) d\epsilon_1 d\epsilon_2;$$

that is

$$\ell_{it} = \ln \int_{-\infty}^{\tilde{\mathbf{z}}_{it}\tilde{\boldsymbol{\alpha}}} \int_{-\infty}^{-\frac{\tilde{\mathbf{x}}_{it}\tilde{\boldsymbol{\beta}}}{\sigma}} \phi_2(\epsilon_1, \epsilon_2; \rho) d\epsilon_1 d\epsilon_2.$$

If $emp_{it} = 1$ and $hour_{it} > 0$,

$$\ell_{it} = \ln \left(\Phi[\frac{\tilde{\mathbf{z}}_{it}\tilde{\boldsymbol{\alpha}} + \frac{\rho}{\sigma}(y_{it} - \tilde{\mathbf{x}}_{it}\tilde{\boldsymbol{\beta}})}{\sqrt{1-\rho^2}}] - \frac{1}{2}(\frac{y_{it} - \tilde{\mathbf{x}}_{it}\tilde{\boldsymbol{\beta}}}{\sigma})^2 - \ln(\sqrt{2\pi}\sigma) \right),$$

where $binormal(\cdot)$ is the probability density function of a bivariate normal distribution containing ρ and σ, and $\Phi(\cdot)$ is the cumulative density function of a standard normal distribution.

The model is also estimated with a pooled MLE and clustered the standard errors at the individual level. Due to no standard commands in Stata, I estimate the model with a user-written command 'cmp' (Roodman, 2011).[5]

3.3 Data

3.3.1 Sample and Variables

This paper uses data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey for the analysis. HILDA is a nationally representative sur-

[5] I also programme the log-likelihood function and estimate the model with the 'ml' command in Stata. Results obtained from both approaches are highly similar.

vey in Australia conducted annually from 2001 to 2019. I only use data from 2012 to 2019 for this study because the variables used as exclusion restrictions in my model are not available until the wave in 2012. The analytical sample includes respondents aged between 20 and 60.[6] I exclude student workers and those unable to work due to health issues before the sampling period.[7] Also excluded are workers not in the wage sector (e.g., the self-employed) as most of these workers can work from home by definition, regardless of health shocks. Thus, the final estimating sample only comprises employees and non-employed individuals, consisting of 40,960 individual-year observations (18,430 male-year and 22,530 female-year observations).

The dependent variable for the selection equation is a binary variable for employment derived from the work status in the survey. It is worth noting that HILDA defines employment as currently having a job, which includes the situation that one is temporarily away from work for some reason (e.g., on leave). The dependent variable for the main equation is a binary variable about home-based work status (for the extensive margin) or a left-censored variable about weekly home-based working hours (for the intensive margin). The information on home-based work is obtained from two consecutive questions for employees. The first question is whether one's job contains usual working hours at home. If so, a follow-up question asks about the weekly working hours at home; otherwise, the home-based working hours are recorded as zero.

The parameter of interest, health shocks, has been measured in multiple ways in previous research. Some studies relying on administration data tend to define health shocks as unexpected but serious diseases, for example, cancer (Jeon & Pohl, 2017) and cardiovascular diseases (Fadlon & Nielsen, 2019). In contrast, studies based on survey data can hardly focus on a specific disease because of an insufficient sample size. Instead, a reduction in self-rated health (Cai et al., 2014) and an adverse health event are widely used in these studies (Jones et al., 2010, 2020). However, the former measurement may introduce some biases into the analysis if

[6] I do not consider respondents younger than 20, as most of them are students. I do not consider respondents older than 60 due to their high intentions to retire. According to the Australian Bureau of Statistics (2020), the eligibility of superannuation at age 60 (the preservation age) makes 46% of retirees leave their last job.

[7] I do not exclude those unable to work due to health problems in the sampling period as this situation can result from health shocks.

the health evaluation is associated with a respondent's social and cultural background (Islam & Maitra, 2012). Therefore, I use the latter measurement in the main analysis and define health shocks as a dummy variable indicating the presence of a *severe injury and illness* in the past 12 months, which appears to involve fewer social and cultural factors. In one of the robustness checks in Section 5.1, I show that the estimation results are qualitatively unchanged based on an alternative measurement of health shocks defined by self-rated health.

I additionally control for some socio-demographic variables and job characteristics in my model. Socio-demographic variables are added in both the selection equation and the main equation, including citizenship, age, marital status, number of children, education, non-labour income and self-rated health. In the main equation, I also control for some job characteristics for employees, including weekly working hours intervals, contract types, company size, working in the public sector, a set of industry indicators and a dummy variable indicating whether the employer tends to offer home-based work.[8] The industry fixed effects are added to the main equation. A list of variables and descriptions are available in Appendix Table 3.A.1.

To identify the non-random selection, a Heckman-type model should include at least one variable as an exclusion restriction in the selection equation. In this paper, the exclusion restrictions are three standardised cognitive ability test scores in the first available year (hereafter referred to as the *baseline period*), which is either 2012 or 2016.[9] Note that I exclude the observations before the baseline period because the test scores in the baseline year should not affect one's behaviours in the past. HILDA measures cognitive ability with three cognitive tests: Backwards Digit Span (BDS), Symbol Digits Modalities (SDM) and a 25-item version of the National Adult Reading Test (NART25), which tests one's memory capability, information process speed and premorbid intelligence, respectively (Wooden, 2013).[10]

[8] Considering potential reverse causality, I only control for the non-labour income and the working hour intervals instead of the total income and the specific working hours. This is because total household income and employment can affect each other, so as home-based work and specific working hours.

[9] HILDA conducted cognitive ability tests in 2012 and 2016. Once the scores are available in the 2012 survey, I include all observations from 2012 onward. If the test scores missing in the 2012 survey but available in the 2016 survey, I include all observations from 2016 onward.

[10] Wooden (2013) provides more details about how these cognitive tests are implemented and scored in the HILDA survey. Cognitive ability has been used as an exclusion restriction in a similar scenario by Semykina (2018), which models women's decision on self-employment.

A valid exclusion restriction in a Heckman-type model should only affect the outcome in the selection equation but not the outcome in the main equation. In this study, validity requires that one's cognitive ability in the baseline period needs to affect the decision on employment but not the decision on home-based work status (for the extensive margin) or home-based working hours (for the intensive margin) in subsequent periods. The first part of the assumption seems plausible as a large volume of studies has documented the persistent impact of cognitive ability on labour supply (Ceci & Williams, 1997; Heckman et al., 2006; Lin et al., 2018). The second part of the assumption could be violated if the cognitive ability is associated with the uptake of home-based work in subsequent periods. In other words, there is a systematic difference in the cognitive levels between the employees choosing and not choosing home-based work. This may happen, for example, when employers that demand workers with high cognitive skills also tend to offer many home-based positions.

However, this potential association should have been captured by a set of job characteristics controlled for in the main equation, especially the employer's tendency to offer home-based work. This tendency is captured by a question that asks whether the employer provides home-based work to a respondent or other employees working at a similar level. Among all employees classifying themselves as ineligible, around 14% indeed adopt home-based work. In contrast, among the employees claiming that they are eligible, 56% are users of home-based work. Thus, while not perfectly reflecting eligibility, this variable represents employers' tendency to offer home-based work. Therefore, even if there is an association between employers' preference for workers with high cognitive skills and their propensity to offer home-based jobs, this association has been controlled for in the main equation. In addition, a set of industry indicators capture the systematic difference in the uptake of home-based work across industries. Therefore, the potential correlation between cognitive skills and home-based work at the industrial level should not be a problem.

Additionally, I address the potential correlation between unobserved individual heterogeneity and covariates via Mundlak's approach. This method requires adding the individual time mean of the time-varying covariates to the model as additional regressors. Among socio-demographic variables, I include the individual time means of age-squared, marital status, number of children, household income, and self-evaluated health in both equations.[11] I also add the individual time means of all job characteristics to the main equation. As Cai et al. (2014) argued, health shocks reflect short-run variation in health and should not be correlated with unobserved individual heterogeneity. Hence, I do not include their mean values in both equations. This assumption is further discussed in one of the robustness checks in Section 3.5.2.

3.3.2 Descriptive Statistics

Table 3.1 below only presents the descriptive statistics for some selected variables. The complete list of descriptive statistics is available in Appendix Table 3.A.2. Panel A summarises the socio-demographic characteristics of the entire sample. According to Panel A, around 88.3% of men and 76.4% of women are employed. Over 70% of men and women reach an education level higher than year 12. Within this group, women are more likely to achieve a bachelor's degree or higher, while men have a higher probability of holding other degrees and certificates. Given that self-rated health is represented by an integer between 1 (very bad) and 5 (very good), the average health at 3.6 for both genders suggests that their health is generally good.[12] Despite that, some health shocks still occur in the sampling period. In total, 6.7% of men and 5.6% of women report a severe injury and illness in the past 12 months.

Job-related variables for employees are summarised in Panel B. I categorise working hours differently for men and women to preserve the sample size of each category. In general, men's weekly working hours are longer than women's as more than 90% of men work over 35 hours per week. In contrast, around 40% of women work fewer than 35 hours per week, corresponding to a part-time job.[13] This may relate to women having a higher chance of holding a casual contract than men.

Panel B of Table 3.1 also summarises the information on home-based work among male and female employees. The prevalence of home-based work seems gender-balanced. Around 30% of the employees, both men and women, state that

[11] The time mean of age is not included as it is collinear with year fixed effects. The time mean of education is not included due to little variation across time.

[12] 3 and 4 represent good and very good, respectively.

[13] A widely accepted cut-off between full-time and part-time jobs is 35 hours per week (Van Bastelaer et al., 1997).

the employer provides them with home-based work. This leads to around 21% of employees choosing to work from home. Among all employees, the weekly home-based hours are 1.7-1.8 hours, while the weekly hours amount to 8.1 hours, conditional on employees using home-based work.

Figure 3.1 takes a first look at how home-based work is related to health shocks. According to Panels A and B, health shocks seem positively correlated with both the extensive and intensive margins of women's home-based work. More precisely, a health shock is associated with a 5% increase in home-based work uptake and a 0.5-hour increase in weekly home-based working hours. However, such a positive association is relatively weak among female home-based work users in Panel C. In contrast, the association between health shocks and home-based work is not clear for men. This graphical description has shown some gender asymmetry. I further present the effect of health shocks on home-based work and its gender heterogeneity in the next section.

Table 3.1. Descriptive Statistics for Selected Variables

Variable	Men Mean	Men s.d.	Women Mean	Women s.d.
Panel A: For the full sample				
employment	0.883	0.322	0.764	0.425
injury and illness	0.067	0.250	0.056	0.229
self-evaluated health	3.577	0.874	3.601	0.849
education: bachelor and higher	0.323	0.467	0.400	0.490
education: diploma and certificate	0.393	0.488	0.312	0.463
education: year 12	0.154	0.361	0.147	0.355
education: less than year 12$^{\text{ref}}$	0.130	0.337	0.141	0.348
Observations	18,430		22,530	
Panel B: For the employed sample				
wfh	0.211	0.408	0.222	0.416
wfh hour	1.731	5.116	1.806	4.974
wfh hour | wfh=1	8.186	8.423	8.135	7.745
weekly working hours: 0-20h$^{\text{ref for women}}$	-	-	0.156	0.363
weekly working hours: 21-34h	-	-	0.252	0.434
weekly working hours: 0-34h$^{\text{ref for men}}$	0.083	0.276	-	-
weekly working hours: 35-40h	0.440	0.496	0.396	0.489
weekly working hours: 41-50h	0.341	0.474	-	-
weekly working hours: $\geq$41h	-	-	0.196	0.397
weekly working hours: $\geq$51	0.136	0.343	-	-
contract type: fixed-term$^{\text{ref}}$	0.089	0.285	0.117	0.321
contract type: casual	0.102	0.303	0.158	0.365
contract type: permanent	0.809	0.393	0.725	0.446
the employer offering home-based work	0.317	0.465	0.291	0.454
Observations	16,265		17,202	

Abbreviation: wfh: work from home.

Variables with a superscript 'ref' are used as a reference group in regression.

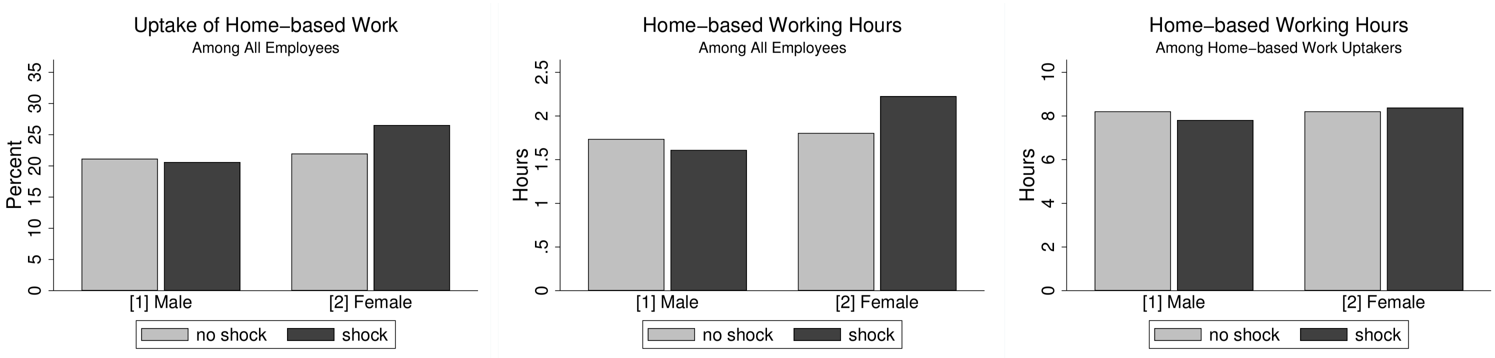

Figure 3.1. Home-based Work Status and Hours by the Occurrence Health Shocks and Gender.

Note: The three graphs show the average uptake of home-based work and hours working from home by gender and health shocks. The average home-based working hours are reported in two ways: the middle graph reports the average hours among all employees, while the right one reports the average hours among all workers who use home-based work. Health shocks in this figure are measured by a severe injury or illness in the past 12 months.

3.4 Estimation Results

3.4.1 Results for the Extensive Margin

Table 3.2 presents the results for the impact of a health shock on the extensive margin of home-based work separately for men and women. I first report the results from a Probit model (Columns 1 & 4), which ignores the non-random selection into work and is solely based on employees. Then, I compare these results with the results from the Heckman-probit model (Columns 2-3 & 5-6), accounting for the non-random selection. When interpreting the Heckman-probit model results, one should bear in mind that the dependent variables for the two steps are different: employment is for the first step, and the uptake of home-based work is for the second step. In non-linear models, the coefficient on a health shock cannot be directly interpreted as a marginal effect. Therefore, I also report the average partial effect (APE) of a health shock on the dependent variables at the bottom of the table. Besides, I report the coefficients on sample selection ($\hat{\rho}$) and exclusion restrictions.

The estimated results from the Probit model, shown in Columns 1 and 4, suggest a large gender difference in the uptake of home-based work in response to a health shock. A health shock cannot significantly alter male employees' home-based work status, while it is associated with the uptake of home-based work for female employees at the 1% level. On average, a severe illness and injury can increase the likelihood of using home-based work by 4.5 percentage points for women.

While the analyses purely based on employees are informative, a more reliable approach should consider the non-random selection into work. Therefore, I present the estimated coefficients using the Heckman-probit model in columns 2-3 and 5-6. The estimated sample selection coefficients ($\hat{\rho}$) are significant at the 1% significance level for both men and women, suggesting the presence of the non-random selection into work. The negative sign of $\hat{\rho}$ implies that those active in the labour market are less likely to choose home-based work. After correcting for this non-random selection, I find that, on average, a health shock can increase the likelihood of working from home by 2.8 percentage points for men and 8.2 percentage points for women, much higher than the APEs in the Probit model. In other words, the non-random selection into work can lead to underestimating the impact of a health shock on the uptake of home-based work.

The results from the Heckman-probit model indicate the presence of a gender difference. For women, the impact of health shocks is significant at the 1% level. Its magnitude (APE=8.2 percentage points) represents 37% of the average uptake of home-based work among the female employees in the analytical sample. However, a health shock only has a modest effect (APE=2.8 percentage points) on men's home-based work status at the 10% significant level. When some other studies document a health shock has a stronger impact on women's labour market participation than men's, they relate this to household specialisation within a couple (Duguet & Le Clainche, 2020; Jones et al., 2020). The same explanation could apply to the gender heterogeneity in the uptake of home-based work. Since women typically undertake domestic work more than men, home-based work can be particularly helpful for them to reconcile their working and non-working tasks in poor health conditions. Women may also have a strong incentive to opt for this working pattern if the effect of home-based work can lead to better long-term labour market outcomes. A supplement analysis in Appendix Section 3.B provides more details on this.

The estimates of the exclusion restrictions are presented in the first step of the Heckman-probit model (Columns 2 and 5). They suggest that cognitive test scores in the baseline year can affect employment decisions in subsequent periods. Two of the three cognitive tests appear to be significantly positive. The remaining one is not significant due to a high correlation between these test scores. Despite that, a joint significance test can reject the null hypothesis that these test scores are jointly equal to zero (p-value<0.01), which underpins the plausibility of using cognitive test scores as exclusion restrictions.

Besides home-based work, based on the first step of the Heckman-probit model, I find that a health shock negatively impacts the probability of being employed for both genders. On average, a severe injury or illness in the last 12 months decreases men's employment by 5.2 percentage points and women's employment by 7.4 percentage points. The estimated impacts are greater than Cai et al.'s (2014) results based on the same dataset (but different waves) and health shock measurements. The stronger impact can be partly attributed to the exclusion of self-employed people from the analytical sample. The labour market participation for self-employed people is expected to be more resilient after a health shock due to the fact that self-employment is highly flexible and entails less commuting. Thus, our first-step results should be considered as the upper bound of the negative effect of a health shock on labour market participation. Particularly, this result is meaningful for those employees who are less likely to get access to self-employment. In addition, the magnitude of this effect is comparable to García-Gómez (2011) (2%-8%) and García-Gómez et al. (2013) (6.5% for men and 8.4% for women for two years).[14]

3.4.2 Results for the Intensive Margin

The results for the effect of health shocks on weekly home-based working hours are displayed in Table 3.3. The layout of this table is similar to Table 3.2. The only difference is the way APEs are reported. In Table 3.3, I report two APEs related to a health shock. The first one is the partial effects applied to all employees regardless of their home-based work status, while the second one only applies to the employees whose home-based working hours are positive. In addition, I do not report the APEs of health shocks on employment for the Heckman-tobit model as they are the same as those for the Heckman-probit model.

Similar to the effect on the extensive margin, remarkable gender heterogeneity can be found in the effect of a health shock on the intensive margin of home-based work. It appears that a health shock cannot significantly alter men's home-based working hours, irrespective of whether the non-random selection is corrected for. By contrast, women increase their working hours from home as a response to a health shock. Without correcting for the non-random selection, the Tobit model (Column 4) shows that, on average, a severe injury or illness can increase weekly home-based working hours by 0.47 hours among female employees and 0.63 hours among the female employees choosing home-based work. After accounting for the non-random selection (Columns 5 & 6), I find these two APEs raise to 0.65 hours and 0.82 hours, respectively. Higher APEs from the Heckman-tobit model than the Tobit model imply that the non-random selection causes an underestimation of the impact of a health shock, which aligns with a statistically significant estimate of sample selection ($\hat{\rho}$). The estimated effects of a severe injury and illness are non-trivial. The average weekly home-based working hours are 1.7 hours among fe-

[14] García-Gómez (2011) conducts cross-country study measuring health shocks with the onset of a chronic disease, which is similar to my definition. My results for injuries and illness (around 5%-7%) have a comparable size to her results in the Netherlands (6.8%), Greece (6.6%) and Spain (8.1%).

male employees and 8.1 hours among the female sub-sample choosing home-based work. Hence, the APEs derived from a Heckman-tobit model correspond to an increase of 35.8% and 10.1%, respectively. Given that people with ill health are less likely to work longer than before (Jones et al., 2020), the rising home-based working hours imply a substitution effect of a health shock on working hours: some work that should have been done in the office without a health shock is now completed at home.

3.5 Robustness Checks

3.5.1 An Alternative Measurement of Health Shocks

Health shocks have been measured in several ways in the existing literature. Except for severe injuries and illness, another measurement widely adopted by the literature is a decline in self-rated health (García-Gómez et al., 2010; Jones et al., 2010; García-Gómez, 2011; Cai et al., 2014; Lenhart, 2019), which could reflect health deterioration over time. I re-estimate my model using this definition to test whether my results remain valid under an alternative measurement of health shocks.

I construct another health shock indicator from the following statement question: *compared to one year ago, how would you rate your health in general now?* Among five possible answers, I consider a health shock occurs if someone believes their current health is *somewhat worse* or *much worse* than last year.[15] In total, 11.12% of respondents think their health has become worse this year (10.44% for *somewhat worse* and 0.68% for *much worse*). However, I do not distinguish between these two answers when defining health shocks due to the small sample size of the latter answer. Unsurprisingly, health shocks are more frequent when measured by worse self-rated health than severe injuries or illness because some mild health issues can reasonably lead to a decline in the former measure but not the latter.

Panel A in Tables 3.4 and 3.5 presents the estimation results for the extensive and intensive margins of home-based work, respectively, using the alternative definition of health shocks. I only report the APEs of a health shock and the sample selection coefficient in a Heckman-type model for space considerations. Once again, the significant sample selection coefficient indicates the presence of non-random

[15] Other possible answers are *unchanged*, *better* and *much better*.

Table 3.2. Impact of a Health Shock on the Extensive Margin of Home-based Work

	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
Models	Probit	Hec-probit 1st step	Hec-probit 2nd step	Probit	Hec-probit 1st step	Hec-probit 2nd step
Dependent Variables	wfh	emp	wfh	wfh	emp	wfh
Injury and illness	-0.008	-0.298***	0.099*	0.180***	-0.297***	0.258***
	(0.058)	(0.050)	(0.053)	(0.058)	(0.046)	(0.052)
$\hat{\rho}$		-0.843***			-0.825***	
		(0.056)			(0.066)	
Exclusion restrictions						
SDM		0.210***			0.182***	
		(0.030)			(0.025)	
NART25		0.0782***			0.0786***	
		(0.024)			(0.023)	
BDS		-0.0334			0.0173	
		(0.022)			(0.019)	
Log-likelihood	-6,728	-12,183		-7,345	-17,202	
Observations	16,265	18,430	16,265	17,202	22,530	17,202
APE on P[y=1|x]						
Injury and illness	-0.002	-0.052***	0.028*	0.045***	-0.074***	0.082***
	(0.013)	(0.010)	(0.016)	(0.015)	(0.012)	(0.0174)

Notes: Coefficients estimates and APEs for health shocks on home-based work status. Health shocks are measured by severe injuries/illness. Columns 1 & 4 are Probit model results, and Columns 2-3 and 5-6 are Heckman-probit model results. The dependent variable for Columns 2 & 4 is employment and for other columns is home-based work uptake. Socio-demographic variables, individual time mean of time-varying covariates and year fixed-effect are controlled for in each column. Job characteristics and their individual time means are additionally controlled for in Columns 1, 3, 4 & 6. APE represents the average partial effect. Standard errors in parentheses are clustered at the individual level. Significance levels are shown as *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3.3. Impact of a Health Shock on the Intensive Margin of Home-based Work

	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
Models	Tobit	Hec-tobit 1st step	Hec-tobit 2nd step	Tobit	Hec-tobit 1st step	Hec-tobit 2nd step
Dependent Variables	wfh hour	emp	wfh hour	wfh hour	emp	wfh hour
Injury and illness	-0.381	-0.309***	-0.003	1.995***	-0.301***	2.448***
	(0.666)	(0.050)	(0.684)	(0.673)	(0.046)	(0.714)
$\hat{\rho}$		-0.287***			-0.302**	
		(0.081)			(0.114)	
Exclusive restrictions:						
SDM		0.211***			0.189***	
		(0.033)			(0.027)	
NART25		0.065**			0.080***	
		(0.027)			(0.025)	
BDS		-0.029			0.028	
		(0.025)			(0.021)	
Log-likelihood	-17,443	-22,921		-19,145	-29,024	
Observations	16,265	18,430	16,265	17,202	22,530	17,202
APE on E[wfh hour|x, employee=1]						
Injury and illness	-0.077	-0.001		0.466***	0.646***	
	(0.132)	(0.147)		(0.169)	(0.212)	
APE on E[wfh hour|x, wfh hour>0]						
Injury and illness	-0.112	-0.001		0.628***	0.818***	
	(0.194)	(0.208)		(0.220)	(0.255)	

Notes: Coefficients estimates and APEs of health shocks on home-based working hours. Health shocks are measured by severe injuries/illness. Columns 1 & 4 are Tobit model results, and Columns 2-3 & 5-6 are Heckman-tobit model results. The dependent variable for Columns 2 & 4 is employment and for other columns is home-based working hours. Socio-demographic variables, individual time mean of time-varying covariates and year fixed-effect are controlled for in each column. Job characteristics and their individual time means are additionally controlled for in Columns 1, 3, 4 & 6. APE represents the average partial effect. Standard errors in parentheses are clustered at the individual level. Significance levels are shown as *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

selection into work for both genders. Compared to the Probit or Tobit model, a Heckman-type model can generate higher APEs for worse self-evaluated health by accounting for the non-random selection.

Despite being less clear, gender heterogeneity still appears under the alternative definition of health shocks. For men, worse self-rated health can increase their uptake of home-based work by 3.4%. The estimate is more precise here than in the main analysis, but the magnitude is similar. However, worse self-rated health still does not significantly alter men's home-based working hours, consistent with the finding in the main analysis. For women, a health shock can raise the chance of home-based work by 4% and weekly hours by 0.38 hours among all employees or 0.47 hours among those with the uptake of home-based work. The less clear gender heterogeneity is mainly attributed to women's home-based work becoming less responsive to health deterioration. A potential reason is that health deterioration includes mild health issues that are less likely to trigger strong labour market effects.

3.5.2 The Predictability of a Health Shock

Islam and Maitra (2012) and Cai et al. (2014) argue that health shocks should reflect the short-run variation in health conditions and thus have an unpredictable nature. Relying on this feature, I consider health shocks an exogenous variable that is uncorrelated with unobserved factors (e.g., unobserved individual heterogeneity). However, this assumption is violated if some health shocks are indeed foreseeable. For example, a foreseeable health shock can be endogenous if associated with certain lifestyles that affect employment and home-based work.

To avoid this possible contamination and reassure the exogeneity of health shocks, I re-estimate the model only with a subset of unanticipated health shocks. I apply Apouey et al.'s (2019) approach to construct this subset, which isolates unanticipated shocks according to the previous year's health expectation. In every wave, respondents evaluate the following statement: *I expect my health to get worse*. I define a health shock as anticipated (unanticipated) if someone has a health shock in one period and expected (did not expect) health to become worse in the previous period.[16]

[16] There are five possible answers to the statement of health expectation: *definitely true*, *mostly true*, *don't*

The composition of health shocks by predictability is displayed in Figure 3.2. This figure shows that most health shocks are unanticipated (more than 70% for men and 80% for women), which, to a large extent, illustrates the unpredictable feature of health shocks. Note that I cannot determine the predictability of less than 10% of the health shocks as the respondent's expectation in the preceding year is missing. Therefore, I exclude these observations in this check.

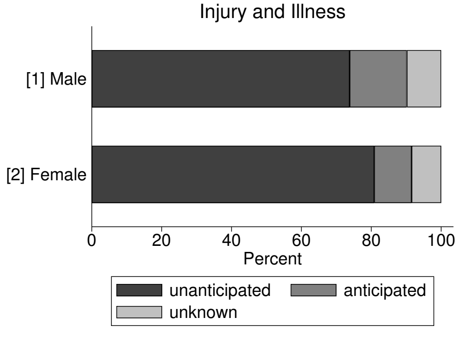

Figure 3.2. Composition of Health Shocks by Predictability.

Note: This graph summarises the proportions of health shocks, measured by severe injuries and illness, by predictability and gender.

The estimation results based on unanticipated health shocks are presented in Panel B of Table 3.4 (for the extensive margin) and Table 3.5 (for the intensive margin). The APEs of an unanticipated health shock are close to the APEs in the main results in both economic and statistical terms, suggesting that the impact on the uptake of home-based work is mainly attributed to exogenous health shocks. Again, I observe substantial gender heterogeneity. A health shock significantly increases women's home-based work uptake and weekly hours. Due to negative selection into work, such an effect becomes larger when the non-random selection is adjusted. Nevertheless, a health shock cannot significantly affect the extensive and intensive margins of men's home-based work irrespective of whether sample selection is adjusted.

know, *mostly false* and *definitely false*. Expecting health to become worse means someone chooses one of the first two as the answer. Not Expecting means someone chooses one of the other three.

Table 3.4. Impact of a Health Shock on the Extensive Margin of Home-based work

	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
Models	Probit	Hec-probit 1st step	Hec-probit 2nd step	Probit	Hec-probit 1st step	Hec-probit 2nd step
Panel A: An Alternative Measurement of Health Shocks						
APE on P[y=1|x]						
Worse health	0.020*	-0.026***	0.034**	0.030***	-0.021**	0.040***
	(0.012)	(0.008)	(0.013)	(0.011)	(0.009)	(0.013)
$\hat{\rho}$		-0.827***			-0.801***	
		(0.0615)			(0.0798)	
Observations	16,309	18,503	16,309	22,602	17,242	17,242
Panel B: Unanticipated Health Shocks						
APE on P[y=1|x]						
Injury and illness	-0.005	-0.039***	0.017	0.041**	-0.078***	0.081***
	(0.015)	(0.011)	(0.017)	(0.017)	(0.014)	(0.020)
$\hat{\rho}$		-0.846***			-0.824***	
		(0.055)			(0.068)	
Observations	16,185	18,309	16,185	17,131	22,424	17,131

Notes: APEs of health shocks on home-based work status and the estimate for the sample selection coefficient. Panel A displays the results for health shocks measure by worse self-evaluated health. Panel B displays the results for unanticipated health shocks, measured by severe injuries/illness. Columns 1 & 4 are Probit model results, and Columns 2-3 & 5-6 are Heckman-probit model results. The dependent variable for columns 2 and 4 is employment and for other columns is home-based work uptake. Socio-demographic variables, individual time mean of time-varying covariates and year fixed-effect are controlled for in each column. Job characteristics and their individual time means are additionally controlled for in Columns 1, 3, 4 & 6. APE represents the average partial effect. Standard errors in parentheses are clustered at the individual level. Significance levels are shown as *** p<0.01, ** p<0.05, * p<0.1.

Table 3.5. Impact of a Health Shock on the Intensive Margin of Home-based work

	Men		Women	
	(1)	(2)	(3)	(4)
Models	Tobit	Hec-tobit	Tobit	Hec-tobit
Dependent Variables	wfh hour	wfh hour	wfh hour	wfh hour
Panel A: An Alternative Measurement of Health Shocks				
APE on E[wfh hour|x, employee=1]				
Worse health	0.163	0.211	0.299**	0.357***
	(0.128)	(0.138)	(0.118)	(0.133)
APE on E[wfh hour|x, wfh hour>0]				
Worse health	0.234	0.293	0.412***	0.466***
	(0.181)	(0.189)	(0.160)	(0.169)
$\hat{\rho}$		-0.282***		-0.285**
		(0.0812)		(0.115)
Observations	16,309	16,309	17,242	17,242
Panel B: Unanticipated Health Shocks				
APE on E[wfh hour|x, employee=1]				
Injury and illness	-0.109	-0.0552	0.396**	0.555**
	(0.148)	(0.162)	(0.183)	(0.225)
APE on E[wfh hour|x, wfh hour>0]				
Injury and illness	-0.161	-0.0783	0.541**	0.716***
	(0.220)	(0.231)	(0.242)	(0.277)
$\hat{\rho}$		-0.283***		-0.275**
		(0.082)		(0.118)
Observations	16,185	16,185	17,131	17,131

Notes: APEs of health shocks on home-based working hours and the estimate of the sample selection coefficient. Panel A displays the results for health shocks measure by worse self-evaluated health. Panel B displays the results for unanticipated health shocks, measured by severe injuries/illness. Columns 1 & 3 are Tobit model results, and Columns 2 & 4 are Heckman-tobit model results (the second step). Socio-demographic variables, job characteristics, the individual time mean of the time-varying variables and year fixed-effect are controlled for in each column. APE represents the average partial effect. Standard errors in parentheses are clustered at the individual level. Significance levels are shown as *** p<0.01, ** p<0.05, * p<0.1.

3.6 Heterogeneous Effects by Education and Age

So far, my analysis has emphasised gender heterogeneity. Besides gender, the uptake of home-based work may also differ across other socio-demographic factors. Among all factors, education and age could be particularly important due to their relevance to the accessibility to home-based work and the severity of a health shock. To explore these heterogeneities, I re-estimate the Heckman-type model based on the sub-samples divided by educational levels or ages. For education, I classify the sample with the possession of a bachelor's (B.A.) degree or higher by assuming higher education is critical for accessing a flexible job. For ages, I use 40 as a cutoff as the older group's health problems might be more severe than the younger group's.

Table 3.6 presents the heterogeneous impacts of a health shock by education (Panel A) and ages (Panel B) separately for men and women. I only show the APEs of health shocks from the preferred Heckman-type models.

Columns 1 and 4 suggest that a health shock has a stronger negative effect on employment for the lower-educated group and the older group for both genders. The lower-educated employees have less access to flexible employment that facilitates them in recovering from a severe injury or illness and thus have to leave the labour market. Older employees tend to exit the labour market as a severe injury or illness may not allow them to continue working. Another strong incentive for some older employees to cease working is that their age may have approached their retirement prospects (Jones et al., 2010).

Consistent with the main analysis, home-based work for men is not significantly altered by a health shock regardless of age and education. In contrast, the estimates differ considerably across ages and education for women. Women obtaining a B.A. degree or higher are more likely to choose home-based work in response to a health shock (APE=9.5%) than their lower-educated counterparts (APE=5.5%). This is plausible as the higher-educated women can make good use of the flexibility they are entitled to since their jobs are reasonably less attached to a specific workplace. However, given the uptake of home-based work, the impact of a health shock on the intensive margin does not differ substantially between the two educational groups. For age, a health shock only significantly increases home-based work for women below 40. Typically, the children of women below 40 are relatively young. These women with ill health may actively use home-based work to take care of children while working. Also, they can manage their health using home-based work as health shocks are less likely to impact their productivity catastrophically at a young age. In contrast, the health shocks for older workers appear to be more serious, and they are close to the expected age for retirement. Thus, old workers may incline to cease working instead of opting for home-based work.

Table 3.6. Heterogeneous Impact of a Health Shock on Home-based Work by Education and Age

	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
APE on	Pr(emp=1)	Pr(wfh=1)	E(wfh hour|wfh=1)	Pr(emp=1)	Pr(wfh=1)	E(wfh hour|wfh=1)
Panel A: By Education						
Lower than B.A.	-0.059***	0.025	0.109	-0.090***	0.055**	1.047**
	(0.013)	(0.016)	(0.285)	(0.018)	(0.025)	(0.492)
Observations	10,725	10,725	1,498	9,524	9,524	1,282
B.A. and above	-0.029**	0.002	-0.101	-0.047***	0.095***	0.898***
	(0.015)	(0.031)	(0.286)	(0.016)	(0.024)	(0.320)
Observations	5,540	5,540	1,941	7,678	7,678	2,537
Panel B: By Age						
Below 40	-0.035***	0.036	0.214	-0.063***	0.087***	1.028**
	(0.013)	(0.023)	(0.318)	(0.017)	(0.025)	(0.423)
Observations	8,678	8,678	1,580	8,900	8,900	1,790
Above 40	-0.066***	0.027	-0.166	-0.080***	0.043	0.507
	(0.014)	(0.020)	(0.292)	(0.018)	(0.038)	(0.316)
Observations	7,587	7,587	1,859	8,302	8,302	2,029

Notes: APEs of health shocks on employment, home-based work status and home-based working hours. Health shocks are measured by severe injuries/illness. Panel A displays the results for people with different education levels. Panel B displays the results for people in different age groups. Results in Columns 1 & 4 are calculated by the first step of a Heckman-probit model. Results in Columns 2 & 5 calculated by the second step of a Heckman-probit model. Results in Columns 3 & 6 are calculated by a Heckman-tobit model. Socio-demographic variables, individual time means of time-varying covariates and year fixed-effect are controlled for in each column. Job characteristics and their individual time mean are additionally controlled for in the second step of a Heckman-type model. APE represents the average partial effect. Standard errors in parentheses are clustered at the individual level. Significance levels are shown as *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

3.7 Conclusion

Given multiple negative labour market outcomes caused by health shocks, employees may alter the uptake of home-based work in response to a recent health shock. This paper investigates the impact of health shocks, measured by severe injuries and illness, on the extensive and intensive margins of home-based work using a longitudinal household survey in Australia between 2012 and 2019. Adopting Heckman-type sample selection models with panel data, I address the issue of sample selection into employment associated with health-related topics in labour economics.

Results from the Heckman-type models reveal that the decisions on employment and home-based work are correlated in an unobserved way, leading to a non-random selection problem. Ignoring this sample selection results in underestimating the impact of health shocks on home-based work. For example, the average partial effect of health shocks on women's home-based work status from a model solely based on employees is around half of the effect from the model jointly considering employment and home-based work. The sizeable downward bias in the estimated effect re-emphasises the importance of adjusting for the non-random selection into work in the research on health-related labour market impacts.

I find substantial gender differences in how health shocks affect the uptake of home-based work. A severe injury and illness can increase the probability of home-based work and weekly home-based working hours for female employees. The impacts are non-trivial as they represent over 35% relative to the average uptake of home-based work for both the extensive and intensive margins. In addition, the female employees holding a B.A. degree or higher and those below 40 contribute more uptake of home-based work when a health shock occurs compared to the lower-educated and the older counterparts. In contrast, I can hardly find that health shocks significantly impact men's extensive and intensive margins of home-based work at the 5% level.

As documented in previous studies (Duguet & Le Clainche, 2020; Jones et al., 2020), this gender heterogeneity could be related to the household specialisation within a couple. Employed women may find this working pattern useful to reconcile their working and non-working tasks with ill health. This is particularly true for women below 40, who typically need to take care of young children. In addition, home-based work following a health shock might benefit men and women differently in terms of labour market outcomes, which also explains the gender asymmetric use of home-based work. An extended analysis in Appendix 3.B examines the effects of home-based work on some labour market outcomes up to the fifth year relative to a health shock separately for men and women. This analysis provides suggestive evidence that home-based work in an adverse health event can alleviate the negative impacts of health shocks on women's labour force participation and household income for two or three years, while these benefits are absent for men's outcomes. The gender asymmetry in the long-term effects of home-based work may exclusively incentivise women to choose home-based work when a health shock occurs.

My findings are informative for policymakers that are making flexible working arrangement policies. First, this paper highlights the importance of improving home-based work availability for workers with health issues. I find some employees (especially women) increase the uptake of home-based work following a health shock. The revealed preference theory suggests that home-based work should yield higher utility for employees with poor health than other available working patterns. However, in some countries, the right to request home-based work is restricted to specific workers (e.g., working parents or disabled workers). My results suggest that it is necessary to enlarge the coverage of this entitlement to employees experiencing a health shock so that they can choose the optimal workplace to accommodate their demands for healthcare at work.

Due to data availability, I can only focus on home-based work in this paper. However, besides this working arrangement, other types of flexible employment (e.g., self-scheduling) emphasising employees' autonomy in different aspects of work can also be useful to tackle the negative labour market consequences of health shocks. With appropriate data, further research can examine how the uptake of other forms of flexible working arrangements is related to a health shock.

3.A Appendix Tables

Table 3.A.1. Variable Description

Variable	Description
	Dependent variables
emp	a dummy variable indicating if someone has a job (emp=1) or not (emp=0)
wfh	a dummy variable indicating if an employee uses home-based work (wfh=1) or not (wfh=0)
wfhhour	home-based working hours per week (wfhhour=0 if an employee does not use home-based work)
	Independent variables
	controlled in both steps of a Heckman-type model
injury and illness	a dummy variable indicating if someone experienced a severe personal injury or illness during the past 12 months
citizenship:	
- local	a dummy variable indicating if someone was born in Australia
- resident	a dummy variable indicating if someone was not born in Australia but is an Australia/New Zealand citizen or an Australia permanent resident
- other	a dummy variable indicating if someone is neither a *local* nor a *resident*
age	age on June 30th in the survey year
age^2	$= age^2/100$
marital status:	
- single	a dummy variable indicating if someone never married and not living with someone in a relationship
- coupled	a dummy variable indicating if someone is married or never married but living with someone in a relationship
- other status	a dummy variable indicating if someone is separated, widowed or divorced
child0-4	number of children between 0 and 4 years old
child5-14	number of children between 5 and 14 years old
health	self-evaluated health ranging between between 1 (poor) and 5(excellent)
non-labour income	the equivalised household financial year non-labour income divided by 10,000 (in 2015 price).
education:	
- bachelor and higher	a dummy variable indicating if one's highest education level is BA or higher
- diploma or certificate	a dummy variable indicating if one's highest education level is other post-school degrees

Table 3.A.1 (Cont.). Variable Definition

Variable	Description
- year12	a dummy variable indicating if one's highest education level is year 12
- below12	a dummy variable indicating if one's highest education level is below year 12
only controlled in the first stage of a Heckman-type model (exclusive restrictions)	
cognitive tests:	
- SDM	standardised test score for symbol-digit modalities. The original score ranges from 0 to 110.
- BDS	standardised test score for backwards digits. The original score ranges from 0 to 8.
- NART25	standardised test score for word pronunciation. The original score ranges from 0 to 25.
only controlled in the second stage of a Heckman-type model	
public	a dummy variable indicating if someone is working in the public sector (public=1) or a private sector (public=0)
eligible	a dummy variable indicating if the employer provides home-based work to someone or other employees working at a similar level
contract type:	
- casual	a dummy variable indicating if someone is employed on a casual basis
- fixed-term	a dummy variable indicating if someone is employed on a fixed-term contract
- permanent	a dummy variable indicating if someone is employed on a permanent or ongoing basis
company size:	
- size20	a dummy variable indicating if the firm size is smaller than 20 employees
- size50	a dummy variable indicating if the firm size is smaller than 50 employees
- size200	a dummy variable indicating if the firm size is smaller than 200 employees
- size200plus	a dummy variable indicating if the firm size is larger than 200 employees
weekly working hours:	
- for a male employee	a series of dummy variables indicating the weekly working hours of a male employee are 0-34 hours, 35-40 hours, 41-50 hours and above 51 hours.
- for a female employee	a series of dummy variables indicating the weekly working hours of a female employee are 0-20 hours, 21-34 hours, 35-40 hours and above 41 hours.
industry	10 dummy variables defined based on the The Australian and New Zealand Standard Industrial Classification (1 digit level)

Abbreviation: emp: emoloyment; wfh: work from home.

Table 3.A.2. Descriptive Statistics

Variable	Men Mean	Men S.D.	Women Mean	Women S.D.
Panel A: For the full sample				
employment	0.883	0.322	0.764	0.425
injury and illness	0.067	0.250	0.056	0.229
cognitive test: SDM	0.240	0.808	0.480	0.777
cognitive test: BDS	0.036	0.975	0.053	0.908
cognitive test: NART25	0.127	1.022	0.108	1.020
citizenship: local^{ref}	0.822	0.383	0.820	0.384
citizenship: permanent resident	0.153	0.360	0.148	0.355
citizenship: other	0.025	0.156	0.032	0.175
age	39.563	11.459	39.412	11.327
age^2/100	16.965	9.257	16.816	9.128
marital status: single^{ref}	0.211	0.408	0.173	0.378
marital status: married	0.702	0.457	0.703	0.457
marital status: other status	0.087	0.282	0.124	0.330
education: bachelor ad higher	0.323	0.467	0.400	0.490
education: diploma and certificate	0.393	0.488	0.312	0.463
education: year 12	0.154	0.361	0.147	0.355
education: less than year 12^{ref}	0.130	0.337	0.141	0.348
equivalised non-labour income/10000	0.852	2.709	1.140	3.566
self-evaluated health	3.577	0.874	3.601	0.849
Observations	18,430		22,530	
Panel B: For the employed sample				
wfh	0.211	0.408	0.222	0.416
wfhhour	1.731	5.116	1.806	4.974
wfhhour | wfh=1	8.186	8.423	8.135	7.745
contract type: fixed-term^{ref}	0.089	0.285	0.117	0.321
contract type: casual	0.102	0.303	0.158	0.365
contract type: permanent	0.809	0.393	0.725	0.446
public sector	0.221	0.415	0.331	0.471
company size: 1-19	0.315	0.464	0.307	0.461
company size: 20-49	0.174	0.379	0.181	0.385
company size: 50-199	0.250	0.433	0.253	0.435
company size: $\geq 200^{ref}$	0.261	0.439	0.259	0.438

Table 3.A.2 (Cont.). Descriptive Statistics

Variable	Men		Women	
	Mean	S.D.	Mean	S.D.
weekly working hours: 0-20h$^{\text{ref for women}}$	-	-	0.156	0.363
weekly working hours: 21-34h	-	-	0.252	0.434
weekly working hours: 0-34h$^{\text{ref for men}}$	0.083	0.276	-	-
weekly working hours: 35-40h	0.440	0.496	0.396	0.489
weekly working hours: 41-50h	0.341	0.474	-	-
weekly working hours: $\geq$41h	-	-	0.196	0.397
weekly working hours: $\geq$51	0.136	0.343	-	-
the employer offering home-based work	0.317	0.465	0.291	0.454
Observations	16,265		17,202	

Abbreviation: wfh: work from home.

Variables with a superscript 'ref' are used as a reference group in regression.

3.B Extended Analysis: the Labour Market Impacts of Home-based Work in an Adverse Health Event

In the main text, I document the gender difference with respect to the uptake of home-based work in response to a health shock. To understand the rationale behind this, I provide an extended analysis to explore a separate but related question about how men and women benefit from home-based work in an adverse health event. Given that a health shock negatively affects multiple labour market outcomes (e.g., employment and working hours), I test whether home-based work alleviates these negative effects by comparing the labour market outcomes of people working from home (treatment group) to those of people working on-site (control group) when a health shock occurs using a differences-in-differences (DiD) analysis.

3.B.1 Sample Construction under a Different Definition of Health Shocks

Due to the prolonged impact of health shocks on labour market outcomes, the model in this section focuses on the effect of a health shock and the mitigating role of home-based work over a relatively long period. Moreover, I include all waves of data between 2001 and 2019 since the DiD approach does not rely on an exclusion restriction, which is first available in wave 12 (2012) for the analyses in the main text. The longitudinal structure of HILDA allows me to capture the time profile of labour market outcomes up to 9 years surrounding a health shock (between 3 years before and 5 years after a health shock).[17]

Also, different from the main analysis, I define health shocks as the onset of a long-term health condition here. The advantages of this definition are twofold. First, respondents report their existing long-term health conditions in the first survey that they participate in. This information allows me to focus on the respondents without any health conditions at the baseline, which guarantees the health condition happening in later waves is unrelated to some former ones and indeed a health shock.[18] Second, although the presence of a health condition is not randomly distributed among the population, the timing of a health condition is relatively exogenous (Trevisan & Zantomio, 2016; Fadlon & Nielsen, 2019; Jones et al., 2020). I exploit this unpredictable onset to construct the treatment and control groups (discussed later).

The analytical sample comprises the respondents aged from 20 to 60 and entering the survey without a long-term health condition but having at least one in the sampling period. In each wave, respondents need to report 17 types of long-term health conditions separately. Given the presence of any conditions, they would indicate whether it is the first development of such a condition. I consider the onset of a new condition as a health shock. In addition, if there are multiple occurrences of different new health conditions across time, I only focus on the earliest event as the later events can be the complications of the first one, which is, to some extent, anticipated. Once a health shock is observed at a given period (year), I include three periods before and five periods after this shock to capture the dynamic effect of a health shock. The final analytical sample consists of 11,868 individual-time observations resulting from 1,970 health shocks identified in the sampling periods.

[17] A longer time profile might also be possible. However, the sample size of the time periods further away from a health shock is relatively small. To preserve the sample size of each time period, I decide to use the range of 9 years.

[18] I could have used this definition in the previous analysis. However, as the waves of survey used in that analysis are limited (2012-2019), the number of health shocks that can be identified under this definition is low.

3.B.2 Differences-in-Differences Model

To examine the mitigating role of home-based work in an adverse health event, I estimate the difference in labour market outcomes between employees with and without home-based work surrounding a health shock. Note that if someone reports a health shock in period j, this health condition should develop at some point between j and the period prior to j (i.e., $j-1$). In this case, I define the treatment and control groups according to the home-based work status at $j-1$. Since the time gap between the survey at $j-1$ and the health shock is short enough, it is reasonable to assume the home-based work status at the occurrence of the health shock remains the same as the status at $j-1$. In addition, due to the unpredictable timing of a health shock, employees cannot opt themselves into the treatment and control groups at $j-1$ by anticipating this shock, which makes the treatment assignment exogenous to a health shock.[19]

However, it is worth noting that the treatment assignment in this context can only partially estimate the mitigating effect of home-based work as this definition does not exclude a change in the workplace in any post-shock periods. For example, someone in the control group can switch to home-based work after a health shock and, thus, gain utility from working from home. Therefore, my estimation should not be interpreted as the effect of working from home throughout all post-shock periods. Instead, it presents some suggestive evidence for how home-based work at the occurrence of health shocks can improve labour market outcomes in subsequent periods.

I implement a DiD estimation with the following two-way fixed-effects model

$$y_{it} = \delta treat_i \times post_{it} + \theta post_{it} + \mathbf{x}_{it}\boldsymbol{\beta} + a_i + u_t + \epsilon_{it}, \tag{3.B.1}$$

where y_{it} is the outcome of interest for individual i in year t; $treat_i$ is a treatment dummy variable indicating i is in the treatment group (=1) or the control group (=0); $post_{it}$ denotes a given year is after the health shock (=1) or not (=0); $\mathbf{x}_{it}$ is a vector of

[19] Instead, defining the treatment and control groups based on the home-based work status at j might introduce some systematic difference between the two groups as the treatment assignment is associated with a health shock. For example, the decision of home-based work at j can be determined by the severity of the health shock. Moreover, the employees who can switch their workplace right after the health shock could be different from those who cannot. The parallel trend assumption of a DiD model is undermined in both cases.

other control variables; a_i and u_t are individual and time fixed effects, respectively; ϵ_{it} is an idiosyncratic error term. I also control for age square, non-labour income, number of children, marital status, self-rated health and regional unemployment rate in $\mathbf{x}_{it}$. If y_{it} is an outcome exclusively for workers (e.g., working hours and wage), I also control for some job-related characteristics in $\mathbf{x}_{it}$, including contract types, company size, a dummy for the public sector and industrial fixed effect. In Eq. (3.B.1), the parameter θ measures the overall effect of a health shock across the post-shock periods compared to the pre-shock periods for the control group. As the parameter of interest, the parameter δ measures the differences in the outcomes between the treatment and the control groups after a health shock, which is the mitigating effect of home-based work.

Moreover, knowing the specific period relative to a health shock, I can re-write Eq. (3.B.1) using an event study framework:

$$y_{it} = \sum_{\substack{j=-3 \\ j\neq -1}}^{5} \delta_j treat_i \times period_{it,j} + \sum_{\substack{j=-3 \\ j\neq -1}}^{5} \theta_j period_{it,j} + \mathbf{x}_{it}\boldsymbol{\beta} + a_i + u_t + \epsilon_{it}, \quad (3.B.2)$$

where the dummy variable $period_{it,j}$ indicates year t is the j^{th} period away from a health shock for individual i. Period -1 is omitted in Eq. (3.B.2) as the reference period. The focal parameter, δ_j, captures the difference in an outcome between the treatment and the control groups in period j compared to period -1.

The DiD approach relies on the parallel trend assumption, suggesting that the outcome variables for the treatment group should have paralleled those for the control group in the absence of home-based work in an adverse health event. This assumption can be violated if some unobserved factors correlated with the treatment assignment also affect the outcomes. One way to examine the validity of this assumption is to test the significance of δ_j at a pre-shock period j ($j = -2$ or -3). If this assumption holds, the outcome variables for the two groups should evolve in the same way before a health shock, which implies δ_j in these periods should be insignificantly different from the reference level in period -1. I will test this assumption using the point estimates for Eq. (3.B.2).

3.B.3 Results

Table 3.B.1 displays the overall effect of home-based work in a health shock on the labour market outcomes across all post-shock periods separately for men and women. First, I present the impact on employment in Column 1 using a linear probability model with an individual fixed-effect. A health shock reduces employment for both men and women in the control group by 7.8% and 11.7%, respectively. For women, the negative impact on employment is significantly alleviated by home-based work. Female employees who work from home in an adverse health event are 6.9% more active in the labour market in the subsequent six years than their counterparts without home-based work. However, such a mitigating effect is not sizeable or statistically significant for men, suggesting that home-based work status does not reduce the drop in labour market participation for men caused by a health shock.

The impacts on weekly working hours, weekly wage (the natural logarithm and deflected to 2001 price) and wage rate (the natural logarithm) given that someone remains labour market active in subsequent periods are presented in Columns 2-4. It seems that home-based work is not able to mitigate these job-related outcomes for both genders. This result could be explained by the selection mechanism emphasised by Trevisan and Zantomio (2016); Jones et al. (2020): the employees who keep employed after a health shock may not be strongly affected by this shock. In this case, the mitigating effect of home-based work on these job-related outcomes can be relatively weak.

Previous research has found that one's health shock has a spill-over effect on spousal labour market outcomes (García-Gómez et al., 2013; Jeon & Pohl, 2017; Riekhoff & Vaalavuo, 2021). Hence, I focus on the gross household income (the natural logarithm and deflected to 2001 price) in Column 5, which examines the mitigating role of home-based work from a household perspective. The result indicates that the household income for the female home-based workers is 6.7% higher than for the female on-site workers after a health shock. The higher household income could be attributed to two factors. First, as shown in Column 1, home-based work raises the chance of being employed in subsequent periods for women, which helps to maintain the income level after a health shock. Second, García-Gómez et al. (2013); Jeon and Pohl (2017) have documented that one's health shock leads to a decline in spousal (especially the male spouse's) labour supply for the caring purpose, known as a *caregiver effect*. However, home-based work might enhance the ill partner's ability to self-care, which increases the household income by weakening the *caregiver effect*.

Apart from the overall effect across all post-shock periods, I also estimate the dynamic effect of home-based work in each period relative to a health shock using an event study framework displayed in Eq. (3.B.2). This estimation not only shows the effect of home-based work on each specific period but also tests the validity of the parallel assumption of a DiD estimation. Figure 3.B.1 depicts the dynamic effects on employment and household income by plotting the estimates of δ_j and their 95% confidence interval.[20]

The dynamic effects for men confirm that home-based work in a health shock does not cause any significant change in men's employment and household income in post-shock periods as none of these point estimations is significantly different from the reference level in period -1. However, the results for women imply that home-based work in a health shock can lead to higher labour market participation and household income in the early years after a health shock, and, more specifically, between period 0 and period 3 for employment and between period 0 and period 2 for household income. Additionally, the treatment effects for women fluctuate between 5% and 8% across all post-shock periods for both outcomes, which corresponds to the overall effect of around 7% (shown in Table 3.B.1).

Moreover, the point estimates for the pre-shock periods can provide some insights into the validity of the parallel trend assumption. For both men and women, most of the point estimates in periods -3 and -2 are insignificantly different from the level at the reference period. This result favours a parallel trend as it indicates that the outcome variables for the treatment group and the control group evolve in the same way before the health shock. The only exception is that the estimate of women's employment in period -2 is significant at the 5% level, suggesting the labour market participation between the treatment and control groups may not parallel at this period. Conservatively, one should interpret these results as causal with cau-

[20] I only show the dynamic effects for employment and household income as they have significant overall effects. The dynamic effects for the other outcomes of interest (working hours, weekly wage and wage rate) are not shown because none of the dynamic effects are significant, which is consistent with the overall effect.

tion as some unobserved factors determining the group assignment might drive the outcomes. However, it is worth noting that the significant estimate may result from the method of sample construction: only the individuals whose home-based work status is observable in period -1 are in my scope. Therefore, by construction, people in both groups are active in the labour market in the reference period. This setting may cause a small difference in the labour market participation in period -2 to be significant. However, a joint test of the point estimates in periods -3 and -2 fails to reject the hypothesis that $\delta_{-3} = \delta_{-2} = 0$ (p-value=0.110). This test result suggests that the point estimates of the pre-shock periods are not jointly different from the reference level, which underpins the parallel trend assumption.

To summarise, this extended analysis examines the labour market effects of home-based work in the subsequent periods of a health shock. Comparing the labour market outcomes between the employees with and without home-based work in an adverse health event, I find women exclusively benefit from home-based work in terms of their subsequent employment and household income. These results are especially prominent in the first three years after a health shock. The extended analysis provides some suggestive evidence to explain the gender asymmetric uptake of home-based work after a health shock, which is discussed in the main text.

Table 3.B.1. Mitigating Effect of Home-based Work following a Health Shock

Variables	(1) Employment	(2) Weekly Hours	(3) Weekly Wage	(4) Wage Rate	(5) Household Income
Panel A: Men					
post	-0.078***	-0.939**	-0.00256	0.014	0.043**
	(0.015)	(0.452)	(0.017)	(0.015)	(0.021)
treat × post	0.011	0.293	-0.00232	0.005	0.011
	(0.023)	(0.672)	(0.033)	(0.029)	(0.041)
Number of ID	912	880	876	876	912
Observations	5,521	4,565	4,436	4,427	5,513
Panel B: Women					
post	-0.117***	-0.029	0.0104	0.007	0.000
	(0.016)	(0.462)	(0.021)	(0.018)	(0.018)
treat × post	0.069***	0.049	0.0262	0.024	0.067**
	(0.022)	(0.866)	(0.035)	(0.031)	(0.031)
Number of ID	1,049	1,010	1,003	1,003	1,049
Observations	6,347	5,009	4,901	4,892	6,339

Notes: Estimates of home-based work's impacts on multiple labour market outcomes surrounding a health shock. Observations in Columns 1 & 5 can be both employed and non-employed. I also control for age square, non-labour income, number of children, marital status, self-rated health and regional unemployment rate in these two regressions. Observations in Columns 2-4 are only for the employed people. Besides the control variables used in columns 1 & 5, I control for some job characteristics in these three regressions, including contract types, company size, public sector and industry fixed effects. All regressions include individual fixed effects and yearly fixed effects. Standard errors in parentheses are clustered at the individual level. Significance levels are shown as *** p<0.01, ** p<0.05, * p<0.1.

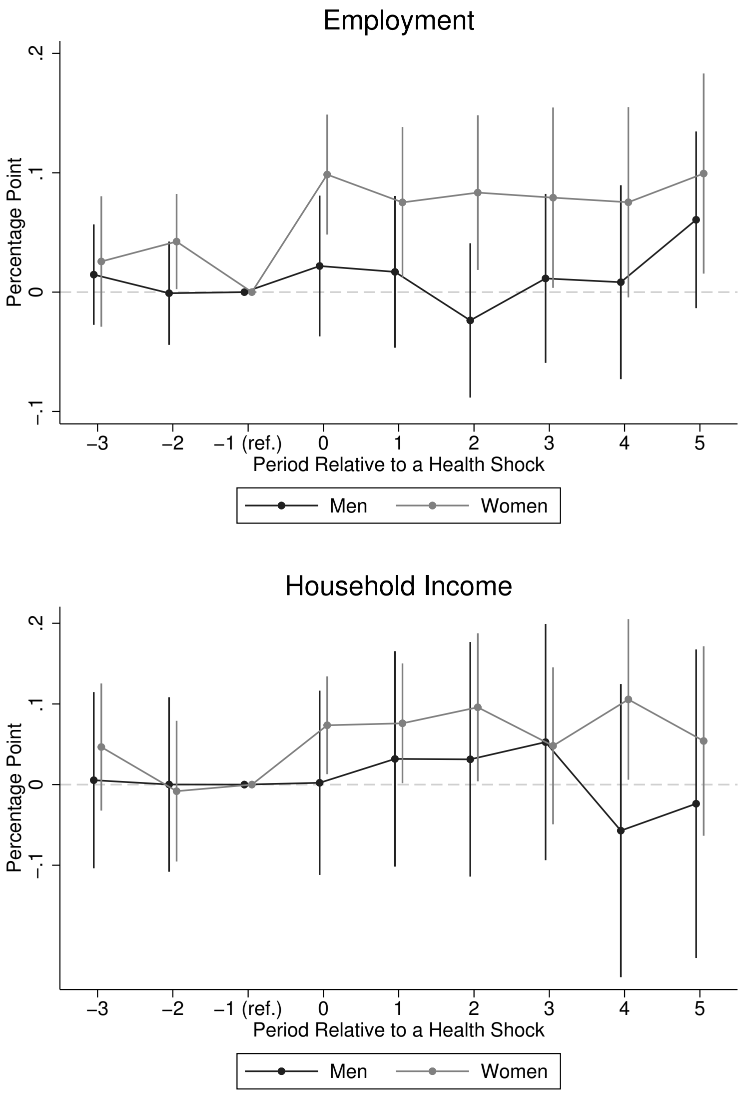

Figure 3.B.1. Dynamic Effects of Home-based Work at the Occurrence of a Health Shock

Chapter 4

The Effect of Commuting on Subjective Well-being and Health: Evidence from Germany*

* This chapter is based on a paper by Peter Eibich and Shuye Yu. The Max Planck Institute for Demographic Research (MPIDR) is acknowledged for hosting Shuye Yu's research stay to collectorate on this project with Peter Eibich. Also, we are particularly grateful to Rob Alessie, Jochen Mierau, Agnieszka Postepska and Stefan Pichler for their comments. We would like to thank participants of the lab talk series at MPIDR and the SOM PHD Conference for their valuable inputs. All errors and omissions are the sole responsibility of the authors.

4.1 Introduction

Commuting is an inevitable part of the daily routine for most workers. Indeed, the time spent on daily commutes has been growing over the last decades. According to the US Census Bureau, the average one-way travel time in 2019 for an American worker reached 27.6 minutes, 10% higher than in 2006 (Burd et al., 2021). A similar trend is also found, e.g., in Germany, where commuters are less reliant on cars due to better developed public transportation systems: among all workers in Germany, 27% of them spent more than 30 minutes commuting per day in 2016, while this proportion was barely over 20% in 1997 (Deutsche Welle, 2017).

Yet, commuting is not considered a pleasant part of daily life. Kahneman et al. (2004) examine people's emotional responses to various daily activities and conclude that commuting generates the lowest level of positive emotion but a high level of negative emotion. This affective reaction during commuting is also characterised as commute stress, which describes the psychological strain induced by commuting (Chatterjee et al., 2020).

This paper investigates how commuting impacts people's overall health and well-being. Our study addresses the endogeneity problem associated with individual choice of the length of commutes, captured by one-way commuting distance, in an instrumental variable (IV) approach, exploiting variation in a set of regional characteristics that are related to individual commuting behaviour. We link individual-level data from the German Socio-Economic Panel (GSOEP), covering the period 2001-2017, to state- and county-level data from a governmental database in Germany operated by the Federal Institute for Research on Building, Urban Affairs and Spatial Development.

The relationship between commuting behaviour and well-being or health has attracted a lot of interest across disciplines such as economics, sociology, regional studies and public health (see Chatterjee et al. (2020) for a review). For example, in one of the first studies, Stutzer and Frey (2008) show that the life satisfaction reported by workers with longer commuting time is systematically lower than those with shorter commuting time. Their back-of-the-envelope calculation based on a sample of German workers suggests that the utility loss of a 22-minute daily commute (one-way), which is the sample mean in their paper, is equivalent to an income loss of 470 euros per month.

Following Stutzer and Frey's (2008) pioneering research, many studies have examined the relationship between daily commutes and well-being using various data sources and measurements of well-being. Most of their findings support this negative association. They find that a long commute is detrimental to one's mental well-being (Clark et al., 2020; Milner et al., 2017; Roberts et al., 2011) and health satisfaction (Künn-Nelen, 2016). Moreover, this correlation also differs across population groups. For example, the negative association is particularly strong for women (Roberts et al., 2011) and workers taking public transport or driving a car (Martin et al., 2014). In addition, some papers also argue that the negative association is non-linear and mainly relevant to those with extremely long commutes (e.g., over 80 km) (Ingenfeld et al., 2019; Milner et al., 2017).

However, whether these associations can be interpreted as causal effects is not clear, as previous studies primarily rely on approaches such as OLS or individual fixed-effects model. As pointed out by Stutzer and Frey (2008), the length of commuting is the result of individual choices in the housing market and the labour market, which determines one's place of residence and workplace. Hence, studies not controlling for job transitions and residential moves may suffer from confounding as both activities could also affect one's well-being. Besides these two factors, the location choice (especially for the residential location) should also depend on other factors (e.g., commuting subsidies, bargaining powers within the household and caregiving demands). Most of these factors are time-varying and difficult to observe, which might bias the OLS or individual FE estimates and undermine a causal claim.

We address the endogeneity issue by exploiting regional variation in the average commuting distance, the average price for building plots and the net number of commuters under the assumption that these regional characteristics are plausibly exogenous factors that can determine the length of commutes. Intuitively, we assume that these instruments capture regional characteristics that affect the location choice of either the place of residence or the workplace (e.g., the cost of housing or the likelihood of finding work within the same county) and are therefore in turn related to the commuting distance. At the same time, we argue that these instruments are plausibly unrelated to health or well-being conditional on a few select covariates. Indeed, the first stage of our IV estimation indicates that these candidate instruments are predictive of commuting distance. We do not detect any violation of the exclusion restriction or monotonicity assumption in two falsification exercises, which suggests that these instruments can be used to identify the causal effect of commuting on health and well-being.

We find a detrimental effect of commuting on SWB and self-rated health. The magnitude of these IV estimates is several times larger than those estimated by an OLS model or an individual FE model, suggesting that the endogeneity associated with individual commuting behaviour biases the effect of commuting downwards in these models. While the effect sizes from our IV estimates are modest, they are economically important, particularly for those with longer commuting distances (e.g., $\geq$25 km). We also explore potential mechanisms of these detrimental effects by looking at the effect of commuting on various domains of health and well-being. It seems that longer commuting distances mainly reduce workers' mental health rather than their physical health. Additionally, in line with poorer mental health, workers with long commutes feel less satisfied with their sleep, leisure time and family life.

Our paper contributes to the growing literature on commuting in three ways. First, our study identifies the causal effect of commuting on health and well-being. The proposed instruments appear to address the endogenous length of commutes effectively. Comparing the effect sizes from our IV estimates to those obtained through OLS or FE estimation suggests that the detrimental effect of commuting has been underestimated in previous studies.

Second, our paper proposes some potential pathways for the detrimental effects of commuting on SWB and health. In terms of SWB, previous research has documented the associations between the length of commutes and satisfaction with two domains: leisure (Clark et al., 2020; Ingenfeld et al., 2019; Lorenz, 2018) and family life (Lorenz, 2018). Our analyses of domain satisfaction confirm the negative impacts on these two domains. In addition, we also highlight similar detrimental effects on other aspects of life (e.g., health and sleep). Similarly, for health, disaggregating general health into several health domains, we conclude that the health effect of long commuting distances is driven by poorer mental health.

Third, our analyses contribute to the debates around home-based work that have arisen in the wake of the COVID-19 pandemic. Our results suggest that measures such as home-based work might alleviate the burden of commuting long distances. This contribution is timely from the policy perspective as there is an ongoing debate on whether home-based work can be a permanent working arrangement in the post-pandemic era. While workers' right to request flexible working arrangements has been guaranteed in many developed countries (e.g., the Netherlands and the UK), home-based work is not one of the options in some countries (e.g., Germany) or applies exclusively to certain groups of workers (e.g., Australia). Our paper suggests enlarging the scope of home-based work so that workers, especially those with long commuting distances, could have an option to reduce the detrimental effects imposed by daily commutes.

The remainder of this paper is organised as follows. Section 4.2 provides some background information on the administrative regions and commuting behaviour in Germany; Section 4.3 discusses the dataset and the variables in our analyses; Section 4.4 describes the method and tests the fundamental assumptions of the identification strategy; Section 4.5 presents the main analyses; Section 4.6 proposes some potential mechanisms for the main effect; Section 4.7 concludes.

4.2 Institutional Setting

4.2.1 Administrative Regions in Germany

Germany is a federal republic consisting of 16 states ("Länder"). States have legislative and executive autonomy in certain areas, e.g., policing and education. States vary considerably in size and population – three of the 16 states are so-called "city states" (Berlin, Hamburg, and Bremen) and only cover the greater metropolitan areas around these cities, whereas the remaining 13 states cover both rural and urban areas. These 13 non-city states vary considerable in size, ranging from 2,571 km^2 (Saarland) to 70,541 km^2 (Bavaria). Similarly, the population size of these states varies between 676,463 (Bremen) or 982,348 (Saarland) to 17,924,591 (Northrhine-Westphalia) as of 2021 (Federal Statistical Office, 2022). It is thus not surprising that there is wide variation across states in economic indicators as well. For example, the unemployment rate in 2020 varied between 3.6% (Bavaria) and 11.2% (Bremen).

Germany is further divided into 401 counties and county-free cities ("Kreise und kreisfreie Städte", for simplicity we refer to these simply as counties). Counties have devolved executive powers and are responsible, e.g., for the organisation and administration of public transport, public schools, the county police as well as public health. Counties are very heterogenous, e.g., the three city states each constitute a single county, whereas each of the 13 non-city states is further subdivided into a number of counties. Eibich and Ziebarth (2014) document this heterogeneity for a wide range of indicators. For example, as of 2011 the area size of the 402 counties varied from 36 km^2 to 5,812 km^2 (which is more than twice the area size of the smallest non-city state). The average available income per month varied between 1,109 euros and 2,702 euros during the period 2006 to 2010.

4.2.2 Commuting Behaviour in Germany

In this study, we consider employees as commuters if they report a usual place of work which is not on the same property as their place of residence. In 2020, this included 98.1% of all employees (Federal Statistical Office, 2020). The modal length of commuting in 2020 was between 10 and 25 km (one-way distance) or between 10 to less than 30 mins. 25.8% of all employees commuted less than 5 km, whereas 19.9% commuted over 25 km. Around 20% of employees commuted for less than 10 mins, whereas 5% commuted for more than an hour. 68% of commuters used a car, and this share has remained fairly stable over time (Federal Statistical Office, 2020). Around 14% of commuters used public transport, 10.4% commuted by bike and 6.1% walked to work (Federal Statistical Office, 2020). Around 40% of all employees crossed a county-border on their way to work (Federal Employment Agency, 2021).

4.3 Data

4.3.1 Data Sources

This study uses data from two sources. First, individual-level data come from the German Socio-Economic Panel (GSOEP), a nationally representative longitudinal household survey in Germany conducted annually since 1984. We also use regional information from the INKAR database ("Indikatoren und Karten zur Raumund Stadtentwicklung") managed by the Federal Institute for Research on Building, Urban Affairs and Spatial Development. The INKAR database contains around 600 indicators that provide a large set of regional statistics covering demographics, the economy and transportation at different levels of regional aggregation.

4.3.2 Variables

Outcomes

We focus on two outcomes in the main analysis: subjective well-being (SWB) and self-rated health. SWB is operationalised using a question on general life satisfaction. Respondents are asked, "All in all, how satisfied are you currently with your life?" The answer is recorded on an 11-point Likert scale, ranging from "0 – completely dissatisfied" to "10 – completely satisfied". This measure is considered to be a cognitive measure of life satisfaction, which captures respondents' satisfaction across different domains such as work, leisure, or family life. Thus, it appears well-suited to examine the potentially complex impact of commuting on well-being.

Self-rated health is measured on a 5-point Likert scale. Respondents are asked, "How would you describe your current health?" Possible replies include "bad", "less good", "satisfactory", "good" and "very good", each of which corresponds to an integer ranging from 1 to 5, respectively. This subjective health measure captures both aspects of physical and mental health, and it has been shown to correlate strongly with more objective measures of health and mortality (Kaplan et al., 1996). Previous studies on the health impact of commuting have considered measures of both mental health, such as MHI5 (Milner et al., 2017) and GHQ-12 (Martin et al., 2014; Roberts et al., 2011), and physical health, e.g., sleep disturbances (Nie & Sousa-Poza, 2018) and overweight (Lopez-Zetina et al., 2006). Therefore, we use self-rated health to capture the overall impact of commuting across different dimensions of health.

Measuring the Burden of Commuting

As the main explanatory variable in this study, the burden of commuting is measured by commuting distance. While commuting time is considered more appropriate in the context of well-being (Stutzer & Frey, 2008), we do not use this measure as it is not available in more recent waves of the GSOEP. Moreover, there is limited overlap in the periods for which commuting time and regional information are both available.[1] In addition, a recent paper by Giménez-Nadal et al. (2021) documents a systematic difference in the time used for morning and evening commutes, which may lead to different interpretations when respondents are required to report a single commuting time.

To our knowledge, a similar asymmetric pattern of commuting distance has not been documented. Also, commuting distance is a good proxy for the burden of commuting (Stutzer & Frey, 2008) and has been widely adopted in previous studies (Ingenfeld et al., 2019; Le Barbanchon et al., 2021; Lorenz, 2018; Wang & Yang, 2019).

To report the information on commuting, respondents are asked how far they travel to work on a typical workday. They can report either the distance in kilometres or respond with one of the two options: (i) "Can't say because workplace varies", or (ii) "Workplace and home are in the same building". Note that the reported commuting distance should be interpreted as the distance of a one-way journey instead of the straight-line distance between home and the workplace.

Instrumental Variables

Our analysis addresses the endogeneity associated with self-reported commuting distance in an IV approach. We consider three time-varying instrumental variables for commuting distance: the average commuting distance in a state, the average price for building plots in a county and the net number of commuters scaled by the number of workers in a county. The state-level commuting distance is the average individual commuting distance of the GSOEP sample in a given state and year. Among the 16 states in Germany, two small states in terms of population and area (Bremen and Saarland) are merged with the neighbouring states (Lower Saxony and Rheinland-Pfalz, respectively).

The other two instruments are drawn from the INKAR database. The average price for building plots is based on all sales of unbuilt land of at least 100 m^2 designated for construction over the last two years within a county. The third instrument only considers the commuters travelling across counties. The net number of com-

[1] The information on commuting time is available in 1985, 1990-1993, 1995, 1998 and 2003. Only the last two periods can be linked to the regional information.

muters is defined as the difference between the number of people commuting into a given county (i.e., who are living in other counties) and the number of people commuting out of the county (i.e., who are living in this county but work elsewhere). This net value is scaled by the total number of employees in the county. We standardise these instruments with the mean of zero and the standard deviation of one. Hence, the estimated coefficients in our later analyses should be interpreted as the marginal effect of a one-standard-deviation change in an instrument on an outcome variable. We show these variables satisfy IV assumptions and thus are appropriate instruments for our study in Section 4.4.2.

Covariates

An IV approach is only adequate if instruments are not correlated with the error term, i.e., all other channels through which instruments can affect an outcome should be controlled for in the model. Therefore, we include two variables to ensure our model has captured other potential channels (see also Section 4.4.1). One variable is dwelling satisfaction, which describes one's satisfaction with the place of residence using the same 11-point Likert scale as our SWB measure. The other variable is the regional GDP per employed person for the county where a respondent lives.

Additionally, we control for a standard set of economic and demographic indicators, including age, age squared, marital status, years of schooling, the number of children, the number of household members (square root) and 14 industry-fixed effects.[2]

4.3.3 Sample Selection

Our working sample includes data from 15 waves of the GSOEP study, covering the period between 2001 and 2017.[3] Data from earlier waves are not included as the question for commuting distance was phrased inconsistently and answered by

[2] The 14 included industrial dummies are defined by the level I codes for the NACE Rev. 1.1 classification. We merge categories with a small sample size to other categories: 1) fishing to agriculture 2) mining to energy and 3) arts, other social activities, household workers and activities of extraterritorial organisations to others.

[3] The information on commuting distance is available in the following years: 2001-2013, 2015 and 2017.

different groups of people in these periods.[4] We restrict our analysis to all workers aged from 18 to 65 that reported a valid commuting distance, accounting for 87% of the total workers. We exclude those whose workplace and home are in the same building and those who reported that their workplace varies. Among all commuters, we exclude those whose commuting distance is longer than the 99^{th} distance percentile (i.e., 200km) to avoid extreme outliers (e.g., 999km). We only include employees and exclude self-employed individuals, even if some have a positive commuting distance. Most self-employed individuals will have more control over the location of their workplace than employed workers, and we would therefore expect more heterogeneity in the effect of commuting on self-employed individuals.[5] The analytical sample in the present study consists of 158,322 person-year observations for 39,516 individuals.

4.3.4 Descriptive Statistics

Table 4.1 provides summary statistics for the variables used in the main analysis. The average one-way commuting distance for our sample is 16.35 km per working day, which closely aligns with the official statistics of 16.91 km released by the Federal Office for Building and Regional Planning (Deutsche Welle, 2017). Additionally, the gender of our sample is relatively balanced, with slightly more men than women. The average age is around 42. Most observations in our sample are married and living with two other household members, but 54% of the observations do not have any children in the household.

4.4 Methods

4.4.1 The IV model

If commuting distance was as good as randomly assigned conditional on control variables, then we could estimate the effect of commuting distance on outcomes

[4] For example, in some earlier waves, only respondents commuting to a different town were asked to report their commuting distance. Since 2001, the phrasing of the question has remained constant, and the question has been answered by all commuters.

[5] Some previous studies also exclude the self-employed people in their analyses, such as Künn-Nelen (2016); Martin et al. (2014); Roberts et al. (2011). We also re-estimate the model by including the self-employed people with positive commuting distance. The results remain similar to the main analysis.

Table 4.1. Descriptive Statistics

Variable	Mean	S.D.	Min	Max
Dependent variables				
SWB	7.25	1.60	0	10
Health	3.58	0.86	1	5
Independent variables				
Commuting distance (km)	16.35	20.45	0	200
Instrumental variables (non-standardised)				
Average commuting distance (km)	16.11	1.76	10.93	22.23
Average price for building plots (euro/m^2)	178.46	213.75	4.80	2428.70
Net number of commuters	-8.41	29.77	-148.90	67.50
Other control variables				
Age	42.07	11.05	18	65
Age square/1000	1.89	0.92	0.32	4.23
Gender	1.51	0.50	1	2
Marital status				
- Single	0.25	0.43	0	1
- Married	0.62	0.49	0	1
- Other marital status	0.13	0.34	0	1
Number of household members	3.01	1.31	1	15
Number of Children in household				
- No child	0.54	0.50	0	1
- One child	0.21	0.41	0	1
- Two children	0.18	0.38	0	1
- More than two	0.07	0.26	0	1
Years of Schooling	12.59	2.69	7	18
County-level GDP	61.00	13.51	33.30	163.60
Satisfaction with dwelling	7.80	1.85	0	10

with the following regression model:

$$y_{isct} = \theta distance_{it} + \mathbf{x}'_{isct}\boldsymbol{\beta} + \mu_t + \omega_s + \alpha_i + \epsilon_{isct}, \tag{4.1}$$

where y_{isct} is the outcome variables of an individual i living in state s and county c at time t; $distance_{it}$ is the individual commuting distance; $\mathbf{x}_{isct}$ is a vector of covariate; ω_s and μ_t denote the state and time fixed effects, α_i is an individual fixed effect, and ϵ_{isct} is the idiosyncratic error term. If all relevant confounders are included in $\mathbf{x}_{isct}$, we can estimate the model using pooled OLS, and the individual fixed effect α_i becomes part of a composite error term, $\nu_{isct} = \alpha_i + \epsilon_{isct}$. This assumption may not be very plausible, and therefore many previous studies have estimated Eq. (4.1) as a fixed effects panel regression model to account for time-invariant unobserved confounders. Yet, time-varying unobserved factors that influence both the commuting distance and the outcome remain a cause of concern in the fixed effects model. This is particularly problematic due to our focus on the commuting distance – identification of the parameter θ in the fixed effects model comes only from a within-person variation of the commuting distance. It seems plausible that most of the within-person variation in commuting distance is driven by either residential moves or job transitions. In the absence of a large natural experiment (e.g., road closures), it is difficult to imagine where within-person variation in the commuting distance would come from if both the residential address and the workplace do not change. Residential moves and job transitions are major events, which may plausibly affect health and SWB through other channels in addition to a change in the commuting distance. Therefore, it is questionable whether a fixed effects approach can resolve the endogeneity problem.

Thus, we consider instrumental variables estimation as an alternative approach to address this endogeneity issue. To do so, we first regress the commuting distance on a set of instrumental variables and other control variables. The corresponding first-stage regression model is as follows:

$$distance_{it} = \mathbf{z}'_{sct}\boldsymbol{\delta} + \mathbf{x}'_{isct}\gamma + \mu_t + \omega_s + \nu_{isct}, \tag{4.2}$$

where $\mathbf{z}_{sct}$ is a vector of one or more instruments. Then, we generate the predicted commuting distance, $\widehat{distance}_{it}$, from Eq. (4.2) and replace the commuting distance in Eq. (4.1) with the predicted value to obtain a consistent estimate of the parameter of interest θ.[6]

The estimated parameter θ can be interpreted as a *local average treatment effect* under three assumptions: *(i) relevance*, *(ii) validity* and *(iii) monotonicity*. Relevance requires that the instrument is correlated with the endogenous variable. Validity means that the instrument itself is as good as randomly assigned (i.e., unconfounded) and that the instrument does not affect the outcome through any pathway other than through its effect on the treatment. Monotonicity means that the effect of the instrument on the treatment should operate in the same direction (i.e., non-negative or non-positive) for all units in the sample.

For this study, we propose three candidate instruments: *(i) the average commuting distance in a certain state and year*, *(ii) the average price for building plots in a certain county and year* and *(iii) the net number of commuters in a given county and year*. All three instruments have in common that they represent characteristics of a region that presumably influence the length of a commute, but they differ in their required assumptions.

The average commuting distance in a certain state and year is a broad measure, which should capture regional characteristics that influence the commuting distance of all employees residing in that state. For example, urban sprawl or an economic infrastructure with large manufacturing plants or logistic hubs located in rural communities might lead to longer commuting distances for residents of a region. Assuming that the average commuting distance reflects such regional characteristics, it should also be predictive of individual commuting distances. The validity of this instrument will depend on the presence of unobserved regional characteristics that are correlated with both the average commuting distance as well as SWB and health. The presence of such factors would imply that the instrument is not as good as randomly assigned. For example, regional transportation links (which are captured by the average commuting distance) might be better developed in more affluent states. We aim to address such potential violations of the validity assumption in three ways. First, in all empirical models (including those for the other two

[6] Note that the error term in our IV model is a composite error, $\nu_{isct} = \alpha_i + \epsilon_{isct}$. Given the plausibility of the IV assumptions, the endogeneity issue can be addressed with an IV model without including individual fixed effects. Thus, we do not employ an FE-IV model in the main analysis despite the longitudinal structure of our data. Appendix Table 4.A.1 presents the FE-IV estimates, which are similar to the IV estimates.

candidate instruments), we control for the county-level GDP per employed person to capture aggregate income differences between regions. Second, our empirical models include a set of state-fixed effects, which should capture unobserved regional characteristics more broadly. Third, we conduct a falsification exercise to detect potential violations of the validity of our instruments (see Section 4.4.2 below).

The average price for building plots per county and year reflects the cost of housing in a county. Assuming that the location of the workplace is fixed or exogenously determined, individuals will choose a place of residence based on a number of relevant factors, e.g., the length of their commute or the cost of housing. All else equal, individuals will be more willing to accept a longer commute if the cost of living in a more distant county is lower. We would therefore expect that living in a county with a lower price for building plots should be correlated with a longer commute. As with the previous instrument, the validity of the price for building plots as an instrument for commuting distance depends on the (non-) existence of other regional characteristics that might be correlated with health and well-being. A particular concern is the quality of housing – in regions with lower cost of housing, individuals might be able to afford housing of higher quality than in regions with higher cost. It seems plausible that the quality of housing affects well-being in particular, which would imply a violation of the exclusion restriction. Therefore, we control for the satisfaction with one's housing ("dwelling satisfaction") as a measure of housing quality.

The third and last instrument is the net number of commuters scaled by the total number of employees in a county and year. This instrument is expected to capture the demand for labour in a county relative to surrounding regions. Counties with a positive number attract more commuters living in other counties than there are residents commuting out of the county for work. This is likely due to the strong demand for labour in the county, which means that residents of the county are likely to find work within the county. On the other hand, in counties with a negative number, more residents are commuting out of the county for work than there are residents of other counties commuting in. This is likely driven by the weaker demand for labour in the county, and therefore residents of the county are more likely to have to commute across county borders. Overall, we would therefore expect that higher values of the instrument are correlated with shorter commutes. As with the previous two instruments, it is possible that the strength of the labour demand in a county is correlated with other county-level characteristics that influence health or well-being. Additionally, high-quality housing may be more accessible in a county where more people reside in (i.e., the value of this instrument is negative). We therefore control for dwelling satisfaction and regional GDP per employee.

In the following section, we also conduct a number of tests and falsification exercises to empirically assess the plausibility of the IV assumption for all three candidate instruments.

4.4.2 Assessing IV Assumptions

Relevance

Table 4.2 below presents the results of the first-stage IV estimation, which regresses commuting distance on the instruments and other control variables. Columns 1-3 show the results when a single IV is included, while Column 4 shows the result including all three IVs jointly. The estimate can be interpreted as the marginal effect of a one-standard-deviation increase in each instrument on individual commuting distance. The statistically significant results suggest that all these instruments are relevant predictors of commuting distance. As expected, the state-level average commuting distance positively affects individual commuting distance. The county-level average price for building plots, representing the trade-off between the cost of living and the length of commuting, and the net number of commuters, representing the regional labour demand, negatively affect individual commuting distance. When all IVs are added to the model (Column 4), their estimates remain similar to those in Columns 1-3, where each IV is included individually. This result implies that these factors affect commuting distance through distinct mechanisms.

Table 4.2 also reports the efficient F-Statistic proposed by Olea and Pflueger (2013), which indicates the strength of the excluded instruments.[7] These F-statistics are considerably larger than the rule-of-thumb threshold of 10. Moreover, most of these F-statistics are also greater than the critical value of 104.7 proposed by Lee et al. (2021) in a recent paper. Therefore, we conclude that the candidate instruments

[7] A user-written Stata command "weakivtest" by Pflueger and Wang (2015) can report this F-Statistic.

are strongly predictive of commuting distance, and weak instrumental variables are not a major concern in our analyses.

IV Validity

As noted above, the instruments might be related to individual health and well-being due to the presence of unobserved regional characteristics. The quality of housing and regional income in particular are causes of concern. High-quality housing is more affordable in regions where the land price is low, and its availability might be higher in residential regions where the number of incoming commuters is small. At the same time, high-quality housing is likely to affect well-being in particular, but potentially also health. Similarly, counties with higher land prices and stronger labour demand (i.e., a higher number of net commuters) are likely to be more affluent, and the effects of aggregate economic conditions on individual health and well-being are well-documented (see Ruhm (2006) for a review). We therefore control for dwelling satisfaction and the county-level GDP per employee in all models.

We conduct a falsification exercise proposed by Angrist et al. (2010) to detect potential violations of this assumption. This test estimates the reduced-form IV model using employees who do not commute. As the main purpose is to examine whether instruments affect outcomes through unobserved channels, there is no particular reason to exclude the self-employed workers that work from home from this falsification test.[8] For the respondents that do not commute, the instrumental variables are not predictive of their commuting distance, i.e., the first stage of the IV regression does not work. Therefore, if the estimate for an instrument in the reduced-form regression is statistically significant, this instrument is suspected to affect our outcomes through pathways other than commuting, which violates the exclusion restrictions.

Table 4.3 displays the results of the falsification test. Across the board, most of the estimates are statistically insignificant, meaning that we fail to detect any uncontrolled channels that undermine the validity assumption for these instruments.[9]

[8] Note that we add an additional dummy variable "self-employed" to capture the effect of being self-employed on outcomes relative to have a paid job.

[9] Appendix Table 4.A.2 provides the estimates of a reduced-form IV regression for commuters. In contrast to the result of this falsification exercise, all instruments are statistically significant.

The only exception is the average commuting distance in Panel B, which is significant at the 10% level. However, we argue that this significant coefficient should not be interpreted as a major threat to the validity assumption for three reasons. First, the average commuting distance is only marginally predictive of self-rated health, given the significance level of 0.1. Second, due to the strong correlation between SWB and health, it is difficult to imagine one instrument affecting health has not affected SWB in a similar way. However, the coefficient in Panel A appears to be statistically insignificant. Third, and most importantly, Table 4.5 in Section 4.5.2 presents the results for the second-stage IV estimation. The effect size of commuting distance predicted by this instrument does not differ substantially from those predicted by other less problematic instruments. In sum, we argue that the validity assumption is plausible in our setting.

Monotonicity

Our instruments may affect the treatment variable heterogeneously across subgroups (e.g., by educational level or gender). The identification of the *local average treatment effect* relies on the assumption of monotonicity, which implies that the impact of any instruments on the treatment variable (i.e., individual commuting distance) should be in the same direction for all observations in the sample. We conduct a falsification exercise, also adopted by Bhuller et al. (2020); Hjalmarsson and Lindquist (2019), to detect potential violations of the monotonicity assumption. We re-estimate the first stage of the IV model for 12 subgroups defined by six socio-demographic variables (i.e., marriage, age, children, gender, working hours and years of schooling). Then, we check whether the sign of the IV estimates for each subgroup is consistent across subgroups and in the same direction as the one presented in Table 4.2.

Figure 4.1 shows the effect and the corresponding 95% confidence interval of each instrument for subgroups with certain characteristics. Most of these point estimates are in the same direction as those reported in Table 1. The only exception is the effect of the average price for building plots for the lower-educated group (years of schooling$<$12), where the point estimate is positive.[10] However, this result should not be interpreted as a violation of monotonicity since the estimate is very

[10] These are individuals without a high school degree.

close to zero and not statistically significant. Hence, we argue that we fail to find evidence for a violation of the monotonicity assumption.

Table 4.2. First-Stage IV Estimates

	(1) IV1	(2) IV2	(3) IV3	(4) All IVs
Average commuting distance	1.567***			1.476***
	(0.152)			(0.151)
Average price for building plots		-0.846***		-0.523***
		(0.0963)		(0.0974)
Net number of commuters			-1.925***	-1.853***
			(0.129)	(0.131)
F-Statistic	107	77	222	154
State FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Individuals	37,552	37,552	37,552	37,552
Observations	153,822	153,822	153,822	153,822

Notes: This table reports the first-stage estimates of the IV estimation. Columns 1-3 provide estimates using each IV separately. Column 4 provides estimates using all IVs jointly. Standard errors in parentheses are clustered at the individual level. Significance levels are shown as *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4.3. Test for the Exclusion Restriction

	(1) IV1	(2) IV2	(3) IV3	(4) All IVs
Panel A: for SWB				
Average commuting distance	-0.037			-0.038
	(0.055)			(0.056)
Average price for building plots		-0.028		-0.038
		(0.034)		(0.035)
Net number of commuters			0.039	0.044
			(0.030)	(0.030)
Panel B: for health				
Average commuting distance	-0.055*			-0.055*
	(0.032)			(0.032)
Average price for building plots		0.008		0.009
		(0.019)		(0.019)
Net number of commuters			-0.006	-0.007
			(0.018)	(0.018)
State FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Individuals	3,325	3,325	3,325	3,325
Observations	8,717	8,717	8,717	8,717

Notes: This table reports the results of the falsification test based on employees without daily commutes (i.e., home-based workers). Columns 1-3 provide estimates using each IV separately. Column 4 provides estimates using all IVs jointly. Standard errors in parentheses are clustered at the individual level. Significance levels are shown as *** p<0.01, ** p<0.05, * p<0.1.

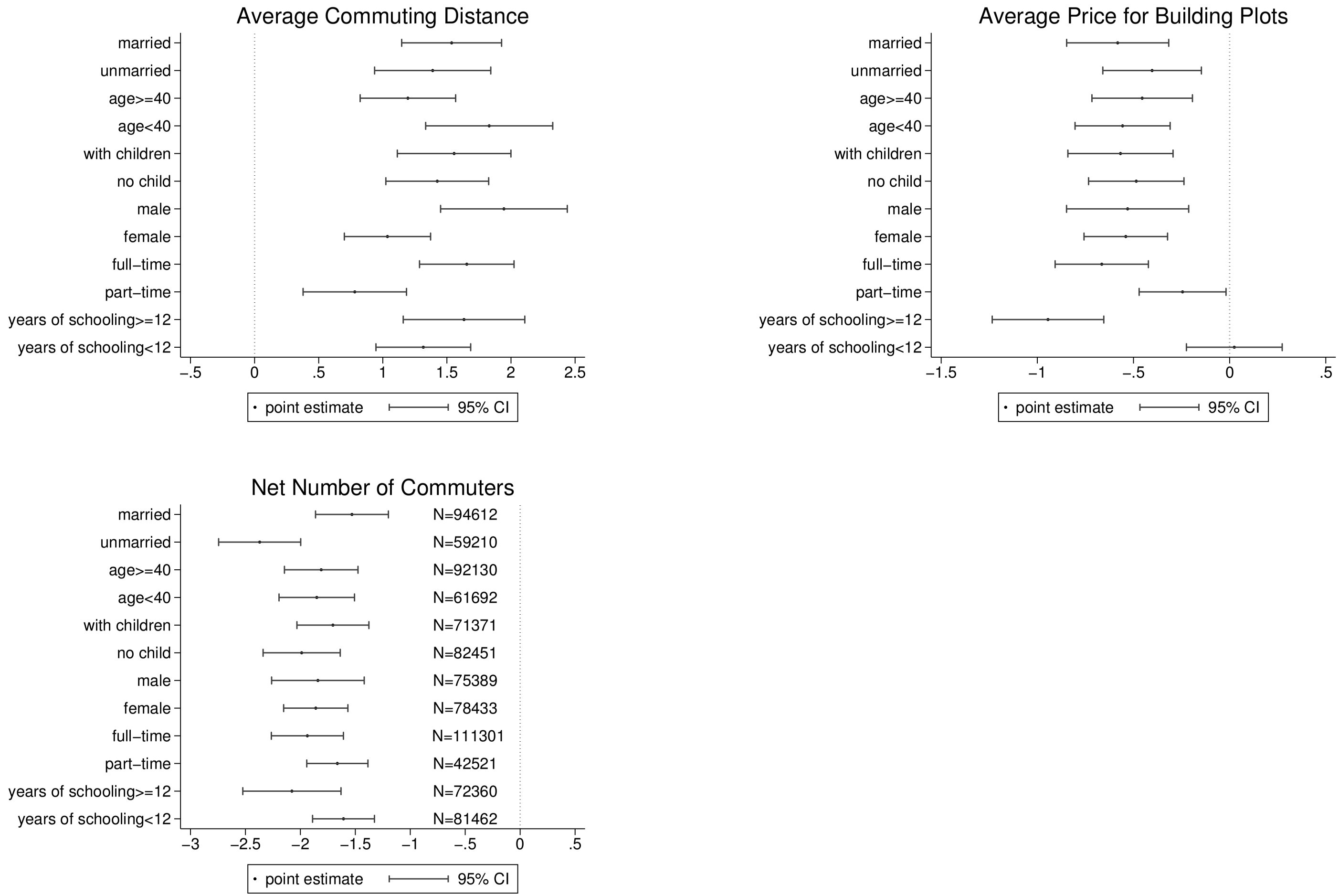

Figure 4.1. First-Stage IV estimates by socio-demographic characteristics

Note: The sample size of each sub-group applied to each sub-figure is shown in the third sub-figure. The dependent variable for these estimations is individual commuting distance.

4.5 Results

4.5.1 Baseline Results

Table 4.4 presents the results from a pooled OLS model and an individual FE model, where we regress our outcome variables on commuting distance. These models do not resolve the endogeneity of commuting distance using the proposed IVs, rather they closely resemble empirical specifications used in previous studies (e.g., Stutzer and Frey (2008)) and will be used as a baseline for comparison with our IV estimates. Due to the small effect size of one-kilometre commuting, point estimates and standard errors are rescaled by ten kilometres of commuting in Table 4.4.[11] The first two columns show the results for SWB, and the following two columns display results for health. These results suggest that commuting distance is negatively associated with SWB and health. Although statistically significant, the effect of commuting distance on the outcomes is very small. For example, the FE estimates indicate that the marginal impact of a 10-kilometre commute is -0.02 for SWB and -0.01 for health, which corresponds to a change in 0.01 standard deviations of each outcome (see Table 4.1). The modest magnitude of the point estimates remains consistent with several previous studies (Künn-Nelen, 2016; Lorenz, 2018; Stutzer & Frey, 2008). Notably, the OLS estimates do not differ substantially from the FE estimates, especially for health, suggesting that endogeneity from unobserved time-invariant personal characteristics does not play a major role. However, time-varying unobserved characteristics may still bias these estimates, and we thus address this endogeneity issue using an IV approach.

4.5.2 IV Results

Table 4.5 reports the results for the second stage of the IV estimation. We regress SWB (Panel A) and health (Panel B) on the predicted commuting distance and other control variables. These estimates suggest a negative impact of commuting distance on SWB and health. For comparison, we plot the point estimates and corresponding 95% confidence intervals from different models in Figure 4.2. It is clear that the effect size of commuting distance estimated in an IV model, regardless of which instrument is used, is considerably larger than the one from a pooled OLS model or

[11] Commuting distance is diplayed on a one-kilometre basis in the rest of the result tables and figures.

a FE model, i.e., the marginal effect of an increase in the commuting distance by 10 km corresponds to a change in 0.15 standard deviations for SWB and 0.07 standard deviations for health. One potential explanation is that estimation through pooled OLS or a FE model does not account for unobserved factors that compensate for the disutility of a lengthy commute, resulting in an upward bias in the estimates for the effect of commuting distance. For example, people might choose to commute longer distances to live closer to their friends or family, which might improve their well-being and health.

We do not find substantial differences in the magnitude across the IV estimates using different instruments in Columns 1-4. Hence, in the following analyses, we only present the results from the specification with all three instruments included jointly.

We also conduct the Durbin-Wu-Hausman test to test the endogeneity of commuting distance and report the χ^2-statistic and its corresponding significance level at the bottom of each panel. All test results reject the null hypothesis that the commuting distance can be treated as exogenous, which supports our IV approach.

Table 4.4. OLS and FE Estimates

	(1)	(2)	(3)	(4)
	SWB		Health	
	OLS	FE	OLS	FE
Commuting distance (10 km)	-0.017***	-0.006*	-0.008***	-0.005***
	(0.003)	(0.003)	(0.002)	(0.002)
State FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Individual FE	No	Yes	No	Yes
Individuals	37,552	25,696	37,552	25,696
Observations	153,822	141,966	153,822	141,966

Notes: This table reports OLS and FE estimates. The estimates and standard errors of commuting distance are displayed on a 10-kilometre basis. Columns 1 & 3 provide the OLS estimates. Column 2 & 4 provides FE estimates. Standard errors in parentheses are clustered at the individual level. Significance levels are shown as *** p<0.01, ** p<0.05, * p<0.1.

In Appendix Table 2, we present a fixed-effects IV model and conduct the endogeneity test. All tests also reject the null hypothesis, which further supports the argument that the endogeneity of commuting distance cannot be fully attributed to unobserved time-invariant personal characteristics.

Table 4.5. Second-Stage IV Estimates

	(1) IV1	(2) IV2	(3) IV3	(4) All IVs
Panel A: for SWB				
Commuting distance	-0.020***	-0.026***	-0.024***	-0.024***
	(0.006)	(0.009)	(0.004)	(0.004)
Durbin-Wu-Hausman test	8.917***	7.626***	32.623***	43.621***
Panel B: for health				
Commuting distance	-0.007**	-0.014***	-0.006**	-0.006***
	(0.003)	(0.005)	(0.002)	(0.002)
Durbin-Wu-Hausman test	3.292*	6.408***	4.550**	10.224***
State FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Individuals	37,552	37,552	37,552	37,552
Observations	153,822	153,822	153,822	153,822

Notes: This table reports the second-stage estimates of the IV estimation. Columns 1-3 provide estimates using each IV separately. Column 4 provides estimates using all IVs jointly. Standard errors in parentheses are clustered at the individual level. The endogeneity test shows the $\chi^2(1)$ statistic and its significance. Significance levels are shown as *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

4.5.3 Robustness Checks

Non-linear Effects

Many previous studies apply a specification that includes the quadratic form of commuting distance or time to allow a non-linear effect of a lengthy commute on

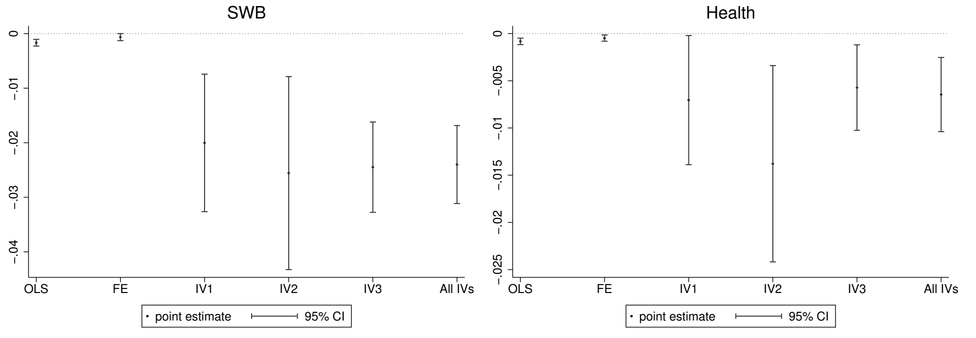

Figure 4.2. Effect of commuting distance on SWB and health

Note: The two graphs plot the estimates for commuting distance in an OLS model and the corresponding 95% confidence intervals, an individual FE model and an IV model, respectively. The outcome variable for the graph on the left (right) is SWB (health).

outcomes (Künn-Nelen, 2016; Lorenz, 2018; Stutzer & Frey, 2008). We therefore add the commuting distance squared to the model to examine the presence of non-linearities.

Given the endogeneity of commuting distance, the quadratic term should also be treated as endogenous. To solve the endogeneity problem for both variables, we adopt a control function approach as suggested by Wooldridge (2015), which corrects for the endogeneity bias by incorporating the residual of the first-stage regression into the second-stage equation. To implement this method, we predict the residual, $\hat{e}_{isct}$, after estimating the first-stage equation (i.e., Eq. (4.2)). Then, we add $\hat{e}_{isct}$ in the second-stage equation as an additional independent variable. The predicted residual should have captured the endogenous part of commuting distance given the exogeneity of the instrumental variables. Thus, once we control for $\hat{e}_{isct}$, we should obtain consistent estimates of the effects of commuting distance and its squared term.

Table 4.6 provides the second-stage results where the commuting distance squared is added to the model in Columns 1 and 3. The standard errors are drawn from 200 bootstrap replications. For ease of comparison, we also duplicate the results without the squared term in Columns 2 and 4 from the main analyses. We find the estimates of the squared term are statistically significant for both outcomes, suggesting a non-linear marginal effect of commuting distance: the marginal effect decays as the commuting distance becomes longer.[12] However, consistent with previous studies, these estimates are too small to become economically significant. Moreover, regardless of the inclusion of the squared term, the estimates of commuting distance and constant remain almost the same.

Figure 4.3 illustrates the similarity of the results for the linear and quadratic specifications by showing their predicted values across different commuting distances. We find that the predicted values generated from both specifications are highly similar except for some long distances that only a small number of people travel. Therefore, while the marginal effect of commuting distance appears to be non-linear, we argue that including the squared term does little to alter our main conclusions.

Table 4.6. Non-linear Effects of Commuting Distance

	(1)	(2)	(3)	(4)
	SWB		Health	
Commuting distance	-0.024***	-0.024***	-0.007***	-0.006***
	(0.002)	(0.004)	(0.001)	(0.002)
Commuting distance sq./1000	0.012***		0.010***	
	(0.003)		(0.002)	
$\hat{e}_{isct}$	0.022***		0.005***	
	(0.002)		(0.001)	
Constant	5.741***	5.737***	3.557***	3.553***
	(0.092)	(0.137)	(0.045)	(0.073)
Turning point (km)	1,020		334	
Individuals	37,552	37,552	37,552	37,552
Observations	153,822	153,822	153,822	153,822

Notes: This table reports the estimates from the quadratic specification using three IVs jointly. Columns 1 and 3 show the results for SWB and health, respectively. For comparison, we duplicate the results without commuting distance squared in Columns 2 and 4 from Columns 4 of Table 4.5. Standard errors in parentheses are calculated using bootstrap with 200 repetitions. Significance levels are shown as *** p<0.01, ** p<0.05, * p<0.1.

[12] The turning point of this trend is at 1,020 km for SWB and 333 km for health. After that, the marginal effect appears to be positive. However, we are highly unlikely to observe this pattern as the distance for the turning point is longer than the maximum commuting distance (200 km) for our sample.

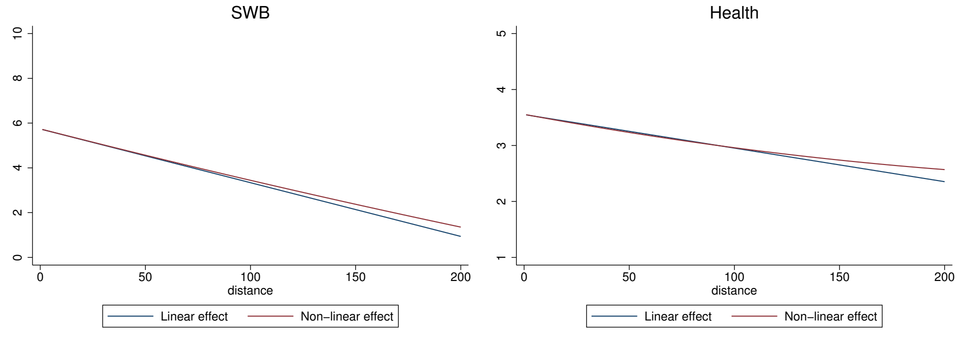

Figure 4.3. Effect of commuting distance and its quadratic term on SWB and health

Note: The two graphs plot the predicted outcomes obtained from the linear specification and the quadratic specification of the IV model. The predicted value is calculated only based on the constant and commuting distance. All other covariates are set to be zero. The outcome variable for the graph on the left (right) is SWB (health).

Relocations

Our identification strategy assumes that the instrumental variables are exogenous predictors of commuting distance, i.e., these regional characteristics influence an individual's location decisions, but they are not themselves affected by individual choices. This assumption appears reasonable, given that an individual's choices on where to work and live are subject to a number of constraints (e.g., due to partnerships and other social ties), but the assumption might be violated in a very mobile population in which relocations across longer distances are common. To mitigate this concern, we re-estimate the IV model using the observations for individuals never moving across counties during the observational period or for individuals who have ever moved but before their first move. We only observe 3,055 residential moves across county borders in our sample, corresponding to 2% of all observations. After excluding these observations, we are left with a sample in which the residential county remains constant across time. Thus, the variation in the instrumental variables should be exogenous rather than the result of residential sorting.

Table 4.7 presents the results for this robustness check where Panels A-C display the estimates for the first-stage regression, second-stage regression for SWB and second-stage regression for health, respectively. All these estimates are broadly similar to the main results. While some estimates for the second-stage regression are less precise, most of them still remain statistically significant at the 5% level (except for one of them, which is significant at the 10% level).

Table 4.7. Effects of Commuting Distance for Non-movers

	(1) IV1	(2) IV2	(3) IV3	(4) All IVs
Panel A: First-stage Estimates				
Average commuting distance	1.518***			1.430***
	(0.153)			(0.153)
Average price for building plots		-0.778***		-0.461***
		(0.100)		(0.101)
Net number of commuters			-1.911***	-1.846***
			(0.135)	(0.137)
Panel B: Second-stage Estimates for SWB				
Commuting distance	-0.023***	-0.025**	-0.025***	-0.025***
	(0.007)	(0.01)	(0.004)	(0.004)
Panel C: Second-stage Estimates for Health				
Commuting distance	-0.005**	-0.008**	-0.012*	-0.005**
	(0.002)	(0.004)	(0.006)	(0.002)
Individuals	37,552	37,552	37,552	37,552
Observations	144,021	144,021	144,021	144,021

Notes: This table reports the first-stage and second-stage estimates of the IV estimation. Columns 1-3 provide estimates using each IV separately. Column 4 provides estimates using all IVs jointly. Standard errors in parentheses are clustered at the individual level. Significance levels are shown as *** p<0.01, ** p<0.05, * p<0.1.

4.6 Effects of Commuting Distance on Health and Life Domains

So far, we have documented the detrimental effects of a lengthy commute on two overall measures of one's well-being: SWB and self-rated health. A natural next question is whether a lengthy commute affects various aspects of health and life differently. Hence, this section explores the heterogeneous effects of commuting on multiple health and life domains. This analysis also provides insights into the mechanisms through which the burden of commuting affects the overall measures of well-being. To examine these heterogeneous effects, we re-estimate the IV model that jointly includes all instruments while using a broad spectrum of domain outcomes as dependent variables.

4.6.1 SF-12

GSOEP has implemented the second version of the 12-Item Short-Form Health Survey (SF-12) in every even-numbered year since 2002. SF-12 contains 12 questions that assess a respondent's health-related quality of life across eight domains. For each question, a respondent evaluates a statement about a certain aspect of health and chooses their answer from two to five possible options. Then, the score of each domain is calculated based on the answers to the corresponding questions and rescaled to a number between 0 and 100. Moreover, these eight scores can be further converted into the scores for the physical component summary scale (PCS) and the mental component summary scale (MCS), measuring one's physical health and mental health with a number ranging from 0 to 100 (Ware Jr et al., 1996).[13]

Note that respondents have reported their commuting distance in odd-numbered years since 2013, causing a mismatch between SF-12 and commuting distance. To preserve the sample size, we impute the information on commuting distance for periods 2014, 2016 and 2018 using the value in the previous period under the assumption that the commuting distance for the working-age population does not change dramatically within one year.

Table 4.8 reports the effects of commuting distance on mental health, physical health and seven health domains.[14] For the two summary scores, MCS and PCS, we find that only the estimate for MCS is significantly negative, suggesting that a lengthy commute affects health through a negative effect on mental health. This claim is further strengthened by looking at the health domains of vitality and mental health, whose estimates are also significantly negative at the 5% level. The former is measured by the statement, "did you have a lot of energy". The neg-

[13] Andersen et al. (2007) discuss the conversion methods used by GSOEP.

[14] The excluded health domain is general health because the question for this domain is exactly the same as the one used for the health outcome in the main analysis.

ative estimate implies that a lengthy commute can lead to fatigue or being exhausted. The latter is assessed by two questions asking if someone has recently felt calm/peaceful and down-hearted/blue. The result indicates that people commuting longer distances may be more depressed and frustrated than those travelling shorter distances. Although some studies have discovered the detrimental impact of commuting on physical health (Lopez-Zetina et al., 2006; Nie & Sousa-Poza, 2018), the insignificant results for PCS and the relevant health domains in Table 4.8 all suggest that a lengthy commute does not seem to affect overall health through the pathway of physical health.

Table 4.8. Effects of Commuting Distance on Health Domains

Dependent var.	MCS (Mental Health)	PCS (Physical Health)	Physical Functioning
Commuting distance	-0.046**	-0.020	-0.016
	(0.023)	(0.020)	(0.020)
Dependent var.	Role Physical	Body pain	Vitality
Commuting distance	-0.036*	-0.018	-0.052**
	(0.021)	(0.023)	(0.023)
Dependent var.	Social Functioning	Role Emotional	Mental Health
Commuting distance	0.001	-0.008	-0.087***
	(0.022)	(0.022)	(0.024)
Individuals	29,482	29,482	29,482
Observations	82,474	82,474	82,474

Notes: This table reports the second-stage estimates of the IV estimation. Outcomes are from the SF-12 survey, including two summary scores: MCS and PCS and seven scores for health domains. Standard errors in parentheses are clustered at the individual level. Significance levels are shown as *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

4.6.2 Domain Satisfaction

We further explore the impact of commuting on satisfaction with seven life domains which are potentially affected by the burden of commuting: health, sleep, job, housework, leisure time, childcare and family life. As with SWB, all domain satisfaction scores are reported on an 11-point Likert scale.

Table 4.9 provides the results for domain satisfaction. It shows that long commuting distances impact satisfaction with the following four life domains: health, sleep, leisure time and family life, meaning that the burden of commuting spills over into other aspects of life. The negative effect on health satisfaction reiterates the health effect of a lengthy commute. The detrimental effect on sleep is in line with the results for vitality discussed above. Note that satisfaction with sleep is a subjective measure of sleep quality. Hence, the negative effect on it does not contradict the absence of a significant effect on physical health. A possible explanation is that while the sleep disturbance caused by the burden of commuting leads to a psychological reaction, it is not severe enough to entail problems for physical health. The negative impacts on the satisfaction with leisure time and family life are also documented by Clark et al. (2020); Ingenfeld et al. (2019); Lorenz (2018). Two possible reasons may explain the negative effects on the satisfaction with leisure time and family life. First, the time spent on commuting may crowd out the time spent on leisure or with family. Second, due to the mental health effects of commuting, people may obtain less enjoyment from leisure and family life. A potential reason for the insignificant estimate of job satisfaction is that respondents are able to distinguish between their affects yielded from commuting and from working despite the connections between these two domains. The insignificant estimates of housework and childcare suggest that these two life domains are not strongly associated with daily commutes.

Table 4.9. Effects of Commuting Distance on Domain Satisfaction

Dependent var.	Health	Sleep	Job	Housework
Commuting distance	-0.021***	-0.011**	-0.004	-0.004
	(0.005)	(0.006)	(0.004)	(0.005)
Individuals	37,551	29,075	37,002	32,799
Observations	153,778	90,503	151,444	120,183
Dependent var.	Leisure Time	Childcare	Family Life	
Commuting distance	-0.020***	-0.006	-0.023***	
	(0.005)	(0.009)	(0.004)	
Individuals	35,030	15,659	31,113	
Observations	138,824	40,527	107,345	

Notes: This table reports the second-stage estimates of the IV estimation. Outcomes are seven domain satisfaction ranging from 0 to 10. Standard errors in parentheses are clustered at the individual level. Significance levels are shown as *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

4.7 Discussion

This study estimates the causal effect of commuting distance on SWB and health. We address the endogeneity of commuting distance by exploiting variation in regional characteristics that are predictive of commuting behaviour but otherwise plausibly unrelated to health and well-being with an instrumental variable strategy. We find that a 10-kilometre increase in commuting reduces SWB by 0.15 standard deviations and health by 0.07 standard deviations. While these effect sizes appear modest, they scale with distance. Even though the consequences of commuting are small for the majority of workers, commuting imposes a major burden on the well-being and health of a substantial group of workers with longer commuting distances. In 2020, the commuting distance for around 20% of employees in Germany was over 25 kilometres Federal Statistical Office, 2020. Our results indicate that commuting such distances reduces SWB and health by more than 37.5% and 17.5% of a standard deviation, respectively.

Moreover, we find that the effect sizes estimated in our IV model are noticeably larger than those estimated in an OLS model or an individual FE model. This suggests that the latter methods - widely adopted by previous studies on this topic - could not completely account for the endogenous commuting behaviour and thus lead to biased impact estimates. When evaluating the impact of commutes, future research may adopt similar instruments proposed in this paper or leverage other natural experiments (e.g., road closures or the adjustment of the timetable for public transport) to account for the endogeneity associated with the length of commutes.

Our paper also examines potential pathways through which the burden of commuting may affect SWB and health. While some studies suggest that a lengthy commute causes sleep disturbances (Nie & Sousa-Poza, 2018) and overweight (Lopez-Zetina et al., 2006), which potentially results in poor physical health, our research does not find evidence that indicates a significant impact of commuting distance on a general evaluation of physical health. In contrast, long commuting distances lower commuters' mental health due to higher stress and fatigue levels. We therefore attribute the health effect of long commuting distances mainly to its burden on mental health. To explain the negative impact on SWB, we explore how commuting distance affects satisfaction with different life domains. Our results suggest that people with a lengthy commute appear less satisfied with their health, leisure time, family life and sleep, the latter of which aligns with poorer mental health.

It may be possible to mitigate the detrimental effects of commuting by promoting flexible employment, especially home-based work. Many countries have enacted policies that entitle employees to the right to request flexible working arrangements. However, home-based work, as a typical form of flexible employment, is not an available option for employees in some countries (e.g., Germany).[15] While employees in other countries can request home-based work, the right to request may not apply to all of them. For example, in Australia, only certain groups of the working population, such as working parents or disabled employees, have access to this entitlement. Although this paper does not compare the health and well-being between commuters and non-commuters, we argue that at least policymakers could consider including home-based work into a set of options for job

[15] In Germany, workers have right to adjust total working hours according to the Section 9a of the Part-Time and Limited Term Employment Act (Gesetz über Teilzeitarbeit und befristete Arbeitsverträge).

flexibility. In such a way, it is possible for people who have suffered a lot from daily commutes to alleviate the detrimental effects of commuting.

Finally, note that some relevant and interesting research questions remain unanswered due to data availability. First, the information on transportation modes is unavailable during our sampling period. Martin et al. (2014) have documented that the negative associations between commuting time and psychological well-being differ across transportation modes. Thus, examining heterogeneous causal effects across transportation modes might be informative for future urban planning. Second, there is also no information on commuting time. We acknowledge that commuting time is a more relevant measure in the context of health and well-being, although it is doubtful whether measuring commuting time by a single number can capture the systematic difference in time used for two-way commuting as documented by Giménez-Nadal et al. (2021). We recommend that further research should re-examine our findings using alternative measures of the length of commutes (e.g., commuting time) and study the role of transportation modes. These analyses can deepen our understanding of the burden of commuting and propose further solutions to alleviate the detrimental effects on health and well-being.

4.A Appendix

Table 4.A.1. Fixed-effects IV Estimates

	(1) First-stage IV	(2) Second-stage IV	(3)
Dependent var.	Commuting distance	SWB	Health
Average commuting distance	0.865***		
	(0.128)		
Average price for building plots	-0.399*		
	(0.210)		
Net number of commuters	-2.207***		
	(0.331)		
Commuting distance		-0.018***	-0.007**
		(0.006)	(0.003)
F-Statistic	32.238		
Durbin-Wu-Hausman test		10.095***	5.382**
Individual FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Individuals	25,696	25,696	25,696
Observations	141,966	141,966	141,966

Notes: This table reports the estimates of the FE-IV estimation. All instruments are jointly used. Column 1 provides the first-stage result. Columns 2-3 provide second-stage estimates for SWB and health, respectively. Standard errors in parentheses are clustered at the individual level. The endogeneity test shows the $\chi^2(1)$ statistic and its significance. Significance levels are shown as *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4.A.2. Reduced-form IV Estimates

	(1) IV1	(2) IV2	(3) IV3	(4) All IVs
Panel A: for SWB				
Average commuting distance	-0.031***			-0.029***
	(0.010)			(0.010)
Average price for building plots		0.022***		0.014*
		(0.007)		(0.007)
Net number of commuters			0.047***	0.045***
			(0.008)	(0.008)
Panel B: for health				
Average commuting distance	-0.011**			-0.010*
	(0.005)			(0.005)
Average price for building plots		0.012***		0.010**
		(0.004)		(0.004)
Net number of commuters			0.011**	0.010**
			(0.004)	(0.004)
State FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Individuals	37,552	37,552	37,552	37,552
Observations	153,822	153,822	153,822	153,822

Notes: This table reports the results of the reduced-form IV estimates. Columns 1-3 provide estimates using each IV separately. Column 4 provides estimates using all IVs jointly. Standard errors in parentheses are clustered at the individual level. Significance levels are shown as *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Chapter 5

Conclusion

Some occupational characteristics causing workplace stress are detrimental to the health and well-being of the working population and impose substantial costs on society. This detrimental impact further lowers workers' future labour market outcomes and personal wealth, which leads to income inequality between people with and without poor health. Workplace stress is particularly strong when conflicts between working and non-working responsibilities intensify. Therefore, it is important to explore the working patterns that can reduce this conflict, thus improving health and well-being in the workplace.

One possible solution is flexible employment, an established and emerging working pattern emphasising employees' control over when, where and how their work is conducted (Thompson & Kossek, 2016). This thesis discusses the role of flexible employment in improving the health and well-being of the working population.

5.1 Summary of Findings

Recent studies have found that parental life satisfaction, or subjective well-being (SWB), declines during the transition into parenthood, which is attributable to a work-family conflict. Chapter 2 investigates whether flexible employment can alleviate the decline during this period. Using Australian household survey data (HILDA), this chapter delivers convincing evidence that working flexibly indeed alleviates the drop in parental SWB. Moreover, the effects of different types of flexible employment on mothers' and fathers' SWB vary by gender. Mothers with a short part-time job (0-20 hours per week) appear to have higher SWB than those with a full-time job. This difference is statistically significant when their children are younger than four. In contrast, fathers adopting self-scheduling and home-based work exhibit higher SWB than those working with a fixed working scheme when their children are one and two years old. Potential reasons for this gender heterogeneity are a classical intra-household time allocation of parents in Australia and typical labour market trajectories of each gender around childbirth.

Using the same dataset from Australia for the period 2012-2019, Chapter 3 examines the effect of a health shock on the uptake of home-based work as one typical form of job flexibility. We find that a health shock increases women's likelihood of home-based work by 8.1 percentage points and their weekly home-based hours by 0.65 hours, corresponding to over 35% of the average uptake of home-based work among female employees. Based on the argument of revealed preference, the positive impact suggests that a health shock increases the likelihood that home-based work is the working pattern that yields the highest level of utility among all available options. However, a health shock does not seem to affect the uptake of home-based work among male employees. One potential reason is related to the household specialisation within a couple. The advantage of home-based work in coordinating between working and non-working tasks becomes useful when a woman's health is poor. Besides, home-based work is positively associated with women's labour market outcomes in the long run but not men's, as shown in a supplementary analysis. Both facts may exclusively encourage women to choose this working pattern in response to health shocks.

Chapter 4 explores the impact of commuting on health and SWB using data from a nationally representative household survey in Germany (GSOEP) for the period 2001-2017. The results show that commuting distance negatively affects SWB and self-rated health. In Germany, 20% of the workers travel over 25 kilometres from home to the workplace. Our estimation implies that this journey reduces their SWB and health by over 37.5% and 17.5% of a standard deviation, respectively. We also find that long commuting distances are particularly harmful to mental health and satisfaction with sleep, family life and leisure time, which explains the health effects of commuting. The detrimental effect of commuting documented in this chapter illustrates the potential benefit of spatial flexibility in relieving the burden of daily commutes.

5.2 Recommendations for Future Research and Policy

Since the outbreak of COVID-19, some measures of flexible employment have been a temporary working pattern. Nowadays, as economies reopen, to what extent flexible work during the pandemic should persist has become an ongoing debate. Although this thesis is not a comprehensive evaluation of the cost and benefit of flexible employment, the working population's gain in health and well-being from this working pattern documented by this thesis should be considered in policy design.

In fact, the right to request a flexible working arrangement has become a formal practice in several countries since the beginning of the new century. However, this entitlement is only granted to a limited group of workers in many countries (OECD, 2016). For example, workers just experiencing a health shock (Chapter 3) are not covered by the current *Flexible Working Arrangement* in Australia unless they are disabled. Additionally, flexible employment is typically not an option for workers commuting long distances (Chapter 4). Thus, this thesis suggests enlarging the scope of the working population eligible for flexible employment so that the workers can request this entitlement for broader purposes.

Additionally, we should be aware of the risk of unequal access to flexible employment across occupations and industries. For example, workers with certain jobs may have little chance of obtaining some types of job flexibility due to their job features (e.g., nurses and professional carers). In particular, among these workers, a large part appears to be low-income people whose jobs involve substantial physical activities in an unchangeable location (e.g., factories). Their lack of accessibility may further increase the disparities in health and well-being across socio-economic groups. Therefore, attention should be paid to advancing the availability of all types of flexible employment at the same time. In this way, workers with diverse job characteristics could find a flexible working pattern compatible with their job, which mitigates the problem of unequal access.

Alongside the promotion of flexible employment, it is crucial to combat the biased view about flexible workers. Chapters 2 argues that flexibility stigma has prevented some workers from adopting their optimal level of job flexibility with the concern of being discriminated against. One solution is to raise public awareness of the consequences of workplace stress. The widespread awareness could be helpful for people to understand the flexible workers around them, which alleviates flexible stigma.

While this thesis has discussed some advantages of flexible employment in health and well-being, the research on this topic is still limited. Further analyses can extend this thesis by using different data from other institutional settings or including information not used in this thesis. The three main chapters are based on household survey data in Australia (Chapters 2 and 3) and Germany (Chapter 4). The prevalence of flexible employment in other countries facilitates a test for the external validity of the results of each chapter. In addition, some unanswered questions in this thesis due to data limitations can be further explored using other data sources. For example, the health shock in Chapter 3 is simply defined as a severe injury or illness. If the information on specific diseases is available, later studies can classify health shocks according to the feature of health problems and examine the heterogeneity in the uptake of home-based work across different types of health shocks. Similarly, the information on commuting time and transportation modes is absent in Chapter 4. Future research with a superior data source can look into the heterogeneous health impacts of commuting across transportation modes or different times of one day (e.g., peak time versus off-peak time).

Further research can also focus on different groups of people or types of job flexibility. For example, Chapter 2 does not consider how one's flexible employment could spill over to affect spousal well-being. This spill-over effect is likely true due to the collective model in the household decision-making process. Furthermore, leveraging a long panel, researchers can explore the inter-generational effect of flexible employment, i.e., how parental flexible employment affects children's health during early childhood. Chapter 3 only discusses the uptake of home-based work in response to a health shock. Later research may replicate this analysis for other types of flexible work (e.g., self-scheduling) to obtain a comprehensive understanding of how job flexibility is related to health shocks.

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Samenvatting

Veel arbeidskenmerken zijn bepalend voor de gezondheid en het welzijn van de beroepsbevolking. Slechte arbeidsomstandigheden (bv. hoge werkdruk en lange werktijden) veroorzaken ernstige gezondheidsproblemen en verminderen het geestelijk welzijn van de werknemers.

Eén benadering ter verbetering van de gezondheid en het welzijn op het werk is flexibele arbeidsvoorwaarden, waarbij de nadruk ligt op de zeggenschap van de werknemers over wanneer, waar en hoe zij hun werk doen. Dit werkpatroon wint sinds de jaren tachtig aan populariteit. Het recht om dit aan te vragen is in veel ontwikkelde landen, zoals het VK, Australië en Nederland, wettelijk vastgelegd.

Dit proefschrift bespreekt in drie hoofdstukken de relaties tussen flexibele arbeidsvoorwaarden en de gezondheid en het welzijn van verschillende groepen van de beroepsbevolking.

Hoofdstuk 2 evalueert de effecten van verschillende soorten flexibele arbeidsvoorwaarden op de levenstevredenheid van ouders tijdens de overgang naar het ouderschap. Gewoonlijk daalt de levenstevredenheid van ouders drastisch na de geboorte van een kind en blijft deze gedurende een aantal jaren laag voordat deze terugkeert naar het niveau van vóór de geboorte. Dit hoofdstuk bespreekt het effect van drie vormen van flexibele arbeidsvoorwaarden (deeltijdwerk, zelfroosteren en thuiswerk) op het verzachten van deze daling. Deze studie maakt gebruik van 16 golven van een longitudinaal huishoudonderzoek in Australië, *The Household, Income and Labour Dynamics in Australia (HILDA)*, van 2002 tot 2017. Deze studie past een individueel fixed-effects model toe in een event-study omgeving om het verloop van levenstevredenheid in de negen jaar rond de bevalling met betrekking tot verschillende vormen van arbeidsflexibiliteit vast te leggen.

Uit de resultaten blijkt dat flexibele arbeidsvoorwaarden de levenstevredenheid van ouders in de eerste jaren van het ouderschap kan verbeteren. Welk type arbeidsflexibiliteit effectief is, hangt echter af van het geslacht: moeders met 0-20 werkuren per week vertonen een grotere levenstevredenheid dan moeders die langer werken, vooral wanneer hun kinderen jonger zijn dan vier jaar; bij vaders leiden zelfroosteren en thuiswerk tot een aanzienlijke toename van de levenstevredenheid in vergelijking met een rigide regeling. Dit geldt vooral voor vaders van een- en tweejarigen.

Op basis van de klassieke tijdsverdeling van ouders binnen het huishouden in Australië is één verklaring dat deeltijdbanen de wekelijkse werktijd van moeders verminderen, waardoor hun tijdconflicten tussen werk en zorg voor kinderen worden verminderd. Voor vaders stelt de mogelijkheid om hun werkplek en werkschema aan te passen hen in staat om wat huishoudelijk werk te verrichten bij een gelijkblijvend totaal aantal werkuren.

Hoofdstuk 3 documenteert hoe een recente blessure en ziekte de opname van thuiswerk beïnvloeden aan de hand van acht golven van de HILDA-enquête tussen 2012 en 2019. Met het argument van revealed preference wordt in deze analyse onderzocht of thuiswerk een gunstige werkregeling is die mogelijk tegemoet komt aan de behoeften van werknemers met een slechte gezondheid.

Arbeidsmarktparticipatie wordt, als endogene keuze, beïnvloed door gezondheid. Mensen met een slechte gezondheid kunnen daarom stoppen met werken. Als zij echter zouden kunnen werken, kan hun keuze voor thuiswerk verschillen van de keuze van degenen die op de arbeidsmarkt actief zijn. Daarom leiden de analyses die alleen gebaseerd zijn op personen die actief zijn op de arbeidsmarkt tot het probleem van niet-willekeurige selectie.

Om dit probleem op te lossen, gebruikt deze studie een reeks Heckman-type modellen die de twee beslissingen over arbeidsmarktparticipatie en thuiswerk en een niet-waargenomen correlatie tussen deze twee beslissingen gezamenlijk kunnen modelleren. Een binair respons panel data model met steekproefselectie dat is aangedragen door Semykina en Wooldridge (2018) wordt gebruikt voor de binaire thuiswerkstatus. Deze studie breidt het model ook uit om gedeeltelijk waarneembare paneldata voor thuiswerkuren te accommoderen.

De resultaten wijzen op de aanwezigheid van een negatieve steekproefselectie, wat betekent dat mensen die actief zijn op de arbeidsmarkt minder vaak kiezen voor thuiswerk. Zonder correctie voor de steekproefselectie onderschat het model het effect van ernstig letsel en ziekte op het gebruik van thuiswerk. De resultaten lijken ook gender-asymmetrisch: voor vrouwen kunnen gezondheidsschokken de waarschijnlijkheid van thuiswerk met 8,1 procentpunten en de wekelijkse thuiswerkuren met 0,65 verhogen. Gezondheidsschokken hebben echter geen significante invloed op het gebruik van thuiswerk door mannen. Een verklaring is dat thuiswerk voor vrouwen nuttig kan zijn om werk en niet-werken te combineren wanneer hun gezondheidstoestand slecht is. Een andere reden, die uit een aanvullende analyse naar voren komt, is dat vrouwen in een ongunstige gezondheidssituatie profiteren van thuiswerk in termen van hun arbeidsmarktparticipatie en huishoudinkomen in de daaropvolgende vijf jaar. Bij mannen ontbreekt een dergelijk effect echter.

Hoofdstuk 4 documenteert het schadelijke effect van langdurig woon-werkverkeer op subjectief welzijn en levenstevredenheid aan de hand van 15 gegevensgolven van *The German Socio-Economic Panel (GSOEP)* tussen 2001 en 2017. De last van het woon-werkverkeer is endogeen omdat deze kan worden beïnvloed door niet-waargenomen determinanten van de woonplaats en de werkplek. In deze studie wordt dit probleem aangepakt met een instrumentele variabele (IV) benadering. Drie regionale kenmerken uit een overheidsdatabank (INKKAR) van the Federal Institute for Research on Building, Urban Affairs and Spatial Development worden gebruikt als instrument voor de individuele pendelafstand: 1) de gemiddelde pendeltijd op het niveau van de deelstaat, 2) de gemiddelde prijs voor bouwstenen op het niveau van de provincie en 3) het netto aantal pendelaars op het niveau van de provincie.

Uit de IV-schatting blijkt dat een lange reisafstand nadelig is voor het subjectief welzijn en de gezondheid: Een toename van de woon-werkafstand met 10 kilometer kan de SWB en de gezondheid met respectievelijk ongeveer 15% en 7% van een standaarddeviatie verminderen. De omvang van het effect is aanzienlijk voor mensen met een lange woon-werkafstand, bijvoorbeeld meer dan 25 km, die 20% van de werknemers in Duitsland uitmaken (Federal Statistical Office, 2020). Deze studie toont verder aan dat lange woon-werkafstanden bijzonder schadelijk zijn voor de geestelijke gezondheid, aangezien mensen met een lange reisafstand naar de werkplek zich depressiever en minder energiek voelen in vergelijking met hun tegenhangers met een korte reisafstand. Bovendien zijn mensen die langer pendelen minder tevreden met hun slaap, gezondheid, vrije tijd en gezinsleven.

Dit proefschrift levert een bijdrage aan de econometrische methoden binnen de gezondheidseconomie. Hoofdstuk 3 breidt een recent ontwikkeld model van Semykina en Wooldridge (2018) uit. Het uitgebreide model accommodeert gedeeltelijk waarneembare paneldata met steekproefselectie. Hoofdstuk 4 geeft de eerste schattingen van het gezondheidseffect van woon-werkverkeer met een instrumentele variabele benadering.

De drie hoofdstukken geven ook gezamenlijk inzicht in de relaties tussen flexibele arbeid en de gezondheid en het welzijn van verschillende subgroepen van de beroepsbevolking. Hoofdstuk 2 laat zien dat flexibele arbeid de vermindering van de levenstevredenheid van ouders in de eerste jaren van het ouderschap kan verzachten. Hoofdstuk 3 geeft aan dat een recente gezondheidsschok het gebruik van thuiswerk stimuleert, vooral voor vrouwen. Hoofdstuk 4 beschrijft de potentiële voordelen van thuiswerk door het nadelige effect van langdurig woon-werkverkeer op de SWB en de gezondheid van werknemers aan te tonen. Deze bevindingen dragen bij aan het huidige debat over de vraag of de flexibele werkregelingen die tijdens de COVID-19-crisis zijn ingevoerd, in het post-pandemische tijdperk moeten blijven bestaan. De dissertatie betoogt dat beleidsmakers de effecten van deze werkregeling op gezondheid en welzijn in overweging moeten nemen.