Doctors at Work: Essays on Medical Careers, Family, and Private Practice

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Introduction

Background

Australia has an excellent health system underpinned by a highly trained health workforce. As a critical building block of the health workforce, medical doctors profoundly influence the quality, accessibility, effectiveness and sustainability of the national health system. Australia's healthcare system is a mix of public and private practice, with private medical practice playing a larger role. Doctors working in private medical practice represent about 80% of medical specialists and most general practitioners (GPs) (Scott et al. 2020). Over the past decade, private healthcare facilities and non-GP specialists in private practice groups have grown rapidly in Australia, which has tended to 'crowd out' healthcare provision in the public sector (Brekke & Sørgard 2007). In the wider context of falling private health insurance membership between 2015 and 2020 and reduced growth in the utilisation of personal medical care since the COVID-19 pandemic, the expansion of private practice is likely to put pressure on the public healthcare sector (Hall 2013, Van Doorslaer et al. 2008). Therefore, a good understanding of the distribution of the medical workforce and factors that influence doctors' choices of public or private practice is important to enhancing the efficiency of healthcare delivery in the national healthcare system.

Another issue is that the gender composition of the Australian medical workforce has changed significantly in recent decades, with women constituting an increasing share of medical graduates and the labour force. Despite more women in medicine, however, gender inequality in earnings remains stubbornly persistent. Lower working hours among female doctors are believed to be the main contributor to the remaining gender earnings gap (Ly et al. 2016, Frank et al. 2019). The onset of parenthood can worsen the earnings gap if children and family responsibilities affect the working hours of male and female doctors differently. Among female professions, not limited to medicine, balancing work and life is a challenge, as females remain primarily responsible for childbearing and domestic duties. Therefore, studying how children and family responsibilities impact working hours and earnings is essential to understand the barriers female doctors face in their medical careers.

Research questions

This thesis primarily focuses on medical doctors' career, family and work sectors. More specifically, the thesis investigates factors that influence doctors' choice of work sector and examines how children and family characteristics can impact female and male doctors' labour market trajectories differently. Additionally, this thesis provides empirical evidence on the role of parenthood on earnings in a highly qualified profession – medical doctors.

In this context, this thesis seeks to answer the following three broad research questions, which form the basic scope of the thesis: 1) How are practice patterns of Australian medical specialists distributed between the public and private sectors, and what factors influence doctors' choices? 2) Do family circumstances influence the number of hours female and male doctors work differently? 3) How does the role of motherhood impact female doctors' earnings over time?

Australia as a case study

This thesis uses Australia as a case study. There are two reasons Australia is an ideal setting to address the above-outlined research questions: (1) Australia has a public and private mixed health care system, and women constitute an increasingly larger share of the Australian medical workforce, and (2) the availability of rich data sources, which are explained in detail below.

Public-private mixed healthcare system and high participation of females in medicine

Australian medical specialists have relatively high levels of freedom in choosing to work in the public or private sectors, or both, compared with doctors in most other OECD countries. Some advantages of the private sector, such as better remuneration, better physical working conditions and more flexible working arrangements, attract medical specialists to work in the private practice group. About two-thirds of the medical specialists in Australia engage in private practice, either exclusively, in private hospitals and clinics, or through dual sector practice. This means just 33% of medical specialists work exclusively in public medical practice.

Women have had gender parity in Australian medical schools and the medical workforce for decades. In 2020, 43% of registered medical practitioners and specialists were women (The Medical Board of Australia 2021), and this proportion is increasing, with 54.3% of new medical graduates in medical schools being women (Dean 2021). However, gender equity in medicine and medical leadership in Australia has not been achieved. Females represent only 28% of medical deans and 12.5% of hospital chief executive officers (Hempenstall et al. 2019). Female doctors, on average, earn 17–45% less than male doctors, and female doctors with children work much lower hours or are more likely to work part-time (Gravelle et al. 2011, Lo Sasso et al. 2011, Theurl & Winner 2011, Cheng et al. 2012, Boesveld 2020, Wang & Sweetman 2013, Gjerberg 2003). All these facts reflect persistent gender inequalities in medicine, even though women doctors have invested equally in education and training.

The availability of rich data sources

Australia has a comprehensive data set on medical doctors – the Medicine in Australia: Balancing Employment and Life (MABEL) survey. MABEL is an annual longitudinal survey administered by The University of Melbourne Faculty of Business and Economics Human Ethics Advisory Group and the Monash University Standing Committee on Ethics in Research Involving Humans. To date, there have been 11 waves covering the period 2008–2018.

The MABEL survey has several unique features. First, it is one of the few large-scale longitudinal surveys of medical professionals that has been in operation for more than 10 years. Second, regarding representation, MABEL uses a nation-wide sample across six states, four doctor types and 43 medical specialities. In Wave 1, all medical doctors in clinical practice in Australia (N=54,750) were invited to participate in the survey. The response rate of the baseline cohort with respect to the sample frame was 19.4%. The baseline cohort was shown to be nationally representative of the population with respect to age, gender, doctor type, geographical location, working hours and medical specialities (Joyce et al. 2010). From the second wave (2009) and each subsequent year, a top-up sample of doctors was invited to participate in the survey to maintain the cross-sectional representation of the survey.

Finally, MABEL is a multipurpose survey that collects information at the individual, household and clinic levels. Therefore, it provides extensive information on doctors' labour market status, financial status, earnings, working hours, medical specialty, workplace and workload, job satisfaction, personal characteristics and family circumstances, which facilitates the conduct of extensive research on the medical workforce.

Structure of this thesis

This thesis contains three main chapters focusing on each of the research questions outlined above. The first chapter uses nine annual waves (2008–2016) of MABEL data to investigate factors influencing doctors' work sector choice and explores how doctors' work sectors change across their career. In particular, Chapter 1 examines the roles of demographic factors, pecuniary factors, family circumstances and medical specialty on specialists' choices of work sector. Labour supply behaviours (including work sector choice) may also be motivated by unobserved personal characteristics, and particular is paid to examining the impacts of unobserved individual heterogeneity by taking advantage of long-wave panel data and the econometric strategy of a Multinomial Logistic Model with a Correlated Random Effect (CRE) framework.

The results show that specialists' work sector choices are significantly associated with their gender, age, cohort, earnings, financial debt, family circumstances and medical specialty. Female doctors, senior doctors and doctors with young children are more likely to work in the private sector, while more recently qualified doctors are less likely to be in private-only practice. Middle-aged doctors and those with PhD degrees are more likely to be dual practitioners, who earn more and owe higher level of business debt than other specialists. Finally, specialists' work sectors vary significantly with their medical specialties, suggesting that it is necessary to control for medical specialties or use a specialty-specific approach to assess the public and private allocation of the specialist workforce in the empirical analysis.

The second chapter of the thesis uses nine annual waves of MABEL data to examine how children and family responsibilities influence the number of hours worked by female and male medical doctors. Chapter 2 exploits the longitudinal nature of the MABEL data to investigate how hours worked change in response to within-doctor changes in family circumstances over time. We find strong evidence of a 'carer effect' of having children for female doctors, whose working hours are significantly reduced by the presence of children, the number of children, and having young children. The working hours of female doctors are also strongly influenced by the employment status of their spouses. In contrast, for male doctors, having children leads to a slight increase in hours worked. The effect of children in dual medical career households is highly asymmetric: female doctors reduce their hours worked by a very large margin, whereas male doctors report not changing their working hours. Finally, we also find evidence of heterogeneous effects of how family circumstances affect hours worked across different quantiles of hours worked.

The third chapter of the thesis uses the 11 waves of MABEL data to examine the earnings effect of motherhood. Chapter 3 uses an event-study framework to explore the causal effects of having children and quantify the period effects on female doctors' earnings before and after their first child. The results show a large and immediate drop in earnings with the onset of motherhood, with the short-term decrease in earnings is estimated to be 38% compared to the year immediately preceding first childbirth. On average, it takes eight years for female doctors' earnings to recover to pre-childbirth levels.

This study also finds heterogeneity in the child penalty in earnings, with motherhood having a stronger negative impact on female GPs' earnings than on female specialists' earning, in both the short and long term. This chapter further identifies the association between having childcare near the workplace and mother-doctors' willingness to return to regular work after birth, which highlights the importance of improving support facilities for female doctors returning from childbearing.

The remainder of the thesis is structured as follows. Chapter 1 investigates factors influencing doctors' choices in public and private practice. Chapter 2 examines how children and family responsibilities affect the number of hours female and male medical doctors work. Chapter 3 explores the child effect on female doctors' earnings. Chapters 1–3 are written as stand-alone papers.

Statement of Authorship

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Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);
ii. permission is granted for the candidate in include the publication in the thesis; and
iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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Chapter 1

An analysis of public and private practice by medical specialists over their career life-cycle

1.1 Introduction

The sustainability of efficient health care delivery is a concern for governments across OECD countries, which face a persistent shortage in medical workforces and increasing overall health care requirements. Australia has a public and private mixed health care system, wherein physicians are allowed to work in both public and private sectors. Private health facilities have been growing rapidly in the past two decades, associated with an increasing proportion of public physicians choosing to split their working hours between the public and private sectors, thereby increasing competition for the medical workforce between the two sectors. Understanding how the workforce of physicians is distributed across sectors, and exploring the determinants of work-sector choice by specialists, is expected to have significant implications for enhancing the efficiency of health care delivery in the national health care system, especially in coping with national emergencies such as the COVID-19 pandemic in 2020.

Australian physicians have a relatively high level of freedom in choosing to work in the public or private health sectors, or both, compared with doctors in most other OECD countries. An earlier study shows that 48% of medical specialists in Australia undertake work in both public and private sectors, with 33% working only in public hospitals and 19% only in private hospitals and private practice (Cheng et al. 2013). Public and private sectors are associated with different work attributes. Private sector work generally provides doctors with better remuneration, better physical working conditions, and more flexible working arrangements. Although there are strong financial and non-financial incentives for specialists to migrate from the public to the private sector, public work can be attractive in some ways. For example, the public hospital sector generally provides more of a team environment, more academic opportunities, and greater opportunities to feel 'needed' and 'relevant' (Ashmore 2013).

A public-private mixed health care system has its advantages but also comes with problems. Allowing physicians to work in both public and private sectors can improve social welfare, generate additional income and increase job satisfaction for health workers (Eggleston & Bir 2006, Ferrinho et al. 2004). However, the advantages offered by the private sector are drawing the medical workforce away from the public health care sector, which makes it difficult for public hospitals to retain doctors (Cheng et al. 2018). The expansion of private health care facilities 'crowds out' health care provision in the public sector (Brekke & Sørgard 2007), which creates a maldistribution of doctors across public and private sectors, leading to a shortage of physicians in public hospitals. From the demand side, the proportion of the population holding private health insurance has been falling gradually over recent decades in Australia, especially among those from low-income families (APRA, 2019). Declining private health insurance membership is expected to increase demand for public hospital care and put greater pressure (e.g. increased waiting times) on the public system (Hall 2013, Van Doorslaer et al. 2008). Therefore, it is essential to explore and understand the factors influencing the choices of medical specialists between public and private practice.

In this paper, I use a unique longitudinal dataset of Australian doctors spanning nine annual waves to investigate factors that influence medical specialists' choice of work sector in terms of public, private or both. The paper examines the roles of gender, age, cohort, children, and employment status of a doctor's partner in influencing doctors' work-sector choices. I also explore the effects of a richer set of pecuniary factors: education and business debt. The role of education debt, in particular, has yet to be examined in previous studies. In addition, I examine the effect of medical specialty on doctors' public-private choices. Given that labour supply behaviors (including work sector choice) may be motivated by unobserved personal characteristics such as risk attitudes and public motivations, particular emphasis is placed on controlling for impacts of unobserved individual heterogeneity by taking advantage of panel data. The research questions addressed are: (1) How are practice patterns of Australian medical specialists distributed between the public and private sectors? (2) How do specialists' work-sector choices differ by gender, age and cohort? (3) How do pecuniary factors, especially business and medical debt, affect specialists' choice of work sectors? and (4) What role do family circumstances play in influencing specialists' work-sector choices?

A point of difference from previous research is this study's use of a longitudinal Australian dataset spanning nine years, which makes it possible not only to analyse the effects of within-doctor changes in work, family and personal characteristics over time, but also to capture the effects of unobserved individual heterogeneity. This research contributes to the literature in the following ways. Firstly, this study examines a more extensive set of pecuniary and demographic factors than previous studies. For instance, I examine the roles of both education debt and business debt in doctors' decision-making in relation to public and private sector activities. Johannessen & Hagen (2014) have previously examined associations with financial debt but not to the same level of detail. Education debt has been shown to be an important factor that influences the specialty choice of medical graduates and young doctors (Hays et al. 2015); however, its effect on a doctor's work-sector choice is as yet unclear. I further investigated how doctors' work-sector choices differ by cohort. Much of the literature has examined the role of age, but there have been few if any attempts to distinguish cohort effects. While new and younger cohorts of physicians have been found to perform similar total hours of work per week to older doctors in Canada (Sarma et al. 2011), studies examining how physicians from different cohorts differ in the sector in which they choose to work are rare. This study reveals a reduced likelihood of specialists opting for private healthcare among individuals in later cohorts. This observation may be correlated with shifts in doctors' attitudes concerning work-life equilibrium and adjustments in doctors' clinical practice approaches.

Second, this study makes use of a comprehensive longitudinal Australian dataset to provide an evidence-based picture of the distribution of medical specialists across public and private sectors in the Australian health care system. A unifying feature of the extant literature is that most studies rely on cross-sectional data (Cheng et al. 2013, Johannessen & Hagen 2014, Scott et al. 2020). To our knowledge, this study is the first to apply a longitudinal panel data set, extending over nine years, to examine the roles of demographic factors, pecuniary factors, family circumstances and medical specialty on work-sector choice by medical specialists. The availability of repeated observations allows me to estimate the effects of within-doctor changes in work, family and personal characteristics and to predict the public-private labour supply behaviours of medical specialists over their career life-cycle.

Third, this study combines a Multinomial Logit (MNL) model with a Correlated Random Effect (CRE) (Mundlak 1978) approach to examine the effects of factors that influence work-sector choices by medical specialists. The CRE-MNL approach not only allows us to estimate the effects of some important time-invariant factors, such as medical specialty and gender, but also enables us to control for the effect of unobserved individual heterogeneity, which can potentially affect doctors' choices. This approach has rarely been applied in the relevant extant literature.

Finally, physicians may respond differently in their choice between public and private work under different medical policy environments; however, few studies of the factors influencing doctors' work-sector choice have been conducted in the context of Australia to date, with the exception of some studies on doctors' public and private sector work settings (Cheng et al. 2013). These analyses, however, focus on describing variations in practice patterns, remuneration contracts, professional arrangements and hours worked across different work sectors rather than examining the role of influencing factors in detail. Moreover, previous studies exploring the role of earnings (Cheng et al. 2018), work attributes and risk attitudes (Scott et al. 2020) on physicians' preferences for public and private sector work have been based on cross-sectional evidence. The chapter of this thesis therefore extends the Australian literature on doctors' public-private sector choices by using longitudinal data to examine the effects of education debt, cohort, demographic factors, family circumstances and medical speciality.

The chapter is structured as follows. Section 1.2 provides the institutional context of the Australian public and private health care system. Section 1.3 is a brief discussion of the relevant literature. The data and variables used in this study are discussed in Section 1.4, followed by the empirical model in Section 1.5. Our key findings are discussed in Section 1.6. Section 1.7 concludes with a summary of our findings.

1.2 Institutional context of the Australian public and private health care system

Australia has a mixed public and private health care system. Medicare, Australia's universal health insurance system, provides free or subsidised treatment by doctors and free public hospital treatment. Doctors in private practice and private hospitals are free to set their fees. The difference between the fees charged and the subsidy from Medicare is passed on to patients as co-payments. Private hospitals' expenses are covered through private health insurance, which is held by roughly 45% of the Australian population.

The definition of 'public' and 'private' may be distinguished by ownership type or by source of funding. Public hospitals are owned and managed by state governments and are jointly funded by both federal and state governments. Private hospitals are privately owned entities and operate as either for-profit or not-for-profit institutions. Public hospitals account for roughly half of all hospitals in Australia, with 693 public hospitals and 657 private hospitals nationwide (Australian Institute of Health and Welfare 2019*b*). Public hospitals make up a large share of national health care activities. In 2017-2018, 60% (6.7 million) of all hospital separations in Australia occurred in public hospitals. The proportion of private hospital separations ranged from 40% to 41% of all separations between 2010 and 2018. Of the 4.5 million separations from private hospitals in 2018, 22% were same-day separations that occurred in private free-standing day hospital facilities, and 78% were overnight separations (Australian Institute of Health and Welfare 2019*b*).

Australia's total health expenditure in 2017–2018 is estimated to have been $185.4 billion, amounting to 10% of GDP, with a total of $74 billion spent on public and private hospitals.

Public hospitals accounted for about 78% ($57.7 billion) of total expenditures, of which 62% was spent on salaries of medical professionals. The remaining 38% comprised non-salary expenditures, including payments to Visiting Medical Officers, superannuation payments, drug supplies, medical and surgical supplies and so on. State and federal governments contributed the most (91.1%) funding to public hospitals. Total expenditure for private hospitals was $16.3 billion in 2017–2018. The majority (71%, about $10.8 billion) of private hospital spending was funded by non-government sources, including private health insurance funds ($8.2 billion) and individuals (out-of-pocket expenses, $2.2 billion) (Australian Institute of Health and Welfare 2019*c*). Government sources provided the remaining 29% ($4.8 billion) in the form of rebates for private health insurance ($2.9 billion) and funding through the Department of Veterans' Affairs ($817 million) (Australian Institute of Health and Welfare 2019*c*). Public spending on private hospitals can occur where state and territory governments contract with private hospitals to provide services to public patients, or where individual public hospitals purchase services from private hospitals for public patients (Australian Institute of Health and Welfare 2019*c*).

The distribution of doctors across public and private sectors varies by doctor type. General practitioners work predominantly in the private sector (92% of total full-time equivalent (FTE)), while hospital non-specialists (92% FTE of total) and specialists-in-training (e.g. specialist registrars) (84% FTE of total) work mainly in public hospitals (Australian Institute of Health and Welfare 2016). Medical specialists, who are the focus of this study, are spread evenly across both public and private sectors, with 49% of all physician hours devoted to the public sector and 51% to the private sector (Australian Institute of Health and Welfare 2016). An earlier study shows that 48% of medical specialists in Australia undertake work in both public and private sectors, with 33% working only in public hospitals and 19% only in private hospitals and private practice (Cheng et al. 2013).

Medical specialists in public hospitals are predominantly salaried employees and may have rights to private practice that allow them to treat private patients in public hospitals on a fee-for-service basis. Many doctors with private practice privileges often do not treat private patients in public hospitals (Cheng et al. 2013). Specialists who work primarily in private practice undertake work from their own consulting rooms or have admitting rights in a private hospital. Much of this work is remunerated through fee-for-service. These doctors can also work in public hospitals as Visiting Medical Officers (VMOs) on a contractual basis paid usually by fee-for-service or by session.

1.3 Literature Review

1.3.1 Dual Practice

Medical doctors are allowed to work simultaneously in the public and private sectors in Australia. Where health professionals provide services in both public and private facilities for profit or as a part of profit-sharing arrangement with the relevant government authority, it is referred as dual practice (Eggleston & Bir 2006, García-Prado & González 2011, Socha & Bech 2011). Dual practice can be found in a range of arrangements in various countries. One example is physicians, who mainly work in public hospitals but also have the right to treat private patients either in private wards inside the public hospital (e.g. Australia, Austria, France, Ireland and Italy) or at their own private clinics (e.g. Australia). Another example is surgeons who perform surgeries in both public and private hospitals, or private specialists who work as VMOs in public hospitals. In some countries, including Australia and the United Kingdom, physicians can be contracted part-time with a public hospital and part-time with a private hospital, alternating between public and private practice in the course of the working day.

Dual practice is common among physicians in many OECD countries, and the literature identifies both positive and negative impacts of dual practice. With the development of the private sector, a rising number of physicians are drawn from public hospitals to private hospitals or clinics due to better remuneration, professional autonomy (Midttun 2007), working conditions (Askildsen & Holmås 2011) and flexible working hours (Cheng et al. 2018). Allowing dual practice can improve social welfare (Eggleston & Bir 2006) and generate additional income and higher professional satisfaction for health workers (Ferrinho et al. 2004). However, doctors' engagement in dual practice also raises a number of concerns, particularly in relation to its potential negative impacts on public performance, such as shortages of medical specialists in some specialties in public hospitals or maldistribution of the medical workforce across the public and private sectors. Negative effects of medical workforce turnover in the health care system have been documented in the health economics literature. For example, public doctors undertaking private practice 'crowd out' public provision and result in lower overall levels of health care provision (Brekke & Sørgard 2007), alteration of the quality of care or processing hours (Mahendradhata et al. 2017, García-Prado & González 2007) in public hospitals, difficulties in the recruitment and retention of public hospital physicians (Cheng et al. 2018), outflows of resources and corruption (Ferrinho et al. 2004) and the problem of doctors' 'cream-skimming' (González 2005, Cheng et al. 2015).

There are wide variations in how governments tackle physicians' dual practice. In Spain and Norway, monetary incentives are provided to public doctors to reduce physicians' engagement in dual practice and prompt physicians to work exclusively for public hospitals. In the UK and France, there have been restrictions on the proportion of the earnings public sector physicians can derive from private practice. In some countries, such as Canada, physicians' dual practice is prohibited, with most doctors being salaried or contracted employees of public hospitals (Chue 2007). In other countries, however, including Australia and Finland, there are no regulations restricting doctors from combining positions in both public and private health care facilities, and dual practice is allowed without any restrictions (Cheng et al. 2018, Johannessen & Hagen 2014).

1.3.2 Factors influencing physicians' work-sector choice

Many studies have examined the factors influencing work-sector choice among medical professionals, with the role of financial incentives receiving the most attention. The literature has focused on three types of financial incentives: wage rate, taxes, and debt. Pecuniary factors have been found to influence doctors' work-sector choice extensively (in terms of which sector to work in, public or private) and intensively (in terms of how much to work in public or private sectors). For instance, the evidence shows that financial debt and interest payments are positively correlated with doctors' engagement in dual practice (Johannessen & Hagen 2014) and that an overall increase in wage or less progressive taxation moves more physicians into working full-time in the private sector (Andreassen et al. 2013). Doctors increase their working hours in the sector in which wages are higher and reduce working hours in the other sector, leaving total working hours slightly higher (Saether 2005) or unchanged (Cheng et al. 2018). In the USA, self-employed physicians have been found to be more sensitive to marginal tax rates (Showalter & Thurston 1997) and changes in wage and non-wage income (Rizzo & Blumenthal 1994) compared with employed physicians. However, some studies reach the opposite finding on the effect of pecuniary factors, reporting either that physicians do not respond to wage differences (Askildsen & Holmås 2011) or that pecuniary factors are not the dominant consideration (Humphrey & Russell 2004) in choosing whether to work in the public sector or elsewhere; instead, hospital-specific factors such as work conditions play a greater role in physicians' decisions (Askildsen & Holmås 2011).

Economic motives are not the only factor that affects physicians choosing public, private or dual practice. Other non-pecuniary factors such as institutional, professional, structural and personal variables also play a role (García-Prado & González 2011). Goodman & Wolinsky (1982) claim that income maximisation is not the sole determinant of physicians' decisions in terms of labour supply, with their choices also reflecting the marginal utility of some non-pecuniary factors. For instance, work values are important predictors of work-sector choice among Norwegian medical specialists (Midttun 2007). It has been reported that a preference for autonomy is positively associated with working hours allocated to the private sector, whereas professional values impact negatively; a higher emphasis on the value of payment and benefit increases the likelihood of engaging in dual practice among public doctors. Some studies also emphasise the role of job satisfaction in doctors' labour supply decisions. Ikenwilo & Scott (2007) use Scottish survey data to estimate a labour supply model for medical doctors, and they identify job satisfaction as the main explanatory variable. Research on Finnish data shows that higher levels of job satisfaction reduce physicians' intention to switch sectors but that the impact of job dissatisfaction on physicians' intention to leave the public sector is only stable over time Kankaanranta et al. (2007). A similar finding has been documented in the Australian literature (e.g. Ellershaw et al. (2012)).

In addition, demographic factors and family circumstances, such as gender, age and experience, and the presence of children, have also been considered important predictors of choice of work sector throughout a doctor's career (Johannessen & Hagen 2014, Cheng et al. 2013, 2018). There is a substantial gender differential in labour supply and earnings among Australian medical doctors (Schurer et al. 2016), and this has been found to be associated with work-sector choices (Cheng et al. 2018). Older workers are assumed to have accumulated higher levels of experience and finance, which in turn are presumed to increase the preference for being self-employed in the general population (Le 1999). Evidence shows that young physicians are more likely to choose salaried contracts rather than fee-for-service roles, which is related to their relatively lower levels of experience and productivity (Sørensen & Grytten 2003). The probability of undertaking private practice increases with age among Australian doctors (Cheng et al. 2013), while dual practice is more appealing for senior doctors in India because private fees in a second job increase with specialisation and years of practice (Chawla 1997). Engaging in dual practice is more common among senior doctors who have built up good reputations and secure financial positions through their work in the public sector, but there are exceptions in some countries. In Peru, young male doctors are more likely to engage in dual practice than males in other age groups and female doctors (Jumpa et al. 2007). Gender differences in choice of work sector have also been documented among medical doctors in Australia, New Zealand and Spain, with men being more likely than women to be in private or dual practice (Dolado & Felgueroso 2007). Regarding family circumstances, existing studies have focused on the impact of having children. For instance, having a newborn baby was negatively correlated with engaging in dual practice for both male and female Norwegian hospital physicians (Johannessen & Hagen 2014). However, studies examining the effect from the spousal side, for example, spouses' working hours or employment status, on doctors' choice of public or private practice are rare.

Finally, I also examine the influence of selected personal characteristics on doctors' work-sector choice, such as risk aversion, desire for achievement and public-sector motivation. The literature reports that people's willingness to take risks decreases over the life course (Dohmen et al. 2017). Thus, age is not only an index of accumulation of capital and experience as noted above, but may also be a proxy for an individual's attitude towards risk, including the risks associated with self-employment (Le 1999). Self-employment is assumed to be risky, and practising entirely or partly in one's own private clinic is a kind of self-employment for medical specialists. Although there have been no studies to date examining the effect of doctors' risk attitudes on their work-sector choices, I expect it would be an important predictor given that people's risk aversion also varies with their marital status, net worth and so on. On the other hand, an individual's risk attitude is immeasurable or unobservable in most of the dataset. Given that risk aversion varies across individuals and may be an important driver of doctors' work-sector choice, findings on the effects of key observed pecuniary and non-pecuniary factors would be misplaced if I failed to account for it (unobserved individual heterogeneity) in the empirical model (Le 1999).

1.4 The MABEL data and variables

This study uses data from nine waves (2008-2016) of the 'Medicine in Australia: Balancing Employment and Life' (MABEL) survey to investigate factors influencing the working sectors of doctors. MABEL is an annual, nationally representative longitudinal survey of Australian medical practitioners, which is unique in providing extensive information on doctors' labour market status, job satisfaction, working hours, medical specialty, workplace and workload, financial status, personal characteristics and family circumstances.

The first wave of MABEL data was collected in 2008 when all medical doctors in clinical practice in Australia (N = 54,750) were invited to participate in the survey. Respondents completed either a paper or an online survey questionnaire, and the baseline cohort comprised 10,498 medical doctors over four doctor types, including 4,596 specialists (43.8%), 3,906 general practitioners (37.2%), 924 specialists-in-training (8.8%) and 1,072 hospital non-specialists (10.2%). The response rate of the baseline cohort with respect to the sample frame is 19.4%, with specialists having the highest response rate (22.3%) among all doctor types. The baseline cohort was shown to be nationally representative of the population with respect to age, gender, doctor type, geographical location, hours worked and specialties (Joyce et al. 2010). For the second wave (2009) and each subsequent year, a top-up sample of doctors was invited to participate in the survey to maintain the cross-sectional representation of the survey. The most recent wave of data (Wave 9) in this study contains 9,225 observations, 4,784 of which are from the initial baseline cohort.

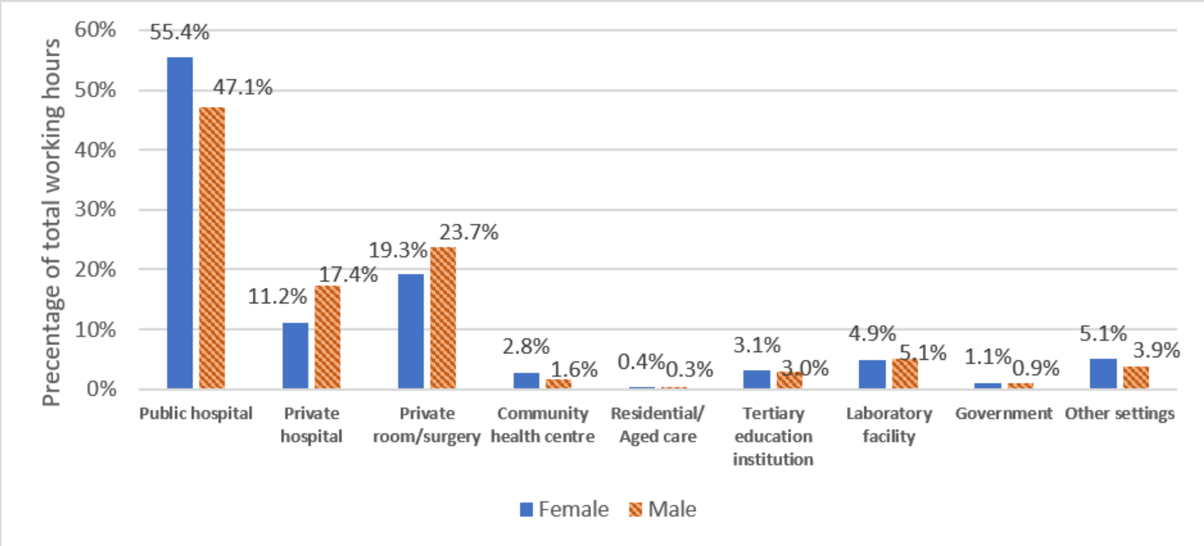
1.4.1 Work settings of MABEL doctors

In each wave of the MABEL survey, medical specialists were asked to report their weekly total working hours and hours in each of the following work settings: public hospital, private hospital, private medical practitioners' rooms/surgery, community health centre, residential/aged care health facility, laboratory or radiology facility, government department, tertiary education institution, and others. Figure 1.1 presents the percentage of hours spent in each work setting by Australian medical specialists over the period 2008–2016. Across all medical specialties, doctors spent a majority of their hours (84%) in public hospitals, private hospitals and private rooms/surgery work settings. More specifically, specialists spent 50% of their working hours on average in public hospitals per week, 15% in private hospitals and 20% in private consulting rooms. A difference in working hours by gender can also be observed in the figure. Female doctors, on average, spent a higher proportion of working hours in public hospitals than male doctors, whereas male doctors tended to allocate more hours to private hospitals and consulting rooms. Australian medical specialists also spent a proportion of time in other work settings, such as government, tertiary education and laboratory facilities. However, the hours worked in these settings (16% in total across six work settings) are not significant compared with hospitals and private rooms.

1.4.2 Sample construction

The MABEL survey covers four broad groups within the workforce: GPs (primary care practitioners), medical specialists, specialists-in-training, and hospital non-specialists (e.g., interns or Medical Officers). Since the main objective of this study is to examine factors that influence doctors' work-sector choice, I use data from the group of MABEL doctors who practised as specialists during the survey period, given that most GPs in Australia work in the private sector,

Figure 1.1: Proportion of time spent in working settings by Australian medical specialists.



while specialists-in-training and hospital non-specialists work predominantly in public hospitals. From the initial sample of 35,947 doctor-year observations (7,658 specialists) in the pooled nine waves of data, I firstly exclude 3,666 observations (about 10.2% of the total sample) who spent more than 50% of their total working hours in work settings other than public hospitals, private hospitals and private rooms/surgery, and focus instead on the group of specialists who predominantly work in the public or private sector. I restrict the sample by dropping 4,801 observations (781 doctors) who worked less than four or more than 100 hours weekly or have missing or incomplete data on working hours. The remaining observations are dropped due to missing information on other key variables of interest. This results in a primary estimation sample of 21,717 doctor-year observations (across 5,924 doctors) over nine years, consisting of 3,911 male (66%) and 2,013 female (34%) specialists.

1.4.3 Defining outcome variable: work sector

The dependent variable is doctors' choice of work sector, which is defined as a three-categories multinomial variable: public-sector only, private-sector only, and dual practice. Doctors in the category public-only work predominantly in public hospitals and spend no time in either private hospitals or private rooms. Doctors undertaking private-only practice are those who mainly work in both private hospitals and private rooms, with zero hours in public hospitals. Dual practice specialists are those who work both in a public setting and in private hospitals or rooms. In each of the three categories, doctors may have some hours spent in the setting termed 'Others', which includes hours worked in community health centres, residential/aged care health facilities, laboratories or radiology facilities, government departments, and tertiary education institutions. As previously mentioned, observations in which half or more of the total allocated hours fell within the 'Others' category were excluded from the analysis sample. Therefore, the inclusion of samples with fewer hours in the 'Others' work setting will not exert any influence on the characterization of public, private, and dual practice definitions.

Table 1.1 shows the distribution of specialists in public, private, and dual practice as well as their corresponding weekly working hours. In the pooled sample, I found about 38% of observations worked entirely in the public sector, while 18% worked entirely at a private hospital or in a private consultation room/surgery. 44% of all observations were doctors engaging in dual practice, undertaking both private and public work. The working hours of doctors vary significantly by work setting. Dual practice specialists worked the longest hours of all specialists, 46 hours weekly on average. Doctors who worked only in the private sector had the lowest hours, 39 hours per week, slightly less than public-only doctors, at 41 hours per week. I also observed gender differences in working hours by doctors in all three categories, with female specialists working 5–8 fewer hours per week compared with their male counterparts.

Further looking into the dynamics of work sector choice along the nine survey years (2008 to 2016). Table 1.2 presents the transition matrix among the three work settings (i.e. public only, private only and dual practice) of medical specialists from the initial survey cohort. The transition matrix provides insights into both the frequency and probability of transitions. The findings reveal a consistent pattern over the nine years. The majority of medical specialists tend to remain within a single work setting, with probabilities ranging from 89% to 92%. Notably, a small proportion, approximately 1%, transition from a public work setting to private practice, while about 6% transition to dual practice. This underscores the preference for stability within specific work settings among medical specialists throughout the study period.

1.4.4 Covariates

The following describes covariates included as predictors of work-sector choice in the empirical model, which includes demographic and pecuniary factors, family circumstances, and medical specialties.

Demographic factors play important roles in influencing the labour supply decisions of doctors. As discussed earlier, there is a substantial gender differential in labour supply and earnings among Australian medical doctors, so a gender difference in the choice of public or private sector work is also expected among medical specialists. The gender variable is represented using a binary indicator, with females assigned as 1. Age and work experience have also been shown to be important in influencing individuals' labour supply decisions. Doctors at different stages of their careers are expected to make different decisions regarding the work sector. I examine the age effect using an age category variable, which includes four values: less than 40 years old, 40–50 years old, 50–60 years old, and 60 years old or over, to capture the stages of a doctor's career and examine the heterogeneous effect of age on doctors' work sector choice. Young doctors (under 40 years old) form the reference group for the analysis. In addition, I examined the cohort effect on work sector choice for doctors, where the cohort is measured by the year of graduation from medical school. The cohort effect is measured using a four-category indicator (graduated pre-1974, graduated 1975–1984, graduated 1985–1994, and graduated 1995–2014) with those who graduated pre-1974 as the reference group. Although specialists require similar training to qualify for registration, some specialists continue their education post-graduation. To capture these differences in human capital, I include an indicator of whether the doctor has a PhD degree.

One main pecuniary variable examined in this study is the amount of financial debt owed by medical doctors. Earlier work suggests that financial debt and interest payments positively affect the probability of doctors' engagement in dual practice (Johannessen & Hagen 2014). Having higher financial debt has also been associated with a higher probability of being involved in self-employment in the general population (Le 1999). Thus, I examined the effect of two types of financial debt variables. One is education debt, which represents the amount of debt from medical education/training; the other is business debt, which captures the amount of debt from owning private practices. Higher education debt is expected to be positively associated with a higher probability of choosing to work in the sector with higher net income, such as mixed-sector practice; while higher business debt is expected to be positively associated with working in the private sector. In addition, I account for doctors' income through doctors' annual gross earnings. It is reasonable to expect that doctors to some extent change their work sector due to the prospect of higher income (Brekke & Sørgard 2000).

Family circumstances have been shown to be important in influencing labour supply decisions among medical doctors. I investigate the role of family circumstances by examining their impact on children and spouses. The main explanatory variables are the number of dependent children, being parents of young children (less than five years old), and the status of doctors' spouses. The number of dependent children is a continuous variable representing the number of children aged under 25 years. Being the parent of young children is a binary indicator, identifying doctors with one or more children under the age of five. Status of the partner is a category variable that takes one of the following values: having no partner, having a partner and the partner is not employed, having a part-time employed partner, and having a full-time employed partner. Doctors with a partner not in the labour market are regarded as the reference group.

The sector in which a doctor chooses to work may vary significantly with the medical field he/she specialises in. Thus, I include dummies for medical specialties in the empirical model and assume that the specialty of a doctor is time-invariant. Doctors' specialty is represented by 15 separate dummy variables: General Medicine, Geriatrics, Pediatric Medicine, Other Internal Medicine, General Surgery, Orthopedic Surgery, Other Surgery, Anaesthesia, Diagnostic Radiology, Emergency Medicine, Intensive care, Obstetrics and Gynaecology, Ophthalmology, Psychiatry, and Others. Doctors in General Medicine form the reference group. In addition, doctors' geographical location and the number of practice locations are also controlled for in the model.

1.4.5 Summary Statistics

Table 1.3 shows descriptive statistics for the pooled-nine-waves sample by work sector. I found that specialists in different work sectors vary in a number of respects. One key difference is gender composition. A higher proportion of female doctors work in the public sector than in the private sector (41% vs. 30%), with the proportion of females engaging in dual practice being the lowest (27%). The distribution of doctors in public and private sectors also varies by other demographic characteristics such as age, cohort and education level. For instance, a higher proportion of public-only doctors are less than 50 years old, while private-only doctors are more likely to be over 50 and a majority of dual practitioners are middle-aged (66% aged 40-59). Doctors with PhD degrees are more likely to work in the public sector, either entirely or through dual practice.

Doctors in each work sector are also distinguishable in terms of earnings and debt. Private-only specialists earned more annually than their colleagues working only in public hospitals ($383,000 vs. $266,000). Doctors in dual practice earned the highest annual income ($408,000), which is due to working the highest number of hours (Table 1.1). Doctors in private practice owed significantly higher levels of financial debt compared with public-only doctors, including debt from medical education ($973 vs. $680 on average) and business debt ($91,000 vs. $3,000 on average).

The distribution of specialists in the public and private sectors also varies by family circumstances, such as the status of children and spouses. Dual-practice doctors were more likely to have more children, and their partners were more likely to work part-time, while public-only doctors were more likely to have pre-school-aged young children and their partners were more likely to be in full-time employment. In addition, medical specialty is another important factor predictor of doctors choosing public or private sectors. For instance, doctors in the Emergency Medicine and Intensive Care categories mostly worked in public hospitals (86.7% and 62.3%) or in dual practice (10.7% and 31.3%), while the majority of surgeons and anaesthetists were dual practitioners.

1.5 Empirical Strategy

Doctors' work-sector choices were analysed using a Multinomial Logit (MNL) model, which is based on an underlying Random Utility Model. The utility U that individual i derives from work sector j at time t is given by:

$$U_{ijt} = \beta_0 X_{1it} + \beta_1 X_{2i} + \eta_i + \varepsilon_{ijt} \tag{1.1}$$

Each specialist i is assumed to choose the alternative j with the highest utility, for which $U_j > U_k$, for any $j \neq k$. The utility function takes three arguments: time-varying factors X_{1it}, time-invariant factors X_{2i} and unobserved individual heterogeneity η_i. The errors ε_{ijt} are assumed to have Type I extreme-value distributions, which are independent and identically distributed across alternatives j. Under the assumption of utility maximisation, the probability that the individual i chooses alternative j at time t is given by

$$Pr(U_{ijt} > U_{ikt}, k \neq j) = \frac{exp(U_{ijt})}{\sum_{j=1}^{J} exp(U_{ijt})} \tag{1.2}$$

Using a MNL model to estimate doctors' work-sector choices creates a risk of bias in the results if effects from unobserved individual heterogeneity are ignored since individual heterogeneity η_i (e.g., risk attitudes, personal motivation) also influences doctors' choice of work sectors. A Stata software package has been developed by Pforr (2014) for estimating a MNL model with unobserved heterogeneity. With the presence of η_i, the parameters of the MNL choice equation can be consistently estimated using a fixed effects estimator. However, this MNL fixed-effect estimator cannot be applied in the context of this study as it does not permit the estimation of coefficients for time-invariant covariates, such as gender and medical specialty. Those time-invariant factors are expected to play an important role in doctors' work-sector choices. In addition, the MNL fixed-effect model does not permit the computation of variables' marginal effects, which makes the interpretation of the coefficients difficult.

Given the limitations discussed above, I employed the correlated random effect (CRE) approach, proposed originally by Mundlak (1978) and Chamberlain (1982), to accommodate both the effect of individual unobserved heterogeneity and the estimation of time-invariant covariates in the MNL model. In the CRE model, the individual-specific effects (heterogeneity) term η_i is expressed as a function of the time averages of the time-varying covariates X_{1it}. Suppose I decompose the individual heterogeneity term $\eta_i = \alpha_0 + \gamma\overline{X_i}^{'} + \delta_i$ where $\overline{X_i} = T_i^{-1}\sum_{t=1}^{T_i} X_{1it}$. It is usually assumed that $E(\delta_i|x) = 0$. For unbalanced panels, which I use in this study, $\overline{X_i}$ is calculated as the time averages of X_{1it} for the number of time periods that are observed for each individual i (Wooldridge 2010a). Hence, the utility function can be written as

$$U_{ijt} = \alpha_0 + \beta_0 X_{1it} + \beta_1 X_{2i} + \gamma\overline{X_i}^{'} + \delta_i + \varepsilon_{ijt} \tag{1.3}$$

The multinomial choice model then is written as

$$Pr(Y_{it} = j) = \frac{exp(U_{ijt})}{\sum_{j=1}^{J} exp(U_{ijt})} = \frac{exp(\alpha_0 + \beta_0 X_{1it} + \beta_1 X_{2i} + \gamma\overline{X_i}^{'} + \delta_i + \varepsilon_{ijt})}{\sum_{j=1}^{J} exp(\alpha_0 + \beta_0 X_{1it} + \beta_1 X_{2i} + \gamma\overline{X_i}^{'} + \delta_i + \varepsilon_{ijt})} \tag{1.4}$$

I estimated the marginal effect of each regressor, which is interpreted as the probability of changing j arising from one-unit change from 0 to 1 change in the regressor.

1.6 Empirical Results

1.6.1 CRE-MNL estimation

Table 1.4 presents the marginal effects of demographic factors, pecuniary variables, family circumstance and medical specialties on doctors' work-sector choice, as estimated using a MNL model with the Correlated Random Effect approach (CRE-MNL). Our results indicate that the choice of work sector depends significantly on gender. As shown in Table 1.4, females were five percentage points more likely to undertake private-only work and three percentage points more likely to undertake public-only work compared to males. However, there was no gender difference in engagement in dual practice. This result is consistent with the findings of a previous Australian cross-sectional study (Cheng et al. 2013) which suggests that choosing dual practice is not significantly associated with doctors' gender.

Doctors' choice of work sector also varied with their age. Compared with doctors aged 40 years or less, the probability of choosing public-only work decreased with age, with older doctors having an increasing probability of working either entirely in the private sector or in dual practice. For example, all else being equal, the probability of doing public-only work was 10.4 to 12.5 percentage points lower for doctors over 50 years, whereas their likelihood of choosing private-only work or dual practice was 6–8 percentage points higher compared with doctors aged less than 40 years. Looking across the career life-cycle of Australian specialists, their choices of work sector followed a pattern of starting in the public sector and moving towards the private sector as they become older, with more engagement in dual practice from middle age.

In addition to the age effects, I find that more recent cohorts of doctors were less likely to undertake private-only work. Compared with specialists who graduated with their basic medical degree before 1974, the probability of choosing to work solely in the private sector was 5.3 and 9 percentage points lower for those who graduated in 1985–1994 and 1995–2014 respectively. This indicates that more recently qualified doctors were less likely to undertake private-only practice. No significant difference is found across cohorts in public-only practice or dual practice. Having a PhD qualification was associated with an increased probability of dual practice but a lower probability of private-only practice.

Pecuniary factors such as annual earnings and financial debt are found to be significantly associated with the sector in which doctors choose to work. The results indicate that doctors with higher earnings were more likely to undertake dual practice but less likely to undertake public-only practice. Having a higher business debt is also associated with higher probability of private-only and dual practice but a lower probability of working entirely in the public sector. However, the effect of education debt is insignificant for doctors in our sample. There are two possible explanations for education debt having an insignificant effect on the choice of work sector. One is the rather small sample size of observations on education debt in our sample. The other consideration reflects the historical background of education debt in Australia. Tuition fees were re-introduced to medical school study in 1989 and since then medical students have borrowed through Higher Education Contribution Scheme (HECS) to pay tuition fees, repaying their debt through the tax system as their income exceeds a threshold level. As a result, the effect of education debt might be mitigated when mixing cohorts from before and after tuition fees were reintroduced, particularly given that a large proportion of doctors in our sample graduated from medical school before 1995.

In terms of the impact of family circumstances, I examined the role of children and partners of specialists. The results show that the presence of young children had a significant impact on doctors' work-sector choice, but the link between the number of children and the work sector was rather weak. In particular, doctors with young children were more likely to work in public-only or private-only settings and less likely to undertake dual practice, which typically involves longer working hours. All else being equal, having pre-school children (4 years or younger) increased the probability of public-only practice by 2.3 percentage points and decreased the probability of dual practice by 4.2 percentage points for all specialists. In addition, I find that doctors' work sector was significantly associated with the employment status of their partners. Compared with those whose spouses are not in the labour market, doctors with an employed partner were less likely to be in public-only practice and more likely to be in dual practice if the partner worked full-time, whereas doctors without partners were more likely to choose private-only practice.

Doctors' work-sector choices varied significantly according to their medical specialties. Compared with doctors who specialised in general medicine, general surgeons were less likely to do public-only practice, and orthopaedic surgeons were more likely to be dual practitioners. Diagnostic radiologists were less likely to undertake dual practice and were associated with a higher probability of working solely in the public or private sectors. For some specialties, doctors' choices of work sector were more homogeneous; for example, Emergency and Intensive Care doctors were significantly more likely to work in public hospitals; in contrast, gynecologists, psychiatrists and ophthalmologists were more likely to do private-only practice.

1.6.2 Effectiveness of Mundlak(1978) adjustment and impact of unobserved heterogeneity

As discussed earlier, I use the CRE approach to capture unobserved individual heterogeneity. To empirically test the significance of the role of individual heterogeneity, I use the Wald test to check the joint significance of the time averages of the time-varying covariates included in the regression model. The test result shows that time average variables are not equal to zero and are jointly significantly distinguishable ($Chi^2(30) = 298.17$). This result indicates that unobserved individual heterogeneity characteristics are important determinants of doctors' work-sector choices.

To assess the sensitivity of our results to the exclusion of unobserved heterogeneity, this study estimated a MNL model on the same covariates without the Mundlak (1978) adjustment. Table A1 shows the marginal effects of key pecuniary and non-pecuniary variables estimated by the MNL model. The estimated parameters are found to be more distinct, and effects are relatively larger compared with those estimated by the CRE-MNL model. For example, MNL estimation shows that doctors having more children or having an employed partner (either part-time or full-time) was significantly and positively associated with the dual practice, while estimations of those family circumstances variables turn out to be insignificant and smaller in the CRE-MNL regression, where I account for individual heterogeneity. Similarly, the effects of pecuniary factors and medical specialty are smaller in the CRE-MNL estimation than in the MNL results.

The difference in estimations between MNL and CRE-MNL models indicates that the existing unobserved heterogeneity means the impacts of observed characteristics, such as pecuniary factors, family factors and specialty, will be overestimated if failing to account for it. Given that the majority of the existing evidence on how doctors' work-sector choices are influenced by economic incentives or family circumstances is based on cross-sectional studies, it is reasonable to infer that the effects reported in the literature would be scaled down after accounting for unobserved individual heterogeneity if panel data were available.

The smaller estimated coefficients in the CRE-MNL model after controlling for unobserved individual heterogeneity also imply negative selection effects when doctors choose work sectors, whereby individuals might self-select into private/public sectors due to monetary motivation or to factors other than pecuniary gains. For example, doctors selecting the public sector are motivated by its advantages in terms of team environment, more academic opportunities etc.

1.7 Conclusion

This study uses a unique longitudinal dataset of Australian doctors spanning nine annual waves to investigate the impact of an extensive list of pecuniary and non-pecuniary factors on doctors' work sector choices. The analysis focuses on medical specialists, who are unevenly distributed in the public and private sectors, with nearly half engaging in dual practice. Using a Multinomial Logit model with a Correlated Random Effect (CRE-MNL) approach has allowed us not only to obtain estimates of important time-invariant factors but also to capture the effect of unobserved individual heterogeneity in driving doctors' choices of public, private and dual practice.

There is strong evidence of age and cohort effects for specialists in making work sector choices. The practice pattern of a specialist varies along the different stages of life. Our results indicate that young doctors are associated with a high probability of starting their career with a public-sector role, and the the probability of engaging in private practice increases with age. Doctors increasingly engage in dual practice as they grow older, until their late 50s. Doctors over 60 are more likely to withdraw from the public sector and only undertake private sector work before retiring, which is likely due to a higher demand for better work-life balance among older doctors. There are also variations in medical specialists' work-sector choices across different generations. The results show that the probability of choosing private health care is lower among specialists in the more recently graduated cohorts. Two factors noted in the literature could explain the changes in doctors' preference for private practice across generations. One is doctors' attitudes towards work-life balance, with doctors born prior to the 1980s perceiving a better work-life balance as leading to higher job satisfaction (Kaliannan et al. 2016). The other reason is the change in doctors' practice patterns. The literature reports that the percentage of GPs in solo practice is much lower than that ten years ago (Britt et al. 2016), with factors discouraging ownership including increased responsibility, greater time commitments and the potential for financial burden (Joyce et al. 2016). This trend may also be applicable to the practice pattern of medical specialists, with younger cohorts less likely to prefer private practice.

Another key finding is the effect of education debt. Education debt is documented as an important factor influencing young doctors' specialty choices. However, this study finds no evidence that medical education debt affects doctors' public-private choice, even after controlling for age and cohort. This finding is important as tuition fees for medical study have been increasing over time since being reintroduced in Australia in 1989. As a result, the number of medical students who owe education debts and the amount of debt they owe has also been increasing. The findings on education debt suggest that financial debt from medical education is likely not significant in doctors' choice of work sector.

In addition, unobserved heterogeneity is an important driver of work-sector choice. This includes work values (Midttun 2007) and public sector motivation (Ashmore 2013), as well as doctors' risk aversion. The questionnaire used in the MABEL survey includes a question about doctors' attitudes to risk-taking: 'How likely are you to engage in each of the following activities: financial risks, career and professional risks and clinical risks?'. Responses are measured on a 1–5 point Likert scale where 1=very unlikely and 5=very likely. Using these scores, I calculated the average of the scores for doctors working in all three practice types. A higher score implies higher risk-taking in a given domain. The results find that doctors' work sectors vary with their risk attitudes. For instance, private-only doctors and dual practitioners are associated with a higher mean score for financial risks, while those in public-only practice are associated with a higher tolerance for clinical risks. Both public-only and dual practice doctors had higher scores in career and professional risk-taking (results are shown in Table 1.5).

This study has a limitation that it is important to acknowledge. The CRE-MNL regression analysis employed an extensive array of variables as explanatory covariates, intending to comprehensively assess their significance in predicting a doctor's choice of medical practice type. This "kitchen sink" modelling strategy encompasses a wide range of variables but without a specific focus. Nonetheless, this approach serves as a valuable exploratory step in our research, effectively exploring a comprehensive list of factors, including gender, age, cohort, earnings, financial debt, medical specialty, family circumstances, and unobserved individual characteristics, all of which emerge as pivotal determinants influencing specialists' choices between public and private practice settings. This comprehensive understanding of the factors shaping medical specialists' work sector preferences also lays a solid foundation for gaining insights into the mechanism of medical workforce distribution. In future research, our focus will shift towards a more nuanced investigation, particularly with regard to gender differences in the significance of explanatory variables. This will involve employing a Kitagawa-Oaxaca-Blinder decomposition on a modified binary outcome while maintaining the remaining covariates as control variables.

To conclude, understanding the determinants influencing the sections of work sectors by medical specialists allows us to develop a clearer picture of the national healthcare capacity across different sectors of the healthcare system. Factors including gender, age, cohort, earnings, financial debt, medical specialty, family circumstances and unobserved individual characteristics all play essential roles in shaping specialists' decisions to practice in either the public or private domains. This information bears particular significance during national emergencies, such as the COVID-19 pandemic in 2020-2022. Notably, specialists in emergency medicine and intensive care specialties, who were essential in managing the pandemic, exhibit a higher propensity to opt for public-sector practice. Furthermore, some potential policy options may serve as effective incentives to encourage specialists to choose public-sector employment. For instance, addressing concerns related to work-life balance in public hospitals by introducing relatively flexible working hours could render positions in the public sector more attractive, especially for female physicians with young children. Additionally, the demonstrated preference for stability within specific work settings among medical specialists underscores the necessity for targeted policies to influence the initial choice of the work sector rather than focusing solely on retention policy.

Tables

Table 1.1: Distribution of specialists and weekly working hours by work sector.

	Distribution		Hours worked per week		
Work-sector choice	Frequency	Proportion	Female	Male	Full sample
Public only	8,193	37.7%	36.6	44.3	41.2
Private only	3,967	18.3%	35.2	40.4	38.8
Dual practice	9,557	44.0%	39.8	48.1	45.9
Total	21,717	100%	37.5	45.4	42.8

Note: Pooled wave 1 to wave 9 (2008-2016) of the MABEL survey data.

Table 1.2: Transition matrix among the three work settings chosen by medical specialists.

Work setting	Public only	Private only	Dual practice	Total
Public only	4,363 (91.93%)	41 (0.86%)	342 (7.21%)	4,746 (100%)
Private only	39 (1.26%)	2,850 (92.26%)	200 (6.47%)	3,089 (100%)
Dual practice	396 (5.53%)	391 (5.46%)	6,368 (89%)	7,155 (100%)
Total	4,798 (32.01%)	3,282 (21.89%)	6,910 (46.10%)	14,900 (100%)

Table 1.3: Sample means of covariates by work sector (in proportions unless otherwise stated).

Variables	Public Only	Private Only	Diff.[a]	Dual Practice	Diff.[b]
Female	0.409	0.298	***	0.260	***
	(0.492)	(0.458)		(0.439)	
Age 40 y.o. or less	0.201	0.081	***	0.167	***
	(0.401)	(0.273)		(0.373)	
Age 40 to 49 y.o.	0.390	0.236	***	0.358	***
	(0.488)	(0.425)		(0.479)	
Age 50 to 59 y.o.	0.257	0.321	***	0.305	***
	(0.437)	(0.467)		(0.460)	
Age 60 y.o. or over	0.152	0.362	***	0.170	***
	(0.359)	(0.481)		(0.376)	
Graduated in pre-1974	0.123	0.301	***	0.134	**
	(0.328)	(0.459)		(0.341)	
Graduated in 1975-1984	0.224	0.326	***	0.291	***
	(0.417)	(0.469)		(0.454)	
Graduated in 1985-1994	0.348	0.230	***	0.311	***
	(0.476)	(0.421)		(0.463)	
Graduated in 1995-2014	0.305	0.142	***	0.265	***
	(0.460)	(0.349)		(0.441)	
PhD degree	0.300	0.247	***	0.276	***
	(0.458)	(0.431)		(0.447)	
Annual earnings ($‘000)	265.569	383.081	***	408.084	***
	(124.357)	(291.028)		(258.754)	
Education debt ($‘000)	0.680	0.973	*	0.960	**
	(7.056)	(9.260)		(8.886)	
Business debt ($‘000)	3.338	91.234	***	84.815	***

Continued on next page

Table 1.3 – continued from previous page

Variables	Public Only	Private Only	Diff.[a]	Dual Practice	Diff.[b]
	(49.943)	(285.528)		(274.512)	
Number of children	1.345	1.215	***	1.599	***
	(1.152)	(1.194)		(1.164)	
Have young children	0.222	0.119	***	0.202	***
(4 y.o. or younger)	(0.415)	(0.324)		(0.401)	
No partner	0.157	0.173	**	0.117	***
	(0.364)	(0.379)		(0.322)	
Partner does not work	0.246	0.238		0.217	***
	(0.431)	(0.426)		(0.412)	
Partner work full-time	0.306	0.246	***	0.274	***
	(0.461)	(0.431)		(0.446)	
Partner work part-time	0.292	0.343	***	0.391	***
	(0.455)	(0.475)		(0.488)	
Number of practice locations	1.705	2.448	***	3.133	***
	(1.167)	(1.915)		(1.769)	
Metro area	0.816	0.872	***	0.805	*
	(0.388)	(0.334)		(0.396)	
General medicine	0.506	0.081	***	0.413	***
	(0.500)	(0.273)		(0.493)	
Geriatrics	0.703	0.032	***	0.265	***
	(0.457)	(0.176)		(0.442)	
Paediatric medicine	0.592	0.075	***	0.333	***
	(0.492)	(0.264)		(0.471)	
Internal medicine	0.378	0.115	***	0.508	***
	(0.485)	(0.319)		(0.500)	

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Table 1.3 – continued from previous page

Variables	Public Only	Private Only	Diff.[a]	Dual Practice	Diff.[b]
General surgery	0.207	0.066	**	0.727	***
	(0.406)	(0.248)		(0.446)	
Orthopaedic surgery	0.096	0.269	***	0.635	***
	(0.295)	(0.444)		(0.482)	
Surgery:other	0.065	0.216	***	0.719	***
	(0.246)	(0.412)		(0.450)	
Anaesthesia	0.268	0.192	***	0.540	***
	(0.443)	(0.394)		(0.498)	
Diagnostic radiology	0.427	0.259	***	0.314	***
	(0.495)	(0.438)		(0.464)	
Emergency medicine	0.867	0.026	***	0.107	***
	(0.340)	(0.159)		(0.310)	
Intensive care	0.623	0.07	***	0.311	***
	(0.485)	(0.249)		(0.464)	
Obstetrics and Gynecology	0.253	0.261	***	0.486	***
	(0.435)	(0.439)		(0.500)	
Ophthalmology	0.017	0.337	***	0.646	***
	(0.130)	(0.473)		(0.479)	
Psychiatry	0.357	0.390	***	0.253	***
	(0.479)	(0.487)		(0.435)	
Other specialty	0.442	0.221		0.337	***
	(0.497)	(0.418)		(0.473)	
Number of observations	8,193	3,967		9,557	

Note: Standard deviation in parenthesis. [a] test of the difference in means of Private versus Public. [b] test of the difference in means of Dual Practice versus Public. Significance: *** 1%; ** 5%; * 10%.

Table 1.4: Marginal effects of pecuniary and non-pecuniary factors on work-sector choice estimated by MNL-CRE model.

Variables	Public Only	Private Only	Dual Practice
Female	-0.031**	0.050***	-0.019
	(0.013)	(0.013)	(0.015)
Age 40 y.o. or less (Ref)			
Age 40 to 49 y.o.	-0.073***	0.043***	0.030**
	(0.012)	(0.013)	(0.015)
Age 50 to 59 y.o.	-0.104***	0.060***	0.044**
	(0.017)	(0.017)	(0.020)
Age 60 y.o. or over	-0.125***	0.078***	0.046*
	(0.023)	(0.021)	(0.027)
Graduated in pre-1974 (Ref)			
Graduated in 1975-1984	-0.010	-0.035	0.045
	(0.033)	(0.025)	(0.034)
Graduated in 1985-1994	0.032	-0.053*	0.021
	(0.036)	(0.030)	(0.040)
Graduated in 1995-2014	0.032	-0.090***	0.057
	(0.038)	(0.033)	(0.041)
PhD degree	0.002	-0.053***	0.051***
	(0.015)	(0.016)	(0.017)
Annual earnings ($‘0000)	-0.002***	0.0001	0.002***
	(0.0003)	(0.0001)	(0.0002)
Education debt ($‘0000)	-0.002	-0.0004	0.002
	(0.004)	(0.002)	(0.004)

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Table 1.4 – continued from previous page

Variables	Public Only	Private Only	Dual Practice
Business debt ($‘0000)	-0.003***	0.001**	0.002***
	(0.001)	(0.0003)	(0.001)
Number of children	-0.004	0.001	0.003
	(0.005)	(0.004)	(0.006)
Have young children	0.024**	0.019**	-0.043***
(4 y.o. or younger)	(0.010)	(0.009)	(0.011)
No partner	-0.011	0.026***	-0.016
	(0.010)	(0.009)	(0.012)
Partner does not work (Ref)			
Partner work full-time	-0.027***	0.006	0.021*
	(0.010)	(0.008)	(0.012)
Partner work part-time	-0.020**	0.009	0.011
	(0.008)	(0.006)	(0.009)
Number of practice locations	-0.039***	-0.008***	0.047***
	(0.004)	(0.002)	(0.004)
Metro area	-0.064**	0.033	0.032
	(0.027)	(0.032)	(0.033)
General medicine (Ref)			
Geriatrics	0.104**	-0.057	-0.047
	(0.041)	(0.059)	(0.055)
Paediatric medicine	0.007	0.022	-0.029
	(0.033)	(0.04)	(0.041)
Internal medicine	-0.112***	0.070*	0.042
	(0.028)	(0.036)	(0.035)

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Table 1.4 – continued from previous page

Variables	Public Only	Private Only	Dual Practice
General surgery	-0.110***	-0.040	0.150***
	(0.040)	(0.047)	(0.043)
Orthopaedic surgery	-0.220***	0.162***	0.057
	(0.047)	(0.043)	(0.046)
Surgery:other	-0.311***	0.142***	0.169***
	(0.045)	(0.043)	(0.045)
Anaesthesia	-0.059**	0.139***	-0.080**
	(0.029)	(0.036)	(0.036)
Diagnostic radiology	0.090**	0.169***	-0.260***
	(0.040)	(0.041)	(0.046)
Emergency medicine	0.200***	-.0050	-0.195***
	(0.037)	(0.054)	(0.051)
Intensive care	0.096**	-0.007	-0.089*
	(0.040)	(0.057)	(0.055)
Obstetrics and Gynecology	-0.132***	0.138***	-0.005
	(0.033)	(0.039)	(0.039)
Ophthalmology	-0.522***	0.280***	0.243***
	(0.071)	(0.046)	(0.059)
Psychiatry	-0.131***	0.265***	-0.134***
	(0.030)	(0.037)	(0.038)
Other specialties	-0.027	0.150***	-0.123***
	(0.028)	(0.036)	(0.036)
2008 (Ref)			
2009	0.028***	0.007	-0.034***

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Table 1.4 – continued from previous page

Variables	Public Only	Private Only	Dual Practice
	(0.008)	(0.007)	(0.008)
2010	0.033***	0.008	-0.041***
	(0.009)	(0.008)	(0.009)
2011	0.047***	0.010	-0.057***
	(0.009)	(0.009)	(0.010)
2012	0.070***	0.046***	-0.115***
	(0.017)	(0.017)	(0.019)
2013	0.068***	0.065***	-0.133***
	(0.017)	(0.018)	(0.019)
2014	0.053***	0.022**	-0.075***
	(0.011)	(0.010)	(0.012)
2015	0.069***	0.021**	-0.091***
	(0.012)	(0.011)	(0.013)
2016	0.054***	0.030***	-0.084***
	(0.012)	(0.011)	(0.013)
Number of observations		21,717	
Pseudo R^2		0.26	
Log Pseudo-likelihood		-16809.24	

Note: Significance: *** 1%; ** 5%; * 10%. Cluster-robust standard errors are reported in the parenthesis; standard errors are clustered at individual level.

Table 1.5: Means of doctors' risk attitudes by work sector.

Variables	Public Only	Private Only	Diff.[a]	Dual Practice	Diff.[b]	Diff.[c]
Financial risks	1.913	2.014	***	2.058	***	
	(1.001)	(1.085)		(1.011)		
Career and professional risks	2.399	2.094	***	2.365		***
	(1.040)	(1.046)		(1.033)		
Clinical risks	2.203	2.002	***	2.192		***
	(0.972)	(0.996)		(0.963)		
Number of observations	3,559	1,611		3,715		

Note: MABEL questions on risk attitudes of doctors available from Wave 6 onwards. They are measured by 1-5 scale score, where 1=very unlikely and 5=very likely. Standard deviation in parenthesis. [a] test of the difference in means of Private versus Public. [b] test of the difference in means of Dual Practice versus Public. [c] test of the difference in means of Dual Practice versus Private. Significance: *** 1%; ** 5%; * 10%.

Appendix

Table A1: Marginal effects estimated by MNL (full sample).

Variables	Public Only	Private Only	Dual Practice
Female	-0.011	0.041***	-0.030*
	(0.012)	(0.013)	(0.014)
Age 40 y.o. or less (Ref)			
Age 40 to 49 y.o.	-0.001	0.025*	-0.024*
	(0.013)	(0.014)	(0.015)
Age 50 to 59 y.o.	-0.012	0.063***	-0.051**
	(0.019)	(0.020)	(0.021)
Age 60 y.o. or over	-0.079***	0.129***	-0.050*
	(0.026)	(0.024)	(0.028)
Graduated in pre-1974 (Ref)			
Graduated in 1975-1984	0.023	-0.048***	0.025
	(0.024)	(0.018)	(0.025)
Graduated in 1985-1994	0.085***	-0.077***	-0.008
	(0.027)	(0.022)	(0.029)
Graduated in 1995-2014	0.088***	-0.102***	0.014
	(0.028)	(0.025)	(0.031)
PhD degree	0.023***	-0.022***	-0.001
	(0.007)	(0.006)	(0.007)
Annual earnings ($‘0000)	-0.005***	0.002***	0.003***
	(0.0003)	(0.0002)	(0.0003)
Education debt ($‘0000)	-0.004	0.007	-0.003
	(0.005)	(0.004)	(0.005)
Business debt ($‘0000)	-0.011***	0.004***	0.007***

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Table A1 – continued from previous page

Variables	Public Only	Private Only	Dual Practice
	(0.002)	(0.001)	(0.001)
Number of children	-0.022***	-0.0004	0.023***
	(0.005)	(0.004)	(0.006)
Have young children	0.011	0.011	-0.021
(4 y.o. or younger)	(0.012)	(0.013)	(0.014)
No partner	-0.028*	0.019	0.010
	(0.016)	(0.014)	(0.017)
Partner does not work (Ref)			
Partner work full-time	-0.056***	-0.006	0.062***
	(0.013)	(0.013)	(0.015)
Partner work part-time	-0.063***	-0.002	0.065***
	(0.012)	(0.011)	(0.013)
Number of practice locations	-0.091***	0.007**	0.085***
	(0.005)	(0.003)	(0.004)
Metro area	-0.0003	0.056***	-0.056***
	(0.013)	(0.014)	(0.015)
General medicine (Ref)			
Geriatrics	0.120***	-0.065	-0.055
	(0.042)	(0.060)	(0.056)
Paediatric medicine	0.016	0.018	-0.034
	(0.034)	(0.043)	(0.041)
Internal medicine	-0.116***	0.068*	0.048
	(0.029)	(0.036)	(0.035)
General surgery	-0.132***	-0.034	0.166***
	(0.040)	(0.047)	(0.043)

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Table A1 – continued from previous page

Variables	Public Only	Private Only	Dual Practice
Orthopaedic surgery	-0.266***	0.184***	0.082*
	(0.048)	(0.043)	(0.046)
Surgery:other	-0.353***	0.159***	0.194***
	(0.046)	(0.043)	(0.045)
Anaesthesia	-0.079***	0.146***	-0.067*
	(0.029)	(0.036)	(0.036)
Diagnostic radiology	0.066*	0.179***	-0.244***
	(0.040)	(0.041)	(0.046)
Emergency medicine	0.227***	-0.014	-0.212***
	(0.038)	(0.054)	(0.051)
Intensive care	0.098**	-0.004	-0.094*
	(0.040)	(0.057)	(0.055)
Obstetrics and Gynecology	-0.154***	0.150***	0.005
	(0.034)	(0.039)	(0.039)
Ophthalmology	-0.565***	0.298***	0.267***
	(0.072)	(0.046)	(0.059)
Psychiatry	-0.129***	0.264***	-0.135***
	(0.031)	(0.037)	(0.038)
Other specialties	-0.032	0.154***	-0.121***
	(0.029)	(0.036)	(0.036)
Number of observations		21,717	
Pseudo R^2		0.24	
Log Pseudo-likelihood		-17226.95	

Note: Significance: *** 1%; ** 5%; * 10%. Cluster-robust standard errors are reported in the parenthesis; standard errors are clustered at individual level.

Supplementary Discussion

1.7.1 Attrition of panel data

Potential biases in inference resulting from attrition are a frequent concern when using long-wave panel data. The over-attrition rate of the full, balanced panel from Wave 1 to Wave 9 is 72.3% with the year-on-year attrition rate decreasing from 22.1% to 9.1%. Due to the nature of the sampling frame (doctors instead of the general population) and the survey method (MABEL is a self-complete survey rather than using interviewers), the attrition rates of Wave 1 and Wave 2 (21.1% and 17.0%) are relatively higher compared with figures in other workforce surveys; however, it has been shown that the impact of attrition on inference about earnings and hours worked is small when modelled with the first four waves of MABEL data (Cheng & Trivedi 2015). Cheng & Trivedi (2015)'s finding aligns with the general view of many influential studies in the literature on the consequence of attrition in panel studies, which report that attrition does not lead to serious biases in the economic sense, even in the presence of statistical evidence of attrition bias, and large sample attrition (Fitzgerald et al. 1998, Neumark & Kawaguchi 2004, Jones 2009). Given the above, the nature of our longitudinal data in terms of the relatively high level of attrition is not a concern.

1.7.2 Independence of Irrelevant Alternatives (IIA) Assumption

The Multinomial Logit (MNL) model relies on a widely recognized assumption known as the Independence of Irrelevant Alternatives (IIA). This assumption posits that the introduction or removal of alternatives should not have any bearing on the relative odds among the remaining alternatives. To examine the validity of this assumption within the MNL model, two prevalent tests are frequently employed: the Hausman-McFadden (HM) test and the Small-Hsiao (SH) test. In this section, both the HM and SH tests were executed using Stata 17, employing the ”mlogtest” command. It is worth noting that, during the testing for the IIA assumption, standard errors were utilized instead of cluster standard errors, primarily because the HM test does not accommodate cluster standard errors.

Table A2: Results of IIA assumption tests

Tests	Null Hypothesis (Ho)	Results
Hausman	Odds (private only vs public only) are independent of dual practice	against Ho
	Odds (dual practice vs. public only) are independent of private only	against Ho
	Odds (dual practice vs private only) are independent of public only	against Ho
Small-Hsiao	Odds (private only vs. public only) are independent of dual practice	against Ho
	Odds (dual practice vs. public only) are independent of private only	against Ho
	Odds (dual practice vs private only) are independent of public only	for Ho

Note: The Hausman and Small-Hsiao tests are based on the baseline MNL model.

Table A2 presents the results of both the Hausman-McFadden (HM) and Small-Hsiao (SH) tests conducted using the baseline Multinomial Logit (MNL) model. The results of these tests are mixed. The HM test indicates a violation of the Independence of Irrelevant Alternatives (IIA) assumption by rejecting all three null hypotheses. Inconsistently, the SH tests failed to reject the null hypothesis when excluding the ”public-only” category. This outcome aligns with our expectations, as existing literature has extensively documented the propensity of these tests to yield conflicting results. In other words, some tests may reject the null hypothesis, while others may not. Furthermore, Long & Freese (2014) evidenced that certain tests may not be particularly useful for detecting violations of the IIA assumption from several simulation studies. However, considering the inconclusive test results under MNL, I estimated the CRE-MNL model to manage the IIA issue.

The Independence of Irrelevant Alternatives (IIA) problem does not apply to the CRE-MNL model in this study. The IIA issue arises because decisions across alternatives are not correlated when employing the Multinomial Logit (MNL) model, as these decisions are arrived at in a pairwise manner (Cameron & Trivedi 2005). To mitigate the IIA concern, various alternative approaches have been introduced, such as the Multinomial Probit and the Nested Logit models, which introduce additional structures to interrelate decisions across different alternatives (Cameron & Trivedi 2005). In the case of the Multinomial Probit model, this is achieved by imposing a normally distributed error structure, thereby linking decisions through these error terms (Cameron & Trivedi 2005). Similarly, in the same vein as the Multinomial

Probit, the CRE-MNL model, which has been estimated in the main body of this text, also addresses the IIA issue through the incorporation of correlated random effects. Consequently, it is worth noting that the widely recognized IIA problem does not pose a concern in the context of this study.

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Name of Principal Author (Candidate)	Jia Song		
Contribution to the Paper	study conception and design, data curation, methodology, software, formal analysis, writing – original draft preparation, review and editing		
Overall percentage (%)	70%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
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Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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Chapter 2

How do gender differences in family responsibilities affect doctors' labour supply? Evidence from Australian panel data

2.1 Introduction

Over the last half century, one marked change in the medical profession across OECD countries is its gender composition, with women constituting an increasingly larger share of the medical workforce. In Australia, the proportion of commencing female medical students increased from 14% in 1960 to 51.8% in 2015. The percentage of female registered doctors has grown from 23.2% in 1993 to 40.7% in 2016 (Australian Institute of Health and Welfare 1996, 2017). In the United States, 48% of medical school graduates were female in 2015, whereas they made up only 6% in 1960; and the share of female physicians has grown from 17% in 1990 to 36% in 2005 (Staff Care 2016). Over the past two decades, the percentage of female medical students in Britain grew from 26.4% to 55% (Centre for Workforce Intelligence 2016).

Despite there being more women in medicine, the gender gap in earnings remains stubbornly persistent. International evidence document that male doctors earn between 17% to 45% more than female doctors (Gravelle et al. 2011, Lo Sasso et al. 2011, Theurl & Winner 2011, Cheng et al. 2012, Boesveld 2020). Differences in how men and women are affected by parenthood and family responsibilities have been found to be a key contributor to the gender earnings gap. In the US, young female physicians earn on average 25% to 33% less after they become married and have children (Sasser 2005). Australian female general practitioners (GPs) with children earn \$30,000 less than their female counterparts without children, whereas male GPs with children earn \$45,000 more than comparable male GPs without children (Schurer et al. 2016). In France, having a child is estimated to reduce earnings by up to 33% for female GPs and specialists (Mikol & Franc 2019).

The onset of parenthood can worsen the gender earnings gap if childbirth and family responsibilities affect working hours of male and female doctors differently. Cursory evidence from Australian doctors can be seen from Figure 2.1. The figure shows how weekly hours worked vary between male and female doctors of different ages. The data come from nine annual waves of the "Medicine in Australia: Balancing Employment and Life (MABEL)" longitudinal survey of medical doctors in Australia. At the early stages of their medical careers, at ages under 35 years, female doctors work nearly as much as male doctors, with a mean difference of 3 hours per week (46 hours vs 49 hours). From their mid thirties to mid forties, females begin to work considerably less, with an average of 35 hours per week at age 35-39 years, and 34 hours at age 40-44 years. Women typically have children in their early thirties in the general population, whereas female professionals tend to have children slightly later, at around the ages of 35 to 39 years (Australian Bureau of Statistics 2016). In contrast, working hours by male doctors fall slightly in their mid thirties, and increase thereafter. Consequently the gender gap in working hours is largest for doctors in this age group. From age mid forties onwards, the hours worked by females begin to increase gradually and follow a similar trajectory as males doctors until retirement (age 65+). These patterns for Australian doctors are consistent with the experience of US physicians. At the start of their careers, the earnings of male physicians are 13% higher than females and the gap increases to 28% eight years on (Esteves-Sorenson & Snyder 2012).

Further evidence is given in Figure 2.2 using MABEL data of doctors age 49 years or younger. Here we show the distribution of hours worked for doctors with and without children. We observe significant differences in working hours for female doctors with children compared with female doctors without children, as well as male doctors. In Panel 1 which shows between gender comparisons, we can see that while female and male doctors without children have very similar number of hours worked, hours worked for females with children are significantly lower than males with children. In Panel 2 where we show within gender comparisons, the working hours of females with children is considerably lower than those without children. These patterns further reinforce the notion that childbirth and family responsibilities are significant drivers of the gender gap in working hours.

In this paper we use a unique longitudinal dataset of Australian doctors spanning nine annual waves to examine how childbirth and family responsibilities influence the number of hours worked by female and male medical doctors. We exploit the longitudinal feature of the data to investigate how hours worked change in response to within-doctor changes in family circumstances over time. We use a rich set of family circumstances, namely the effect of having children, number of children and the age of the youngest child. We examine how these circumstances influence the number of hours worked per week and how it differs for female and male doctors. We further examine how the employment status of a doctor's partner influence hours worked when doctors have children, and whether it matters that a doctor's spouse is also a medical doctor.

The institutional context of our study is the Australian medical labour market. Australia has a mixed public and private health care system. Medicare, the country's tax financed health insurance system, provides free or subsidised treatment by doctors and free public hospital treatment. Around 45% of the total medical workforce in Australia are employed in public hospitals (Australian Institute of Health and Welfare 2019*a*). Doctors operating in the private system are free to charge patients what the market will bear, with a fixed subsidy from Medicare. Payment modalities depend largely on whether doctors work in the public or private system. General practitioners operate primarily in the private system and in a non-hospital setting, and are predominantly renumerated via fee-for-service (Cheng et al. 2012). Public hospital-based medical specialists, as well as more junior doctors such as career medical officers and specialists registrars, are largely salaried public sector employees, while those working in private hospitals are predominantly paid via fee-for-service (?). Doctors can also can combine public sector work in public hospitals with private work in private hospitals and private consulting rooms. Approximately half of all medical specialists undertake both public and private work.

We contribute to the literature in the following ways. First, previous studies on medical doctors have focused on gender differences in earnings, and the role of wages and income on doctors' labour supply. Few papers, on the other hand, study how the presence of children affects working hours by doctors. In a closely related study to ours, Wang & Sweetman (2013) analyse cross-sectional data from Canada and find that female physicians with children devote a smaller number of hours working in the labour market, and larger number hours on household work compared with male physicians. In a study of Norwegian doctors, Gjerberg (2003) finds that women with young children are more likely to be working part-time compared with women without children. For men, children does not affect the likelihood of working part-time. The presence of children, especially young ones, has also been shown to affect practice activities and career intentions (Dumontet & Franc 2015, Buddeberg-Fischer et al. 2010).

There are a number of reasons why studying working hours is important to understand barriers female doctors face in their career advancement. Among professions not limited to medicine, there is a widely held perception among employers that shorter working hours reflect a lower level of commitment to one's role and job, leading to a work culture that values full-time work and devalues part-time workers (Jenkins 2004). For females striving to balance between family and work commitments, there are concerns that part-time work results in a lack of access to high status roles and promotion opportunities, as well as poor workplace support (McDonald et al. 2009). The transition into part-time work after parenthood can also limit opportunities for professional networking that is important for career advancement due to time constraints (Durbin & Tomlinson 2010).

A unifying feature of the extant literature is that many studies rely on cross-sectional data. Longitudinal data allow us to observe how family circumstances change over time and quantify its impact on hours worked, controlling for other time-varying characteristics. Furthermore, the availability of repeated observations allows us to estimate within-doctor changes in working hours to address potential endogeneityselectivity bias that arises from unobserved factors such as doctors' preferences for work that are correlated with the decision to have children, or to choose to have children at a later age.

Second, compared with prior studies, our study examines a more extensive set of family covariates describing not only the presence and number of children, but also the age of a doctor's youngest child, as well as spousal employment status. Gjerberg (2003) and Wang & Sweetman (2013) analyse the effects of children and the number of children, both using cross-sectional data. Recent work by Cao & Rammohan (2020), done independently of ours using data from the MABEL survey, considers the presence of dependent children but not the effect of children's age. We further study whether doctors in dual medical career households – households where both partners are medical doctors – respond differently to family responsibilities compared to sole-doctor households.

Finally, previous studies focus on estimating conditional mean effects, and ignore potential heterogeneous effects of how family circumstances affect hours worked across the distribution of hours worked. In contrast, we also quantify the presence of heterogeneous effects using a panel data quantile regression model that accommodate individual fixed effects estimated using the method of moments estimator proposed by Machado & Silva (2019).

Our paper is structured as follows. Section 2.2 provides a brief discussion of the relevant literature. The data and variables used in this study is discussed in Section 2.3, followed by the empirical model in Section 2.4. Our key findings are discussed in Section 2.5. Section 2.6 concludes with a summary of our findings.

2.2 Literature Review

Despite the increasing feminisation of the medical workforce over the last half century, the difference in earnings between male and female doctors has persisted over time. This phenomenon stems from the traditional view of the household and the roles played by males and females, and is not specific to medical doctors. Women are viewed as having a comparative advantage in home production, while men have a comparative advantage in the labour market (Lundberg &

Rose 2000). Studies of the general population show that married men are likely to work longer hours in the labour market and have higher earnings compared with single men, and that married women have lower working hours and earnings (Antonovics & Town 2004, Pollmann-Schult 2011).

The aforementioned patterns are also found in highly educated professionals. For example, the presence of children results in shorter work hours and greater career discontinuity for females MBA graduates (Bertrand et al. 2010). These career disruptions translate to a lower earning capacity as highly education women lose human capital as they temporarily exit the workforce (Viitanen 2014). Parenting responsibilities further constraint transitions to full-time work, and encourage shifts from full-time to part-time work for Norwegian mothers (Kitterød et al. 2013). Specific to medical doctors, differences in working hours and labour force attachment have been found to contribute to the earnings differential among Australian GPs (Schurer et al. 2016).

There are many potential factors that explain the difference in the hours worked by male and female medical doctors. One reason may be that the labour supply decisions of female physicians are more responsive to variations in earnings of their spouse compared to that of males. Rizzo & Blumenthal (1994) find that the elasticity of working hours with respect to spousal earnings is slightly larger for females compared with males. The gender difference in working hours in medicine may reflect a compensating differential across medical specialty. Specialties such as family medical (general practice) and dermatology allow for flexibility in the choice of working hours to allow female doctors to balance work, family and lifestyle considerations (Gjerberg 2003). These specialties allow for more flexibility with lower hours, and less on-call compared with traditional ”all-consuming” fields such as surgery.

A number of studies have found that earnings of male and female doctors are affected differently as a result of childbearing and family responsibilities. In particular, the onset of parenthood have been found to negatively affect earnings by female doctors but not male doctors. Young female physicians in the US earn on average 25% to 33% less after they become married and have children (Sasser 2005). In Australia, female GPs with children have been found to earn $30,000 less than their female counterpart without children, whereas male GPs with children earn $45,000 more than comparable male GPs without children (Schurer et al. 2016). Having a child is estimated to reduce earnings by up to 33% for French female GPs and specialists (Mikol & Franc 2019).

Few studies examined how the presence of children affect working hours by doctors. Wang & Sweetman (2013) use cross-sectional data from Canada and find that female physicians with children devote a smaller number of hours working in the labour market, and larger number hours on household work compared with male physicians. Fatherhood on the other hand has little effect on labour supply by male doctors, unless there are three or more children where hours worked are observed to increase. Gjerberg (2003), in a study of Norwegian doctors, finds that women with young children are more likely to be working part-time compared with women without children. For men, children does not affect the likelihood of working part-time. The odds of shifting to part-time work are also increasing in the number of children, and higher for women married to medical doctors.

As discussed above, childbearing and family responsibilities are documented as key factors driving gender differences in earnings among medical doctors. Yet few studies examine how the supply of labour, namely working hours, is affected by parenthood.

2.3 Data and Sample

2.3.1 The MABEL longitudinal survey of medical doctors

This study uses data from nine waves (2008–2016) from the “Medicine in Australia: Balancing Employment and Life (MABEL)” survey. MABEL is an annual nationally representative longitudinal survey of Australian medical practitioners, which captures extensive information on doctors’ labour market status, job satisfaction, working hours, medical specialty, workplace and workload, finance status, personal characteristics and family status. This rich data allow us to investigate how changes over time in family circumstances – that of children and partners – affect the labour supply of male and female doctors.

The first wave of MABEL data was collected in 2008, where all medical doctors in clinical practice in Australia (N = 54,750) were invited to participate in the survey. Respondents either completed a paper or an online survey questionnaire. The baseline cohort in Wave 1 comprises of 10,498 medical doctors over four doctor types: 4,596 specialists (43.8%), 3,906 general practitioners (37.2%), 924 specialists-in-training (8.8%) and 1,072 hospital non-specialists (10.2%). The response rate of the baseline cohort with respect to the sample frame is 19.4%, with specialists having the highest response rate (22.3%) among all doctor types. The baseline cohort is nationally representative of the population with respect to age, gender, doctor type, geographical location, hours worked and specialties (Szawlowski et al. 2019). From the second wave (2009) and each subsequent year, top-up samples comprising of new entrants to the medical workforce or doctors re-entering active clinical practice (e.g. returning from overseas) were invited to participate in the survey to maintain the cross-sectional representativeness of the survey. Each wave contains between between 9,000 to 10,900 observations.Comparing the MABEL cohort with the population of doctors in the sample frame over the nine waves, younger doctors, females, and those working in remote and rural areas are generally over-represented (Szawlowski et al. 2019).

2.3.2 Sample construction

The MABEL survey covers four doctors types: General Practitioners (primary care practitioners), medical specialists, specialists-in-training, and hospital non-specialists (e.g., interns or Medical Officers). We use complete case data from nine annual waves from all four doctor types over the survey period of 2008 to 2016. Complete case analysis has been shown to lead to consistent estimates in situations where the data is missing at random and even missing completely at random (see Hughes et al. 2019). From the initial sample of 88,792 doctor-year observations in the nine years of data, we exclude 6365 observations with missing information on hours and 2,952 observations with missing information on the number of dependent children. After excluding observations with missing information on other covariates, we arrive at an estimation sample comprising an unbalanced panel of 73,663 doctor-year observations comprising of 19,740 doctors. 8,904 doctors are from the initial 2008 cohort (45,819 doctor-year observations) and 10,836 doctors from the top-up samples (27,844 doctor-year observations) added from 2009 onwards. 36% of our sample are general practitioners, 40% specialists, 13% specialists-in-training and 11% hospital non-specialists.

2.3.3 Variables

Our key variable of interest is working hours per week. In each year of the MABEL survey, doctors were asked to provide information on their working hours with the following question: "Excluding after-hours and on-call, how many hours in your most recent usual week at work did you spend on the following activities?". We use responses that doctors provide on their "total hours worked per week" as our outcome variable of interest.

The key explanatory variables we used in the empirical analysis are of doctors' family circumstances, namely that of children and of spouses/partners. We capture the information on children using a variety of measures: an indicator variable of whether doctors have any dependent children, the number of dependent children (0, 1, 2, or 3+), and the age of the youngest child (for doctors with children). Over the observation period, 1,534 doctors became the first time parents, while 1,030 doctors had more children; 8,556 doctors had decreasing number of dependent children. Partner status is measured by three variables: an indicator variable of whether doctors are living with a partner, partner's employment status (working part-time, full-time or not in labour force), and whether the partner is a medical doctor. We control for an extensive set of time-varying covariates include age, self-employment status, health status, geographical location, and medical specialty and doctor type . Self-employed doctors as those who report to be either a Principal/Partner or an Associate in a question asking about the business relationship doctors have with their medical practice. The reference category comprises of doctors who are salaried or contracted employees of the practice, locums, or have other forms of contractual arrangements.

Table 2.1 shows the characteristics of our sample. Male doctors have longer working hours, with average weekly working hours at 45 hours compared with 39 hours for female doctors. Male and female doctors have very different family characteristics. Male doctors are more likely to have children, and have more children compared with female doctors. Male doctors are more likely to have a partner, and are also more likely to have partners who are not working or working part-time. A higher proportion of female doctors on the other hand have partners that are engaging in full-time work. A slightly higher proportion of female doctors are married to medical doctors compared with male doctors. Females are also younger and are less likely to be self-employed. A higher proportion of male doctors in the sample are medical specialists whereas a higher proportion of female doctors are General Practitioners, hospital non-specialists and specialists-in-training.

A key shortcoming of longitudinal data is the problem of non-response and attrition. Attrition occurs when a doctor fails to complete or return the survey questionnaire in a subsequent wave after having enrolled into the MABEL survey as either part of the baseline cohort or top-up sample. The attrition in the MABEL data is non-trivial: in the 2008 baseline cohort, the cumulative balanced panel attrition after four years is 45.7% – i.e. roughly 5,700 out of the 10,498 doctors answered all four survey waves from 2008 to 2011 (Szawlowski et al. 2019). Attrition rates for the top-up samples are generally higher as these doctors are younger and are professionally more mobile which makes it harder to follow up. Overall, year-on-year attrition rates are substantially higher in the initial years and decline over time. While attrition raises the potential of attrition bias, it has been shown that despite significant attrition in the MABEL survey, the impact of attrition on inference is small. i.e. there is no evidence of significant biases in the estimates from econometric analyses (Cheng & Trivedi 2015). The consensus in the literature supports the conclusion that attrition does not lead to serious biases in the economic sense, even in the presence of large sample attrition and statistical evidence of attrition bias (Jones 2009). We formally address the issue of attrition using inverse probability weighting to assess if panel attrition leads to significant biases in our estimates (Section2.5.5).

2.4 Econometric strategy

Our empirical strategy uses fixed-effect estimation to identify within-doctor variations in family responsibilities over time to identify the effect family circumstances have on doctors' labour supply. To quantify the effect of children on the number of hours worked, we estimate the following model:

$$Y_{it} = \alpha_0 + \alpha_1 Female_i + \alpha_2 Child_{it} + \alpha_3 Female_i \times Child_{it} + X'_{it}\delta + \gamma_i + \varepsilon_{1it} \tag{2.1}$$

where Y_{it} is the logarithm of weekly hours worked by doctor i in time t. $Child$ represents our children variables. We use three different information on children to identify the role children have on doctors' labour supply. These are (i) whether doctors have any children, (ii) the number of children (0, 1, 2, or 3+), and for those with children (iii) the age of the youngest child. A separate regression is estimated for each of the three children indicators. To distinguish the effect of children by doctors' gender, we interact the $Child$ variable with an indicator of whether a doctor is female ($Female$). X'_{it} denotes a vector of covariates; α and δ are coefficients to be estimated. γ_i captures individual-specific unobserved effects that affects work. We used the logarithm transformation of weekly working hours, following the approach in related studies that had used the same survey of Australian medical doctors being used here (Kalb et al. 2018, Cheng et al. 2012, Schurer et al. 2016).

A potential issue of endogeneity bias arises if there are unobserved factors such as doctors' preferences for work that are correlated with the decision to have children, or choose to have children at a later age. This is manifested in the model where the time-invariant individual-specific effect, γ_i, is correlated with $Child_{it}$ and X_it. To eliminate this effect, we apply "within" transformation to equation (2.1) and estimate the model using the fixed effects "within" estimator. The use of within transformation to difference out the individual unobserved effect hinges on the effect being time-invariant. As a robustness check, we relax this assumption and allow for unobserved effects that vary over time, by including individual time trends and time (year) fixed effects. This is discussed in detail in Section 2.5.5.

To examine whether the employment status of a doctor's partner influences the effect of children on labour supply, we estimate a variant of the model in Equation (2.1) where the partner's employment status is interacted with the child variable. This model is shown in Equation (2.2).

$$Y_{it} = \beta_0 + \beta_1 Partner_{it} + \beta_2 Child_{it} + \beta_3 Partner_{it} \times Child_{it} + X'_{it}\lambda + \gamma_i + \varepsilon_{2it} \tag{2.2}$$

Measures of partner's employment status includes (i) whether the partner is employed part-time, full-time or does not work; and (ii) whether the partner is also a medical doctor. For the *Child* variable, we use the binary indicator of whether doctors have any children. Again, a separate regression is estimated for each of the two partner indicators. Each regression is separately estimated for female and male doctors to allow the partner's status to vary by gender. Equation (2.2) is also estimated using the fixed effects "within" estimator.

The "within" estimates from equations (2.1) and (2.2) identify the mean effects of children, and of partners' employment status, on the conditional mean of the logarithm of hours worked. The focus on conditional mean effects ignores potential heterogeneous effects of how family circumstances affect hours worked across the distribution of hours worked. We quantify the presence of heterogeneous effects using the method of moments estimator proposed by Machado & Silva (2019) for panel data quantile regression that accommodates individual fixed effects. Suppose we rewrite equation (2.1) as

$$Y_{it} = \gamma_i + \tilde{X}'_{it}\delta + (\eta_i + Z'_{it}\delta)U_{it} \tag{2.3}$$

where $\tilde{X}$ contains X, and the gender and children variables; Z is a transformation of components in $\tilde{X}$, and U an unobserved random variable. Parameters γ_i and η_i capture the i-th individual's fixed effects. From equation (2.3), the conditional quantiles can be expressed as

$$Q_Y(\tau|X) = (\gamma_i + \eta_i q(\tau)) + \tilde{X}'_{it}\delta + Z'_{it}\delta q(\tau) \tag{2.4}$$

Of primarily interest is the marginal effects of the children variables on the τ-th quantile of Y. Here, we assess the impact of children on hours worked at various points of the conditional distribution of hours by varying τ from 0.1 to 0.9. The quantile-τ fixed effects, $\gamma_i + \eta_i q(\tau)$, represent time-invariant individual characteristics that have different impacts on different regions of the conditional distribution of Y. We use the split-panel jackknife bias correction of Dhaene & Jochmans (2015) which was shown to minimize bias arising from the incidental parameters problem (Machado & Silva 2019).

2.5 Results

2.5.1 Effect of children on hours worked

The parameter estimates showing the conditional mean effects of having children on hours worked by gender are presented in Table 2.2. The estimates are interpreted as a percentage change in weekly hours as the dependent variable is the logarithm of hours. Our results show that having children affects female and male labour supply differently. For female doctors, having children reduces working hours by 20.4%. Relative to the sample mean, this estimate imply that having children reduces the hours work by female doctors by 7.9 hours per week. In contrast, for male doctors, having children leads to a slight increase in hours worked by 4.2% (1.9 hours per week).

The gender difference in the effect of children becomes more apparent when we examine the number of dependent children doctors have. For female doctors, having one, two, or three or more children lead to a reduction of hours worked by between 19% and 21% compared to doctors without children. These reduction corresponds to a drop in working hours of 7.4 to 8.1 hours worked per week. For male doctors, having one or two children leads to a slight increase in hours worked by 3.1% and 5.6% (1.4 to 2.6 hours) respectively. Male doctors with three or more children increase their hours work by 7.3%. Relative to the sample mean, this effect corresponds to an increase in hours work by about 3.3 hours per week.

We further find evidence that the magnitude of the reduction in labour supply for female doctors depends on the age of their youngest child. Compared with female doctors with adult children aged 18+ years, females with children aged 0–4 years reduce their hours worked by 21.3% (7.1 hours). Those with children aged 5–11 years reduce their working hours by 8.6% (2.9 hours). Hours worked by females with children in the age group 12–17 years are slightly (1.9%) lower compared from those with adult children. The impact of children's age for males is in stark contrast to those of females. For male doctors, having young children of age 0–4 and 5–11 years leads to an increase in weekly hours worked by 5.7–6.5% (2.7–3.1 hours).

The full set of regression estimates is shown in Table B1. Weekly hours fall starting from 35 years of age, increases at 45-54 years, and begins to fall again at age 55 and over. Working hours is increasing in weekly earnings and higher for doctors who are self-employed. Doctors in better health are also likely to work longer hours. Doctors in the earlier stages of their careers, namely hospital doctors and specialists-in-training, have a higher number of hours worked.

2.5.2 Effect of partner's employment status

We examine if the partner's employment status influence the impact of having children on doctors labour supply. These results are shown in Table 2.3; the estimates in Panel A are for female doctors, and Panel B for male doctors. For females, the employment status of their partner significantly influences their labour supply. Female doctors with a non-working partner reduce their weekly hours worked by 10.7% when they have children. Those with a partner working part-time reduce their hours worked by a larger magnitude (16.3%). In contrast, female doctors with partners engaging in full-time employment reduce their labour supply by more than a quarter (26.6%).

For male doctors, whether or not they have a partner in employment impacts their labour in a different way compared with female doctors. Male doctors report slightly increasing their hours worked (3.0%) if their partner works part-time. Doctors with a partner that is not engaged in the labour force increase their labour supply by 9.1%.

2.5.3 Effect by whether partner is a medical doctor

Table 2.3 also shows how the impact of parenthood vary by whether or not a doctor's partner is also a medical doctor. In dual medical career households, the presence of children results in females reducing their labour supply by 31.4% while male doctors did not report a change. Female doctors, whose partners are not medical doctors, reduce their hours worked by 21.1%, with the magnitude of a reduction being 10 percentage points lower than that of females in dual-doctor households. Parenthood has no impact on labour supply for males in dual doctor households, and leads to a slight increase in hours worked in sole-doctor households.

2.5.4 Heterogeneous effects by quantile of working hours

The estimates presented in Tables 2.2 and 2.3 represent the mean effects of children and partners' employment status on the conditional mean of hours worked which may conceal the presence of heterogeneous effects. We estimate fixed effects quantile regression models to quantify this heterogeneity. The estimates for females are summarised in Figures 2.3 and 2.4; the regression estimates are presented in Table B2. Each dot in these figures shows the effects of children and partners' employment status for the tenth to ninetieth percentiles (or 0.1 to 0.9 quantiles) of hours worked.

Overall, for female doctors, we find evidence of heterogeneous effects by quantiles of working hours for the presence of children, number of children and for doctors with a partner in full-time employment. The effects are decreasing in magnitude, i.e. the effect sizes becoming less negative, at higher percentiles of hours. For example, having children reduces weekly hours worked for females doctors by 25.9% at the 20th percentile and 15.0% at the 80th percentile. The corresponding conditional mean effect is a 20.4% decline in hours worked. Having a partner working full-time reduces hours worked by 32.7% at the 20th percentile and 20.5% at the 80th percentile when female doctors have children (the conditional mean effect is 26.6%).

The quantile estimates for male doctors are shown in Figures B1 and B2. We find that the effects are also decreasing in size at higher percentiles of hours, although the magnitudes vary less across the distribution of hours for males compared to females.

2.5.5 Robustness checks

We undertake a number of additional analyses to assess the robustness of our estimates. First, we discussed in Section 2.3 that there is significant attrition in the MABEL data. To formally address the issue of attrition, we use inverse probability weighting (IPW) to assess if panel attrition leads to significant biases in our estimates. IPW resolves the attrition problem if the data are assumed to be missing at random (MAR) – i.e. conditional on the observed covariates the probability of response is not systematically related with the outcome we analyse, namely hours worked. The IPW estimator is applied by first estimating the probability of response in each wave as a function of the observed covariates in the first wave of the data (Wooldridge 2010*b*). We estimate this response function using a pooled probit regression. The outcome equation is then weighted by the inverse of the fitted probabilities of response. We use the first differences estimator for the outcome equation in place of the within "fixed effects" estimator as the latter does not permit the use of probability weights. Both the unweighted first differences and within-estimators produce quantitatively similar results. The estimates of the effects of children on hours worked, with and without IPW, are shown in Table 2.4. The weighted and unweighted estimates on each of the children indicator are similar in magnitude, suggesting that attrition does not lead to significant biases in our estimates.

In a second set of robustness analysis, we relax the assumption of time-invariant individual effects in equation (2.1) and allow for within-person unobserved effects to vary over time. This is to capture unobserved time-varying factors influencing doctors' time allocation that are potentially correlated with family circumstances and other characteristics. To this end, we follow the approach by Jacobson et al. (2005) and augment equation (2.1) to include individual time trends and time (year) fixed effects. Given the large number of individual effects and individual time trends, we estimate the model using the method developed by Guimaraes & Portugal (2010) via an iterative approach to estimate high-dimensional fixed effects. The estimates we obtained when allowing for individual time trends are slightly smaller in magnitude compared with our baseline estimates in Table 2.2 though on the whole both sets of estimates are qualitatively very similar. For example, in the model with time-varying individual effects, having children reduces hours worked for female doctors by 19.2%, compared with 20.4% in the baseline specification. The full set of results showing the effects of children on hours worked estimated using time-varying individual effects are shown in Table B3.

Finally we also examine the sensitivity of our results to a different measure of hours worked that is focused on time spent in clinical work. The MABEL survey collects data on the number of hours spent on direct patient care (e.g. face-to-face and phone consultations). We re-estimated our models using logarithm of direct patient care hours as a dependent variable. The estimates we obtained are slightly smaller in magnitude compared with our baseline estimates in Table 2.2 though on the whole both sets of estimates are qualitatively very similar. For example, in the model with direct patient care hours, having children reduces hours worked for female doctors by 18.6%, compared with 20.4% in the baseline specification.

2.6 Discussion and concluding remarks

We use a unique longitudinal survey of Australian doctors spanning nine annual waves to examine how having children and family circumstances influence the number of hours worked by female and male medical doctors. We find strong evidence of a 'carer effect' of having children for female doctors, whose working hours are significantly reduced after having children. We find large reductions in hours for female doctors whether they have one, two or three or more children. The magnitude of the reduction in hours is largest for females with very young children aged 0–4 years. Our results also demonstrate that female doctors progressively increase their engagement with the labour market as their children becomes older.

Changes in labour market engagement for females is strongly influenced by the employment status of their spouses. Females with a full-time working partner report reducing their working hours by the largest margin, compared with those with a part-time or non-working partner. The effect of children in dual medical career households – where both spouses are doctors – is highly asymmetric. Female doctors reduce their hours worked by a very large margin, whereas male doctors report not changing their working hours. Collectively these findings point to the presence of strong gender division in family responsibilities among medical doctors, even in households comprising of two highly qualified professionals. We also find evidence of heterogeneous effects where the effect sizes are smaller in magnitude at higher levels of hours worked.

Our findings are broadly comparable with that of other studies in the literature. Wang & Sweetman (2013), for instance, show for the case of Canadian doctors that having one, two, and three or more children reduce hours worked by 6, 7 and 9 hours per week respectively. We observe very similar effect sizes – reductions of between 7 to 8 hours per week – in our panel sample of Australian doctors. Gjerberg (2003) studies the balance between career and family life in Norwegian doctors and find that females doctors are more likely to move from full-time into part-time work if they have given birth to children in the prior year, and if female doctors are married to another doctor. Consistent with our conclusions for Australian doctors, the Norwegian study also observes that male doctors do not fully share domestic and caring responsibilities at home.

Our study has several limitations. First, the outcome measure we study, namely hours worked per week, reflects the intensive margin of labour supply, i.e. hours worked among doctors who were actively working in clinical practice. This is by design of the MABEL survey. Doctors who are on maternity leave, on home duties or childcare, or are not in clinical practice at the time of survey are asked to provide information on their current status, but are not required to complete the remaining of the survey. The focus on hours worked for doctors with non-zero hours in clinical practice therefore understates the true effect of family circumstances on labour force attachment. Consequently the female-male difference in labour force attachment is expected to be larger than that conveyed by our results if career disruptions such as maternity leave is considered.

The second limitation stems from the use of a self-reported respondent-recalled measure of hours worked. Recalled hours may contain measurement errors. In our application, these measurement errors can arise from the inability to accurately recall the actual number of hours worked, or that doctors' work schedules would vary to such a large degree making it difficult to define what a usual week is. Studies have shown that hours worked reported by employers can differ from what workers recall (Bound et al. 1994). The use of recalled hours, in comparison with more accurate time use information with a short recall, has been shown lead to upward biases in the estimates of labour supply response to changes in labour market programs (Barrett & Hamermesh 2019).

When measurement errors occur in the dependent variable, as with our application in the use of recalled hours worked, the regression coefficients are still consistent though the standard errors would be inflated when the linear regression model is used (Wooldridge 2010*b*). This result extends to the case of linear panel data regression models with fixed effects. Measurement errors in the covariates are more problematic as it potentially leads to inconsistent estimates, which are compounded when panel data are used. We cannot completely rule out the presence of measurement errors, and acknowledge this issue as a limitation of our study.

Studies on physician behaviour have shown that payment modalities can affect labour supply and work effort. We control indirectly for payment modalities through self-employment status, distinguishing between self-employed doctors (e.g. principal, associate) from those who are salaried. Unfortunately we are unable to adopt a finer categorisation of payment modalities due to data constraints. We acknowledge this as a limitation. The Australian health system permits doctors to combine public and private sector work and this raises the question of how the choice of work sector is affected by family circumstances. This could potentially be examined through a stratified analysis by physicians' work sector. However we do not explore this line of inquiry as only medical specialists work in both sectors, while GPs and junior doctors work predominantly in the private and public systems respectively. We acknowledge that the issue of public private work is potentially a relevant one.

The increased feminisation of the medical workforce is expected to result in a reduction in the effective supply of medical services, which in turn have implications on access to health services. Medical workforce policy needs to consider the productivity implications arising from career interruptions of women doctors striving to meet family demands. In addition to comprehensive family leave programs, policy makers should consider the design of policies to better ease the transition back into work by supporting flexible working hours and work arrangements, and to ensure that doctors undertaking part time work are equally supported at work compared to their full-time peers, as well as having equal access to opportunities for career advancement. Greater female representation in leadership positions, by reserving a proportion of leadership roles for females, can also support the retention of women in the medical workforce (Betron et al. 2019).

Figures

Figure 2.1: Working hours of Australian doctors by gender and age.

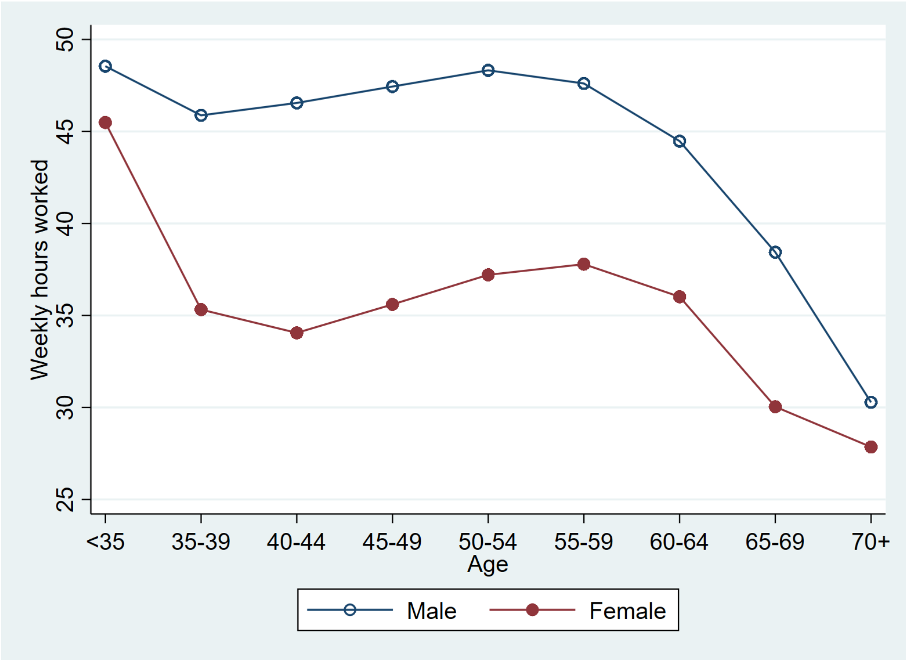


Figure 2.2: Distribution of hours worked by female and male doctors with/without children.

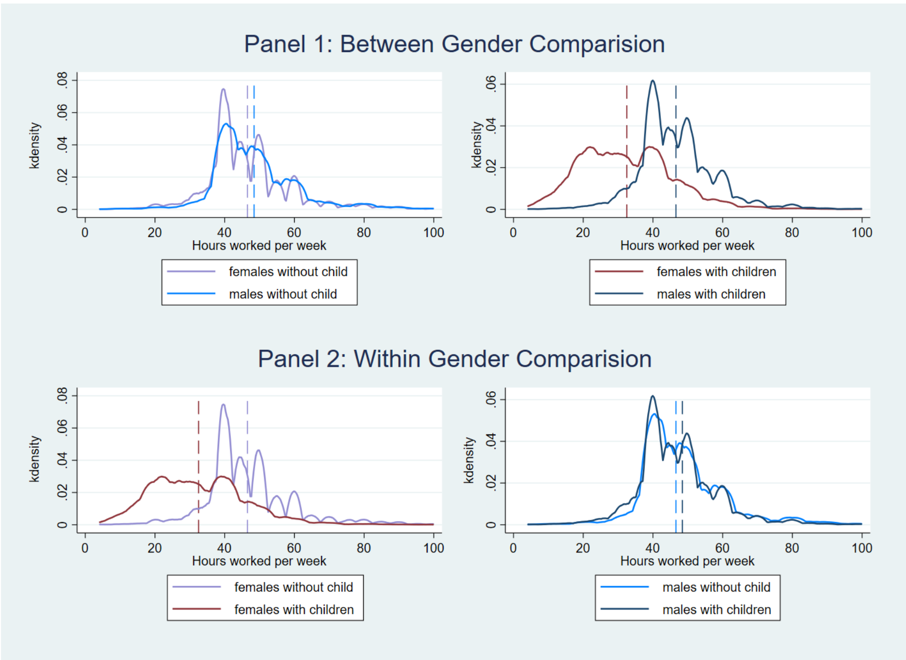
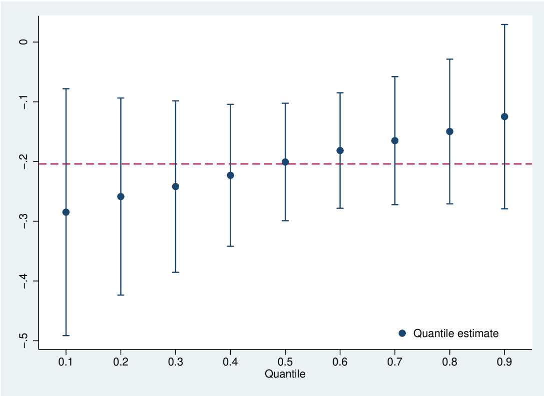
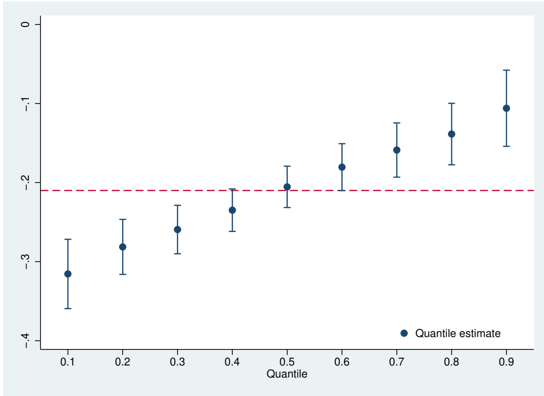


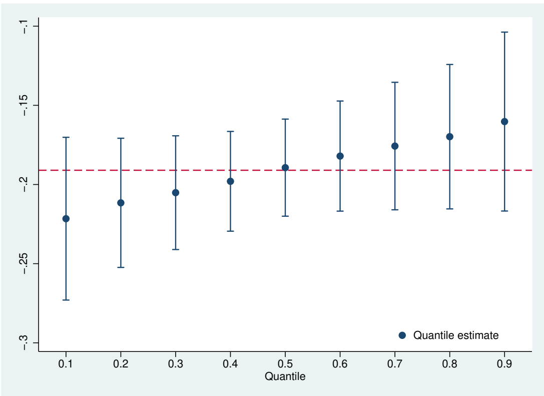
Figure 2.3: Quantile estimates of the effects of children on hours worked (Females)



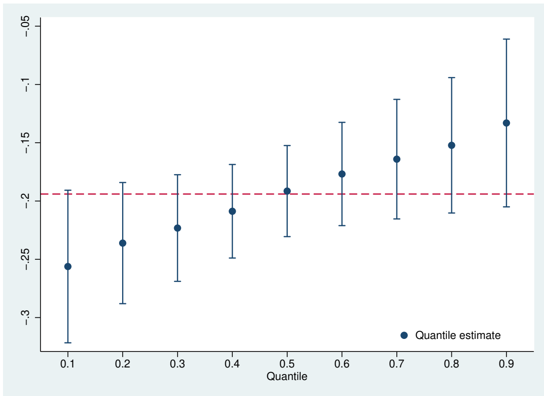
(a) Have children



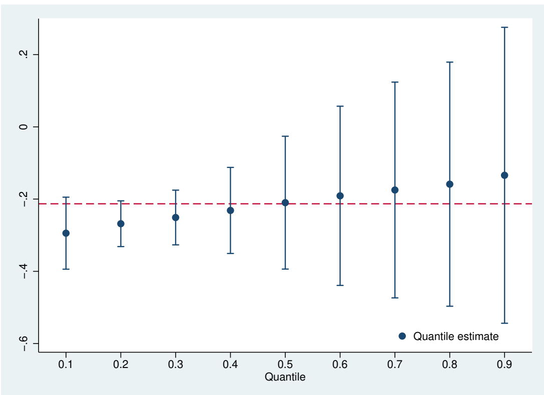
(b) 1 dependent child



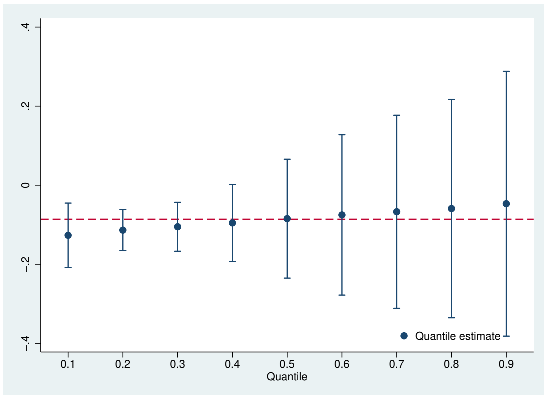
(c) 2 dependent children



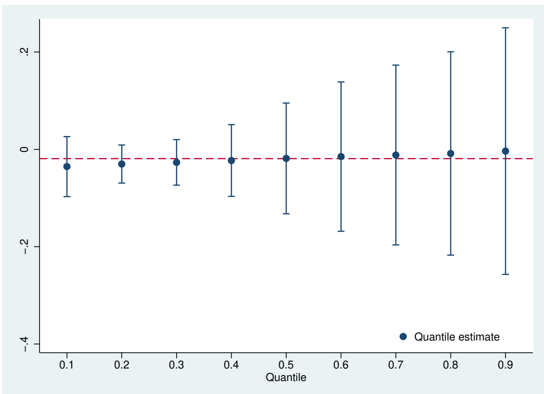
(d) 3+ dependent children



(e) Youngest child age 0–4 years



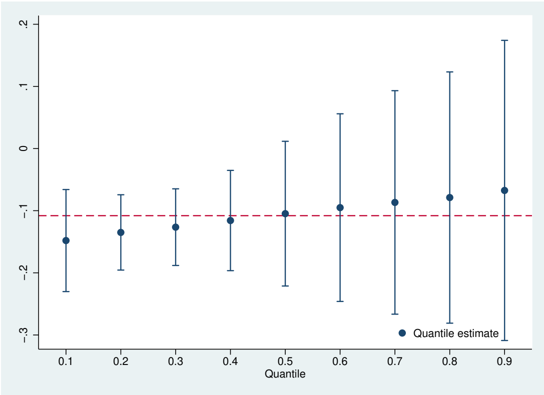
(f) Youngest child age 5–11 years



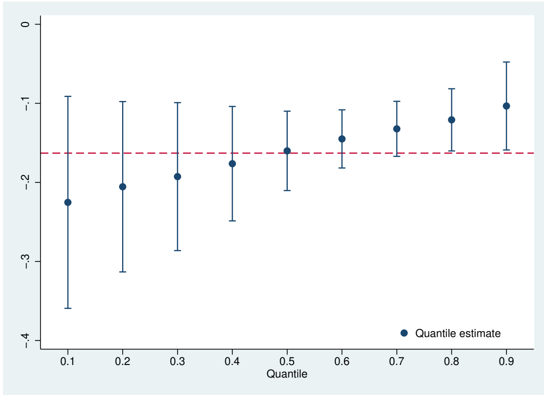
(g) Youngest child age 12–17 years

Notes. Vertical bars are 95% confidence intervals. Dash lines show mean effects.

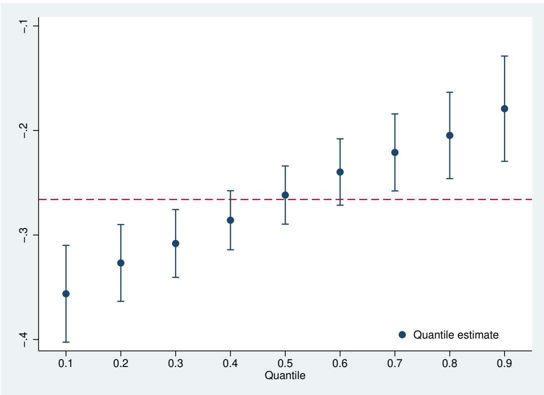
Figure 2.4: Quantile estimates of the effects of spousal employment on hours worked (Females)



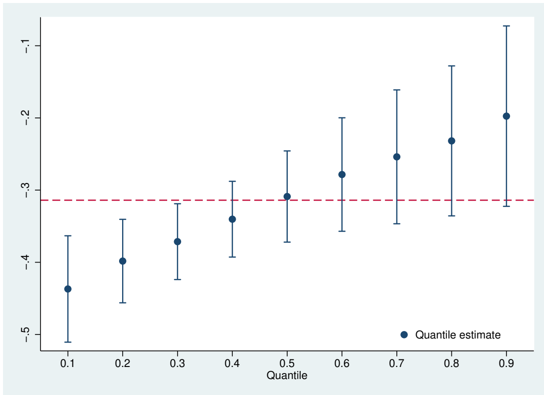
(a) Partner does not work



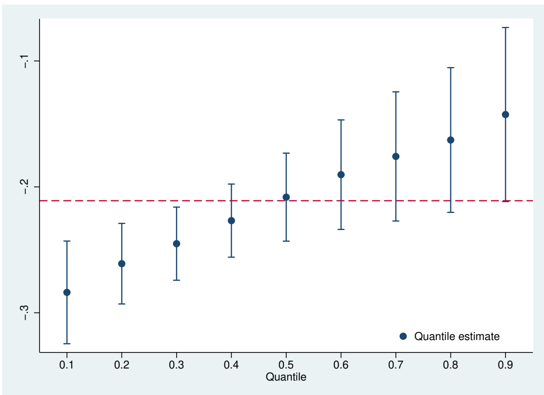
(b) Partner works part-time



(c) Partner works full-time



(d) Partner is an MD



(e) Partner is not an MD

Notes. Vertical bars are 95% confidence intervals. Dash lines show mean effect.

Tables

Table 2.1: Summary of sample means by gender.

Variables	Female	Male	Diff.[a]
Outcome variable:			
Weekly working hours	38.50 (14.93)	45.30 (14.23)	***
Covariates on children			
Have children	0.52 (0.50)	0.57 (0.50)	***
Number of dependent children	1.04 (1.13)	1.19 (1.19)	***
Age of the youngest child 0-4 y.o.	0.18 (0.38)	0.17 (0.37)	
Age of the youngest child 5-11 y.o.	0.16 (0.36)	0.15 (0.36)	**
Age of the youngest child 12-17 y.o.	0.11 (0.31)	0.13 (0.34)	***
Age of the youngest child 18+	0.55 (0.50)	0.55 (0.50)	***
Covariates on spousal status			
Living with a partner	0.73 (0.44)	0.86 (0.35)	***
Have a partner do not work	0.15 (0.36)	0.32 (0.47)	***
Have a partner work full-time	0.69 (0.46)	0.27 (0.44)	***
Have a partner work part-time	0.16 (0.36)	0.41 (0.49)	***
Partner is a medical doctor	0.13 (0.34)	0.09 (0.29)	***
Other covariates:			
Age less than 35 years	0.31 (0.46)	0.17 (0.38)	***
Age 35-44 years	0.28 (0.45)	0.22 (0.41)	***
Age 45-54 years	0.24 (0.43)	0.26 (0.44)	***
Age 55+	0.17 (0.37)	0.35 (0.48)	***
Self-employed	0.43 (0.49)	0.51 (0.50)	***
Metro area	0.78 (0.41)	0.74 (0.44)	***
Health status is excellent	0.38 (0.48)	0.36 (0.48)	***
Health status is very good	0.39 (0.49)	0.38 (0.48)	**
Health status is good	0.18 (0.38)	0.19 (0.40)	***
Health status is fair	0.05 (0.22)	0.06 (0.24)	***
Health status is poor	0.01 (0.09)	0.01 (0.09)	
General practitioners	0.40 (0.49)	0.32 (0.47)	***
Specialists	0.29 (0.46)	0.48 (0.50)	***
Hospital non-specialists	0.17 (0.37)	0.10 (0.30)	***
Specialists-in-training	0.14 (0.34)	0.10 (0.30)	***
No. of observations:	33,125	40,538	

Note: Standard deviation shown in parenthesis. [a]Two sample mean comparison test. Significance: *** 1%; ** 5%; * 10%.

Table 2.2: Effects of having children on weekly hours worked.

Variables	(1) Female	(1) Male	(2) Female	(2) Male	(3) Female	(3) Male
Have children	-0.204***	0.042***				
	(0.013)	(0.007)				
Ref: Number of dependent children: No children						
1 dependent child			-0.210***	0.031***		
			(0.013)	(0.007)		
2 dependent children			-0.191***	0.056***		
			(0.015)	(0.008)		
3+ dependent children			-0.194***	0.073***		
			(0.018)	(0.010)		
Ref: Age of the youngest child: 18+ years						
Age 0-4 years					-0.213***	0.057***
					(0.018)	(0.010)
Age 5-11 years					-0.086***	0.065***
					(0.015)	(0.009)
Age 12-17 years					-0.019*	0.047***
					(0.011)	(0.007)
Mean values of hours	38.51	45.81	38.51	45.81	33.45	47.23
Number of observations	73,663		73,663		40,221	

Note: Significance: *** 1%; ** 5%; * 10%. Cluster-robust standard errors in parenthesis, clustered at individual level. All regressions include age, self-employment, metro location, health status, and medical speciality.

Table 2.3: Effects of children on hours worked by spousal employment status.

Panel A: Female doctors

	(1)	(2)	(3)	(4)	(5)
	Partner does not work	Partner works part-time	Partner works full-time	Partner is a MD	Partner is not a MD
Have children	-0.107***	-0.163***	-0.266***	-0.314***	-0.211***
	(0.020)	(0.020)	(0.015)	(0.022)	(0.014)
Mean value of hours	40.09	35.66	36.49	34.97	36.67
Number of observations	24,285	24,285	24,285	24,285	

Panel B: Male doctors

	(1)	(2)	(3)	(4)	(5)
	Partner does not work	Partner works part-time	Partner works full-time	Partner is an MD	Partner is not an MD
Have children	0.091***	0.030***	0.014	-0.013	0.042***
	(0.011)	(0.009)	(0.009)	(0.015)	(0.007)
Mean value of hours	44.14	47.54	45.58	46.10	45.57
Number of observations	34,768	34,768	34,768	34,768	

Note: Significance: *** 1%; ** 5%; * 10%. Cluster-robust standard errors in parenthesis, clustered at individual level. 'MD' refers to whether or not the spouse is a medical doctor. All regressions include age, self-employment, metro location, health status, and medical speciality.

Table 2.4: Accounting for panel attrition using inverse probability weighting (IPW)

	(1)		(2)		(3)	
Variables	No IPW	IPW	No IPW	IPW	No IPW	IPW
Have children	0.009	0.009				
	(0.007)	(0.007)				
Have children X Female	-0.232***	-0.244***				
	(0.016)	(0.016)				
Ref: Number of dependent children: No children						
1 dependent child			0.001	0.002		
			(0.007)	(0.007)		
2 dependent children			0.024***	0.024***		
			(0.009)	(0.009)		
3+ dependent children			0.036***	0.037***		
			(0.010)	(0.011)		
1 dependent child X Female			-0.217***	-0.228***		
			(0.016)	(0.016)		
2 dependent children X Female			-0.270***	-0.285***		
			(0.020)	(0.021)		
3+ dependent children X Female			-0.282***	-0.300***		
			(0.026)	(0.026)		
Ref: Age of the youngest child: 18+ years						
Aged 0-4 years					-0.008	-0.006
					(0.009)	(0.010)
Aged 5-11 years					0.014*	0.015*
					(0.009)	(0.009)
Aged 12-17 years					0.012*	0.014*
					(0.007)	(0.007)
Aged 0-4 years X Female					-0.327***	-0.329***
					(0.017)	(0.018)
Aged 5-11 years X Female					-0.227***	-0.231***
					(0.017)	(0.018)
Aged 12-17 years X Female					-0.110***	-0.116***
					(0.014)	(0.014)
Number of observations	51,859		51,859		40,221	

Note: Significance: *** 1%; ** 5%; * 10%. Cluster-robust standard errors are reported in the parenthesis, and standard errors are clustered at the individual level.

Supplementary Materials

Table B1: Full regression estimates for Table 2.2; Effect of children on doctors' working hours

Variables	(1)	(2)	(3)
Ref: Having any children: No children			
Having children	0.042***		
	(0.007)		
Ref: Female X No children			
Female X Having children	-0.247***		
	(0.014)		
Ref:Number of dependent children: 0 child			
Having 1 child		0.031***	
		(0.007)	
Having 2 children		0.056***	
		(0.008)	
Having 3+ children		0.073***	
		(0.010)	
Ref:Female X 0 child			
Female X 1 child		-0.241***	
		(0.015)	
Female X 2 children		-0.246***	
		(0.017)	
Female X 3+ children		-0.267***	
		(0.020)	
Ref:Age of the youngest child: 18+ y.o			

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Table B1 – continued from previous page

Variables	(1)	(2)	(3)
The youngest child aged 0-4 y.o.			0.057***
			(0.010)
The youngest child aged 5-11 y.o.			0.065***
			(0.009)
The youngest child aged 12-17 y.0.			0.047***
			(0.007)
Ref: Female X youngest child 18+ y.o.			
Female X youngest child 0-4 y.o.			-0.269***
			(0.020)
Female X youngest child 5-11 y.o.			-0.151***
			(0.017)
Female X youngest child 12-17 y.o.			-0.066***
			(0.013)
Ref: Age less than 35 y.o.			
Age 35-44 y.o.	-0.044***	-0.048***	0.007
	(0.009)	(0.009)	(0.013)
Age 45-54 y.o.	-0.012	-0.017***	0.030**
	(0.010)	(0.010)	(0.014)
Age 55+ y.o.	-0.057***	-0.057***	0.013
	(0.011)	(0.011)	(0.016)
Self-employed	0.019***	0.018***	0.020***
	(0.006)	(0.006)	(0.007)
Health status	0.004*	0.004**	0.002

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Table B1 – continued from previous page

Variables	(1)	(2)	(3)
	(0.002)	(0.002)	(0.003)
Metro area	-0.010	-0.010	-0.024*
	(0.008)	(0.008)	(0.013)
Ref: General medicine			
Geriatrics	0.008	0.009	-0.011
	(0.043)	(0.043)	(0.047)
Paediatric medicine	0.022	0.021	-0.002
	(0.033)	(0.033)	(0.030)
Internal medicine	-0.006	-0.007	-0.010
	(0.024)	(0.024)	(0.024)
General surgery	-0.066	-0.064	-0.117**
	(0.051)	(0.051)	(0.053)
Orthopaedic surgery	-0.041	-0.044	-0.102
	(0.067)	(0.067)	(0.072)
Surgery:other	0.042	0.041	-0.009
	(0.036)	(0.036)	(0.038)
Anaesthesia	0.031	0.030	0.013
	(0.031)	(0.031)	(0.031)
Diagnostic radiology	0.026	0.024	-0.061
	(0.038)	(0.038)	(0.043)
Emergency medicine	0.146***	0.145***	0.063*
	(0.032)	(0.032)	(0.035)
Obstetrics and Gynecology	0.137**	0.136**	0.118

Continued on next page

Table B1 – continued from previous page

Variables	(1)	(2)	(3)
	(0.066)	(0.066)	(0.089)
Ophthalmology	0.006	0.004	-0.041
	(0.077)	(0.076)	(0.101)
Psychiatry	0.061	0.060	0.039
	(0.042)	(0.042)	(0.049)
Other specialties	0.026	0.025	-0.002
	(0.026)	(0.026)	(0.027)
GPs	0.018	0.019	0.006
	(0.027)	(0.027)	(0.034)
Hospital doctors	0.183***	0.185***	0.106***
	(0.026)	(0.026)	(0.032)
Specialist-in-training	0.187***	0.189***	0.123***
	(0.025)	(0.025)	(0.028)
Constant	3.673***	3.669***	3.638***
	(0.027)	(0.027)	(0.031)
Number of observations	73,663	73,663	40,221
R^2	0.152	0.155	0.187

Note: Significance: *** 1%; ** 5%; * 10%. Cluster-robust standard errors are reported in the parenthesis, and standard errors are clustered at the individual level. Effects of parenthood status are estimated using three separate fixed-effects regressions. Effects of children's age are estimated with a subsample of doctors who have children. All regressions include age, self-employment, metro location, health status, and medical speciality.

Table B2: Quantile regression estimates

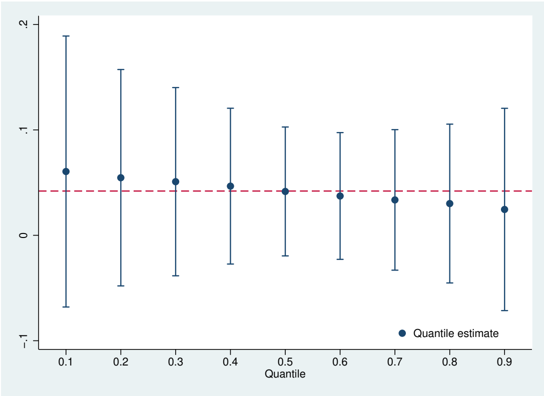
	Quantiles								
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Females									
Have children	-0.285	-0.259	-0.242	-0.223	-0.201	-0.182	-0.165	-0.150	-0.125
1 dependent child	-0.316	-0.281	-0.259	-0.235	-0.205	-0.180	-0.159	-0.139	-0.106
2 dependent child	-0.222	-0.212	-0.205	-0.198	-0.189	-0.182	-0.176	-0.170	-0.160
3+ dependent child	-0.256	-0.236	-0.223	-0.209	-0.191	-0.177	-0.164	-0.152	-0.133
Age of youngest child:									
0-4 years	-0.294	-0.268	-0.251	-0.231	-0.210	-0.191	-0.175	-0.159	-0.134
5-11 years	0.127	-0.114	-0.105	-0.095	-0.085	-0.075	-0.067	-0.059	-0.047
12-17 years	-0.035	-0.030	-0.027	-0.023	-0.019	-0.015	-0.012	-0.008	-0.004
Partner not work	-0.148	-0.135	-0.126	-0.116	-0.105	-0.095	-0.087	-0.079	-0.067
Partner works part-time	-0.225	-0.206	-0.193	-0.176	-0.160	-0.145	-0.132	-0.121	-0.103
Partner works full-time	-0.356	-0.327	-0.308	-0.286	-0.262	-0.240	-0.221	-0.205	-0.179
Partner is an MD	-0.437	-0.398	-0.371	-0.340	-0.309	-0.278	-0.254	-0.232	-0.198
Partner is not an MD	-0.284	-0.261	-0.245	-0.227	-0.208	-0.190	-0.176	-0.163	-0.143
Males									
Have children	0.061	0.055	0.051	0.047	0.042	0.037	0.034	0.030	0.025
1 dependent child	0.043	0.039	0.036	0.033	0.030	0.027	0.025	0.022	0.019
2 dependent child	0.088	0.078	0.071	0.063	0.054	0.046	0.040	0.034	0.023
3+ dependent child	0.101	0.092	0.086	0.080	0.072	0.065	0.059	0.053	0.045
Age of youngest child:									
0-4 years	0.059	0.058	0.058	0.057	0.056	0.056	0.055	0.055	0.054
5-11 years	0.071	0.069	0.068	0.067	0.065	0.064	0.062	0.061	0.059
12-17 years	0.055	0.052	0.051	0.048	0.046	0.044	0.043	0.041	0.038
Partner not work	0.151	0.132	0.118	0.105	0.089	0.075	0.063	0.051	0.032
Partner works part-time	0.035	0.033	0.032	0.031	0.029	0.028	0.027	0.026	0.025
Partner works full-time	0.018	0.016	0.015	0.015	0.013	0.012	0.012	0.011	0.009
Partner is an MD	-0.029	-0.023	-0.020	-0.016	-0.012	-0.008	-0.005	-0.002	0.003
Partner is not an MD	0.063	0.056	0.051	0.047	0.042	0.037	0.033	0.029	0.022

Table B3: Effects of having children on weekly hours worked using time-varying individual effects.

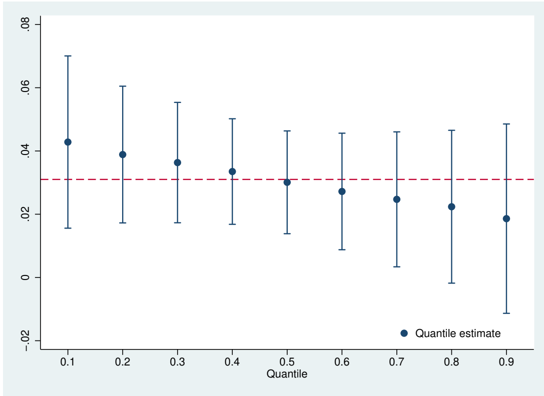
	(1)		(2)		(3)	
Variables	Female	Male	Female	Male	Female	Male
Have children	-0.192***	-0.013				
	(0.022)	(0.011)				
Ref: Number of dependent children: No children						
1 dependent child			-0.190***	-0.018*		
			(0.022)	(0.011)		
2 dependent children			-0.201***	0.002		
			(0.029)	(0.013)		
3+ dependent children			-0.222***	0.001		
			(0.040)	(0.016)		
Ref: Age of the youngest child: 18+ years						
Age 0-4 years					-0.307***	-0.023
					(0.025)	(0.014)
Age 5-11 years					-0.207***	-0.007
					(0.023)	(0.014)
Age 12-17 years					-0.100***	-0.002
					(0.007)	(0.013)
Mean values of hours	38.51	45.81	38.51	45.81	33.45	47.23
Number of observations	73,663		73,663		40,221	

Note: Significance: *** 1%; ** 5%; * 10%. Cluster-robust standard errors are reported in the parenthesis, and standard errors are clustered at the individual level. Effects of parenthood status are estimated using three separate regressions. Effects of children's age are estimated with a subsample of doctors who have children. Model specification includes time-varying covariates (age, self-employment, metro location, health status, medical speciality); individual fixed effect, year indicator, and an individual time trend.

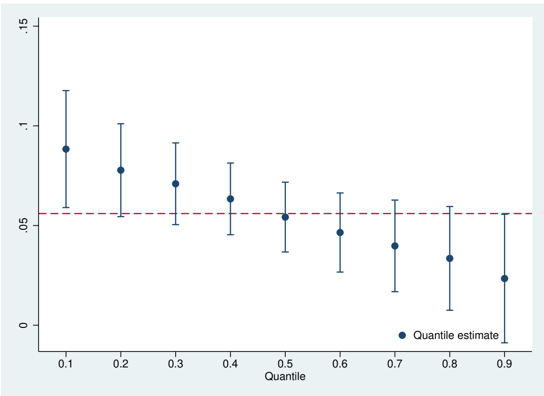
Figure B1: Quantile estimates of the effects of children on hours worked (Males)



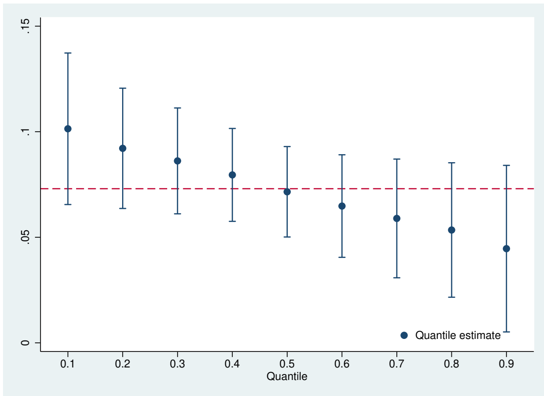
(a) Have children



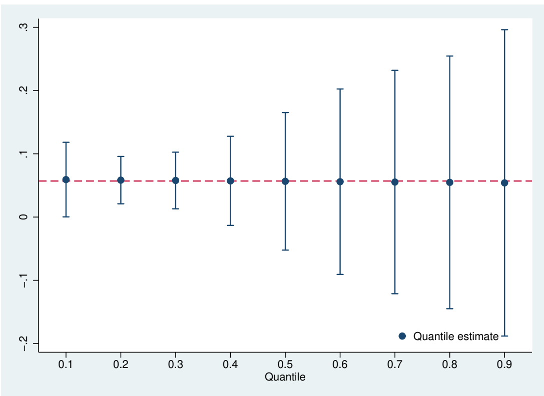
(b) 1 dependent child



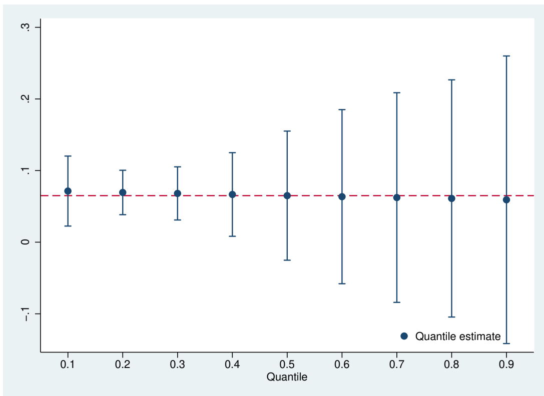
(c) 2 dependent children



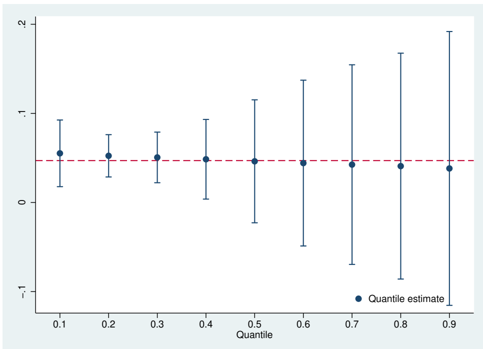
(d) 3+ dependent children



(e) Youngest child age 0–4 years



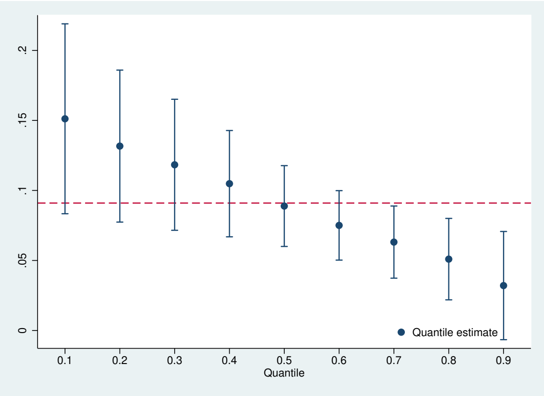
(f) Youngest child age 5–11 years



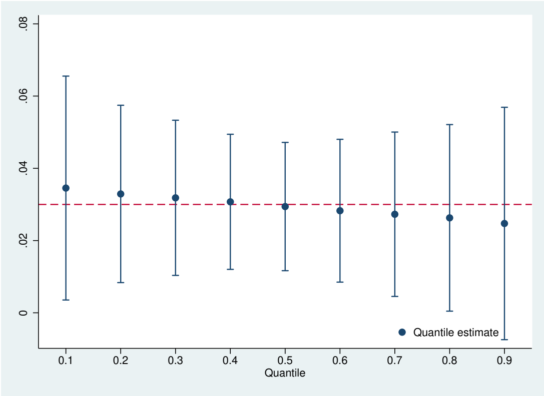
(g) Youngest child age 12–17 years

Notes. The figures show the fixed-effects quantile regression estimates of the logarithm of weekly hours worked on the presence of children. Vertical bars are 95% confidence intervals. Dash lines show mean effects from the linear fixed effects model. All regressions include age, self-employment, metro location, health status, and medical specialty.

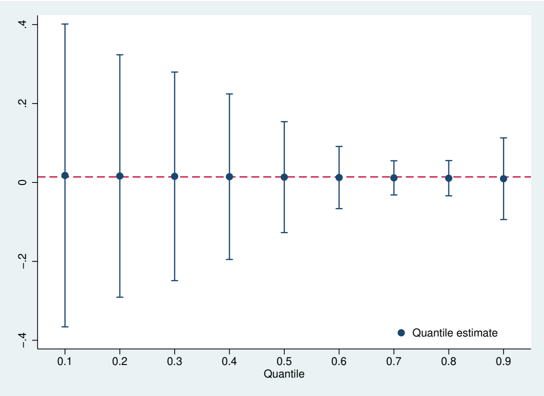
Figure B2: Quantile estimates of the effects of spousal employment on hours worked (Males)



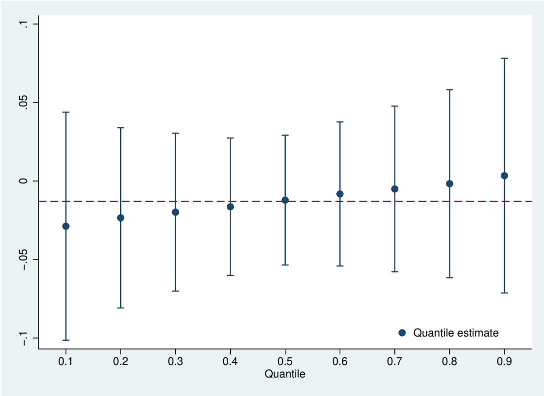
(a) Partner does not work



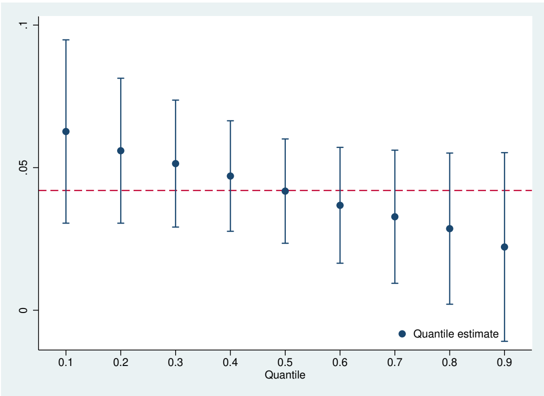
(b) Partner works part-time



(c) Partner works full-time



(d) Partner is an MD



(e) Partner is not an MD

Notes. The figures show the fixed-effects quantile regression estimates of the logarithm of weekly hours worked on the presence of children. Vertical bars are 95% confidence intervals. Dash lines show mean effects from the linear fixed effects model. All regressions include age, self-employment, metro location, health status, and medical specialty.

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Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	23/03/2023

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

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Chapter 3

The impact of motherhood on female medical doctors' earnings

3.1 Introduction

Over the past century, decreasing gender differences in education and the implementation of anti-discrimination policies have resulted in considerable gender convergence in the labour market. Within the same period, the entry of women – especially mothers – into high-income occupations has been one of developed countries' major economic and social developments (Ortiz-Ospina & Tzvetkova 2017). Women in rich countries have significantly increased their investment in human capital by obtaining higher levels of education and delaying childbirth. As a result, an increasing number of women are working in top-end occupations (Cortes et al. 2018), such as doctors, lawyers and engineers, with high salaries and prestige, despite the earning gap in these segments remaining unchanged. Swedish research has shown that in occupations with high incomes, women as a group still earn less than men who have equivalent jobs, and the gender difference in earnings has remained more or less the same over the past fifty years (Magnusson & Nermo 2019).

The existing earning gap in top-end occupations cannot be explained by women's level of education and work-life experience. One possible explanation is that women still have primary responsibility for family and children. Given the demands of motherhood, many women become pessimistic about their ability to both work outside the home and fulfil their responsibilities at home, and this tendency is especially pronounced among highly-educated women (Kuziemko et al. 2018). Moreover, high-prestige professions, such as medical doctors, are often more time-consuming and require travel, overtime work and being available during inconvenient working hours. Those work commitments make it harder for females, especially mothers, to balance their work and family roles. Hertz (2020) emphasises that women earn less than men in a given field because they are socialised to make different job choices and trade-offs given the reality of their taking on multiple non-work roles, such as a parent, to a greater extent than men.

The birth of a first child is a significant life transition for women. New mothers experience a sudden increase in time constraints, which create incentives to reduce their work commitments, which in turn impacts upon their income. The existing literature reports that labour market trajectories for men and women are similar in the year leading up to parenthood but diverge sharply with the arrival of children, with little recovery for mothers in the medium to longer term (Angelov et al. 2016, Kleven, Landais & Søgaard 2019, Chung et al. 2017, Fitzenberger et al. 2013). Part of this arises because women disproportionately shift to lower-pay jobs that better accommodate their family responsibilities, such as jobs in the public sector and in more ”family-friendly” firms (Hotz et al. 2018, Kleven, Landais & Søgaard 2019). The observed motherhood earnings penalty appears to be due to a decline in labour supply, both on the intensive (fewer working hours) and extensive (low participation) margins, as well as a decline in wage rates (Cortés & Pan 2020). The results described in the previous chapter demonstrate that the presence of children leads to significant declines in hours worked by Australian female doctors, while for male doctors working hours remained unchanged (Song & Cheng 2020). Therefore, it is essential to extend the study to examine how earnings change following the arrival of the first child for female medical doctors, who have invested as much in education and specialty training as their male counterparts.

In this study, I examine the causal effect of having children on the labour market trajectories of medical doctors, focusing specifically on the earning effect of motherhood. This study applies an event study to female physicians undertaking clinical practice in Australia using the longitudinal 'Medicine in Australia: Balancing Employment and Life' (MABEL) data from 2008 to 2018. As long as the hypothesis that the timing of first birth is uncorrelated with trends in the unobserved determinants of individuals' incomes stands, the event-study approach yields causal estimates of the effects of motherhood on earnings. The research is guided primarily by the following two questions: (a) what is the size and scope of annual earnings change over time for female doctors with the onset of motherhood? (b) how does the child effect vary for women doctors across different medical specialties and for different family sizes?

This paper contributes to the literature in three ways. First, this study uses an event-study framework to track female doctors' earnings change around the birth of their first child. The event-study approach not only can examine the causal effect of having children, but also has the ability to quantify the period effect on female doctors' earnings before and after motherhood.

A wave of recent papers have used an event-study framework to examine how women's and men's labour supply and earnings evolve in the years before and after the arrival of children in various countries and time periods (*e.g.*Kuziemko et al. (2018), Kleven, Landais & Søgaard (2019), Kleven, Landais, Posch, Steinhauer & Zweimuller (2019), Sieppi & Pehkonen (2019)); however, few examine the child effect on elite professions and high performers in the labour market. One recent event-study analysis by Bütikofer et al. (2018) uses Norwegian administrative data to examine the effect of parenthood on the earnings of a set of high-achieving professions. They find that the effects of parenthood differ with respect to the convexity of wage structure, with women in professions with linear wage structures (Goldin 2014), such as medicine and STEM, suffering a smaller and less persistent child penalty than women in professions with nonlinear wage structures (finance and law). However, the analysis of Bütikofer et al. (2018) is restricted to mothers and fathers in the first three years after graduation, whereas the present study extends the literature by analysing a comprehensive sample specific to medical doctors and avoiding any restriction to professionals on early career tracks.

Existing studies that analyse the role of parenthood on the gender gap among medical doctors are mostly associations-based. A small number of studies use a fixed-effect strategy to study the impact of the birth of a child on the evolution of annual labour income for male and female physicians (Schurer et al. 2016, Mikol & Franc 2019, Sasser 2005). Both the fixed-effect approach and event-study approach with panel data can be indicative of the causal effects of having a child on the earnings change. However, the fixed-effect method can only document the average change over the fixed time period, not trace the evolution of doctors' earnings in the years before and after having a child, so it has less ability to untangle coincident trends in doctors' work and family planning.

In addition, the present analysis does not follow other physician earning gap literature in comparing the earnings between gender (Mikol & Franc 2019) or within gender (Schurer et al. 2016). The event-study approach also has advantages in exploiting within-person variation in the timing of childbirth. I focus on investigating individual-level variation mainly because of concerns about unobserved productivity or preference for labour-force-attachment-related differences in earnings between males and females or among individuals.

Finally, this study uses rich, nation-wide data from 11 waves of the annual longitudinal survey MABEL. MABEL captures rich information on Australian doctors' income, financial status, work settings and family circumstances. This high-quality panel data offers advantages in investigating the motherhood effect for a specific group of women, female medical doctors. The results will be valuable in cross-industry and cross-country comparisons. Research on the general population across a diverse set of Europe countries finds that the child effect on mothers' earnings differs considerably across countries, with the earning penalties for women in Scandinavia countries being around 20–25%, compared to about 30–40% in the USA and the UK, and 50–60% in German-speaking countries (Kleven, Landais, Posch, Steinhauer & Zweimuller 2019). These differences in the size of child earnings penalties could be influenced by cross-country differences in family policies, gender norms, wage-setting institutions and/or and demographic composition.

Studies examining the impact of parenthood on earnings in the context of Australia are limited, especially for top-end professionals. Cheng et al. (2012) investigate factors that influence the earnings of general practitioners and medical specialists using the first wave of MABEL data. They find that Australian doctors' earnings are associated with gender, experience, the size of the GP practice, employment type, specialty and characteristics of doctors' location of work; however, they ignore the impacts of a doctor's family circumstances, which it is believed can influence a doctor's labour market outcomes. One existing Australian study concerning the overall earning gap for medical professionals and their family situations shows a large income difference between female GPs with and without children (Schurer et al. 2016). More specifically, it finds that female GPs with children earn, on average, above AU$30,000 less than comparable female GPs without children, while male GPs with children earn more than their male counterparts without children. However, the estimate of within-gender differences in earnings is based on a cross-sectional analysis, which does not allow a causal interpretation of the earning effect of having children. Therefore, this study aims to fill the gap in the Australian literature on the earning effect of parenthood and physicians' earnings inequality.

The remainder of the study is structured as follows: Section 3.2 presents the MABEL data, analysis sample and variables. Section 3.3 discusses the empirical econometric strategy. Section 3.4 discusses the results and the study concludes in Section 3.5.

3.2 Data, sample and variables

3.2.1 The MABEL longitudinal survey of medical doctors

This study uses longitudinal data from the MABEL survey from 2008 to 2018. MABEL is an annual, nationally representative survey of Australian medical practitioners, which captures extensive information on doctors' labour market status, earnings, working hours, medical specialty, workplace and workload, finance status, job satisfaction, personal characteristics and family status. The MABEL survey categorises doctors into four types: General Practitioners (primary care practitioners), medical specialists, specialists-in-training, and hospital non-specialists (e.g., interns or Medical Officers). This rich data allows us to investigate how the onset of motherhood affects female doctors' employment outcomes and to capture heterogeneous effects across a variety of doctor types.

3.2.2 Sample construction

MABEL data includes 107,586 doctor-year observations [24,280 individuals] over 11 survey years, with female observations accounting for 46.5%. In order to understand the full implications of child effects over time, I focus on female doctors who have given birth in the period 2008–2018 and restricted the analysis to individuals who are observed at least three times in the survey including at least once before and once after birth. Whenever possible, I also observe respondents over the full period of their most likely child-bearing years (less than 50 years old). After excluding observations with missing information, the estimation sample comprises an unbalanced panel of 7,191 doctor-year female observations. This analysis uses the complete case sample instead of constructing a balanced sample .

3.2.3 Variables and statistical description

The outcome variable Y is gross annual earnings. I control for time-varying characteristics, such as age, marital status, health status, and dummies for undertaking on-call duty and being self-employed. Additionally, I control for individuals' time-invariant characteristics by including individual-fixed effects in the regression analysis. Table 3.1 presents sample means at two time points around childbirth, which are one year before the birth of the first child ($t-1$) and one year after the firstborn ($t+1$).

As shown, the mean value of annual gross earnings after childbirth at $t+1$ is slightly lower than that before childbirth at $t-1$, and the pair-wise difference is significant at the 1% level. Compared with samples at the benchmark $t-1$, females observed at $t+1$ are more likely to be living with a partner, are less likely to undertake on-call duty and are more likely to be self-employed. There is no statistical difference between samples at $t-1$ and $t+1$ in characteristics of the location, whether completing medical school in Australia and health status. Sample means are also distinguished in the composition of doctors in terms of practice types, where there are more GP and specialist observations but fewer hospital doctors and specialists-in-training at $t+1$ compared with the benchmark. Thus, heterogeneity effects analysis will apply to female doctors by their speciality types.

3.3 Econometric strategy

To investigate the role of the motherhood penalty on the earnings of female medical doctors, I adopt the general scope of the event-study approach used by Kleven, Landais & Søgaard (2019) and adjust it with respect to the specific features of the MABEL data.

The analysis sample is restricted to female doctors who gave birth between 2008 and 2018. The MABEL data does not include a variable that directly illuminates the year in which a doctor gives birth, but each wave of the survey includes two important pieces of information related to children: 'the number of dependent children' and 'age of the first, second, and third youngest dependent child', which depends on the number of children a doctor has. Based on children variables in each survey year s, an individual is regarded as 'giving birth in the year s' if the doctor has one or more children more in survey year s than the number of children in the previous survey year $s-1$; in addition, a doctor is classified as a first-time mother if she reported having no child in survey $s-1$. Childbirth is also considered to have occurred for observations in wave 1 with one or more children where the age of the youngest child is less than one year. Thus, in the analysis sample, the birth mother observations can be classified into two types: (i) mothers who gave birth to their first child and/or more children between 2008 and 2018; (ii) mothers who gave birth to their second and/or third child between 2008 and 2018.

Let $t=0$ present the event-time when a female doctor becomes a mother, which may happen at any survey year s covered by MABEL data, i.e., between 2008 and 2018. I define the event time with respect to the two types of birth. For those who are observed giving birth to their first child, indexing variable 'event- time' t is more straightforward. I define $t=0$ for each individual i on the survey year s that a doctor gives birth to her first child. Using $t=0$ as the reference, the variable 'event time' is indexed via the calculation of the current survey year minus the year of first birth on set for each individual. For those who give birth to the second or/and third children, I can not directly observe the year when the first child is born, but it can be calculated by subtracting the current survey year and the age of the least young child on that year. Then event time for the second group of mothers can be indexed using the same process as for first-time mothers. This results in an unbalanced panel of women doctors, for whom I observe earnings at each event-time, from four years before the first childbirth to eight years after. The event-study model is specified in the following form:

$$Y_{ist} = \alpha + \sum_{j \neq -1} \beta_j \cdot I[t = j] + X'_{ist}\gamma + \lambda_i + \delta_s + \varepsilon_{ist} \tag{3.1}$$

where the outcome of interest, Y_{ist}, is the annual gross earnings for individual i in survey year s and at event time t, relative to the year in which the first childbirth occurs. The indicator on the right side includes event time dummies, which are equal to one if the event year is equal to any element in the event-time set (-4, -3, -2, 0, 1, ..., 8), where event year $t-1$ is not included as it is the benchmark in the analysis. Hence, the event time coefficients β_t are the key parameters of interest, which measure the effect on annual earnings of having a child in each event year, relative to the average earnings on the last year before childbirth ($t = -1$). X_{ist} includes the time-variant control variables mentioned above, and λ_i denotes individual time-invariant fixed effects, such as graduation from medical school in Australia and doctor types. δ_s represents survey year dummies. By including a full set of age dummies and survey year dummies, it is able to control nonparametrically for underlying life-cycle trends and time trends such as wage inflation and business cycles (Kleven, Landais & Søgaard 2019). Having estimated the event time coefficients β_t, I calculate the effect of children at each event time as a percentage of the counterfactual outcome, i.e., not becoming a mother, using one year before the first birth as the benchmark in the analysis. Then the percentage event-year-t effect is $P_t \equiv \hat{\beta}_t / E[\tilde{Y}_{ist}|t]$, where $\tilde{Y}_{ist}$ is the prediction of the model omitting the contribution of the event dummy. The converted estimation P_t can be interpreted as female doctors' gross earnings at t as a percentage P relative to event time -1 after control for life-cycle trends, time trends and other individual fixed effects. According to Kleven, Landais & Søgaard (2019), this approach provides a plausible method to identify the causal effect of parenthood.

3.4 Results

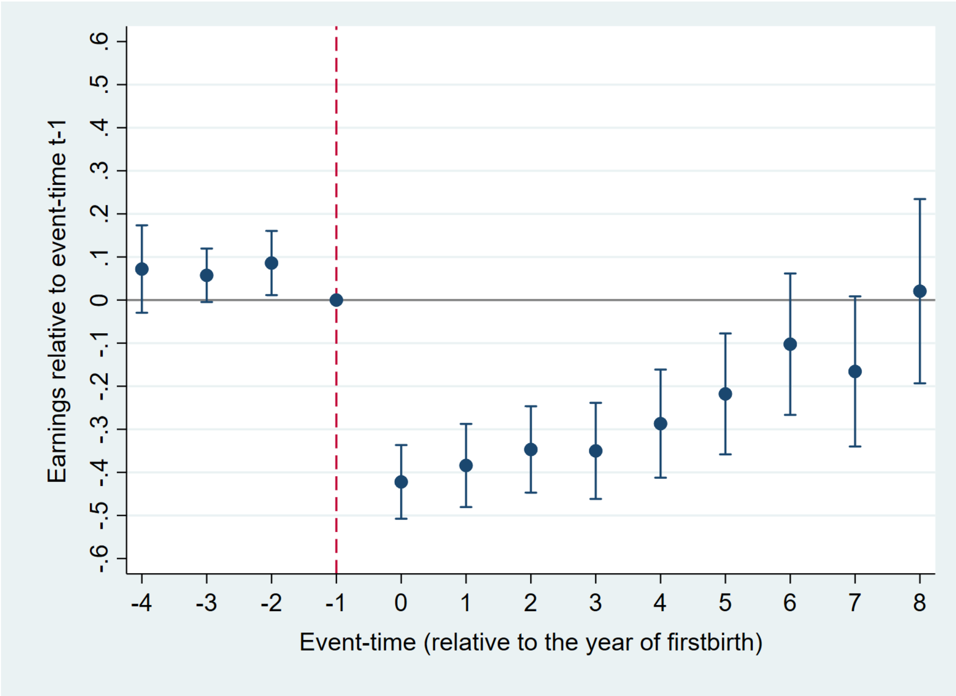
3.4.1 Child effects on mothers' earnings

The estimated coefficients β_t and coefficients of control variables in Model 3.1 are reported in Appendix Table C1. As the sample is restricted to females who became first-time mothers between 2008 and 2018, the β-coefficients depend only on the timing of fertility and not on the decision to have a child. In Figure 3.1, I plot the effect of $P_t \equiv \hat{\beta}_t / E[\tilde{Y}_{ist}|t]$, which shows event time effects as a percentage of the predicted annual earnings for female doctors when omitting the contribution of event dummies in each year relative to the year before the first childbirth. The vertical line indicates 't minus' for the pre-birth period and 't plus' for the post-birth period.

The results show female doctors experience a large, immediate and enduring drop in earnings with the birth of children. As shown in Figure 3.1, female doctors' annual earnings are stable before the onset of motherhood. Tracking back to four years before the first childbirth, female doctors' earnings are at about the same level as the year just before childbirth. However, the earnings of women doctors decrease immediately in the year t when the first child is born, dropping by an average of 42.2% relative to their mean levels in time $t-1$. The large negative child effect continues and recovers slightly over the next few years following the first birth. Three years after the birth, however, earnings are still on average 35.0% lower when compared with the benchmark. Female doctors' earnings start to rebound faster after the fourth year post the first birth. The child effect measured at $t+6$ is 10.2% lower than the benchmark. At the eighth year post firstborn, the earnings of female doctors on average have fully recovered, jumping back to a similar level to the year immediately preceding childbirth. As event time increases, I identify the effects of mothers who give birth earlier in the panel, resulting in less sample observation and larger standard errors, and consequently, the confidence bands at $t+8$ become much wider.

I further find evidence that the magnitude of the reduction in gross earnings of female doctors depends on the timing of birth. As shown in Figure 3.1, the negative post-birth effect in the first three years after motherhood onset is at the lowest level, which ranges between –42.2% and –34.7% relative to the year before the first birth. This result is aligned with findings in the

Figure 3.1: Effect of having children on female doctors' annual earnings



Notes: Black dots represent percentage converted time event dummies coefficient estimates of the change in the annual gross earnings relative to event time t-1 using equation 3.1 for event periods of t-4 to t+8. The vertical dash line indicates t-1, which is the year just before childbirth, separating the pre-birth and post-birth periods. Caps indicate 95% confidence intervals.

previous chapter by Song & Cheng (2020), where we find that female doctors with children aged 0–4 years are associated with the highest working-hours reduction. This phenomenon also reflects the required school entry age in Australia. According to the Departments of Education and Early Childhood Development in each Australian state or territory, five years is the cut-off date at which a child must begin to attend school. Age 4 is thus a critical transition year to school for children in Australia, and mothers' labour market inputs and outputs are significantly influenced by this timing. This finding implies that female doctors take larger responsibilities for children's care, schooling and education in their households than do male doctors.

The results of this study are generally in line with findings of previous literature on the child earning penalty, which observes strong and persistent negative earning effects for females due to childbirth. However, earning trends after birth are different between female physicians in

Australia and the general female population in Scandinavian and German-speaking countries [see Kleven, Landais, Posch, Steinhauer & Zweimuller (2019) and Sieppi & Pehkonen (2019)]. Firstly, the short-run child effects on Australian women doctors' earnings are much smaller than those observed in the female population in Sweden (62.0%), Finland (61.0%), Austria (83.0%) and Germany (79.0%). Secondly, the gross annual earnings of females in Scandinavian countries and German-speaking countries rebound substantially as early as one year after the first child is born; however, the onset of motherhood reduces Australian women doctors' earnings consistently for years, only beginning to rebound four years after childbirth, which relates to the fact that Australian women spend more time with children until schooling. Finally, Australian female doctors' earnings recover more quickly after four years and can return to the same level as pre-birth earnings after eight years on average. In contrast, the long-run child effects on earnings remain at 25% below pre-birth for females in Scandinavian and German-speaking countries.

When compared with findings of a related study of highly qualified women conducted by Bütikofer et al. (2018), I find that Australian female doctors encounter larger short-run child penalties in labour earnings but follow a similar dynamic earnings pattern as Norwegian female medical graduates. The difference in the magnitude of estimated child effect between this study and Norwegian medical doctors is due to the difference in sample settings. In a comparative context within Australia, a recently published paper by the Australian Treasury (Bahar et al. 2023) conducted a parallel analysis focused on the general population of the Australian workforce. This study reveals that the birth of children leads to an average reduction of 55 percent in female earnings during the 5 years following parenthood. Furthermore, the earning gap persists at a significant level even in the 10 years following the arrival of children. This finding suggests that female doctors in Australia exhibit a higher capacity for economic recovery after parenthood compared to the broader female population in the country. In essence, female doctors seem to enjoy greater access to workplace flexibility, which in turn enhances their ability to remain employed after becoming parents.

3.4.2 Heterogeneous effects

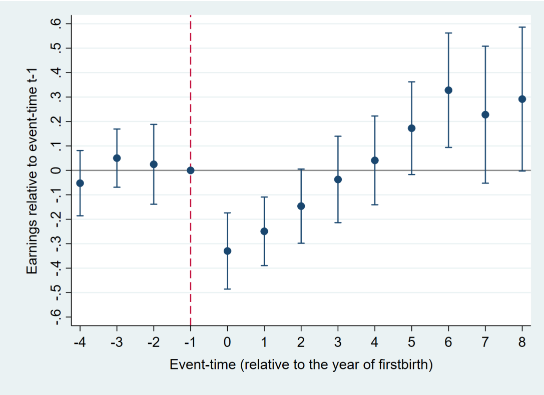
I further investigate whether the onset of motherhood negatively affects the earnings of specific subgroups in the sample at different magnitudes. The results, showing the heterogeneous effects of motherhood on female doctors' annual earnings, are illustrated in Figures 3.2 and 3.4 respectively, with the estimation results reported in Tables C2 and C3.

By family structure

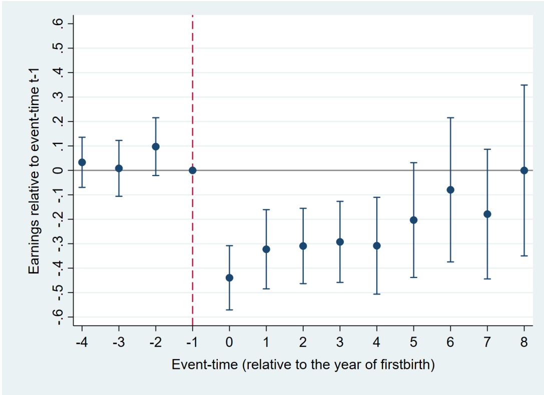
Looking further into the sample of the main regression, many doctors experience more births after their first pregnancy. The 7,191 doctor-year female samples can be classified into three subgroups with respect to the total times of birth they gave in the survey period 2008 to 2018. Thus, the original sample includes 2,951 observations that include one birth, which is the first child; 2,704 observations include two births, and 1,536 include three or more births. I apply the event study (Model 3.1) to the three subgroups of female doctors separately, which stand in for three types of family structures. The results show marked heterogeneity across family structures.

The results by family structure (Figure 3.2) provide evidence of the total impact of children on later-life incomes for mothers with more than one child. The short-run child effects are similar across mothers with different family sizes. The earnings of female doctors with only one child take the shortest time to recover to the same level as before birth, with earnings measured at event time $t+4$ is 4.1% higher than the benchmark year. For mothers with two children, earnings take eight years on average to return to a similar level as the year before the first birth. The motherhood effect is highest for those with three or more children, for whom a significant negative child effect continues for years (below 20 per cent lower as the benchmark), with the long-term effect measured at event time $t+8$ still being 1.3% below the benchmark year. The findings are associated with the fact that mothers with more children work fewer hours. For example, on average, Australian female doctors with three or more children work 7.5 hours less per week than their female counterparts, and this figure is even higher for those with pre-school age children (Song & Cheng 2020).

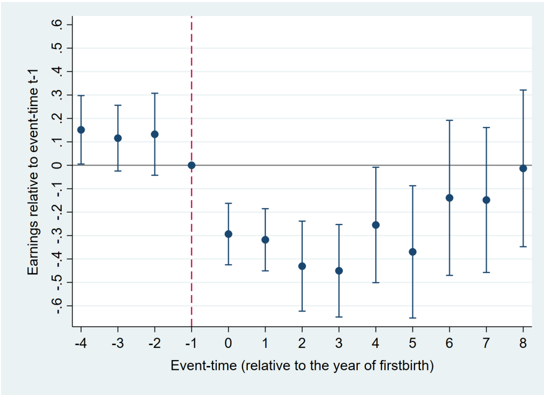
Figure 3.2: Event estimates of child effects on female doctors' annual earnings by family structure



(a) Have one child



(b) Have two children

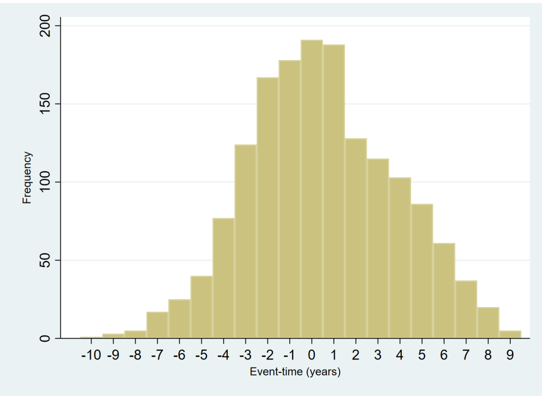


(c) Have three or more children

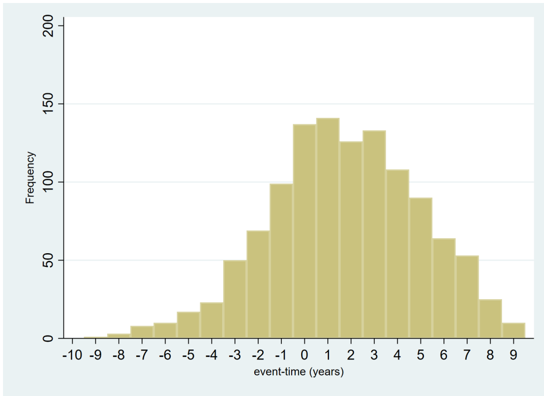
By doctor type

The MABEL survey covers four doctors types: general practitioners (primary care practitioners), medical specialists, specialists-in-training, and hospital non-specialists (e.g., interns or Medical Officers). Figure 3.3 shows the distribution of sample frequency in each event year by doctor type. In the analysis sample, general practitioners are symmetrically distributed around the event time 0, and the sub-sample size is reasonably large in pre- and post-event years, which allows me to analyse the anticipated and post-birth effect with female GPs. The female specialist sample is distributed mainly across post-birth event years but includes sufficient sub-samples located in pre-event years until $t-4$. When looking at the sample distributions of hospital doctors and specialists-in-training, both are left-skewed along the event axis. Sizes of the sub-sample in post-event years are not large enough to conduct post-event analysis. Therefore, the analysis of heterogeneous effects by doctor types will focus on female GPs and female specialists, including 2,451 and 2,111 observations in each subgroup.

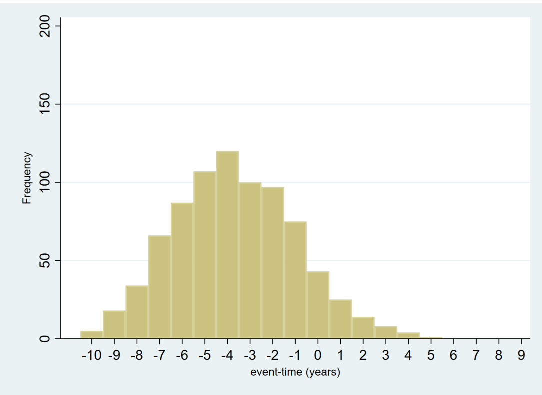
Figure 3.3: Frequency distribution of female sample by doctor type and event-time years



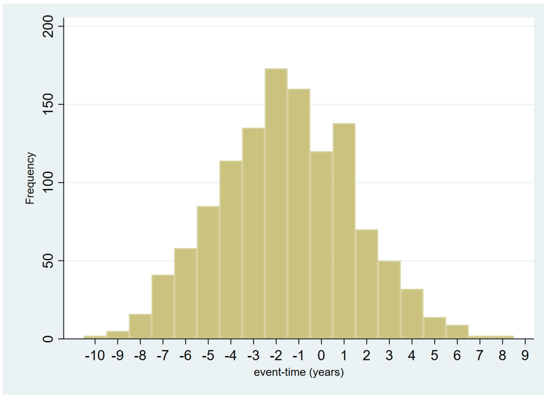
(a) general practitioners



(b) specialists



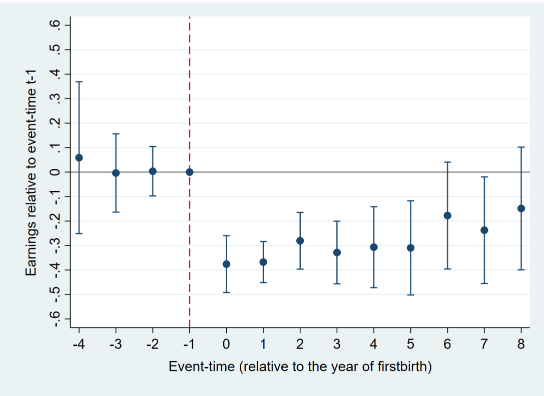
(c) hospital no-specialists



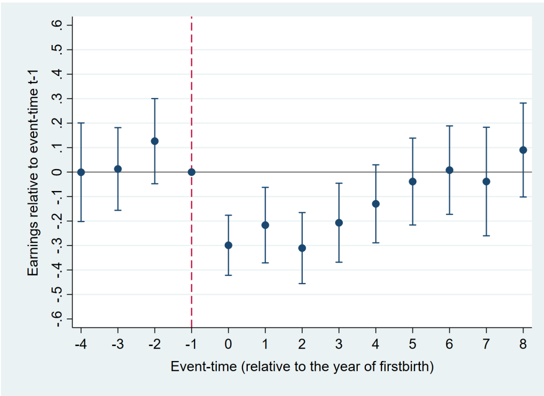
(d) specialists-in-training

Table 3.4 presents heterogeneous effects by doctor types. Overall, the onset of motherhood shows a larger negative impact on earnings for female GPs' than for female specialists in the short and long term. In the year of birth onset, female GPs, on average, earn 37.6% less than the year before giving birth to their first child, while female specialists' earnings decline to 30.0% below the benchmark. In the years post the first birth, the child effect for female GPs is in the range 36.7% to 28.1%, but specialists' earnings quickly recover from -22.0% at $t+1$ to -3.8% at $t+5$. Further on, the earnings path after birth differs between female GPs and specialists. The estimated child effects persist longer for female GPs, and their earnings only start to rebound after five years of the first birth. In contrast, female specialists' earnings start to rebound soon after the first birth, and they can recover to a similar level as pre-birth after about five years. The earnings of GPs and specialists are thus influenced differently by the arrival of children. This may be associated with different types of childcare selected by mothers for their pre-school age children. I discuss the relationship between childcare and female doctor's earnings in the following section.

Figure 3.4: Event estimates of child effects on female doctors' annual earnings by doctor types



(a) general practitioners

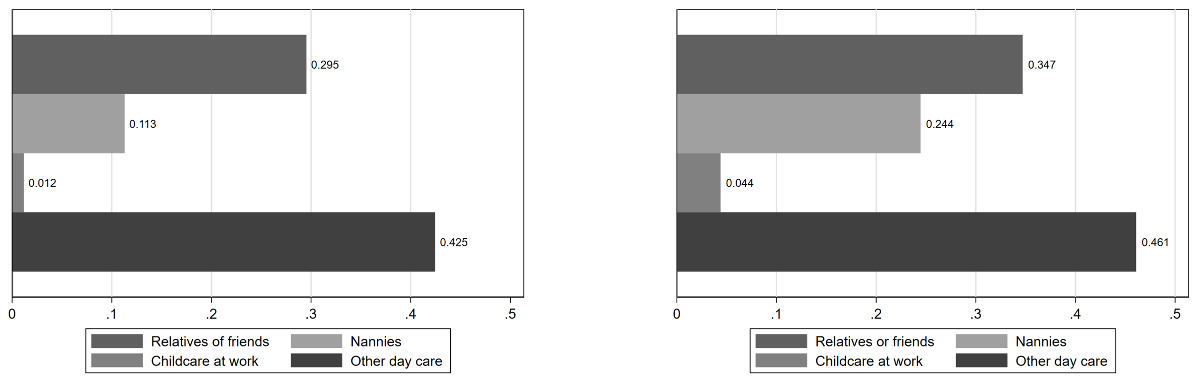


(b) specialists

3.4.3 Childcare and female doctors' employment outcomes

Figure 3.5 presents the form of childcare that female doctors choose to use. As shown, Australian female doctors mainly use four types of childcare: relatives and friends, nannies, childcare at work and other daycare. I labelled each type of childcare bar with the proportion of the sample of each doctor-subgroup that uses that form of childcare. Overall, female GPs use less of each type of childcare service for their pre-school age children when compared with female specialists, which is consistent with the finding of a larger negative children effect on GPs in the first five years post birth. There are similarities between GPs and specialists in childcare choice. 'Other day care' is the most popular choice of childcare service for both female GPs and specialists, with over 40% of individuals recorded in each subgroup sample. However, 'childcare at work', which is the most convenient form of childcare service, is least used by Australian female doctors, with the survey recording only 1.2% of GPs and 4.4% of specialists access such care in the sample. The rest mainly choose relatives, friends or nannies to look after their pre-school-age children. Moreover, there is a significantly higher proportion of female specialists who use nanny services than female GPs, which may be associated with the difference in income between specialists and GPs.

Figure 3.5: Types of childcare used by female GPs and female specialists for their children of pre-school age

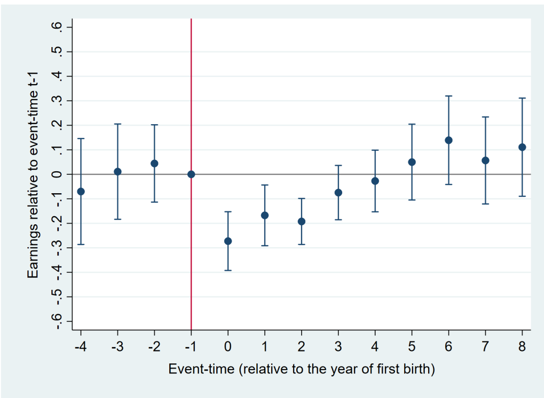


(a) general practitioners (b) specialists

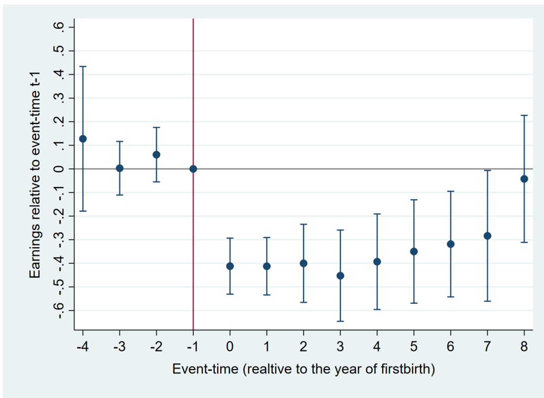
The MABEL survey also includes another childcare-related question: to what degree are doctors restricted in their employment and/or the time and hours they work due to lack of available childcare? In addition to the description of female doctors' choices of type of childcare, I ran an event-study regression on doctors who are restricted by childcare to examine the relationship between mother-doctors' work attachment and the availability of childcare. I apply Model (3.1) to female GPs and female specialists who have been restricted by childcare and who have not been affected by the availability of childcare respectively.

As shown in Figure 3.6, the annual earnings of doctors who are restricted by childcare are less affected by childbirth in magnitude in both the short and long term when compared with those who reported that their employment/working hours are not restricted by the availability of childcare. Although this result is opposite to our expectations, it is meaningful. It involves an endogenous issue: doctors reporting that their employment/working hours are restricted by childcare are those intending to return to their job. They will search for childcare centres near their workplaces and eventually find one somewhere else or choose other types of childcare. In contrast, those new mother-doctors who decide to take on more parental duties and do not plan to return to work will not care about the availability of childcare. More importantly, the significant effect on earnings for mothers who reported agreeing or strongly agreeing that their work is restricted by childcare indicates that the availability of childcare near the workplace influences mother-doctors' return to regular work. The 45% of female GPs and specialists who responded 'agree with' or 'strongly agree with' in the questionnaires indicates a potential shortage of childcare supply near healthcare facilities.

Figure 3.6: Event estimates of children's effect on female doctors' annual earnings by self-reported accessibility to childcare



(a) Being restricted to childcare



(b) Not being restricted

3.5 Discussion and concluding remarks

This chapter has studied the causal effect of a child's birth on Australian doctors' earning path and contributes to the literature on the parenthood effect on high-prestige professions. The study uses an event-study approach to estimate the child effect on the labour market earnings of medical doctors based on data from the Australian longitudinal survey MABEL. The sample includes female doctors who become first-time parents between 2008 and 2018, for whom I observed gross earnings four years before childbirth and eight years after. The study results show that female doctors experience a large and immediate drop in earnings with the first birth. The earnings loss estimated in the short run is 38.4% and in the medium run is 21.8% below the year immediately preceding birth of a first child. Australian female doctors take less time to recover from their earnings rebound than the general female population in Scandinavian countries. Female doctors' earnings can fully recover to pre-birth levels approximately eight years after the first birth. This is in contrast to previous research findings that women encounter persistent child penalties in gross labour earnings in the medium to long term (Kleven, Landais & Søgaard 2019, Kleven, Landais, Posch, Steinhauer & Zweimuller 2019, Sieppi & Pehkonen 2019). Moreover, the negative children effect is larger and lasts longer for female doctors if they are GPs or have three or more children. In addition, the availability of childcare near the workplace influences mother-doctors' returning to regular work.

The results of this study are generally consistent with the findings of related research. Women experience large short-term child penalties in labour market outcomes (Kleven, Landais & Søgaard 2019, Kleven, Landais, Posch, Steinhauer & Zweimuller 2019, Sieppi & Pehkonen 2019); however, the results diverge when looking at the medium- and long-term effects. Australian female doctors' earnings recover more quickly from childbirth compared with the general female population in Denmark and other Scandinavia countries. Australian female doctors experience a larger child effect on labour earnings, but follow a similar post-birth dynamic earning pattern as other female professions (including medicine) in Norway. The above findings potentially reflect two factors. On the one hand, higher education and human capital accumulation may help women recover from career interruptions more easily. On the other hand, differences in women's return to regular work after childbirth may be due to variations in maternity leave and parenthood support policies across countries.

The results of this study highlight three facts about female doctors and the healthcare labour market in Australia. Firstly, the significant and persistent negative children effect suggests that highly qualified female professionals, such as women physicians, still play the dominant carer roles in their households. This fact is consistent with the finding of the previous chapter that women in dual-physician couples with children, on average, work 11 fewer hours per week compared to dual-career female physicians with no children. In contrast, no changes in hours are observed among male physicians with children compared to their childless counterparts (Song & Cheng 2020). Thanks to the prestige skills they have obtained and their higher human capital, female doctors can recover more easily and quickly from birth-giving and return to regular work.

In addition, the low availability of and restricted access to childcare services near work is another significant barrier for women physicians with pre-school-age children. Many mother-doctors are restricted by childcare contraints from returning to a full-time workload. Healthcare organisations should spend time and resources to address this issue. Developing strategies to help doctors to access childcare services near their workplaces would be valuable for improving the efficiency of healthcare provision, particularly for female doctors returning from maternity leave.

Furthermore, weak negotiation skills might be another potential issue influencing female doctors' earnings after fertility. Women physicians with children returning to the workforce may receive disparate treatment by employers in terms of trade-offs between lower salaries and favourable work schedules. Thus, providing additional information to women physicians could enhance their ability to negotiate fairer outcomes with their employers, which could help address the gender inequality issue in earnings due to parenthood. With the increasingly large share of women among young physicians, supporting and encouraging female physicians to quickly return to work after having children would improve the provision of patient care and further enhance the efficiency of healthcare delivery in Australia.

Tables

Table 3.1: Summary of sample means at one year before and one year after the first birth.

Variables	one year before the first birth t-1	one year after the first birth t+1	Diff.[a]
Outcome variable:			
Annual gross earnings ($'000)	138.35 (96.02)	128.74 (137.92)	*
Covariates:			
Living with a partner	0.94 (0.24)	0.97 (0.17)	***
Complete medical school in Australia	0.85 (0.35)	0.84 (0.36)	
Doing on-call duty	0.55 (0.50)	0.46 (0.50)	***
Self-employed	0.30 (0.46)	0.37 (0.48)	***
Metro area	0.78 (0.41)	0.76 (0.43)	
Health status is excellent	0.44 (0.50)	0.43 (0.50)	
Health status is very good	0.38 (0.49)	0.37 (0.48)	
Health status is good	0.12 (0.33)	0.16 (0.36)	**
Health status is fair	0.05 (0.21)	0.03 (0.16)	**
Health status is poor	0.01 (0.08)	0.01 (0.09)	
General practitioners	0.33 (0.47)	0.39 (0.49)	**
Specialists	0.22 (0.41)	0.32 (0.47)	***
Hospital non-specialists	0.14 (0.35)	0.06 (0.24)	***
Specialists-in-training	0.30 (0.46)	0.24 (0.42)	***
Age less than 35 years	0.65 (0.48)	0.40 (0.49)	***
Age 35-39 years	0.28 (0.45)	0.44 (0.50)	***
Age 40-44 years	0.06 (0.23)	0.14 (0.35)	***
Age 45-49 years	0.00 (0.06)	0.01 (0.12)	**
Age 50-54 years	0.00 (0.06)	0.00 (0.05)	
No. of observations:	1,038	744	

Note: Standard deviation shown in parenthesis.

[a]Two sample mean comparison test. Significance: *** 1%; ** 5%; * 10%.

Appendix

Table C1: Full regression estimates for Figure 3.1: Effect of first child-birth on female doctors' annual gross earnings

Variables	Estimated Coefficients
Event T-4	7641.22
	(1.39)
Event T-3	6099.55*
	(1.81)
Event T-2	9123.79**
	(2.26)
Event T	-44852.20***
	(-9.67)
Event T+1	-40803.10***
	(-7.80)
Event T+2	-36859.82***
	(-6.78)
Event T+3	-37204.84***
	(-6.15)
Event T+4	-30479.84***
	(-4.48)
Event T+5	-23149.08***
	(-3.04)
Event T+6	-10888.00
	(-1.22)
Event T+7	-17614.48*

Continued on next page

Table C1 – continued from previous page

Variables	Estimated Coefficients
	(-1.86)
Event T+8	2183.55
	(0.19)
age[30-34]	16706.00**
	(2.08)
age[35-39]	9888.15
	(1.30)
age[40-44]	18631.51**
	(2.04)
age[45-49]	37831.91***
	(2.77)
age[50-54]	49652.91
	(1.54)
have partner	-19170.22***
	(-2.68)
complete medical school in Australia	8320.12
	(0.98)
doing on-call duty	20225.59***
	(7.84)
being self-employed	34909.65***
	(5.07)
health status is very good	-5508.60
	(-1.56)
health status is good	-8322.97
	(-1.61)

Continued on next page

Table C1 – continued from previous page

Variables	Estimated Coefficients
health status is fair	-19496.74**
	(-2.35)
health status is poor	-27965.00
	(-1.64)
metro area	-5046.62
	(-0.88)
specialist	74997.49***
	(6.45)
hospital non-specialist	-2353.34
	(-0.34)
specialist-in-training	5042.84
	(0.74)
year dummies	Yes
constant	169006.52***
	(10.45)
Observations	7191
Adjusted R^2	0.219

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C2: Full regression estimates for Figure 3.2: Motherhood effects by family size

Variables	(1) 1 child	(2) 2 children	(3) 3+ children
Event T-4	-6449.68	3595.02	23328.35**
	(-0.77)	(0.63)	(2.03)
Event T-3	6180.52	897.69	17847.78
	(0.83)	(0.14)	(1.62)
Event T-2	3060.38	10616.15	20416.13
	(0.30)	(1.61)	(1.48)
Event T	-40603.41***	-47991.98***	-45255.27***
	(-4.15)	(-6.55)	(-4.39)
Event T+1	-30692.43***	-35240.35***	-49011.13***
	(-3.48)	(-3.90)	(-4.70)
Event T+2	-18009.04*	-33788.50***	-66378.12***
	(-1.89)	(-3.94)	(-4.39)
Event T+3	-4570.47	-31954.09***	-69413.04***
	(-0.41)	(-3.46)	(-4.47)
Event T+4	5030.27	-33670.97***	-39277.34**
	(0.44)	(-3.05)	(-2.03)
Event T+5	21236.64*	-22200.42*	-56977.59**
	(1.78)	(-1.70)	(-2.57)
Event T+6	40371.78***	-8684.66	-21434.64
	(2.75)	(-0.53)	(-0.82)
Event T+7	28054.44	-19538.55	-22841.37
	(1.59)	(-1.32)	(-0.94)
Event T+8	35908.53*	-42.55	-2027.16

Continued on next page

. **Table C2 – continued from previous page**

Variables	(1) 1 child	(2) 2 children	(3) 3+ children
	(1.94)	(-0.00)	(-0.08)
age[30-34]	-13533.05	24240.00	48581.39***
	(-0.83)	(1.51)	(3.21)
age[35-39]	2147.63	15301.41	36797.41***
	(0.15)	(0.97)	(2.77)
age[40-44]	7422.40	24006.83	24660.06
	(0.48)	(1.29)	(1.39)
age[45-49]	27481.44	52235.00	95323.77
	(1.52)	(1.41)	(1.00)
age[50-54]	60524.09	376042.32***	0.00
	(1.59)	(10.68)	(.)
have partner	-27375.12	-22684.29**	-33122.44
	(-1.42)	(-2.02)	(-1.61)
complete medical school in Australia	3852.84	22329.34	36746.36
	(0.39)	(0.98)	(1.12)
doing on-call duty	23181.97***	22266.54***	20666.53***
	(4.96)	(5.09)	(2.84)
being self-employed	34502.45***	36613.05**	47972.36***
	(3.16)	(2.59)	(3.41)
health status is very good	-16409.96*	-4885.45	-15648.51*
	(-1.80)	(-1.01)	(-1.75)
health status is good	-28311.96**	11731.81	-24118.34
	(-2.54)	(1.25)	(-1.65)
health status is fair	-46459.40***	-7136.06	2011.49

Continued on next page

. **Table C2 – continued from previous page**

Variables	(1) 1 child	(2) 2 children	(3) 3+ children
	(-2.64)	(-0.56)	(0.10)
health status is poor	-73049.13**	9106.69	32341.41
	(-2.04)	(0.45)	(1.72)
metro area	-4957.36	1116.00	-23344.17
	(-0.39)	(0.12)	(-1.47)
specialist	60251.87***	91978.11***	104630.89***
	(2.99)	(3.82)	(3.82)
hospital non-specialist	-14490.06	14008.60	12375.16
	(-1.00)	(1.19)	(0.87)
specialist-in-training	4808.08	15400.48	20380.21
	(0.35)	(1.08)	(1.02)
year dummies	Yes	Yes	Yes
constant	207462.97***	124668.23***	124199.53***
	(7.01)	(4.15)	(2.75)
Observations	2951	2704	1536
Adjusted R^2	0.194	0.277	0.296

*R*obust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C3: Full regression estimates for Figure 3.4 Motherhood effects by doctor types

Variables	(1)	(2)
	GP	Specialist
Event T-4	7729.51	-112.29
	(0.37)	(-0.01)
Event T-3	-475.22	2199.16
	(-0.04)	(0.15)
Event T-2	474.51	21855.05
	(0.07)	(1.42)
Event T	-49271.41***	-51701.71***
	(-6.35)	(-4.78)
Event T+1	-48203.02***	-37461.18***
	(-8.59)	(-2.75)
Event T+2	-36794.78***	-53675.98***
	(-4.75)	(-4.20)
Event T+3	-43066.15***	-35767.21**
	(-5.03)	(-2.51)
Event T+4	-40223.60***	-22408.90
	(-3.64)	(-1.59)
Event T+5	-40594.99***	-6689.82
	(-3.15)	(-0.43)
Event T+6	-23286.90	1386.76
	(-1.60)	(0.09)
Event T+7	-31121.14**	-6663.61
	(-2.14)	(-0.34)
Event T+8	-19469.99	15589.25
	(-1.16)	(0.92)

Continued on next page

Table C3 – continued from previous page

Variables	(1)	(2)
	GP	Specialist
age[34-39]	2408.68	11139.68
	(0.32)	(1.01)
age[40-44]	7875.52	26907.19*
	(0.62)	(1.79)
age[45-49]	21544.28	42214.56**
	(1.00)	(2.07)
age[50-54]	78503.23	29550.69
	(1.44)	(0.79)
have partner	-30885.37*	-37602.69
	(-1.73)	(-1.28)
complete medical school in Australia	31313.52	0.00
	(1.48)	(.)
doing on-call duty	9443.60	42678.88***
	(1.52)	(4.92)
being self-employed	15996.92**	35964.71***
	(2.51)	(3.10)
health status is very good	2231.73	-21304.12**
	(0.44)	(-2.09)
health status is good	3137.57	-29116.22**
	(0.44)	(-2.03)
health status is fair	-9306.80	-59685.82**
	(-0.73)	(-1.98)
health status is poor	-13583.48	-86393.35***
	(-0.47)	(-3.49)

Continued on next page

Table C3 – continued from previous page

Variables	(1)	(2)
	GP	Specialist
metro area	6966.17	6229.02
	(0.79)	(0.30)
year dummies	Yes	Yes
constant	70987.26**	176854.41***
	(2.38)	(4.06)
Observations	2451	2111
Adjusted R^2	0.086	0.197

*R*obust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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