Three Essays on Skilled Migration to Australia

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Abstract

This thesis contains three essays on diverse aspects of skilled migration in Australia. The first chapter uses novel administrative data to analyse the extent of out-migration for Australian permanent migrants across different skill measures and cohorts using survival data methods. The use of this dataset reduces estimation biases inherent in cross-sectional or panel datasets used in previous studies. This study finds that migrants from high-income countries are more likely to out-migrate than those from low-income countries. The analyses also indicate that out-migration is sensitive to the business cycle, as measured by the unemployment rate. However, out-migration is the highest for high-skilled migrants, with every year of education increases the hazard rate by around 4 percent. Moreover, migrants targeted by skill-based policies are more likely to leave. These results, therefore, highlight challenges in retaining skilled migrants recruited through points-based policies.

The second chapter uses linked administrative and panel datasets to study associations between skilled temporary worker flows and the labour market outcomes of Australian workers. It finds no statistically significant negative effect of such migration on the either their wages or unemployment. However, the analysis reports a positive association between the wages of workers with a bachelors degree or above and skilled temporary worker flows. Further analysis studies how temporary migration induces occupational switching. Highlighting a possible channel through which immigration affects labour market outcomes, our results indicate that such migration induces Australian workers to specialise in communication skills.

Focussing on a specific high-skilled occupation, medical practitioners, the third chapter enhances empirical evidence on policies aimed at resolving rural workforce shortages by evaluating the impact of the Districts of Workforce Shortage program, which restricts International Medical Graduates (IMGs) to under-served rural and remote areas of Aus-

tralia. The analysis uses a difference-in-differences design to find that the program is effective at reducing the growth of inequality in affected regions. It also studies changes in medical workforce outcomes to finds a corresponding fall in workload measures, such as working hours or waiting times. However, no robust evidence of a fall in price measures, such as consultation fees or bulk billing rates, is observed. Last, there is suggestive evidence that the fall in workload, particularly in hours, is higher for IMGs. This finding highlights possible imperfect substitutability of natives and migrants even in narrow occupational groups.

Preface

Chapter one was joint work with my supervisor, Dr. Andrew Clarke. While the ideas and direction of this chapter was jointly determined , I was solely responsible for the execution and preparation of the work. All coauthorship has taken place in accordance with the Graduate Research Training Policy of the University of Melbourne

I am thankful for funding provided by the University of Melbourne in the form of an International Research Scholarship, full fee remission, and a Research Higher Degrees Studentship.

Declaration

This is to certify that:

- the thesis comprises only my original work towards the PhD except where indicated in the Preface,
- due acknowledgement has been made in the text to all other material used,
- the thesis is fewer than 100 000 words in length, exclusive of tables, maps, bibliographies and appendices

Laxman Bablani

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Chapter 1

Introduction

Driven by the growing internationalisation of professional occupations and tertiary education, skilled migration has become a major pathway for contemporary international migrants (OECD, 2008). Developed countries increasingly compete for high skill migrants because they perform better in the labour market, and can respond better to economic shifts, such as the growing occupational importance of science, technology, engineering & mathematics (STEM). Skilled migration policy uses more selective procedures compared to those used in previous decades, which focussed on family reunification or asylum seekers. Migration programs targeting skilled migrants are also increasingly designed for temporary immigrants, the general trend is towards an increase in the share of temporary visas relative to permanent visas (Boucher & Cerna, 2014).

Simultaneously, perceptions of immigration have played an important role in recent events, such as the prospective exit of the United Kingdom from the European Union. Despite the economic, political, and social consequences of immigration, much controversy surrounds the economic impact of migration. Exacerbating this uncertainty is the fact that the labour market effects of migration are dependent on numerous factors, such as the relative skill of the migrant cohort, and the institutions of the destination country. Establishing the general impact of migration is therefore contingent on the identification of patterns from studies across many countries with similar migration policies. While the majority of studies focus on the United States (Manacorda, Manning & Wadsworth, 2012), many other major English speaking countries promote high-skill immigration through points-based policies[1].

Australia is, therefore, a relevant laboratory to conduct analyses of skilled migration. The country has promoted different forms of points based immigration since 1989, which have been tightened nearly every decade. Nearly 28 percent of Australians residents were born overseas in 2017, the third highest proportion in the OECD following Luxembourg and Switzerland. Australia also shares vital policies with two other major migrant destination countries - Canada and New Zealand. These include points based migration policies, and a growing emphasis on demand-driven and temporary migration. This thesis, therefore, conducts three independent studies on skilled migration in Australia. The overarching theme across chapters is to utilise contemporary econometric techniques and new data sets to analyse such migration.

The Return Migration of Australian Migrants

This chapter studies the out-migration decisions of offshore permanent migrants to Australia. Migration decisions are not permanent, and many migrants go back home or emigrate to a third country. Understanding this process can improve migration policy because return migration influences both the net migration and the overall skill selection of migrants to the host country.

This study uses a novel dataset of the population of immigrant arrivals and departures from Australian ports to analyse the extent of out-migration between different arrival cohorts and skill measures. By doing so, it contributes to the literature in two ways. First, the dataset captures the time of departure at a high resolution (actual date, vs year of out-migration) allowing for studies to be run at a quarterly level to capture changes in macroeconomic conditions, such as the unemployment rate, on return migration. Second, previous studies on out-migration often use panel or cross-sectional data and suffer from estimation errors since the construction of weights in these studies does not usually take immigrant status into account (Dustmann & Weiss, 2007). Our dataset ameliorates the resulting biases inherent in the use of survey data.

The results indicate that migrants from high-income countries are more likely to out-migrate than those from low-income countries. Out-migration is also sensitive to the

[1] Australia, Canada, New Zealand, and the United Kingdom

business cycle, as measured by the unemployment rate. Also, out-migration is highest for the most skilled migrants, with every additional year of education required by an occupation increasing out-migration by around four percent. Moreover, migrants targeted by skilled migration visas associated with better economic outcomes are more likely to leave.

The findings of the study are consistent with a theoretical model proposed by Borjas and Bratsberg (1996) and suggest that Australia has a lower return to skill compared to many of its source countries. This result highlights the need for effective policy aimed at retaining skilled migrants to Australia, with a focus on highly skilled migrants. Furthermore, the non-random out-migration of the cohort which performs best in the Australian labour market is likely to downward bias estimates of immigrant wage assimilation studies, many of which find null to low results (for example, Antecol, Kuhn and Trejo (2006), Mcdonald and Worswick (1999)).

The Impact of Skilled Temporary Worker Flows on the Labour Market Outcomes of Australian Workers

Whereas the previous chapter focusses on the skill selection and retention of Australian permanent migrants, the third chapter analyses the labour market effects of temporary long-term skilled migrant workers to Australia. Temporary migrant programs are increasingly important in the recruitment of a skilled workforce in OECD countries, and the large and growing role of such programs has invited much media and public commentary (Bahn, Barratt-Pugh & Yap, 2012). However, there is a limited understanding of the economic and social consequences of such migration. These issues are compounded by a lack of consensus within the economic literature (see Borjas, 2003 and Ottaviano and Peri, 2008). Further, only a small number of studies analyse the impact of temporary migration.

This essay analyses the labour market consequences of the Australian 457 temporary worker program, which is the dominant program for employer nominated migration to Australia. This chapter contributes to the literature by being the first econometric analysis looking impact of temporary workers in Australia. Further, despite the global importance of temporary immigration, this is one of the few studies that focus on such migration. To perform the analysis, administrative data on 457 temporary worker flows is matched to the Household Income and Labour Dynamics in Australia (HILDA) longitudinal survey of Australian households. Because migrant flows are endogenous with regards to occupational demand, the analysis uses instrumental variables estimation techniques. It also follows the double instrumentation strategy of Ruist, Stuhler and Jaeger (2017) that aims to control for serial correlation, as well as separating out the short- and long-run impacts of migration.

The findings indicate that that increases in 457 utilisation are not associated with a reduction in wages or increased unemployment of Australian workers. Given the null to the weakly positive impact of 457 migration, the essay also investigates possible mechanisms for such findings. Using the O*NET dataset of job characteristics, each occupational group is assigned a score of relative communication to manual skills. The analysis of patterns of occupational switching finds that increases in 457 migration within occupational groups induce Australian workers to switch to occupations specialising in communicative tasks. These results support the contemporary economic literature which emphasises occupational upgrading as an important channel used by native workers adjusting to immigration shocks (Peri & Sparber, 2009).

The Effect of Coercing International Medical Graduates on the Rural Medical Workforce

The fourth chapter focusses on a narrow occupational class with a high proportion of skilled migrants - general practitioners (or physicians). International Medical Graduates (IMGs) constitute around 25 percent of the GP workforce in the United States, 35 percent in the United Kingdom, Ireland, and Australia, and 45 percent in New Zealand (WHO, 2010). Despite the large proportion of IMGs in the health workforce of OECD countries, considerable debate exists on their role, often with little to no evidence (see Birrell (2013)).

This chapter studies the workforce impact of IMGs through an evaluation of the Districts of Workforce Shortage (DWS) policy, which provides non-financial incentives for new IMGs to work in under-served areas of Australia. Using panel datasets and the variation in DWS designations over time, it conducts an event study on the effect of the program using a difference-in-difference-in-differences setting. It first analyses the effect of the DWS program in changing the number of GPs in DWS areas relative to non-DWS areas. By doing so, it contributes to an important field of health economics, the analysis of medical workforce shortage policy.

Second, it analyses the effect of increases in workforce competition caused by DWS on medical workforce outcomes. These outcomes, measuring prices and workload, are important determinants of medical system efficiency (McGrail, Humphreys, Joyce, Scott and Kalb, 2012; Richardson, Peacock and Mortimer, 2006). Finally, it examines if a differential effect exists in these outcomes between native and IMG GPs. Models of medical workforce competition for GP services often assume the workforce to be homogeneous (e.g. Gravelle, Scott, Sivey and Yong, 2016). By contrast, there is a growing consensus in the economic literature that immigrants and natives are imperfect substitutes for each other. Through these analyses, it contributes to the literature on medical competition, which is particularly important given the large proportion of IMGs in many developed countries.

The results indicate that the DWS program has a positive impact on the number of GPs in an area. Moreover, the effect is mainly due to an increase in IMG GPs. They also show a fall in workload because of the DWS program, although there is no robust evidence of a corresponding change in prices. Last, the analysis finds suggestive evidence that the fall in workload is higher for IMGs rather than natively trained GPs. This differential effect is suggestive of imperfect substitution between natives and immigrants even in a single occupational group, and highlights the need for further research in this area.

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This thesis is organised as follows. Chapters 2-4 are as previously discussed. Chapter 5 concludes by summarising the key findings. Each chapter contains all relevant tables and figures. Appendices to each essay are at the end of the thesis.

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Chapter 2

The Return Migration of Australian Migrants

Abstract

Using a novel dataset for the population of immigrant arrivals and departures from Australian ports, this paper analyses the extent of out-migration across different arrival cohorts and skill measures. It finds that migrants from high-income countries are more likely to out-migrate than those from low-income countries and that out-migration is sensitive to the business cycle, as measured by the unemployment rate. The analyses also find that out-migration is highest for the most skilled migrants, with every additional year of education required by an occupation increasing out-migration by around 4 percent. Moreover, migrants targeted by skill-based migration policies are more likely to leave. These results, therefore, highlight the challenges in retaining skilled migrants acquired through points-based migration policies.

2.1 Introduction

Many migrant workers do not make permanent migratory decisions: they may instead go back home, or emigrate to another country. As countries worldwide turn increasingly to skilled migration or guest worker programs to meet local workforce demands, it is increasingly important to understand the nature and motivations behind migrants leaving their country of origin, entering their destination country, and possibly deciding to return to their home countries or out-migrate to a third country. Better understanding this process can inform migration policy because the costs of migration as determined by policy makers determine not only the number of migrants to a country, but also return migration, and therefore net migration and overall skill selection of migrants to the destination country.

The existing literature has outlined two main motivations for return migration. First, the presence of wage (or consumption) differentials, and second, uncertainty about a migrant's job prospects in the destination country. Other relevant factors that may also play a role include the higher purchasing power of the home country's currency, a disutility of consumption in the host country, and the faster accumulation of skills relevant to the source country in the destination country. For example, neoclassical models of migration such as Todaro (1969), Todaro (1976), Lalonde and Topel (1997) and Stark (1995) point out that a worker may prefer consuming in the home country, either because of preferences or because of a price differential. Borjas and Bratsberg (1996) also provided a model to illustrate the role of skill selection in return migration. Their study used data from the 1980 US Census and administrative data from the Immigration and Naturalisation Service to show that immigrants from wealthy countries are more likely to out-migrate. They also found that out-migration intensifies the skill selection of the immigrant population left in the United States - if returns to skill are higher (lower) in the source country compared to the destination, only the least (most) skilled migrants remain. For example, the Borjas and Freeman (1992) study of Puerto Rican return migration finds that Puerto Ricans who migrate permanently are less educated than those who migrate temporarily, and Puerto Rico had a higher return to education than the United States at the time.

Other empirical studies have been conducted in European and American contexts on the relationship between skill and the propensity to out-migrate. For example, Dustmann and Weiss (2007) look at return migration in the UK and find that out-migration rates for migrants from richer countries are higher than for migrants from poorer countries such as India. Beenstock (1996) showed that Israeli migrants are more likely to out-migrate if they are highly educated. Jensen and Pedersen (2007) and Coniglio, De Arcangelis and Serlenga (2009) also showed that out-migration is increasing in educational attainment, for Danish and Italian migrants respectively. Aydemir and Robinson (2008) use Canadian Landing Records (LIDS), Canadian Census microdata and the Canadian Longitudinal Immigration Data Base (IMDB) to examine the time path of migration, and find that skilled male immigrants who are of working age, and especially entrepreneurs are more likely to leave. In an American context, Zakharenko (2008) finds that out-migration rates are lower for highly skilled migrants using CPS data while in contrast, Carrión-flores (2006) used data from the Mexican Migration Project to find that high educational attainment increases the likelihood of Mexican migrants to the U.S. returning. In an Australian context, Lukomskyj and Richards (1986) used administrative data to find migrants from Asia are less likely to depart than migrants from Europe and North America, and found that professionals, managers, and technicians were least likely to depart and labourers were most likely to out-migrate. Burkhauser, Hahn, Hall and Watson (2016) uses the HILDA socio-economic panel dataset to find that first-generation migrants are much more likely to depart than second-generation migrants. They also found that migrants with University degrees are the most likely to emigrate.

Both the theoretical and empirical literature above emphasise that the skill-selection effect of out-migration is context-dependent. To enhance evidence on out-migration in an Australian context, this chapter uses a novel dataset of migrant inflows and outflows - the Overseas Arrival and Departure (OAD) dataset obtained from the Department of Immigration and Border Protection of Australia (DIBP) - to analyse out-migration rates amongst different migrant cohorts. This dataset is constructed using arrival and departure cards filled by travellers at Australian ports. It provides an identifier for each visitor, along with the intent to stay or leave, and information on the occupation, sex, age, marital status, visa type (permanent or temporary) and subclass (e.g. student, employer-sponsored, family sponsored, etc.), the date of arrival or departure, and the duration of stay. The OAD dataset contains the entire population of migrants who indicate they are either "Permanently arriving in" or "Permanently departing" Australia at arrival or departure, respectively. At present this essay chooses to focus on this cohort because the majority of temporary migrants, such as holidaymakers, are expected to leave in any case.

Access to such an administrative dataset strengthens the analysis in many ways - First, compared to census or household panel data, the OAD data allows us to capture out-migration much more accurately, because it is known when the immigrant has actually departed, compared to assuming survey non-response as a departure. Second, the time of migration is at a high resolution (actual date, vs year of migration) and so analyses can be conducted on a quarterly or monthly level and the effect of changes in macroeconomic indicators, such as the unemployment rate, on out-migration can be calculated. Third, most papers using panel or repeated cross-section data (such as the CPS, Census, or Labour Force Survey data) suffer from estimation errors in calculating the degree of out-migration by different cohorts since the construction of weights in such data does not usually use immigrant status. Fourth, it is not possible to identify return migration using such panel or cross-section datasets, i.e. if a migrant leaves the country for a few years and then re-enters. Using such an administrative dataset of migrant departures and arrivals, therefore, improves upon many issues inherent in an analysis of estimating out-migration. A key shortcoming with the dataset, however, is it captures migrant characteristics only at entry - therefore, it is not possible to observe if a migrant changes occupations or visa types once in Australia using this dataset. Another shortcoming is that because it only captures off-shore permanent migration, these results will not be representative of the on-shore permanent migration of students and temporary migrants.

The analysis uses a proportional hazard survival model on the OAD dataset over the period 2004-2015. The estimates indicate that migrants born in higher-income countries are more likely to out-migrate to another country and that the hazard of out-migration is higher for highly skilled or more successful migrants. They also find that increases in the unemployment rate within Australia increase the out-migration rate of migrants. It finds however that migrants from India and China are less likely to leave even if the unemployment rate rises. A source-country wage effect may cause this differential effect in response to destination country economic shocks. These findings are robust to a number of specifications. Given the theoretical model of Borjas and Bratsberg (1996), these results indicate that Australia presents a lower return to skill compared to most of its sending countries.

This research has several contributions. First, it quantifies the extent of selective out-migration amongst different immigration cohorts. Also, the results have implications for research involving the estimation of immigrant's earnings profiles within Australia - the non-random out-migration of the most skilled or highest-income cohort shall cause estimates of an immigrant's wage profile to be biased downwards. This finding may explain why numerous studies on the wage assimilation of Australian immigrants find negligible to small effects. For example, Mcdonald and Worswick (1999) find little or no wage assimilation for immigrants from non-English speaking countries. Using Census data, Antecol, Kuhn and Trejo (2006) also find low wage assimilation but Clarke and Skuterud (2013) find strong wage assimilation effects once they compare migrants from the same source country- say, the U.K., India, and China. More recently, Breunig, Hasan and Salehin (2013) found that wage assimilation occurs slowly for all cohorts within their study using HILDA unit record data.

The paper proceeds as follows. Section 2 provides a brief overview of Australian migration policy. Section 3 reviews the Borjas and Bratsberg selective outmigration model which provides insights into the interpretation of the results. Section 4 summarises the data sources and outlines the econometric methodology used to analyse the data. Last, Section 2.5 presents the results of the analysis. Section 6 concludes.

2.2 A brief overview of Australian Migration Policy

Australia's started to drop off the last vestiges of the "White Australia" policy in 1973 to transition to a non-discriminatory migration program divided into skilled, family and humanitarian migration categories. Since 1979, Australia has used a point test to determine which applicants qualify for skilled migration, the first such point test being the Numerical Multifactor Assessment System (NUMAS). Furthermore, since the Fitzgerald review of 1988, the quota for skilled and business migrants has risen compared to the allowance for family reunions - for instance, family migration is restricted to only a third of its total annual permanent migrant intake of 180,000 (Sprinks, 2016).

Australia's general skilled migration program for individuals focusses on points testing of applicants on observable characteristics such as age, English language ability for non-native speakers (measured using IELTS or TOEFL test scores), and being qualified in an occupation listed in the Skilled Occupation List (SOL), which is designed to list occupations involving high skilled vocationally specific academic or trade fields (Hawthorne, 2005). Points are awarded for obtaining educational qualifications in Australia, and for an applicants' work experience, both within Australia and abroad. Such points-tested migrants may arrive independently, or be sponsored by an Australian business, state or regional area. The overall effect is enabling highly skilled applicants to obtain higher points, and therefore lowering migration costs for such applicants.

While the above permanent migration pathways still exist, they have been increasingly outnumbered by "two-step" migration pathways or permanent migration by those who initially arrived on temporary visas with work entitlements. Currently, around one-half of permanent visas are allocated to such migrants (Gregory, 2014). This has substantial implications for the labour market outcomes of migrants who are now more likely to work part-time and obtain Australian educational qualifications as a pathway to permanent migration.

Importantly, the dataset consists of overseas arrivals and departures where only those undertaking permanent migration decisions on arrival can be identified, and the analyses are unable to study the characteristics of the important "two-step" permanent migration pathway noted above. This essay, therefore, focusses on return migration decisions for a cohort with permanent migration visas obtained off-shore.

2.3 Model: The Borjas and Bratsberg model of skill-selective out-migration

To motivate the results, we illustrate the Borjas and Bratsberg model, where the log of wages in the source country w_0 and destination country w_1 for an individual are:

$$w_0 = \mu_0 + \lambda s \tag{2.1}$$

$$w_1 = \mu_1 + s \tag{2.2}$$

where μ_0 and μ_1 are the mean log earnings in the source and destination country, and $s \sim \mathcal{N}(0, \sigma_s^2)$ is a stochastic deviation in skill (or human capital) for the individual compared to the mean. and λ represents the relative price of skills in the source country compared to the destination country. If a decision to migrate is made, the migrant must incur costs of migration, $C \geq 0$. It is assumed that the worker makes the decision to migrate at time $t = 0$ and dies at $t = 1$.

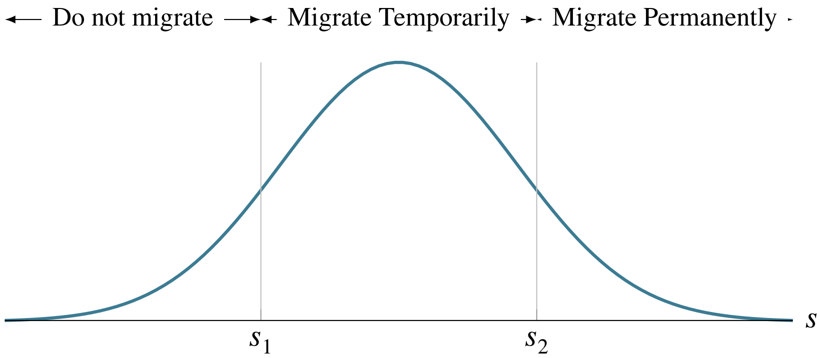
With out-migration, the individual may choose to migrate to the destination country for time t before returning to the source country earning log wages w_{10} equal to (ignoring discounting):

$$w_{10} = tw_1 + (1 - t)(w_0 + t\kappa) \tag{2.3}$$

where κ is the return to experience abroad when the individual returns to the source country. Assuming the costs of migration to be $C \geqslant 0$ and ignoring the costs of returning to the source country, the individual chooses to stay in the source country if $w_0 > w_1 - C$ and $w_0 > w_{10} - C$; chooses to migrate permanently if $w_1 - C > w_0$ and $w_1 - C > w_{10} - C$; and chooses to migrate temporarily if $w_{10} - C > w_0$ and $w_{10} - C > w_1 - C$.

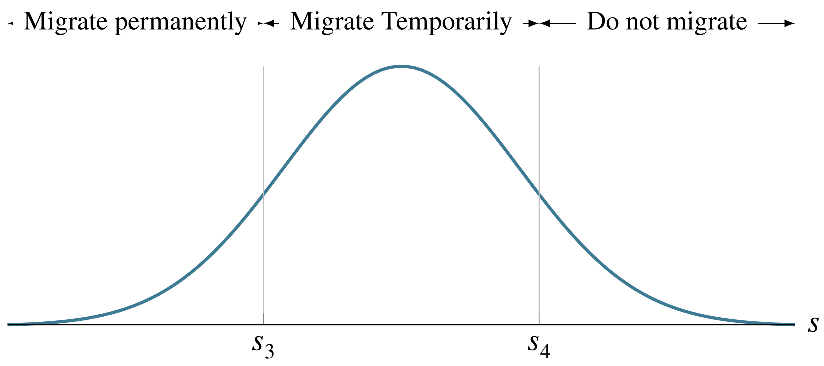
Given the above conditions, Figure 2.1 illustrates the case in which $\lambda < 1$, i.e. if the source country has a lower return to skill than the destination country. The lowest skilled individuals, i.e. with skill below $s_1 = \frac{\mu_0 - \mu_1 + C/t - \kappa(1-t)}{1-\lambda}$ do not migrate, and the highest skilled individuals, i.e. those with skill above $s_2 = \frac{\mu_0 + t\kappa - \mu_1}{1-\lambda}$ migrate permanently. Individuals with skill between the two thresholds s_1 and s_2 will return to the source country. It can be shown that reducing the cost of migration increases return migration by reducing the threshold for return migration, s_1. Similarly, an increase in the average wage in the source country μ_0, or a decrease in the average wage in the host country μ_1 increases out-migration.

Figure 2.1: SKILL SORTING IN THE BORJAS & BRATSBERG SELECTION MODEL; $\lambda < 1$



Similarly, Figure 2.2 illustrates the results of the model if $\lambda > 1$, i.e. if the source country has a higher return to skill than the destination skill. The lowest skilled migrants, i.e. with skill below $s_3 = \frac{\mu_1 - \mu_0 - t\kappa}{\lambda - 1}$ choose to migrate permanently, while the highest skilled migrants, i.e. those with skill above $s_4 = \frac{\mu_1 - \mu_0 - C/t + \kappa(1-t)}{\lambda - 1}$ do not migrate. Migrants with skill between s_3 and s_4 choose to engage in return migration.

Figure 2.2: SKILL SORTING IN THE BORJAS & BRATSBERG SELECTION MODEL; $\lambda > 1$ i.e. the source country has a higher return to skill than the destination country



In either case, the model intensifies the skill-selection inherent in migration decisions - only the least (most) skilled migrants will migrate permanently if the destination country has a low (high) return to skill. The key hypotheses according to this model are:

1. increasing the wage differential $w_1 - w_0$ between the destination and source countries reduces out-migration. i.e. as μ_0 increases, out-migration should increase.

2. lowering the cost of migration C increases the proportion of individuals that engage in return migration between the two countries.

3. Lastly, if Australia has a low return to skill compared to the sending country, it is expected that more-skilled migrants to out-migrate faster than less-skilled migrants. On the other hand, if Australia has a high return to skill compared to the source country, lower-skill migrants out-migrate faster than higher-skilled ones.

2.4 Data and Empirical Methodology

2.4.1 Data sources

Overseas Arrivals and Departures

The principal data source used is administrative individual-level data from the Australian Department of Citizenship and Border Protection (DIBP) for all permanent arrivals and departures from Australia during the time-period July 2004-June 2015. For each immigrant, this presents us with a subset of information obtained from their arrival or departure cards at the port of entry, including the date of arrival or departure along with the country of birth, and citizenship, their destination state within Australia, age, marital status, visa type, and occupation. The use of a unique identifier within the dataset also allows us to track when each migrant enters, and possibly departs.

To avoid left censoring, the analyses focus on the subset of the dataset that indicates that the individual intended to migrate permanently after 1st July 2004. Only 2 percent of such migrants report an entry more than once, and it is assumed that the first entry is the entry into risk for out-migration. It is assumed that a migrant indicating he or she is "departing permanently" is the event of failure once a migrant is at risk. Around 24 percent of migrants report this multiple times, and the first departure is assumed as the failure event for such migrants. Such multiple departures could be due to circular migration (when a migrant returns to Australia after migrating temporarily to a third country), or due to human error at the time of departure. The analysis of the results is largely unchanged by choosing the data of last permanent departure as the time of failure.

The data provides detailed information on the migrant's visa class at entry - there were 49 visa classes within the sample, which were divided into five main types. Skilled Nominated visas are awarded to migrants who are nominated by either an Australian business, or state & territory governments. This category, therefore, contains the majority of migrants using demand-driven skilled migration programs. In contrast, skilled independent visas are used by migrants who are not sponsored by family members, businesses or governments. This category constitutes the supply driven component of the Australian skilled migration program. Family visas are for individuals sponsored by Australian family members, such as spouses and parents. Investment visas are provided to individuals who start a business within Australia or invest a minimum amount in Australian Commonwealth Bonds. Refugee visas are awarded to migrants fleeing persecution in their home countries. Lastly, special category visas are provided to citizens of New Zealand to live and work indefinitely in Australia.

Countries of birth in the sample are reclassified according to the Standard Australian Classification of Countries (SACC) devised by the ABS. This classification divides the sample into nine regional groups. To provide additional clarity on migrants from Australia's most important migrant-sending countries, the United Kingdom, New Zealand, India and China were separated out from these regional groups for the analysis, for a total of 13 regional categories.

A breakdown of the dataset by ANZSCO occupational major group and region of birth is provided in Table 2.1. Migration from India and China predominantly focusses on the "Managers" and "Professionals" occupational classes. Migrants from New Zealand, who are likely to face the lowest cost of migration, are the predominant source of lower skilled migrants who work in occupations such as sales workers, machinery operators, and labourers. This is consistent with what it is expected based on the theoretical model - migration from countries that face a lower cost of migration should be lower skilled than those from countries that face a higher cost of migration.

The sample statistics by the occupational major group and visa category are presented in Table 2.2. Migrants with skilled migration visas are likely to belong to higher skilled occupations such as Managers or Professionals. While this is also true for those on non-skill-selective visas (such as family, refugee or New Zealand special category migration visas), there is a higher proportion of migrants with lower-skilled occupations such as labourers entering through those visa categories. Intuitively, more skill selective visa categories are less likely to let in lower skilled migrants than non-skilled selective visas.

Last, sample statistics by region of birth and visa category are presented in Table 2.3 - Migrants from the United Kingdom, India and China are likely to use the Skilled migration and family migration pathways, while Chinese managers dominate the Investment category.

Table 2.1: SAMPLE CHARACTERISTICS BY REGION OF BIRTH AND ANZSCO OCCUPATIONAL CATEGORY AT ENTRY (JUL 2004- JUN 2015)

	Occupational Major Group								
Region of birth	Managers	Profession-als	Technicians	Community Workers	Clerical Workers	Sales Workers	Machinery Operators	Labo-urers	Total
United Kingdom	4,569	20,027	16,865	4,136	3,318	1,513	503	394	51,325
New Zealand	4,620	16,383	14,179	6,153	6,481	4,899	3,979	2,191	58,885
India	3,014	25,383	8,307	785	2,082	700	170	325	40,766
China	16,272	15,015	2,764	649	3,317	1,628	140	249	40,034
Other Oceania	570	2,851	1,915	679	1,008	444	656	499	8,622
Other N.W. Europe	1,440	6,696	3,959	854	1,009	382	126	162	14,628
S.E. Europe	1,426	6,471	2,520	1,011	1,044	506	266	290	13,534
N. Africa & Middle East	1,609	9,339	4,662	945	977	713	583	801	19,629
S.E. Asia	4,927	21,069	6,265	2,255	3,546	2,268	378	2,522	43,230
Other N.E. Asia	1,356	3,030	1,722	326	835	265	35	155	7,724
Other Sth.and Cen. Asia	1,980	12,700	2,785	478	1,395	366	160	486	20,350
Americas	1,045	7,185	1,694	979	963	588	141	188	12,783
Sub-Saharan Africa	2,263	11,437	4,221	770	1,509	667	244	273	21,384
Total	45,091	157,586	71,858	20,020	27,484	14,939	7,381	8,535	352,894

Source: Overseas Arrivals and Departures microdata, Department of Immigration and Border Protection, Australia

Table 2.2: SAMPLE CHARACTERISTICS BY ANZSCO OCCUPATIONAL CATEGORY AT ENTRY AND VISA CATEGORY (JUL 2004- JUN 2015)

	Visa Type						
Occupational Major Group	Family	Skilled Nominated	Skilled Independent	Refugee	Special Category (NZ)	Investment	Total
Managers	11,807	5,301	5,720	629	5,698	15,920	45,075
Professionals	42,760	22,356	65,308	2,126	24,471	515	157,536
Technicians and Trades Workers	16,044	10,721	25,815	1,692	17,507	42	71,821
Community and Personal Service Workers	7,492	2,977	1,298	783	7,416	47	20,013
Clerical and Administrative Workers	11,788	2,885	3,742	198	8,658	196	27,467
Sales Workers	6,378	828	1,205	336	6,123	68	14,938
Machinery Operators and Drivers	1,760	100	275	268	4,968	7	7,378
Labourers	3,189	201	344	2,071	2,713	13	8,531
Total	101,218	45,369	103,707	8,103	77,554	16,808	352,759

Source: Overseas Arrivals and Departures microdata, Department of Immigration and Border Protection, Australia

Table 2.3: SAMPLE CHARACTERISTICS BY REGION OF BIRTH AND VISA CATEGORY (JUL 2004- JUN 2015)

	Visa Type						
Region of birth	Family	Skilled Nominated	Skilled Independent	Refugee	Special Category (NZ)	Investment	Total
United Kingdom	13,431	8,735	25,486	0	3,231	383	51,266
New Zealand	33	63	125	0	58,659	4	58,884
India	9,609	9,434	19,965	77	1,617	59	40,761
China	11,584	4,718	8,890	142	965	13,727	40,026
Other Oceania	2,701	726	1,048	7	4,118	17	8,617
Other North-West Europe	6,499	2,068	5,524	0	418	109	14,618
Southern and Eastern Europe	8,573	1,285	2,779	10	814	66	13,527
North Africa and Middle East	9,643	1,809	4,374	2,964	666	167	19,623
South-East Asia	18,409	6,171	13,039	2,757	2,065	776	43,217
Other North-East Asia	2,521	1,429	2,015	0	741	1,016	7,722
Other South and Central Asia	5,492	4,465	8,108	1,495	663	119	20,342
Americas	7,713	1,305	3,021	25	674	36	12,774
Sub-Saharan Africa	5,010	3,161	9,333	626	2,923	329	21,382
Total	101,218	45,369	103,707	8,103	77,554	16,808	352,759

Source: Overseas Arrivals and Departures microdata, Department of Immigration and Border Protection, Australia

Measures of skill

The analyses supplement occupation data within the OAD dataset by imputing a number of measures of skill. First, they add average weekly earnings by occupation in 2014, following a number of studies in both the Australian and international literature (see Goos, Manning and Salomons (2009), Acemoglu and Autor (2011)). One of the concerns with this approach is that earnings reflect not only skill utilisation, but also external factors such as union density, stricter employment protections, and public sector shares for each occupation.

Second, the analysis includes average years of schooling by occupation for the Australian born population as a skill measure. Coelli and Borland (2016) points out the difficulty in using this measure due to different post-secondary qualifications in Australia such as certificate III/IV-level study which is often accompanied by an apprenticeship in production trades. Allocating standard "years of education" for such trade qualifications, therefore, leads them to be ranked lower than when skill level is proxied using average earnings.

Last, the ABS allocated skill levels to each of the ANZSCO occupations in terms of formal education and training, previous experience, and on-the-job training. Skill level 1 occupations, the highest, have a level of skill commensurate with a bachelor's degree or higher whereas the lowest skill level (level 5) has occupations roughly comparable with compulsory secondary education and no formal qualification and on-the-job training. The analyses follow Wilkins and Wooden (2014), and Esposto (2011) by using the ABS skill levels as a discrete measure of skill for the occupations.

Country Characteristics

The analysis also includes a dataset of country characteristics from the World Bank's World Development Indicators such as the per-capita average income for a country. Although the Gini coefficient is an imperfect measure of the return to skill, there is a lack of compelling evidence on how the return to skills varies across countries, and this chapter, therefore, follows Borjas and Bratsberg(1996) by using the Gini coefficient as a measure of return to skill in the source country and Australia.

2.4.2 Empirical Methodology

The analyses estimate a Cox proportional hazards model analysis to better understand the patterns of return and out migration, where t is the time until an immigrant indicates they are permanently leaving after arriving in Australia, or returns after indicating they are permanently leaving. The basic estimation strategy is then:

$$\begin{aligned}\lambda(t|X) = &\lambda_0(t)\exp(\beta_1 X_{source} + \beta_2 X_{occupation} + \beta_3 X_{individual} + \beta_4 X_{AU} + \\ &\beta_5 \sum_{i=2004}^{2015} Year_i + \beta_6 \sum_{j=1}^{4} Quarter_j)\end{aligned} \tag{2.4}$$

where X_{source} is a vector of source country characteristics, such as average per capita income, region, etc. $X_{occupation}$ is a vector of measures of skill of occupation, $X_{individual}$ is a vector of characteristics of the individual - such as their age, visa category, and occupation, and lastly X_{AU} is a vector of economic indicators for the Australian economy, such as the unemployment rate. To control for any time-varying omitted variables that may affect the results, we add a vector of year and quarter dummies.

Because survival models usually assume time to be continuous and this essay uses discrete time data, the model above is also estimated using the discrete time proportional hazard model below, where t represents the number of quarters since migration. We present these results along with the Cox proportional hazard estimates, and they remain similar throughout our analyses:

$$\begin{aligned}P(Fail = 1|t, X) = &1 - \exp(-\exp(\beta_1 X_{source} + \beta_2 X_{occupation} + \beta_3 X_{individual} + \beta_4 X_{AU} + \\ &\beta_5 f(t)) + \beta_6 \sum_{i=2004}^{2015} Year_i + \beta_7 \beta_6 \sum_{j=1}^{4} Quarter_j)\end{aligned} \tag{2.5}$$

In the above specifications, the event of failure is taken to be to be the migrant departing Australia while indicating that he or she is "Leaving Australia permanently". The dataset also provides information on the migrant's country of intended residence post departure, so there are two competing events - migrating back to the country of birth, or migrating to another country. In such a competing risks setting, the results above may not appropriately estimate the hazards for the incidence of each event. A different hazard function is therefore defined as the probability of the event given that an individual has survived up to time t without any event or has the competing event prior to time t. This is the Cox proportional hazard of the competing risk, which is the following for event j belonging to the set of competing events J, is:

$$\Pr(j|t, X, \beta) = \frac{\lambda_j(t|\mathbf{X}, \beta)}{\sum_{i=1}^{J} \lambda_i(t|\mathbf{X}, \beta)}$$

These estimates are useful for measuring the association of covariates on the incidence of the event of interest, taking into account the contribution of the other event. The analyses therefore estimate the Cox competing risk hazard for both out-migrating to the country of birth, and departing to another country. The results are presented below in Subsection 2.5.4

2.5 Results

2.5.1 The effect of the characteristics of the Country of Birth

Figure 2.3 presents the non-parametric hazard by region from the dataset. It is evident than migrants from New Zealand are the most likely to leave, whereas those from Sub-saharan Africa, India, and South and Central Asia the least likely to leave.

Table 2.4 shows the results of the Cox regression of the hazard rate of outmigration concerning the thirteen regional dummies, with the United Kingdom as the reference group. In column 1, no additional controls are included - the results, therefore, mirror those shown in the hazard curve above. Column 2 adds a vector of controls including visa type, the occupational major group, age, sex and marital status. Whereas most category estimates remain the same, one exceptional case is for migrants born in New Zealand - controlling for the special migration visas offered to New Zealand citizens, migrants born in New Zealand who now are just as likely to out-migrate as those from the United Kingdom. Lastly, Column 3 adds year and quarter dummies to the regression and Column 4, estimates the discrete time continuous log-log model. Estimates in both columns are largely similar to those in column 2. These results are consistent with the theoretical model's prediction that out-migration rates are higher for higher-

Figure 2.3: HAZARD OF LEAVING BY REGION OF BIRTH FOR AUSTRALIAN PERMANENT MIGRANTS

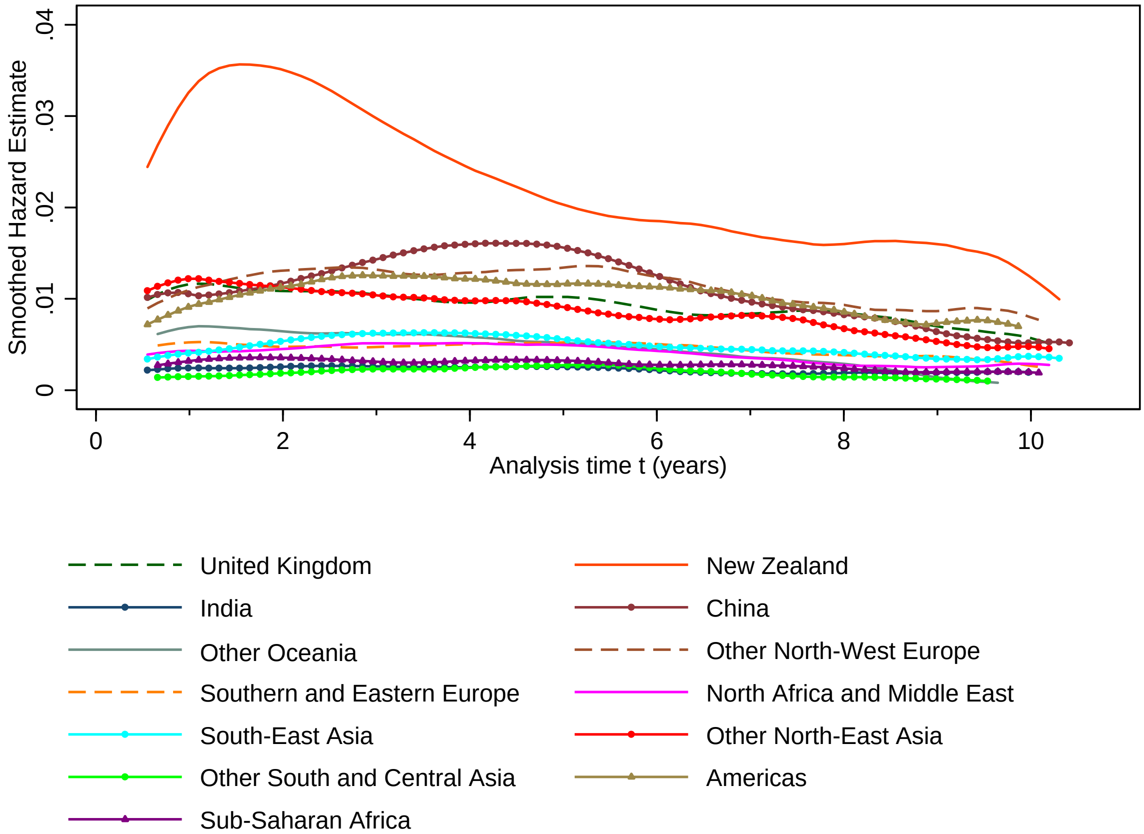


Table 2.4: COX REGRESSION COEFFICIENTS BY REGION OF BIRTH FOR AUSTRALIAN PERMANENT MIGRANTS

	(1) No controls	(2) Controls	(3) Time dummies	(4) Cloglog
Reference Group: *United Kingdom*				
New Zealand	0.997***	0.0128	0.0127	0.0125
	(0.0211)	(0.0348)	(0.0348)	(0.0347)
India	-1.387***	-1.439***	-1.443***	-1.443***
	(0.0494)	(0.0506)	(0.0507)	(0.0513)
China	0.251***	0.0439	0.0426	0.0419
	(0.0263)	(0.0319)	(0.0319)	(0.0313)
Other Oceania	-0.650***	-1.123***	-1.124***	-1.124***
	(0.0659)	(0.0683)	(0.0683)	(0.0677)
Other North-West Europe	0.125***	0.149***	0.148***	0.148***
	(0.0377)	(0.0383)	(0.0383)	(0.0382)
Southern and Eastern Europe	-0.646***	-0.693***	-0.695***	-0.695***
	(0.0541)	(0.0552)	(0.0552)	(0.0555)
North Africa and the Middle East	-0.707***	-0.646***	-0.648***	-0.649***
	(0.0494)	(0.0517)	(0.0517)	(0.0517)
South-East Asia	-0.759***	-0.770***	-0.771***	-0.771***
	(0.0352)	(0.0366)	(0.0367)	(0.0365)
Other North-East Asia	0.0676	-0.107*	-0.107*	-0.108*
	(0.0493)	(0.0505)	(0.0505)	(0.0510)
Other Southern and Central Asia	-1.667***	-1.685***	-1.687***	-1.689***
	(0.0783)	(0.0791)	(0.0792)	(0.0792)
Americas	0.0361	0.00553	0.00446	0.00424
	(0.0412)	(0.0423)	(0.0423)	(0.0423)
Sub-Saharan Africa	-0.939***	-1.070***	-1.071***	-1.071***
	(0.0495)	(0.0501)	(0.0502)	(0.0498)
Observations	7610475	7610475	7610475	7610475
Number of subjects	349117	349117	349117	
Pseudo chi squared	10386.1	12063.1	12143.2	11312.0
Time Dummies	No	No	Yes	Yes
Controls	No	Yes	Yes	Yes

Standard errors in parentheses

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

Migrants from the United Kingdom act as the reference group. Controls added include age, sex, marital status, occupation, and visa type. Time dummies indicate the addition of year and quarter dummies to the regression income countries compared to lower-income countries. For example, a migrant from India, which has a per capita GDP of approximately 1,200 USD is ($e^{-1.44}$ =)0.23 times as likely to out-migrate compared to one from the United Kingdom, which has a per capita GDP of 40000 USD,. However, a migrant from New Zealand (per capita GDP of approx. 40000 USD) is about as likely to out-migrate as one from the United Kingdom.

Table 2.5: COX REGRESSION COEFFICIENTS BY PER CAPITA GDP ('000S) FOR AUSTRALIAN PERMANENT MIGRANTS

	(1) No controls	(2) Controls	(3) Time dummies
GDP Per capita	0.0228***	0.0125***	0.0125***
	(57.18)	(10.87)	(10.87)
Observations	7474118	7474118	7474118
Number of subjects	342265	342265	342265
Chi squared	3268.1	11910.7	11990.4
Time Dummies	No	No	Yes
Controls	No	Yes	Yes

t statistics in parentheses

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

Controls added include region dummies, age, sex, marital status, occupation, and visa type. Time dummies indicate the addition of year and quarter dummies to the regression

To further quantify the effect of a country's average income (μ_0) on out-migration rates, Table 2.5 shows the results of a Cox regression model where GDP per capita('000s) in 2010 is included as a covariate. Column 1, which contains no additional controls, shows that an increase of GDP per capita by a thousand US Dollars increases the hazard rate of out-migration by ($e^{0.0228} - 1$ =)2.3 percent. Columns 2 and 3 includes the vector of controls as well as region dummies, and column 3 also adds year and quarter dummies to the regression results. Both columns now indicate that increasing the GDP per capita by one unit (USD 1,000) increases the hazard rate for out-migration by about ($e^{0.125} - 1$ =)1.25 percent - this disparity is explained by noting that it now controls for differential migration policy offered to residents of higher-income countries. Higher income country citizens are offered lower cost migration policies in Australia, either through a relaxation of criterion (such as the requirement for English testing), or in the case of New Zealand, allowing free movement of labour. Such low-cost migration policies should increase out-migration according to the theoretical model, and controlling for such policies through the addition of region and visa dummies lowers the sensitivity of out-migration to income in the source country.

2.5.2 Visa type

The type of visa chosen by the migrant plays a key role in determining out-migration, by both causing skill-selection and affecting the cost of migration. We now analyse the effect of the type of visa chosen by the migrant on his or her out-migration rate. Figure 2.4 presents the hazard curves by visa

Figure 2.4: HAZARD CURVES BY VISA TYPE FOR AUSTRALIAN PERMANENT MIGRANTS

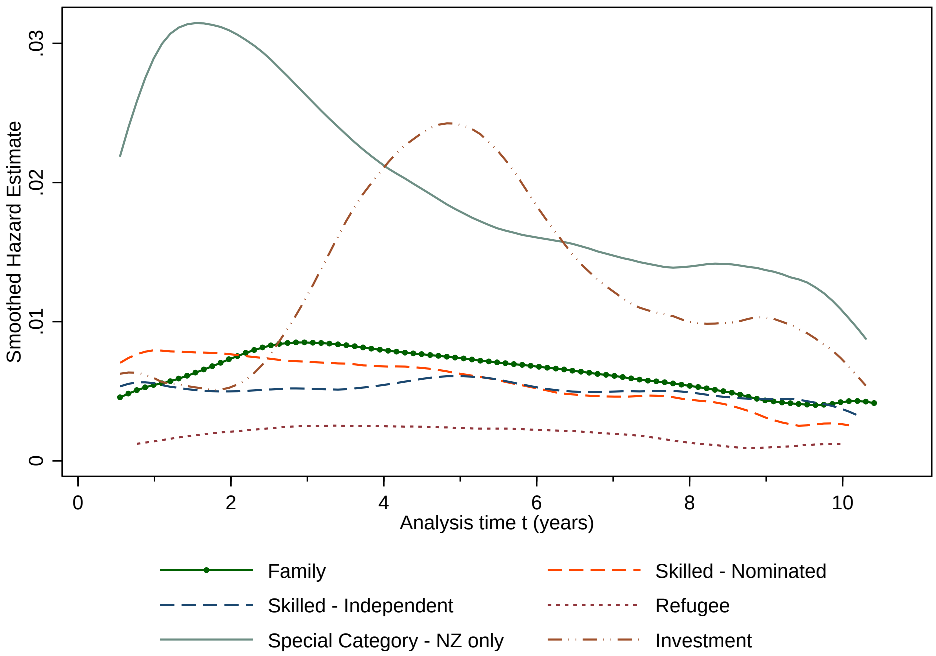


Table 2.6 shows the results of the Cox regression with respect to visa type, where migrants on Family visas are our reference class. Column 1 shows the results of the regression estimates when no additional controls are included - migrants on refugee visas are the least likely to out-migrate, which is expected to be driven by socioeconomic and humanitarian issues in their home countries. Migrants on the demand-driven skilled

Table 2.6: COX REGRESSION COEFFICIENTS BY THE VISA AT ARRIVAL FOR AUSTRALIAN PERMANENT MIGRANTS

	(1) No controls	(2) Controls	(3) Time dummies	(4) Cloglog
Reference Group: *Family visas*				
Skilled - Nominated	0.0781*	0.169***	0.164***	0.165***
	(0.0311)	(0.0331)	(0.0331)	(0.0332)
Skilled - Independent	-0.107***	-0.0668*	-0.0671*	-0.0667**
	(0.0240)	(0.0264)	(0.0264)	(0.0259)
Refugee	-1.261***	-0.745***	-0.748***	-0.748***
	(0.127)	(0.130)	(0.130)	(0.130)
Special Category - NZ only	1.316***	0.943***	0.938***	0.939***
	(0.0198)	(0.0437)	(0.0438)	(0.0433)
Investment	0.896***	0.538***	0.535***	0.537***
	(0.0318)	(0.0433)	(0.0433)	(0.0436)
Observations	7610475	7610475	7610475	7610475
Number of subjects	349117	349117	349117	
Pseudo chi squared	8235.7	12063.1	12143.2	11312.0
Time Dummies	No	No	Yes	Yes
Controls	No	Yes	Yes	Yes

Standard errors in parentheses

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

Family migration visas are the reference group. Controls added include region of birth, occupation, age, sex, and marital status. Time dummies indicate the addition of year and quarter dummies to the regression model

Sponsored stream are more likely to leave than those on supply-driven skilled Independent visas.

In column 2, the analyses add our vector of controls (age at arrival, sex, occupation, the region of birth, and marital status), whereas in our preferred specification in column 3, they add year and quarter dummies to control for any time-varying omitted variables. Skilled nominated visas are around ($e^{0.165} - 1 =$)17.9 percent more likely to out-migrate than those on family visas, whereas those on skilled independent visas are around ($e^{0.0667} - 1 =$)6.4 percent less likely to out-migrate than those on family visas. Also, migrants using the investment visa class are ($e^{0.535} - 1 =$) 71 percent more likely to out-migrate than those on family visas. Cobb-Clark (2000) found that relative to refugees or family migrants, immigrants on skilled visas have higher labour force participation rates, and lower unemployment rates. Migrants on skilled nominated visas and investment visas have better labour outcomes than those on skilled independent visas. Cully (2011) also examined the impact of visa categories on labour market outcomes in Australia and found that those on employer-sponsored visas had higher earnings and participation rates than those on skilled independent visas. He notes that at least part of this effect is driven by the education and experience of the migrant, as these play a role in the decision to grant a visa. Our results broadly indicate that success in the Australian labour market is likely to increase the out-migration rate.

Across specifications, New Zealand Special Category visa holders are the most likely to leave - their hazard of out-migration is ($e^{0.938} - 1 =$)1.55 times higher than Family visas. This is likely to be driven by two factors. Firstly, the Trans-Tasman Agreement ensures free movement of labour between the two countries thus lowering the cost of migration. As previously discussed, a low cost of migration increases both migrations and return migration between the source and destination countries. Secondly, Special Category visas issued after 2001 do not allow the migrant to access social security payments in Australia, and restrict the pathways available for Australian Citizenship or Permanent Residence status, therefore lowering the benefit to permanent migration.

2.5.3 Occupation and Skill

Figure 2.5 presents the hazard curves by occupation from our dataset. The figure indicates that labourers and professionals are least likely to leave, while managers and sales workers seem to be occupational groups most likely to leave.

Table 2.7 shows the results of the Cox regression of the hazard of out-migration with respect to occupation. Managers, the highest earning occupational major group, act as the reference group[1]. Column 1 contains no controls and therefore mirrors the hazard curve above, Sales workers are the most likely to leave, and professionals and labourers the least likely. Column 2 adds controls, and our preferred specification in column 3 also adds year and time dummies to control for any time-varying omitted variables that may affect outcomes. In estimates which control for other factors, professionals are as statistically likely to leave as managers, while machinery operators and labourers the least

[1]Source:6306.0 - Employee Earnings and Hours, Australian Bureau of Statistics, May 2016

Figure 2.5: HAZARD CURVES BY OCCUPATION FOR AUSTRALIAN PERMANENT MIGRANTS

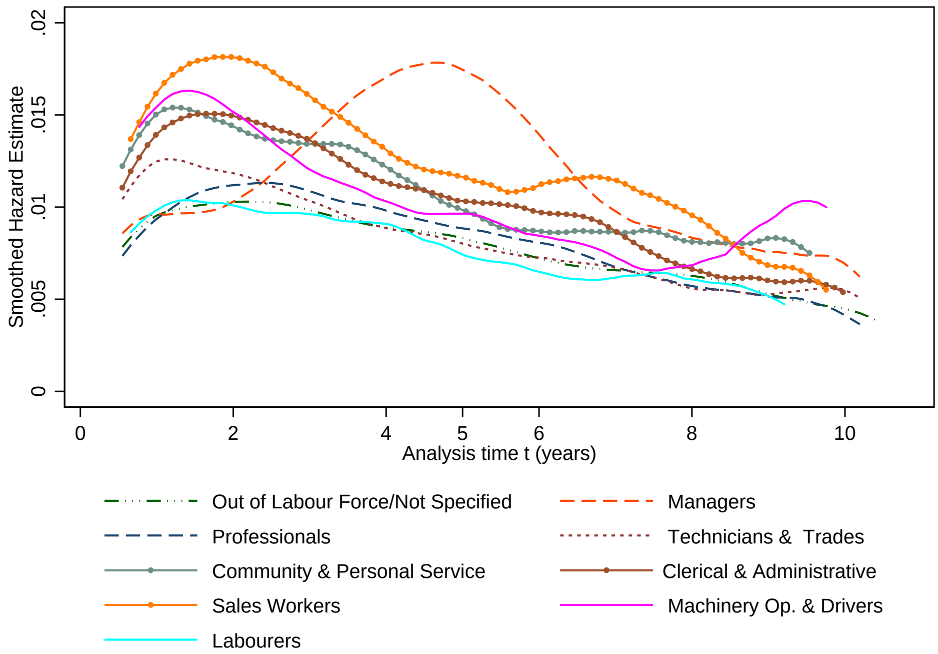


Table 2.7: COX REGRESSION COEFFICIENTS FOR THE OCCUPATIONAL MAJOR GROUP AT ARRIVAL FOR AUSTRALIAN PERMANENT MIGRANTS

	(1) No controls	(2) Controls	(3) Time dummies	(4) Cloglog
Reference Group: *Managers*				
Professionals	-0.306***	0.00851	0.00641	0.00670
	(0.0218)	(0.0267)	(0.0267)	(0.0265)
Technicians and Trades Workers	-0.238***	-0.140***	-0.141***	-0.141***
	(0.0241)	(0.0290)	(0.0290)	(0.0290)
Community and Personal Service Workers	-0.00609	-0.199***	-0.201***	-0.201***
	(0.0334)	(0.0369)	(0.0369)	(0.0369)
Clerical and Administrative Workers	-0.0421	-0.0665*	-0.0664*	-0.0663*
	(0.0292)	(0.0329)	(0.0329)	(0.0328)
Sales Workers	0.131***	-0.0700	-0.0706	-0.0706
	(0.0347)	(0.0379)	(0.0380)	(0.0379)
Machinery Operators and Drivers	-0.00496	-0.448***	-0.449***	-0.449***
	(0.0491)	(0.0522)	(0.0522)	(0.0526)
Labourers	-0.346***	-0.297***	-0.299***	-0.300***
	(0.0556)	(0.0580)	(0.0580)	(0.0586)
Observations	7610475	7610475	7610475	7610475
Number of subjects	349117	349117	349117	
Pseudo chi squared	415.1	12063.1	12143.2	11312.0
Time Dummies	No	No	Yes	Yes
Controls	No	Yes	Yes	Yes

Standard errors in parentheses

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

Managers act as our reference group. Controls added include region of birth, age, sex, marital status, occupation, and visa type. Time dummies indicate the addition of year and quarter dummies to the regression model likely to leave. As Table 2.1 shows, a majority of migrants in lower skilled occupations such as Sales Workers and Machinery drivers are likely to arrive from high-income countries such as New Zealand or the United Kingdom, while low-income countries such as India and South-East Asia are more likely to send higher skilled migrants. Given that migrants from low-income countries are less likely to out-migrate than those from high-income countries, controlling for the region of origin and visa type makes it clear that individuals with relatively high skilled occupations such as Managers or Professionals are more likely to leave than relatively low-skilled occupations such as Labourers or Machinery Operators.

To further emphasise the increased outmigration of skilled migrants, we separate out highly skilled STEM (Science, Technology, Engineering, and Mathematics) workers and health professionals from other managerial, professional or technical jobs for our analysis. Table 2.8 presents the results for these occupations. STEM workers are around 6.4 percent more likely to out-migrate than our reference group which consists of other managers, while health professionals are around 5.6 percent less likely to out-migrate than our reference group. Table 2.9 breaks the health professions down further - within this subgroup, Nurses & midwives (our reference group), and other health diagnostic professionals (such as pharmacists) are the least likely to leave. General practitioners are around ($e^{0.132} - 1 =$) 14 percent more likely to leave than a nurse, and specialists & surgeons are ($e^{0.681} - 1 =$)97 percent more likely to leave. In both tables, changes in sign between column (1) and (3) can be explained by high skilled immigrants being more likely to have arrived from a low-income country.

To understand the link between skill and out-migration better, the model is re-estimated with the inclusion of multiple measures of skill. Table 2.10 shows the results of the Cox regression where ABS measures of skill by occupation are used to proxy for skill, with Skill Level 1, which requires a bachelors degree or equivalent qualification as the reference class. Prima facie, without including any controls it seems that out-migration is higher for occupations at Skill Level 2 (Diploma Level qualification) and Skill Level 4 (Certificate II level qualifications). However, controlling for migrant characteristics in column 3 shows that out-migration is highest for migrants at the highest skill level, with all other skill levels facing lower rates of out-migration. This is again due to a higher proportion of workers at lower skill levels coming from high-income countries. Adding controls, therefore, makes the coefficients for these skill levels negative.

Table 2.8: COX REGRESSION COEFFICIENTS FOR STEM AND HEALTH PROFESSIONALS

	(1) No controls	(2) Controls	(3) Quarter dummies
Other Professionals	-0.333**	0.0222	0.0212
	(0.0249)	(0.0300)	(0.0300)
Other Technicians and Trades Workers	-0.262**	-0.146**	-0.146**
	(0.0243)	(0.0301)	(0.0301)
STEM Occupations	-0.359**	0.0648+	0.0625+
	(0.0323)	(0.0367)	(0.0368)
Health Professionals	-0.309**	-0.0570+	-0.0571+
	(0.0288)	(0.0338)	(0.0339)
Observations	5851744	5848457	5848457
Number of subjects	271810	271710	271710
Pseudo chi squared	219.0	8876.7	8936.0
Quarter Dummies	No	No	Yes
Controls	No	Yes	Yes

Standard errors in parentheses

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

All other managers act as our reference group. Controls added include region of birth, age, sex, marital status, and visa type. Time dummies indicate the addition of year and quarter dummies to the regression

Table 2.9: COX REGRESSION COEFFICIENTS FOR HEALTH PROFESSIONALS

	(1) No controls	(2) Controls	(3) Quarter dummies
Health Diagnostic and Promotion Professionals	-0.0413	-0.0641	-0.0620
	(0.0647)	(0.0689)	(0.0689)
Health Therapists and Dental Practitioners	0.00451	0.0979	0.0978
	(0.0632)	(0.0660)	(0.0661)
General Practioners and Residents	-0.441**	0.132^{+}	0.132^{+}
	(0.0622)	(0.0687)	(0.0688)
Specialistics and Surgeons	-0.0131	0.711^{+}	0.681^{+}
	(0.380)	(0.382)	(0.384)
Observations	905665	905257	905257
Number of subjects	40760	40745	40745
Pseudo chi squared	59.46	1705.9	1732.6
Quarter Dummies	No	No	Yes
Controls	No	Yes	Yes

Standard errors in parentheses

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

"Nurses & Midwives" acting as our reference group. Controls added include region of birth, age, sex, marital status, and visa type. Time dummies indicate the addition of year and quarter dummies to the regression

Table 2.10: Cox regression coefficients for the ABS Skill Level of the occupation declared at arrival for Australian Permanent Migrants

	(1)	(2)	(3)
	No controls	Controls	Time dummies
Skill Level 2	0.114***	-0.240***	-0.241***
	(0.0250)	(0.0526)	(0.0526)
Skill Level 3	-0.0105	-0.216***	-0.216***
	(0.0192)	(0.0646)	(0.0646)
Skill Level 4	0.302***	-0.175**	-0.177**
	(0.0200)	(0.0647)	(0.0647)
Skill Level 5	-0.0349	-0.249**	-0.255**
	(0.0431)	(0.0798)	(0.0800)
Observations	7610475	7610475	7610475
Number of subjects	349117	349117	349117
Chi squared	247.0	12089.6	12169.7
Time Dummies	No	No	Yes
Controls	No	Yes	Yes

Standard errors in parentheses

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

Skill Level 1 (the highest) acts as our reference group. Controls added include region of birth, age, sex, marital status, occupation, and visa type. Time dummies indicate the addition of year and quarter dummies to the regression

Another measure of the complexity of each occupation was obtained from the O*NET database of occupational definitions, which is maintained by the US Bureau of Labour Statistics. The O*NET dataset measures the functional requirements for each US-SOC occupational code in terms of 52 abilities and skills, such as manual dexterity, verbal ability, or arithmetic reasoning. Using a US-SOC to ANZSCO crosswalk, the analysis calculates occupational skill scores for each ANZSCO 4 digit occupation. Following Peri and Sparber (2009), it then aggregates the sum of Manual and Communication ability scores for each ANZSCO occupation. Last, because these scores are arbitrarily scaled, Australian Census data for 2011 is used to re-scale them as the percentile utilisation for both types of skills amongst the Australian workforce. For example, a communications skill score of 97 for a General Practitioner means only 3 percent of Australian workers use communication skills more intensively. Because the O*NET skill profile closely identifies an occupation, occupation dummies were not included. The resulting model estimates with O*NET skills are presented in Table 2.11. Our results initially point to occupations relying on manual skills being more likely to leave, but on adding controls and time dummies (Column 3), migrants in occupations with a higher requirement for communication skills are more likely to leave, with a one percentile increase in the analytical intensity increasing outmigration by around 0.23 percent. In contrast, a one percentile increase in manual skill intensity reduces outmigration by approximately 0.14 percent.

Similarly, Table 2.12 shows the results of the Cox regression when the average years of education of the native population for a given occupation, derived from the 2011 Census, is used as a measure of skill. While adding no controls shows that out-migration is decreasing in education, i.e. each year of education reduces the hazard rate of out-migration by about 5%, adding controls makes the coefficient positive and each year of education increases the chance of out-migration by around 4.67 % according to our preferred model (3)

Lastly, Table 2.13 shows the results of the Cox regression when the average weekly earnings ('000s) by occupation declared at arrival are used as a measure of skill. An increase in weekly income by one unit (1,000 AUD) increases the chance of out-migration by around 4% according to our preferred model in column 3.

Table 2.11: COX REGRESSION COEFFICIENTS FOR THE O*NET SKILL SCORES FOR THE OCCUPATION DECLARED AT ARRIVAL

	(1) No controls	(2) Controls	(3) Time Dummies
Communication Skill	0.000320	0.00228***	0.00228***
	(0.000303)	(0.000319)	(0.000319)
Manual Skill	0.00102***	-0.00142***	-0.00142***
	(0.000282)	(0.000300)	(0.000300)
Observations	7475307	7475307	7475307
Number of subjects	343937	343937	343937
Pseudo chi squared	13.67	11865.4	11888.2
Quarter Dummies	No	No	Yes
Controls	No	Yes	Yes

Standard errors in parentheses

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

Controls added include region of birth, age, sex, marital status, and visa type. Time dummies indicate the addition of year and quarter dummies to the regression

Table 2.12: COX REGRESSION COEFFICIENTS FOR THE YEARS OF EDUCATION FOR THE OCCUPATION DECLARED AT ARRIVAL

	(1) No controls	(2) Controls	(3) Time dummies
Years of Education	-0.0548***	0.0446**	0.0457***
	(0.00512)	(0.0137)	(0.0138)
Observations	7610475	7610475	7610475
Number of subjects	349117	349117	349117
Chi squared	114.8	12073.7	12154.2
Time Dummies	No	No	Yes
Controls	No	Yes	Yes

Standard errors in parentheses

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

Years of education derived from the native population using census data. Controls added include region of birth, age, sex, marital status, occupation, and visa type. Time dummies indicate the addition of year and quarter dummies to the regression

Table 2.13: COX REGRESSION COEFFICIENTS USING AVERAGE WEEKLY EARNINGS (IN '000S AUD) FOR THE OCCUPATION DECLARED AT ARRIVAL

	(1) No controls	(2) Controls	(3) Time dummies
Average Weekly Earnings	-0.0295*	0.0396*	0.0398*
	(0.0125)	(0.0179)	(0.0179)
Observations	7496098	7496098	7496098
Number of subjects	344463	344463	344463
Chi squared	5.624	11941.6	12022.4
Time Dummies	No	No	Yes
Controls	No	Yes	Yes

Standard errors in parentheses

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

Controls added include region of birth, age, sex, marital status, occupation, and visa type. Time dummies indicate the addition of year and quarter dummies to the regression

2.5.4 Choice of country of out-migration

Migrants can choose to out-migrate to a country other than the one they were born in. In our dataset, the migrant's intended country of residence is observed at departure and can, therefore, classify out-migration as being one of two events - migrating to the country of birth, or migrating to another country.

These competing risks are modelled using the Cox competing risks model discussed above and present our estimates for the competing risk model in 2.14. Other controls included in both columns included the age, sex and marital status of the migrant. Column 1 presents the Cox competing risk hazard coefficients for the risk of migration to the country of birth. With regards to our reference group, i.e. migrants from the United Kingdom, the risk of migrating to the country of birth is lower for migrants from low-income countries, such as India and Sub-Saharan Africa. Secondly, compared to Managers (who are our reference group for the occupation at arrival), the risk of return migration is lower for lower skill occupations such as Labourers or Machinery Operators and Drivers. Lastly, compared to those on family visas, the risk of leaving for the country of birth is higher for migrants on Investment visas or those nominated by employers or Australian states, and lowest for migrants on Refugee visas.

Table 2.14: COX COMPETING RISK ESTIMATES

	(1) To COB	(2) To Third Country
New Zealand	1.630***	-1.547***
	(0.0709)	(0.0588)
India	-1.856***	-0.711***
	(0.0686)	(0.0787)
China	0.0855*	-0.340***
	(0.0361)	(0.0747)
Other Oceania	-2.210***	-0.387***
	(0.172)	(0.0818)
Other North-West Europe	-0.0335	0.591***
	(0.0461)	(0.0702)
Southern and Eastern Europe	-1.276***	0.152
	(0.0829)	(0.0786)
North Africa and the Middle East	-1.192***	0.188*
	(0.0750)	(0.0761)
South-East Asia	-1.277***	0.0608
	(0.0507)	(0.0584)
Other North-East Asia	-0.392***	0.472***
	(0.0667)	(0.0804)
Other Southern and Central Asia	-2.727***	-0.561***
	(0.148)	(0.0990)
Americas	-0.0657	0.187*
	(0.0501)	(0.0800)
Sub-Saharan Africa	-1.906***	-0.164*
	(0.0889)	(0.0678)
Professionals	-0.000963	0.00978
	(0.0312)	(0.0521)
Technicians and Trades Workers	-0.0744*	-0.363***
	(0.0335)	(0.0588)
Community and Personal Service Workers	-0.157***	-0.365***

	(0.0420)	(0.0787)
Clerical and Administrative Workers	-0.0450	-0.137*
	(0.0380)	(0.0661)
Sales Workers	-0.0445	-0.138
	(0.0436)	(0.0775)
Machinery Operators and Drivers	-0.308***	-1.102***
	(0.0569)	(0.139)
Labourers	-0.255***	-0.414***
	(0.0667)	(0.117)
Skilled - Nominated	0.181***	0.109
	(0.0391)	(0.0622)
Skilled - Independent	-0.0172	-0.245***
	(0.0311)	(0.0504)
Refugee	-1.533***	-0.259
	(0.270)	(0.151)
Special Category - NZ only	-0.613***	1.980***
	(0.0776)	(0.0746)
Investment	0.608***	-0.123
	(0.0484)	(0.113)
Observations	7610409	7610409
Number of subjects	349114	349114
Pseudo chi squared	13870.7	3305.7
Time Dummies	Yes	Yes
Controls	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Controls include Age, marital status.
Time dummies indicates the presence of year and quarter dummies in the analysis

Column 2 gives the Cox competing risk hazard coefficients for the risk of migration to the country other than the country of birth. Compared to our reference group (The United Kingdom) we see similar patterns - Migrants from North-West Europe, North-East Asia (ex-China), the Americas and South and Eastern Europe are the most likely to migrate to a different country. In contrast, those from India are the least likely to do so. Again, migrants who declared more skilled occupations at arrival are more likely to depart than less skilled ones. For example, Professionals have nearly the same hazard as managers for out-migrating to a third country while Labourers have a hazard rate of out-migration around 40 percent lower than our reference group. Compared to our reference visa group (Family visas), only those on Skilled-Independent visas have a lower hazard for migrating to a third country - Here, around 24.4 percent lower. Refugees are just as likely as those on family visas to relocate to a third country.

2.5.5 The effect of changing unemployment rates in Australia

To study the effect of how migration is affected by changes to macroeconomic conditions within Australia, the analysis adds data on the trend-adjusted unemployment rate within Australia to the dataset. Table 2.15 presents the results showing how unemployment rate affects out-migration - our estimates indicate a 1 percent increase in the unemployment rate increases the hazard for out-migration by around 5 percent. In Table 2.16, the unemployment rate is interacted with the region of birth dummy for each migrant - the effect of the unemployment rate on out-migration is still positive and is statistically significant for $p < 0.1$ for the average migrant. However, the results indicate that migrants from India and China are less likely to out-migrate if the unemployment rate increases, with migrants from India 31 percent less likely to out-migrate if the unemployment rate rises by 1 percent. These results may indicate that such out-migration is sensitive to source country economic conditions, and increasing as wages in the source country increase. Last, the unemployment rate interacts with occupational dummies in Table 2.17- the result is still positive, and significant at $p < 0.1$. The results fail to indicate significant differences amongst occupational groups. They, therefore, do not provide evidence of unemployment affecting out-migration differentially amongst skill groups, controlling for other factors.

Table 2.15: IMPACT OF CHANGES IN THE UNEMPLOYMENT RATE

	(1) No controls	(2) Controls	(3) Quarter dummies
Unemployment Rate	0.0855***	0.0563***	0.0550***
	(0.0134)	(0.0137)	(0.0137)
Observations	7610475	7610475	7610475
Number of subjects	349117	349117	349117
Pseudo chi squared	40.71	12080.0	12102.8
Quarter Dummies	No	No	Yes
Controls	No	Yes	Yes

Standard errors in parentheses

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

Controls added include region of birth, age, sex, marital status, occupation, and visa type. Time dummies indicate the addition of year and quarter

Table 2.16: IMPACT OF CHANGES IN THE UNEMPLOYMENT RATE ON THE HAZARD RATE OF OUT-MIGRATION INTERACTED WITH REGION OF BIRTH

	(1) No controls	(2) Controls	(3) Quarter dummies
Unemployment Rate	0.0814**	0.0515	0.0505
	(0.0315)	(0.0315)	(0.0315)
Interacted with:			
New Zealand	0.0403	0.0521	0.0518
	(0.0369)	(0.0369)	(0.0369)
India	-0.306***	-0.311***	-0.312***
	(0.0837)	(0.0837)	(0.0837)
China	-0.0706	-0.0912*	-0.0917*
	(0.0457)	(0.0458)	(0.0458)
Other Oceania	-0.0474	-0.0968	-0.0972
	(0.115)	(0.115)	(0.115)
Other North-West Europe	0.0400	0.0649	0.0647
	(0.0660)	(0.0658)	(0.0658)
Southern and Eastern Europe	-0.0343	-0.0130	-0.0133
	(0.0939)	(0.0938)	(0.0939)
North Africa and Middle East	-0.0736	-0.0370	-0.0375
	(0.0860)	(0.0859)	(0.0859)
South-East Asia	-0.0334	0.00279	0.00247
	(0.0612)	(0.0612)	(0.0612)
Other North-East Asia	-0.147	-0.140	-0.141
	(0.0851)	(0.0851)	(0.0852)
Other South and Central Asia	-0.00739	0.0376	0.0369
	(0.138)	(0.137)	(0.137)
Americas	0.0816	0.0936	0.0934
	(0.0723)	(0.0722)	(0.0722)
Sub-Saharan Africa	0.163	0.154	0.154
	(0.0883)	(0.0881)	(0.0881)
Observations	7610475	7610475	7610475
Number of subjects	349117	349117	349117
Pseudo chi squared	10454.6	12120.4	12143.3
Quarter Dummies	No	No	Yes
Controls	No	Yes	Yes

Standard errors in parentheses

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

Controls added include region of birth dummies, age, sex, marital status, occupation dummies, and visa type.

Table 2.17: IMPACT OF CHANGES IN THE UNEMPLOYMENT RATE ON THE HAZARD RATE OF OUT-MIGRATION INTERACTED BY MAJOR OCCUPATIONAL GROUP DECLARED AT ARRIVAL

	(1) No controls	(2) Controls	(3) Quarter dummies
Unemployment Rate	0.113***	0.0639	0.0627
	(0.0324)	(0.0327)	(0.0328)
Interacted with:			
Professionals	-0.0340	0.0115	0.0113
	(0.0382)	(0.0386)	(0.0386)
Technicians and Trades Workers	-0.000971	-0.0311	-0.0311
	(0.0424)	(0.0427)	(0.0427)
Community and Personal Service Workers	-0.0350	-0.0367	-0.0368
	(0.0587)	(0.0589)	(0.0589)
Clerical and Administrative Workers	0.00150	-0.00971	-0.00954
	(0.0513)	(0.0515)	(0.0515)
Sales Workers	-0.0236	-0.0131	-0.0131
	(0.0611)	(0.0613)	(0.0613)
Machinery Operators and Drivers	0.0102	0.0218	0.0218
	(0.0873)	(0.0876)	(0.0876)
Labourers	-0.159	-0.0978	-0.0981
	(0.0969)	(0.0972)	(0.0972)
Observations	7610475	7610475	7610475
Number of subjects	349117	349117	349117
Pseudo chi squared	467.5	12083.0	12105.8
Quarter Dummies	No	No	Yes
Controls	No	Yes	Yes

Standard errors in parentheses

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

Controls added include region of birth, age, sex, marital status, occupation, and visa type.

2.5.6 Robustness Check with a Discrete Mixture Frailty

The Cox proportional hazard estimates above assume that the event time t follows a univariate distribution and that any heterogeneity is accounted for by the observable characteristics in $\lambda(t)$. However, this independence assumption may be violated if failure times are correlated even in the presence of our model parameters - such internal clustering of failure times is known as unobserved heterogeneity in the context of survival time data. The application of standard survival models in the presence of unobserved heterogeneity can lead to biased parameter estimates and incorrect predictions (Liu, 2014)

A variety of methods have therefore been developed to account for unobserved heterogeneity. Because some clusters of individuals are more failure prone (“frail") than others, an unobservable random effect known as a frailty is often used to account for the extra variance. This random effect is usually modelled explicitly according to a gamma- or Weibull-distributed frailty. However, Heckman and Singer (1984) show that the resulting estimates are often sensitive to the distribution of the frailty. They propose a Non-Parametric Maximum Likelihood Estimator (NPMLE) that allows for an arbitrary distribution for the unobserved heterogeneity. Their method assumes that there are a fixed number of types of individuals and these individuals can be probabilistically assigned to different types. For instance, the hazard function with two types of individuals ($type \in \{1, 2\}$) is as follows:

$$P(Fail = 1|type, t, X) = 1 - \exp(-\exp(\mathbf{m_{type}} + \beta + \beta_1 X) \tag{2.6}$$

Where, the mass point $\mathbf{m_{type}}$ is the discrete point of support for a binomial distribution, with $m_{t=1}$ normalised to zero. The second mass point is then $m_{t=2} + \beta$. The procedure also calculates the probability of belonging to type $t = 1$ in the entire population as $\pi_{t=1}$ ($\pi_{t=2} = 1 - \pi_{t=1}$). The NPMLE then maximises log-likelihood to estimate the two extra model parameters.

Results from the Heckman-Singer discrete mixture model with two mass points[2] are presented in Table 5.A.4 as part of the Appendix. Excluding factors from Cox models leads to estimates which are smaller in magnitude than the true effects (Struthers & Kalbfleisch, 1986). Therefore, estimates from the Cox proportional hazards model are

[2]Models with three or more mass points failed to converge

generally attenuated compared to those with the Heckman Singer frailty. However, these differences in magnitude are small, and the qualitative analyses presented in this essay remain unchanged.

2.6 Discussion and conclusion

Using a dataset of migration decisions for the population of off-shore permanent migrants to Australia, this essay contributes to the literature by establishing the rate of out-migration amongst various migration cohorts. The overall rate of out-migration is quite low across the sample cohort, although two-step migration, where temporary migrants move to permanent residency status, is outside the scope of this paper. The findings establish that migrants from wealthier countries are more likely to out-migrate than those migrants from lower-income countries, and the rate of out-migration increases by 1.25 percent as per capita GDP in the source country rises by 1,000 USD. The analyses also estimate the association between economic conditions in Australia, as measured by the unemployment rate, and out-migration. These results indicate that the hazard of out-migration increases by around five to six percent for a one percent increase in the trend-adjusted unemployment rate. However, migrants from India and China are less likely to out-migrate in response to increasing unemployment rates in Australia. This result additionally highlights the role that source country conditions play in the out-migration decision.

The essay also conducts analyses on the skill selection of out-migration from Australia. High skilled migrants are more likely to out-migrate than less skilled migrants, with the hazard rate of out-migration rising by around 4.5 percent for each additional year of education possessed by native workers engaged in that occupation. Moreover, visa types associated with better labour market outcomes in Australia have higher rates of out-migration. According to our theoretical hypothesis, such results arise because the destination country has a lower return to skill than the source. Indeed, Australia has a Gini coefficient of income inequality lower than the majority of source countries, i.e. India, China, the U.K. and the majority of South East Asia and Oceania, while New Zealand has a Gini coefficient about the same as Australia's [3]. Greater policy focus is

[3] World Bank Gini Index, 2016

therefore required in retaining skilled migrants, mainly highly skilled migrants, that are attracted through Australian migration policy.

This research also has significant implications for an important research theme in the economic literature - estimating immigrant wage assimilation into the destination labour market. The non-random out-migration of the highest skilled migrants causes estimates of wage assimilation to be biased downwards - this may explain why Australians studies typically find little to no wage assimilation for migrants, especially for migrants from non-English speaking countries. Models of wage assimilation should, therefore, control for outmigration rates or non-random panel attrition between subgroups when they use cross-sectional and panel datasets respectively.

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Chapter 3

The Impact of Skilled Temporary Worker Flows on the Labour Market Outcomes of Australian Workers

Abstract

Temporary migration is an important pathway for the recruitment of a skilled workforce in developed nations. Using linked administrative and panel data sources, this paper looks at associations between skilled temporary worker flows in Australia and the wages of Australian workers. It finds no statistically significant negative effect of temporary worker flows on wages, although workers with a bachelor's degree or higher show weak statistical evidence of wage increases of around six to ten percent for every one percent increase of such workers in the occupational workforce, relative to those who do not. It also studies how skilled temporary migration affects occupational switching and finds evidence that such migration induces Australian workers to specialise in communication skills. Particularly, workers with a bachelor's degree or above keep increasing communicative skills utilisation in the long run. This research contributes to the literature by providing evidence towards the impact of temporary migrants on labour market outcomes, as well as task specialisation induced by such migration.

This chapter uses data collected from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Survey Project was initiated and is funded by the Department of Social Services (DSS) and is managed by the Melbourne Institute: Applied Economic & Social Research. The findings and views reported in this paper, however, are those of the author and should not be attributed to either DSS or the Melbourne Institute. HILDA analysis data was extracted using PanelWhiz v4.0, a Stata add-on package written by Professor John P. Haisken-DeNew.

3.1 Introduction

Temporary labour migration programmes have become increasingly important in the recruitment of a skilled workforce in OECD nations. Temporary migrants are effective in meeting local labour market shortages and allow much greater flexibility in managing the stock of migrants compared to permanent immigrant workers. Further, temporary migrants have lower fiscal impacts as they are not able to access social welfare benefits in the majority of their destination countries. The growing political and economic preference for temporary migrants is reflected in migrant composition across English speaking countries, such as the United States, Australia, New Zealand, or Canada, where temporary migrants with work rights outnumber permanent workers (Akbari & MacDonald, 2014).

The large and growing role of such programmes has correspondingly been subject to much media and public commentary over the last few years (Bahn, Barratt-Pugh & Yap, 2012). However, there is a limited understanding of issues such as the impact and social consequences of temporary skilled migration. In Australia for instance, it has been acknowledged that there are large lead times required to train a sufficient domestic workforce for many occupations, e.g. medical occupations and that temporary workers allow businesses to better respond to growing demand (OECD, 2008). However, many argue that the program reduces domestic skills training and puts Australian jobs at risk (Toner and Woolley, 2008; Richards, 2006). It has also been argued that they reduce wages for Australian workers.

These issues are exacerbated by the lack of consensus within the economic literature which analyses the impact of temporary migration, or even migration in general. Theoretically, there is a lack of consensus amongst labour economists with regards to immigration. One prevalent view, driven by simple supply-demand models is that immigrants tend to depress earnings for native workers, particularly less-skilled natives (Borjas, Freeman, Katz, DiNardo and Abowd, 1997;Borjas, 1999b;Borjas, 2003; Borjas and National Bureau of Economic Research, 2007). Another view (G. I. Ottaviano and Peri, 2008; Friedberg, 2001; E. G. Lewis, 2005) is that immigration has a positive effect on earnings for native workers due to migrants causing natives to specialise in occupations reliant on analytical and communication skills rather than manual skills.

Furthermore, only a small number of studies analyse the empirical impacts of temporary migration. Peri, Shih and Sparber (2015, S1) analyse the impact of H1B driven STEM worker growth on the wages and employment of American workers and find significant increases in wages paid to college-educated natives and smaller, but significant effects for non-college educated natives. They also find a positive and significant effect of such workers on total factor productivity growth. In contrast, Bound, Braga, Golden and Khanna (2015, S1) analyse the impact of the same program in a structural setting to find that wages for computer scientists were lowered 2.6 to 5.1 percent as a result of the influx of foreign IT workers. Similarly,Gross and Schmitt (2012) finds limited evidence that the Canadian Temporary Foreign Worker (TFW) programme was associated with poor labour market outcomes, especially for low skilled Canadian workers. Australian evidence on the impact of such programs is extremely limited and it not likely that the impact of temporary migrants in Australia is the same as that in the other countries. These differences may be caused by labour market institutions, such as unionisation or minimum wage levels, which have a large impact on the effects of immigration. Moreover, the two studies above highlight that the Canadian TFW programme mainly focusses on low-skilled workers, while Information Technology workers dominate the U.S. H1B temporary worker programme. Australian temporary migrants have a different skill profile to those in the U.S. or Canada, and consequently, different labour market effects. (Manacorda, Manning & Wadsworth, 2012)

This paper looks at the effect of the Australian 457 visa temporary worker program, which is the predominant program for employer skilled migration in the country, on the labour market outcomes of Australian Workers over 2010-2015. To do this, it uses an administrative dataset of 457 worker stocks by occupation and country of origin and matches this data to the Household Income and Labour Dynamics in Australia panel survey of Australian households. Within occupation groups, this chapter estimates a series of regressions that progressively aim to absorb observable and unobservable factors that isolate the partial effect of immigrant supply on native wages, as well as occupational switching for native workers. Because migrant flows are influenced by occupational demand, it also uses instrumental variable estimation by constructing shift-share instruments. This method uses the aggregate compositional change in 457 source countries to 'separate-out' demand-driven changes in migrant composition. Furthermore, it follows Ruist, Stuhler and Jaeger (2017) in using a double instrumentation strategy that controls for the serial correlation inherent in shift-share instrumentation and separates out the short run impact and the long run adjustment processes of migration. This is the first econometric analysis looking at associations between the increased hiring of 457 migrant workers and Australian workers; this is also one of the few studies focussed primarily on temporary immigration worldwide.

The results do not find increases in 457 utilisation to be associated with statistically significant reductions in wages or increased unemployment of Australian workers in the next period. On the contrary, there is weak evidence of wage increases of between six to ten percent wages for workers possessing a bachelor's degree or higher when the proportion of 457 workers in the overall workforce increases by one percent. Although these estimates seem large, 457 utilisation in Australia is low, averaging around one percent of the workforce. Our results require corresponding large increases, of between 25 to 100 percent, in the 457 occupational workforce.

Given null to positive impacts of 457 migration, it also investigates the mechanisms which may be responsible for these findings. To perform this analysis, the analyses use the O*NET dataset of job characteristics, compiled by the United States Department of Labour. O*NET has been previously linked to standard occupational identifiers in other countries and is also commonly used in studies on the immigration literature. For instance, Peri and Sparber (2009), D'Amuri and Peri (2014)and Foged and Peri (2016) use O*NET to estimate patterns of occupational mobility induced by immigration in the United States, Western Europe, and only Denmark respectively. Following the construction used in Peri and Sparber, 2009, each ANZSCO 2 digit occupational code is assigned a score of relative communication to manual skills. These scores, of between 1 and 100, capture the relative utilisation of communicative skills within the Australian workforce as of the 2011 census. A one-point increase, therefore, implies that an individual increased her utilisation of communication skills by one percentile compared to the Australian workforce in 2011. Although this method may introduce measurement error into the analysis (because the data is measured for the US, not Australia), such an error is unlikely to bias results since it is expected to be uncorrelated with the share of migrants in each occupation.

The analysis of patterns of occupational switching finds that a one percent increase in 457 migration for the occupational workforce increases the relative specialisation of communication skills for Australian workers by around 4 percentile points. Notably, there is also weak evidence that university graduates continue to specialise in the long run in response to 457 migration. It, therefore, supports the contemporary immigration literature which emphasises occupational upgrading, and specialisation towards communicative tasks as important channels used by workers adjusting to migration shocks. These results may also be influenced by the lower employment mobility of temporary workers, since they require another employer to sponsor them within 90 days if they switch employers, although a study of this channel is beyond the scope of this paper.

The rest of this paper is organised as follows: Section 2 provides an overview of the 457 subclass temporary migration program. Section 3 establishes key threads of both theoretical and empirical evidence surrounding migration. Section 4 presents the empirical methodology, whereas Section 5 introduces the data sources used. Section 6 reviews and discusses the results. Lastly, I conclude.

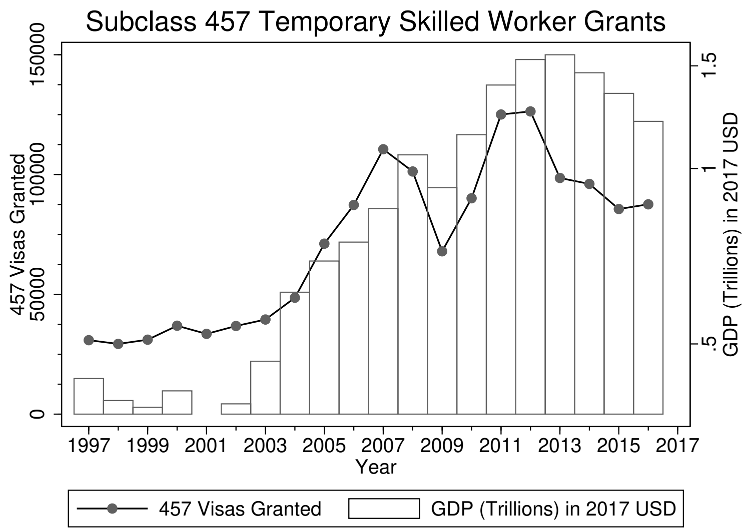
3.2 Background: Subclass 457 Temporary Skilled Migration Program

The 457 visa subclass, also known as the Temporary Work (Skilled) or Temporary Work (Long Stay) visa is an uncapped program, designed primarily to address local labour shortages[1] (DIBP, 2017). A 457 visa application involves a three-step process, in which an employer first becomes an approved sponsor and then nominates a skilled migrant to fill a specific position (Larsen, 2013). The migrant is then required to lodge a linked visa application. Employers must meet prescribed training benchmarks for Australian citizens and temporary migrants, and at least 75 percent of their workforce must be Australian. They must also pay 457 sponsored employees a rate comparable to local wages, and commit to not underpaying their employees or making deductions without the worker's permission. In Australia, the lowest wage acceptable for 457 temporary employees was AUD 53,900 in 2017 and is indexed annually using the wage price index produced by the Australian Bureau of Statistics. Further, subclass 457 workers are required to maintain employer sponsorship throughout their tenure in Australia, except for a 90-day moratorium if they switch to another (sponsoring) employer.

457 temporary workers play an important role in the Australian economy. Figure 3.1 describes trends in the number of temporary 457 visas granted by the Australian Depart-

[1] In contrast to the H1B program in the US, which is capped at 85,000 visas per year

Figure 3.1: 457 SUBCLASS - TEMPORARY WORK (SKILLED) VISAS GRANTED: 1996-2015



Source: data.gov.au, World Bank Development Indicators

ment of Immigration and Border Protection (DIBP) over the period from 1997 to 2016, along with Australian GDP, measured in 2017 US Dollars, to indicate employment demand. There is a positive association between the 457 visa grants and economic output. Over this period, 457 visa grants have nearly tripled - from 25,786 in 1996 to 87,580 in 2016, accompanying a rise in output from 400 billion USD to 1.2 trillion USD. The number of visas granted annually is sizeable, accounting for slightly less than one percent of the overall Australian workforce. This study focusses on the period 2010-2015, and growth is seen from 2010-2013, with 126,348 visas granted in 2013 and a subsequent fall corresponding to decreased mining investment, which was a major source of Australian economic growth in previous years. Moreover, such temporary onshore workers also accounted for over 50 percent of skilled *permanent* residency visas granted in Australia during the study period (Gregory, 2014). This "two-step migration" process has become increasingly important in the eventual selection of highly skilled workers and their permanent residency in Australia and is likely to have substantial labour market impact.

3.3 Literature review

3.3.1 Theoretical Frameworks

There are two key theoretical frameworks in the immigration literature. The first uses variations on simple demand and supply models. In such frameworks, a *ceterus paribus* increase in labour supply caused by migration lowers the marginal product of labour, and therefore wages. For instance, Borjas (2003) assumes the aggregate production function for the national economy with capital K at time t,

$$Y_t = [\lambda_{Kt} K_t^{\nu} + \lambda_{Lt} L_t^{\nu}]^{1/\nu} \tag{3.1}$$

with L_t being the aggregate labour input, with a nested CES structure incorporating the contributions of workers who differ in both education and experience. A fundamental assumption made here is that natives and immigrant workers are perfect substitutes, within the CES groups for the labour input L_t. Another assumption is keeping capital fixed, over a relatively long time horizon of more than ten years. Using reduced form estimation based on these CES structural models, Borjas finds that immigration caused a 3.2 percent decrease in the wages of an average native worker, with the impact being much higher (8.9 percent decrease) for high school dropouts. G. I. P. Ottaviano, Peri and Wright (2013) build on the model above and assume that migrant and native workers are imperfect substitutes for each other. They also allow capital stocks to adjust in the short-run, contrary to the models such as the one above. They find a much smaller drop in wages for high school dropouts (-1.1 percent), whereas the majority of the US workforce gain from immigration. Reduced form estimations are identified by the structural assumptions of the theoretical models, and are therefore sensitive to the structural assumptions used (Borjas, 2014).

A growing literature also highlights channels through which the imperfect substitutability of native and immigrant workers affects the labour market outcomes of the two groups. Peri and Sparber (2009) demonstrate that native workers progressively specialise in communication-intensive occupations when faced with the increases in low skilled immigrants, who comparatively specialise in manual tasks. Foged and Peri (2016) use Danish data over the period 1991-2008 to show that refugee immigrant workers increase native worker mobility into occupations requiring higher analytical and communication skill utilisation and lower manual skill utilisation, accompanied by permanent wage increases of two percent for low-skilled natives. Capital-skill complementarity (E. Lewis, 2011), human capital externalities (Moretti, 2004; Docquier, Ozden and Peri, 2014) and migrants' contributions to innovation (Kerr & Lincoln, 2010) present additional channels through which simple demand-supply based models may not explain the impacts of immigration.

3.3.2 Empirical Studies

The theoretical frameworks above are complemented by associative studies on migration. Immigration is partially driven by labour demand in the areas of settlement, causing associations to be positively biased. It is therefore extremely common in the empirical literature to use fixed effects to absorb time-invariant location or occupational variables, as well as time-fixed effects to non-parametrically control for economy-wide trends.

For instance, Borjas (2003) demonstrates the impact of permanent migration on the labour market outcomes using the share of migrants in the overall workforce, i.e. the variable $p_{Mt} = M_t/(N_t + M_t)$, where M_t is the number of migrants at time t, while N_t is the number of native workers. These analyses indicate immigration has a negative effect on competing workers, with Borjas (2003) indicating a 3 to 4 percent decrease in native wages when supply is increased by 10 percent.

Card and Peri (2017) argue that this specification may cause results to be downward biased since the estimates of the coefficient of interest p_{Mt} in the presence of fixed effects mechanically also capture the effect of an increase in native supply. The variable of interest should be:

$$m_t = M_t - M_{t-1}/(N_{t-1} + M_{t-1}) \tag{3.2}$$

To avoid such spurious correlations, this study uses this form of the coefficient of interest.

Studies in the Australian context are rare and use panel data sources to supplement census data. Breunig, Hasan and Salehin (2013) uses HILDA, Australian Census, and Australian Survey of Income and Housing data to analyse correlations between immigration and the labour market outcomes of natives in a framework similar to Borjas (2003). Their analysis finds some negative effects of recent migrants on the labour market outcomes of incumbent natives, but positive results when looking at weekly hours worked and labour force participation. Their results are also sensitive to small changes in the empirical methodology, such as adding a dummy variable for skill groups. These results overall paint an inconclusive picture with relatively small effects and no robust evidence of a negative effect on workers. Notably, the use of the Borjas style estimator is likely to negatively bias the result. This study, therefore, follows this vein of the literature, by analysing the impact of temporary migration on Australian workers (Australian citizens, as well as recent permanent migrants).

A key issue in the empirical immigration literature is the endogenous selection problem - observable and unobservable factors related to labour demand influence both immigrant settlement and labour market outcomes. For instance, a positive demand shock will lead to higher wages for natives, accompanied by greater immigrant settlement. Although policy changes and push-driven changes (such as political instability in the source country) can be used to identify the impact of migration, such changes are not available for most countries. However, it has been increasingly observed that new immigrants tend to settle into groups with large immigrant populations. Furthermore, they select into groups with previous immigrants from the same country of origin. Therefore an instrument can be created using the previous share of the immigrant population from each country of origin in each group, along with contemporary inflows of immigrants from each country of origin at the aggregate level (Card, 2001). This shift-share instrumentation strategy has become increasingly common in the literature studying the effect of migration (e.g. Saiz, 2007, E. Lewis and Peri, 2014, Basso 2015). The construction of such an instrument tries to remove *local, group-specific* demand based factors from migrant shares by using variation in the *aggregate* source country distribution of migrants. Recall our variable of interest, $m_t = M_t - M_{t-1}/(N_{t-1} + M_{t-1})$. The shift-share instrument then, for group i at time t, given the source country distribution for migrants from country $c \in C$:

$$\hat{m}_{i,t} = \frac{\hat{M}_{it} - \hat{M}_{it-1}}{N_{it-1} + \hat{M_{it-1}}} \text{ where } \hat{M}_{i,t} = \sum_{C} M_{i,t_0,c} \times \frac{M_{ct}}{M_{c,t_0}} \tag{3.3}$$

The exogeneity of such an instrument is based on the assumption that the initial distribution of migrants from country c across groups i is likely to be unrelated to changes in labour demand in the future. However, past immigrants usually locate following past demand shocks and the long-run persistence of these shocks may violate the exclusion condition and introduce omitted variable bias (Borjas, 1999a). Arguments for such *serial* *correlation* therefore present one source of potential bias with shift-share instruments.

Further, Ruist et al. (2017) argues that general equilibrium adjustments to a supply shock may also bias estimates with shift-share instruments - local supply shocks may trigger prolonged general equilibrium adjustments that offset their initial local impact. For instance, a region hit by a negative shock may eventually experience positive wage growth, and such adjustments may take a decade or longer. In the presence of such an adjustment process, the shift-share instrument offers a weighted average (with context-specific weights) of the short and long-run effects of the shock. Because most studies only wish to capture the short-run effect of immigration, shift-share estimates are inconsistent. The presence of either serial correlation or dynamic equilibrium adjustments in local outcomes, therefore, violates the exogeneity condition of a shift-share instrument, and caution should be exercised in the interpretation of such results.

They show that these sources of bias can be mitigated by regressing the past settlement instrument $\hat{m}_{it}$ onto its lag $\hat{m}_{it-1}$. The residual isolates innovations in immigrant flows that are uncorrelated with previous settlement and can be used to instrument current immigration flows. In practice, the same coefficient on wage inflows can be obtained using the following estimator:

$$Y_{it} = \beta_0 + \beta_1 m_{it} + \beta_2 m_{it-1} + \epsilon_{it} \tag{3.4}$$

Where, the first stage equations are:

$$m_{it} = \gamma_{10} + \gamma_{11}\hat{m}_{it} + \gamma_{12}\hat{m}_{it-1} + \nu_{it} \tag{3.5}$$

$$m_{it-1} = \gamma_{20} + \gamma_{21}\hat{m}_{it} + \gamma_{22}\hat{m}_{it-1} + \mu_{it} \tag{3.6}$$

$$\tag{3.7}$$

Demand shocks may endogenously influence labour market outcomes *and* immigrant inflows, m_{it} and m_{it-1} are instrumented by both $\hat{m}_{it}$ and $\hat{m}_{it-1}$ to address the endogenous selection problem. The inclusion of the lag term, m_{it-1}, and instrumentation ensure that the exogeneity condition required for a consistent estimation is met. Overall, this procedure isolates an exogenenous component of observed inflows that is uncorrelated to local demand and past supply shocks.

Last, their estimator separates out long-run general equilibrium adjustment process that can bias results. β_1 is the short run effect of migration, which is usually the coefficient of interest in associational studies. β_2 captures the long run adjustment process to past supply shocks. Although one could be tempted to sum up the two to capture the overall effect of migration, the estimates capture the *relative* impact of migration between two groups. Because the short run impact of migration flows in a particular group can also affect labour market outcomes for other groups in the *long* run, the aggregate impact across groups is hard to interpret using this estimator. However, the procedure is data demanding, as the two instruments are typically highly collinear, and requires sufficient variation in the settlement patterns of migrants. Using this strategy on U.S. Census data, they find that the short-run labour market impact is less positive than the conventional shift-share instrument estimator, while the (lagged) long run adjustment process is more positive than without instrumentation. This pattern is consistent with the standard competitive model of a positive adjustment following a negative shock.

A degree of caution should be exercised with regards to the external validity of such empirical results outside the country they are based in. The US from 1970-2010 has drawn lower skilled migrants, particularly those without high school qualifications, as the dominant migrant cohort. Most U.S. specific studies tend to focus on this cohort. Most other migrant-receiving countries such as Australia, Canada, New Zealand and the United Kingdom receive migrants with higher skills. Manacorda et al. (2012) provides evidence from the United Kingdom where the majority of migrants are university educated and above, and UK natives are largely unaffected by such immigration. They also show that native and immigrant workers are imperfect substitutes.

The papers above provide numerous motivations and varying evidence on the impact of migration. Whether the result is positive or negative, almost all papers show relatively small impacts of immigration. This chapter contributes to the literature by providing additional evidence from Australia - a country where immigration, both temporary and permanent, is highly skill-selected and highlights potential channels responsible for the results.

3.4 Empirical Methodology

To methodically analyse the impact of 457 driven immigration on the labour market outcomes of Australian workers, we conduct a number of regression analyses that aim to absorb observable and unobservable factors which may bias estimates. The results focus on occupational groups, and the primary variable of interest is the supply shift linked with 457 migration at time t in occupation o,

$$m_{o,t} = \frac{457_{o,t} - 457_{o,t-1}}{E_{o,t-1}} \tag{3.8}$$

Essentially this is the *annual* change in 457 flows, normalized to the total employment in the occupation o at time $t-1$. The construction of the variable of interest in equation 3.8 avoids concerns about spurious correlations in previous studies, as highlighted above.

The simplest regression estimator looks at the short-run impact in a setting with occupation-time fixed effects, which allows us to control for omitted variable bias, observable or unobservable, that is time-invariant and specific to each occupation across the study period, or linked to economy-wide trends. Due to the use of panel data, the analyses additionally include individual fixed effects that control for all time-invariant and individual-specific factors such as personality type, gender, or ethnicity. The first regression estimate is then of the following type for worker i in occupation o at industry n at year t:

$$y_{i,o,n,t} = \varphi_i + \varphi_o + \varphi_{nt} + \gamma m_{o,t} + \beta\,\mathrm{Controls}_{oit} + \varepsilon_{oit} \tag{3.9}$$

Where the variable y is the log of the weekly wage received; γ is the coefficient of interest, capturing the effect of changes in the proportion of 457s within the overall workforce. φ_i, φ_o, and φ_{nt} are individual, occupation, and industry-year fixed effects. The addition of industry-year fixed effects non-parametrically controls for trends common to workers in industry n at time t, regardless of occupation. Additional controls include a vector of location dummies, and age squared. Lastly, ε is a vector of errors distributed with mean zero. four, standard errors are clustered at the individual level.

Second, some of the outcomes, such as per-cent time spent unemployed or the ratio of communicative to manual skills, are dependent on occupational switching. Because controlling for a contemporaneous occupation perfectly identifies such estimates, the following specification is used:

$$y_{i,o,n,t,t-1} = \varphi_{o,t-1} + \varphi_{nt} + \varphi_i + \gamma m_{o,t-1} + \beta \,\text{Controls}_{oit} + \varepsilon_{oit} \tag{3.10}$$

Principally, since this specification is identified through occupational switching in later periods, The analyses control for the lag of occupation as well as the lagged 457 proportion variable. Additionally, industry time fixed effects are used, with the industry set to a worker's lagged industry (i.e. n_{t-1}) if a worker is unemployed or out of the labour force in the current year.

As highlighted in Subsection 3.3.2, the correlations above are likely to biased if there are relative demand shocks for a given occupation that affect the labour market outcomes of natives. For instance, an unobservable positive demand shock (e.g. an increase in coal or iron ore prices, given that Australia is a resource based economy) may be correlated with rising wages for natives, as well as increasing demand for 457s in that position. To remove such omitted variable bias, the next specification controls for supply-driven shifts of the immigration population rather than controlling for demand changes. It does this by constructing a "shift-share" instrument. The construction of the instrument uses $457_{o,c,t_0}$, the population of 457s by country of origin c in occupation o in base year t_0, which is 2009 for this study. These are then scaled by the ratio of 457 migrants from country c in year t compared to the base year i.e. $t_0 = 2009$, or $\frac{457_{ct}}{457_{c,t_0}}$. The instrument is then:

$$\hat{m}_{o,t} = \frac{\hat{457}_{ot} - \hat{457}_{ot-1}}{AUS_{ot-1} + \hat{457}_{ot-1}} \text{ where } \hat{457}_{o,t} = \sum_c 457_{o,t_0,c} \times \frac{457_{ct}}{457_{c,t_0}} \tag{3.11}$$

The study period for estimations using the instrument begins in 2010. The instrumental variable is valid if the relevance condition is met, i.e. the first stage regression should have a sufficiently large F criterion, usually $F > 10$. The exogeneity restriction assumes that the distribution of foreign-born 457s of nationality c in occupation o in t_0 is uncorrelated with subsequent demand shifts and productivity changes for that occupation. The instrument is then driven by changes in the country of origin profile over the study period.

Given potential issues with the validity of the exogeneity condition above, the last specification uses the "double instrumentation" strategy proposed by Ruist et al. (2017) and described in the literature review to estimate:

$$y_{i,o,n,t,t-1} = \varphi_i + \varphi_o + \varphi_{nt} + \gamma_1 m_{o,t} + \gamma_2 m_{o,t-1} + \beta\,\text{Controls}_{oit} + \varepsilon_{oit} \tag{3.12}$$

and when examining outcomes driven by occupational switching, this becomes:

$$y_{i,o,n,t,t-1,t-2} = \varphi_i + \varphi_{o,t-1} + \varphi_{nt} + \gamma_1 m_{o,t-1} + \gamma_2 m_{o,t-2} + \beta\,\text{Controls}_{oit} + \varepsilon_{oit} \tag{3.13}$$

The two endogenous variables of interest are instrumented by $m_{o,t}$ and $m_{o,t-1}$ as defined above. As explained earlier in section 3.3, the double instrumentation strategy's inclusion of $m_{o,t-1}$ controls for serial autocorrelation in migrant inflows between time periods, mitigating such biases in estimates for $m_{o,t}$. It also allows for estimation of both the causal short-run impact and long-run adjustment process of a 457 migration shock. Simultaneously, because immigrant inflows are endogenously determined by occupational demand the instrumentation of m_o, t and $m_{o,t-1}$ by the shift-share instruments constructed using aggregate migrant composition, $\hat{m}_{o,t}$ and $\hat{m}_{o,t-1}$, satisfies the exogeneity condition required for an instrumental variable for 457 inflows. For these reasons, it is the preferred methodology.

3.5 Data

This chapter uses three data sources - administrative data on the number of 457 holders within each occupation, the Household Income and Labour Dynamics in Australia (HILDA) panel survey, and the O*NET job characteristics data set.

The administrative data from the Department of Immigration and Border Protection which contains the quarterly number of 457 temporary visa holders from Q2 2009 to Q2 2016, by occupation (ANZSCO 4 digit occupation) and the country of origin. This data was merged with quarterly estimates from the ABS Labour Force Survey data on the number of employed individuals during the study period across ANZSCO 4 digit occupational codes. Because the 457 data source is updated quarterly, and the HILDA survey is annual, data for quarter two of the year is used to avoid seasonality in 457 trends. Data from this quarter directly precedes the collection of HILDA data, which is collected in quarters 3 and 4. A robustness check where the analyses use 3rd quarter 457 data, which is when the majority of HILDA data collection occurs, is presented in the appendix, and the results are qualitatively similar.

Since the shift-share instruments are driven primarily by changes in source country distributions, the aggregated number of migrants from English[2] and Non-English speaking countries are presented in Figure 3.2. The figure does indicate a shift in the source country profile over the study period, primarily a relative increase in 457 migrants from Non-English speaking countries from 2013 onwards.

Figure 3.3 illustrates the number of 457 visa holders for the occupational subgroups with the ten highest utilisations of such visas over the study period. There is a large increase in food trade workers and hospitality managers, accompanied by smaller increases in ICT workers, and Business, HR, & Marketing professionals. The pattern is unclear for the remaining occupational groups.

Second, the analysis uses the HILDA longitudinal survey (Watson & Wooden, 2012). HILDA is a nationally representative longitudinal survey of youth and adults from more than 7,600 households, with an emphasis on employment, income, and family. The survey commenced in 2001, and the most recent publically available wave at the time of writing is wave 15 which corresponds to data from 2015. Because the 457 temporary migrant variable is only available from 2009, and the first year is reserved for the calculation of shift-share instrument, only waves from 2010-2015 were used for this analysis. The key variables used here are the log wage in the main occupation; employment status, and the occupation if employed.

[2]Canada, Ireland, The United Kingdom, The United States, New Zealand

Figure 3.2: 457 FLOWS FROM ENGLISH AND NON-ENGLISH SPEAKING COUNTRIES

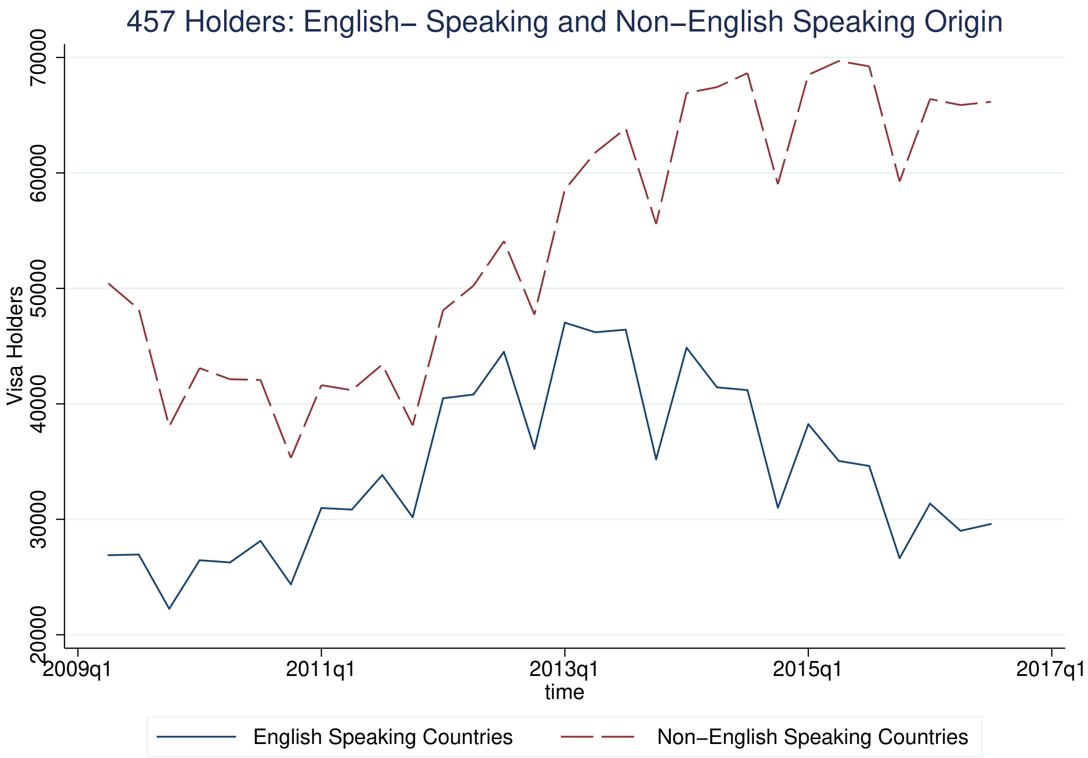
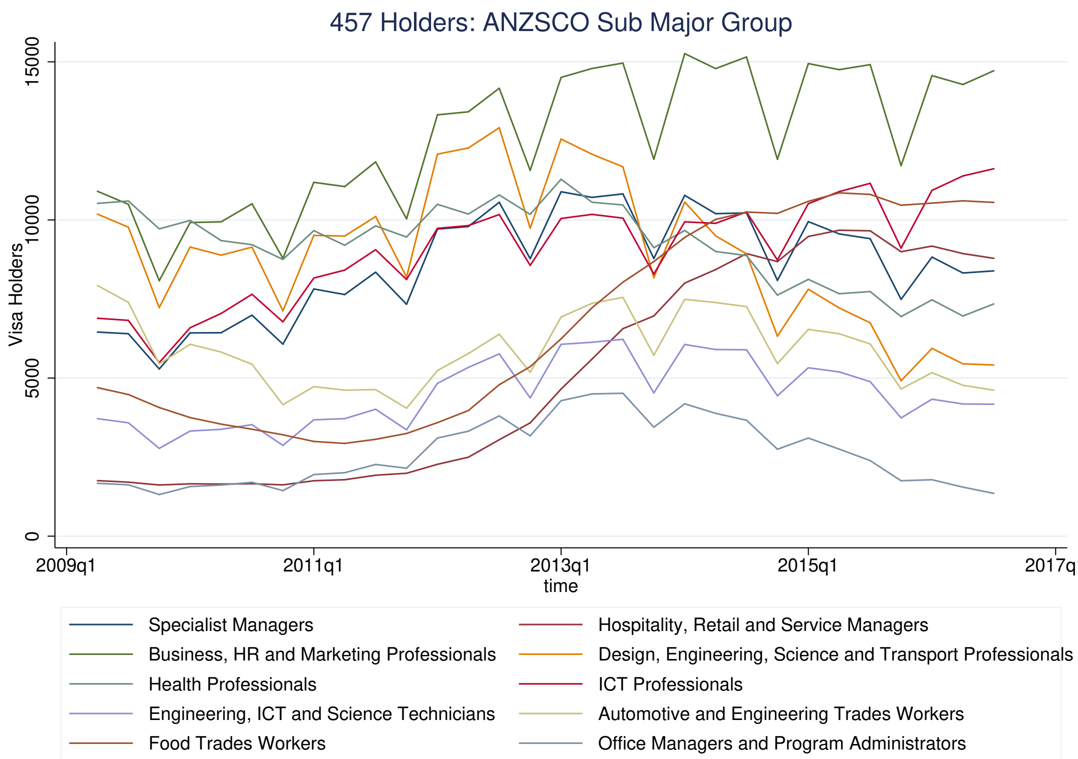


Figure 3.3: 457 HOLDERS WITHIN THE TEN OCCUPATION SUB-MAJOR GROUPS WITH HIGHEST UTILISATION



Last, the O*NET job characteristics data set is produced for the United States Department of Labor and measures the importance of over 52 abilities for occupations within a given US Standard Occupational Code (SOC). These include both physical (e.g. strength, coordination) and communicative (e.g. oral and written comprehension) abilities. The data is collected from occupational analysts and reflects current use of skills within occupations. The relative importance of both manual (m_o) and communication skills (c_o) for each occupational code was calculated using the construction described in Peri and Sparber (2009). The data was joined to ANZSCO codes using a crosswalk between US-SOC and ANZSCO 4 digit occupational codes. Because the available release of HILDA contains the broader 2 digit ANZSCO codes, the analysis uses the average manual and communication skill utilisation scores in each 2-digit ANZSCO cell. In the final dataset health professionals, CEOs, and legal professions have high communication scores, while cleaners and laundry workers have low communication scores. Similarly, construction workers were found to be the occupational class with the highest utilisation of manual skills while clerical workers had low manual skill utilisation scores. The final outcome is the ratio of communicative to manual tasks (c_o/m_o). Because the raw O*NET scores are arbitrarily scaled, they are rescaled using the number of workers in each ANZSCO 2 digit group according to the 2011 census to come up with the relative importance of communicative skills. For instance, Construction and Mining Labourers had a final c_o/m_o score of 2.27, indicative that 97.73 percent of Australian workers had a higher relative utilisation of communication skills. Similarly, Business, HR and Marketing Professionals had a c_o/m_o score of 93.1, indicating that only 6.82 percent of Australian workers have a higher relative utilisation of communication skills.

Descriptive statistics for key outcomes, demographic and location variables are presented in Table 3.1. As expected, workers with a bachelor's degree have higher wages and spend a smaller proportion of their time unemployed. Further, they have a greater relative communication skill utilisation compared to workers without a bachelor's degree.

Figure 3.4 plots the *means* of the three primary outcomes, the log of weekly wages (top left), percent time spent unemployed (top right) and relative communication skill utilisation (bottom) within each occupational (ANZSCO 2 digit) group against the average change in 457 utilisation across occupational groups (i.e. average m_{t-1} across 2010-2015). The size of each bubble corresponds the sample size for each occupation within HILDA and a trend line fit to the data is also shown. The first two panels illustrate the association of increases in 457 migration being linked to better labour market outcomes viz. higher wages, and lower unemployment. The graphs also indicate that changes in 457 flows have been higher in occupations with higher communicative skill utilisation. Such a relationship reflects the endogenous selection issue inherent in immigration studies, i.e. an increase of immigrant workers in a particular occupational market is positively correlated with its labour market outcomes.

In contrast, figure 3.5 plots aggregate *changes* in outcomes, the log of weekly wages (left) and percent time spent unemployed (right), within occupational groups across 2010-2015 against the change in 457 utilisation over the corresponding period in each ANZSCO 2 digit occupation (i.e. $\frac{457_{o,2015} - 457_{o,2010}}{E_{o,2010}}$). Communication skill utilisation is not shown because it is perfectly identified within each occupation. The trend line in each case is much flatter, showing a very small decline in weekly wages and a small increase in time spent unemployed[3]. Although only illustrative, it demonstrates the value of occupational and other fixed effects within the analysis

[3]These trends results are not statistically significant.

Table 3.1: HILDA SUMMARY STATISTICS; TOTAL AND BY EDUCATION

	(1) Total	(2) < Bachelors Degree	(3) ≥ Bachelors Degree
log(weekly wage)	6.94	6.82	7.16
	(0.70)	(0.68)	(0.69)
Per-cent time spent unemployed	4.06	4.80	2.42
	(16.51)	(18.14)	(11.96)
Relative communication skill utilisation	53.26	43.42	71.94
	(29.52)	(28.27)	(21.83)
Per-cent occupational 457 utilisation	0.95	0.73	1.34
	(1.05)	(0.99)	(1.04)
Per-cent Australian Born	73	75	70
	(44)	(43)	(46)
Per-cent Female	52	49	57
	(50)	(50)	(49)
Age	42.06	42.48	41.06
	(10.39)	(10.48)	(10.09)
Proportion of sample by state of residence			
Reference Category is New South Wales			
Victoria	0.25	0.23	0.29
	(0.43)	(0.42)	(0.45)
Queensland	0.21	0.23	0.17
	(0.41)	(0.42)	(0.37)
South Australia	0.09	0.09	0.07
	(0.28)	(0.29)	(0.25)
Western Australia	0.09	0.09	0.08
	(0.29)	(0.29)	(0.27)
Tasmania	0.03	0.03	0.02
	(0.17)	(0.18)	(0.15)
Northern Territory	0.01	0.01	0.01
	(0.09)	(0.09)	(0.10)
ACT	0.02	0.02	0.03
	(0.14)	(0.12)	(0.18)
Observations	63119	44441	18678

Figure 3.4: MEAN OUTCOMES AND AVERAGE CHANGE IN 457 UTILISATION ACROSS OCCUPATION GROUPS

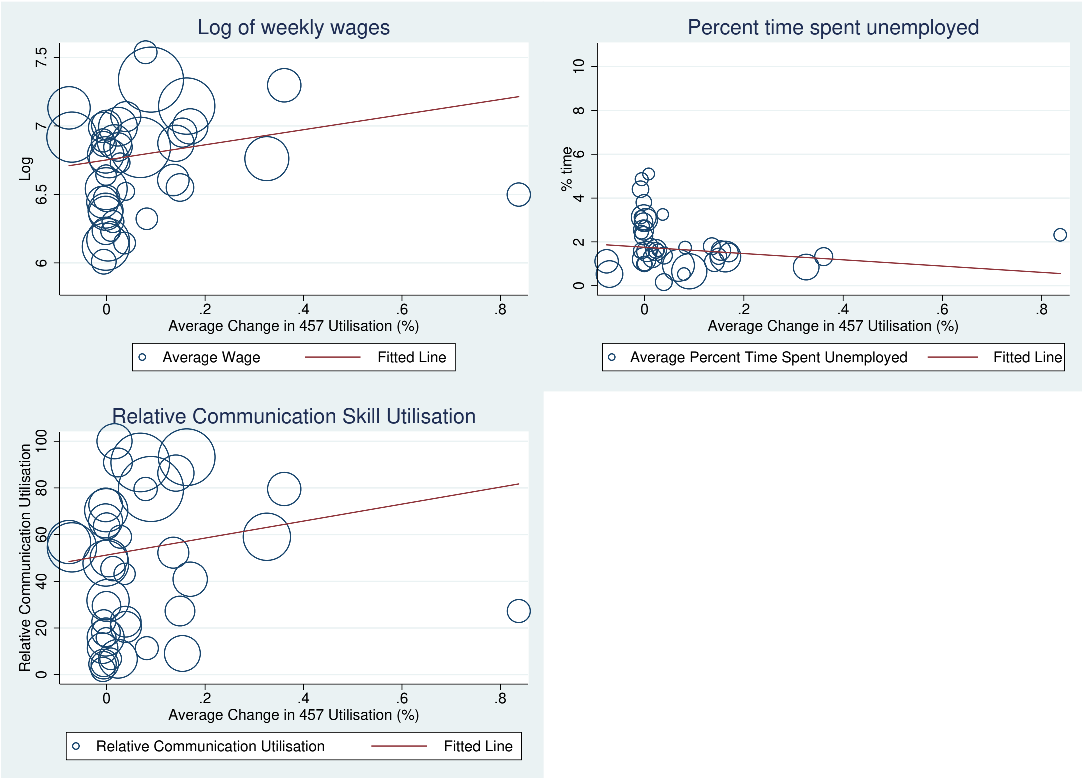


Figure 3.5: CHANGE IN OUTCOMES AND CHANGE IN 457 UTILISATION ACROSS OCCUPATION GROUPS (2010-2015)

3.6 Results

3.6.1 Effects on wage income

Table 3.2: LOG OF WEEKLY WAGES

	(1) No IV	(2) Shift Share	(3) No IV with lag	(4) Double Instrumentation
$m_{o,t}$	0.00915	0.00404	0.0239	0.0266
	(0.0129)	(0.0208)	(0.0163)	(0.0277)
$m_{o,t-1}$			-0.0234	-0.0152
			(0.0146)	(0.0223)
Controls	Yes	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes
Occupation Fixed effects.	Yes	Yes	Yes	Yes
Location Fixed effects.	Yes	Yes	Yes	Yes
IV First Stage F-statistics:				
$m_{o,t}$		2420.13		1230.89
$m_{o,t-1}$				2066.76
Observations	27379	27379	20853	20853

Cluster robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.2 presents the results of the estimation methodologies on the log of weekly wages. Column 1 presents the results of the methodology in equation 3.9, while column 2 uses the shift-share instrument for $m_{o,t}$. Column 3 presents the results of strategy with the lag $m_{o,t-1}$ in equation 3.12 *without instrumentation*, while Column 4 instruments both $m_{o,t}$ and $m_{o,t-1}$. F-statistics for the instruments are extremely high, indicative of high serial correlation in immigrant flows. Across estimators, results are not significant, although there is a positive effect of around 2.3 percent is noticeable for the estimates in column 3. These estimates also indicate a close-to-significant negative effect of around 2.33 percent for the lagged value $m_{o,t-1}$. Because the 457 program is demand-driven, demand shocks are likely to influence the estimates of both $m_{o,t}$ and $m_{o,t-1}$ without instrumentation. For instance, in one period high occupational demand will be associated with high 457 hiring, as well as higher wages. In the next period, a high value of $m_{o,t-1}$ compared to $m_{o,t}$ is associated with lower occupational demand and therefore lower wages. The results from column 3 are therefore consistent with the cyclical nature of the demand cycle. Last, the double instrumentation procedure produces a short-term impact estimate ($m_{o,t}$)that is more positive than the shift-share instrument in column 2, while having a more positive long-run adjustment ($m_{o,t-1}$) than those in column 3. Due to the low precision of the estimates above and the demand-driven nature of estimates in columns one and three, it is not possible to form a reliable inference on the causal impact of 457 migration on wages, although the overall impact is small across estimators.

The effect of 457 driven migration is likely to be heterogeneous with the education level of workers as the 457 policy is targetted towards occupations that require at least a Bachelors degree or equivalent qualifications. It is therefore important to check for differential effects between cohorts with a Bachelor's degree, and those without.

Table 3.3 presents results for the subset of HILDA who are university graduates. A strong positive effect of 457 migration on the wages of this cohort is noticeable in columns 1 and 2. Particularly, column 2 which uses a shift-share instrument predicts that the result of a one-percent increase of 457s in the occupational workforce increases wages by around 10 percent, although the estimates are only weakly significant, with a p value of 0.099. Although the estimates seem large, it is important to recognise that 457s are a small percentage of the overall workforce across occupations - for instance, only 3 percent of IT workers in Australia are on 457s. To increase by a further *one percent of the occupational workforce* the number of 457 visa holders will need to increase sharply, by around 33-100 percent for most occupations. The estimates in column 2 are somewhat comparable to Peri et al. (2015, S1) who study the effect of the demand-driven H1B program on the wages of native STEM workers in the United States, and find estimates of wage increases of between 4 to 9 percent for each percent increase of H1Bs in the overall workforce. Column 3 predicts an increase of wages by 6 percent, although the results are only weakly statistically significant. Lastly, the double instrumentation strategy, which is the preferred estimation strategy, finds imprecise increases of around 7 in the short run, while it presents a further estimate of 4 percent due to long-run adjustments respectively. Despite the lack of a significant result from the most demanding strategy, the results do not show negative effects of 457 migration on the education cohort most directly targeted by the program. The majority of results indicate weak significant positive results of 457 migration, although they correspond to large increases in 457 migration.

Table 3.3: Log of Weekly Wages; Bachelors Degree or above

	(1) No IV	(2) Shift Share	(3) No IV with lag	(4) Double Instrumentation
$m_{o,t}$	0.0640**	0.105*	0.0606*	0.0664
	(0.0273)	(0.0619)	(0.0349)	(0.0625)
$m_{o,t-1}$			-0.00559	0.0454
			(0.0280)	(0.0476)
Controls	Yes	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes
Occupation Fixed effects.	Yes	Yes	Yes	Yes
Location Fixed effects.	Yes	Yes	Yes	Yes
IV First Stage F-statistics:				
$m_{o,t}$		492.06		419.03
$m_{o,t-1}$				862.10
Observations	10264	10264	8017	8017

Cluster robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.4: log of weekly wages; education less than Bachelors degree

	(1) No IV	(2) Shift Share	(3) No IV with lag	(4) Double Instrumentation
$m_{o,t}$	-0.0202	-0.0301	-0.0112	-0.0243
	(0.0149)	(0.0198)	(0.0181)	(0.0276)
$m_{o,t-1}$			-0.0182	-0.00854
			(0.0177)	(0.0250)
Controls	Yes	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes
Occupation Fixed effects.	Yes	Yes	Yes	Yes
Location Fixed effects.	Yes	Yes	Yes	Yes
IV First Stage F-statistics:				
$m_{o,t}$		1839.34		652.34
$m_{o,t-1}$				1300.78
Observations	17028	17028	12772	12772

Cluster robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.4 presents the results of 457 linked migration for those with an education level less than a Bachelor's degree. The results are highly imprecise across the four estimators and indicate a negative effect. As noted in Aydemir and Borjas (2011), it is possible that these results may be attenuated due to relatively small sample frame within occupational cells compared to the entire workforce. However, the largest survey of the Australian population, the Census, reports weekly wages in intervals making it unlikely that significant results could be obtained using larger datasets. Despite this, it is clear that the effect of 457 migration on wages is more positive for workers with a bachelor's degree or above than those without.

3.6.2 Effect on percent time unemployed

The analyses now look at the effect of 457 migration on participation for affected workers in the labour market. The outcome is now the percentage of time in the survey year spent unemployed. Using occupation groups identified by contemporaneous employment at the time of survey completion will bias the results of the estimates, so the estimators in equations 3.10 and 3.13 are used to perform the analysis.

The results in table 3.5 indicate both positive and negative imprecise effects on time spent unemployed in the short run ($m_{o,t-1}$) throughout estimators 1 to 4. The estimates are between 0.3 percent more and 0.25 percent less time unemployed in the next period following a one percent increase in 457s as a proportion of the occupational workforce. Estimates in both column 1 and 3 do not use instrumental variables and are therefore likely to be biased by occupational demand factors, similar to the wage results presented above. Again, while column 3 presents a non-significant decrease of time spent in unemployment by 0.2 percent in the short run, this is accompanied by an insignificant long run *increase* in time spent unemployed of around 0.08 percent. Column 4, which uses the double instrumentation strategy, also has non-significant estimates, indicating that the result is -0.25 and -0.5 percent less time spent unemployed in the short and long run respectively.

This paper also studies the heterogeneity of 457 migration across the two educational groups, and table 3.6 presents the results across estimation strategies for workers with a bachelor's degree or above, and no statistically significant effect is observed. Particularly, coefficient sizes are small but positive, varying between around 0.8 and .01 percent and the standard errors are large.

In comparison Table 3.7 presents the results for the four estimating strategies for workers without a bachelor's degree. All estimates are again imprecise. Overall, it highlights that no statistical effect of 457 migration on unemployment in the next period is observed for either cohort.

Table 3.5: PER CENT TIME UNEMPLOYED

	(1)	(2)	(3)	(4)
	No IV	Shift Share	No IV with lag	Double Instrumentation
$m_{o,t-1}$	0.311	0.396	-0.185	-0.250
	(0.258)	(0.391)	(0.343)	(0.448)
$m_{o,t-2}$			0.0825	-0.504
			(0.438)	(0.642)
Controls	Yes	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes
Lagged Occupation Fixed effects.	Yes	Yes	Yes	Yes
Location Fixed effects.	Yes	Yes	Yes	Yes
IV First Stage F-statistics:				
$m_{o,t-1}$		2450.84		2558.79
$m_{o,t-2}$				1039.86
Observations	25224	25224	17738	17738

Cluster robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.6: Per cent time unemployed; Bachelors Degree or above

	(1) No IV	(2) Shift Share	(3) No IV with lag	(4) Double Instrumentation
$m_{o,t-1}$	0.0161	0.764	0.170	0.255
	(0.364)	(0.728)	(0.422)	(0.554)
$m_{o,t-2}$			0.263	0.483
			(0.599)	(1.287)
Controls	Yes	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes
Lagged Occupation Fixed effects.	Yes	Yes	Yes	Yes
Location Fixed effects.	Yes	Yes	Yes	Yes
IV First Stage F-statistics:				
$m_{o,t-1}$		483.51		929.39
$m_{o,t-2}$				269.15
Observations	9268	9268	6672	6672

Cluster robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.7: Per cent time unemployed; Education less than Bachelors degree

	(1) No IV	(2) Shift Share	(3) No IV with lag	(4) Double Instrumentation
$m_{o,t-1}$	0.484	0.175	-0.358	-1.180
	(0.358)	(0.513)	(0.517)	(0.729)
$m_{o,t-2}$			0.0503	-0.305
			(0.558)	(0.734)
Controls	Yes	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes
Lagged Occupation Fixed effects.	Yes	Yes	Yes	Yes
Location Fixed effects.	Yes	Yes	Yes	Yes
IV First Stage F-statistics:				
$m_{o,t-1}$		2093.70		1269.79
$m_{o,t-2}$				971.04
Observations	15890	15890	11011	11011

Cluster robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.6.3 Effects on skill specialisation

The results indicate weakly significant positive to null changes in labour market outcomes for the Australian population. This is contrary to simple supply-demand models which predict negative consequences, at least in the short run. It is, therefore, necessary to analyse the effect of mitigating factors, such as the increased specialisation of Australian workers. Using the relative communication utilisation scores that were constructed, the analyses now look at the effect of 457 migrants on inducing the specialisation of workers in communicative tasks. Since these scores are time-invariant by construction, these estimates are identified by occupational switching and the methodology in equations 3.10 and 3.13 is used because controlling for the contemporaneous occupation will perfectly identify the estimates. The estimates in this section essentially look at the result of 457 migration on inducing skill specialisation, measured through the ratio of communication to manual utilisation scores. As explained in the data section, these scores are scaled to the Australian workforce in the 2011 Census.

Table 3.8 shows the effect of 457 migration across the HILDA sample of Australian workers. Estimates in column 1 and 3, which are endogenous with respect to unobserved occupational demand, present increases of between 1 and 1.5 points. Column 2 which includes a single shift-share instrument indicates an increase of 1.8 points in the scaled communication to manual ratios for workers. Notably, column 4 which uses the preferred double instrumentation strategy respectively indicates that a one-per-cent increase of 457 temporary workers in the workforce induces an increase of 4.8 percent in relative communication skill utilisation compared to the Australian workforce in 2011. This estimate is also highly significant.

Tables 3.9 presents estimates when the cohort is restricted to workers with a bachelor's degree. The estimates produced are imprecise in the columns without instruments, although the results are positive across specifications. Particularly, column 2 which uses shift-share instruments predicts a highly significant inducement of specialisation in communicative skills, with affected workers increasing their relative communication skill utilisation scores by around 4.6 percent. Column 4, which uses the double instrumentation strategy presents a short-run casual impact of 3 points, and a continuing weakly significant increase of 4.9 percent compared to the 2011 Australian workforce in the long run.

In contrast, Table 3.10 presents the results for workers without a bachelor's degree. Results are positive with the ratio of communicative to manual skills increasing by between 0.5 and 5.5 percentile points in the short run as a result of 457 migration. Almost all estimates are not significant, but our preferred double instrumentation approach produces results significant at the 1% level. The analyses above indicate that 457 migrants have a more positive effect on the cohort with a bachelor's degree compared to those without. As such, these results indicate the weakly significant increase in wages is associated with the more educated cohort specialising in communication skills across the short and long run; Additionally, it explains why results are null across specifications. Summarily, these results highlight an important channel for the findings concerning labour market outcomes. The imperfect substitution of migrants in the Australian workforce induces changes in the relative valuation of communicative skills, which increases wages for incumbents.

Table 3.8: RELATIVE COMMUNICATION TO MANUAL SKILLS

	(1) No IV	(2) Shift Share	(3) No IV with lag	(4) Double Instrumentation
$m_{o,t-1}$	1.028*	1.853**	1.573**	4.764***
	(0.548)	(0.822)	(0.700)	(1.018)
$m_{o,t-2}$			0.663	0.890
			(0.757)	(1.179)
Controls	Yes	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes
Lagged Occupation Fixed effects.	Yes	Yes	Yes	Yes
Location Fixed effects.	Yes	Yes	Yes	Yes
IV First Stage F-statistics:				
$m_{o,t-1}$		2257.79		2406.72
$m_{o,t-2}$				913.47
Observations	23490	23490	16428	16428

Cluster robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.9: RELATIVE COMMUNICATION TO MANUAL SKILLS; BACHELORS DEGREE OR ABOVE

	(1) No IV	(2) Shift Share	(3) No IV with lag	(4) Double Instrumentation
$m_{o,t-1}$	1.516*	4.586***	1.173	3.168**
	(0.910)	(1.769)	(1.008)	(1.471)
$m_{o,t-2}$			1.569	4.915*
			(1.321)	(2.850)
Controls	Yes	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes
Lagged Occupation Fixed effects.	Yes	Yes	Yes	Yes
Location Fixed effects.	Yes	Yes	Yes	Yes
IV First Stage F-statistics:				
$m_{o,t-1}$		483.51		929.38
$m_{o,t-2}$				269.15
Observations	8698	8698	6264	6264

Cluster robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.10: RELATIVE COMMUNICATION TO MANUAL SKILLS; EDUCATION LESS THAN BACHELORS DEGREE

	(1) No IV	(2) Shift Share	(3) No IV with lag	(4) Double Instrumentation
$m_{o,t-1}$	0.523	0.816	1.468	5.404***
	(0.711)	(0.998)	(1.021)	(1.547)
$m_{o,t-2}$			0.484	-0.157
			(0.957)	(1.332)
Controls	Yes	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes
Lagged Occupation Fixed effects.	Yes	Yes	Yes	Yes
Location Fixed effects.	Yes	Yes	Yes	Yes
IV First Stage F-statistics:				
$m_{o,t-1}$		1913.04		1189.93
$m_{o,t-2}$				844.71
Observations	14738	14738	10119	10119

Cluster robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.7 Conclusion

This chapter contributes to the small literature focussing on temporary migrants, and particularly skilled temporary migration. Its analyses indicate that although the overall labour market (wages and unemployment) effect of such migration on Australian workers is null. However, the results find statistical evidence of a positive association of around 6 to 10 percent increase in wages for bachelor's degree holders who face a one percent increase in the 457 occupational workforce, compared to bachelor's degree holders who do not. These results are robust to most specifications, although they lose statistical significance with the most demanding double instrumentation strategy. It is again important to re-iterate that these results are relatively small, given that they require large increases in overall 457 migration. This chapter also further examines mechanisms that may be responsible for these results and finds that 457 temporary migration is inducing Australian workers to switch to positions requiring a greater utilisation of communication abilities, rather than manual abilities. As such, these results support the Peri and Sparber (2009) and G. I. P. Ottaviano et al. (2013) hypothesis of imperfect substitutability of immigrants.

The impact of immigration is determined extensively by the labour market context and the skill profile of immigrants within a particular country. Caution is advised with regards to the validity of these results outside the Australian context of skilled temporary migrants. Despite this, this study's results are concordant with the results of a number of studies which highlight that the effect of high skilled migration is more positive than that of low skilled migration. Particularly, the estimates of a 6 to 10 percent increase in wages for workers with bachelor's degrees are similar those of the Peri et al. (2015, S1) study of temporary H1B visa driven high skilled migration in the United States. Such results hint at complementarities between skilled native and immigrant workers, and present directions for future research.

This study also does not examine the role of mechanisms inherent in the 457 (and other) temporary worker programs - they are designed to resolve skill shortages, are market tested, and restrict both the bargaining power and mobility of sponsored workers. These may offer additional mechanisms e.g. the higher occupational mobility of native workers, through which they may be able to obtain better labour market outcomes. Further work is therefore also required to analyse the effect of these mechanisms.

In conclusion, temporary migration is becoming increasingly important to developed countries such as the EU, Canada, the United States, Australia, and New Zealand in their quest to resolve local workforce shortages. This paper contributes to the much needed limited empirical evidence around both temporary and skilled migration that is needed for the economic and social implications of such policies to become clearer. ‘

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Chapter 4

The Effect of Coercing International Medical Graduates on the Rural Medical Workforce

Abstract

Empirical evidence on policies aimed at resolving rural workforce shortages is sparse. This paper studies the impact of the Districts of Workforce Shortage program, which restricts International Medical Graduates (IMGs) to work in under-served rural and remote areas of Australia. Using a difference-in-difference-in-differences design on panel datasets of the Australian doctor workforce, the results indicate that the program is effective at reducing the growth of GP inequality in newly affected regions. These changes in the workforce are accompanied by a fall in the number of patients seen by affected GPs and the number of hours worked per week. However, there is no robust evidence of a corresponding fall in standard consultation fees or increase in bulk-billing rates. Lastly, the analysis finds suggestive evidence that the fall in workload, and particularly the fall in hours worked, is higher for IMGs.

This research used data from the MABEL longitudinal survey of doctors conducted by the University of Melbourne and Monash University (the MABEL research team). Funding for MABEL comes from the National Health and Medical Research Council (Health Services Research Grant: 2008-2011; and Centre for Research Excellence in Medical Workforce Dynamics: 2012-2017) with additional support from the Department of Health (in 2008) and Health Workforce Australia (in 2013). The MABEL research team bears no responsibility for how the data has been analysed, used or summarised in this research.

4.1 Introduction

Most countries face health-care workforce inequalities in rural and remote areas compared to their urban regions. In Australia for instance, major cities have 95.4 FSE[1] GPs per 100,000 population compared to 85.7 and 67.6 FSE GPs in outer regional and remote areas (Productivity Commission, 2016). These inequalities in the rural workforce distribution play an important role in causing large gaps in health-care outcomes between urban and rural populations. The rate of preventable hospitalisations, a key indicator of access to primary care, is around 70 per 100,000 population in remote areas of Australia, compared to around 30 per 100,000 population in major cities (Katterl, 2012). Similarly, Australians in remote and very remote areas face mortality rates 40 percent higher than those in inner cities. Similar patterns have been extensively noted in China (Wang, Wang, Zhou, Wang & Xu, 2013), the United States (Hartley, 2004), the European Union (E. A. Richardson, Pearce, Mitchell, Shortt & Tunstall, 2014), and the United Kingdom (Ellis & Fry, 2010).

Countries use a number of policies to improve primary health access in such communities. One important strategy is the use of financial incentives for GPs who practice in rural areas. For instance, Australia offers the General Practice Rural Incentive Program which offers up to 60,000 AUD for doctors in the most remote areas of Australia (DoHS, 2017). Another key policy includes the use of non-financial incentives or coercive approaches, where directive measures are taken by governments to channel GPs to rural areas. Such measures can take many forms - for instance, billing numbers are used to restrict where new GPs can practice. Similarly, rural placement policies focus on training new GPs in rural areas. Last, international medical graduates (IMGs) are used to fill gaps in the rural health workforce. This is particularly advantageous because recruitment of IMGs circumvents the long training pipeline involved in increasing the domestic production of medical graduates. The use of IMGs is more prevalent in countries that have higher migration, and particularly those reliant on skilled migrants. The WHO (2010) noted that foreign-trained doctors comprised around 25 percent of the GP workforce in the United States; 35 percent in the United Kingdom, Ireland, & Australia; and 45 percent in New Zealand.

Despite these numerous approaches aimed at reducing healthcare workforce inequal-

[1] Full Service Equivalent, a measure of both GP headcount and utilisation

ity, there exists a lack of evidence around their effectiveness in attracting and retaining a sustainable rural workforce. Systematic reviews such as Wakerman et al. (2008) identify that most papers do not represent "rigorous and comprehensive evaluations but rather a preponderance of largely descriptive studies". While there have been a number of studies looking at the impact of rural background and placement on overcoming these shortcomings (Wilkinson, Laven, Pratt & Beilby, 2003), (McGrail, Humphreys & Joyce, 2011), these play only one role in an effective framework for decreasing primary care maldistribution. Secondly, despite the large role of IMGs in resolving such maldistribution, considerable debate exists on their impact often with little to no evidence. For instance, Birrell (2013) and the Rural Doctors Association of Australia (Borrello, 2016) argue that IMGs are not culturally equipped and fail to solve skill shortages that exist in rural and remote areas.

This paper presents a systematic evaluation of the Districts of Workforce Shortage (DWS) program, a coercive policy that restricts new IMGs to work in under-served areas of Australia. This is primarily through restricting IMGs and Foreign Graduates of Accredited Medical Schools (FGAMSs) to a five-to-ten year moratorium which confines access to Medicare provider number for such GPs. Medicare is Australia's public insurer and the predominant source of expenditure for primary care services (AIHW, 2016). The DWS policy is, therefore, a strong non-financial incentive for IMG GPs to move to affected areas. DWSs are assessed regularly by the Australian Department of Health (they were determined quarterly in the time frame of this study) by assessing geographical areas that have lower access to medical services than the national average, based on Medicare billing statistics.

Using panel datasets and the variation in DWS designations over time, this paper analyses the effect of the program using an event study with a difference-in-difference-in-differences design. It does so for three sets of outcomes. Firstly, using the Australian Medical Publishing Company's (AMPCo) Medical Directory of Australia, it analyses the effect of the DWS program on the number of GPs in DWS areas relative to non-DWS areas. By doing so, the analysis establishes the *mechanism* of action to analyse follow-on outcomes of the DWS program.

Second, given that this chapter's findings establish the mechanism of action for the DWS program, the paper analyses the effect of the resulting increase in GP supply and therefore workforce competition, on a number of market outcomes using MABEL, a large representative survey of medical practitioners in Australia. These include measures of workload - the number of hours worked and patients seen. Falls in workload are linked to both increased professional satisfaction and workforce retention and are particularly important because rural doctors work longer hours than those in cities (McGrail, Humphreys, Joyce, Scott & Kalb, 2012). This chapter also studies changes in measures of prices, both the fee charged for a standard consultation and the percent of patients bulk billed (i.e. billed directly to the public insurer). These outcomes are the primary determinants of both access to primary care, and patient and government medical expenditure, given the relative inelasticity of demand for medical services (J. R. J. Richardson, Peacock & Mortimer, 2006).

Third, exploiting the fact that DWSs act primarily through coercing overseas GPs, the essay examines if a differential effect exists in workforce outcomes between native and IMG GPs. Models of medical workforce competition in the market for GP services often assume the GP workforce to be homogeneous (e.g. Gravelle, Scott, Sivey and Yong (2016)), which is at odds with a growing consensus within the immigration literature that immigrants and natives are imperfect substitutes for each other. If such imperfect substitutability exists, the impact of adding additional IMGs to an area's workforce should be higher on recent immigrants than native workers A common issue with such studies is that migration is influenced by native employment opportunities, which biases the estimated effects. This study relies on the variation in DWS areas across time for identification, which helps overcome such biases.

The contribution of this chapter is twofold. First, it advances the literature in an important field of the health economics, i.e. the analysis of medical workforce shortage policy. An evaluation of DWS allows us to make policy recommendations with regards to healthcare inequity in Australia. Many countries face shortages of GPs in rural areas, and evidence on the DWS program is therefore useful in designing and improving health workforce policy in comparable health care systems. Importantly, this work also analyses the competitive impact of the policy on workforce outcomes and identifies differential impacts, if any, of the policy. This advances a small literature on medical competition, particularly given the large proportion of IMGs in most developed countries.

The results indicate that the DWS program has a positive effect on the number of GPs in an area. An additional 0.35 GPs arrive each year in a treated SLA. Moreover, the majority of this effect is due to an increase in IMG GPs. The findings also highlight large pre-existing trends of increases in GP inequity between DWS and the comparison group, which points to an urgent need for more effective policies that reduce GP inequity, particularly for native GPs. The results also indicate caution with regards to policy shifts by the Commonwealth Department of Health, which has asked for medical occupations to be removed from the Skilled Occupation List.[2]. The presence of an occupation on skilled occupation lists is necessary for skilled migration to Australia, and these changes are likely to increase healthcare inequity in the absence of other policies aimed at domestic medical graduates.

The results of the analysis on the competitive effect of increased GP supply are compared to a spatial oligopoly theoretical model of the GP workforce proposed by Gravelle et al. (2016). According to this model, an increase in the number of doctors results in prices and workload declining due to the resulting competition. The findings of this chapter support the competitive effect with regards to workload, with GPs seeing 2.6 fewer patients and working 0.6 fewer hours a week every year DWS is turned on. However, the analysis fails to find robust evidence of a competitive effect with regards to a GP level change in prices. However, there is weak evidence of an area level drop in average fees charged. This could be due to the compositional changes in the workforce, and because IMGs charge lower fees compared to native doctors.

Last, the results provide suggestive, but not conclusive, evidence that the fall in workload is higher for IMGs rather than native doctors. Particularly, IMGs work 1.6 fewer hours per week every year the DWS program is turned on, while natively trained doctors do not see a statistically or economically significant fall in hours. This heterogeneity may be suggestive of differential changes in time use for native and IMG doctors, including spending time on practice management, offering longer consultations, or being able to induce more demand than IMGs. Given the large importance of IMGs in the healthcare systems of most developed countries, I highlight the need for further research in this area.

The remainder of the paper is organised as follows: Section 2 outlines the institutional context for the provision of primary health in Australia, while section 3 reviews the conceptual framework. Section 4 presents the empirical methodology, and Section 5 summarises key data sources and statistics. Section 6 discusses the results. Lastly, the

[2]http://www.abc.net.au/news/2016-08-09/calls-to-stop-giving-overseas-trained-doctors-visas/7706612

chapter concludes.

4.2 Institutional Context: Primary care in Australia

General Practitioners act as gatekeepers in delivering specialist care in Australia and provide the most commonly used primary health service in Australia. They typically work in private practices with a variety of ownership structures, and patients are free to see any GP of their choosing. Medicare Australia, the Australian universal health scheme, subsidises services provided by GPs. These subsidies are increasing in the length and complexity of a consultation. Furthermore, GPs can either choose to bill patients at the Medicare rate, i.e. bulk-bill their patients or charge a fee above the subsidy, in which case the patients covers the difference between the GP's fee and Medicare subsidy. Medicare is the principal source of expenditure for referred and unreferred primary care medical services, spending 91 percent of the total 22.3 bn AUD spent on these services in 2014-15 (AIHW, 2016).

Driven by an increasingly unequal distribution of general practitioners in Australia (Johnston and Wilkinson, 2001; Mason, 2013), the Commonwealth government of Australia put into force a number of measures to make access to healthcare more equitable. GPs receive an additional subsidy of $8.75 ($5 before 2010) if they bulk-bill children under 16 or concession card holders. Additionally, a variety of grants and incentives are available to GPs working in rural and remote locations. These also include additional subsidies for patients in designated rural and metropolitan areas. Additionally, grants are available under the Practice Incentive Program which provides incentives for treating chronic conditions such as asthma and diabetes, as well as for treating indigenous and aged people. Payments with higher loadings for rural and remote locations are also provided under the Practice Nurse Incentive Program, which aims to promote an expanded role for nurses in general practice.

To compel IMGs to work in under-served areas of Australia, the Districts of Workforce Shortage (DWS) program was legislated in 2001 and enforced from 2004. A District of Workforce Shortage is a geographical area in which the local population has less access to Medicare-subsidised medical services when compared to the national average. These areas were defined each quarter during the period of study using Medicare Australia billing data and Australian Bureau of Statistics population data. DWS specifically targets Overseas Trained Doctors (OTDs), i.e. IMGs who complete medical schooling in a medical school outside Australia, and foreign graduates of an accredited medical school (FGAMSs), i.e. IMGs who complete medical schooling in Australia. Furthermore, DWS acts as a coercive policy by restricting IMGs through Section 19AB of the *Health Insurance Act 1973*. Section 19AB restricts such OTDs and FGAMs from obtaining access to Medicare benefits and provider numbers unless they work in DWS areas for up to 10 years from their first Australia medical registration to access Medicare benefits arrangements. Until 2015, DWS classifications for general practice were calculated on the statistical local area 2004 (SLA) designations derived by the Australian Bureau of Statistics on a quarterly basis. Post-2015, DWS classifications were calculated on the Statistical Area 2 2011 (SA2) designation on a yearly basis. Due to this change in determining designations, the analysis is restricted to the period before 2015 where data is available, i.e. 2008-2014.

Because GP services are primarily funded through Medicare, blocking access to Medicare provider numbers for OTDs and FGAMs restricts their ability to access the market for primary care services. Consequently, designating an SLA as a DWS area allows much greater access to the primary care services market in that area, and new IMGs are provided with an incentive to move to such areas. Consequently, DWS causes a higher proportion of overseas trained GPs to practice in rural and remote areas compared their native counterparts.

4.3 Conceptual Framework

The DWS program primarily functions to increase the number of GPs in an area, particularly through restricting IMG and FGAMSs to work in only DWS areas. As such, the entry of alternate providers should have an impact on both prices, i.e. fees and bulk billing rates; and workload, i.e. hours worked, and patients seen. The literature on the competitive effect of such an entry of GPs remains sparse (Gaynor & Town, 2011). However, most theoretical models assume GP markets to be monopolistically competitive as they posit that GP markets have a large number of sellers who sell slightly differentiated services and entry into a local market is relatively easy. Wong (1996) formally conducted an empirical test of the market structure of GP services and found that the monopolistic competition model fits empirical data better than the competing hypothesis of monopoly, perfect competition, or monopolistic competition with consumer information asymmetry. Gunning and Sickles (2013) also concludes that US GPs have significant market power.

However, recent studies have taken into consideration that the cost of entry may be larger than previously assumed, and that geographic markets may be fairly limited, and that buyers who wish to use GP services may have fewer sellers than it may appear. Lastly, the monopsony of large insurance or public health networks, as is the case of Medicare in Australia, may skew outcomes from monopolistic competition. For instance, Gravelle et al. (2016)'s spatial oligopoly model allows for homogeneous GPs in a Vickrey Salop model of monopolistic competition, where GPs compete in both price and workload measures. It also allows for a monopsony insurer and for GPs to charge a price above that provided by the insurer, or bulk-billing. The model predicts a fall in prices (decrease in fees and increase in bulk billing rates) and decreases in workload (both patients seen and hours worked) as a new GP enters. They also empirically determine the impact of GP distances using cross-sectional MABEL data and find that areas with a more distant GPs competitors charge higher prices and see fewer patients per week.

A number of factors may affect these competitive results. For example, Gravelle et al. (2016) outlines that the quality of care for a given patient may be endogenously determined by the competition for healthcare services in the area. If patients have a marginal valuation for quality and pay for their services, there is an increase in quality which moderates the competitive fall in prices. However, their empirical tests fail to find a statistically significant increase in quality, as measured by consultation lengths, as a result of increasing physician density in a geographic market. Similarly, switching costs, such as patient loyalty to existing providers, may undermine the price lowering effect of increasing competition (Klemperer, 1995).

An important assumption in the existing literature in this field is that GPs are homogeneous. The contemporary immigration literature recognises the imperfect substitutability (Manacorda, Manning and Wadsworth (2012); Ottaviano and Peri (2005)) and differences in skill endowments (Peri & Sparber, 2009) of native and immigrant workers. Due to such imperfect substitution, the entry of IMG GPs into the workforce should have a greater effect on previous IMGs compared to native GPs. Secondly, differences in skill endowments between natives and IMGs may cause native workers to change their output mix in a way that reduces the impact of increased GP supply. MABEL data allows the identification of both cohorts and the analysis tests for such differential impacts as a result of the DWS program.

4.4 Empirical Methodology

Participation in the DWS program is endogenous with regards to the GP workforce outcomes in each SLA - only areas with Medicare Billing Statistics below the average are chosen to be a DWS in any given period. Although controlling for these billing statistics would remove the endogeneity, they are not released at the SLA level to researchers due to potential privacy concerns (Mazumdar, Konings, Butler & McRae, 2013). The analyses, therefore, exploit the differential selection of areas into the DWS program, using difference-in-differences estimators to analyse the impact of DWS on GPs. For illustration, the simplest DiD estimator is:

$$Y_{at} = \alpha_1 + \alpha_2 Treatment_a + \alpha_3 Post_t + \alpha_4 Treatment \times Post_{at} + \varepsilon \tag{4.1}$$

Where, $Treatment_a$ is a dummy if the observation in area a is in the treatment group, which controls for level differences between the treatment and control group; $Post_t$ is a dummy for a period t that is post-treatment. The coefficient of interest is then α_4, the mean difference in outcomes between treatment and control groups after the policy is introduced. DiD strategies perform a before-after comparison of the treated units, while control groups help eliminate economy-wide factors from the estimator.

The identifying assumption of the DiD strategy is the parallel-trends assumption, which implies that the change in the comparison group over time represents the counterfactual change in the treatment group if there was no treatment. A DiD study also requires data from a minimum of two time periods - at least one pre-intervention, and another post-intervention. Given these requirements, the analysis focusses on SLAs that have turned on at least once in in 2008-2014 as the treatment group. Correspondingly, non-treated SLAs that have never had DWS turned on act as the comparison group. Regions that have DWS turned on before the study period (2008) cannot be used to identify the effect of the program, and are excluded from the study. Also, because all SLAs were evaluated quarterly *throughout* the study period, different SLAs may be at various stages with regards to their participation in the DWS program in any given year. To illustrate, in a given year some SLAs may just have had DWS introduced, whereas others may have had DWS turned on a year, two years, three years, or longer. The analysis therefore groups control SLAs using event time, τ. For instance, event time $\tau = -5$ means an SLA will turn on the DWS program five years from the year of observation. Similarly, event time $\tau = 0$ represents SLAs that had the DWS program turned on in the corresponding year of observation. Event time $\tau = 2$ means a given SLA has had DWS turned on for two years in the year of observation. Given the above discussion, the DiD estimator for the event-study is:

$$Y_{at} = \alpha + \mu_t + \gamma_a + \pi_1(1(DWS)_{at}) + \pi_2(\tau \times 1(DWS)_{a\tau}) + \beta X_{at} + \epsilon_{at} \tag{4.2}$$

Where Y_{at} is one of the outcome variables - the total number of GPs, the number of IMG GPs; and measures of labour market outcomes in an SLA a in year t. The SLA fixed effects, γ_a, control for all permanent unobserved determinants of outcomes across SLAs. These fixed effects absorb the coefficient on $Treatment_a$ mentioned above. The inclusion of year fixed effects, μ_t, non-parametrically adjusts for national trends in the outcomes. Year fixed effects absorb the coefficient on $Post_t$ above. $1(DWS)_{a\tau}$ is a dummy variable equalling one if the DWS policy is in force in area a in year t, i.e. the policy is turned on. It estimates the average *mean-shift* in outcomes caused by the DWS policy once it is turned on. Next, $\tau \times 1(DWS)_{a\tau}$ is a set of dummy variables equalling 1 if the DWS policy has been turned on for τ years in an area a. The DWS program is likely to take time for an effect because IMG GPs are required to move to affected SLAs, and this parameter allows the analysis to capture the *trend-shift* involved with such time-variant effects. X_{at} is a vector of controls such as population density, median income, and the median age in each SLA to better adjust for differential rates of changes in the outcomes.

In the presence of more than two time periods, as is the case with this study, a difference-in-difference-in-differences (DDD) estimator can also be used. Such a model controls for pre-existing differences in trends between treatment and control groups. The DDD estimator effectively relaxes the parallel-trends assumption of DiD estimators and instead uses the weaker parallel-growths assumption i.e. a deviation from the trend identifies the impact of the program. This is effectively a parallel trends assumption in first differences (Friedman, 2013). Due to their weaker identifying restrictions than DiD models, DDD coefficients are more robust, and therefore the preferred specification for the analysis. The DDD estimator is:

$$Y_{at} = \alpha + \mu_t + \gamma_a + \pi_0 \tau_{at} + \pi_1(1(DWS)_{at}) + \pi_2(\tau \times 1(DWS)_{a\tau}) + \beta X_{at} + \epsilon_{at} \quad (4.3)$$

This equation adds an additional control for τ_{at}, which is a vector of event time dummies before and after the policy was implemented. Given that differences in pre-existing trends between treatment and comparison groups are a major source of endogeneity for the DWS program, this further allows for the control of pre-existing trends and some time-varying endogeneity that may exist in event time τ.

The results from equations 4.2 and 4.3 are supplemented by a visualisation of trends in the outcome variables using the following non-parametric estimator, as used in Greenstone and Hanna (2014):

$$Y_{at} = \alpha + \mu_{\mathbf{t}} + \gamma_{\mathbf{a}} + \sum_{\tau} \sigma_\tau D_{\tau,at} + \beta X_{at} + \epsilon_{at} \quad (4.4)$$

Where the vector $D_{\tau,at}$ is composed of a separate indicator value for each of the years before and after the DWS policy is in the force. τ is normalised to zero in the year the DWS policy is first enacted and ranges from -5 to 5. All τ's are set to zero for the comparison group and the comparison group observations aid in the identification of year effects and βs. The parameter of interest is the vector σ_τ, which measures the average of each outcome in the years before and after the DWS policy's implementation. The variation in timing of the adoption of the DWS policy allows for separate identification of the last two parameters accurately. The estimated σ_τ vector is plotted against the τs along with the estimates.

The results of the DiD and DDD estimators used in this study are nested within this nonparametric visualisation. Since both (DiD and DDD) place assumptions on either the

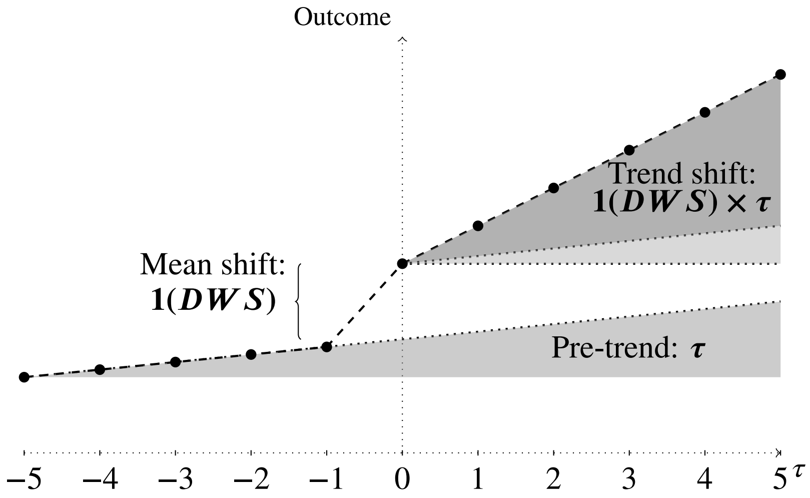

Figure 4.1: A simplified illustration of my empirical strategy

stability of pre-existing level differences or pre-existing trends between the treatment and control groups, these graphs help us assess potential issues with robustness and assist with the identification of the best specification. These graphs are also useful in interpreting the analysis by allowing a visual inspection of the effect of DWS on the outcome variables. Mainly, these figures help make more informed decisions about the interpretation of results from the analyses above.

The empirical strategy is summarised with a graphical representation of the equations above in Figure 4.1. The black dots represent the σ_τ vector from the nonparametric estimator in 4.4 and allows for the visual inspection and understanding of the underlying relative trends in outcomes for treated regions as event time τ varies. The DiD estimator in equation 4.2 and DDD estimator in equation 4.3 estimate the slope of the pre-trend τ, the trend shift $1(DWS) \times \tau$, as well as the mean shift parameter $1(DWS)$. In this figure, there is a positive pre-existing trend τ. This causes the DiD equation in 4.2 to estimate a trend-shift effect that is biased upwards, using both the light grey and dark grey area, due to an incorrect parallel paths assumption. It can similarly be shown that a pre-existing negative trend would cause DiD estimates to underestimate the effects of a program. In contrast, 4.3 which is based on the parallel trends assumption, would correctly estimate the trend shift effect using the dark grey area.

The quasi-experimental design presented here is robust to all time-invariant factors that may affect the results, as well as all economy-wide, and some time-variant factors specific to treatment regions. However, there is always a form of unobserved heterogeneity that can explain the findings without a causal explanation. Specifically, lower than average billing statistics may directly cause changes in future GP outcomes. These issues are discussed further in the results section.

It is important to clarify some further econometric issues that arose in the analysis. The effects of the DWS program were analysed using two separate datasets which shall be discussed shortly. The AMPCo sample frame of doctors in Australia was used to study how the program affects the number of GPs in affected SLAs. Next, the MABEL data set is used to study the effect of the program on market outcomes, with patients seen in an average week acting as my measure of workload, and fees charged for a standard consultation as a measure of prices. Because the MABEL data set allows access to a richer set of GP covariates, the analyses additionally control for a doctor's age, experience, relationship status, and the number of children in such estimates. They also control for GP fixed effects in equations to estimate doctor-level market outcomes, which alters the estimating DiD and DDD equations, for a GP i in area a and year t:

$$Y_{iat} = \alpha + \delta_i + \mu_t + \gamma_a + \pi_1(1(DWS)_{iat}) + \pi_2(\tau \times 1(DWS)_{ia\tau}) + \beta X_{iat} + \epsilon_{iat} \quad (4.5)$$

$$Y_{iat} = \alpha + \delta_i + \mu_t + \gamma_a + \pi_0 \tau_{iat} + \pi_1(1(DWS)_{iat}) + \pi_2(\tau \times 1(DWS)_{ia\tau}) + \beta X_{iat} + \epsilon_{iat} \quad (4.6)$$

Where δ_i is the GP fixed effect, and the rest of the equation remains unchanged. The addition of GP fixed effects controls for any observed or unobserved time-invariant individual specific confounders, such as personality type or gender. This results in greater precision compared to the estimators in Eqs. 4.2 and 4.3. These are therefore the preferred specification for studying doctor-level outcomes.

Last, Bertrand, Duflo and Mullainathan (2004) note that it is important to control for serial autocorrelation within units while performing such analyses. The analyses, therefore, cluster all observations at the SLA level when using SLA fixed effects, and the GP-id level while conducting analyses using GP fixed effects.

4.5 Data and Descriptive Statistics

4.5.1 Data sources

This paper uses two data sets to conduct its analyses - The Australian Medical Publishing Company (AMPCo) Medical Directory of Australia, and the Medicine in Australia: Balancing Employment and Life panel (MABEL) panel survey. The medical directory is a national database of doctors in Australia, managed by the Australian Medical Association. AMPCo data has been shown to be highly correlated with data from administrative surveys of doctors conducted within Australia (Mazumdar et al., 2013). For each doctor, the AMPCo sample frame contains information such as the mailing address, qualifications, and doctor type (GP, specialist, or hospital GP). Importantly, the AMPCo medical directory also forms the sampling frame used by MABEL. Using the AMPCo sample frame for the period 2008-2015, each GP's address was geocoded and assigned an SLA using GIS software. Next, using qualification information within the dataset GPs were assigned to either IMG or Australian trained categories for the analysis. A key limitation of the AMPCo data frame is that although overseas trained GPs can be identified using this data set, it does not identify IMGs who have trained in Australian medical schools, i.e. Foreign Graduates of Accredited Medical Schools (FGAMS). Nonetheless, it allows for an analysis of the extent to which the DWS program raises the proportion of overseas trained GPs in affected areas.

The medical directory is supplemented with MABEL, an annual longitudinal survey of medical practitioners in Australia. MABEL focusses primarily on medical labour supply and its determinants. Wave 1 of MABEL was conducted in 2008 and the latest publicly available version at the time of writing was Wave 8, collected in 2015. Rural and remote areas are an important area of interest for MABEL, and it provides a pre-paid monetary incentive to ensure higher response rates from such areas. MABEL captures a rich panel of variables including labour market outcomes such as patients seen, hours worked, fees charged, and bulk billing. It also provides an array of control variables such as GPs' ages, sex, practice type, experience, and some patient care outcomes such as waiting times.

Last, a panel of DWS status for each SLA was also obtained from the Department of Health for the period 2007-2015. Importantly, DWS designations were not updated in 2014 to prepare for changes to the program implemented in 2015 and the 2014 designations are therefore the same as those in Quarter 4, 2013. Since annual data is used for measuring outcomes, quarterly changes in the DWS program need to be collapsed to annual changes. Given that these quarterly changes were 'noisy' (Mcgrail, Humphreys, Joyce, Scott & Kalb, 2011) and the presence of significant logistical hurdles in hiring an IMG (Mason, 2013), the analyses smooth out such the noise in DWS designations by considering an SLA to have DWS turned on in that year if the program was turned on for *two or more quarters* in any particular year. Robustness checks were performed on this assumption, taking areas with one or more quarters in any year as treated DWS areas. These demonstrate that the qualitative results are unchanged, and are presented in the Appendix to this chapter.

4.5.2 Descriptive Statistics

Figure 4.2 illustrates the rise in both total GPs and IMG GPs over the period 2008-2014 using AMPCo data. The figure indicates that much of the rise in total GPs is driven by the rise in overseas trained doctors, with each having risen by around 3000 doctors in the study period.

Figure 4.3 illustrates the distribution of GPs across Australia, where each black dot indicates a single GP. It illustrates patterns of GP inequality in Australia, and a visual inspection makes it clear that most GPs are clustered around Australian capital cities - Melbourne, Canberra, Sydney, Adelaide, Perth, Brisbane, and Hobart. The density of GPs drops sharply as one moves further away from the coast.

Figure 4.4 visually presents the DWS designations for each SLA, based on the information obtained from the Department of Health. SLAs in white were DWS SLAs before the period 2008-2014, and are not included in the analysis. SLAs in light red turned on in the period 2008-2014, and act as the treated group; while SLAs in dark red never had the DWS program turned on, and act as the comparison group. A cross comparison of this figure with Figure 4.3 indicates the endogeneity which is inherent within the DWS program - SLAs in dark red have higher GPs densities compared with SLAs in light red. SLAs in white have the lowest GP densities. Essentially, areas with pre-existing fewer GPs are more likely to be a DWS region.

Table 4.1 presents DWS switching information for blue SLAs that turned on after

Figure 4.2: The total number and number of IMG GPs according to the AMPCo data frame 2008-2014

2008 as a function of event time τ. Recall that event time $\tau = -5$ means an SLA that will turn on the DWS program five years from the year in the top row. Similarly, event time $\tau = 0$ represents SLAs that had the DWS program turned on in the corresponding year.

From looking at the $\tau = 0$ row, it is evident that around 30-50 SLAs are turned on each year. Following the diagonal, close to 20 percent of these SLAs lose their DWS status in the next year, i.e. $\tau = 1$. However, the majority of SLAs, once turned on, remain as DWS regions beyond five years.

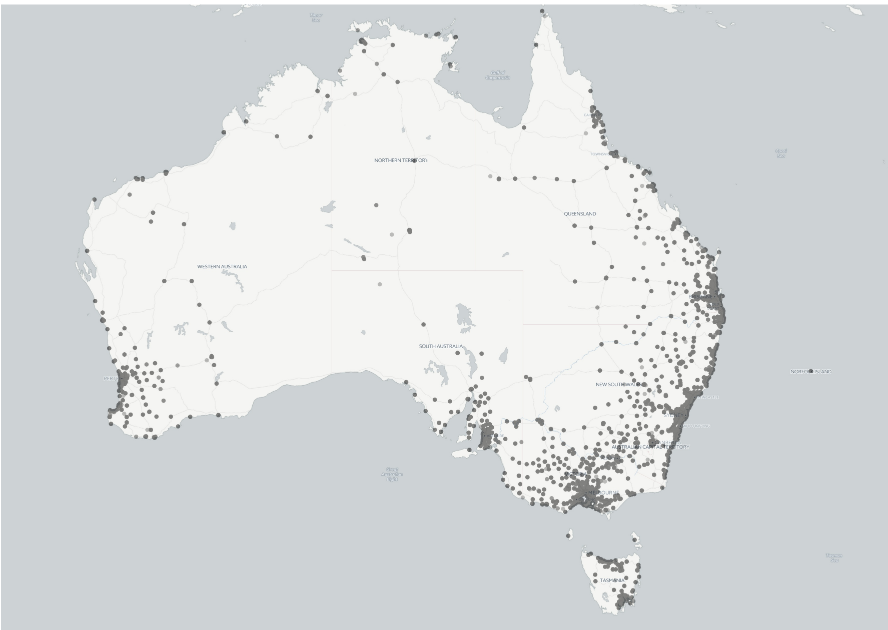

Figure 4.3: The distribution of GPs across Australia using the pooled (2008-2014) AMPCo data frame. Each black dot indicates a GP.

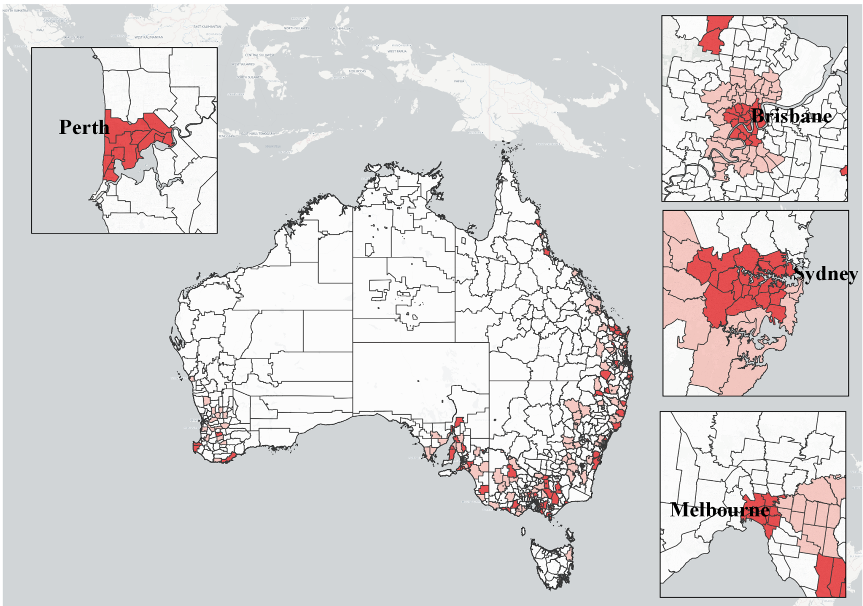

Figure 4.4: DWS Status by SLA. Source: Commonwealth Department of Health

Table 4.1: DWS SWITCHING: EVENT TIME AND YEAR

	year							
t	2008	2009	2010	2011	2012	2013	2014	Total
-5	22	9	0	0	0	0	0	31
-4	27	23	9	0	0	0	0	59
-3	24	30	31	11	0	0	0	96
-2	37	27	30	40	11	0	0	145
-1	39	42	31	51	42	11	0	216
0	37	38	42	31	50	44	12	254
1	0	30	32	31	24	48	35	200
2	0	0	27	29	30	21	42	149
3	0	0	0	20	27	23	22	92
4	0	0	0	0	21	27	21	69
5	0	0	0	0	0	18	26	44
Total	186	199	202	213	205	192	158	1,355

DWS switching information for SLAs that turned on after 2008, in groups of event time τ and sampling year.

Lastly, Table 4.2 summarises the means for key GP characteristics and socioeconomic variables in 2008 & 2014 using the MABEL dataset for the Always DWS (i.e. turned on before 2008), Treated DWS (light red SLAs i.e. turned on between 2008 and 2014), and Never DWS groups (dark red SLAs, i.e. DWS was never on). Always DWS areas have the lowest number of GPs, and Never DWS areas have the highest number of GPs across the three types of regions. All three types of areas see an increase in GP counts over the study period, with Never DWS regions gaining around 3.4 additional GPs, treated areas gaining 1.4 GPs, and always DWS regions gaining around 0.7 GPs. The increase in Australian trained GPs is greatest in never DWS areas, while growth in GP numbers is primarily driven by IMGs in DWS areas.

It is also evident that GPs in DWS areas see a higher number of patients than those in never DWS areas across the panel even though they work in areas with lower population density. Doctors in DWS areas are also likely to work a marginally larger number of hours, be slightly older, and simultaneously charge higher consultation fees while bulk billing a higher percentage of patients. Last, DWS regions are also likely to have somewhat lower median incomes. [3]

[3] A table of standard deviations is available in the Appendix

Table 4.2: SAMPLE CHARACTERISTICS: AMPCO SAMPLE FRAME AND MABEL

	(1) Always DWS 2008	(2) Always DWS 2014	(3) Treated DWS 2008	(4) Treated DWS 2014	(5) Never DWS 2008	(6) Never DWS 2014
Number of GPs	15.2	15.9	22.0	23.4	28.0	31.4
Number of IMG GPs	4.9	5.9	7.4	9.2	8.3	10.5
Number of Native GPs	10.2	10.0	14.7	14.3	19.6	20.9
Hours worked	40.3	37.9	40.4	36.5	39.5	36.1
Number of Patients Seen	112.2	101.8	111.7	98.9	105.9	94.5
Consultation Fee	45.4	55.7	45.8	55.8	45.5	54.2
Proportion bulk-billed	58.8	61.4	63.5	64.1	61.7	61.8
Consultation Length	16.5	16.6	16.3	16.2	17.4	17.1
Income (000s)	167.7	217.0	162.0	195.9	158.2	196.7
Number of children	1.5	1.2	1.4	1.2	1.4	1.2
Living with Partner	0.9	0.9	0.9	0.9	0.9	0.9
Per cent Female	0.4	0.4	0.4	0.4	0.4	0.4
Age	50.6	53.1	50.7	54.1	49.1	52.1
popdensity	1066.7	966.1	1725.2	1657.4	1750.1	2016.2
medianincome	527.5	713.7	529.4	701.2	571.0	714.3
medianage	36.2	38.5	36.9	38.3	37.2	38.6
N_{SLA}	585	573	237	234	273	274
$N_{doctors}$	1381	781	783	564	1145	895

Means for key labour market and socioeconomic variables for the 2008 and 2014 using the MABEL dataset and AMPCo data frame. MABEL data weighed using cross-sectional weights for each year.

4.6 Results

4.6.1 Effects on the distribution of doctors

Figure 4.5, based on estimates from equation 4.4, presents trends on the relative distribution of GPs between treatment and control regions, with the total number of GPs and the number of IMG GPs in treated areas on the left- and right-hand side panels respectively. In both graphs, the vertical line at $\tau = 0$ separates pre- and post-intervention trends. The horizontal line presents a visual baseline for the level at $\tau = -1$, the last year before treatment. A definite negative pre-existing trend is evident in both graphs. Such pre-existing trends make it apparent that the DDD design is more appropriate than a DiD estimator which assumes parallel trends. Both graphs also make it clear that the DWS program is not completely effective at reversing the decline in GP numbers, but is effective in roughly halving the extent of the decline between the treatment and control regions. Specifically, the number of GPs in treatment regions (compared to the comparison group) falls by around 3 GPs in the period before the DWS program was turned on, but only one GP is lost after the DWS program is implemented. A clearer mean-shift and trend-shift are apparent with regards to IMG GPs, with around 1.75 GPs lost in the five years before the DWS program, but less than one GP lost in the five years after the DWS program.

Formal estimates of the impact of the DWS program on the total number of GPs are presented in table 4.3[4]. Column 1 estimates the DiD estimator in equation 4.2, without including area and fixed effects. As explained above, participation in the DWS program is endogenously determined, and areas with fewer GPs are selected into the program. This column, therefore, indicates that the DWS program is associated with a mean shift of around 4.071 less GPs to be present in participating areas. Secondly, because the estimator does not control for the national trend of an increase in GP numbers each year (see Figure 4.2 and Table 4.2), this column indicates an increase of around 1 GP per year in participating areas.

[4]A full version of all tables with all coefficients is presented in the Appendix

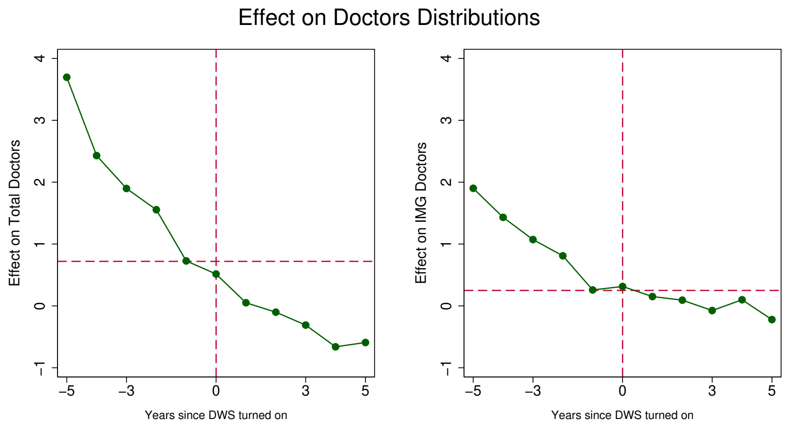

Figure 4.5: Trends for the impact of the DWS program on the distribution of GPs across treatment and comparison areas

Table 4.3: OUTCOME: NUMBER OF GPS IN AN SLA

	(1) DID without FE	(2) DID with FE	(3) DDD with FE
τ			-0.672***
			(0.160)
$1(DWS)$	-4.071**	-0.896***	0.282
	(1.884)	(0.217)	(0.320)
$1(DWS) \times \tau$	1.067*	-0.279**	0.325*
	(0.576)	(0.121)	(0.190)
Controls	Yes	Yes	Yes
Year Fixed Effects	No	Yes	Yes
SLA Fixed Effects	No	Yes	Yes
Observations	2998	2998	2998

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors clustered by SLA.

Column 2 fully estimates the DiD estimator in equation 4.2. As indicated in the descriptive study graph above, participating areas lose GPs in each year of the program. This column, therefore, indicates that each area loses 0.28 GPs each year, a loss consistent with Figure 4.5. Lastly, Column 3 presents the results of the DDD style analysis in equation 4.3. Consistent with the trends presented above, this column indicates that each area loses 0.67 GPs each year before the DWS program is turned on. The high significance of the coefficient on τ indicates that the parallel trends assumption for the DID program is not correct and estimates in column 2 are biased. The program has no statistically significant mean-shift, and an inspection of the $1(DWS) \times \tau$ coefficient shows that there is weak evidence that the DWS program has a trend-shift of around 0.325 additional GPs a year. Overall, these estimates indicate that selection into the DWS program reduces the pre-existing trends in GP inequality but does not completely alleviate them. The overall effect is roughly halving the growth in the GP inequality between treatment and comparison regions.

Table 4.4: OUTCOME: NUMBER OF IMG GPS IN AN SLA

	(1) DID without FE	(2) DID FE	(3) DDD with FE
τ			-0.347***
			(0.0782)
$1(DWS)$	-0.831	-0.249*	0.360**
	(0.747)	(0.144)	(0.161)
$1(DWS) \times \tau$	0.281	-0.101	0.211*
	(0.236)	(0.0888)	(0.111)
Controls	Yes	Yes	Yes
Year Fixed Effects	No	Yes	Yes
SLA Fixed Effects	No	Yes	Yes
Observations	2998	2998	2998

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors clustered by SLA.

Table 4.4 formally estimates the impact on IMG GPs, the cohort specifically targeted by the program. Again, the coefficient on τ is highly significant, indicating negative differential pre-trends and the DID assumption of parallel paths is likely invalidated. Estimates from the preferred DDD estimation in column 3 indicate that the DWS program has a statistically significant mean impact of an additional .36 IMGs in year 0 of the program, with a trend-shift of an additional 0.21 IMGs each year. Comparing the magnitudes of the estimates in Table 4.4 and 4.3 suggests that the majority ($0.211/0.325 \approx$ 65 percent) of the increase in total GP numbers is due to IMG GPs. As mentioned previously, FGAMSs who completed medical schooling in Australia are identified as Australian trained in the AMPCo data frame and may contribute to the remaining increase due to the DWS program.

As mentioned in the empirical methodology section, the results of this analysis could be biased by endogeneity related to low GP access. However, a number of qualitative factors reinforce the validity of the analysis. Figure 4.5, particularly in the IMG GP panel, indicates stable pre- and post-intervention trends, with a clear trend break at time $\tau = 0$, the first year of the DWS program. Second, the policy intends to coerce IMGs into working in such areas. The estimates of the mean- and trend-shift are more significant for IMGs, despite generally smaller effect-sizes. They also indicate that the majority of the increase in GP supply is due to IMGs. Last, the literature on health inequalities indicates that such inequalities *increase* with greater market exposure (see Hart, 1971). Although the results may still be biased, none of these factors directly contradict the causal nature of the findings.

4.6.2 Effects on Doctor Workload

Given that the analysis establishes the effectiveness of the DWS program, it is now used as an event study to determine the effect of the program on doctor workloads. I begin by examining two measures of doctor workload - the number of patients seen, and hours worked per week. As mentioned in the conceptual framework, an increase in GP supply implies a fall in both outcomes, if the market is relatively competitive.

Figure 4.6 presents the descriptive trends analysis for the number of patients seen per week by each GP before and after DWS is implemented. The panel on the left uses a design where only SLA level fixed effects were included, whereas the panel on the right includes both SLA and GP fixed effects. As previously discussed, the relative number of GPs in the treated group decreases in each year before the DWS program is turned on. Models of the GP workforce predict that such a decrease causes the relative number of patients per GP and the fee to increase and such trends are visible in both panels. A clear shift in trends is visible after the DWS program is turned on, with a fall after the DWS program is turned on.

I now formally test the effect of the DWS program on the the number of patients seen by a GP by using the empirical methodology in equations 4.2 and 4.3 which control for only SLA fixed effects and equation 4.6 which controls for both SLA and Doctor fixed effects. Table 4.5 presents the results for both estimation techniques. The first column contains estimates from a DiD design with no fixed effects. These results of the mean-shift are biased upwards as treated SLAs have a higher number of patients seen per GP (see Table 4.2). Secondly, a national trend of GPs seeing fewer patients may bias estimates as well. I, therefore, add SLA and year fixed effects in column 2. The estimates no longer show that the DWS program causes a mean shift regarding patients seen, although a trend shift of 1.95 fewer patients per week after each year is still observed. Column 3 presents the results of the DDD design with SLA and year fixed effects and mirrors the results seen in the figure above - the pre-existing trend is an increase of around 1.2 patients per year, although these estimates lack precision. The impact of the DWS program is a weakly significant shift in trend by 3.1 fewer patients seen per week *per year* after the program is introduced. Results in column 4 add GP fixed effects, and now show a trend shift of 2.58 fewer patients per week each year the program is turned on. GP fixed effects control for all time-invariant GP specific factors that may affect the estimates. The net result is higher precision. Last, although the coefficient on τ in both column 3 and 4 is not statistically significant, it indicates a pre-existing trend of an increase of around one patient per week every year in the average treated SLA. This explains why the results in column 2 for the trend-shift are lower than those in columns 3 and 4. As mentioned above, DDD estimates have weaker identifying assumptions compared to DiD results and are therefore more robust.

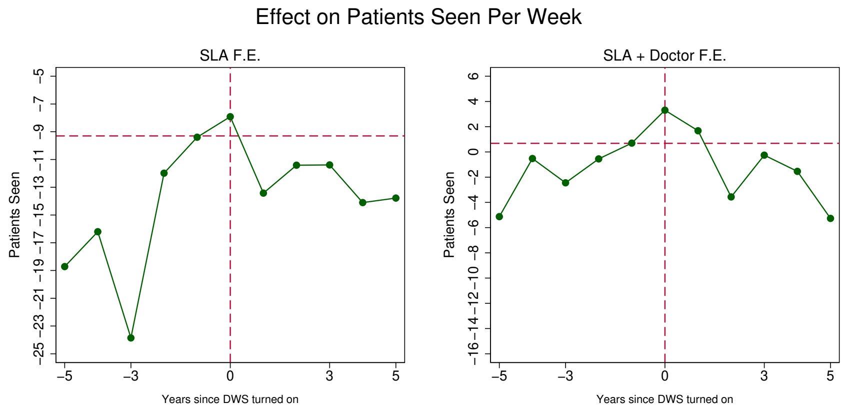

Figure 4.6: Trends for the impact of the DWS program on the number of patients seen in an average week; across treatment and comparison areas

Table 4.5: OUTCOME: AVERAGE NUMBER OF PATIENTS SEEN

	(1) DiD with Pooled OLS	(2) DiD with SLA Fixed effects	(3) DDD with SLA Fixed Effects	(4) DDD with SLA+ Doctor Fixed Effects
τ			1.234	0.924
			(1.696)	(1.107)
$1(DWS)$	4.297**	0.791	-1.150	1.823
	(2.108)	(2.121)	(3.043)	(2.479)
$1(DWS) \times \tau$	-2.332***	-1.950**	-3.104*	-2.580**
	(0.880)	(0.842)	(1.811)	(1.201)
Controls	Yes	Yes	Yes	Yes
SLA Fixed Effects	No	Yes	Yes	Yes
Doctor F.E.	No	No	No	Yes
Observations	8809	8809	8809	8809

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors clustered by SLA in column 1,2,3 and GP ID in column 4.

To provide further evidence towards the impact of the DWS program in influencing doctor workload, Figure 4.7 and Table 4.6 present the analysis for the impact on hours worked per week, another key measure of doctor workload. Similar trends and results are observed, and the preferred specification in column 4 indicates a fall of around 0.6 hours per year of the DWS program being turned on.

Again, these results may be biased by pre-existing low GP counts in affected areas. However, the graphs again point to (relatively) stable pre- and post-intervention trends with a trend break strongly associated with the DWS program. From a theoretical standpoint, supplier-induced demand contradicts the results, implying an increase in workload with increases in GP supply. However, GPs do not induce demand if there is low GP supply since primary demand is close to working capacity (Zweifel et al., 2009). Pre-existing low GP counts, therefore, imply a low effectiveness of the supplier-induced demand channel in DWS areas. It can, therefore, be argued that these do not contradict the findings which point to a decrease in workload when the DWS program being turned on.

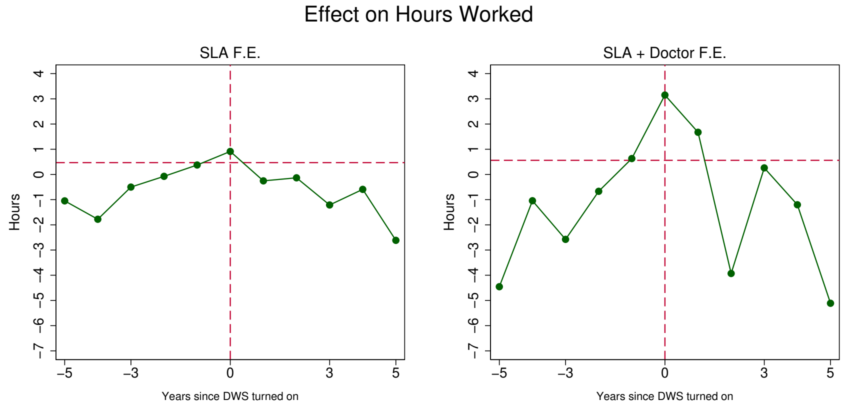

Figure 4.7: Trends for the hours worked in an average week

Table 4.6: OUTCOME: HOURS WORKED IN AN AVERAGE WEEK

	(1) DiD with Pooled OLS	(2) DiD with SLA Fixed effects	(3) DDD with SLA Fixed Effects	(4) DDD with SLA+ Doctor Fixed Effects
τ			0.496	0.208
			(0.365)	(0.272)
$1(DWS)$	0.623	0.606	-0.172	-0.236
	(0.499)	(0.591)	(0.753)	(0.535)
$1(DWS) \times \tau$	-0.690***	-0.540**	-1.005**	-0.627*
	(0.222)	(0.267)	(0.427)	(0.321)
Controls	Yes	Yes	Yes	Yes
Year + SLA Fixed Effects	No	Yes	Yes	Yes
Doctor F.E.	No	No	No	Yes
Observations	9831	9831	9831	9831

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results of my estimation strategy for the average number of hours worked per GP per week. Standard errors clustered by SLA in column 1,2,3 and GP ID in column 4.

4.6.3 Effects on Measures of Prices

The analysis now looks at two measures of prices, the standard consultation fee charged by a GP and the bulk billing rate. It should be re-iterated that the bulk-billing rate, i.e. the proportion of GP presentations billed to the public insurer without any co-pay, is an inverse measure of prices, i.e. a decrease in prices should be accompanied by a *increase* in bulk-billing rates.

Figure 4.8 presents trends for the standard consultation fee charged by a GP, before and after the DWS program is implemented. The panel on the left controls SLA fixed effects, and a general trend of a rise in fees by around a dollar each year in the years before the program is observed, though fees are stable afterwards. In contrast, the panel of the right contains both individual and SLA fixed effects. This figure indicates a stable trend of a small fall in fees between $-3 \leq \tau \leq 4$. However a large persistent mean shift upward is observed at $\tau = -4$, and another kink is observed at $\tau = 5$. Such "kinks" may bias the results of the formal econometric analysis since the identifying restriction of DID or DDD estimators is the presence of stable pre-intervention levels or trends. A robustness check on the formal estimates is therefore run, restricting the sample to event time $-3 \leq \tau \leq 3$.

Table 4.7 presents the results of a formal analysis on the change in fees for a standard consultation for an average GP. Column 1 presents the results of the estimating strategy in equation 4.2, but without year or SLA fixed effects. The coefficient on $1(DWS)$ indicates that the DWS program causes a mean-shift of 2.0 AUD, while the coefficient on $1(DWS) \times \tau$ indicates that there is no mean shift. Again, these results are biased both by DWS regions having fewer GPs, and an economy-wide trend of higher fees over time. Column (2) adds SLA and Year fixed effects. It can no longer be concluded that the DWS program causes a mean-shift in fees. Column (3) estimates the DDD equation in Eq. 4.3 equation 4.3 with only SLA fixed effects shows a pre-existing trend of a rise in fees by around 1.1 AUD in each year before the program was turned on, and the DWS program causes a trend shift of around (-)1.4 AUD. Column (4) which estimates equation 4.6 with SLA and GP fixed effects shows a similar pattern. Both equations have a significant coefficient for τ, indicating the DiD parallel paths assumption has failed, and the results in Column (2) are biased.

However, kinks are observed at $\tau = -4$ and $\tau = 5$ in the trends above. These kinks are far before, or far after the DWS program is implemented, and it is very likely that they are independent of the program itself. A robustness check is run on the results above, using Eq. 4.3 and 4.6 and restricting event time to $-3 \leq \tau \leq 3$. This excludes the kinks which may bias the estimates of both the pre-trend τ and trend shift $1(DWS) \times \tau$. Table 4.7 presents the estimates from the robustness check. Estimates in Column 1 lose significance, although this may be due to the drop in sample sizes which particularly affects the treatment group [as mentioned in section 4, comparison regions have event times normalised to zero]. The results in column 2 indicate the trends in fees do not have economic or statistical significance when the sample is restricted to this period. I posit that the difference between these two columns may be explained by compositional changes in the GP workforce caused by the DWS program. IMG GPs earn less than native GPs per service[5] and changes in composition by the DWS program may cause a relative rise in fees before the program was implemented, and a relative fall after. The inclusion of GP fixed effects absorbs the change in composition in the workforce caused by the DWS program. Given that the results from the preferred specification are no longer significant after conducting the robustness check, the hypothesis that the DWS program causes a fall in fees, especially on an individual GP level, cannot be accepted.

Last, Figure 4.9 and Table 4.9 present the results of the estimates for bulk billing rates, another key measure of prices in the healthcare system. The trend graphs indicate significant noise, although bulk billing rates three years before and three years after DWS are roughly the same. Formal estimates indicate a non-significant ($p = 0.09$) increase in bulk-billing rates in the preferred specification. Overall, the estimates for both bulk-billing rates and fees indicate a statistically non-significant decrease in measures of prices as a result of the DWS program.

[5] Source: Department of Health GP Workforce Statistics

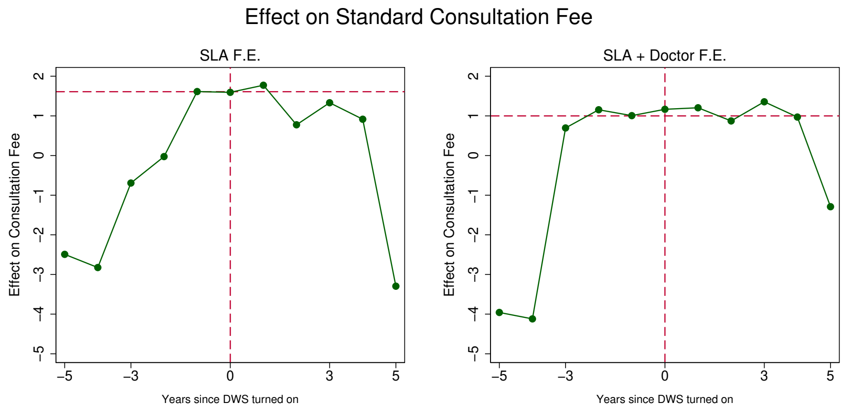

Figure 4.8: Trends for the fees charged for a standard consultation

Table 4.7: OUTCOME:FEE CHARGED FOR A STANDARD CONSULTATION

	(1) DiD with Pooled OLS	(2) DiD with SLA Fixed effects	(3) DDD with SLA Fixed Effects	(4) DDD with SLA+ Doctor Fixed Effects
τ			1.119*	0.910*
			(0.647)	(0.540)
$1(DWS)$	2.069**	1.031	-0.734	-1.063
	(0.827)	(0.903)	(1.271)	(0.983)
$1(DWS) \times \tau$	-0.0174	-0.496	-1.543**	-1.111*
	(0.364)	(0.426)	(0.773)	(0.590)
Controls	Yes	Yes	Yes	Yes
Year + SLA Fixed Effects	No	Yes	Yes	Yes
Doctor F.E.	No	No	No	Yes
Observations	8402	8402	8402	8402

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors clustered by SLA in column 1,2,3 and GP ID in column 4.

Table 4.8: Outcome: Fee Charged for a Standard Consultation
$-3 \leq \tau \leq 3$

	(1) SLA Fixed Effects	(2) SLA+Doctor Fixed Effects
τ	1.064	0.0333
	(0.752)	(0.608)
$1(DWS)$	-0.817	0.156
	(1.345)	(1.028)
$1(DWS) \times \tau$	-1.301	-0.256
	(0.941)	(0.673)
Controls	Yes	Yes
Year + SLA Fixed Effects	Yes	Yes
Doctor F.E.	No	Yes
Observations	8012	8012

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors clustered by SLA in column 1,2,3 and GP ID in column 4.

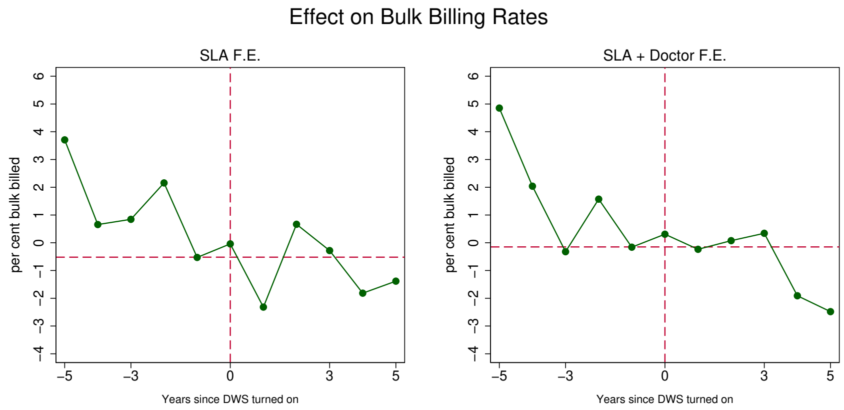

Figure 4.9: Trends for the hours worked in an average week

Table 4.9: OUTCOME: BULK BILLING RATES

	(1) DiD with Pooled OLS	(2) DiD with SLA Fixed effects	(3) DDD with SLA Fixed Effects	(4) DDD with SLA+ Doctor Fixed Effects
τ			-0.637	-0.824
			(0.827)	(0.539)
$1(DWS)$	0.0559	-0.544	0.456	1.443
	(0.978)	(0.931)	(1.506)	(1.014)
$1(DWS) \times \tau$	1.015**	0.0306	0.626	0.495
	(0.436)	(0.469)	(0.935)	(0.590)
Controls	Yes	Yes	Yes	Yes
Year + SLA Fixed Effects	No	Yes	Yes	Yes
Doctor F.E.	No	No	No	Yes
Observations	8933	8933	8933	8933

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors clustered by SLA in column 1,2,3 and GP ID in column 4.

Last, Figure 4.9 and Table 4.9 present the results of the estimates for bulk billing rates, another key measure of prices in the healthcare system. The trend graphs indicate significant noise, although bulk billing rates three years before and 3 years after DWS are roughly the same. Formal estimates indicate a non-significant ($p = 0.14$) increase in bulk-billing rates in the preferred specification. Overall, the estimates for both bulk-billing rates and fees indicate non-significant changes in measures of prices as a result of the DWS program.

4.6.4 Evidence of Imperfect Substitutability

Most theoretical models of the healthcare market assume perfect substitutability between IMG and native GPs, which generates a more competitive effect with the entry of IMG GPs in an SLA. However, the migration literature has reported evidence that migrants and native workers are not perfect substitutes even within narrowly defined skill groups (Ottaviano & Peri, 2008). This imperfect substitutability implies that immigrants and native workers have different skill endowments. Natives can, therefore, specialise in skills they have a comparative advantage in, which limits the competitive impact of an increase in the labour supply. For instance, if natively trained GPs have higher communication skills which are inputs to the primary healthcare supply process, this advantage could limit the competitive impact of an increase in IMG GPs. I, therefore, check for differential outcomes between natively trained and IMG GPs on the entry of IMGs from the DWS program.

A modified empirical strategy is used to run separate regressions for natively trained GPs and IMGs. One set of estimates restricts the sample to treated natively trained GPs and all GPs in the comparison group. The second set of estimates then compares treated IMG GPs to all GPs in non-treated SLAs. It is also important to clarify that the analysis now only focusses on the period from $-3 \leq \tau \leq 3$. This is primarily to ensure large enough sample sizes for the two types of GPs for each group in event time τ, although the number of treated IMGs within MABEl is relatively small, approximately 300 GPs and 900 observations across the study period.

Figure 4.10 presents trend graphs for the two groups, while Table 4.10 presents formal estimates from the DDD methodology. Because there are differences in sample size between the two groups and there are likely to be underlying differences in variances which affect the validity of standardised differences in coefficients (say, through a χ^2 test), I compare unstandardised coefficients between them (i.e. differences in means)

Focussing on patients seen in an average week, the results indicate natively trained IMGs lose 3.46 patients per year of the DWS program being active. The estimates for IMGs are higher, at around 4.7 fewer patients every year, although these estimates are not precise. With regards to hours, much of the drop in hours results from IMG GPs, with IMGs working around three hours less per week, but natives working one hour less after DWS is implemented for three years. Estimates on hours worked, although imprecise, reflect these differences in trends, with IMGs working less by around 1.6 hours per week every year the DWS program is turned on, while natively trained GPs show a very small, non statistically significant fall in hours. Such differences may be due to native workers increasing consultation lengths, changing time-use patterns towards practice management rather than direct patient care, or native doctors being able to induce more demand than IMGs. However, the investigation of such further mechanisms is beyond the scope of this paper and its datasets.

With regards to fees and bulk billing rates, all estimates are not statistically significant, as with the overall estimates.

Although these results are inconclusive, these results are suggestive of the higher impact of IMGs on pre-existing IMGs rather than natively trained GPs; and more research is required particularly in specific occupations such as the medicine where immigrants constitute a large proportion of the workforce.

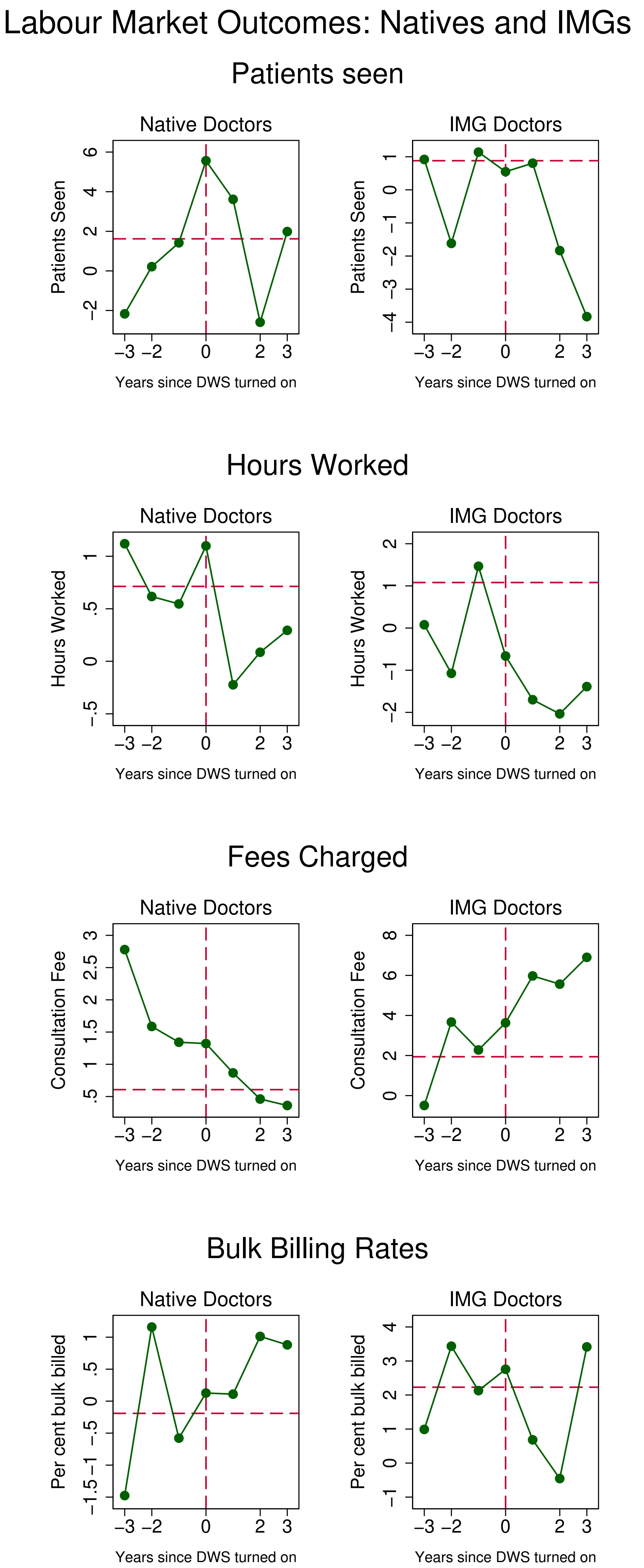

Figure 4.10: Trends for labour market outcomes: Natively trained vs IMG GPs

Table 4.10: HETEROGENEITY BETWEEN NATIVE AND IMG WORKERS

	(1) Natively trained	(2) IMG
Patients Seen		
τ	1.134	3.823
	(1.813)	(2.931)
$1(DWS)$	2.891	-3.634
	(3.479)	(5.642)
$1(DWS) \times \tau$	-3.460*	-4.730
	(1.923)	(3.300)
Observations	7782	6322
Hours Worked		
τ	-0.507	1.282*
	(0.419)	(0.722)
$1(DWS)$	0.710	-3.212**
	(0.696)	(1.284)
$1(DWS) \times \tau$	-0.0665	-1.676*
	(0.501)	(0.975)
Observations	8430	6836
Consultation Fee		
τ	-0.263	1.340
	(0.680)	(1.320)
$1(DWS)$	0.540	-0.759
	(1.162)	(2.134)
$1(DWS) \times \tau$	0.0381	-0.838
	(0.756)	(1.472)
Observations	7426	6036
Bulk Billing Rates		
τ	-0.754	-0.913
	(0.748)	(1.002)
$1(DWS)$	1.074	0.551
	(1.238)	(1.788)
$1(DWS) \times \tau$	0.852	0.447
	(0.818)	(1.232)
Observations	7903	6415

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

All results include a standard vector of controls; as well as area, time and individual fixed effects. Standard errors clustered by ID.

4.7 Conclusion

This paper is the first to present quantitative evidence on the impact of coercive policies that restrict IMG general practitioners to work in under-served areas. The analysis indicates a pre-existing trend of increasing inequality in the distribution of GPs between DWS and non-DWS regions, with DWS treated SLAs between 2008 and 2014 losing around 0.67 GPs per year compared to non-DWS SLAs. The DWS program is effective at reducing, but not eliminating these inequalities, adding an additional 0.32 GPs per year to treated areas.

Secondly, this essay also analyses the impact of the DWS policy on the local health workforce on two key outcomes - the number of patients seen, and the fees charged for a standard consultation. Although standard competitive models predict a fall in both outcomes as a result of increasing competition, the results indicate that only the number of patients seen is affected, with GPs in DWS regions seeing around 2.5 fewer patients per year once the program is implemented. On the other hand, no significant result is observed with regards to the impact on standard consultation fees for an individual doctor. One possible mechanism for these results may be the presence of switching costs, such as patients preferring their existing providers or other psychological costs, and highlights the need for further research into the dynamics of general practice competition. Also, although individual doctors do not change prices, IMG doctors charge lower fees than a comparable natively trained doctor, and there is some evidence that the compositional change in the workforce may cause prices to drop in the market overall.

Lastly, the analysis finds inconclusive evidence of a differential effect of IMG entry between natively trained and overseas trained GPs. It suggests that IMGs work fewer hours compared to natively trained doctors as a result of the DWS program. This indicates the need for further research into mechanisms such as native doctors undertaking longer consultations, changing time-use patterns from direct patient care to practice management, or being able to induce more demand.

Concerning Australian migration and health policy, The Commonwealth Department of Health has requested the removal of overseas trained doctors from the Australian skilled occupation list due to projected oversupply, as well as upcoming changes to the temporary worker program. The DWS program is designed to reduce inequality between rural and remote regions, and IMGs play a primary role within the program.

However, more effective policies to make rural and remote areas attractive to native GPs are required. A dramatic reduction in the number of IMGs in Australia is also likely to exacerbate healthcare inequalities between urban, rural, and remote Australia unless policies can be designed to incentivise native doctors to practice in such areas. This chapter concludes by highlighting the urgent need for effective utilisation of all policy levers - financial and non-financial incentives, rural retention, and IMGs to eliminate rural-remote inequity.

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Chapter 5

Conclusion

This thesis uses contemporary econometric techniques across a variety of contexts and datasets to understand and analyse immigration policy. Below, I summarise the research findings from the three essays, as well as their implications for policy and future research. Lastly, I conclude.

Summary of Findings

The first chapter studies the out-migration of Australian permanent migrants using a comprehensive dataset of overseas arrivals and departures. It establishes the rate of out-migration amongst various migrant cohorts to find that migrants from high-income countries are more likely to out-migrate than those from low-income countries. It also finds that out-migration is sensitive to the business cycle. However, migrants from India and China are less likely to out-migrate than those from the United Kingdom in response to increases in the unemployment rate. Last, it studies the skill-selection inherent in out-migration to find that highly skilled migrants & those on visas associated with better labour market outcomes are more likely to out-migrate. These results support the hypothesis that Australia has a lower return to skill than the majority of its migrant-source countries.

The second chapter looks at the labour market effects of the (subclass 457) skilled temporary visa program. Across specifications, the analysis fails to find a statistically significant negative impact of such migration on either wages or unemployment. However, there is a positive association between the wages of Australian workers with a bachelor's degree and increased occupational utilisation of 457 workers. The analysis supplements these results with an analysis of occupational switching, which finds that an increase in such temporary migration induces Australian workers to switch to positions requiring greater specialisation in communication tasks.

The third chapter presents quantitative evidence on the impact of the Districts of Workforce Shortage (DWS) policy, which restrict IMGs to work in under-served areas of Australia. The analysis indicates a pre-existing trend of increasing inequality in the distribution of GPs between DWS and non-DWS regions, with DWS treated SLAs losing around 0.67 GPs per year compared to non-DWS SLAs. The DWS program is effective at reducing, but no eliminating these inequalities, adding 0.32 GPs per year to treated areas. These increases in IMG supply are accompanied by decreases in workload measures such as hours worked, or patients seen - GPs in DWS regions see around 2.5 fewer patients per year once the program is implemented. On the other hand, there is no significant result with regards to the impact on standard consultation fees for an individual doctor.

Implications of Findings

Our findings from the first paper emphasise that migration decisions are not permanent. They also highlight the difficulty faced by Australia in retaining skilled migrants. Greater policy focus is therefore required by Australian governments to retain skilled migrants, particularly those that are highly skilled. Such non-random out-migration of the highest skilled migrants also causes estimates of immigrant wage assimilation to be biased downwards - this may explain why studies find little to no wage assimilation for migrants, especially for migrants from non-English speaking countries. As such, empirical studies into wage assimilation should correct for such non-random attrition or out-migration.

The second chapter contributes Australian evidence towards the Ottaviano, Peri and Wright (2013) hypothesis of imperfect substitutability of immigrants. Our results also hint at complementariness between skilled native and immigrant workers, and present directions for future research. However, there is scope for further research into the mechanisms inherent in temporary migration programs - lower bargaining power, and restricted occupational mobility of sponsored migrants. This chapter also contributes to the much required empirical evidence surrounding temporary and skilled migration.

The last chapter presents important quantitative evidence regarding programs aimed at solving rural medical shortages. With regards to policy, the Commonwealth Department of Health has requested the removal of overseas trained doctors from the Australian skilled occupation list. Our results imply the need for effective policies that make rural and remote areas attractive to native GPs before the reliance of IMGs can be reduced. Lastly, we find suggestive evidence that the reductions in hours as a result of the DWS program is higher to IMGs compared to natively trained doctors. The differential reduction in workload is suggestive of imperfect labour market substitution even within narrow occupational groups.

Concluding Remarks

This thesis sheds light on the skill selection of out-migration for Australian permanent residents using a novel dataset, produces empirical evidence on associations between temporary skilled migration and native worker labour market outcomes, and studies the impact of IMGs on the medical workforce. By analysing skilled migration policy in varied contexts, the contribution of this thesis is to produce original studies surrounding policies that lack systematic evidence.

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Appendix

5.A Appendices for Chapter 2

5.A.1 Miscellaneous Results

Effect of Age

Table 5.A.1 shows the results of the Cox regression where we study the impact of the age at arrival on the hazard rate of out-migration. To avoid specifying the functional form of the age, we divide age into five year categories i.e. 20-25, 25-30, etc. With the 20-25 group as the reference group we note that, generally, the older the migrant is at arrival, the lower is the hazard rate of out-migration. For example, A migrant who is aged 50-55 is 38 per cent less likely to out-migrate than a migrate who is 20-25.

We can explain this by noting that older migrants have a lower return to returning and working in the source country because of a smaller working lifetime remaining compared to younger migrants.

The effect of gender

Figure 5.A.1 presents the hazard curves by sex from our dataset.

Table 5.A.2 shows the results of the Cox regression by sex. Women are more likely to leave than men.

The effect of marital status

Table 5.A.3 shows the results of the Cox regression by marital status.

	(1) No controls	(2) Controls	(3) Time dummies	(4) Cloglog
main				
25-30	-0.686***	-0.191***	-0.190***	-0.190***
	(0.0235)	(0.0243)	(0.0243)	(0.0245)
30-35	-0.782***	-0.266***	-0.265***	-0.265***
	(0.0240)	(0.0255)	(0.0255)	(0.0255)
35-40	-0.744***	-0.354***	-0.352***	-0.352***
	(0.0256)	(0.0273)	(0.0273)	(0.0272)
40-45	-0.611***	-0.340***	-0.339***	-0.339***
	(0.0267)	(0.0288)	(0.0288)	(0.0287)
45-50	-0.563***	-0.428***	-0.427***	-0.427***
	(0.0319)	(0.0334)	(0.0334)	(0.0334)
50-55	-0.325***	-0.359***	-0.358***	-0.358***
	(0.0387)	(0.0395)	(0.0395)	(0.0396)
55-60	-0.365***	-0.359***	-0.358***	-0.359***
	(0.0482)	(0.0487)	(0.0487)	(0.0486)
60-65	-0.498***	-0.379***	-0.379***	-0.380***
	(0.0712)	(0.0718)	(0.0718)	(0.0719)
Observations	7610475	7610475	7610475	7610475
Number of subjects	349117	349117	349117	
Pseudo chi squared	1289.9	12063.1	12143.2	11312.0
Time Dummies	No	No	Yes	Yes
Controls	No	Yes	Yes	Yes

Standard errors in parentheses

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

Table 5.A.1: Impact of age

	(1) No controls	(2) Controls	(3) Time dummies	(4) Cloglog
main				
Female	-0.00362	0.0470***	0.0469***	0.0468***
	(0.00900)	(0.00939)	(0.00939)	(0.00944)
Observations	21875122	21853932	21853932	21853932
Number of subjects	1019038	1018010	1018010	
Pseudo chi squared	0.161	32749.1	32898.9	30436.6
Time Dummies	No	No	Yes	Yes
Controls	No	Yes	Yes	Yes

Standard errors in parentheses

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

Table 5.A.2: Impact of sex on out-migration

	(1) No controls	(2) Controls	(3) Time dummies	(4) Cloglog
main				
Married	0.122***	0.219***	0.218***	0.218***
	(0.0165)	(0.0172)	(0.0172)	(0.0171)
Widowed	-0.246**	0.345***	0.345***	0.346***
	(0.0789)	(0.0806)	(0.0806)	(0.0807)
Divorced	0.511***	0.399***	0.399***	0.399***
	(0.0471)	(0.0480)	(0.0480)	(0.0481)
De facto	0.464***	0.177***	0.174***	0.174***
	(0.0279)	(0.0291)	(0.0291)	(0.0290)
Separated	-0.162	0.0690	0.0693	0.0697
	(0.119)	(0.120)	(0.120)	(0.120)
Not stated	1.162***	0.272***	0.273***	0.273***
	(0.0156)	(0.0224)	(0.0224)	(0.0226)
Observations	21875122	21853932	21853932	21853932
Number of subjects	1019038	1018010	1018010	
Pseudo chi squared	13539.4	32749.1	32898.9	30436.6
Time Dummies	No	No	Yes	Yes
Controls	No	Yes	Yes	Yes

Standard errors in parentheses

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

Table 5.A.3: Impact of marital status on out-migration

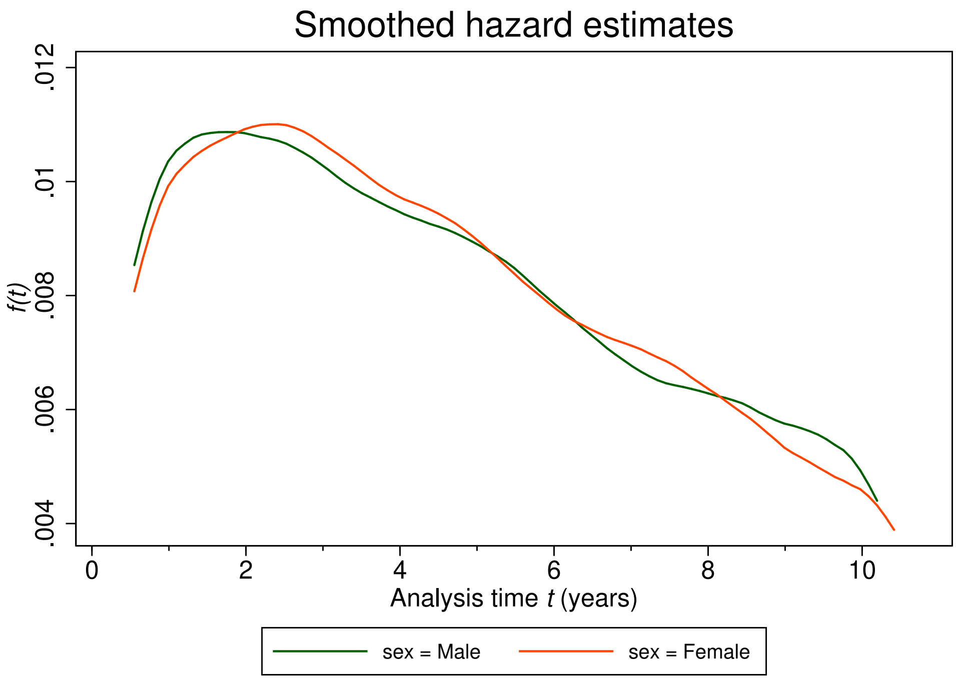


Figure 5.A.1: Survival Curves by sex for Australian Permanent Migrants

5.A.2 Estimates including Heckman-Singer Discrete Mixture Frailty

Table 5.A.4: Estimates with a Heckman-Singer Discrete Mixture Frailty

	(1) Cox PH with Time Dummies	(2) Heckman-Singer with Time Dummies
main		
New Zealand	0.0127	0.0290
	(0.0348)	(0.0408)
India	-1.443***	-1.496***
	(0.0507)	(0.0525)
China	0.0426	0.0682
	(0.0319)	(0.0353)
Other Oceania	-1.124***	-1.234***
	(0.0683)	(0.0729)

Other North-West Europe	0.148***	0.169***
	(0.0383)	(0.0421)
Southern and Eastern Europe	-0.695***	-0.732***
	(0.0552)	(0.0582)
North Africa and the Middle East	-0.648***	-0.683***
	(0.0517)	(0.0545)
South-East Asia	-0.771***	-0.810***
	(0.0367)	(0.0389)
Other North-East Asia	-0.107*	-0.0758
	(0.0505)	(0.0561)
Other Southern and Central Asia	-1.687***	-1.745***
	(0.0792)	(0.0809)
Americas	0.00446	0.00730
	(0.0423)	(0.0462)
Sub-Saharan Africa	-1.071***	-1.143***
	(0.0502)	(0.0528)
Professionals	0.00641	-0.0168
	(0.0267)	(0.0309)
Technicians and Trades Workers	-0.141***	-0.146***
	(0.0290)	(0.0336)
Community and Personal Service Workers	-0.201***	-0.228***
	(0.0369)	(0.0429)
Clerical and Administrative Workers	-0.0664*	-0.0908*
	(0.0329)	(0.0383)
Sales Workers	-0.0706	-0.0864
	(0.0380)	(0.0448)
Machinery Operators and Drivers	-0.449***	-0.515***
	(0.0522)	(0.0602)
Labourers	-0.299***	-0.324***
	(0.0580)	(0.0668)
Female	0.0364*	0.0309
	(0.0157)	(0.0179)
25-30	-0.190***	-0.231***

	(0.0243)	(0.0288)
30-35	-0.265***	-0.306***
	(0.0255)	(0.0300)
35-40	-0.352***	-0.393***
	(0.0273)	(0.0320)
40-45	-0.339***	-0.385***
	(0.0288)	(0.0337)
45-50	-0.427***	-0.491***
	(0.0334)	(0.0386)
50-55	-0.358***	-0.416***
	(0.0395)	(0.0461)
55-60	-0.358***	-0.446***
	(0.0487)	(0.0562)
60-65	-0.379***	-0.437***
	(0.0718)	(0.0825)
Married	0.217***	0.232***
	(0.0286)	(0.0303)
Widowed	0.527**	0.611**
	(0.195)	(0.212)
Divorced	0.292***	0.330***
	(0.0845)	(0.0914)
De facto	0.182***	0.197***
	(0.0443)	(0.0472)
Separated	0.0702	0.0939
	(0.191)	(0.202)
Not stated	0.266***	0.277***
	(0.0366)	(0.0391)
Skilled - Nominated	0.164***	0.168***
	(0.0331)	(0.0355)
Skilled - Independent	-0.0671*	-0.0759**
	(0.0264)	(0.0282)
Refugee	-0.748***	-0.740***
	(0.130)	(0.132)

Special Category - NZ only	0.938***	1.091***
	(0.0438)	(0.0495)
Investment	0.535***	0.527***
	(0.0433)	(0.0484)
Constant		-16.99
		(24.66)
m2		12.32
		(24.66)
logitp2		-0.610***
		(0.0537)
Prob. Type 1		0.648***
		(0.0122)
Prob. Type 2		0.352***
		(0.0122)
Observations	7610475	7610475
Number of subjects	349117	
Pseudo chi squared	12143.2	
Time Dummies	Yes	Yes
Controls	Yes	Yes

Standard errors in parentheses

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

5.B Appendices for Chapter 3

5.B.1 Estimates with Quarter 3 457 Data

Effects on wage income

Table 5.B.1: LOG OF WEEKLY WAGES

	(1) No IV	(2) Shift Share	(3) No IV with lag	(4) Double Instrumentation
$m_{o,t}$	0.0163	0.0204	0.0292*	0.0329
	(0.0125)	(0.0216)	(0.0155)	(0.0290)
$m_{o,t-1}$			-0.0183	-0.0106
			(0.0138)	(0.0212)
Controls	Yes	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes
Lagged Occupation Fixed effects.	Yes	Yes	Yes	Yes
Location Fixed effects.	Yes	Yes	Yes	Yes
IV First Stage F-statistics:				
$m_{o,t-1}$		2244.22		843.62
$m_{o,t-2}$				1880.53
Observations	27398	27398	20968	20968

Cluster robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.B.2: LOG OF WEEKLY WAGES; BACHELORS DEGREE OR ABOVE

	(1) No IV	(2) Shift Share	(3) No IV with lag	(4) Double Instrumentation
$m_{o,t}$	0.0621**	0.128**	0.0559*	0.0618
	(0.0254)	(0.0614)	(0.0320)	(0.0662)
$m_{o,t-1}$			0.00901	0.0536
			(0.0243)	(0.0444)
Controls	Yes	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes
Lagged Occupation Fixed effects.	Yes	Yes	Yes	Yes
Location Fixed effects.	Yes	Yes	Yes	Yes
IV First Stage F-statistics:				
$m_{o,t-1}$		481.76		273.27
$m_{o,t-2}$				640.78
Observations	10262	10262	8023	8023

Cluster robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.B.3: LOG OF WEEKLY WAGES; EDUCATION LESS THAN BACHELORS DEGREE

	(1) No IV	(2) Shift Share	(3) No IV with lag	(4) Double Instrumentation
$m_{o,t}$	-0.0149	-0.0246	-0.00475	-0.0173
	(0.0144)	(0.0206)	(0.0173)	(0.0285)
$m_{o,t-1}$			-0.0227	-0.0121
			(0.0172)	(0.0243)
Controls	Yes	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes
Lagged Occupation Fixed effects.	Yes	Yes	Yes	Yes
Location Fixed effects.	Yes	Yes	Yes	Yes
IV First Stage F-statistics:				
$m_{o,t-1}$		1496.59		481.57
$m_{o,t-2}$				1217.62
Observations	17049	17049	12881	12881

Cluster robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Effects on Unemployment

Table 5.B.4: Per cent time unemployed

	(1) No IV	(2) Shift Share	(3) No IV with lag	(4) Double Instrumentation
$m_{o,t-1}$	0.297	0.372	-0.0755	-0.0393
	(0.247)	(0.388)	(0.324)	(0.457)
$m_{o,t-2}$			-0.0748	-0.592
			(0.367)	(0.513)
Controls	Yes	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes
Lagged Occupation Fixed effects.	Yes	Yes	Yes	Yes
Location Fixed effects.	Yes	Yes	Yes	Yes
IV First Stage F-statistics:				
$m_{o,t-1}$		3963.34		1901.70
$m_{o,t-2}$				1978.54
Observations	25358	25358	17939	17939

Cluster robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.B.5: PER CENT TIME UNEMPLOYED; BACHELORS DEGREE OR ABOVE

	(1) No IV	(2) Shift Share	(3) No IV with lag	(4) Double Instrumentation
$m_{o,t-1}$	0.00563	0.560	0.156	0.215
	(0.303)	(0.589)	(0.364)	(0.551)
$m_{o,t-2}$			0.227	0.408
			(0.482)	(0.870)
[1em] Controls	Yes	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes
Lagged Occupation Fixed effects.	Yes	Yes	Yes	Yes
Location Fixed effects.	Yes	Yes	Yes	Yes
IV First Stage F-statistics:				
$m_{o,t-1}$		2244.22		843.62
$m_{o,t-2}$				1880.53
Observations	9274	9274	6686	6686

Cluster robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.B.6: PER CENT TIME UNEMPLOYED; EDUCATION LESS THAN BACHELORS DEGREE

	(1) No IV	(2) Shift Share	(3) No IV with lag	(4) Double Instrumentation
$m_{o,t-1}$	0.509	0.184	-0.214	-0.858
	(0.363)	(0.543)	(0.505)	(0.741)
$m_{o,t-2}$			-0.225	-0.831
			(0.495)	(0.634)
Controls	Yes	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes
Lagged Occupation Fixed effects.	Yes	Yes	Yes	Yes
Location Fixed effects.	Yes	Yes	Yes	Yes
IV First Stage F-statistics:				
$m_{o,t-1}$		2865.91		1005.34
$m_{o,t-2}$				1485.35
Observations	16019	16019	11196	11196

Cluster robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Effects on Skill Specialisation

Table 5.B.7: RELATIVE COMMUNICATION TO MANUAL SKILLS

	(1) No IV	(2) Shift Share	(3) No IV with lag	(4) Double Instrumentation
$m_{o,t-1}$	0.781	2.011**	0.931	3.996***
	(0.528)	(0.801)	(0.648)	(0.967)
$m_{o,t-2}$			1.332**	2.463**
			(0.648)	(0.967)
Controls	Yes	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes
Lagged Occupation Fixed effects.	Yes	Yes	Yes	Yes
Location Fixed effects.	Yes	Yes	Yes	Yes
IV First Stage F-statistics:				
$m_{o,t-1}$		3690.79		1784.60
$m_{o,t-2}$				1776.89
Observations	23607	23607	16608	16608

Cluster robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.B.8: RELATIVE COMMUNICATION TO MANUAL SKILLS; BACHELORS DEGREE OR ABOVE

	(1) No IV	(2) Shift Share	(3) No IV with lag	(4) Double Instrumentation
$m_{o,t-1}$	0.750	3.911***	0.259	2.518*
	(0.811)	(1.474)	(0.908)	(1.434)
$m_{o,t-2}$			2.187**	4.743**
			(1.065)	(1.944)
Controls	Yes	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes
Lagged Occupation Fixed effects.	Yes	Yes	Yes	Yes
Location Fixed effects.	Yes	Yes	Yes	Yes
IV First Stage F-statistics:				
$m_{o,t-1}$		933.32		656.03
$m_{o,t-2}$				545.79
Observations	8704	8704	6276	6276

Cluster robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.B.9: RELATIVE COMMUNICATION TO MANUAL SKILLS; EDUCATION LESS THAN BACHELORS DEGREE

	(1) No IV	(2) Shift Share	(3) No IV with lag	(4) Double Instrumentation
$m_{o,t-1}$	0.551	1.099	1.122	4.929***
	(0.720)	(1.037)	(0.970)	(1.487)
$m_{o,t-2}$			0.962	1.772
			(0.852)	(1.170)
Controls	Yes	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes
Lagged Occupation Fixed effects.	Yes	Yes	Yes	Yes
Location Fixed effects.	Yes	Yes	Yes	Yes
IV First Stage F-statistics:				
$m_{o,t-1}$		2673.60		938.32
$m_{o,t-2}$				1305.19
Observations	14849	14849	10287	10287

Cluster robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.C Appendices for Chapter 4

5.C.1 Additional Descriptives

MABEL Doctor Switching information Table 5.C.1 shows the distribution of DWS regions that turned on after 2008 as a function of event time τ i.e. an event time of -5 means a GP is in an SLA that will turn on the DWS program five years from the year in the top row. Similarly, event time $\tau = 0$ represents GPs who were in SLAs that had the DWS program turned on in the corresponding year.

Table 5.C.1: MABEL DWS Switching: Event Time & Year

	Year							
τ	2008	2009	2010	2011	2012	2013	2014	Total
-5	68	25	0	0	0	0	0	93
-4	49	60	23	0	0	0	0	132
-3	38	66	112	23	0	0	0	239
-2	280	40	51	125	24	0	0	520
-1	173	264	46	109	125	16	0	733
0	57	166	260	42	122	99	22	768
1	0	36	142	185	33	115	101	612
2	0	0	31	118	189	20	91	449
3	0	0	0	21	120	147	21	309
4	0	0	0	0	19	96	134	249
5	0	0	0	0	0	15	108	123
Total	665	657	665	623	632	508	477	4,227

The distribution of GPs in SLAs that will turn, in groups of event time τ and sampling year

Table 5.C.2: Standard Deviations: AMPCo sample frame and MABEL

	(1) Always DWS 2008	(2) Always DWS 2014	(3) Treated DWS 2008	(4) Treated DWS 2014	(5) Never DWS 2008	(6) Never DWS 2014
Number of GPs	27.07	31.59	31.50	33.10	31.89	34.57
Number of IMG GPs	9.10	11.88	12.45	15.46	11.06	13.22
Number of Native GPs	19.13	21.06	20.86	19.99	23.24	24.13
Hours worked	16.21	14.95	15.08	15.29	14.82	15.44
Number of Patients Seen	61.58	56.41	59.52	57.09	61.96	55.83
Consultation Fee	21.16	27.49	20.70	36.41	24.10	29.29
Proportion bulk-billed	31.70	31.83	30.08	29.84	31.59	32.23
Consultation Length	6.91	6.82	5.54	5.99	8.92	7.37
Income (000s)	114.00	148.10	109.15	132.52	110.72	122.86
Number of children	1.41	1.28	1.32	1.30	1.31	1.25
Living with Partner	0.33	0.34	0.31	0.35	0.35	0.35
Per cent Female	0.49	0.49	0.48	0.49	0.49	0.49
Age	11.23	10.99	11.38	10.56	11.26	11.40
popdensity	1056.01	1014.29	1791.82	1787.65	1829.03	2543.79
medianincome	161.52	269.64	127.30	217.18	192.90	261.48
medianage	7.20	10.54	4.82	12.29	6.42	8.55
N_{SLA}	585	573	237	234	273	274
$N_{doctors}$	1381	781	783	564	1145	895

Standard Deviations for key labour market and socioeconomic variables for the 2008 and 2014 using the MABEL dataset and AMPCo data frame. MABEL data weighed using cross-section weights.

5.C.2 Expanded Tables

Table 5.C.3: Expanded Table: **Total Number of GPs in an SLA**

	(1)	(2)	(3)
	DID without FE	DID with FE	DDD with FE
τ			-0.672***
			(0.160)
$1(DWS)$	-4.071**	-0.896***	0.282
	(1.884)	(0.217)	(0.320)
$1(DWS) \times \tau$	1.067*	-0.279**	0.325*
	(0.576)	(0.121)	(0.190)
SEIFA IRSAD Index	0.0148	-0.00478	-0.00639
	(0.0164)	(0.00704)	(0.00710)
Population Density	0.00917***	0.00295***	0.00284***
	(0.00142)	(0.000663)	(0.000646)
Median Income	-0.0293***	0.000856	0.00145
	(0.00889)	(0.00307)	(0.00290)
Median Age	-0.125	0.0488	0.0428
	(0.310)	(0.0575)	(0.0529)
year=2008		0	0
		(.)	(.)
year=2009		0.342**	0.460***
		(0.167)	(0.170)
year=2010		0.874***	1.061***
		(0.232)	(0.238)
year=2011		0.560*	0.825***

		(0.288)	(0.293)
year=2012		1.129***	1.412***
		(0.355)	(0.355)
year=2013		1.790***	2.059***
		(0.446)	(0.442)
year=2014		2.292***	2.559***
		(0.561)	(0.553)
SLA Fixed Effects	No	Yes	Yes
Observations	2998	2998	2998

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.C.4: Expanded Table: **Number of IMG GPs in an SLA**

	(1) DID without FE	(2) DID FE	(3) DDD with FE
τ			-0.347***
			(0.0782)
$1(DWS)$	-0.831	-0.249*	0.360**
	(0.747)	(0.144)	(0.161)
$1(DWS) \times \tau$	0.281	-0.101	0.211*
	(0.236)	(0.0888)	(0.111)
SEIFA IRSAD Index	-0.0124*	-0.00245	-0.00328
	(0.00661)	(0.00454)	(0.00454)
Population Density	0.00247***	0.00114***	0.00109***
	(0.000603)	(0.000363)	(0.000361)
Median Income	-0.0108***	-0.00000247	0.000307

	(0.00304)	(0.00236)	(0.00226)
Median Age	-0.112	-0.0490	-0.0520
	(0.0996)	(0.0530)	(0.0508)
year=2008		0	0
		(.)	(.)
year=2009		0.332***	0.393***
		(0.110)	(0.113)
year=2010		0.758***	0.855***
		(0.160)	(0.165)
year=2011		0.741***	0.878***
		(0.215)	(0.219)
year=2012		1.175***	1.321***
		(0.283)	(0.285)
year=2013		1.537***	1.676***
		(0.346)	(0.346)
year=2014		1.859***	1.997***
		(0.441)	(0.438)
SLA Fixed Effects	No	Yes	Yes
Observations	2998	2998	2998

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.C.5: Expanded Table: **Patients Seen in an Average Week**

	(1)	(2)	(3)	(4)

	DiD with Pooled OLS	DiD with SLA Fixed effects	DDD with SLA Fixed Effects	DDD with SLA+ Doctor Fixed Effects
t			1.234	0.924
			(1.696)	(1.107)
policy	4.297**	0.791	-1.150	1.823
	(2.108)	(2.121)	(3.043)	(2.479)
policy_t	-2.332***	-1.950**	-3.104*	-2.580**
	(0.880)	(0.842)	(1.811)	(1.201)
popdensity	0.00201***	-0.00000655	0.0000527	-0.00189
	(0.000451)	(0.00124)	(0.00125)	(0.00142)
medianincome	0.00438	-0.0203*	-0.0209*	-0.00250
	(0.00399)	(0.0119)	(0.0121)	(0.0131)
medianage	-0.209**	0.170	0.162	-0.0000149
	(0.0919)	(0.188)	(0.196)	(0.223)
percent_under5	0.695	-3.640	-3.640	-1.662
	(0.674)	(2.969)	(2.967)	(2.390)
percent_above65	-0.110	-0.573	-0.576	0.770
	(0.153)	(0.600)	(0.601)	(0.704)
seifa_irsad	0.00139	-0.208	-0.213	-0.166*
	(0.0576)	(0.134)	(0.134)	(0.0993)
seifa_irsd	-0.240***	-0.0221	-0.0215	0.0506
	(0.0384)	(0.0967)	(0.0966)	(0.0706)
seifa_ier	0.222***	0.112	0.114	0.0549
	(0.0391)	(0.104)	(0.104)	(0.0677)
seifa_ieo	-0.0443	0.108	0.111	0.0860

	(0.0302)	(0.117)	(0.117)	(0.0839)
seifa_	-0.0403***	0.0343	0.0362	0.0410
	(0.0149)	(0.0312)	(0.0309)	(0.0344)
agesq	0.0105***	0.0115***	0.0115***	0.0173
	(0.00211)	(0.00339)	(0.00339)	(0.0466)
expersq	-0.0239***	-0.0255***	-0.0256***	-0.0711
	(0.00391)	(0.00646)	(0.00646)	(0.0459)
pigeni	-39.39***	-38.14***	-38.15***	0
	(1.200)	(2.156)	(2.157)	(.)
isimg	9.823***	9.677***	9.684***	0
	(1.414)	(2.735)	(2.737)	(.)
fclp	-2.028	-3.506	-3.523	3.923
	(1.775)	(2.797)	(2.796)	(2.981)
fcndc	-0.200	-0.0926	-0.0984	-0.323
	(0.485)	(0.875)	(0.875)	(0.832)
Year + SLA Fixed Effects	No	Yes	Yes	Yes
Doctor F.E.	No	No	No	Yes
N	8809	8809	8809	8809

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.C.6: Expanded Table: **Hours Worked Per Week**

	(1) DiD with Pooled OLS	(2) DiD with SLA Fixed effects	(3) DDD with SLA Fixed Effects	(4) DDD with SLA+ Doctor Fixed Effects
t			0.496	0.208

			(0.365)	(0.272)
policy	0.623	0.606	-0.172	-0.236
	(0.499)	(0.591)	(0.753)	(0.535)
policy_t	-0.690***	-0.540**	-1.005**	-0.627*
	(0.222)	(0.267)	(0.427)	(0.321)
popdensity	-0.0000689	-0.000519	-0.000497	-0.000261
	(0.000118)	(0.000442)	(0.000445)	(0.000598)
medianincome	-0.00298***	-0.000291	-0.000547	0.00262
	(0.00105)	(0.00420)	(0.00420)	(0.00442)
medianage	-0.0320	0.0679	0.0646	0.0262
	(0.0234)	(0.0642)	(0.0661)	(0.0687)
percent_under5	-0.641***	-1.715**	-1.716**	-2.080***
	(0.166)	(0.697)	(0.698)	(0.786)
percent_above65	-0.168***	-0.370**	-0.371**	-0.355**
	(0.0391)	(0.149)	(0.149)	(0.143)
seifa_irsad	-0.0498***	-0.0435	-0.0452	-0.0572*
	(0.0150)	(0.0358)	(0.0360)	(0.0337)
seifa_irsd	-0.0454***	-0.0169	-0.0166	0.000707
	(0.00923)	(0.0250)	(0.0251)	(0.0195)
seifa_ier	0.0665***	0.0377	0.0382	0.0430*
	(0.00991)	(0.0271)	(0.0271)	(0.0231)
seifa_ieo	0.0350***	0.0437*	0.0447*	0.0130
	(0.00790)	(0.0255)	(0.0256)	(0.0257)
agesq	0.000657*	0.00106	0.00106	-0.00991

	(0.000375)	(0.000739)	(0.000740)	(0.0125)
expersq	-0.00457***	-0.00488***	-0.00488***	0.00931
	(0.000697)	(0.00136)	(0.00136)	(0.0121)
pigeni	-12.05***	-11.56***	-11.56***	0
	(0.290)	(0.522)	(0.522)	(.)
isimg	0.374	0.435	0.436	0
	(0.330)	(0.574)	(0.574)	(.)
Year + SLA Fixed Effects	No	Yes	Yes	Yes
Doctor F.E.	No	No	No	Yes
N	9831	9831	9831	9831

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.C.7: Expanded Table: **Average Fee for a Standard Consultation**

	(1) DiD with Pooled OLS	(2) DiD with SLA Fixed effects	(3) DDD with SLA Fixed Effects	(4) DDD with SLA+ Doctor Fixed Effects
t			1.119*	0.910*
			(0.647)	(0.540)
policy	2.069**	1.031	-0.734	-1.063
	(0.827)	(0.903)	(1.271)	(0.983)
policy_t	-0.0174	-0.496	-1.543**	-1.111*
	(0.364)	(0.426)	(0.773)	(0.590)
popdensity	-0.00112***	-0.000523	-0.000469	0.000559
	(0.000237)	(0.000652)	(0.000646)	(0.000641)
medianincome	0.0146***	0.00471	0.00412	-0.000335

	(0.00198)	(0.00579)	(0.00591)	(0.00513)
medianage	-0.0308	0.130	0.123	0.0378
	(0.0475)	(0.102)	(0.106)	(0.0741)
percent_under5	-1.844***	-1.537	-1.535	-1.575
	(0.289)	(1.303)	(1.306)	(1.999)
percent_above65	0.226***	0.437*	0.434*	0.0698
	(0.0706)	(0.251)	(0.251)	(0.325)
seifa_irsad	-0.0714***	0.0403	0.0359	-0.00241
	(0.0270)	(0.0592)	(0.0596)	(0.0369)
seifa_irsd	0.276***	0.139***	0.140***	0.0603
	(0.0188)	(0.0465)	(0.0467)	(0.0368)
seifa_ier	-0.0853***	-0.0519	-0.0503	-0.0117
	(0.0181)	(0.0431)	(0.0434)	(0.0287)
seifa_ieo	-0.00700	-0.0119	-0.00937	0.0191
	(0.0140)	(0.0536)	(0.0538)	(0.0352)
agesq	-0.000342	-0.000194	-0.000187	0.00684
	(0.000884)	(0.00128)	(0.00128)	(0.0223)
expersq	-0.00104	-0.00125	-0.00127	-0.0342
	(0.00172)	(0.00238)	(0.00238)	(0.0230)
pigeni	0.716	0.256	0.249	0
	(0.539)	(0.881)	(0.881)	(.)
isimg	-7.367***	-7.276***	-7.266***	0
	(0.654)	(1.260)	(1.260)	(.)
fclp	2.440***	2.605**	2.587**	0.510

	(0.808)	(1.249)	(1.249)	(1.378)
fcndc	0.225	0.0740	0.0685	0.0856
	(0.219)	(0.328)	(0.329)	(0.306)
Year + SLA Fixed Effects	No	Yes	Yes	Yes
Doctor F.E.	No	No	No	Yes
N	8402	8402	8402	8402

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.C.8: Expanded Table: **Consultation Fee, $-3 \leq \tau \leq 3$**

	(1) SLA Fixed Effects	(2) SLA+Doctor Fixed Effects
t	1.064	0.0333
	(0.752)	(0.608)
policy	-0.817	0.156
	(1.345)	(1.028)
policy_t	-1.301	-0.256
	(0.941)	(0.673)
popdensity	-0.000546	0.000595
	(0.000614)	(0.000645)
medianincome	0.00115	0.00324
	(0.00721)	(0.00489)
medianage	0.164	-0.0135
	(0.128)	(0.0662)
percent_under5	-1.367	0.0266

	(1.349)	(1.992)
percent_above65	0.528**	0.301
	(0.254)	(0.328)
seifa_irsad	0.0657	0.00357
	(0.0620)	(0.0381)
seifa_irsd	0.152***	0.0435
	(0.0484)	(0.0374)
seifa_ier	-0.0773*	-0.0133
	(0.0450)	(0.0297)
seifa_ieo	-0.0283	0.0280
	(0.0560)	(0.0356)
agesq	-0.000202	0.0136
	(0.00130)	(0.0237)
expersq	-0.00127	-0.0404
	(0.00240)	(0.0246)
pigeni	0.271	0
	(0.906)	(.)
isimg	-7.003***	0
	(1.271)	(.)
fclp	2.315*	0.673
	(1.264)	(1.395)
fcndc	0.0728	0.154
	(0.334)	(0.326)
[1em] Year + SLA Fixed Effects	Yes	Yes

Doctor F.E.	No	Yes
N	8012	8012

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.C.9: Expanded Table: **Average Bulk-Billing Rate**

	(1) DiD with Pooled OLS	(2) DiD with SLA Fixed effects	(3) DDD with SLA Fixed Effects	(4) DDD with SLA+ Doctor Fixed Effec
t			-0.637	-0.824
			(0.827)	(0.539)
policy	0.0559	-0.544	0.456	1.443
	(0.978)	(0.931)	(1.506)	(1.014)
policy_t	1.015**	0.0306	0.626	0.495
	(0.436)	(0.469)	(0.935)	(0.590)
popdensity	0.00113***	0.000239	0.000211	0.000371
	(0.000256)	(0.000669)	(0.000669)	(0.000643)
medianincome	-0.0127***	-0.0102	-0.00992	-0.00482
	(0.00227)	(0.00733)	(0.00733)	(0.00577)
medianage	0.0546	-0.00890	-0.00467	0.0655
	(0.0515)	(0.0945)	(0.0943)	(0.0761)
percent_under5	3.777***	-0.0208	-0.0211	0.390
	(0.333)	(1.942)	(1.943)	(2.075)
percent_above65	0.116	0.0512	0.0525	0.242
	(0.0778)	(0.390)	(0.389)	(0.337)
seifa_irsad	0.0761**	0.0627	0.0651	-0.0521
	(0.0297)	(0.0714)	(0.0715)	(0.0416)

seifa_irsd	-0.252***	-0.114**	-0.115**	-0.0758**
	(0.0196)	(0.0517)	(0.0517)	(0.0368)
seifa_ier	0.0485**	-0.0105	-0.0114	0.0503
	(0.0195)	(0.0582)	(0.0581)	(0.0314)
seifa_ieo	-0.0202	-0.115**	-0.117**	0.0262
	(0.0154)	(0.0559)	(0.0562)	(0.0389)
agesq	0.00103	-0.000432	-0.000437	0.0141
	(0.000924)	(0.00140)	(0.00140)	(0.0203)
expersq	0.000433	0.00243	0.00244	-0.00171
	(0.00175)	(0.00260)	(0.00260)	(0.0197)
pigeni	-4.016***	-4.068***	-4.063***	0
	(0.642)	(1.217)	(1.217)	(.)
[1em] isimg	8.953***	8.204***	8.199***	0
	(0.708)	(1.270)	(1.270)	(.)
fclp	-2.727***	-2.095	-2.085	0.798
	(0.913)	(1.380)	(1.379)	(1.312)
fcndc	-1.078***	-0.398	-0.395	0.110
	(0.259)	(0.442)	(0.442)	(0.392)
[1em] Year + SLA Fixed Effects	No	Yes	Yes	Yes
Doctor F.E.	No	No	No	Yes
N	8933	8933	8933	8933

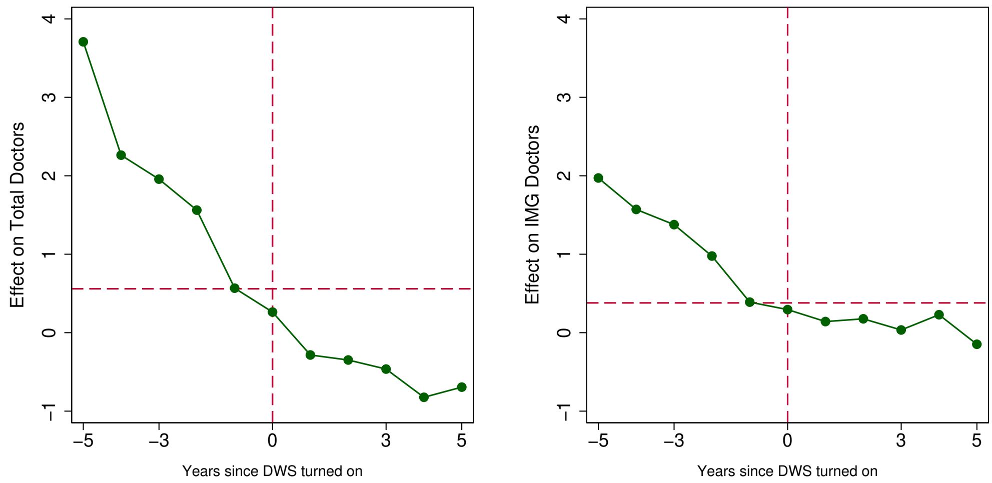
Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

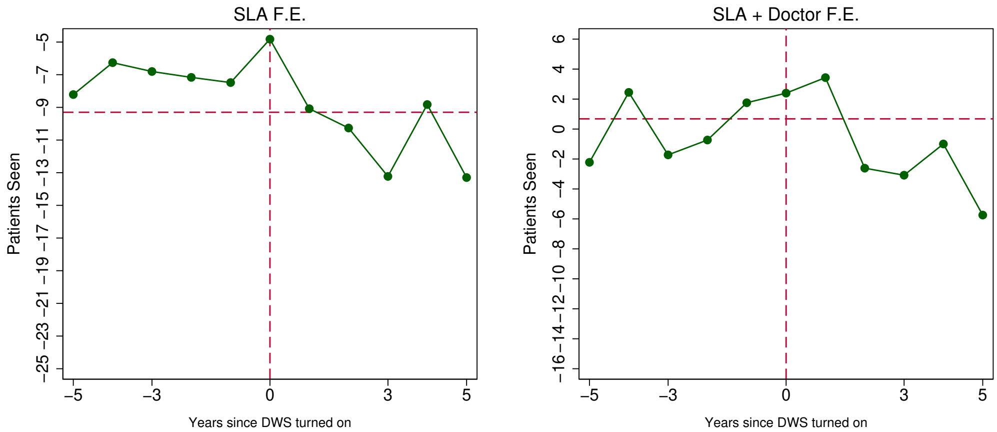
5.C.3 Robustness: Considered DWS with ≥ 1 quarter

The following estimates were obtained when the treatment sample restriction of having DWS turned on for two or more quarters in a year was changed to having the program turned on for one or more quarter in a year. The results are qualitatively similar to those in our preferred estimates.

Effect on Doctors Distributions



Effect on Patients Seen Per Week



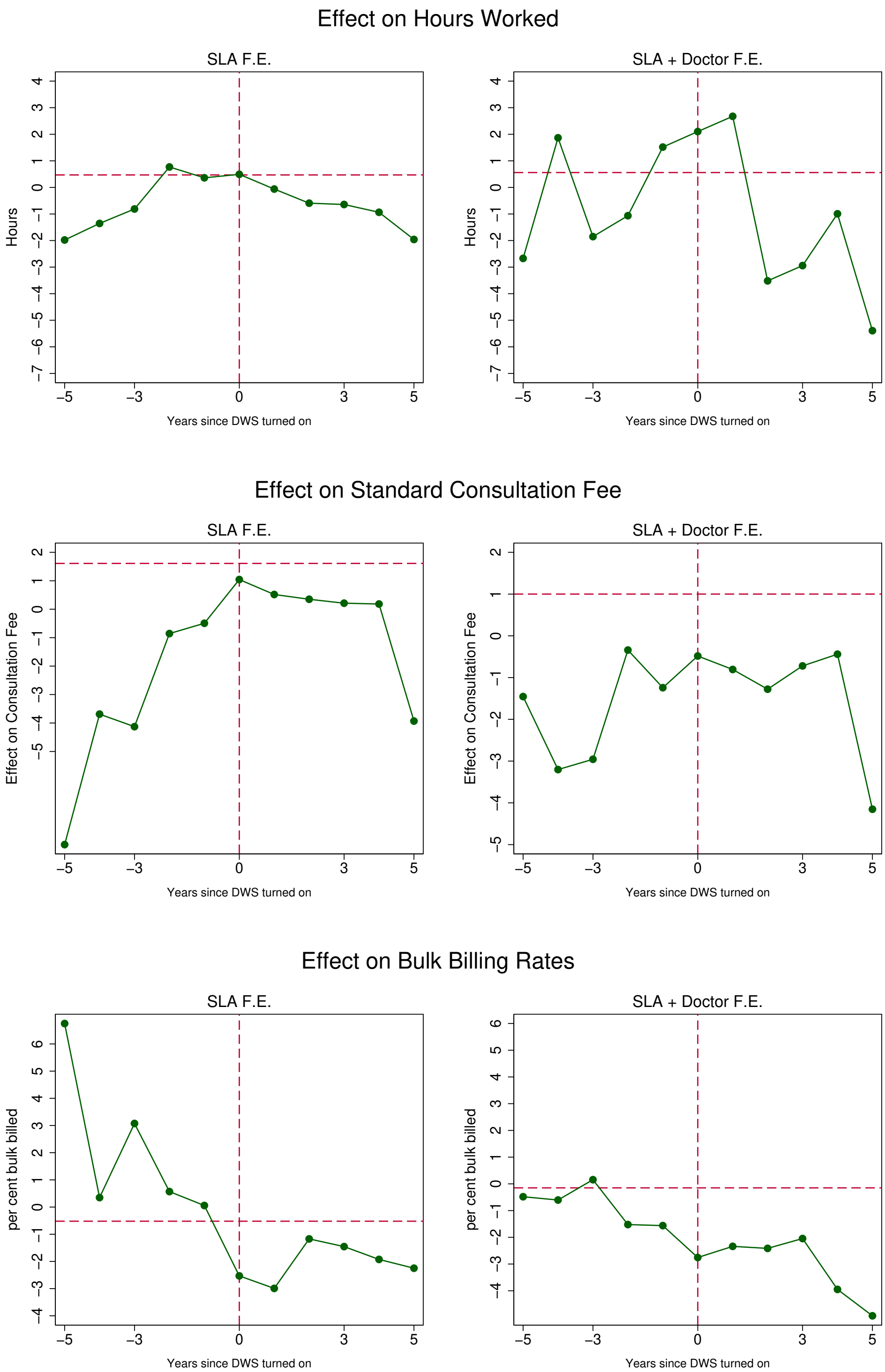


Figure 5.C.1: Sample restriction dropped: Trends in all outcomes

Table 5.C.10: OUTCOME: NUMBER OF GPS IN AN SLA

	(1) DID without FE	(2) DID with FE	(3) DDD with FE
τ			-0.672***
			(0.170)
$1(DWS)$	-4.187**	-1.067***	0.126
	(2.027)	(0.238)	(0.333)
$1(DWS) \times \tau$	1.739**	-0.245*	0.377*
	(0.829)	(0.135)	(0.212)
Controls	Yes	Yes	Yes
Year Fixed Effects	No	Yes	Yes
SLA Fixed Effects	No	Yes	Yes
Observations	2705	2705	2705

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results of my estimation strategy for the total number of GPs in an SLA. Standard errors clustered by SLA.

Table 5.C.11: OUTCOME: NUMBER OF IMG GPS IN AN SLA

	(1) DID without FE	(2) DID FE	(3) DDD with FE
τ			-0.391***
			(0.0891)
$1(DWS)$	-1.211	-0.413**	0.283
	(0.788)	(0.162)	(0.191)
$1(DWS) \times \tau$	0.683**	-0.0549	0.307**
	(0.336)	(0.100)	(0.129)
Controls	Yes	Yes	Yes
Year Fixed Effects	No	Yes	Yes
SLA Fixed Effects	No	Yes	Yes
Observations	2705	2705	2705

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results of my estimation strategy for the number of IMG doctors in an SLA. Standard errors clustered by SLA.

Table 5.C.12: OUTCOME: AVERAGE NUMBER OF PATIENTS SEEN

	(1) DiD with Pooled OLS	(2) DiD with SLA Fixed effects	(3) DDD with SLA Fixed Effects	(4) DDD with SLA+ Doctor Fixed Effects
τ			-0.503	0.568
			(1.607)	(1.029)
$1(DWS)$	5.293**	-0.232	0.575	0.890
	(2.128)	(2.181)	(3.240)	(2.307)
$1(DWS) \times \tau$	-2.562***	-2.148**	-1.674	-2.449**
	(0.915)	(0.945)	(1.745)	(1.143)
Controls	Yes	Yes	Yes	Yes
SLA Fixed Effects	No	Yes	Yes	Yes
Doctor F.E.	No	No	No	Yes
Observations	8185	8185	8185	8185

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results of my estimation strategy for the average number of patients seen per GP per week. Standard errors clustered by SLA in column 1,2,3 and GP ID in column 4.

Table 5.C.13: OUTCOME: HOURS WORKED IN AN AVERAGE WEEK

	(1) DiD with Pooled OLS	(2) DiD with SLA Fixed effects	(3) DDD with SLA Fixed Effects	(4) DDD with SLA+ Doctor Fixed Effects
τ			0.544	0.550**
			(0.427)	(0.252)
$1(DWS)$	0.757	0.240	-0.626	-0.734
	(0.495)	(0.609)	(0.900)	(0.544)
$1(DWS) \times \tau$	-0.667***	-0.369	-0.882*	-0.851***
	(0.224)	(0.277)	(0.479)	(0.304)
Controls	Yes	Yes	Yes	Yes
Year + SLA Fixed Effects	No	Yes	Yes	Yes
Doctor F.E.	No	No	No	Yes
Observations	9136	9136	9136	9136

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results of my estimation strategy for the average number of hours worked per GP per week. Standard errors clustered by SLA in column 1,2,3 and GP ID in column 4.

Table 5.C.14: OUTCOME:FEE CHARGED FOR A STANDARD CONSULTATION

	(1) DiD with Pooled OLS	(2) DiD with SLA Fixed effects	(3) DDD with SLA Fixed Effects	(4) DDD with SLA+ Doctor Fixed Effects
τ			1.376*	0.375
			(0.704)	(0.540)
$1(DWS)$	2.393***	1.995**	-0.217	0.209
	(0.821)	(0.953)	(1.370)	(0.986)
$1(DWS) \times \tau$	-0.231	-0.411	-1.708**	-0.525
	(0.366)	(0.480)	(0.816)	(0.601)
Controls	Yes	Yes	Yes	Yes
Year + SLA Fixed Effects	No	Yes	Yes	Yes
Doctor F.E.	No	No	No	Yes
Observations	7800	7800	7800	7800

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results of my estimation strategy for the average fee charged for a standard consultation. Standard errors clustered by SLA in column 1,2,3 and GP ID in column 4.

Table 5.C.15: OUTCOME: FEE CHARGED FOR A STANDARD CONSULTATION
$-3 \leq \tau \leq 3$

	(1) SLA Fixed Effects	(2) SLA+Doctor Fixed Effects
τ	1.443	0.241
	(0.923)	(0.734)
$1(DWS)$	-0.490	0.320
	(1.572)	(1.187)
$1(DWS) \times \tau$	-1.664	-0.406
	(1.063)	(0.798)
Controls	Yes	Yes
Year + SLA Fixed Effects	Yes	Yes
Doctor F.E.	No	Yes
Observations	7422	7422

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results of my estimation strategy for the average fee charged for a standard consultation. Standard errors clustered by SLA in column 1,2,3 and GP ID in column 4.

Table 5.C.16: OUTCOME: BULK BILLING RATES

	(1) DiD with Pooled OLS	(2) DiD with SLA Fixed effects	(3) DDD with SLA Fixed Effects	(4) DDD with SLA+ Doctor Fixed Effects
τ			-0.820	-0.334
			(0.900)	(0.568)
$1(DWS)$	-1.157	-2.605**	-1.293	-0.568
	(0.977)	(1.009)	(1.702)	(1.065)
$1(DWS) \times \tau$	1.546***	0.255	1.027	0.128
	(0.438)	(0.486)	(0.986)	(0.636)
Controls	Yes	Yes	Yes	Yes
Year + SLA Fixed Effects	No	Yes	Yes	Yes
Doctor F.E.	No	No	No	Yes
Observations	8303	8303	8303	8303

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results of my estimation strategy for the percent of patients bulk-billed. Standard errors clustered by SLA in column 1,2,3 and GP ID in column 4.