Immigrant Skill Selection and Utilization: A Comparative Analysis of Australia, Canada, and the United States [*]

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Abstract

We compare literacy skills and relative wage and employment outcomes of Australian, Canadian and U.S. immigrants. We find substantially higher immigrant skill levels at the lower end of the distribution in Australia, especially among recent arrivals, but little difference at the top. In addition, we identify larger wage returns to immigrant skill in the U.S., which we argue reflects language-skill complementarities. Our results suggest that the benefit of a point system lies in its potential to limit unskilled immigration, rather than in raising skills at the upper end of the distribution where the growth potential of immigration is likely greatest.

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1 Introduction

Recent years have save seen a shift in the discourse surrounding national immigration policies towards a greater emphasis on economic objectives and in particular the goal of attracting skilled migrants. This has been most evident in immigration reform discussions in the U.S., where there has been a renewed push for more merit-based immigration in place of long-standing family reunification objectives. But it has also been evident in both the U.K. – where a point system for selecting skilled migrants was phased in between 2008 and 2010 – and in Australia and Canada – where more than three decades after introducing point systems, policymakers continue to grapple with finding the optimal set of criteria for screening migrants with the right skills.

Two factors appear to underlie the heightened emphasis on immigrant skills. On one hand is growing evidence of rising wage inequality and the belief that skill-biased technological change is in large part to blame. Exacerbating the labour market challenges of unskilled domestic workers by flooding markets with low-wage foreign substitute labour is increasingly seen as unsound policy in an environment of rising income inequality. But at the same time, there is increasing recognition of the potential for immigration flows at the top end of the skill distribution to raise economic growth. A growing body of research from the U.S. and Europe suggests that skilled immigrants, particularly those in the STEM fields (Science, Technology, Engineering, and Mathematics), are not only more innovative than their native-born counterparts (Hunt and Gauthier-Loiselle 2010) but also have the potential to produce positive productivity spillovers on their native-born coworkers (Peri, Shih and Sparber 2014). Taken together, this evidence points clearly to the urgency for national immigration policies that attract skilled migrants.

But setting optimal policy in the new "global war" for skilled workers and talent is far from straightforward.[1] While a point system modelled on the Australian and Canadian systems is held up as a solution to the U.S.'s large unskilled migrant labour flows, the Australian and Canadian systems themselves appear to produce starkly different results. While both systems have very clearly increased the share of new immigrants with university degrees over the past three decades, in Canada higher average education levels appear not to have translated into higher average earnings. There is overwhelming evidence of a persistent deterioration in the earnings of new Canadian immigrants concomitant with the increase in their education levels (Aydemir and Skuterud 2005), a phenomenon which is not apparent in the Australian data (Clarke and Skuterud 2013). The critical question for Canadian policymakers is whether the deterioration reflects shortfalls in the

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[1]Beechler and Woodword (2009) attribute the idea of a "global war for talent" to a 1999 report by U.S. management-consulting firm McKinsey & Company, who concluded that the most important corporate resource over the next two decades will be individuals in the tails of the skill distribution.

skills of highly-educated Canadian immigrants, relative to their Australian counterparts, perhaps due to differences in educational quality or English (or French) language abilities across source countries, or an under-utilization of immigrant skills, arising from either discriminatory behaviour or employer difficulties assessing foreign credentials.

Differences in selection and settlement policies between Australia, Canada and the United States provide an ideal setting to inform what types of policies are more effective in attracting skilled migrants and ensuring the efficient use of their skills. The analytical hurdle, however, is finding data that allows one to directly compare the skill levels of immigrant workers across host countries. Antecol, Cobb-Clark and Trejo (2003) compare education levels and incomes of immigrants using 1990/1991 Census data and conclude that Australian and Canadian immigrants have higher average skills than U.S. immigrants, which they attribute to higher Latin American migration to the U.S. rather than an effect of selective immigration policies. However, as the Canadian experience emphasizes, not only are observed education levels poor measures of skill for foreign-educated workers, but differences in immigrants' relative incomes across host countries may say more about how labour market institutions and settlement policies affect the utilization of immigrant skills than anything about immigrants' actual skills.

In this paper, we compare literacy test scores of Australian, Canadian and U.S. immigrants, using data from the OECD's 2003/2006 Adult Literacy and Life Skills Survey (ALLS), a survey designed to enable inter-country comparisons of adult literacy skills. Although literacy is only one dimension of workplace skill, existing research using similar data has interpreted these test scores broadly as cognitive skill (e.g., Green and Riddell 2003; Blau and Kahn 2005; Barrett 2012). Moreover, because the tests are completed in the official language of the host country, they also have the potential to capture the language abilities of individuals with a foreign native language. Using Canadian data, Ferrer, Green and Riddell (2006) find that literacy test scores account for about two-thirds of the earnings gap of university-educated immigrants in Canada, much of which presumably reflects language abilities, as opposed to cognitive skills.

The results presented in this paper confirm these findings – literacy test scores matter for host country labour market performance as evidenced by large wage returns to literacy among native-born and immigrant workers in all three countries. Of primary interest to us, however, is whether observed differences in the literacy skills of Australian, Canadian and the U.S. immigrants, as well as estimated returns to these skills, appear consistent with salient differences in their immigration policies. In particular, is there any evidence that Australia and Canada's selective point systems – often cited as a model for U.S. immigration reform – result in higher immigrant skills, particularly at the upper end of the distribution where productivity spillovers to natives are

most likely? And is there any evidence that Australia's immigration reforms of the late 1990s, which not only introduced mandatory pre-migration language testing, but also placed greater emphasis on pre-arranged employment and formal foreign credential information systems, led to better selection and integration of skilled immigrants? Finally, is there evidence of more efficient utilization of immigrant skills in the U.S., due to the greater role of employers in immigrant selection and less regulated labour markets, which might make it harder for immigrants with foreign credentials to integrate in Australia and Canada?

Our analysis leads to three main findings. First, Australia's immigration reforms of the late 1990s appear to have substantially reduced the proportion of Australian immigrants with literacy levels below the threshold at which individuals are deemed functionally illiterate. Consequently, average literacy among all recent immigrants in Australia was, by the mid-2000s, significantly higher than in either Canada or the United States. Second, among immigrants with a foreign mother tongue, that is not Spanish in the U.S. case, the upper half of the literacy skill distribution is virtually identical in all three countries. To the extent that measured literacy in the ALLS data is correlated with unobserved productivity characteristics, this result is inconsistent with both positive self-selection of immigrants to the United States and with the belief that a point system for the U.S. will raise immigrant skills at the top end of the distribution where the economic growth potential of immigration is likely greatest. Third, there is no evidence that immigrants to either Australia or Canada earn a wage return to literacy that is different from their native-born counterparts. However, our estimates do point to a higher relative return to literacy skills for U.S. immigrants whose mother tongue is neither English nor Spanish. Comparing measured literacy skills in the ALLS data to occupation-level measures of required literacy from the O*NET database, suggests that this result is not explained by a greater access to higher paying occupations for immigrants in the U.S., relative to Australia or Canada. Rather, we argue that higher relative returns to immigrant literacy skills in the U.S. reflect a complementarity between language skills and cognitive skills, coupled with a higher return to cognitive skill for all workers in the United States.

The remainder of the paper is organized as follows. In the following section we provide background discussion of the most relevant policy and institutional differences between Australia, Canada and the United States. We then then describe the ALLS data in detail. In the fourth section, we present our results by first considering differences in relative immigrant literacy test scores and then examining the labour market returns to these scores. We conclude with a discussion of what we see as the key policy differences that are likely to be driving the main findings.

2 Background

An ideal research setting would allow us to attribute all differences in immigrant literacy skills across destination countries, as well as the labour market returns to these skills, to immigrant selection and settlement policies. But, of course, there are numerous policy and institutional differences across countries that will influence these outcomes, but that have little or nothing to do with immigration policy. Before examining the data, it is instructive to consider what these broader differences are and how we expect them to influence our findings.

In terms of immigrant skill levels, we expect the U.S. to attract a greater flow of unskilled immigrants, due primarily to the existence of large undocumented migration flows from Latin America, but also because of its greater emphasis on family reunification objectives, as opposed to human capital screening, in immigrant selection policy. On the other hand, more generous minimum wages in Australia and a greater union presence Canada will tend raise wages at the lower end of the wage distribution, relative to the United States. Inasmuch as these wage differentials do not create barriers to immigrant employment, we would expect them to attract unskilled migrant flows. If we were to look beyond migration from Latin America, we might then expect to find the U.S. immigrant skill distribution dominates at the lower end. Since the late 1990s, however, deregulation of Australian labour markets, most notably the dismantling of its awards system for setting wages across entire sectors, as well as the ramping up of immigrant selection criteria in its point system, should have stemmed unskilled immigration flows, especially relative to Canada, where the point system up to 2003 required no formal assessment of applicants' English or French language abilities. We should therefore see a relative upskilling of more recent Australian immigration flows.

Factors that influence immigrant selection at the upper end of the distribution are, however, different. Conditioning on immigrants from a similar set of source countries, we expect U.S. immigration flows to dominate, due primarily to larger wage returns to skill in the U.S., combined with relatively low marginal income tax rates at the upper end of the income distribution (Borjas 1987). Additionally, a relatively small but important segment of immigrants to the U.S. are admitted directly as skilled workers or on temporary student visas and then transition to permanent status after obtaining employment in the United States. Inasmuch as employers are able to extract better information to identify exceptional talent, relative to the broad criteria of the points system, there is further reason to expect the skills of U.S. immigrants to dominate at the top end of the distribution. Indeed, based on the perceived success of this two-step selection process, Australia made a shift in the late 1990s towards a similar system, in which migrants admitted on a student or work visa transition to permanent status after having demonstrated some form of successful integration,

usually in the form of permanent employment (Gregory 2014).[2] We might, therefore, expect the skills of more recent cohorts of Australian immigrants to look more like the U.S. at the top end. Lastly, if for some reason the United States is more attractive to all immigrants, regardless of skill level, for example if all immigrants perceive there is greater opportunity in the U.S. (including for their children), then there will be queues for migration to the United States. Combined with employer selection for skilled workers, this should provide the U.S. with further advantage in the skills of immigrants the top end of the distribution.

Effective immigration policy must not only attract skilled migrants, but also insure efficient utilization of their skills following their arrival. A critical consideration in this respect are foreign-educated immigrants, who may have difficulties obtaining employment commensurate with their skills if there are information frictions in evaluating their foreign credentials. The crudeness of the Canadian points system criteria, particularly the absence of screens on educational quality, language abilities and current labour market needs, suggests skill utilization should be least efficient in Canada.[3] The introduction of formal credential recognition systems in Australia in late 1990s suggests we should see higher returns to skills for recent Australian immigrants. Although the share of immigrants admitted through employer selection is quite small, employer pre-migration vetting of immigrant credentials in U.S. makes skill utilization issues less likely there. Consequently, we expect relative wage returns to immigrant skills to be lowest in Canada, followed by Australia and the United States.

Finally, we have argued that labour market institutions that regulate wage rates are most prevalent in Australia, followed by Canada. A consequence of these institutions may be that immigrant literacy deficits or information frictions that make it difficult for employers to evaluate immigrant skills manifest themselves through access to employment, opposed to wage rates. Consistent with this idea, Antecol, Kuhn and Trejo (2006) find that whereas immigrant assimilation in the U.S. is evident primarily through weekly earnings, in Australia it is more evident in relative employment rates. Two recent audit studies of local Canadian labour markets (Oreopoulos (2011); Dechief and Oreopoulos (2012)), showing lower employer interview requests for applicants with 'non-English' sounding names, similarly highlight the importance of the employment margin in understanding the labour market challenges of Canadian immigrants. This emphasizes the importance of considering both wage and employment returns to immigrant literacy skills in evaluating relative skill

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[2]The Canadian government has also been moving in this direction in recent years. In 2008, it introduced the Canadian Experience Class program allowing temporary residents with Canadian university degrees and work experience to transition directly to permanent residency. Moreover, in January 2015 the Canadian government plans to introduce a two-step Expression of Interest (EOI) system, in which prospective migrants are first put into an online pool, from which employers can identify candidates with skills that are in demand.

[3]Note that Canada has, since the collection of the ALLS data in 2003, followed the Australian example of screening pre-migration language tests in their Federal Skilled Worker Program.

utilization across immigrant destination countries.

In summary, differences in immigrant selection policies, as well as domestic labour market institutions and geography, should produce higher skills at the lower end of the distribution in the U.S., followed by Canada and Australia. However, Australian policy changes of the late 1990s, should have substantially reduced unskilled migration flows to Australia, potentially reversing its position relative to Canada, and perhaps also the U.S.. At the upper end of the skills distribution, on the other hand, we expect the U.S. immigrants to dominate, due to both self-selection and the role of employers in immigrant selection. Finally, due primarily to the contrast in information available to employers, relative to the broad criteria of point systems, we expect returns to literacy skills to be highest in the U.S., followed by Australia and Canada. However, once again, Australian policy reforms providing employers with a greater role in selection, may not only have raised skills at the upper end of the Australian distribution, but also resulted in higher labour market returns to those skills.

3   Data

The Adult Literacy and Life Skills Survey (ALLS) was the second initiative of Statistics Canada and the Organisation for Economic Co-operation and Development (OECD) to collect internationally comparable data measuring adult literacy skills.[4] In addition to providing objective measures of literacy and numeracy skills, the ALLS provides information on a rich set of individual economic and social characteristics, including country of birth and year of migration. In Canada and the United States, data collection took place in 2003 (in Canada between March and September and in the U.S. between January and June), while in Australia data were collected between July 2006 and January 2007. In Canada and the U.S., the survey was administered to one person aged 16 to 65 years in selected households, whereas for Australia sampling was restricted to individuals aged 15 to 74 years. In all three countries, the sampling frame was the resident non-institutionalized civilian population.

The ALLS data facilitate international comparisons since each country used the same psychometric test to assess skills across three domains:[5]

1. Prose Literacy: The knowledge and skills needed to understand and use various kinds of information from text including editorials, news stories, brochures and instructions manuals;

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[4]The International Adult Literacy Survey (IALS) was conducted in 23 countries, including Australia, Canada and the U.S., between 1993 and 1998. We were unable to use these data as only public-use files, which provide limited information on labour market earnings, were available for Australia and U.S..

[5]Australian Bureau of Statistics (2007)

2. Document Literacy: The knowledge and skills required to locate and use information contained in various formats including job applications, payroll forms, transportation schedules, maps, tables and charts; and

3. Numeracy: The knowledge and skills required to effectively manage and respond to the mathematical demands of diverse situations.

The assessment of these skills involved questions that emphasized the implementation and use of these skills in daily activities. It is this emphasis on 'essential skills' that makes the data particularly useful for estimating an overall return to skill across labour markets within a country.[6]

Proficiency in all domains is measured along a continuous scale ranging from 0 to 500. Each individual's score denotes a point at which they have an 80 per cent chance of successfully completing tasks with a similar level of difficulty.[7] The survey used item response theory and multiple imputation methods to generate five plausible values or proficiency scores for each skill domain. This methodology is widely used in educational testing and large scale surveys such as the OECD's Programme for International Student Assessment (PISA), Trends in International Mathematics and Science Study (TIMSS), and Progress in International Reading Literacy Study (PIRLS). Given the set of item responses, each of the five plausible values are all equally valid estimates of an individual's skill.

The data contain a population sampling weight, representing the inverse of the probability of inclusion in the sample, which we use to estimate all means and regression coefficients. The estimation is conducted separately for each plausible value in a skill domain and the results are averaged across the five plausible values to obtain the final estimates that we report. In addition, a set of replicate weights is used to apply a jackknife variance estimator that takes account of the complex survey design. The Australian data contain 60 replicate weights while the Canadian and U.S. data contain a set of 30 replicate weights. Consequently the jackknife variance estimator requires 305 separate regressions for Australia and 155 separate regressions for Canada and the United States.

Finally, the standard errors are calculated by combining the sampling variance and the impu-

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[6]In Australia and Canada, there are two additional skill domains available, problem solving and health literacy. As these are unavailable for the United States, they were not examined in our analysis.

[7]For example, an individual with an assessed score of 250 has a probability of 0.8 of correctly answering a task with an estimated difficulty level of 250. The same individual would have a probability of more than an 0.8 of correctly answering a simpler task and a diminished but non-zero probability (less than 0.8) of successfully completing a more difficult task.

tation variance.[8] Further details on statistical procedures for working with plausible values can be found in PISA (2009).

Consistent with Green and Riddell (2003) and Barrett (2012), we find that an individual's score is highly correlated across the three skill domains in the ALLS, making it difficult to separately identify the effect of each skill domain on employment or earnings outcomes. Rather than combine domains, which would invalidate the variance estimation, we completed our analysis separately using each of the three skill domains. However, for the sake of brevity, we only report the results for document literacy, which we think is most likely to capture the vocational skills critical for immigrant labour market integration. Although none of our main findings are sensitive to the choice of domain, the precision of the estimated immigrant wage returns was in some cases improved slightly when using document literacy.

Several sample restrictions are imposed in order to create a consistent sample that can be used to compare relative immigrant labour market outcomes across destination countries. First, all samples are restricted to individuals currently aged 18-64. Second, since the paper is concerned with the relationship between skills and labour market outcomes, students are also excluded, as cognitive skills presumably play a much weaker role in determining student labour market outcomes. Similarly, the self-employed are excluded from the analysis since their earnings likely reflect returns to both cognitive skills and capital investments. Third, in in order to avoid spurious correlations in our sample between age at migration and years since migration, arising as a consequence of our overall age restriction, we also exclude all immigrants who migrated before the age of 14. Finally, the principal outcome variable of interest is the hourly wage rate on the main job held over the previous year, which is constructed using information on weekly earnings in the main job and usual hours of work per week in this job. In order to ensure that the estimates are not driven by extreme observations in the earnings distribution, individuals in approximately 1% of the top and bottom of the earnings distribution are excluded from the analysis.

There are important differences in the source country composition of immigrants in these countries reflecting historical immigration policies and geographic proximity. For example, the U.S. will always have larger immigration flows from Mexico, and Australia from New Zealand, but we would not want to attribute differences in average immigrant literacy skills that arise from these flows to current immigration policies. Rather, we want to control for these compositional difference in our

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[8]Standard errors are estimated using:

$$\text{Var}(\bar{b}) = \frac{1}{J} \sum_j \text{Var}(\bar{b}_j) + \left(1 + \frac{1}{J}\right) \frac{1}{J-1} \sum_j (\bar{b}_j - \bar{b})$$

where $\bar{b}$ is the average of J estimates $\bar{b}_j$; $\text{Var}(\bar{b}_j)$ is estimated using the full set of jackknife replicate weights provided; and J represents the number of plausible values, which in the ALLS data is 5.

analysis in order isolate the influence of current selection policies. While it is possible to identify whether an individual was born outside the country of interview for all three destination countries, no further information regarding country of birth is available for the U.S., and in Australia and Canada the information is limited to a small set of the largest source countries. We do, however, have information on respondents' first language learned and understood, allowing us to distinguish immigrants according to whether or not they have a native mother tongue (English in Australia or the United States; English or French in Canada). Moreover, for the United States we can also distinguish immigrants with a Spanish mother tongue. By comparing U.S. immigrants with a foreign mother tongue that is not Spanish to Australian and Canadian immigrants with a foreign mother tongue (non-English in Australia and non-English/French in Canada), we obtain samples that are much more similar in source country composition.

Table 1 uses Census data to provide some evidence of the effectiveness of our strategy. Specifically, for each destination country we identify the top 20 foreign-language immigrant source countries, but for the U.S. also exclude Spanish-speaking countries. For the most part, the distinctions are made according to whether English or French is an official language of the country. However, where multiple official languages exist, we also exploit information in the 2006 Canadian Census to determine the predominant mother tongue of migrants from those countries.[9] The results reveal that looking beyond Latin American immigration to the U.S., the source countries of immigrants to Australia, Canada and the U.S. are remarkably similar. This suggests that the group of U.S. immigrants with a non-Spanish foreign mother tongue is roughly comparable to the group of Australian and Canadian immigrants with a foreign mother tongue. Specifically, 6 of the top 8 source countries are common across all three destination countries (China, Vietnam, Italy, India, Philippines, and Germany); another 3 appear in the top-20 of all three destination countries (Hong Kong, Korea, and Poland); and another 10 appear in at least two destination countries (Greece, Netherlands, Lebanon, Sri Lanka, Portugal, Pakistan, Iran, Taiwan, Russia, and Haiti). Interestingly, the top 20 countries account for over 70% of all foreign-language countries of birth in Canada and the United States, while in Australia they only account for 45%, indicating more diversity in the source country distribution in Australia.

Table 2 reports sample means in our extracted immigrant and native-born samples from the Australian, Canadian and U.S. ALLS data. The results for the native-born reveal little difference in mean age across countries. However, there are quite large differences in the educational attainment. While only 11.5% of Americans and 17.2% of Canadians did not graduate from high school,

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[9]Most notably, we classify Hong Kong, India, Pakistan and the Philippines as foreign-language countries as 6.6%, 13.7%, 13.0% and 20.7% of Hong Kong, Indian, Pakistani and Filipino immigrants in Canada identify English as a mother tongue.

31.8% of Australians do not have a high school diploma. At the upper end of the education distribution, however, the differences are smaller. Specifically, the shares of Australians, Canadians and Americans with a university degree are 20.0%, 19.2%, and 25.7% respectively. The occupational distribution, including the incidence of non-employment in the previous 12 months, is also very similar across native-born samples in the three destination countries.

With regard to immigrants, Table 2 reveals a similar mean age for Australian and Canadian immigrants to Australia and Canada, which is significantly greater than the mean age for the native-born. However, for the U.S. there is little difference in the mean age of immigrants and the native-born. Further analysis indicates that the lower mean age for U.S. immigrants is primarily driven by immigrants with a Spanish mother tongue. U.S. immigrants with a non-Spanish foreign mother tongue tend to be slightly older, on average, than the native-born, as in Australia and Canada. More important, there are large differences in the relative educational attainment and occupations of immigrants across destination countries. The share of Australian and Canadian immigrants with university qualifications is similar at 32.6% and 32.2%, respectively, which in both cases is significantly greater than the share of native-born individuals with university. In contrast, in the U.S., the share of university qualified immigrants is more similar, at 31.3%, to the share native-born Americans with a university qualification. Similarly, the share of immigrants in white collar jobs is higher in Australia (33.0%) and Canada (28.1%) than in the U.S. (24.0%), while the share in both skilled and unskilled blue collar jobs is lower in the U.S. (30.3% compared to 16.3% in Australia and 26.7% in Canada). These differences presumably reflect the emphasis of the Australian and Canadian point systems on post-secondary qualifications. This, however, masks some important heterogeneity between mother tongue groups within the U.S.. While less than 10% of U.S. immigrants with a Spanish mother tongue have university qualifications, over 50% of U.S. immigrants with a foreign mother tongue that is not Spanish do. By comparison, 35.4% of Australian and 31.2% of Canadian immigrants with a foreign mother tongue have a university qualification.

Table 3 reports the proportions of immigrants with and without a foreign mother tongue separately for recent immigrants, that is those arriving in the destination country within the previous 10 years, and established immigrants. Reflecting the persistent effect of historical immigration policy favoring migrants from English-speaking countries, as well as proximity to New Zealand, 40% of immigrants to Australia have a native mother tongue. The corresponding shares are 22.8% and 15.7% in Canada and the U.S., respectively. Among U.S. immigrants with a non-English mother tongue (approximately 85% of all immigrants), roughly half have a Spanish mother tongue, while the rest provide the group of greatest interest when comparing to foreign-language immigrants in

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Australia and Canada. Unfortunately, the ALLS sample size for the U.S. is small, leaving us with only 97 immigrants in this non-Spanish foreign mother tongue category. Nonetheless, some robust differences for U.S. immigrants are evident in the data across skill domains, in terms of both the literacy skill levels and labour market outcomes. Also, the fact that in all three destination countries roughly 40% of immigrants are observed within 10 years of their arrival, provides sufficient sample sizes to shed light on the influence of recent immigration policies, particularly in the case of Australia.

4 Results

4.1 Relative Immigrant Literacy

We begin our analysis of immigrant skills by comparing mean document literacy scores between Australian, Canadian and U.S. immigrants. Table 4 reports sample means separately by immigrants' gender, age, education, occupation, mother tongue and years since arrival. In all three destination countries, the mean literacy score in the full sample of all immigrants is lower than in the native-born population. The difference is greatest in the United States and smallest in Australia, and is in all cases statistically significant. In the U.S., the immigrant gap is equivalent to the difference between the 48th and 18th percentiles of the U.S. native-born distribution, whereas in Australia it is the difference between the 47th and 27th percentiles of the native-born distribution, and in Canada the 47th and 21st. Comparing directly across destination countries, mean immigrant literacy skills are highest in Australia (255.8), followed by Canada (248.1) and the U.S. (228.6).[10]

An examination of Table 4 reveals that source country distributions are important in explaining these differences in sample means across all immigrants. Approximately 40% of immigrants to Australia have a native mother tongue and these immigrants have higher average test scores in all countries, particularly in Australia. Similarly, approximately 44% of immigrants to the United States have a Spanish mother tongue and their literacy test scores are, on average, exceptionally low. To inform the efficacy of selection policy in raising average immigrant skills, one needs to condition on these broad native language differences, since they are by and large driven by factors beyond the influence of selection policy, most notably geography. Comparing Australian immigrants with a foreign mother tongue to U.S. immigrants with a foreign mother tongue that is not Spanish, the

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[10]Among the native-born, mean document literacy scores are similar in Australia (284.2) and Canada (286.6), but considerably lower in the United States (275.0). This difference holds across all education levels, broad occupations, and age categories. It is also worth noting that for Canada and the U.S., mean document literacy in the native-born population is increasing in education level. However, in Australia it is lower for those with a certificate/diploma than for high school graduates. This result primarily reflects that, historically, some post-secondary credentials were earned without high school completion. Consequently, holders of certificates/diplomas might have fewer years of schooling than high school graduates with no further post-secondary qualifications.

mean skill scores of recent immigrants are remarkably similar across countries and not statistically distinguishable (256.6, 248.0, and 253.6, respectively). This is not consistent with the expectation that the Australian and Canadian pursuit of skilled migrants through its selective immigration policies leads to higher immigrant skills, on average.

Further examination of Table 4 indicates that the average skill level of Australian immigrants arriving after 1995 is, however, substantially higher than among earlier cohorts (271.9 compared to 245.6). This large difference is not evident in either Canada or the United States. Although some of the increase is evident among those with an English mother tongue (300.0 compared to 279.5), it is considerably more evident among recent Australian immigrants with a foreign mother tongue (256.6 compared to 219.2). This suggests that Australia's immigration reforms of the late 1990s, which not only introduced mandatory pre-migration language testing, but also placed greater emphasis on pre-arranged employment and formal foreign credential information systems, did indeed lead to better selection of skilled migrants, at least in terms of the skills measured in the ALLS survey.

To obtain a better sense of the role of immigration policy, we next explore whether the differences in sample means are driven by differences at the bottom or top end of the skill distributions. Figure 1 plots skill percentiles for selected types of immigrants. The top-left panel reveals that the Australian distribution stochastically dominates that for Canada and the United States above the 20th percentile. Comparing this panel to the bottom-left panel for immigrants with a foreign mother tongue suggests that the Australian advantage in the first panel mainly reflects Australia's larger share of immigrants with an English mother tongue. Below the 20th percentile in the bottom-left panel, Australian immigrants have considerably lower test scores than either Canadian or non-Spanish U.S. immigrants with a foreign mother tongue and are similar to U.S. immigrants with a Spanish mother tongue. However, beyond the 20th percentile the Australian distribution quickly converges to that of the Canadian and U.S. distributions.

These patterns become more salient when we restrict attention to recent immigrants in the top- and bottom-right panels of Figure 1. Above the median there is little difference in the skills of similar immigrants to Australia, Canada, and the U.S., particularly when we restrict attention to immigrants with a foreign non-Spanish mother tongue. However, between the 10th and 50th percentiles the Australian distribution clearly dominates. This suggests that Australia's immigration reforms of the late 1990s served almost exclusively to raise skill levels between the 10th and 50th percentiles. We attribute this to two factors. First, going back to at least the early 1990s, roughly 10 percent of new immigrants to Australia (and Canada and the U.S.) were admitted as refugees. Since the admission criteria for refugees are unrelated to skill, it is not surprising that the points system reforms of the late 1990s did nothing to raise skill levels below the 10th

percentile, where refugees are presumably concentrated. However, beyond the 10th percentile, where Australian immigrants were subject to heightened skill thresholds, most notably minimum English-language standardized test scores, there is a clear upturn in the Australian skill distribution. Moreover, beyond the median, where the minimum thresholds of the points system are less likely to be binding, there is little difference across the three destination countries. Interestingly, the upturn in Australian skills beginning at the 10th percentile appears noticeably larger among all recent immigrants (top-right panel), corroborating existing evidence that an important part of the overall improvement in the labour market performance of Australian immigrants reflects a shift in immigration towards migrants with an English mother tongue (Clarke and Skuterud 2014).

Figure 2 presents quantile-quantile plots of the document literacy distributions of recent immigrants with a foreign mother tongue to the three destination countries. Again, to make comparisons more reflective of selection policy, we restrict attention to U.S. immigrants with a non-Spanish mother tongue. With the exception of some small differences at the very bottom and top, the Canadian and U.S. distributions are remarkably similar. Alternatively, the Australian skill distribution clearly dominates both the Canadian and U.S. distributions between roughly the 20th and 80th percentiles. There is, however, no strong evidence for a U.S. skills advantage above the 80th percentile. One could, of course, argue that the skills that make U.S. immigrants exceptional are different than those captured by the ALLS. But, whatever these other skills are, the data suggest that they do not provide a advantage in test scores. This also appears true in the prose literacy and numeracy domains. To the extent that the ALLS test scores are correlated with the unobserved skills of exceptionally skilled immigrants, our results do not appear consistent with the positive self-selection at the top end of the skill distribution that the Borjas (1987) model of immigrant self-selection implies. Alternatively, the skills that are measured by the ALLS data might not be sufficiently correlated with the unobserved skills of the exceptionally skilled immigrants in the Borjas (1987) model. This is consistent with the nature of tests in the ALLS data that are primarily concerned with distinguishing between functional literacy and functional illiteracy rather than distinguishing between functionally literate and functionally very literate workers. In this case, we are unable to make strong conclusions regarding positive self selection of immigrants above the 80th percentile.

Interestingly, however, the skill distribution for U.S. immigrants does appear to dominate that of Australian immigrants in the bottom fifth of the distribution. This is consistent with the observed difference in labour market institutions between Australia and the U.S.. In the presence of higher minimum wages, relatively more centralized labour markets, and the existence of a welfare safety net, less skilled immigrants would prefer Australia over the U.S.. This is a form of immigrant self-

selection resulting in the U.S. being able to attract higher skilled immigrants, relative to Australia, at the bottom end of the skill distribution. This effect might also be strengthened by a perception of greater opportunity in the U.S., together with a greater supply of unskilled jobs.

Overall, the evidence presented in Table 4 and Figures 1 and 2 suggests that there is very little to distinguish the skills measured in the ALLS data, of immigrants with a foreign mother tongue to Australia and Canada from immigrants to the United States with a non-Spanish foreign mother tongue. Moreover, this result not only holds at the mean but across most of the entire distribution of skills. There is no clear evidence that Australia and Canada's selective points systems have lead to higher immigrant skills. This result is consistent with the conclusions of Antecol et al. (2003) based upon education and income measures in Census data. However, higher immigrant skills in the middle of the skill distribution in Australia are particularly evident among recent arrivals who were subject to heightened language-ability requirements introduced in the late 1990s.

The evidence presented in 1 reveals that comparing Australian, Canadian and U.S. immigrants with a foreign mother tongue, but excluding Spanish immigrants for the U.S., provides a comparison that captures the important heterogeneity in source country distributions across the three destination countries. It is possible that our result – that there is little difference in the skill of immigrants to Australia, Canada, and the U.S. with a foreign mother tongue – arises from averaging the skill distribution across a diverse group of source countries. While the source country distributions might be similar across the three countries, the characteristics of the immigrants within a particular source country might be different, reflecting differences in labour market institutions, immigrant selection and settlement policies. In order to check for this we look at China – the biggest source country in the non-Spanish group – to see whether there is any difference in skills of Chinese immigrants across the three countries. [11] The resulting skill distributions in Figure 3, once again, offer little evidence that skills of U.S. immigrants dominate those of Australian or Canadian immigrants above the median. There is, however, some evidence that, relative to Australia, and to a lesser extent Canada, the U.S. is able to attract better quality Chinese immigrants at lower levels of measured skill. As noted above, this result is entirely consistent with the differences in labour market institutions between destination countries, as well as the relatively more generous welfare safety net provided by Australia.

The similarity of the skill distributions at the top end suggest that the primary benefit of a points system for selecting immigrants, such as that in Australia or Canada, lies in its potential to

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[11]Note that the Australian sample does not provide sufficient detail to be able to identify immigrants with a Chinese mother tongue. Consequently, for the Australian sample, immigrants with a Chinese mother tongue are constructed from information on country of birth. As a result, the classification for Canada and the U.S. is broader, as it includes immigrants from other Asian nations, such as Malaysia, Laos, and Vietnam, who have a Chinese mother tongue.

limit unskilled immigration flows, rather than in raising immigration levels at the top end where the economic growth potential of immigration is most likely. Furthermore, the current U.S. policy of linking limited work visas for foreigners with pre-arranged employment, most notably for foreign students, combined with family-reunification allowances appears successful in terms of attracting highly skilled migrants. Moving to a points system similar to Australia, is likely to raise the skills of immigrants with a Spanish mother tongue that are admitted, who have lower skills, but it is unlikely to improve the skills of immigrants with a non-Spanish mother tongue for whom any restrictions under a points system will not be binding. In addition, a point system will have little influence on the large flow of undocumented immigrants with a Spanish mother tongue, whose skills do not meet the thresholds of the system.

4.2 Log Wage Returns to Immigrant Literacy Skills

In competitive labour markets workers receive wage rates equal to the marginal productivity of their jobs, which depends on both the skills of the worker and the mix of other productive inputs employed in the job. Consequently, the marginal influence of measured skill on wage rates should be similar across workers employed in similar jobs. However, non-competitive factors, such as discrimination in hiring or credential recognition issues, can result in the under-utilization of immigrant skills driving wedges between the returns of immigrant and native-born workers.

To obtain evidence on the relative utilization of immigrant skills in Australia, Canada and the U.S., we estimate the following reduced-form specification:

$$\ln w_i = \beta_0 + \beta_S \, \tilde{S}_i + \beta_M \, M_i + \beta_{MS} \left\{ M_i * \tilde{S}_i \right\} + \mathbf{X}_i \, \beta + \varepsilon_i, \tag{1}$$

where $\ln w_i$ represents the natural logarithm of hourly earnings in the main job held in the previous twelve months; M_i is a dummy variable indicating that individual i is foreign-born; $\tilde{S}_i$ is the ALLS measure of document literacy; $\mathbf{X}_i$ is a vector of characteristics of individual i that includes a quadratic in age, controls for geographical region of residence, urban/rural area of residence, and an indicator for gender; and ε_i is a random error component with mean zero and variance that potentially varies across individuals.[12]

Differences in the return to measured skills for the native-born in Australia, Canada, and the United States, will be reflected in differences in the estimates of β_S across destination countries. Similarly, differences in the returns to immigrant skills will be reflected in differences in the estimates

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[12]The sample we use to estimate equation (1) includes all individuals that worked at least one hour in the last year. The estimated relative immigrant returns to skill could reflect hours variation if: (i) hourly wages are increasing in hours of work; (ii) hours vary systematically with skill; and (iii) preferences for work vary between natives and non-Spanish immigrants. However, it turns out that including controls for weekly hours of work in the wage equation has only a negligible effect upon the estimated relative returns to skill.

of $(\beta_S + \beta_{MS})$ across countries. In order to simplify the interpretation of the estimates, the literacy measure has been divided by a factor of 10 and scaled to represent the difference of the score from 225.[13] Similarly, age has been scaled to measure years above thirty years. Consequently, the intercept term represents the mean log wage for a thirty year-old native-born male, with an assessed literacy score of 225, residing in some urban reference region (New South Wales for Australia, Ontario for Canada, and the North-East for the United States), whereas the estimated coefficient on the immigrant dummy represents the difference in the mean log wage for an individual with an assessed literacy score of 225 and some common set of $\mathbf{X}_i$ characteristics.

A complication in estimating the measured skill returns in equation (1) is whether to condition on educational attainment. On the one hand, education can be viewed as an input into the production of the skills captured in the ALLS data test scores, in which case we would not want to control for education in estimating the returns to skill. On the other hand, one could argue that the estimated returns to measured skill also capture labour market returns to other skills correlated with measured literacy skills, including cognitive skills not directly assessed in the ALLS data, as well as non-cognitive skills. If the correlation between measured and unmeasured skills is different for immigrants than natives, this will show up as differential returns to skill (that is, nonzero estimates of β_{MS}), even in the absence of differences in skill utilization. But to the extent that education captures these other skills, perhaps again because it is an input in producing them, conditioning on education is more likely to produce estimates of β_{MS} that reflect differences in skill utilization. Since we are ultimately agnostic to the role of education, we have also examined a separate set of estimates that control for three broad education groups (high school or less, some post-secondary, and university degree). Although including education controls substantially reduces the estimated skill returns in all countries, none of our main findings regarding the relative returns to immigrant skills are affected by their inclusion.[14]

Table 5 presents ordinary least squares (OLS) estimates of equation (1). Similar to Figures 1 and 2, average returns to skill are estimated for the full sample of all immigrants within each destination country, as well for: (i) all recent immigrants (within 10 years of arrival); and (ii) recent immigrants with a foreign (and non-Spanish in the U.S. case) mother tongue. This is done by estimating three separate regressions, which rather than including an overall M_i dummy, include increasing numbers of immigrant indicators distinguishing between immigrant types.[15] In each

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[13]A skill score of 225 is regarded by the survey developers as the "minimum required for individuals to meet the complex demands of everyday life and work in the emerging knowledge-based economy" (Statistics Canada (2005), p.35). Accordingly, individuals with a skill score below 225 would be deemed as functionally illiterate.

[14]These results are available from the authors upon request.

[15]Due to limited immigrant sample sizes, particularly in the U.S. sample, we are forced to restrict the coefficients on the conditioning vector $\mathbf{X}_i$ to be the same for immigrants and natives.

case, we also report the unconditional (on measured skill) immigrant wage gaps, in order provide an indication of the relative importance of literacy skills in driving immigrant wage gaps across the three destination countries.

Looking first at the estimated immigrant wage gaps that do not condition on measured skill (but do condition on $\mathbf{X}_i$), mean log wages across all immigrants are 6 log points lower in Australia; 23 log points lower in Canada; and 18 log points lower in the United States. Interestingly, the substantially larger gaps in Canada and the U.S., relative to Australia, appear consistent with their larger gaps in mean immigrant skills (relative to natives) identified in Table 4. However, when we restrict attention to recent immigrants, the wage gaps in Australia and Canada increase, while in the United States it decreases, such that the U.S. gap is roughly similar to Australia (14 log points compared to 9), but much larger in Canada (36 log points). These results appear somewhat inconsistent with the changes in mean skills of recent immigrants, where large gains in Australia, but little change in either Canada or the U.S., would suggest a falling wage gap in Australia and little change in Canada or the United States. Of course, with conditioning on skill, these gaps will also reflect differences in returns to immigrants' skills across countries. Much larger wage gaps for recent immigrants in Canada, relative to the U.S., despite a similar difference in mean skills, would thereby suggest a relative under-utilization of immigrant skills in Canada.

As noted above, differences in mean immigrant skills across destination countries largely disappear when we restrict attention to recent immigrants with a foreign mother tongue (non-English in Australia, non-English/French in Canada, and non-English/Spanish in the U.S.). However, the third set of results in Table 5 reveal remarkably different unconditional (on skill) wage gaps across destination countries for this group of immigrants. In Australia, the gap is roughly twice as larger as the gap among all recent immigrants (19 log points compared to 9), while in Canada it is almost unchanged (40 log points compared to 36). However, in the U.S. the wage gap is essentially zero. Of course, part of the explanation for these differences is that the mean skill of the native-born benchmark is substantially lower in the U.S. than in Australia or Canada. Regardless, these large differences in mean wage gaps in a sample of immigrants with virtually identical mean measured skills is, once again, appears consistent with our expectation of superior immigrant skill utilization in U.S. labour markets.

To obtain more direct evidence on skill utilization, we next turn to the estimated returns to document literacy in Table 5. First to note is that there is considerable variation in returns for natives across the three countries. A ten-point increase in document literacy is associated with a log wage increase of 3.1 log points in Australia, 3.4 log points in Canada, and 4.1 log points in the United States. These differences appear consistent with differences in labour market institutions

across countries. Although, Australia experienced significant labour market deregulation in the 1990's, most notably the dismantling of its award system for wage standardization across sectors of the national economy, the labour market in Australia is still relatively regulated compared to Canada and the United States. For example, using 2006 OECD data, the ratio of the minimum wage to median wages for full-time workers was 0.54 in Australia, 0.40 in Canada, and 0.33 in the United States. Similarly, the OECD's index of the strictness of employment protection for individual and collective dismissals, was 1.42 for Australia, 0.92 for Canada, and 0.26 for the United States in 2006. The ranking of the estimated returns to measured skill across the three countries is also consistent with the findings in Hanushek at al. (2013) of lower estimated returns to skill in countries with higher union density, stricter employment protection legislation, and larger public sectors.

Turning to the relative immigrant returns to skill in the second row of Table 5, the point estimates for Australia and Canada are both small, relative to the overall returns in the first row, and not statistically different from zero. Equal marginal returns to skill for immigrant and native-born workers in Australia and Canada suggest that the unconditional wage gaps among immigrants reflect something other than an under-utilization of their skills. In Australia, the immigrant intercept is now also no longer negative, indicating that the unconditional wage gap is entirely explained by lower mean immigrant skills. In Canada, on the other hand, a wage gap of 10 log points persists across the skill distribution, the source of which is unclear, but is consistent with, for example, a concentration of immigrants within low-wage firms (Aydemir and Skuterud 2008) or even employer tastes for discrimination that are independent of skill.

The U.S. results in Table 5 appear even less consistent with an under-utilization of immigrant skills, as the return to measured skill for U.S. immigrants exceeds the already-large return for U.S. natives. Specifically, a 10-point increase in measured document literacy is associated with a 5.6 log point increase for U.S. immigrants, compared to a 4.1 log point increase for U.S. natives, a difference that is statistically significant at the 10% significance level. Given the negligible coefficient on the immigrant dummy, the results imply an immigrant wage *advantage* (conditional on $\mathbf{X}_i$)) above a skill level of 225, which is roughly the 40th percentile of the U.S. immigrant skill distribution. This is starkly different from the Canadian results, where immigrant wage disparities are evident across the entire skill distribution.

What explains a higher return to literacy skills for U.S. immigrants? One possibility is that the measured literacy in the ALLS data is correlated with latent productivity characteristics and the return to these characteristics is higher for immigrants. But, since immigrants interact with the same labour market institutions as natives, it is difficult to isolate a mechanism that could generate this difference in returns. Another possibility is that the correlation between measured

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literacy and latent productive characteristics is higher for U.S., than Australian or Canadian, immigrants. Although there is no way to rule out this possibility, we are suspicious for two reasons. First, the result is evident even when education controls, which might be expected to capture this latent productivity, are included, although the difference in the immigrant return is estimated less precisely.[16] Second, as noted earlier, if U.S. immigrants are exceptional on other skill dimensions, it is difficult to explain why it does not provide them with an advantage in their ALLS test performance. One would have to argue that the productive characteristics that give rise to the exceptional relative wage performance of U.S. immigrants are independent of the skills captured in the ALLS data.[17]

There is, however, an explanation for the U.S. results that does not appeal to unobservable skills of of U.S. immigrants, but rather recognises a fundamental complication in the measurement of immigrant skills in the ALLS data that has been overlooked in the current literature. While it may be reasonable to interpret literacy scores of native-born workers as cognitive skills, for immigrants with a foreign mother tongue the scores will reflect a combination of English-language ability (or French in the Canadian data) and cognitive skills. However, without independent measures of cognitive skills from tests conducted in an immigrant's mother tongue, there is no way to separate these two dimensions of skill for immigrants in the literacy test scores.

Some evidence for this differing interpretation of the test scores for native born and immigrant individuals is provided by looking at university educated workers only.[18] For native born university educated workers in Australia and Canada there is virtually no wage return to literacy indicating little variation in cognitive skills for the most skilled workers.[19] This is consistent with the nature of tests in the ALLS data that are primarily concerned with distinguishing between functional literacy and functional illiteracy rather than distinguishing between functionally literate and functionally very literate workers. In contrast, there is a significant return to literacy for university educated immigrant workers, consistent with the wage return to their test scores mainly reflecting the labour market return to language ability. Some further evidence for the differing interpretation of the test scores for native born and immigrant individuals can be obtained by looking at immigrants with an English mother tongue. Their test score distribution is almost identical to that of the native born, particularly at the top end consistent with their test scores reflecting cognitive ability only

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[16]Specifically, the immigrant return to a 10-point increase in literacy is 3.6 log points, compared to 2.5 log points for natives. This p-value on this difference is 0.201.

[17]Of course, it is also true that a larger relative correlation between measured and unobserved skill for immigrants to the United States would imply that a score of say 300 for an immigrant to Australia and Canada would not be equivalent to a test score of say 300 for an immigrant to the U.S., since the score for the U.S. immigrant would reflect a greater quantity of unobserved skill. This would undermine the principal advantage of the ALLS data, the international comparability of the measures of skill.

[18]These results are available from the authors.

[19]Insufficient sample size prohibits conducting this exercise for immigrants in the U.S. sample

since they have identical language skills.

To see the consequences of this measurement problem for estimated returns to skill for immigrants, consider the following model of wage determination:

$$\ln w_i = \alpha_0 + \alpha_C\, C_i + \alpha_{CL}\, C_i(L_i - \bar{L}) + v_i$$

where C_i denotes cognitive skills and L_i denotes language ability, where $L_i \in [0, \bar{L}]$. The lower bound of zero denotes the minimum language requirement in the job that requires the least language ability. Note that $(L_i - \bar{L}) < 0$ so language ability deficits reduce wages. Assume that all native-born workers have the maximum language ability of $\bar{L}$.[20] A marginal improvement in cognitive skills for immigrants has a direct effect on wages through α_C, as well as an additional effect that is decreasing in the size of the language deficit. The logic is that in many production processes implementation of cognitive skills requires communication skills. This idea is consistent with the evidence of Berman, Lang and Siniver (2003) showing wage returns to Hebrew-language acquisition among Israeli immigrants employed in high-skill occupations.

Suppose, on the other hand, that measured skill in the ALLS data is additive in cognitive skills and language abilities, such that:

$$S_i = C_i + (L_i - \bar{L}).$$

For native-born workers, with $L_i = \bar{L}$, measured skills directly measure cognitive skills. For immigrant workers, their skill score will be less than their 'true' cognitive ability due to language deficiencies and cultural distance. Suppose that immigrant selection policy screens primarily on cognitive skills, such that marginal differences in immigrant test scores at the upper end of the skill distribution primarily reflect improvements in language abilities, as opposed to cognitive skills. Without loss of generality, consider the extreme case that all immigrants have the same level of cognitive skill $\bar{C}_M$, such that all of the variation in immigrants' measured skills reflect variation in language skills. In this case, native and immigrant wages will be determined by:

$$\ln w_i = \begin{cases} \alpha_0 + \alpha_C\, S_i + v_i & \text{if native-born} \\ \alpha_0 + \alpha_C\, \bar{C}_M + \alpha_{CL}\, \bar{C}_M(S_i - \bar{C}_M) + v_i & \text{if immigrant} \end{cases}$$

such that the return to measured skills S_i is given by α_C for the native-born and $\alpha_{CL}\, \bar{C}_M$. Provided $\alpha_{CL}\, \bar{C}_M > \alpha_C$, the immigrant return to skill will exceed the native-born return to skill.[21]

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[20]Note that language only affects wages through its 'complementarity' with cognitive skills. An independent return to language, say α_L, would imply a value of language even in the absence of any cognitive skills, which seems implausible.

[21]Note that this result requires that cognitive skills C_i and language abilities L_i are more complementary in wage determination than in the production of test scores. In the example, we present the extreme case in which C_i and L_i are multiplicative in wage determination, but additively separable in test score outcomes.

In countries where labour market institutions do more to standardize wages, such as Australia and to a lesser extent Canada, both the economy-wide return to skill (α_C) and the attenuating effect of language on this return (α_{CM}) will tend to be small. Hence, their difference will be small. In the U.S., on the other hand, where the return to skill is large, the attenuating effect of language will also tend to be large. Consequently, it becomes more likely that marginal improvements in language ability produce big wage gains. As evidence of this alternative explanation, the return to measured skill for U.S. immigrants becomes even larger when it is estimated separately for recent U.S. immigrants with a foreign mother tongue (that is not Spanish). The third set of estimates Table 5 suggest that a 10-point increase in literacy is associated with a 6.8 ($0.041 + 0.027$) log point increase in wages of recent non-English/Spanish U.S. immigrants, compared to a 4.1 log point increase for U.S. natives (the p-value for the difference of 0.027 is 0.057).

In contrast to the U.S. estimates, the comparable estimates for recent Canadian immigrants with a foreign mother continue to suggest essentially no difference in the return to immigrant skill, although the immigrant intercept continues to point to a large (23 log points in the case of recent immigrants with a foreign mother tongue) wage disparity across the entire skill distribution. For Australia, on the other hand, there is, if anything, some evidence of a lower return to immigrant skills when we restrict attention to recent immigrants with a foreign mother tongue. This suggests to us that Australia's immigration reforms of the late 1990s, which not only introduced mandatory pre-migration language testing, but also put greater emphasis on pre-arranged employment and formal foreign credential information systems, did not result in a greater utilization of immigrant skills.

Finally, it is worth noting the estimates in Table 5 suggest that recent U.S. immigrants with a Spanish mother tongue, receive substantially lower returns to skill than their native-born counterparts. This result is in sharp contrast to the estimates for other U.S. immigrants with a foreign mother tongue, who receive significantly higher skill returns than natives. What explains this difference? To understand it, one must keep in mind that the skill distribution of recent Spanish immigrants in the U.S. lies substantially below that of other U.S. immigrants with a foreign mother tongue. Specifically, roughly three-quarters of recent Spanish immigrants have a skill score below the intercept value of 225, compared to one-quarter of other foreign mother tongue immigrants. The lower marginal return to skill for Spanish immigrants means that a decrease in skill below 225 *reduces* the immigrant wage gap. With an immigrant intercept of -14.9 log points, the gap in the immigrant return of 2.9 log points implies no wage differential for Spanish immigrants at a skill level of 175 and a wage advantage below 175, which is roughly 40% of all recent Spanish-speaking

U.S. immigrants.[22] But at these extremely low measured skill levels, there is essentially no labour market competition from native-born workers (this is the 3rd percentile of the native-born population distribution, including those not participating in labour markets). Consequently, their relative wages are high. But as the skill level of jobs increases, there is increasing competition from U.S. workers with comparable skills. If for some reason Spanish workers are unable to compete, if for example they experience discrimination in more skilled labour markets, we would expect wage gaps conditional on skill, which is precisely what appears in the estimates.

4.3 Required Literacy of Immigrants' Occupations

The results in Table 5 indicate little or no difference in relative returns to skill for Australian and Canadian immigrants, but significantly higher relative returns to immigrant skills in the U.S., particularly among those with a non-English/Spanish mother tongue. We have argued that this difference is more likely to reflect higher economy-wide returns to skill in the United States, rather than unobserved differences in the skills of U.S. immigrants. But given the difficulty in distinguishing returns to language abilities from returns to other skills in the estimated returns to literacy for immigrants, we cannot rule out the possibility that the differences identified reflect, at least in part, more efficient immigrant skill utilization in the U.S., compared to Australia or Canada, perhaps resulting from a greater role of employers in immigrant selection.

The higher wage return to literacy for U.S. immigrants might reflect more efficient utilization of immigrant skill through either better access to higher paying occupations or higher wages within occupations. While, given the relatively small sample size of the ALLS data it is difficult to examine the latter, it is feasible to examine whether the higher wage return to literacy for U.S. immigrants reflects better access to higher paying occupations by exploiting the Occupational Information Network (O*NET) database.

To do this we extracted 12 descriptors of document literacy in the O*NET database and used a principal component analysis, weighting observations by U.S. occupational employment levels, to reduce these descriptors to a single factor. We then linked this single factor to the 4-digit International Standard Classification of Occupations (ISCO88) codes provided in the ALLS data using a crosswalk with the Standard Occupational Classification codes used by the O*NET. Finally, we standardized the single factor, such that it had a weighted mean of 225 and standard deviation of 50 in the weighted sample, thereby making our *required* document literacy score, based on O*NET data, roughly comparable to the *measured* document literacy score in the ALLS data. Four-digit

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[22]To see this, note that the immigrant intercept implies a wage gap of 14.9 log points at a skill level of 225. The immigrant-specific return of -0.029 means that reducing skill by 10 points serves to reduce this gap by 2.9 log points, so that it is 12 log points at a skill level of 215. Following this logic, the gap will be zero at a skill level $225 - (0.149/0.029) * 10 = 174$.

occupation codes were, unfortunately, not available for the Australian ALLS data, so this analysis was only possible with the Canadian and U.S. data.[23]

In Table 6 we report the results from estimating equation (1) when we replace the log wage dependent variable with our measure of the required document literacy of individual i's 4-digit occupation. Comparing the unconditional (on measured literacy) immigrant gaps in required literacy, the results point to an almost identical disparity of roughly of 15 points for Canadian and U.S. immigrants. When we condition on measured literacy, the returns for native-born workers in Canada and the U.S. are also almost identical suggesting that a 10-point increase in the ALLS literacy test score is associated with an increase of roughly 3.5 points in required occupational literacy. Under-utilization of immigrant skills should be reflected in this return being lower for immigrants. However, in both Canada and the U.S. the returns are significantly larger for immigrants. Specifically, a 10-point increase in measured literacy is associated with an increase of 4.6 ($3.528 + 1.078$) and 5.3 points ($3.631 + 1.698$) in the required literacy of Canadian and U.S. immigrants' occupations, respectively, a difference that is statistically indistinguishable. These results do not provide any clear evidence that immigrant skills are under-utilized across occupations in Canada or more efficiently utilized across occupations in the United States.

Estimating these effects separately for recent immigrants and recent immigrants with a foreign mother tongue does essentially nothing to change the findings. The estimates continue to suggest that marginal improvements in literacy skills do more to boost the occupational attainment of immigrants than natives. The sole exception is, once again, U.S. immigrants with a Spanish mother tongue, whom appear to be highly concentrated in exceptionally low-skill labour markets where returns to skill are low. But what explains the returns of Canadian immigrants with a non-English/French mother tongue and U.S. immigrants with a non-English/Spanish mother tongue? Our suspicion is that what underlies these high returns is, once again, that marginal improvements in immigrant literacy skills in large part reflect differences in language abilities, which are complementary with other skills, much of which may have been obtained in immigrants' source countries. To the extent that this interpretation is correct, what the large immigrant returns to measured literacy in Table 6 suggest is that language acquisition benefits immigrants by enabling them to make transitions to occupations that are more commensurate with their skills.

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[23]We used the 12 level descriptors identified by LaPolice, Carter and Johnson (2008, Table 9) as relevant for document literacy. They included 3 abilities (written comprehension; deductive reasoning; and information ordering); 3 skills (writing; active learning; and judgement and decision making); one knowledge (English language); and 5 work activities (getting information needed to do the job; processing information; scheduling work and activities; organizing, planning, and prioritizing work; and documenting and recording information. To collapse 6-digit occupation codes in the O*NET down to 4-digit SOC2000 codes, we took unweighted averages of each of the 12 descriptors. To collapse the 12 descriptors down to a single factor, we used principal component analysis weighting observations by occupational employment levels for the U.S. in 2005. Also, in some cases there were multiple SOC2000 codes for a single ISCO88 code. In these cases., we took the average of the SOC2000 codes weighted by their employment levels.

4.4 Employment Probabilities Conditional on Literacy

In order to investigate the possibility that under-utilization of immigrant skills occurs through access to jobs, rather than through wage rates, equation (1) is also estimated replacing log wages with two alternative binary indicators of employment. In the first case, we include both labour market participants and non-participants and define individuals as employed if they held a job at any time in the previous twelve months. Since some of this variation is likely to reflect labour supply decisions, that are likely themselves correlated with literacy skills, we also estimate the model restricting attention to labour market participants and defining employment as working positive hours for pay in the survey reference week. While this variable gets closer to a measure of involuntary unemployment, there are some concerns about its consistency across the three countries. Specifically, in the Australian survey, unemployment is defined according to the international definition, which classifies an individual as unemployed if: (i) they are not employed; (ii) had actively searched for work at any time in the four weeks up to the end of the reference week; and (iii) were available for work in the reference week if they had found a job. However, in the Canadian and U.S. versions of the survey there is no indication that the reporting of unemployment requires active job search in the previous four weeks or availability for work.[24]

Given the binary dependent variable, which has a sample mean above 0.9 when we restrict attention to labour force participants, our preference is to estimate equation (1) using a probit model. This, however, makes the interpretation of the marginal effects of skill across the distribution more complicated. Therefore, rather than present the estimates in tables, in Figures 4 and 5 we plot the predicted relative immigrant employment and unemployment probabilities implied by the probit estimates.[25] More specifically, the figures plot the difference in the predicted employment or unemployment rate between a 30-year-old male immigrant residing in some reference urban region and his native-born counterpart.

The plots in Figure 4 once again provide essentially no evidence of skill under-utilization, most notably in Australia, where we expect regulated labour markets to make the access-to-employment margin more relevant. Whether looking across all immigrants or recent immigrants with a foreign mother tongue, there is no indication of disparities in the employment rates of Australian immigrants across the skill distribution. For Canada, on the other hand, there is evidence of employment gaps among all recent immigrants with a foreign mother tongue regardless of their skill level. Given

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[24]Comparing the March 2003 Current Population Survey (CPS) with the U.S. ALLS, indicates significantly higher unemployment rates in the ALLS, particularly for the least educated native-born workers. The share of native-born workers in the least-educated group is, however, very similar in the ALLS and CPS, suggesting the difference in unemployment rates reflects measurement, as opposed to sampling, issues.

[25]The probit estimates underlying both figures are provided in the Appendix.

the large wage gaps also facing this group, it may be that their employment shortfalls primarily reflect labour supply choices. Finally, for the U.S., there is some evidence of employment gaps among higher-skilled immigrants. The gaps appear much larger for Spanish immigrants, although one must keep in mind that predictions for this group beyond a skill level of 225 are essentially out of sample. As for other U.S. immigrants with a foreign mother tongue, who are much higher skilled and do well in terms of wage outcomes, it is unclear to what extent the gaps reflect labour supply decisions, in particular of spouses.

Restricting the sample to labour force participants suggests that the employment rate gaps of non-Spanish U.S. immigrants with a foreign mother tongue do, in fact, reflect labour supply choices. The bottom two panels of Figure 5 provide no evidence of higher unemployment rates for this group. The results continue, however, to point to employment challenges for recent Canadian immigrants with a foreign mother tongue. Although the gap in unemployment rates for this group appears to grow slightly with literacy, the difference in the slope parameter is poorly identified and not statistically significant. Lastly, there continues to be no real evidence that Australian immigrants face challenges relative to their native-born counterparts with similar skills accessing jobs. Taken as a whole, the results contrast to some extent with the current literature, as we find little evidence of a tradeoff in assimilation between prices prices and quantities (Antecol, Kuhn and Trejo 2006). Rather, in Australia and the U.S., where wage gaps for immigrants are either small or non-existent (once we condition on literacy skills), there is also no evidence of employment shortfalls. In Canada, on the other hand, where there is evidence of substantial wage gaps across the skill distribution, there is also evidence of pervasive employment gaps.

5 Conclusions

We think there are three main policy-relevant conclusions to draw from our analysis. First, the results suggest that point systems for selecting immigrants have the potential to raise average skill levels of immigration flows. However, they do so not by raising skill levels at the top end of the distribution, where the economic growth potential of immigration is likely greatest. Rather, the benefit of a point system lies appears to lie primarily in its potential to influence immigration flows at the bottom end of the skill distribution. This is most evident in the improvement in the literacy skills of Australian immigrants admitted after the ramping up of its selection criteria in the late 1990s.

Second, we do not find any compelling evidence that providing employers with a greater role in immigrant selection leads to greater immigrant skill utilization, in terms of greater access to high paying occupations commensurate with their measured skills. Although wage returns to immigrant

literacy skills appear exceptionally large in the U.S., where employers have played a larger role in immigrant selection, our reading of the evidence is that they reflect larger returns to skill for workers in the U.S economy driven by labour market institutions that generate larger complementarities between language and skills. Most notably, our findings relating measures of required literacy skills of immigrants' occupations, obtained from the O*NET database, to their measured literacy skills in the ALLS data, suggest little difference in the relative utilization of immigrant skills across occupations in Canada and the United States.

Finally, there is a presumption in much of the Canadian policy discourse that wage and employment disparities of recent immigrants reflect an under-utilization of immigrant skills owing primarily to credential recognition issues. Our results based on wage and employment returns to literacy skills, as well as the skill requirements of immigrants' occupations, are not consistent with this view. Rather, we find that the labour market challenges facing recent immigrants to Canada with a foreign mother tongue are substantial in comparison to their Australian and U.S. counterparts, both in terms of wage outcomes and employment probabilities, and are pervasive across the skill distribution. These gaps are beyond the scope of this paper to explain. However, a possible explanation is that they reflect firm, as opposed to immigrant, heterogeneity. More specifically, the role of ethnic social networks may be more influential in the sorting of immigrants across employers in Canada, such that Canadian immigrants are more concentrated in low-wage firms. There is, in fact, evidence of this type of sorting for Canada (Aydemir and Skuterud 2008; Pendakur and Woodcock 2010). A comparative analysis for the Australia or the U.S. would appear to be a potentially fruitful area for future research.

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Table 1: Top 20 Foreign-Language (Excluding Spanish) Immigrant Source Countries: Australia, Canada, and the United States

Rank	Australia		Canada		United States	
	Country	N	Country	N	Country	N
1	China	206,591	China	466,940	Philippines	1,369,070
2	Italy	199,123	India	443,690	India	1,022,552
3	Vietnam	159,849	Philippines	303,195	China	988,857
4	India	147,106	Italy	296,850	Vietnam	988,174
5	Philippines	120,538	Hong Kong	215,430	Korea (total)	864,125
6	Greece	109,988	Germany	171,405	Germany	706,704
7	Germany	106,524	Poland	170,490	Italy	473,338
8	Malaysia	92,337	Vietnam	160,170	Poland	466,742
9	Netherlands	78,927	Portugal	150,390	Haiti	419,317
10	Lebanon	74,848	Pakistan	133,280	Japan	347,539
11	Hong Kong	71,803	Netherlands	111,990	Russia	340,177
12	Sri Lanka	62,256	Sri Lanka	105,670	Taiwan	326,215
13	Korea (total)	52,819	Korea (total)	98,560	Iran	283,226
14	Poland	52,255	Iran	92,090	Ukraine	275,153
15	Croatia	50,993	Romania	82,645	Pakistan	223,477
16	Indonesia	50,975	Lebanon	75,275	Brazil	212,428
17	Fiji	48,141	Greece	73,125	Laos	204,284
18	Malta	43,701	Taiwan	65,205	Hong Kong	203,580
19	Macedonia	40,655	Russia	64,130	Portugal	203,119
20	Singapore	39,969	Haiti	63,350	Thailand	169,801
Total (top 20)		1,809,398		3,360,080		10,087,878
Total foreign language		4,018,365		4,611,270		14,054,078
Total immigrants		5,782,137		6,186,950		31,107,889
Top 20 share of foreign language		0.450		0.725		0.718

Notes: Foreign-language countries exclude all countries where English or French is an official language, except where data from 2006 Canadian Census indicates a large majority of emigrants have a foreign mother tongue. This includes India, Pakistan, Hong Kong and Singapore. In addition, countries where Spanish is an official language are excluded. These include: Argentina, Bolivia, Chile, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Mexico, Nicaragua, Panama, Paraguay, Peru, Uruguay, Spain, and Venezuela. The data for Australia and Canada are from the 2006 Census of Population, while the data for the United States are from the 2000 Census.

Table 2: Sample characteristics

	Immigrants						Native-Born					
	Australia		Canada		USA		Australia		Canada		USA	
	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean
Gender												
Male	503	0.473	977	0.485	121	0.480	2,168	0.487	5,935	0.485	1,054	0.473
Female	628	0.527	1,195	0.515	137	0.520	2,653	0.513	7,567	0.507	1,309	0.527
Age		44.570		43.507		38.822		39.074		40.017		40.560
18-24	39	0.045	95	0.045	24	0.086	585	0.170	1,745	0.138	308	0.133
25-34	186	0.183	411	0.207	80	0.296	1,133	0.234	2,522	0.217	522	0.208
35-44	307	0.260	649	0.278	83	0.321	1,191	0.234	3,486	0.258	583	0.258
45-54	301	0.269	565	0.255	43	0.186	1,029	0.205	3,455	0.237	537	0.233
55-64	298	0.243	452	0.216	28	0.111	883	0.156	2,294	0.150	417	0.169
Education												
Less than high school	258	0.230	320	0.166	87	0.302	1,632	0.317	3,328	0.172	308	0.115
High school	181	0.180	437	0.200	38	0.193	780	0.183	3,032	0.250	624	0.327
Certificate or diploma	317	0.264	659	0.312	53	0.192	1,397	0.299	5,004	0.386	793	0.302
University	375	0.326	756	0.322	80	0.313	1,012	0.201	2,138	0.192	642	0.257
Occupation												
White collar	428	0.330	675	0.281	62	0.240	1,810	0.380	4,354	0.352	853	0.360
Clerks or sales	239	0.196	438	0.196	47	0.182	1,160	0.248	3,249	0.253	540	0.228
Skilled blue collar	138	0.101	362	0.187	52	0.202	676	0.156	2,255	0.183	375	0.158
Unskilled blue collar	74	0.062	161	0.080	26	0.101	243	0.050	888	0.054	153	0.065
Not employed last 12 months	252	0.312	533	0.256	71	0.275	932	0.166	2,733	0.158	446	0.188

Notes: Sample means are weighted using the provided population weights. Sample is restricted to individuals aged 18-64 and excludes students and the self-employed.

Table 3: Immigrant sample characteristics

	Australia		Canada		USA	
	N	Mean	N	Mean	N	Mean
Native mother tongue	522	0.400	547	0.228	36	0.157
Foreign mother tongue	609	0.600	1,625	0.772		
Spanish mother tongue		...		...	125	0.443
Other foreign mother tongue		...		...	97	0.400
Recent immigrants	427	0.389	1,076	0.440	111	0.438
Recent: Native mother tongue	175	0.136	180	0.076	15	0.073
Recent : Foreign mother tongue	252	0.253	896	0.364		
Recent: Spanish mother tongue		...		...	56	0.201
Recent: Other foreign mother tongue		...		...	40	0.164
Not recent immigrants	704	0.611	1,096	0.560	147	0.562
Not Recent: Native mother tongue	347	0.264	367	0.152	21	0.084
Not Recent : Foreign mother tongue	357	0.347	729	0.408		
Not Recent: Spanish mother tongue		...		...	69	0.242
Not Recent: Other foreign mother tongue		...		...	57	0.236
Total immigrants	1,131	0.205	2,172	0.182	258	0.117

Notes: For Australia and the United States, individuals are characterised as having a native mother tongue if English was their first language learned and currently understood. For Canada, English and French are defined as a native mother tongue. Recent immigrants are defined as foreign-born individuals that have resided in the destination country for less than 10 years. Sample means are weighted using the provided population weights.

Table 4: Mean document literacy across selected immigrant characteristics

	Australia		Canada		USA	
	Mean	Std.error	Mean	Std.error	Mean	Std.error
Gender						
Male	266.4	4.15	254.8	4.05	231.8	8.09
Female	246.2	3.51	241.7	3.25	225.6	6.07
Age						
18-24	269.2	9.87	257.5	9.30	228.1	11.08
25-34	277.3	5.20	265.6	5.06	225.0	8.52
35-44	261.7	4.32	252.0	3.90	239.4	9.35
45-54	251.3	5.06	244.0	4.88	223.8	9.98
55-64	235.8	6.29	229.0	4.55	215.0	12.66
Education						
Less than high school	204.8	5.77	185.3	4.47	184.7	5.50
High school	235.8	5.09	226.9	4.15	212.7	9.63
Certificate or diploma	261.4	3.71	257.3	3.59	221.8	9.06
University	298.1	3.10	284.7	3.01	284.7	7.57
Occupation						
White collar	294.3	3.56	290.0	3.17	275.5	5.16
Clerks or sales	258.9	4.30	254.6	4.47	229.6	11.04
Skilled blue collar	235.5	6.82	223.2	6.16	185.1	6.65
Unskilled blue collar	225.8	11.12	209.5	7.33	198.7	11.70
Not employed last 12 months	209.1	6.66	227.1	5.05	208.2	7.13
Language						
Recent Immigrants	271.9	3.93	252.6	3.88	230.6	5.69
Recent: Native mother tongue	300.0	4.52	274.8	11.17	285.9	14.14
Recent: Foreign mother tongue	256.6	5.59	248.0	4.47	219.5	6.57
Recent: Spanish mother tongue	...	...	...	...	191.6	7.97
Recent: Other foreign mother tongue	...	...	...	...	253.6	10.96
Not Recent Immigrants	245.6	3.97	244.5	3.07	227.0	6.35
Not Recent: Native mother tongue	279.5	3.66	272.4	6.05	263.8	12.67
Not Recent: Foreign mother tongue	219.2	5.28	234.1	3.23	220.5	6.63
Not Recent: Spanish mother tongue	...	...	...	...	196.6	6.40
Not Recent: Other foreign mother tongue	...	...	...	...	245.1	11.78
All immigrants	255.8	2.75	248.1	2.45	228.6	4.72
All native-born	284.2	1.06	286.6	0.84	275.0	1.33

Notes: Reported means $\bar{y}$ are unweighted averages of five weighted means $\bar{y}_j$, each estimated separately using one of five provided plausible values and the population weights. Standard errors are estimated using $\mathrm{Var}(\bar{y}) = J^{-1} \sum_j \mathrm{Var}(\bar{y}_j) + (J+1)(J(J-1))^{-1} \sum_j (\bar{y}_j - \bar{y})$, where $\mathrm{Var}(\bar{y}_j)$ is estimated using 30 jackknife replicate weights.

Table 5: Immigrant log hourly wage differential conditional on document literacy level

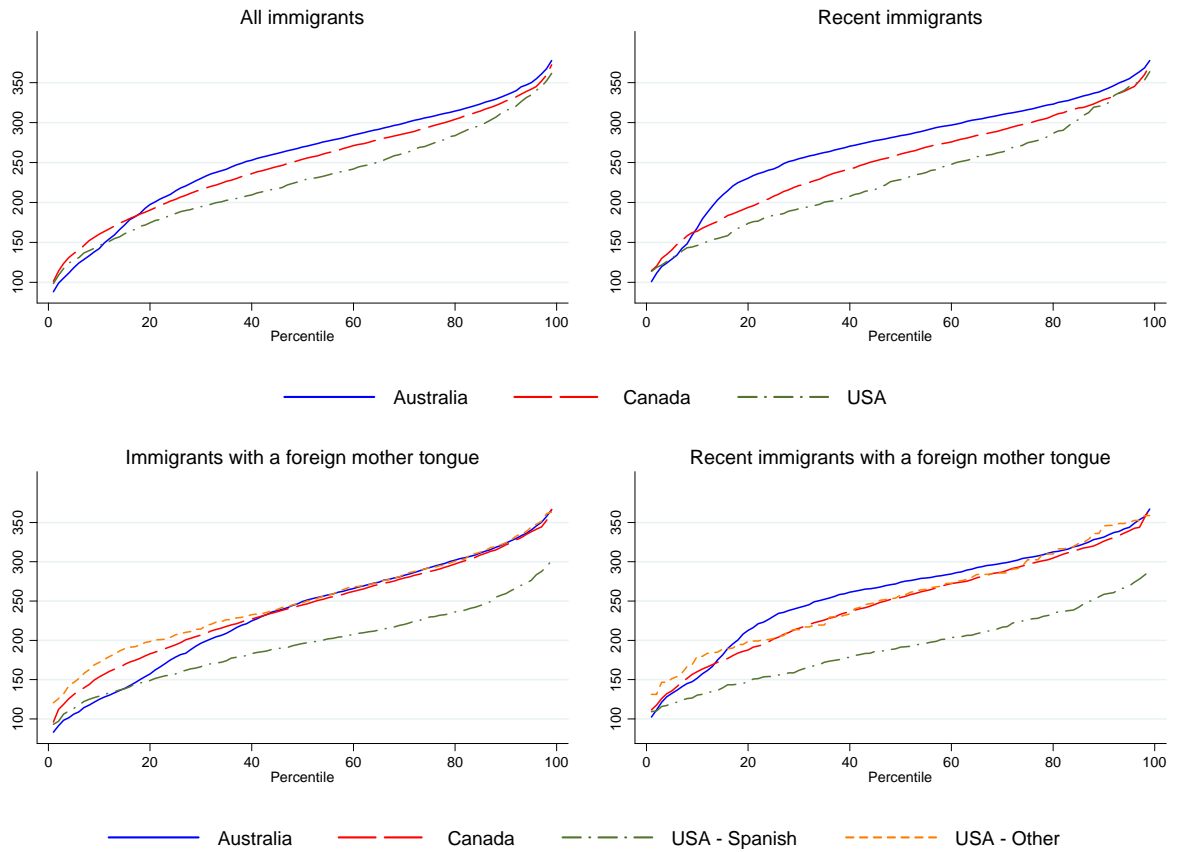|	Australia			Canada			United States		
	Coeff.	Std.error	p	Coeff.	Std.error	p	Coeff.	Std.error	p
All Immigrants									
Literacy	0.031	(0.003)	0.000	0.034	(0.002)	0.000	0.041	(0.003)	0.000
Literacy*Immigrant	−0.003	(0.004)	0.551	−0.001	(0.005)	0.871	0.015	(0.008)	0.064
Immigrant	0.010	(0.030)	0.736	−0.097	(0.032)	0.003	0.030	(0.062)	0.634
Intercept	2.937	(0.027)	0.000	2.627	(0.025)	0.000	2.594	(0.041)	0.000
R^2		0.157			0.230			0.267	
Unconditional Wage Gap									
Immigrant	−0.064	(0.026)	0.019	−0.233	(0.033)	0.000	−0.175	(0.058)	0.003
Recent Immigrants									
Literacy	0.031	(0.003)	0.000	0.034	(0.002)	0.000	0.041	(0.003)	0.000
Literacy*Recent	−0.001	(0.005)	0.891	0.000	(0.007)	0.999	0.011	(0.013)	0.371
Literacy*Not-recent	−0.002	(0.006)	0.749	0.001	(0.005)	0.829	0.019	(0.010)	0.053
Recent immigrants	−0.047	(0.040)	0.241	−0.223	(0.047)	0.000	0.044	(0.088)	0.618
Not-recent immigrants	0.043	(0.036)	0.230	0.001	(0.036)	0.981	0.020	(0.072)	0.782
Intercept	2.942	(0.028)	0.000	2.638	(0.024)	0.000	2.594	(0.041)	0.000
R^2		0.158			0.236			0.267	
Unconditional Wage Gap									
Recent immigrants	−0.091	(0.037)	0.017	−0.359	(0.047)	0.000	−0.143	(0.085)	0.091
Not-recent immigrants	−0.042	(0.032)	0.196	−0.125	(0.031)	0.000	−0.200	(0.070)	0.005
Recent Immigrants with									
Foreign Mother Tongue									
Literacy	0.031	(0.003)	0.000	0.034	(0.002)	0.000	0.041	(0.003)	0.000
Literacy*Recent foreign	−0.009	(0.006)	0.138	−0.005	(0.008)	0.510	...	...	...
Literacy*Recent Spanish	...	...	...	...	...	...	−0.029	(0.015)	0.051
Literacy*Recent other foreign	...	...	...	...	...	...	0.027	(0.014)	0.057
Literacy*Not-recent foreign	−0.003	(0.007)	0.608	0.002	(0.006)	0.742		...	...
Literacy*Not-recent Spanish	...	...	...	...	...	...	0.010	(0.015)	0.504
Literacy*Not-recent other foreign	...	...	...	...	...	...	0.014	(0.016)	0.395
Recent foreign	−0.070	(0.047)	0.134	−0.230	(0.050)	0.000		...	...
Recent Spanish	...	...	...	...	...	...	−0.149	(0.097)	0.125
Recent other foreign	...	...	...	...	...	...	0.046	(0.132)	0.726
Not-recent foreign	0.022	(0.045)	0.627	−0.018	(0.039)	0.639	...	...	...
Not-recent Spanish	...	...	...	...	...	...	−0.016	(0.103)	0.878
Not-recent other foreign	...	...	...	...	...	...	0.030	(0.088)	0.735
Intercept	2.947	(0.028)	0.000	2.639	(0.024)	0.000	2.594	(0.040)	0.000
R^2		0.160			0.237			0.270	
Unconditional Wage Gap									
Recent foreign	−0.193	(0.047)	0.000	−0.401	(0.053)	0.000	...	...	...
Recent Spanish	...	...	...	...	...	...	−0.425	(0.067)	0.000
Recent other foreign	...	...	...	...	...	...	0.018	(0.123)	0.881
Not-recent foreign	−0.133	(0.043)	0.003	−0.183	(0.036)	0.000	...	...	...
Not-recent Spanish	...	...	...	...	...	...	−0.408	(0.088)	0.000
Not-recent other foreign	...	...	...	...	...	...	−0.090	(0.095)	0.343

Notes: Reported coefficients $\bar{b}$ are unweighted averages of five ordinary least squares (OLS) estimates $\bar{b}_j$, each using one of the five plausible values of literacy and the population weights. Standard errors are estimated using $\mathrm{Var}(\bar{b}) = J^{-1} \sum_j \mathrm{Var}(\bar{b}_j) + (J+1)(J(J-1))^{-1} \sum_j (\bar{b}_j - \bar{b})$, where $\mathrm{Var}(\bar{b}_j)$ is estimated using 30 jackknife replicate weights. Literacy is adjusted by subtracting 225 and dividing by 10. Regressions include a quadratic in age, controls for geographical region of residence, urban/rural area of residence, and an indicator for gender. The samples are restricted to individuals aged 18-64 who were employed in the previous 12 months. The immigrant sample is restricted to individuals who arrived in their destination country at age 14 or higher after 1955. For Australia and the United States, individuals are characterised as having a foreign mother tongue if English was not their first language learned and understood. For Canada, a foreign mother tongue is defined for first languages other than English or French. Recent immigrants refer to foreign-born individuals that have less than ten years of residence in the destination country.

Table 6: Immigrant differential in required document literacy conditional on measured document literacy

|	Canada			United States		
	Coeff.	Std.error	p	Coeff.	Std.error	p
All Immigrants						
Literacy	3.528	(0.225)	0.000	3.631	(0.208)	0.000
Literacy*Immigrant	1.078	(0.376)	0.004	1.698	(0.679)	0.013
Immigrant	−4.098	(2.716)	0.131	2.403	(3.708)	0.517
Intercept	220.655	(2.775)	0.000	230.910	(2.951)	0.000
R^2		0.201			0.223	
Unconditional Gap						
Immigrant	−14.609	(2.952)	0.000	−15.286	(4.455)	0.002
Recent Immigrants						
Literacy	3.543	(0.225)	0.000	3.632	(0.208)	0.000
Literacy*Recent	1.157	(0.614)	0.060	1.693	(1.146)	0.140
Literacy*Not Recent	0.942	(0.445)	0.035	1.744	(0.741)	0.019
Recent Immigrants	−0.339	(3.404)	0.921	0.800	(6.470)	0.902
Not Recent Immigrants	−7.135	(3.434)	0.038	3.643	(4.743)	0.443
Intercept	220.265	(2.741)	0.000	230.934	(2.977)	0.000
R^2		0.202			0.223	
Unconditional Gap						
Recent immigrants	−10.882	(3.752)	0.004	−14.952	(6.780)	0.036
Not recent immigrants	−17.857	(3.198)	0.000	−15.544	(6.654)	0.027
Recent Immigrants with						
Foreign Mother Tongue						
Literacy	3.544	(0.225)	0.000	3.629	(0.208)	0.000
Literacy*Recent NESB	1.129	(0.694)	0.104	...	...	...
Literacy*Recent Spanish	...	...	...	−1.755	(1.760)	0.319
Literacy*Recent Other	...	...	...	2.879	(1.063)	0.007
Literacy*Not Recent NESB	1.230	(0.428)	0.004	...	...	...
Literacy*Not Recent Spanish	...	...	...	−1.351	(1.380)	0.327
Literacy*Not Recent Other	...	...	...	0.680	(1.380)	0.622
Recent NESB	−0.426	(3.619)	0.906	...	...	...
Recent Spanish	...	...	...	−23.748	(7.821)	0.002
Recent Other	...	...	...	12.822	(7.171)	0.074
Not Recent NESB	−8.352	(2.922)	0.004	...	...	...
Not Recent Spanish	...	...	...	−23.605	(8.836)	0.008
Not Recent Other	...	...	...	21.330	(5.887)	0.000
Intercept	220.173	(2.687)	0.000	231.051	(2.877)	0.000
R-Squared		0.202			0.240	
Unconditional Gap						
Recent NESB	−13.842	(4.228)	0.001	...	...	...
Recent Spanish	...	...	...	−17.587	(6.406)	0.010
Recent Other	...	...	...	20.219	(6.904)	0.007
Not Recent NESB	−23.368	(3.156)	0.000	...	...	...
Not Recent Spanish	...	...	...	−21.282	5(.859)	0.001
Not Recent Other	...	...	...	21.816	5(.258)	0.000

Notes: Dependent variable is constructed by merging 4-digit occupation codes with 14 document literacy descriptors in the O*NET data. For more detail, see section 3.3. With the exception of the dependent variable, the estimation is identical to that reported in Tables 5 and 6.

Figure 1: Distribution of document literacy levels of immigrants in Australia, Canada, and the United States

Figure 2: Recent immigrants with a foreign mother tongue: quantile-quantile plot of document literacy levels for Australia, Canada, and the United States
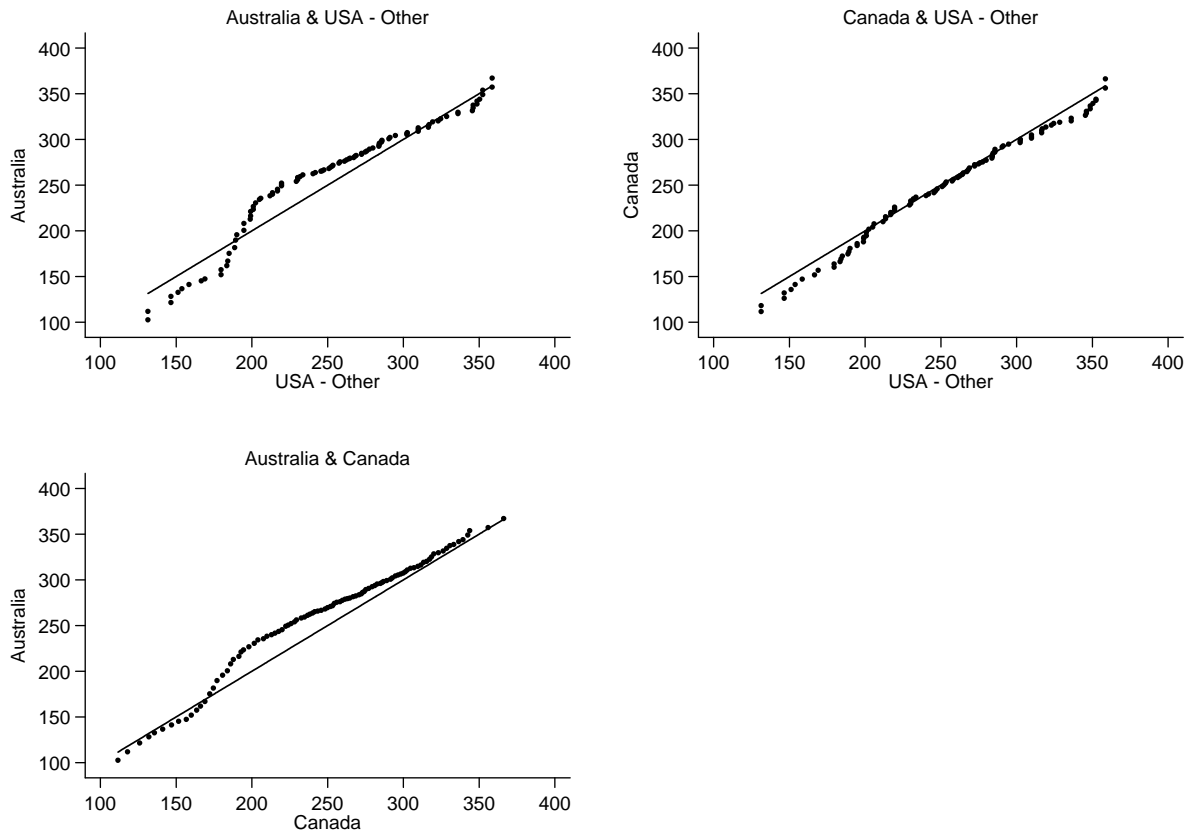
Notes: The percentiles are the unweighted averages of 5 percentile estimates using each plausible value separately. Sample is restricted to individuals aged 18-64 and excludes students and the self-employed.

Figure 3: Distribution of document literacy levels of Chinese immigrants in Australia, and the United States
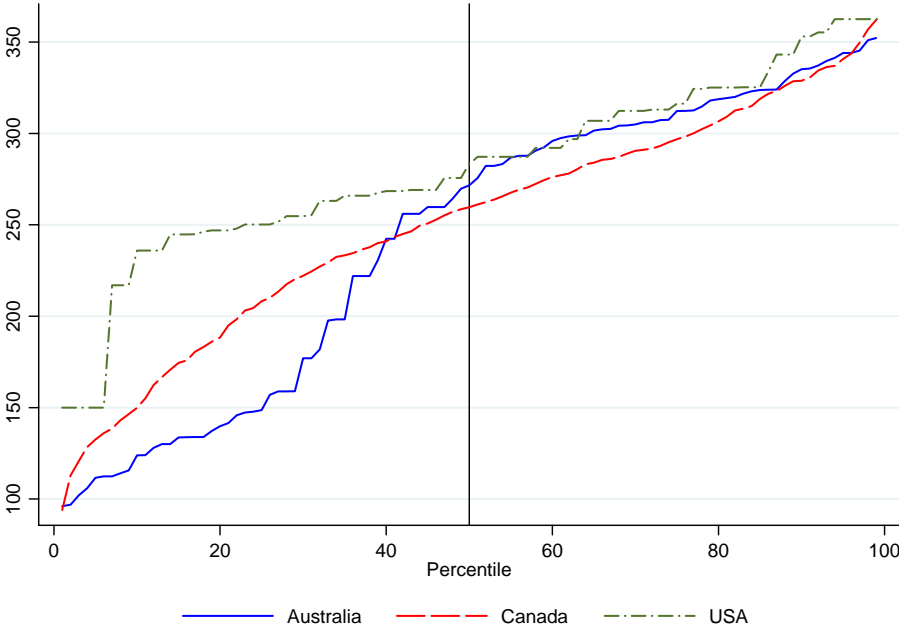

Notes: Plotted percentiles are the unweighted averages of 5 percentile estimates using each plausible value separately. Sample is restricted to individuals aged 18-64 and excludes students and the self-employed.

Figure 4: Predicted immigrant employment rate differentials by document literacy level
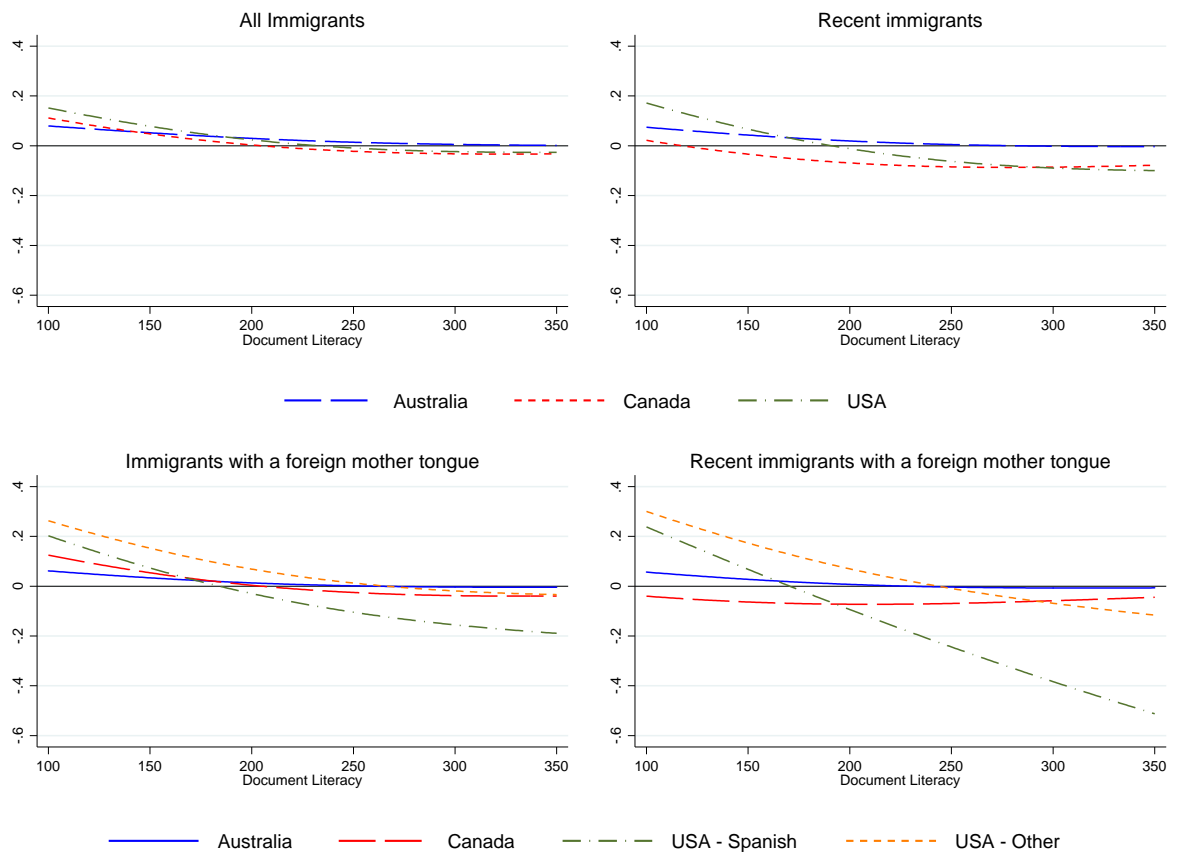
Notes: Predictions are derived from the Probit model estimates in Appendix Table 1.

Figure 5: Predicted immigrant unemployment rates differentials by document literacy level

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Table A.1: Probit employment regression conditional on document literacy level

	Australia			Canada			United States		
	coeff.	Jackknife Std. Err	p	coeff.	Jackknife Std. Err	p	coeff.	Jackknife Std. Err	p
All Immigrants									
Literacy	0.069	(0.005)	0.000	0.065	(0.006)	0.000	0.070	(0.008)	0.000
Literacy*Immigrant	−0.008	(0.010)	0.424	−0.035	(0.013)	0.007	−0.035	(0.016)	0.035
Immigrant	0.140	(0.062)	0.025	−0.071	(0.059)	0.231	−0.028	(0.116)	0.811
Intercept	1.324	(0.091)	0.000	1.365	(0.083)	0.000	1.258	(0.125)	0.000
Recent Immigrants									
Literacy	0.068	(0.005)	0.000	0.064	(0.006)	0.000	0.070	(0.008)	0.000
Literacy*Recent	−0.012	(0.016)	0.461	−0.038	(0.015)	0.010	−0.060	(0.024)	0.014
Literacy*Not Recent	−0.004	(0.013)	0.750	−0.027	(0.016)	0.082	−0.003	(0.020)	0.870
Recent Immigrants	0.070	(0.102)	0.492	−0.409	(0.094)	0.000	−0.203	(0.164)	0.216
Not Recent Immigrants	0.178	(0.073)	0.015	0.195	(0.086)	0.024	0.259	(0.162)	0.111
Intercept	1.330	(0.092)	0.000	1.412	(0.082)	0.000	1.281	(0.124)	0.000
Recent Immigrants with									
Foreign Mother Tongue									
Literacy	0.068	(0.005)	0.000	0.064	(0.006)	0.000	0.070	(0.008)	0.000
Literacy*Recent NESB	−0.013	(0.019)	0.492	−0.021	(0.019)	0.277	...	...	...
Literacy*Recent Spanish	...	...	...	...	...	...	−0.125	(0.051)	0.015
Literacy*Recent Other	...	...	...	...	...	...	−0.099	(0.035)	0.005
Literacy*Not Recent NESB	−0.009	(0.017)	0.576	−0.046	(0.013)	0.001	...	...	...
Literacy*Not Recent Spanish	...	...	...	...	...	...	−0.040	(0.031)	0.194
Literacy*Not Recent Other	...	...	...	...	...	...	−0.013	(0.046)	0.770
Recent NESB	0.006	(0.116)	0.962	−0.381	(0.101)	0.000	...	...	...
Recent Spanish	...	...	...	...	...	...	−0.680	(0.272)	0.012
Recent Other	...	...	...	...	...	...	0.183	(0.316)	0.563
Not Recent NESB	0.066	(0.101)	0.515	0.208	(0.074)	0.005	...	...	...
Not Recent Spanish	...	...	...	...	...	...	0.003	(0.204)	0.987
Not Recent Other	...	...	...	...	...	...	0.333	(0.185)	0.072
Intercept	1.350	(0.092)	0.000	1.414	(0.084)	0.000	1.305	(0.121)	0.000

Notes: Dependent variable is a dummy variable indicating whether an individual worked at any time in the past year. Reported coefficients $\bar{b}$ are unweighted averages of five probit estimates $\bar{b}_j$, each using one of the five plausible values of literacy and the population weights. Standard errors are estimated using $\mathrm{Var}(\bar{b}) = J^{-1} \sum_j \mathrm{Var}(\bar{b}_j) + (J + 1)(J(J-1))^{-1} \sum_j (\bar{b}_j - \bar{b})$, where $\mathrm{Var}(\bar{b}_j)$ is estimated using 30 jackknife replicate weights. Literacy is adjusted by subtracting 225 and dividing by 10. Regressions include a quadratic in age, controls for geographical region of residence, urban/rural area of residence, and an indicator for gender. The samples are restricted to individuals aged 18-64 who were employed in the previous 12 months. The immigrant sample is restricted to individuals who arrived in their destination country at age 14 or higher after 1955. For Australia and the United States, individuals are characterised as having a foreign mother tongue if English was not their first language learned and understood. For Canada, a foreign mother tongue is defined for first languages other than English or French. Recent immigrants refer to foreign-born individuals that have less than ten years of residence in the destination country.

Table A.2: Probit employment regression conditional on document literacy level, labour force participants only

	Australia			Canada			United States		
	coeff.	Jackknife Std. Err	p	coeff.	Jackknife Std. Err	p	coeff.	Jackknife Std. Err	p
All Immigrants									
Literacy	0.049	(0.010)	0.000	0.047	(0.009)	0.000	0.057	(0.010)	0.000
Literacy*Immigrant	−0.017	(0.015)	0.263	−0.017	(0.016)	0.287	−0.039	(0.023)	0.083
Immigrant	−0.017	(0.110)	0.878	−0.195	(0.109)	0.073	0.137	(0.134)	0.304
Intercept	1.346	(0.113)	0.000	1.088	(0.137)	0.000	0.962	(0.148)	0.000
Recent Immigrants									
Literacy	0.049	(0.010)	0.000	0.046	(0.009)	0.000	0.057	(0.010)	0.000
Literacy*Recent	−0.009	(0.021)	0.667	−0.014	(0.019)	0.451	−0.047	(0.034)	0.165
Literacy*Not Recent	−0.021	(0.019)	0.275	−0.017	(0.020)	0.401	−0.029	(0.029)	0.317
Recent Immigrants	−0.075	(0.159)	0.636	−0.359	(0.147)	0.015	0.090	(0.199)	0.650
Not Recent Immigrants	0.011	(0.140)	0.938	−0.017	(0.119)	0.885	0.188	(0.140)	0.179
Intercept	1.348	(0.114)	0.000	1.107	(0.138)	0.000	0.965	(0.147)	0.000
Recent Immigrants with Foreign Mother Tongue									
Literacy	0.049	(0.010)	0.000	0.046	(0.009)	0.000	0.058	(0.010)	0.000
Literacy*Recent NESB	−0.030	(0.024)	0.201	−0.026	(0.023)	0.256	...	...	...
Literacy*Recent Spanish	...	...	...	...	...	...	−0.097	(0.083)	0.246
Literacy*Recent Other	...	...	...	...	...	...	−0.055	(0.035)	0.113
Literacy*Not Recent NESB	−0.033	(0.026)	0.205	−0.033	(0.019)	0.086	...	...	...
Literacy*Not Recent Spanish	...	...	...	...	...	...	−0.035	(0.036)	0.332
Literacy*Not Recent Other	...	...	...	...	...	...	0.009	(0.060)	0.876
Recent NESB	−0.077	(0.162)	0.637	−0.322	(0.145)	0.027	...	...	...
Recent Spanish	...	...	...	...	...	...	−0.275	(0.414)	0.507
Recent Not Spanish	...	...	...	...	...	...	0.423	(0.203)	0.037
Not Recent NESB	−0.124	(0.166)	0.453	−0.053	(0.132)	0.688	...	...	...
Not Recent Spanish	...	...	...	...	...	...	0.498	(0.283)	0.079
Not Recent Other	...	...	...	...	...	...	0.218	(0.306)	0.476
Intercept	1.365	(0.115)	0.000	1.121	(0.141)	0.000	0.942	(0.149)	0.000

Notes: Dependent variable is a dummy variable indicating whether an individual's current work status is employed. Reported coefficients $\bar{b}$ are unweighted averages of five probit estimates $\bar{b}_j$, each using one of the five plausible values of literacy and the population weights. Standard errors are estimated using $\text{Var}(\bar{b}) = J^{-1} \sum_j \text{Var}(\bar{b}_j) + (J + 1)(J(J-1))^{-1} \sum_j (\bar{b}_j - \bar{b})$, where $\text{Var}(\bar{b}_j)$ is estimated using 30 jackknife replicate weights. Literacy is adjusted by subtracting 225 and dividing by 10. Regressions include a quadratic in age, controls for geographical region of residence, urban/rural area of residence, and an indicator for gender. The samples are restricted to individuals aged 18-64 who were employed in the previous 12 months. The immigrant sample is restricted to individuals who arrived in their destination country at age 14 or higher after 1955. For Australia and the United States, individuals are characterised as having a foreign mother tongue if English was not their first language learned and understood. For Canada, a foreign mother tongue is defined for first languages other than English or French. Recent immigrants refer to foreign-born individuals that have less than ten years of residence in the destination country.