Does the United States Admit the Best and Brightest Computer and Engineering Workers? *

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Abstract

Using the American Community Surveys of 2009 and 2010, I examine the wages of immigrants compared to natives among computer and engineering workers. In samples of workers in computer and engineering occupations, immigrants have higher weekly wages than natives: by 15.7% for computer workers and 6.8% for engineering workers. In samples of workers with computer and engineering bachelor's degrees, immigrants are less successful: immigrants with computer bachelor's degrees earn 2.5% more than their native counterparts, while immigrants with engineering bachelor's degrees earn 10.3% less than their native counterparts. Immigrants are less successful in education–based samples because the return to English is higher in these samples: successful degree holders are promoted from technical occupations to management, for which good English is required. The government could increase lifetime immigrant earnings by following the Australian example of a pre–immigration English test.

The United States has established certain visas for the express purpose of permitting entry for highly productive workers. These include temporary work visas, such as the H–1B specialty occupation visas and the L–1 intra-company transfer visas, and certain classes of employment-based green cards (permanent residence). It is therefore natural to ask whether with these or other visas, the United States is succeeding in its objective of attracting the best and brightest workers. Some commentators are convinced immigrants are highly productive, and also increase productivity growth and native productivity through their innovation, skills complementary to those of natives, and positive spillovers on direct co–workers. These commentators call for increased numbers of visas targetting skilled workers.[1] Other commentators contest the claim that the United States admits the best and brightest immigrants, and call for major reforms to skilled immigration visas.[2] The context in which this view is voiced is typically that of the H–1B visa program, which admits workers in "speciality occupations" who must have a bachelor's degree or equivalent, and who in recent years have typically been scientists, engineers and computer workers.

In this paper, I seek to reconcile these views by highlighting the importance of the particular samples of immigrants studied and the native comparison groups used. I also consider how the United States could increase the productivity of skilled immigrants. I use the 2009 and 2010 American Community Surveys (ACS) to investigate the relative wages of immigrants and natives among engineering and computer workers in the U.S. labor market, and I study the importance of English proficiency, an issue that has not been examined in the context of skilled immigration. By studying these particular workers, I focus on two groups of particular interest in the policy debate: engineers are critical to technogical innovation and patent more than workers with any other training (Hunt et al. 2012), while computer workers are at the center of the claims that immigrants are not

[1] Brookings–Duke Immigration Policy Roundtable (2009), Bush et al. (2009), Kirkegaard (2007), Papademetriou and Yale–Loehr (1996), The Partnership for a New American Economy and the Partnership for New York City (2012).

[2] Hira (2007), Matloff (2002–3, 2008), Miano (2007). They also believe that the purportedly skilled immigrants undercut native wages, reduce native wages and facilitate off–shoring of American jobs.

particularly skilled. These workers' shared human capital also makes them a naturally coherent group to evaluate for evidence immigrants are the best and brightest among them. By using representative cross–sections, I study immigrants with various lengths of stay in the United States, with an appropriate emphasis (automatically generated by the cross–section sampling) on those with longer stays, who influence the United States more. If immigrants earn considerably more than natives, their productivity is considerably higher, and they are also more likely to contribute to U.S. productivity growth and have positive spillovers on native colleagues. If they are very similar to natives, it is likely that they are close substitutes, which increases the possibility that they reduce the wages of their native counterparts (though they may nevertheless increase overall native welfare). If immigrants earn considerably less than natives, and are hence poor substitutes, they are less likely to reduce native wages, but also contribute less to the U.S. economy overall.

Existing survey–based evidence supports the view that skilled immigrants are beneficial to the U.S. economy. Hunt (2010) finds that increases in college–educated immigrants translate into increased patenting per capita in the United States; Kerr and Lincoln (2010) find increased H–1B visa caps also increase patenting per capita. Hunt (2011) shows using the 2003 National Survey of College Graduates that immigrants outperform natives in wages, patenting and publishing. Immigrants who originally arrived on student or temporary work visas (including H–1Bs and L–1s), in particular, are indeed the best and brightest. Immigrants' concentration in science and engineering fields of study explains most of their patenting advantage, while it combines with immigrants' higher level of education to explain the publishing advantage. Unlike for patenting and publishing, in terms of wages immigrants are at a considerable disadvantage compared to natives conditional on covariates, with only those who arrived as college students and those who arrived on temporary work visas earning about the same as natives. In another paper using survey data, Mithas and Lucas (2010) find that immigrants earn considerably more than natives among information technology professionals, both unconditionally and conditional on covariates. The concern with this paper is that the web–based sampling method may not have yielded a representative sample. My new paper complements Hunt (2011), by studying samples which while narrower include potentially highly productive workers without a bachelor's degree, and by using data on English proficiency.

A different set of papers focuses on administrative data on H–1B applicants or holders, and appears to paint a more negative picture of immigrants. The advantage of studying a particular visa type is that the link to policy is more direct. Beyond the scarcity of datasets with visa information, the disadvantages of distinguishing immigrants by current visa type are that there is no natural native comparison group, and that immigrants' performance is not assessed over their whole stay in the United States. Lofstrom and Hayes (2011) use individual–level data from U.S. Citizenship and Immigration Services on all individuals who obtained or renewed an H–1B visa in 2009, and focus their analysis on those in science, engineering, health and post–secondary teacher occupations. The difficulty lies in choosing a native comparison group: the authors choose natives aged 22–64 with a bachelor's degree, using the American Community Survey. Since an H–1B is typically an immigrant's first visa (or second, after a student visa), and people tend to migrate when they are young, the H–1B sample is more than nine years younger than the native sample. The average H–1B wage is therefore much lower than the natives', despite immigrants' higher education. Recognizing that this comparison is uninformative, the authors adjust for age, and after this adjustment, immigrants earn 12–34% more. A smaller wage advantage persists for all groups except scientists after controls for education, occupation and industry. Other authors reject the notion that age should be adjusted for (Matloff 2006), and concentrate on wage differences within detailed occupations. Hence, based on immigrant computer occupation wages reported in approved preliminary applications for H–1B visas (Labor Condition Applications – LCAs) and native wages reported by the Bureau of Labor Statistics, Miano (2005) finds that (young) immigrants have low wages compared to natives of (all ages) in the same detailed computer occupation and state, and concludes immigrants are not the best and brightest.

The role of English proficiency is little mentioned in these papers; nor do the datasets on which they are based contain information on English. In both the academic and public debate over immigration of scientists and engineers, the assumption seems to be that highly educated immigrants have sufficiently good English for the technical occupations in which they are heavily represented. Lewis (2011) finds that for workers in general, English skills play a key role in rendering immigrants and natives imperfect substitutes, and the implication of this is that any negative wage impact of immigrants is smaller than it would otherwise be.

In this paper, I show that whether immigrants appear to be the best and brightest depends upon whether the samples of computer and engineering workers are defined based on occupation or education. In occupation–based samples, immigrants have higher weekly wages than natives: by 15.7% for computer workers and 6.8% for engineering workers. In these samples, immigrants could be considered the best and brightest. However, immigrants appear less successful in education–based samples: immigrants with computer bachelor's degrees earn 2.5% more than their native counterparts, while immigrants with engineering bachelor's degrees earn 10.3% less than their native counterparts. Immigrants in these samples fail the best and brightest test. Although there is no correct way to define the samples, the education–based samples lend themselves better to welfare analysis, since we are concerned with the welfare and performance of people rather than jobs.

I find that English proficiency is a key factor determining whether an immigrant is among the best performers in the education–based samples: the high return to English explains why immigrants are not the best and brightest in these samples. Successful natives are promoted out of technical occupations to management jobs requiring excellent English, while immigrants find their progress blocked. Screening out the 22% of immigrants with the worst English would eliminate two thirds of the immigrant disadvantage among engineering degree holders.

The return to English proficiency is much lower in the occupation–based samples, which by definition exclude those promoted out of technical jobs. Highly educated and able immigrants remain in technical occupations, for which their English is adequate, while their native counterparts leave these samples, accounting in part for why immigrants are the best and brightest in the occupation samples. A large fraction of immigrants in computer occupations hold engineering bachelor's degrees, earning wages above the average for computer occupations but below the average for engineering degree holders.

The results imply that immigrants are likely to be closer substitutes for natives in their computer or engineering occupation than for natives with their computer or engineering education. This is important to bear in mind for authors undertaking the difficult task of assessing the impact of skilled immigration on native wages. Immigrants could have a negative effect on the wages associated with computer and engineering occupations without having much effect on the wages of natives who work in these occupations at some time in their career, if natives move more quickly than they would otherwise have done into complementary management positions or other more remunerative and language–intensive jobs. Peri and Sparber (2011) provide evidence for just such a native response in a more general sample of skilled workers. The discussion of the impact of engineering immigrants is usually at the level of the occupation rather than the worker, however, despite the fact that welfare concerns relate to people rather than jobs. This is true both in public discourse, and in the small academic literature: for example, Zavodny (2003) uses state variation in the ratio of LCAs to total employment in computer–related occupations. Even with her focus on occupations, however, she finds that immigrants raise native wages.

Although I argued in Hunt (2011) that firms use temporary work visas to hire workers who are very productive if they remain in the United States, the new results suggest that the government could improve their productivity further. For holders of engineering degrees, the return to English rises with age, and if immigrants do not stay with their initial employer sufficiently long, firms will discount the importance of English over the worker's career and obtain visas for those immigrants who are most productive in the short term rather than the long term. The imposition of a minimum English test score for applicants for skilled work visas (including green cards), and not only for student visa applicants as currently, could be effective in increasing their English proficiency and productivity. While it is not clear that the return to English is a causal one, rather than also capturing unobserved ability, the distinction is not vital for policy purposes.[3]

[3] Dustmann and van Soest (2002) provide evidence that the true return to German in Germany is in

Clarke and Skuterud (2012) show that the Australian government raised skilled immigrant earnings through the introduction of a pre–immigration English test. The test was first used in 1989, and by 1996 was a requirement for all student and skilled visas.[4] The scores required on the test depend upon the type of visa (including permanent residence) the immigrant is applying for and the type of visa, if any, the immigrant already has. Clarke and Skuterud (2012) credit this policy change for an increase in new immigrant earnings in Australia compared to Canada in the years that followed, an increase that came via a reorientation of the source countries towards those whose residents have better English skills on average.

Though the results of the paper indicate that immigrants' overall private productivity could be increased with improved English, it is not possible to test whether improved English skills increase the probability of patenting or of innovating more generally. However, the wage return to English found in all four samples, coupled with the observation in Hunt et al. (2012) that managers frequently have large numbers of patents, so are likely to be complementary to technically innovative workers, suggests that this may be the case. If so, an improvement in English skills of engineering degree holders would not simply provide a one–time increase in productivity, but would stimulate an increase in productivity growth through innovation.

1 Theoretical considerations

If the international pool of applicants from which universities, firms and hospitals choose students, workers and interns is larger than the American pool, and particularly if the foreign applicants are positively self-selected in terms of education, initiative and ambition, immigrants may outperform natives. However, because migrants tend to move when young, applicants from abroad are unlikely to be more experienced than applicants from

fact higher than the OLS effect, due to measurement error in language proficiency.

[4] See Hawthorne (2011) and Australian Government, Department of Immigration and Citizenship (2012), www.immi.gov.au/skilled/general-skilled-migration/pdf/points-tested-visas.pdf, accessed 5 September 2012.

within the United States, which means they are unlikely to outperform natives (of all ages) immediately upon arrival.

In order for immigrants to outperform natives of the same age, the positive selection effect must be large enough to offset obstacles immigrants in general tend to face on arriving in a new country. Prior to and upon arrival, immigrants are unfamiliar with local workplace conventions and institutions, may not have professional networks helpful for job search, have not had a chance to job shop to find their best match with a U.S. employer, and often do not have a perfect command of English. With time, much of this can be remedied, and immigrants' wages would be expected to converge from below towards those of natives. A vast empirical literature confirms this pattern for immigrants generally (Duleep 2013). At the same time, immigrants who arrive as youths would be expected to resemble natives much more closely than immigrants arriving at older ages, as they learn English more easily, obtain U.S. education, and enter and learn about the U.S. labor market at the same age as natives. This too has much empirical support.[5]

Many immigrants who do not arrive as youths never fully catch up with natives of their age. Skills honed on jobs abroad may not be portable to the United States: the empirical literature confirms that there is no return at all to experience gained abroad.[6] The quality of education in many foreign countries is lower than in the United States and would command a lower return: the empirical literature confirms this.[7] Discrimination could also hinder immigrant success: immigrants could encounter discrimination based on their status as immigrants, or, for many, based on their race or religion. Oreopoulos (2011) demonstrates this for skilled immigrants to Canada.

These various factors that have been studied for immigrants generally are likely to apply also to science and engineering workers, though possibly to a lesser extent. Educated immigrants may arrive with better English skills than immigrants generally, and technical skills are particularly likely to transcend languages and borders, which is presumably why

[5] Bleakley and Chin (2004), Friedberg (1992), Schaafsma and Sweetman (2001).
[6] Akee and Yuksel (2008), Aydemir and Skuterud (2005).
[7] Akee and Yuksel (2008), Chiswick and Miller (2008).

many immigrants are in these fields. Hunt (2011) finds that for skilled workers generally, a highest degree obtained in the United States commands a 19% wage premium, but finds no such premium for the probability of patenting or publishing. This is consistent with the hypothesis that long term success for science and engineering workers implies moving out of narrowly technical jobs, and that English skills, in particular, are necessary to do so. This raises the possibility that the firms that hire young immigrants choose those who will be most productive in the short run, without considering the potential for longer term productivity if the immigrant stays in the United States, since by then the immigrant is likely to be at another firm.

The possibility that immigrants may be willing to or forced to work for less than natives because they have fewer outside options is particularly salient for H–1B holders. For these workers, changing employer is administratively complex and may endanger a pending application for a green card. For some workers, in administrative limbo between the expiry of their H–1B visa (after a maximum of six years) and the granting of their green card, changing employer is impossible. Like the discrimination theory, this raises the possibility that immigrants are being paid less than their marginal product, which would call into question the equivalence of wage and productivity. I nevertheless use wage and productivity interchangeably in the paper, while bearing in mind the possibility of a small discrepancy between the two.

By contrast, a theory of immigrants undercutting native wages supported by some non-economists appears to rely on wages being divorced from productivity. In this view, immigrants, specifically those on H-1B visas, are appealing to firms because they are cheap because they are younger than natives. Computer and engineering workers are said to have difficulty finding employment in their occupations after around age 35, and this is attributed to wages rising with age in technical occupations in the absence of any productivity growth with age.[8] The importance of this theory is that its proponents insist

[8] Matloff (2006). Specifically, Matloff avers that employers do not want to hire older workers because they are too expensive, and they do not want to hire them at lower wages because they will leave for a higher wage. It cannot be the case in equilibrium that employers do not want to hire workers at the market wage.

that (young, since recently arrived) H-1B workers' wages be compared to those of natives of all ages. Unsurprisingly, this makes H-1B workers appear to fail the best and brightest test. With more general samples of immigrants, the issue does not arise, since immigrants and natives have similar ages.

2 Data

I use the IPUMS micro–data for the American Community Surveys of 2009 and 2010 (Ruggles et al. 2010). I use these particular years because beginning in 2009, respondents with a bachelor's degree are asked in which field it was obtained. I include respondents aged 18–64 employed full year (there were few part–year workers, and many of them had implausible wages), dropping those currently enrolled or self–employed (worker class 13 or 14). I drop observations with imputed values of variables I use in the analysis.

I construct four samples: workers in computer occupations (excluding computer systems managers, whom I count as managers), workers in engineering occupations (excluding drafters and technicians), workers with computer bachelor's degrees, and workers with engineering bachelor's degrees (including architecture and computer engineering, excluding technology). Some detailed occupational categories became more detailed in 2010, and I collapse them to correspond as closely as possible to the 2009 classification. Details of the occupations and degrees are given below in the descriptive statistics.

I compute weekly wages by dividing annual earnings by 52, and hourly wages by dividing weekly wages by usual weekly hours. I leave the topcoded annual earnings as coded by the Census Bureau: the top 0.5% of earners are assigned the average earnings of the top 0.5%. Given the short time period involved, and the absence of information on the month of the survey, I use nominal wages (though I include a year dummy in regressions). I drop observations with wages above $750 per hour if usual weekly hours are less than or equal to 15, or with wages below $5 per hour.

The ACS asks whether each person in the household speaks a language other than English at home. If the answer is yes, the survey asks whether that person speaks English very well, well, not well, or not at all. Very few people in my samples report speaking English not well or not at all, so I collapse the bottom three categories into the category of speaking English less well.

3 Method

I first present detailed descriptive statistics, which both indicate the degree of wage success enjoyed by immigrants relative to natives, and give indications of what may lie behind differences in immigrant and natives wages. I then proceed to regression analysis to quantify the factors determining the differences. The regressions are simple linear log wage regressions, weighted with sample weights:

$$log\ w_{it} = \alpha + \beta_1 I_{it}^F + \beta_2 I_{it}^C + \beta_3 I_{it}^T + \gamma X_{it} + \delta Z_{it} + \nu_t + \epsilon_{it}, \qquad (1)$$

where w represents either the weekly or hourly wage, I^k are dummies for the foreign–born, X represents characteristics of the worker i and Z characteristics of the worker's job. I^T indicates a worker born in a U.S. territory, I^C indicates a worker born abroad as a U.S. citizen, and I^F indicates the other foreign–born workers, the main group of interest, whom I refer to as immigrants. The coefficient of interest is therefore β_1. I begin with a regression for log weekly wages, before concentrating on hourly wages, a better measure of productivity. I gradually increase the number of covariates to ascertain which are most influential for the immigrant–native wage gap β_1. I control for worker characteristics before job characteristics.

The Xs include dummies for educational degrees: if immigrant education is of lower quality than U.S. education, or if a given degree corresponds to fewer years of education, β_1 will be biased down. The Xs also include dummies for age: the low portability of experience abroad is also likely to be reflected in a lower β_1 than would otherwise obtain.

4 Descriptive statistics

The four samples studied have only limited overlap. Only 51% of holders of computer bachelor's degrees work in computer occupations, and a mere 23% of workers in computer–related occupations have computer bachelor's degrees. In engineering, only 34% of holders of bachelor's degrees in engineering work in engineering occupations, while 64% of workers in engineering occupations hold bachelor's degrees in engineering. The number of workers in computer occupations is about double the number of holders of computer bachelor's degrees, while the ratio is about half for engineering.

Figure 1 plots weekly wages against age for each of the four samples. At early ages, average wages are similar across the samples, but the profiles gradually diverge. Holders of engineering bachelor's degrees have the fastest and longest wage growth, growing until about age 50. Wages of computer occupations workers grow the most slowly and for the shortest time, plateauing at about age 40. The profiles of the engineering occupations sample and the computer degree sample lie in between.

Immigrants' large share of all four samples is shown in the odd columns of Table 1's upper panel: 22% of workers in computer occupations, 28% of workers with computer bachelor's degrees, 19% of workers in engineering occupations and 31% of workers with engineering degrees. Workers born in U.S. territories form 0.3–0.4% of each sample, while U.S. citizens born abroad represent slightly more than 1% of each sample.

The even columns show the average weekly wage of each group. Workers in engineering samples earn more than workers in occupation samples, while workers in the bachelor's degree samples earn more than workers in the occupation samples. Immigrants have a large advantage over natives in computer occupations (column 2): with \$1678 per week compared to \$1450 for natives, they enjoy 15.7% higher earnings. The advantage is much smaller in the sample of computer bachelor's degree holders, however, at only 2.5% (column 4). Immigrants earn 6.8% more per week than natives in the sample of engineering occupations (column 6), but earn 10.3% less in the sample of holders of engineering bachelor's degrees (column 8). Thus, immigrants are the best and brightest in computer and engineering occupations, but not among holders of bachelor's degrees in these fields. In the remainder of the paper, I probe the reasons for these patterns.

The lower panel of Table 1 breaks down immigrants into countries or regions of origin. The odd columns shows that in all samples except engineering occupations, workers from India are by far the largest group, representing nearly 9% of the samples (they represent 3.9% of workers in engineering occupations; column 5). The next largest group is workers from the developed countries of Europe, Canada, Australia and New Zealand, representing 3.6–5.9% of the samples. Workers from China, from the rest of East, Southeast and South Asia, and from the Americas (other than Canada) have slightly smaller shares of 2–5% each.

The highest earning immigrants in each sample are the developed country immigrants and the Chinese, with the developed country workers having a slight edge in three of the four samples (even columns). These immigrants greatly outearn natives in computer and engineering occupations and among computer degree holders (by 13–31%, except for Chinese with computer bachelor's degrees, who have only a 7.4% advantage in column 4). But because they earn similar or lower wages in the engineering degree sample (column 8), even these immigrants cannot be unambiguously called the best and brightest. Indian and other non–Chinese Asian immigrants perform better than natives in occupation–based samples, but the same or worse in education–based samples, while immigrants from the non–Canadian Americas consistently earn less than natives.

In Table 2, I turn to tabulating the educational attainment of the occupation samples, showing that by this metric, computer occupations are not particularly skilled, at least for natives: 40.1% of natives in the sample have less than a bachelor's degree, and only 13.7% have more than a bachelor's degree (column 1). By contrast, only 11.6% of immigrants in the computer occupation sample have less than a bachelor's degree, while 43.8% have more than a bachelor's degree, most of them master's degrees (column 2). That this dichotomy is brought about by the visa selection process for adult immigrants is confirmed by the (untabulated) fact that immigrants in the sample who arrived aged less than 18 are only slightly more educated than the natives. Since it is well known that certain computer occupations are not particularly skilled, some readers might prefer to have them eliminated from the analysis (on the grounds, for example, that workers in such occupations do not innovate). But once subjective changes to the sample are made, it is hard to know where the sample bounds should lie.

Engineering occupations (columns 4–6) are more skilled, although here too immigrants are more educated than natives, with a much larger share of workers with more than a bachelor's degree: 39% of immigrants hold a master's degree, compared to 20% for natives, and full 11.6% hold a doctoral degree, compared to 1.7% for natives. For both samples, the weekly earnings columns (3 and 6) suggest a considerable return to education.

The education distribution for the education–based samples is shown in Table 3. Immigrants are again much more educated than natives, particularly for the computer degree sample, where they have a 20 percentage point higher share with a master's degree (compared to a 10 percent point difference for the engineering degree sample). A key component of immigrant success is thus obvious from Tables 2 and 3: within each sample, immigrants are considerably more educated than natives, and the gap is particularly large in the occupation–based samples, where the wage gap is also highest. As yet unexplained is why immigrants earn less than natives in the engineering degree sample, though this is the sample where the immigrant education advantage is smallest.

For members of the occupation samples who hold bachelor's degrees (a subsample), it is instructive to examine the field of the degree, which I do in Table 4. The first two columns, for computer occupations, show a contrast between immigrants and natives: while similar shares (34–35%) hold computer bachelor's degrees, 37.5% of immigrants hold engineering bachelor's degrees, compared to only 13% of natives. (The rows sum to slightly more than 100%, as some respondents have more than one bachelor's degree.) The third column shows that engineering bachelor's degrees are those paid the most in computer occupations ($1851 per week, compared to only $1627 for workers with computer degrees). Conversely, 20.5% of natives have degrees in business and 24% in a field unrelated to science or technology, both of which are associated with low weekly wages, compared to only 9% and 7% respectively for immigrants.

Immigrants in engineering occupations also hold bachelor's degrees in more remunerative fields than natives (columns 4–6), but the contrast is much smaller than in computer occupations. The field of the large majority of workers is engineering: 78% for natives and 84% for immigrants, though the apparent contrast with computer occupations in this regard ignores both the heterogeneity of engineering degrees and the overlap between an electrical engineering degree and a computer degree. Table 4 thus helps explain why immigrants earn more in the occupation samples, especially the computer sample: they are not only more educated, but those with bachelor's degrees have types of degrees that have a higher return in the relevant occupation.

In order to describe immigrants–native contrasts more richly, in Table 5 I provide detail on the distribution of sub–occupations for the computer occupation samples. The highest–paid computer occupation is that of computer software engineer, whose average weekly wage is $1781 (column 4), while the lowest is that of computer support specialist ($1093). It is precisely for these two occupations that the distributions of immigrants and natives contrast: 44% of immigrants are in the highest–paid occupation, compared to only 24% of natives, while a mere 7.7% of immigrants are in the lowest paid, compared to 16.7% of natives. For immigrants in engineering occupations, there are no such striking differences in occupation, though immigrants are somewhat overrepresented in electrical engineering, an occupation that pays above the average (Appendix Table 1). The evidence that immigrants are in higher paying occupations for computing but less evidently so for engineering is consistent with their larger pay advantage in computer occupations.

I perform the same exercise for the education–based samples in Table 6, using broader occupation categories. The highest paying occupation is management, associated with $2095 per week in the computer degree sample (column 3), and $2561 in the engineering degree sample (column 6), indicating that to a certain degree success in computing and engineering consists in being promoted out of narrow computing and engineering occupations. Immigrants are underrepresented in management: 19% of computer degree immigrants work in management, compared to 24% of natives, while in the engineering degree sample the shares are 24% and 29% respectively. While these contrasts are less dramatic than some seen in connection with the occupation samples, they nevertheless suggest that something is preventing immigrants from being promoted out of computing and engineering occupations, and that this is why the immigrant wage advantage is smaller in the education–based samples than the occupation–based samples. A candidate for the obstacle is English skills, which are more necessary in management than in technical tasks, and I pursue this possibility below.

The largest contrast in Table 6 is the large share of immigrant engineering degree holders compared to natives who work in computing occupations: 22%, compared to only 8% for natives (columns 4 and 5). This is a contributing factor to immigrants' relatively high wage in the computer occupation sample, but pulls down their wages in the engineering degree sample (columns 3 and 6).

Before turning to English proficiency, I analyze the detailed degree fields of workers in the bachelor's degree samples, beginning with the computer degree sample in Table 7. By far the best compensated field is computer science, with a weekly wage of $1802 (column 3), and immigrants are overrepresented in this degree by 14 percentage points (columns 1 and 2): 75% have a computer science degree, compared to only 61% of natives. Natives are overrepresented in all other computer degrees, particularly computer and information systems degrees. I confine the detail for the engineering degree sample to Appendix Table 2, as the immigrant–native differences are not striking: immigrants are somewhat overrepresented among electrical engineering degrees, which pay above average. One component of immigrants' pay advantage in the education–based samples is thus that they have bachelor's degrees in subfields which are particularly lucrative, but especially so for the computer degrees.

In Table 8, I show the distribution of self–reported English proficiency for the immigrants in the four samples (a small share of natives reports speaking a language other than English at home, but I do not tabulate this). Across the samples, 15–20% report speaking English only at home (odd columns), while the majority, 61–66%, report speaking English very well. The shares are not very different by sample, although immigrants in the computer samples have lower shares in the least proficient category.

The wages by language (even columns) indicate a return to English proficiency (or possibly the unobserved ability or social skills with which it is correlated). The returns vary considerably across samples, being larger in the education–based samples than the occupation–based samples, and largest in the engineering degree sample. There is an enormous penalty for an engineering degree holder who speaks English less well (column 8): his or her immigrant counterpart who speaks English very well earns 43% more. This difference is only 19% for the computer degree sample, and about 8% for the occupation samples, confirming that while it is possible to perform well in technical occupations with limited English, it is not possible to keep up with bachelor's degree colleagues who may be promoted out of technical occupations. The premium of English only over English spoken very well is 16% in the engineering degree sample, 10% in the computer degree sample, and 7% and 4% in the engineering and computer occupation samples respectively.

As would be expected, English proficiency varies greatly by origin region, though in the interest of conciseness I do not tabulate these figures. For the engineering degree sample, where English appears to matter most, Chinese immigrants have the smallest share speaking only English (6.4%), and the largest share speaking English less well (33.6%, similar to the share for the non–Canadian Americas), and therefore the worst English. While only 7.9% of Indians speak English only, 82% speak English very well, leaving them with the second smallest share speaking English less well (10.1%, similar to the 9.2% share for the "other" group). Immigrants from developed countries have the highest share speaking English only at home, at 35.1%, but 23.1% report speaking English less well.

These tables have shown that immigrants have higher education than natives and have bachelor's degrees in more remunerative fields, distinctions which are more marked in occupation–based samples than education–based samples, and for computer workers than engineering workers (in part due to immigrants with engineering bachelor's degrees working in computer occupations). This likely accounts for immigrants earning more than natives in both occupation–based samples and in the sample of computer degree holders. The high return to English for holders of engineering bachelor's degrees is likely to be the factor causing immigrants to earn less than natives in this sample, despite higher education, possibly because their mobility out of technical occupations is blocked. In turn, this suggests a possible explanation for why immigrants appear particularly successful in the occupation–based samples: while the best immigrants are promoted out of the samples, the best immigrants remain, held back by their limited English. I now quantify these factors in regressions. Appendix Table 3 contains the means by sample of most of the covariates used in the regression analysis which have not already been tabulated.

5 Results

5.1 Immigrant–native wage differences

In Table 9, I present the coefficient on the immigrant dummy from log wage regressions for the four samples; each sample has its own panel in the table. Consider the first two columns, whose only covariates are the foreign–born dummies and a year dummy. In the first column, for weekly wages, the gaps are approximately the same as in Table 1, but with the year dummy forming a partial adjustment for inflation and reported in log points rather than percent. In column 2, I switch to hourly wages as the dependent variable, which increases the immigrant wage compared to the native wage: immigrants earn an enormous 17.9 log points more in computing occupations (panel A), 5.2% more among computer degree holders (panel B), a large 9.6 log points more in engineering occupations (panel C), and a still large 9.2 log points less among holders of engineering degrees (panel D). In the following columns, I add covariates to the hourly wage regression.

I begin with the level of education, in column 3. This explains two thirds of the enormous immigrant computer occupation advantage, and all of the smaller immigrant advantages in the computer degree and the engineering occupation samples. Controlling for education worsens the immigrant disadvantage in the engineering degree sample by about 50%, to a very large 13.9%. Next (column 4), I control for the detailed field of study of bachelor's degree (in the occupation samples, interacted with a dummy for having a bachelor's degree). Controlling for immigrants' more remunerative field of study reduces the immigrant advantage in the computer occupation sample from 5.9% to 1.0%, but has less effect in the other samples – essentially none in the engineering degree sample – nevertheless leaving the immigrants with statistically significantly lower conditional wages in these samples.

In column 5, I control for English proficiency. As expected from the tables, given that the English proficiency distributions are similar across the samples but the return to English proficiency is much higher in the engineering degree sample, the controls have the largest effect for this sample (panel D). If immigrants all had the proficiency of English–only speakers (the omitted category), they would have conditional wages identical to natives, rather than 13% lower. English proficiency is thus vital for this sample. As expected, controlling for English also has a large effect of more than nine log points for the computer degree sample (panel B), with lesser effects in the occupation–based samples. The result is that after controlling for English proficiency, the immigrant–native wage gaps are much more similar across samples than before. Readers might suspect that English proficiency is proxying for quality of education, but I show in a later table that controlling for immigrant region of origin does not affect the return to English.

Many participants in the debate on immigrant engineering and computer workers stress immigrants' youth. Immigrants in my samples are only slightly younger than natives (see Appendix Table 3), and in fact, controlling for age in column 6 of Table 9 reduces rather than increases the immigrant advantages, suggesting that immigrants are older than natives with similar other characteristics. The effects are small for computer workers, and slightly larger for engineering workers.

In column 7, I control for the last of the individual characteristics, gender, which does not change the coefficient of interest much. Thus, compared to workers with similar personal characteristics, immigrants in both computer samples earn 6% more than natives (panels A and B), immigrants in engineering occupations earn a statistically insignificant 1.1% more, and immigrants in the engineering degree sample earn 1.9% less. It appears possible that relative to natives, immigrant computer workers have better unobserved positive characteristics such as talent, due to selection into migration or the computer field, or the visa selection process, that are not outweighed by assimilation difficulties, leaving immigrants with a higher wage. For engineering workers, unobserved factors more or less cancel, leaving immigrant conditional wages similar to native wages.

In the following two columns, I control for the detailed occupation (column 8), and for firm type and industry (column 9), which moves all the coefficients slightly closer to zero. Characteristics of the job, especially the occupation, may be considered outcomes in their own right, related to the wage gap, rather than explanatory factors for the wage gap, so it could be argued that column 7 is preferred to column 9.[9]

In the final column, 10, I control for state dummies, which reduces immigrant wages relative to natives' by about two log points, leaving both engineering samples' immigrants statistically significantly lower than natives (by 2–3%). It is unclear whether these controls are desirable: if wage differences across states reflect nominal differences in the cost of living, state dummies should be included. If they represent productivity differences, they should not. Probably they reflect a combination of both. With or without state dummies, however, the differences between immigrants and natives are very small conditional on personal and job characteristics.

5.2 Distinctions by region of origin

The regressions of Table 9 indicated that immigrants' lack of English proficiency, particularly in the engineering degree samples, is a large handicap. These regressions did not control for immigrants' region of origin, however, leaving open the possibility that English proficiency was proxying for education quality. In Tables 10 and 11, I repeat the regressions of Table 9, replacing the immigrant dummy with six dummies for immigrants from different regions. Table 10 shows that the enormous wage advantages of Indians and Chinese in the computer occupation sample (21.2 and 29.3 log points respectively in column 1) and in the computer bachelor's degree sample (9.8 and 12.6 log points respectively in column 6) are almost entirely explained by superior levels and fields of education

[9] In the occupation samples, occupation dummies are for the 3–digit (sub–) occupations. In the education samples, I control for 3–digit computer and engineering occupations, and 2–digit other occupations.

(columns 2 and 7). About half of the similar or larger wage advantages of immigrants from developed countries are explained by education.

Columns 3 and 8 show that immigrants from all origins would earn considerably more if they had excellent English, with the effects larger for the degree sample than the occupation sample. The largest effect is for Chinese bachelor's degree holders, whose coefficient rises 12.5 log points between columns 7 and 8.

For engineering occupations, Table 11 columns 1 and 2 show that for this sample too Chinese immigrants' very large 20 log point advantage is explained by their education. Once Indians' education is accounted for, their large 12.5 log point advantage becomes a statistically significant 4.5% disadvantage relative to natives. Chinese and Indians are the only immigrants to have a wage advantage in the engineering degree sample (column 6), and the effect of controlling for education is largest for Chinese among the immigrant groups (column 7). Conditional on education and field of study, all immigrant groups earn less than natives.

Similarly to the occupation samples, all origin groups in the engineering samples would gain from excellent English, especially so in the education sample (compare columns 3 and 2 and 8 and 7). The largest benefit would be for Chinese bachelor's degree holders, whose coefficient rises 18.1 log points between columns 7 and 8. Tables 10 and 11 show a wealth of interesting results, but the role of the return to English may be examined more concisely by looking at it directly, as I do in the next tables.

5.3 Returns to English proficiency

In this section, I examine whether the return to English is proxying for the poor quality of education in countries whose immigrants have worse English; whether the return increases with age, as would be expected if English is less necessary in early career technical jobs than in later jobs requiring more general skills; and how much of any increasing return with age acts through the mechanism of moving into more highly paid occupations. In Table 9, I controlled for English proficiency before controlling for age, but to examine whether the return increases with age, it is necessary to control also for the main effect of age. I therefore begin the analysis of each sample with the specification of column 7 in Table 9, which includes all personal characteristics, but not the job characteristics which might be considered outcomes.

In Table 12, I examine the two computer samples. In the base specification for computer occupations (column 1), there is only a 1.3% wage handicap for those speaking English very well, rather than English only, but a larger 10.0 percent point handicap for those speaking English less well. These coefficients change little when I replace the single immigrant dummy with the immigrant origin region dummies in column 2. In column 3, I investigate whether the return to English increases with age: the coefficient on the interaction of speaking English very well with age is indeed statistically significantly negative. However, it is useful to attempt to distinguish between aging and assimilation factors, so I control in column 4 for immigrant age at arrival (I could equivalently have controlled for years since arrival). In this specification, the coefficients on the interaction of age and English are small and statistically insignificant. There is a penalty associated with less good English in computer occupations, but it does not increase with age. The magnitude of the penalty is not affected by controls for occupations in column 5: English thus matters for immigrant productivity within a computer occupation, but does not affect the occupation.

In columns 6–10, I examine the computer degree sample. The return to English is higher for this sample (column 6), as already suspected: workers who speak English very well rather than English exclusively earn 3.7% less, and those who speak English less well have a very large 22 log point penalty. Again, replacing the single immigrant dummies with the immigrant origin dummy has little effect (column 7). The coefficients on the two interactions of English with age in column 8 have substantial negative magnitudes, indicating a penalty for poor English that is increasing with age, though only one of the two is statistically significant. As was the case for the occupation sample, however, controlling for age at arrival renders the interaction coefficients much smaller and statistically insignificant (column 9). Controlling for occupations (column 10) does affect the return to English, however. As is more easily seen in the computed returns to English at different ages displayed in the lower panel, about half the penalty for speaking English very well or less well disappears with these controls, suggesting that throughout the career of a computer bachelor's degree holder, poor English closes off certain better–paying occupations.

I present the corresponding regressions for engineers in Table 13. The return to English for the occupation sample lies between that for the two computer samples (column 1): very good English yields a 2.7% lower wage than English only, while the penalty for less good English is 9.7 %. Controlling for immigrant origin has little effect (column 2), and column 3 appears to indicate that the return to English increases with age. The latter result is not robust to controlling for age at arrival, however (column 4), and controls for occupation have little effect (column 5).

Columns 6–10 present the results for the sample for which we already know English is most important: holders of engineering bachelor's degrees. The return in column 6 is the largest of the four samples: very good English is penalized 4.8% compared to English only, while the penalty for less good English is enormous, at 39.6 log points. Controlling for immigrant origin increases the penalty for very good English in column 7, to 7.0%. Column 8 suggests the return to English rises with age, and while the magnitudes fall with the addition of the age at arrival covariate in column 9, the result is qualitatively robust and the magnitude still large. The lower panel shows that the penalty for very good English rises from 1.5% at age 30 to 6.6% at age 50, while the penalty for less good English rises from an already enormous 23.9 log points at age 30 to 34.4 log points at age 50.

Controlling for occupations in column 10 halves the coefficient on the interaction between very good English and age, and reduces the coefficient on the interaction between less good English and age by 70%. The implications of this can be seen in the lower panel: within occupation, the penalty for very good English rises only from 1.0% to 3.5% between ages 30 and 50, and the penalty for less good English rises only from 15.4% to 18.6% over the same age range. In summary, roughly half of the level of the return to English and half of its increase with age operates through the immigrant's occupation.

In addition to showing that English proficiency is not proxying for country of origin, the results have shown that the return to English is lower for computer workers than engineering workers, and for occupation samples than education samples, as already indicated by the tables. For the occupation samples, the return to English does not increase with age, and does not appear to be a factor in immigrant selection into (sub–) occupations. For the computer degree sample, the return does not increase with age, but about half the return to English reflects selection into occupations. For the engineering degree sample, the return to English is the highest, and also rises with age, a factor that firms obtaining entry visas for immigrants might not consider. About half the return to English, and half its increase with age, operates through immigrant selection into occupations: immigrants with poor English cannot enter certain well–paying occupations such as management, and increasingly so with age, imposing an increasing wage and productivity penalty.

6 Conclusions and policy recommendations

Among computer and engineering workers, immigrants perform better in samples of computer and engineering occupations than they do in samples of computer and engineering bachelor's degree holders. This is because success for computer and engineering degree holders involves leaving purely technical occupations for occupations such as management, and immigrants' access to non–technical occupations is impeded by their lower English proficiency. While immigrants are clearly the best and brightest among workers in computer and engineering occupations, they are not the best and brightest among holders of bachelor's degrees in these fields: immigrants with a computer bachelor's degree earn only slightly more than their native counterparts, while immigrants with an engineering bachelor's degree earn considerably less than their native counterparts.

For engineering degree holders, the return to English grows over the career. For this reason, firms which facilitate immigrants' visa acquisition early in their careers may not select workers with sufficiently good English. This leaves a role for government intervention in the form of requiring minimum scores on an English test for approval of applications for skilled visas. Alternatively, the government could provide free English instruction to immigrants, as in Quebec,[10] but for skilled immigrants it is unlikely that it is the direct cost of lessons that is the barrier to English proficiency.

The effectiveness of such an Australian–style English test may be gauged by dropping poor English speakers from my data (though an English requirement need not imply lower immigration). If the 22% of immigrants with an engineering degree who speak English less well are dropped from my sample, the average weekly wage of immigrants in the sample rises 7.5%, reducing their wage disadvantage by two thirds. A more subtle approach would yield better results, however. As Chinese immigrants have the worst English (with 34% speaking it less well in the engineering degree sample), they would be most affected by a binding English test. Yet their education is so high that the average weekly wage of Chinese speaking English less well is higher than the native wage in the engineering degree sample. The English threshold required for a visa should therefore be set lower for applicants with higher education. Such rules need not imply a transition to an Australian or Canadian–style points system, since having a job in the United States would remain a requirement for admission, rather than merely a factor that raises an applicant's points.

[10] www.immigration-quebec.gouv.qc.ca/en/french-language/learning-quebec/index.html, accessed 15 September 2012.

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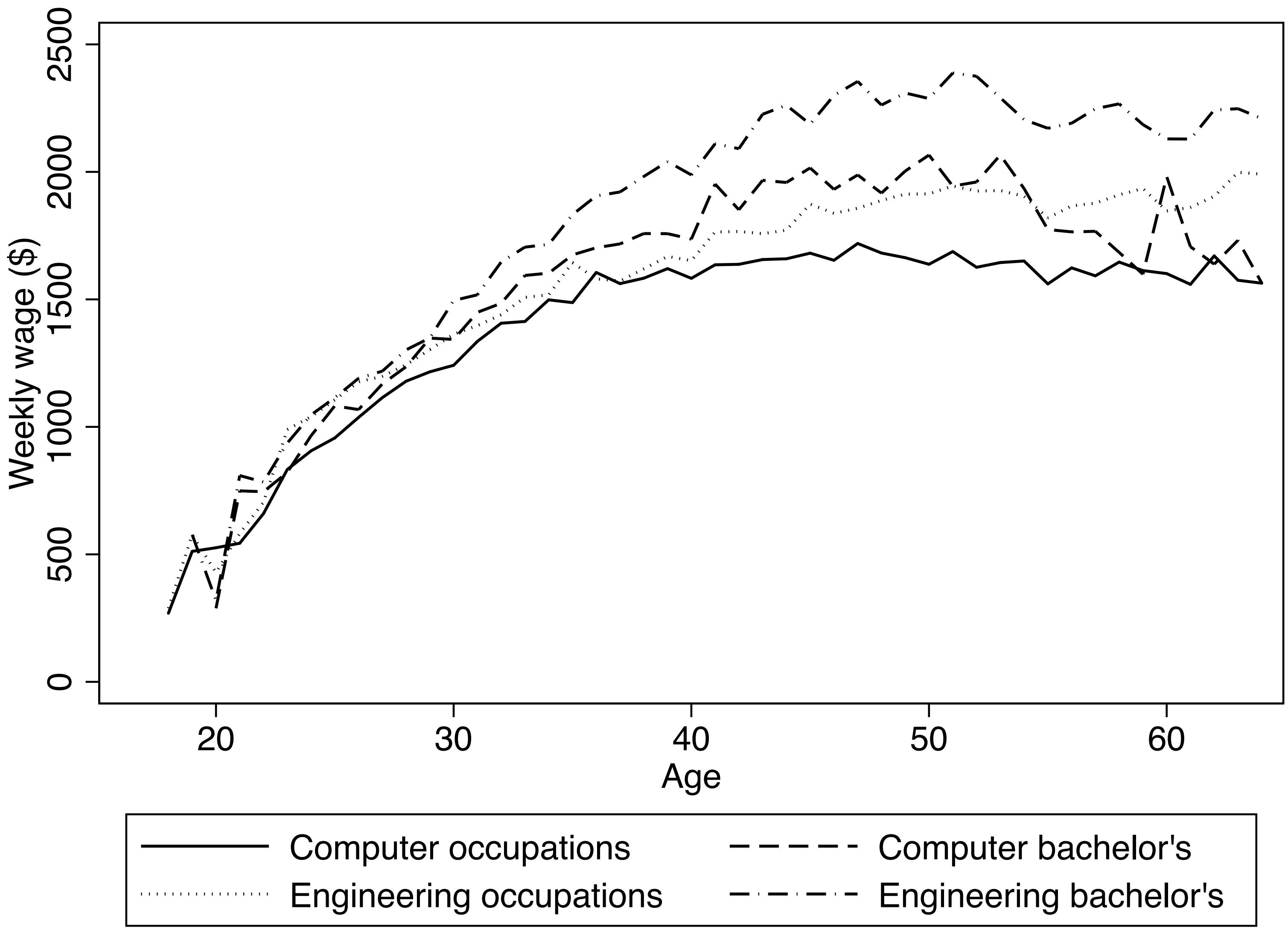
Figure 1: Age–earnings profiles



Note: The sample contains non-enrolled workers ages 18-64, employed full year but not self-employed, who are working in a computer occupation, hold a computer bachelors degree, are working in an engineering occupation or hold an engineering bachelors degree. Data are for 2009 and 2010.

Table 1: Share of immigrants among computer and engineering workers, defined by occupation or education

	Computer				Engineering			
	Occupations		Bachelor's degrees		Occupations		Bachelor's degrees	
	Share (%)	Wage ($)	Share (%)	Wage ($)	Share (%)	Wage ($)	Share (%)	Wage ($)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Natives	76.3	1450	70.5	1670	78.2	1657	67.1	2049
Immigrants	22.2	1678	27.8	1712	19.4	1769	31.4	1837
U.S. citizens born abroad	1.2	1450	1.3	1709	1.1	1808	1.1	2079
Born in U.S. territories	0.3	1347	0.4	1252	0.4	1457	0.4	1745
All	100.0	1500	100.0	1681	100.0	1680	100.0	1982
Observations	41,820		18,549		25,295		47,011	
Immigrants from								
India	8.8	1676	8.7	1672	3.9	1773	8.9	1934
China	3.2	1833	4.1	1794	3.4	1909	4.0	1950
Other East, Southeast, South Asia	2.9	1524	4.1	1497	3.9	1692	4.8	1641
Americas except Canada	2.1	1337	3.3	1369	2.6	1537	4.8	1469
Europe, Canada, Australia, New Zealand	3.6	1898	5.0	2129	3.7	1868	5.9	2068
Other	1.6	1608	2.7	1680	1.9	1782	3.0	1844
All immigrants	23.2	1678	27.8	1712	19.7	1769	32.3	1837

Note: Computed using survey weights. The sample contains non-enrolled workers ages 18-64, employed full year but not self-employed, who are working in a computer occupation (columns 1 and 2), hold a computer bachelor's degree (columns 3 and 4), are working in an engineering occupation (columns 5 and 6) or hold an engineering bachelor's degree (columns 7 and 8). Data are for 2009 and 2010.

Table 2: Education and weekly earnings of workers in computer and engineering occupations

	Computer occupations			Engineering occupations		
	Natives (%) (1)	Immigrants (%) (2)	Weekly earnings (3)	Natives (%) (4)	Immigrants (%) (5)	Weekly earnings (6)
GED or no high school diploma	1.1	0.6	1062	0.5	0.0	1085
High school diploma or <1 year college	10.9	2.4	1174	5.9	1.3	1257
More than 1 year college, no diploma	15.7	4.5	1279	6.3	2.5	1399
Associate's degree	12.4	4.1	1222	8.8	3.6	1336
Bachelor's degree	46.2	44.6	1537	55.6	40.3	1652
Master's degree	12.5	38.7	1838	20.2	38.7	1912
Professional degree	0.4	1.2	1809	1.0	1.8	1945
Doctoral degree	0.8	3.9	2272	1.7	11.6	2280
All	100.0	100.0	1500	100.0	100.0	1680
Observations	32,996	8824	41,820	20,655	4640	25,295

Note: Computed using survey weights. The sample contains non-enrolled workers ages 18-64, employed full year but not self-employed, who are working in a computer occupation (columns 1-3) or an engineering occupation (columns 4-6). Data are for 2009 and 2010. American citizens born abroad and workers born in U.S. territories are included in columns 3 and 6 only.

Table 3: Education and weekly earnings of workers with computer and engineering bachelor's degrees

	Computer bachelor's degrees			Engineering bachelor's degrees		
	Natives (%) (1)	Immigrants (%) (2)	Weekly earnings (3)	Natives (%) (4)	Immigrants (%) (5)	Weekly earnings (6)
Bachelor's degree	79.9	57.0	1556	65.7	49.6	1771
Master's degree	18.1	38.0	1988	28.7	38.4	2243
Professional degree	1.0	1.1	2315	2.5	2.3	2818
Doctoral degree	1.2	2.9	2331	3.1	9.7	2454
All	100.0	100.0	1681	100.0	100.0	1982
Observations	13,716	4833	18,549	33,020	13,991	47,011

Note: Computed using survey weights. The sample contains non-enrolled workers ages 18-64, employed full year but not self-employed, who hold a computer bachelor's degree (columns 1-3) or an engineering bachelor's degree (columns 4-6). Data are for 2009 and 2010. American citizens born abroad and workers born in U.S. territories are included in columns 3 and 6 only.

Table 4: Field of study of bachelor's degree workers in computer and engineering occupations

	Computer occupations			Engineering occupations		
	Natives	Immigrants	Weekly earnings	Natives	Immigrants	Weekly earnings
	(1)	(2)	(3)	(4)	(5)	(6)
Computer-related	33.6	35.8	1627	2.6	4.9	1930
Engineering, architecture	13.2	37.5	1851	77.6	84.1	1784
Science and mathematics	11.4	12.1	1829	7.1	6.7	1878
Technology (engineering and other)	1.7	3.3	1549	3.9	1.9	1497
Business	20.5	9.0	1542	4.3	1.8	1606
None of the above	24.0	7.0	1460	6.9	2.4	1516
All	~100.0	~100.0	1639	~100.0	~100.0	1761
Observations	19,838	7840	28,074	15,987	4318	20,588

Note: Computed using survey weights. The sample contains non-enrolled workers ages 18-64, employed full year but not self-employed, who are working in a computer occupation and hold a computer bachelor's degree (columns 1-3) or are working in an engineering occupation and hold an engineering bachelor's degree (columns 4-6). Data are for 2009 and 2010. American citizens born abroad and workers born in U.S. territories are included in columns 3 and 6 only. Most technology bachelor's degrees are in engineering technology, but they also include family and consumer sciences, military technologies, nuclear, industrial radiology and biological technologies. Medical technology degrees are not included.

Table 5: Specific occupations of workers in computer occupations

	Natives (1)	Immigrants (2)	Weekly earnings (3)
Computer scientists and analysts	25.0	21.0	1509
Computer programmers	14.1	15.1	1526
Computer software engineers	23.7	44.1	1781
Computer support specialists	16.7	7.7	1093
Database administrators	3.7	3.4	1453
Computer systems and network analysts	8.5	4.4	1338
Network systems and data communications analysts	8.3	4.5	1349
All	100.0	100.0	1500
Observations	32,393	8824	41,820

Note: Computed using survey weights. The sample contains non-enrolled workers ages 18-64, employed full year but not self-employed, who are working in a computer occupation. Data are for 2009 and 2010. American citizens born abroad and workers born in U.S. territories are included in column 3 only. Based on a harmonization of 2009 and 2010 detailed occupation codes.

Table 6: Occupations of workers with a computer or engineering bachelor's degree

	Computer bachelor's degrees			Engineering bachelor's degrees		
	Natives	Immigrants	Weekly earnings	Natives	Immigrants	Weekly earnings
	(1)	(2)	(3)	(4)	(5)	(6)
Managerial	23.8	19.4	2095	28.7	23.8	2561
Engineering, architecture	2.9	4.1	1931	38.3	25.6	1785
Computer related	49.1	56.9	1627	8.3	21.8	1851
Science, mathematics, technology, health	2.3	2.3	1503	3.6	4.8	1842
Education	2.4	2.3	1269	2.2	3.3	1585
Other	19.6	15.0	1353	18.9	20.7	1685
All	100.0	100.0	1681	100.0	100.0	1982
Observations	13,410	4833	18,549	32,322	13,991	47,011

Note: Computed using survey weights. The sample contains non-enrolled workers ages 18-64, employed full year but not self-employed, who hold a computer bachelor's degree (columns 1-3) or an engineering bachelor's degree (columns 4-6). Data are for 2009 and 2010. American citizens born abroad and workers born in U.S. territories are included in columns 3 and 6 only.

Table 7: Detailed field of study of workers with computer bachelor's degree

	Natives (1)	Immigrants (2)	Weekly earnings (3)
Computer and information systems	22.3	15.6	1460
Computer programming and data processing	2.1	1.8	1398
Computer science	60.9	75.1	1802
Information science	7.6	4.5	1462
Computer information management and security	3.5	1.2	1460
Computer networking and telecommunications	4.3	2.6	1334
All	~100.0	~100.0	1681
Observations	13,410	4833	18,549

Note: Computed using survey weights. The sample contains non-enrolled workers ages 18-64, employed full year but not self-employed, who hold a computer bachelor's degree. Data are for 2009 and 2010. American citizens born abroad and workers born in U.S. territories are included in column 3 only. Columns 1 and 2 do not sum exactly to one, because some workers have two bachelor's degrees.

Table 8: English proficiency of immigrants

	Computer				Engineering			
	Occupations		Bachelor's degrees		Occupations		Bachelor's degrees	
	Share (%)	Wage ($)	Share (%)	Wage ($)	Share (%)	Wage ($)	Share (%)	Wage ($)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Only English at home	17.1	1761	17.6	1906	19.6	1890	15.7	2219
Speaks English very well	65.7	1687	64.9	1729	61.6	1771	62.2	1916
Speaks English less well	17.2	1559	17.5	1452	18.9	1635	22.1	1342
All	100.0	1678	100.0	1712	100.0	1767	100.0	1837
Observations	8824		4833		4640		13,991	

Note: Computed using survey weights. The sample contains immigrant non-enrolled workers ages 18-64, employed full year but not self-employed, who are working in a computer occupation (columns 1 and 2), hold a computer bachelor's degree (columns 3 and 4), are working in an engineering occupation (columns 5 and 6) or hold an engineering bachelor's degree (columns 7 and 8). Data are for 2009 and 2010. Speaks English less well is an aggregation of the categories Speaks English well, not well and not at all.

Table 9: Wage determinants for computer and engineering workers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A. Computer occupation										
	0.166***	0.179***	0.059***	0.010*	0.068***	0.058***	0.060***	0.048***	0.043***	0.017**
	(0.005)	(0.005)	(0.005)	(0.006)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)
R^2	0.02	0.03	0.12	0.15	0.15	0.26	0.27	0.32	0.36	0.39
B. Computer degree										
	0.027***	0.052***	-0.006	-0.030***	0.064***	0.056**	0.060***	0.051***	0.043***	0.014
	(0.009)	(0.009)	(0.009)	(0.009)	(0.013)	(0.013)	(0.013)	(0.011)	(0.011)	(0.011)
R^2	0.00	0.00	0.05	0.08	0.09	0.16	0.19	0.36	0.41	0.44
C. Engineering occupation										
	0.066***	0.096***	0.003	-0.020***	0.037***	0.009	0.011	0.010	0.003	-0.021**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
R^2	0.01	0.01	0.11	0.15	0.15	0.31	0.31	0.33	0.37	0.40
D. Engineering degree										
	-0.136***	-0.092***	-0.139***	-0.134***	-0.003	-0.023***	-0.019***	-0.007	-0.016***	-0.034***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.009)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)
R^2	0.01	0.01	0.06	0.08	0.10	0.19	0.19	0.37	0.41	0.43
Wage measure	Weekly	Hourly	Hourly	Hourly	Hourly	Hourly	Hourly	Hourly	Hourly	Hourly
Education	--	--	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field, if bachelor's	--	--	--	Yes	Yes	Yes	Yes	Yes	Yes	Yes
English proficiency	--	--	--	--	Yes	Yes	Yes	Yes	Yes	Yes
Age	--	--	--	--	--	Yes	Yes	Yes	Yes	Yes
Gender	--	--	--	--	--	--	Yes	Yes	Yes	Yes
Detailed occupation	--	--	--	--	--	--	--	Yes	Yes	Yes
Firm type, industry	--	--	--	--	--	--	--	--	Yes	Yes
State	--	--	--	--	--	--	--	--	--	Yes

Note: The table reports the immigrant dummy coefficient from least squares regressions on 41,820 observations (panel A) and 18,549 (panel B) and 25,295 (panel C) and 47,011 (panel D), weighted with survey weights. All regressions include a dummy for 2010 and dummies for American born abroad and born in U.S. territories. Education controls are seven dummies (panels A, C) or three dummies (panels B, D), field of study 5 dummies (panels A) or 11 dummies (panels D) or a maximum of 38 dummies (panels A and C), English proficiency two dummies, age 8 dummies, detailed occupation six dummies (panel A) or 13 dummies (panel C), or a maximum of 333 dummies (panels B and D), firm type of dummies for non-profit, federal government, state government, local government, unpaid family worker, industry of a maximum of 267 dummies.

Table 10: Computer workers – hourly wage distinctions by origin region

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
			Computer occupations				Computer bachelor's degrees		
Immigrant from									
India	0.212***	-0.006	0.053***	0.097***	0.048***	0.098***	-0.019	0.064***	0.031**
	(0.008)	(0.008)	(0.011)	(0.010)	(0.009)	(0.014)	(0.014)	(0.018)	(0.015)
China	0.293***	0.054***	0.129***	0.082***	0.032***	0.126***	0.002	0.127***	0.019
	(0.013)	(0.013)	(0.015)	(0.014)	(0.013)	(0.020)	(0.019)	(0.023)	(0.019)
Other East, Southeast,	0.101***	0.016	0.076***	0.036***	-0.015	-0.067***	-0.087***	0.018	-0.027
South Asia	(0.013)	(0.013)	(0.014)	(0.013)	(0.012)	(0.020)	(0.019)	(0.022)	(0.018)
Americas	-0.097***	-0.117***	-0.070***	-0.090***	-0.085***	-0.206***	-0.217***	-0.130***	-0.101***
except Canada	(0.015)	(0.015)	(0.015)	(0.014)	(0.013)	(0.021)	(0.021)	(0.023)	(0.019)
Europe, Canada,	0.250***	0.112***	0.154***	0.125***	0.074***	0.207***	0.133***	0.198***	0.102***
Australia, New Zealand	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)	(0.018)	(0.017)	(0.019)	(0.016)
Other	0.108***	-0.036**	0.011	-0.005	-0.037**	-0.004	-0.064**	-0.000	-0.031
	(0.018)	(0.017)	(0.018)	(0.017)	(0.015)	(0.024)	(0.023)	(0.025)	(0.020)
R^2	0.04	0.15	0.16	0.27	0.40	0.02	0.09	0.09	0.42
Observations			41,820				18,549		
Education, field	--	Yes	Yes	Yes	Yes	--	Yes	Yes	Yes
English proficiency	--	--	Yes	Yes	Yes	--	--	Yes	Yes
Age	--	--	--	Yes	Yes	--	--	--	Yes
Other covariates	--	--	--	--	Yes	--	--	--	Yes

Note: The table reports the immigrant dummy coefficient from least squares hourly wage regressions. All regressions include a dummy for 2010 and dummies for American born abroad and born in U.S. territories. See notes to Table 9 for a full description of the covariates.

Table 11: Engineering workers– hourly wage distinctions by origin region

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Engineering occupations					Engineering bachelor's degrees			
Immigrant from									
India	0.125***	-0.045***	0.013	0.042***	0.018	0.035***	-0.017**	0.092***	0.040***
	(0.014)	(0.013)	(0.016)	(0.014)	(0.013)	(0.009)	(0.009)	(0.012)	(0.010)
China	0.204***	0.006	0.082***	0.054***	0.006	0.041***	-0.082***	0.099***	-0.001
	(0.015)	(0.014)	(0.017)	(0.015)	(0.015)	(0.013)	(0.013)	(0.015)	(0.012)
Other East, Southeast,	0.069***	0.005	0.074***	0.029**	-0.033**	-0.173***	-0.158***	0.005	-0.059***
South Asia	(0.014)	(0.013)	(0.015)	(0.014)	(0.013)	(0.012)	(0.011)	(0.013)	(0.011)
Americas	-0.064***	-0.101***	-0.045***	-0.060***	-0.073***	-0.384***	-0.375***	-0.208***	-0.132***
except Canada	(0.017)	(0.016)	(0.017)	(0.016)	(0.015)	(0.012)	(0.011)	(0.013)	(0.011)
Europe, Canada,	0.114***	0.023*	0.063***	0.017	-0.003	-0.056***	-0.094***	0.027**	-0.013
Australia, New Zealand	(0.014)	(0.013)	(0.014)	(0.013)	(0.012)	(0.011)	(0.010)	(0.011)	(0.009)
Other	0.083***	-0.037**	0.015	-0.040**	-0.057***	-0.124***	-0.170***	-0.076***	-0.082***
	(0.020)	(0.019)	(0.020)	(0.018)	(0.017)	(0.014)	(0.014)	(0.015)	(0.013)
R^2	0.02	0.16	0.16	0.28	0.40	0.03	0.09	0.11	0.43
Observations			25,295				47,011		
Education, field	--	Yes	Yes	Yes	Yes	--	Yes	Yes	Yes
English proficiency	--	--	Yes	Yes	Yes	--	--	Yes	Yes
Age	--	--	--	Yes	Yes	--	--	--	Yes
Other covariates	--	--	--	--	Yes	--	--	--	Yes

Note: The table reports the immigrant dummy coefficient from least squares hourly wage regressions. All regressions include a dummy for 2010 and dummies for American born abroad and born in U.S. territories. See notes to Table 9 for a full description of the covariates.

Table 12: Effect of English proficiency on hourly wages, computer workers

	Computer occupations					Computer bachelor's degrees				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Speaks English very well	-0.013*	-0.017**	0.049**	0.009	-0.020	-0.037***	-0.038***	0.020	-0.034	-0.041
	(0.008)	(0.008)	(0.024)	(0.024)	(0.023)	(0.013)	(0.013)	(0.041)	(0.041)	(0037)
× age	--	--	-0.0017***	-0.0005	0.0004	--	--	-0.0015	0.0002	0.0008
			(0.0006)	(0.0006)	(0.0006)			(0.0010)	(0.0010)	(0.0009)
Speaks English less well	-0.100***	-0.108***	-0.054	-0.097**	-0.144***	-0.222***	-0.216***	-0.061	-0.142**	-0.083
	(0.012)	(0.012)	(0.043)	(0.043)	(0.042)	(0.019)	(0.019)	(0.071)	(0.071)	(0.065)
× age	--	--	-0.0014	0.0004	0.0016	--	--	-0.0040**	-0.0010	-0.0003
			(0.0010)	(0.0010)	(0.0010)			(0.0017)	(0.0018)	(0.0016)
Tab. 9 col. 7 covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Immigrant origin	--	Yes	Yes	Yes	Yes	--	Yes	Yes	Yes	Yes
Age at arrival	--	--	--	Yes	Yes	--	--	--	Yes	Yes
Occupations	--	--	--	--	Yes	--	--	--	--	Yes
English very well	--	--	-0.003	-0.005	-0.007	--	--	-0.025*	-0.030*	-0.018
at age 30			(0.009)	(0.009)	(0.009)			(0.015)	(0.015)	(0.014)
English very well	--	--	-0.037**	-0.014	0.001	--	--	-0.055***	-0.026	-0.003
at age 50			(0.010)	(0.011)	(0.010)			(0.018)	(0.018)	(0.016)
English less well	--	--	-0.094***	-0.085***	-0.095***	--	--	-0.180***	-0.171**	-0.093***
at age 30			(0.016)	(0.016)	(0.015)			(0.025)	(0.025)	(0.023)
English less well	--	--	-0.121***	-0.079***	-0.063***	--	--	-0.259***	-0.191***	-0.100***
at age 50			(0.015)	(0.016)	(0.016)			(0.027)	(0.028)	(0.026)
Observations			41,820					18,549		

Note: The table reports coefficients from least squares hourly wage regressions. All regressions include a dummy for 2010 and dummies for American born abroad and born in U.S. territories. The omitted English category is speaks English only at home. Age at arrival has value zero for natives. See notes to Table 9 for a full description of the covariates.

Table 13: Effect of English proficiency on hourly wages, engineering workers

	Engineering occupations					Engineering bachelor's degrees				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Speaks English very well	-0.027***	-0.030***	0.063**	0.022	0.027	-0.048***	-0.070***	0.129***	0.061**	0.027
	(0.009)	(0.009)	(0.027)	(0.027)	(0.027)	(0.008)	(0.009)	(0.025)	(0.025)	(0.022)
× age	--	--	-0.0022***	-0.0009	-0.0010*	--	--	-0.0047***	-0.0025***	-0.0012**
			(0.0006)	(0.0006)	(0.0006)			(0.0006)	(0.0006)	(0.037)
Speaks English less well	-0.097***	-0.109***	-0.044	-0.069	-0.075	-0.396***	-0.383***	0.014	-0.082**	-0.106***
	(0.013)	(0.014)	(0.052)	(0.052)	(0.051)	(0.011)	(0.011)	(0.041)	(0.041)	(0.037)
× age	--	--	-0.0015	-0.0000	0.0001	--	--	-0.0090***	-0.0053***	-0.0016
			(0.0011)	(0.0012)	(0.0011)			(0.0009)	(0.0009)	(0.0008)
Tab. 9 col. 7 covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Immigrant origin	--	Yes	Yes	Yes	Yes	--	Yes	Yes	Yes	Yes
Age at arrival	--	--	--	Yes	Yes	--	--	--	Yes	Yes
Occupations	--	--	--	--	Yes	--	--	--	--	Yes
English very well at age 30	--	--	-0.005	-0.006	-0.004	--	--	-0.013	-0.015	-0.010
			(0.011)	(0.011)	(0.011)			(0.011)	(0.011)	(0.010)
English very well at age 50	--	--	-0.050***	-0.024**	-0.025**	--	--	-0.107***	-0.066***	-0.035***
			(0.011)	(0.011)	(0.011)			(0.010)	(0.010)	(0.009)
English less well at age 30	--	--	-0.090***	-0.069***	-0.071***	--	--	-0.256***	-0.239***	-0.154***
			(0.021)	(0.021)	(0.021)			(0.017)	(0.017)	(0.016)
English less well at age 50	--	--	-0.120***	-0.070***	-0.069***	--	--	-0.436***	-0.344***	-0.186***
			(0.016)	(0.016)	(0.016)			(0.012)	(0.013)	(0.012)
Observations			25,295					47,011		

Note: The table reports coefficients from least squares hourly wage regressions. All regressions include a dummy for 2010 and dummies for American born abroad and born in U.S. territories. The omitted English category is speaks English only at home. Age at arrival has value zero for natives. See notes to Table 9 for a full description of the covariates.

Appendix Table: 1 Specific occupations of workers in engineering occupations

	Natives (1)	Immigrants (2)	Weekly earnings (3)
Architecture	6.9	5.9	1538
Aerospace	8.1	6.9	1901
Biomedical, agricultural	0.7	0.8	1673
Chemical	3.3	3.4	1945
Civil	15.9	14.1	1603
Computer hardware	2.4	5.0	1777
Electrical	11.9	16.1	1757
Environmental	2.0	1.5	1561
Industrial	10.4	7.4	1462
Marine, naval architecture	0.7	0.4	1545
Materials	18	1.9	1536
Mechanical	12.3	10.3	1509
Mining	1.7	1.4	2452
Nuclear, miscellaneous	21.9	25.1	1756
All	100.0	100.0	1680
Observations	20,316	4640	25,295

Note: Computed using survey weights. The sample contains non-enrolled workers ages 18-64, employed full year but not self-employed, who are working in an engineering occupation. Data are for 2009 and 2010. American citizens born abroad and workers born in U.S. territories are included in column 3 only. Based on a harmonization of 2009 and 2010 detailed occupation codes.

Appendix Table 2: Detailed field of study of workers with engineering bachelor's degree

	Natives (1)	Immigrants (2)	Weekly earnings (3)
General	9.7	14.0	1873
Aerospace	3.2	1.2	2141
Biological	0.9	1.2	1609
Agricultural	0.5	0.3	1614
Biomedical	0.8	0.5	2243
Chemical	6.8	6.5	2273
Civil	12.3	9.5	1892
Computer	4.6	8.5	1849
Electrical	21.9	30.3	2109
Engineering mechanics	0.9	0.8	2065
Environmental	0.9	0.4	1707
Geological, geophysical	0.3	0.1	2126
Industrial, manufacturing	5.0	3.5	1968
Materials	1.0	0.9	1956
Mechanical	19.8	16.2	2022
Metallurgical	0.5	0.7	2070
Mining, mineral	0.4	0.3	2180
Marine, naval architecture	0.5	0.3	2131
Nuclear	0.6	0.3	2451
Petroleum	0.6	0.4	3339
Miscellaneous	2.0	1.5	1913
All	~100.0	~100.0	1982
Observations	32,322	13,991	47,011

Note: Computed using survey weights. The sample contains non-enrolled workers ages 18-64, employed full year but not self-employed, who hold an engineering bachelor's degree. Data are for 2009 and 2010. American citizens born abroad and workers born in U.S. territories are included in column 3 only. Columns 1 and 2 do not sum exactly to one, because some workers have two bachelor's degrees.

Appendix Table 3: Table of means not given elsewhere

	Computer				Engineering			
	Occupations		Bachelor's degrees		Occupations		Bachelor's degrees	
	Native	Immigrants	Native	Immigrants	Native	Immigrants	Native	Immigrants
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age	41.6	38.6	40.4	38.1	43.0	43.6	42.9	42.4
	(10.5)	(8.9)	(9.9)	(8.5)	(11.0)	(10.0)	(10.6)	(9.8)
Female	0.26	0.24	0.24	0.28	0.13	0.17	0.13	0.17
Private for profit firm	0.79	0.89	0.79	0.87	0.85	0.87	0.81	0.86
Not for profit firm	0.07	0.04	0.07	0.04	0.02	0.02	0.04	0.04
Federal employee	0.06	0.02	0.05	0.02	0.07	0.04	0.08	0.03
State government employee	0.05	0.03	0.04	0.04	0.04	0.04	0.04	0.05
Local government employee	0.03	0.02	0.04	0.03	0.03	0.04	0.04	0.04
Unpaid family worker	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Age at arrival	--	23.0	--	22.5	--	23.3	--	25.6
		(9.0)		(8.8)		(10.2)		(10.0)
Observations	32,393	8824	13,410	4833	20,316	4640	32,322	13,991

Note: Computed using survey weights. The sample contains non-enrolled workers ages 18-64, employed full year but not self-employed, who are working in a computer occupation (columns 1 and 2), hold a computer bachelor's degree (columns 3 and 4), are working in an engineering occupation (columns 5 and 6) or hold an engineering bachelor's degree (columns 7 and 8). Data are for 2009 and 2010.