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ABSTRACT

Using the American Community Surveys of 2009 and 2010, I examine the wages of immigrants compared to natives among engineering workers. Among workers in engineering occupations, immigrants are the best and brightest thanks to their high education level, enjoying a wage distribution shifted to the right of the native distribution. Among workers with an engineering degree, however, immigrants underperform natives, despite somewhat higher education. The gap is particularly large in the lower tail, where immigrants work in occupations not commensurate with their education. In the upper tail, immigrants fail to be promoted out of technical occupations to management, handicapped by imperfect English and their underrepresentation among older age groups. In both samples, immigrants from the highest income countries are the best and brightest workers.

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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 transferee visas for managers and specialty workers, and certain classes of employment-based green cards (conferring 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 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]

In this paper, I assess the labor market performance of immigrant engineers in the United States, using the 2009 and 2010 American Community Surveys (ACS). I also investigate reasons for performance differences between immigrants and natives, including the role of English proficiency. English proficiency is rarely mentioned in the academic and public debates over immigration of scientists and engineers; the implicit assumption is that highly educated immigrants have sufficiently good English for the technical occupations in which they are heavily represented. I focus on engineers because of their critical role in technological innovation: Hunt et al. (forthcoming) show that the fields of study associated with most patenting are electrical engineering, physical science, chemical engineering and mechanical/industrial engineering. Engineers' shared human capital also makes them a naturally coherent group to evaluate for evidence that immigrants are the best and brightest among them. I choose the ACS because the data are recent, the sample is large enough to allow a focus on engineers, and the variables include the field of study

[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.

of any bachelor's degree and self–reported English proficiency. My study complements a companion piece on computer workers (Hunt 2012), and the study of Hunt (2011), which examines various performance measures for immigrant college graduates using the 2003 National Survey of College Graduates (NSCG), a dataset which contains visa and patenting information but no English information.

I show that whether immigrants appear to be the best and brightest depends upon whether the sample of engineers is defined based on occupation or education. Among those working in engineering occupations, immigrants are the best and brightest thanks to their higher education, earning 9.6% more per hour than natives on average, 6.5% more at the 95th percentile compared to the native 95th percentile, and 11 log points more at the 10th percentile. However, among holders of engineering bachelor's degrees, immigrants perform less well than natives despite an education advantage, earning 9.2% less on average, 15.5 log points less at the 95th percentile, and a huge 27 log points less at the 10th percentile. I do identify unambiguously best and brightest groups: thanks to their good English and favorable unobservable characteristics, immigrants from primarily anglophone developed countries and from western Europe far outearn natives throughout the distribution in the degree sample as they do in the occupation sample.

There are several reasons for immigrants' worse performance in the degree sample than in the occupation sample. First, the immigrant education advantage is lower than in the occupation sample, as the degree sample excludes the less–educated natives forming the lower tail of the occupation sample. Though immigrants' higher education boosts mean immigrant earnings relative to native earnings, education plays no role in explaining immigrant–native wage differences in the tails of the degree sample. Second, the degree sample includes a disproportionately immigrant lower tail of workers in occupations not commensurate with their education. Supplemental analysis of the 2003 NSCG suggests that this tail should not be wholly attributed to families arriving based on ties to relatives already in the United States. Such immigrants are likely to have been admitted on a green card, and when immigrants who arrived on green cards are dropped from the NSCG sample of engineering degree holders, the immigrant 10th percentile wage rises relative to the native 10th percentile, but stays below it (the same is true of the mean and the 95th percentile). Third, immigrants' underrepresentation in the oldest age groups (in both samples) contributes to their poor performance in the upper tail in the degree sample, unlike in the occupation sample, reflecting a higher return to age (experience) in the degree sample. Assuming immigrants' relative youth is due to low immigration in earlier decades, this implies more immigrants will move to the top of the wage distribution with time.

Fourth, the return to English proficiency, or possibly to unobserved ability correlated with English proficiency, is much higher in the degree sample than in the occupation sample, particularly in the tails. This is in part because analysis of the degree sample captures that component of the return to English which permits promotion out of technical occupations into more language–intensive occupations such as management. The high return to English in the upper tail thus constitutes a barrier for top immigrants, despite their relatively good English. The return to English is equally high in the lower tail, though operating principally through higher pay within occupation, and is compounded by the poor English of the lowest–paid immigrants.

These same four factors explain the contrast between engineering degree holders and computer degree holders, among whom Hunt (2012) shows immigrants hold a wage advantage. In the computer degree sample, immigrants' education advantage is larger; there is a much smaller lower tail of immigrants working in occupations not commensurate with their degree, possibly due to greater international portability of computer skills; the return to age (experience) is lower; and the return to English is modest, with promotion to management less of a factor in success.

The contrast between the two engineering samples highlights that a visa policy focused on admitting immigrants who would be the best and brightest in technical occupations would admit immigrants lacking the skills (whether English or related unobserved ability) that would allow them to rise to the top later in their career. Supplementary analysis of the 2003 NSCG data shows top–paid engineers and engineers in management positions are the most prolific patentees, results which reinforce the desirability of admitting immigrants who will sooner or later work in highly–paid management positions. The current U.S. visa system may promote just such a focus on technical occupations, however. The delays of up to a year in obtaining an H–1B visa (if the cap is filled immediately), the legal expense of preparing an application dossier for the first and second preference employment–based green cards, and the wait times of longer than a year for third preference employment–based green cards may effectively preclude the use of immigrants for top jobs which must often be filled at short notice and cannot be performed even temporarily by others at the firm. At the same time, employers will not screen applicants for technical positions for management potential, since they cannot be promoted to management while on an H–1B visa, and may leave the firm once promotion is possible.

Assuming English proficiency does not proxy entirely for unobserved ability, the English proficiency results imply that immigrants are likely to be closer substitutes for natives in their engineering occupation than for natives with their engineering education (Lewis forthcoming). This implies any negative impact immigrants might have on the wages of natives in engineering occupations is likely to be larger than the effect on natives with an engineering degree. Natives may also attenuate any negative effect on wages in engineering occupations by moving into more language–intensive jobs, as suggested by Peri and Sparber (2011) for a more general sample of skilled workers. The discussion of the impact of skilled 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.

The evidence of this paper adds pieces to the puzzle of the contribution of skilled immigrants partially assembled by several earlier papers with an emphasis on innovation. Hunt and Gauthier–Loiselle (2010) find 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 that college–educated immigrants outperform college–educated 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. It is significant that she finds immigrants' concentration in science and engineering fields of study explains most of their patenting advantage, while field of study combines with immigrants' higher level of education to explain the publishing and wage advantages. The evidence of this paper indicates immigrants would contribute more to the U.S. economy if they were not merely heavily concentrated in engineering, where they patent at the same high rate as natives, but also rose higher in the non–technical engineering hierarchy.

The results of my paper paint a more positive picture of immigrant wages than certain papers using administrative data on H–1B applicants or holders. The disadvantages of focusing on holders of a particular 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. The Lofstrom and Hayes (2011) native comparison group is more than nine years older than the immigrant sample and has commensurately higher wages. Adjusted for age, immigrants earn 12–34% more, while a smaller wage advantage persists after controls for education, occupation and industry. Miano (2005) finds that (young) immigrants have low wages compared to natives (of all ages) in the same detailed computer occupation and state.[3]

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 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

[3] Using a possibly unrepresentative web–based sample of readers of a business technology magazine, Mithas and Lucas (2010) find that immigrants earn considerably more than natives among information technology professionals, both unconditionally and conditional on covariates.

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.[4]

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.[5] 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.[6] 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. Furthermore, not all immigrants who arrive as adults have the language aptitude to bring their English reading and writing to the native level, while others calculate that the financial or opportunity cost of doing so is not worthwhile. Immigrants who arrive as adults can rarely rid themselves of their foreign accent, which in many cases impedes their ability to communicate at work. 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.

These various factors that have been studied for immigrants generally are likely to

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

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 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 suggests that while technical skills may be portable across countries, other skills may be less portable, posing a barrier to advancement beyond technical occupations. 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.

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 define immigrants as though those born abroad, except those born in U.S. territories and born abroad as U.S. citizens. I construct two samples: workers in engineering occupations (excluding drafters and technicians) and workers with engineering bachelor's degrees (including architecture and computer engineering, but excluding technology).

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.

I do not use the NSCG 2003 as my primary data, because they are somewhat outdated and do not contain information on English proficiency. However, they do contain information on patenting (unlike the new wave of the NSCG, about to be released) and entry visa, so I provide some information from them. All respondents who have ever worked are asked a series of questions concerning the five–year window since October 1998, including how many U.S. patents they had been granted and how many granted patents had resulted in commercialized products or processes or had been licensed. My NSCG sample contains respondents 64 or younger (the youngest respondent is 23, but few are younger than 26), and exclude the enrolled and the self–employed. The Data Appendix provides some additional details on the sample and variable construction.

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. I run either least squares or quantile log wage regressions, weighted with sample weights:

$$log\ w_{it} = \alpha + \beta_1 I_{it}^F + \beta_2 I_{it}^C + \beta_3 I_{it}^T + \gamma E_{it} + \delta A_{it} + \phi X_{it} + \nu_t + \epsilon_{it}, \tag{1}$$

where w_i represents the hourly wage of worker i, I^k are dummies for the foreign–born, E represents dummies for self–reported English ability, A represents dummies for age, and X represents other worker and job characteristics. 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 gradually increase the number of covariates to ascertain which are most influential for the immigrant–native wage gap β_1.

The age dummies are included to control for potential experience, but I do not attempt to distinguish between foreign and U.S. experience. The low return to foreign experience is therefore likely to be reflected in a lower β_1 than would otherwise obtain. 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 also be biased down.

I also estimate an extended specification where I interact the English dummies E with a linear term in age, to test the hypothesis that the return to English changes over the career. The return to English could increase if excellent English is required for promotion to non–technical occupations. When including these interactions, I also control for age at arrival (equivalently in a single cross–section, for years in the United States), since English proficiency could be proxying for assmilation along other dimensions.

4 Descriptive statistics

In this section, I begin by using the NSCG data to show the relation between patenting and wages for immigrants and natives, before examining immigrant and native wages and other characteristics in the ACS samples.

4.1 Patents and wages in the NSCG sample

The 2003 NSCG data indicate that immigrants with an engineering degree were granted an average of 0.21 patents in the previous five years, similar to the value of 0.19 for their native counterparts, and compared with 0.04 for all college–educated natives. Figure 1 shows that patenting and wages are strongly positively correlated. Patents per capita rise with the (pooled) wage decile for both immigrant and native holders of engineering degrees, and jump in the top decile: native earners in the top 10% of all earners were granted 0.5 patents per capita in the five previous years, while immigrants in the top 10% of all earners were granted 0.75 patents per capita in the five previous years. These results indicate that identifying top earners is closely related to identifying top innovators.

4.2 Wages in the ACS sample

I next turn to the analysis of immigrants and natives in the two ACS samples. The samples overlap less than might be expected. 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 engineering occupations is about half the number of holders of engineering bachelor's degrees.

Immigrants' large share of both samples is shown in the odd columns of Table 1's top panel: 19% of workers in engineering occupations (column 1) and 31% of workers with engineering degrees (column 3). Workers born in U.S. territories form 0.4% of each sample, while U.S. citizens born abroad represent 1.1% of each sample. The even columns show the average hourly wage of each group. Immigrants earn 10.3% more per hour than natives in the sample of engineering occupations (column 2), but earn only 93% of native wages in the sample of holders of engineering bachelor's degrees (column 4). The relatively lower earnings of the immigrant engineering degree holders contrasts with Hunt (2011)'s results for all immigrants with a college degree and with Hunt (2012)'s results for computer degree holders.[7]

Figure 2 plots wages against age for each of the samples. Graph A, for natives, shows that at early ages, average wages are similar in the two samples, but the bachelor's degree holders gradually pull ahead. The picture for immigrants is quite different in graph B,

[7] The contrast with Hunt (2011) is not due to the data, however; in the NSCG 2003, immigrants also earn less than natives among engineering degree holders.

where there is little difference in the profiles of the two samples.

In Figure 3, I further investigate the relative wages of immigrants and natives, by considering the entire distributions of log wages. For engineering occupations, in graph A, the immigrant distribution is more equal and shifted to the right compared to the native distribution. Graph B indicates that immigrants earn less than natives in the degree sample because immigrants are overrepresented in the bottom 10%, and underrepresented between the 10th percentile and the median. The upper halves of the immigrant and native distributions are similar.

It is useful to replot these distributions in graphs C and D, so as to allow degree and occupation samples to be compared on the same graph. The native degree–holder distribution is shifted rightwards compared to the occupation distribution (graph C). For immigrants, by contrast, the share of degree holders with low wages is much higher than the share in the occupation sample (graph D). The right tail is slightly thicker for the degree sample.

The middle panel of Table 1 breaks down immigrants into countries or regions of origin. Column 3 show that Indians are the largest group among degree holders, representing 8.3% of the sample. No individual origin country has as large a share of the occupation sample, as indicated in column 1, though Asians together represent 11.3% (compared to 17.7% of the degree sample). I distinguish finely among developed countries for the purposes of identifying top earners and of grouping primarily anglophone countries, though I have left Japan with other Asian countries. The primarily anglophone countries (dominated by the United Kingdom and Canada; also including Ireland, Australia and New Zealand) and the western European countries outearn natives in both samples (by 17-24%), as do Indians to a lesser degree. Chinese also perform well, while immigrants from the non–Canadian Americas (including the Carribbean) have the lowest earnings, the only group to earn less than natives in the occupation sample.

The bottom panel of Table 1 indicates that while one quarter of immigrants in the occupation sample arrived age 17 or younger (column 1), the share is only 17% for the degree sample (column 2). For the occupation sample, young arrival is associated with a wage disadvantage (column 2), while the opposite is true for the degree sample (column 4).

4.3 Education

I turn next to tabulating the educational attainment of engineers in the two samples. Table 2 shows that among workers in engineering occupations, immigrants are more educated than natives, with a much larger share holding more than a bachelor's degree: 39% of immigrants hold a master's degree (column 2), compared to 20% for natives (column 1), and fully 11.6% hold a doctoral degree, compared to 1.7% for natives. The share of workers with less than a bachelor's degree is 21.5% for natives compared to only 7.4% for immigrants. Considering the three education categories containing most of the immigrants, immigrants earn more (columns 3 and 4) than natives in the lowest (bachelor's degree) and less in the higher ones (master's, doctoral).

The education distribution for holders of engineering bachelor's degrees is shown in Table 3. Immigrants are again more educated than natives, with only 49.6% holding a bachelor's degree only (column 1), compared to 65.7% for natives (column 2), but the education gap is less than in the occupation sample. Furthermore, immigrants earn less than natives at every education level. For natives, unlike for immigrants, there is a large increase in average education in moving from the occupation to the degree sample, explaining why the native wage–earnings profile is steeper for the degree sample in Figure 2.

Immigrants' relative earnings may not only be affected by the level of education, but also the field of study of the bachelor's degree. Table 4 shows among those in the occupation sample who hold a bachelor's degree (a subset), more immigrants than natives have the most highly–paid computer, science or mathematical backgrounds. I also analyze the detailed fields of study of workers in the bachelor's degree sample. I confine the detail to Appendix Table 1, as the immigrant–native differences are not striking: immigrants are somewhat overrepresented in electrical engineering, a field of study associated with above average pay.

4.4 Occupations and English proficiency

In order to describe immigrants–native contrasts more richly, I turn to a comparison of the occupations in which they work. There are no striking immigrant–native differences in occupation in the occupation sample, though immigrants are somewhat overrepresented in electrical engineering, an occupation that pays above the average (Appendix Table 2). However, there are considerable differences in the education–based sample, tabulated in Table 5. The highest–paying large occupation is management, associated with a wage of about $54 per hour for both natives and immigrants (columns 3 and 4), suggesting that to a certain degree success in engineering consists in being promoted out of narrow engineering occupations. Only 24% of immigrants work in management, compared to 29% of natives (columns 1 and 2), which is one source of the native wage disadvantage among engineering degree holders. Another is also apparent in the table: while the share of immigrants and natives working in "other" occupations is not so different at 20.5% and 18.1% respectively, the immigrant average wage in this category, at only $28.3, is far below the native average of $39.5. These immigrant occupations represent the thick lower tail seen in the wage distribution of Figure 3. The largest occupation contrast is in the share of engineering degree holders who work in computing occupations: 22% of immigrants compared to only 8% of natives (columns 1 and 2).

While it may appear surprising to lament a lack of immigrants in management if innovation is an important concern, managers in fact obtain many patents. Columns 5 and 6, based on the NSCG data, show that immigrant managers with engineering degrees average 0.52 patents granted over the previous five years, compared to 0.35 for their counterparts working as engineers, and that for natives, the average number of patents is similar for managers and engineers (0.23–0.24). While some of managers' patents may have been awarded before they were promoted to management, the statistics coupled with anecdotal evidence suggest that management is complementary to the innovative process.[8]

As Figure 1 showed that the top 10% of (pooled) engineering degree earners are par-

[8] Management is defined more narrowly in the NSCG than in the ACS.

ticularly prolific patentees, I tabulate separately the occupations of the top 10% of immigrants and natives with engineering degrees in Table 6, columns 1 and 2. The top 10% of immigrants earn $100 per hour, less than the top 10% of natives at $109 per hour (not tabulated). The share of managers is much higher than for the full sample, and only slightly lower for immigrants (51%) than natives (53%). The share working as engineers is only a small minority of 18% for both groups. The differences between immigrants and natives lie in the much higher share of immigrants working in computer occupations (13%, compared to 5% for natives), the lower share of immigrants working as lawyers and physicians (only 1.8%, compared to 6.4% of natives), and the lower share of immigrants working in "other" occupations.

Given the thick lower tail of immigrants with engineering degrees observed in Figure 3, it is also informative to examine the occupations of the bottom 10% of immigrant and native workers with engineering degrees, which I do in columns 3 and 4 of Table 6. Fully 69% of such immigrants and 43% of such natives work in "other" occupations (columns 1 and 2), which Table 5 showed are the lowest paid occupations other than education. Workers in the bottom tail of natives, especially immigrants, are working in occupations not commensurate with their education. It is also possible that field of study contains some measurement error.

The NSCG can help us understand on which visas the top and bottom of the immigrants in the bachelor's degree sample first entered the United States. Though the 2003 information is somewhat dated (in recent years, more entries have been on temporary visas than in the past), the comparison of top and bottom earners could still be informative. The first row of Table 7 shows that the bottom 10% of earners are almost twice as likely as the top 10% to be admitted on a green card (i.e. with permanent residence), and are hence much more likely to have been admitted on the basis of family ties. Conversely, the bottom 10% are half as likely to be admitted on temporary work visas (typically H–1B or L–1 visas for skilled workers) or on student visas. An immigrant who arrived as the child of the holder of a temporary work or student visa would hold a dependent's visa. It is useful to note, however, that in the NSCG immigrants still earn less than natives at the 10th and 95th percentiles as well as the mean if immigrants who originally entered on green cards are dropped.

One aspect of assimilation to the United States is English proficiency, which I tabulate for immigrants in the two samples in Table 8 panel A (a small share of natives reports speaking a language other than English at home, but I do not tabulate this). 20% of immigrants in engineering occupations report speaking English only at home (column 1), while the majority, 62%, report speaking English very well. The shares are similar for the degree sample in column 2. There is a large wage return to English proficiency, or possibly to the unobserved ability or social and cultural skills with which it is correlated, for the degree sample (column 4), but almost none for the occupation sample (column 2). There is an enormous penalty for an engineering degree holder who speaks English less well (column 4): his or her immigrant counterpart who speaks English very well earns 38% more. In panels B and C, I tabulate English proficiency for the top and bottom 10% of immigrant earners, respectively. As would be expected, speakers of English only are overrepresented among the top 10% and underrepresented among the bottom 10%, and particularly so in the degree sample. The English of the bottom 10% of the engineering sample is particularly poor, with fully 49% speaking English less well. The table is consistent with an important role for English skills in immigrant success in the engineering degree sample, though also with other interpretations that will be considered below.

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 more, Chinese and eastern European immigrants have the worst English (with 35% and 42% respectively reporting speaking English less well, and less than 10% speaking only English at home), closely followed by immigrants from the non–Canadian Americas (with 33% speaking English less well, and 14% speaking English only). While only 8% of Indians speak English only, 83% speak English very well, leaving them a share speaking English less well (10%) similar to that of western European immigrants (9%), and significantly surpassed only by immigrants from primarily anglophone countries (0.5%). 27% of western European immigrants report speaking

English only.[9] Appendix Table 3 contains the means of most of the covariates used in the regression analysis which have not already been tabulated.

5 Results

In this section, I use regressions analysis to pursue the roles of education, age and English in the immigrant–native wage differences.

5.1 Immigrant–native wage differences

In Table 9, I present the coefficient on the immigrant dummy from log wage regressions for the occupation sample (panel A) and the degree sample (panel B). In the first column, whose only covariates are the foreign–born dummies and a year dummy, immigrants earn a large 9.6 % more in engineering occupations, and a large 9.2% less among holders of engineering degrees.[10] The addition of education controls in column 2 explains all of the immigrant advantage in the occupation sample, and worsens the immigrant disadvantage in the engineering degree sample by about 50%, to a very large 13.9%. Next (column 3), I control for the detailed field of study of bachelor's degree (in the occupation sample, interacted with the dummy for having a bachelor's degree). This reduces the immigrant wage by two log points compared to natives in the occupation sample, making it statistically significantly lower than the native wage, but has a smaller effect in the engineering sample (where the possible fields are more circumscribed). In columns 4 and 5, I control for age and gender, which has only small effects on the immigrants coefficients.

In column 6, I control for English proficiency. As expected from the descriptive tables, the controls have a large effect in the degree sample (panel B). If all immigrants with an engineering degree had the proficiency of English–only speakers (the omitted category), they would have conditional wages very close to those of natives natives (1.9% lower),

[9] There could be differences across country in how confident respondents are in a given quality of English.

[10] The immigrant–native wage gaps differ from those in Table 1 due to the difference between the mean of log wages and the log of mean wages.

rather than 13% lower. In the occupation sample (panel A), the English controls have only a small effect, raising the immigrant coefficient by three log points. I investigate in later tables to what degree the English controls reflect language facility versus assimilation along other dimensions. The similarity of the conditional wages in this specification suggests that any unobservable advantages immigrants have relative to natives, due to positive selection into migration or the engineering field, or due to the visa selection process, are offset by assimilation difficulties or discrimination.

In the following two columns, I control for the detailed occupation (column 7), and for firm type and industry (column 8), which does not change the immigrant coefficients greatly.[11] 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. In the final column, 9, I control for state dummies, which probably capture a mix of nominal price differences and genuine productivity differences. The controls reduce immigrant wages relative to natives' by about two log points, leaving both samples' immigrant wages statistically significantly lower than natives (by 2–3%).

Table 9 is informative about the average performance of immigrants and natives, but is not informative about top performers, who are most likely to influence U.S. growth through innovation. I therefore repeat some of the Table 9 specifications using quantile regression at the 95th percentile: choosing such a high percentile leads to large standard errors, but guarantees that the part of the wage distribution being examined is where Figure 1 indicated that much patenting occurs. The first column of Table 10 panels A and B indicates that conditional on only a year dummy and the other foreign born dummies, the 95th percentile immigrant earns more than his or her native counterpart in the occupation sample (by 6.5%, panel A), but considerably less in the degree sample (15.5 log points, panel B). Immigrants could therefore be characterized as being some of the the best and brightest workers in the occupation sample.

Column 2 shows that for the occupation sample (panel A), immigrants' higher edu-

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

cation and more remunerative fields of study explain why the 95th percentile immigrant earns more than the 95th percentile native, just as at the mean, leaving immigrants and natives very similar conditional on education. These controls have only a small effect on the immigrant disadvantage in the degree sample (panel B), however.

Column 3 shows that for the degree sample (panel B), 70% of the remaining immigrant wage disadvantage is explained by age, despite the unimportance of this variable in the mean regressions. Although immigrants' average age is only slightly below that of natives (see Appendix Table 3), the distribution is rather different: immigrants are very overrepresented among engineering degree holders in their 30s, and underrpresented at older and very young ages. The lack of older immigrants, due either to the low immigration in the 1970s and earlier, or to selective return migration, means immigrants tend not to reach the top of the wage distribution. The role of age in the occupation sample is qualitatively similar, but small (panel A): the unreported age dummies show the return is lower than in the degree sample. The gender control in column 4 has little effect on the immigration coefficient in either sample.

Column 5 shows that in the degree sample (panel B), English plays almost as large a role as age in explaining the immigrant–native wage gap. The 95th percentile immigrant in this sample would earn (a statistically insignificant) 3% more than the native at the 95th percentile if all immigrants spoke English only, instead of suffering the 4% disadvantage conditional on education, age and gender only. For the occupation sample, on the other hand, the English controls raise immigrant relative wages by a more modest 2.5 log points. The effect of English in both samples is similar to the effect in the mean regressions. Controls for occupation reduce the immigrant coefficients slightly (column 6). I do not add further controls due to the difficulty of reaching convergence with large numbers of covariates.

It is important not only to examine the upper tail and potential stars, but also to understand the reason for the underperformance of immigrants in the thick lower tail of the degree sample. Consequently, in panels C and D of Table 10, I present the results of quantile regressions at the 10th percentile.[12] For the occupation sample, panel C shows that the immigrant advantage of 11 log points is more than explained by level and type of education (compare columns 1 and 2), and immigrants would have lower wages if they had the native age distribution (compare columns 2 and 3). English proficiency controls raise the immigrant relative wage by eight log points (compare columns 4 and 5), much more than at the mean. The immigrant coefficient is close to zero in this specification, and is not much changed by the occupation controls (column 6).

The results for the degree sample (panel D) are rather different. Controls for level and type of education in column 2 make little difference to the enormous 27 log point disadvantage of immigrants, while age has only half the effect it did in the occupation sample (column 3), though a larger effect than at the mean. Conditional on education, age and gender, immigrants still have a 30 log point wage disadvantage (column 4). The English controls in column 5 explain two thirds of this disadvantage, reducing it to ten percent. Column 6 shows that two thirds of the remaining gap is accounted for by differences in occupations. Lack of English proficiency therefore plays a large role in the thickness of the lower tail of the distribution of wages for immigrants with engineering degrees, as well as in the underperformance of the 95th percentile immigrants.

5.2 Returns to English proficiency

In this section, I examine the coefficients on the English dummies directly, test whether they are robust to immigrant origin, distinguish between English proficiency and assimilation along other dimensions, and check how much of the return to English works through entering specific occupations. I also check whether the return changes with age.

I present the English proficiency coefficients for the two samples in Table 11 panels A and B, beginning with those from the specifications of Table 9 column 6 (controls for education, age and gender, as well as English). The omitted dummy is for speaking only

[12] I do not look at the 5th percentile, which would provide symmetry with the analysis of the 95th percentile, because the 10th percentile is low enough to investigate the underperformance of immigrants with an engineering degree, while yielding lower standard errors than analysis at the 5th percentile.

English at home. For the occupation sample (panel A), the penalty for speaking English well is only 2.7%, while the penalty for speaking English less well is larger at 9.7%. The corresponding penalties are much larger for the degree sample in panel B: 4.8% for speaking English very well, and an enormous 40 log points for speaking English less well. In column 2, I replace the control for immigrant with the seven region of origin controls shown in Table 1. These controls slightly reduce the penalties for speaking something other than English at home.

Because English proficiency increases with time in the United States, and because immigrants who arrive young have better English skills and are more assimilated to the United States at a given number of years in the United States, English proficiency could be proxying in part for assimilation along dimensions other than English. I test this by controlling for age at arrival (indistinguishable from years in the United States in a single cross–section) and its square in column 3, which reduces the English penalties. The penalty for speaking English very well is small in both samples with these controls (-0.3% and -1.6% for occupation and degree samples respectively), and the penalty for speaking English less well is modest in the occupation sample (-4.5%). The penalty for speaking English less well remains very large for the degree sample, however, at 25 log points. The English coefficients still need not capture English per se, but could also capture factors correlated with linguistic ability and English knowledge, which might include general ability and cultural knowledge acquired from English language study that goes beyond the average of the origin region.

In column 4, I test how much of the effect of English proficiency operates through access to higher–paying occupations, rather than higher wages within occupations. For the occupation sample, with its limited set of occupations, the answer is none (panel A). For the degree sample (panel B), occupation controls account for approximately half of the effect of English. I have experimented with adding groups of related occupations separately, rather than all occupations, but no single group accounts for a large part of the reduction in the return to English. Column 5, for example, shows that adding a dummy for being in a management occupation does little to change the English coefficients compared to column 3.

I investigate the return to English further for the degree sample, where it is larger, presenting the 95th and 10th percentile results in panels C and D respectively. In panel C, the specification of column 1, with education, age and gender as additional controls, shows a penalty of 5.4% for speaking English well, similar to the effect at the mean, and a very large penalty of 30 log points for speaking English less well that is nevertheless smaller than the penalty at the mean. As at the mean, controlling for country or region of origin reduces the coefficients slightly (column 2), which given the larger standard errors at the 95th percentile renders the coefficient on speaking English very well statistically insignificant despite a point estimate of -4.1%. In column 3, I control for age at arrival and its square, but this scarcely changes the English dummies. In this preferred specification, the return to English is greater than in the mean regressions. Column 4 shows that that two thirds or more of the return to English operates through access to higher–paying occupations, leaving within–occupation penalties of only 1.3% and 10 log points for speaking English very well and less well respectively. The final column, 5, shows that most of the effect of the occupation dummies on the English coefficients can be captured with a single dummy for being in a management occupation: the unreported return to being in a management occupation is 45 log points, compared to only 16 log points at the mean, so at the 95th percentile even a small immigrant–native difference in the share in management can have a large wage consequence.

At the 10th percentile (panel D), the penalty for very good English, conditional on education, field, age and gender, is 6.9% (column 1), larger than at the mean or 95th percentile, though not statistically significantly so, while the penalty for less good English is statistically significantly larger than at the mean or 95th percentile, at 57 log points. The controls for immigrant origin reduce the latter penalty considerably to 43 log points (column 2), while increasing the penalty for speaking English very well (though statistically insignificantly). The penalites are reduced by the addition of age at arrival in column 3, leaving the penalty for speaking English very well at 4.4%, and for speaking English less well at 31 log points, penalties similar to those of the 95th percentile regressions. The addition of the occupation dummies in column 4 shows that most of the return to English comes from increased earnings within occupation, rather than access to better–paid occupations.

In summary, Table 11 shows that for the degree sample at the mean and the 10th percentile, but not the 95th percentile, some of what was attributed to English in Tables 9 and 10 in fact reflected other factors, particularly assimilation. Nevertheless, the return to English remains higher in the degree sample than the occupation sample even once these other factors are taken into consideration. The higher return to English at the tails than the mean in the degree sample (Table 11 column 3) seems consistent with a genuine role for English, rather than with its proxying entirely for unobserved ability, since low returns in technical occupations in the middle of the distribution and a high return to English in language–intensive occupations in the upper tails had been expected, while the return to ability seems likely to vary monotonically along the distribution. The qualitative results of Tables 9 and 10, that English has the largest effect on the degree sample immigrant–native wage gap in the lower tail (where English proficiency is poor and the return to English high), followed by the upper tail (where English proficiency is good but the return to English high) and the mean (where English proficiency is intermediate and the return to English low), remain.

I probe the effect of English further by investigating whether the return increases with age, as would be expected if access to management occupations in later career is an important channel for the effect of English. Appendix Table 4 shows that there is no such increase in the mean regressions, but confirms the increase in the return with age in the 95th percentile regressions, and further shows that the increase operates largely through access to management occupations.

5.3 Distinctions by region of origin

I next investigate how immigrant performance varies according to country or region of origin. In Tables 12 and 13, I repeat the regressions of Table 9, replacing the immigrant dummy with six dummies for immigrants from different regions.

For engineering occupations (Table 12), all immigrant groups except those from the non–Canadian Americas earn more than natives (column 1). A comparison of columns 1 and 2 shows that superior education explains 22 log points of Chinese immigrants' large 18 log point advantage, and 18 log points of Indian immigrants' 13 log point advantage, leaving both groups at a statistically significant conditional disadvantage of 4–5% compared to natives. All immigrants groups look worse conditional on education than unconditionally, and only immigrants from primarily anglophone countries earn statistically significantly more (12.4 log points) than natives conditional on education (though the point estimate for western Europeans is 4.8%). Controls for age (column 3) have a large effect on the Indian coefficient; Indians' youth explains their underperformance conditional on education.

All origin groups except primarily anglophone countries would gain considerably if all members spoke English only (compare columns 4 and 5). Nevertheless, in the specification with English controls, only immigrants from primarily Anglophone countries have a statistically significant wage advantage, though only immigrants from the non–Canadian Americas, eastern Europeans and the "other" immigrants have a statistically significant wage disadvantage. Controlling for all remaining covariates in column 6 leaves the coefficients similar.

In Table 13, I present the results for the degree sample, where immigrants from India, primarily anglophone countries and western Europe have a wage advantage (column 1). The effect of controlling for education in column 2 is small for many immigrant groups, but very large for Chinese (13 log points), who unconditionally earn the same as natives. Conditional on education and field of study, immigrants from primarily anglophone countries still enjoy an 18 log point wage advantage, immigrants from western Europe enjoy a 6% wage advantage, while all other groups earn the same (Indians) or considerably less than natives. Age controls (column 3) again have the largest effect on the young Indians. All origin groups except primarily anglophone countries would gain considerably if all members spoke English only (compare columns 4 and 5). The largest benefits would be for those noted above as having the worst English: Chinese, other Asians, non–Canadian Americans and eastern Europeans, who would all gain 11–15 log points. The addition of the remaining covariates in column 6 reduces the conditional immigrant–native gaps.

In order to identify the best and brightest, it is again helpful to use quantile regression at the 95th percentile. Because the effect of covariates is broadly similar to their effect at the mean, I report only the unconditional (except for the year and other foreign born dummies) immigrant–native wage gaps between the 95th percentiles, in Table 14 columns 1 and 2. The table shows that workers from primarily anglophone countries and western Europe clearly include stars in both samples, with wage advantages ranging from 17.6 log points to 41.5 log points. For the engineering degree sample, workers from all other countries or regions strikingly fail to provide top earners, with wage disadvantages ranging from 16.9 to 35.2 log points.[13]

It is also useful to identify the origin regions of the immigrants in the lower tail, particularly for the underperforming lower tail of the degree sample, and I present the corresponding results at the 10th percentile in Table 14 columns 3 and 4. In the occupation sample (column 3), only immigrants from the non–Canadian Americas earn statistically significantly less than natives, while most other groups earn statistically significantly more. For the degree sample in column 4, the results are more varied. Two immigrant groups' 10th percentile worker earns statistically significantly more the native 10th percentile worker: Indians and immigrants from primarily anglophone countries, both with a 15.7 log point advantage. Chinese and western Europeans earn the same as natives, while remaining groups have large disadvantages, the largest being for immigrants from the non–Canadian Americas (72 log points).

[13] I have not gone through origin countries one by one to identify those whose immigrants are particularly high performing. For example, I leave Japanese immigrants, likely to be high performers, in the residual Asian group.

6 Conclusions

In this paper, I have shown that immigrants are the best and brightest in engineering occupations, thanks to their high education, but not among holders of engineering degrees, despite the excellent performance of immigrants from the highest income countries. However, the nature of survey data is such that the performance of true stars, such as founders of major companies, cannot be evaluated, and indeed, I exclude the self–employed from my analysis. I have uncovered an important role for English proficiency, or, equivalently for policy, for correlated unobserved ability, in being promoted out of technical occupations to the top ranks. This implies that the current visa system targetting skilled workers may need revision. Assuming English proficiency is not proxying entirely for unobserved ability, the return to English suggests that immigrants and natives are imperfect substitutes among engineering degree holders, and that natives might be able to attenuate any negative wage effects from immigration by moving to more language–intensive occupations.

Data Appendix

American Community Survey

I compute hourly wages by dividing weekly wages by usual weekly hours multiplied by 52. 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.

I drop observations with imputed values of variables I use in the analysis. 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.

National Survey of College Graduates 2003

The survey is a stratified random sample of respondents to the 2000 census long form who reported having a bachelor's degree or higher, and the data may be downloaded at sestat.nsf.gov/datadownload/.

I compute hourly wages by dividing the annual salary by the number of weeks it was based on and by the usual weekly hours on this job. I drop observations with missing or zero wage values and observations with hourly wage values below \$5.15, the federal minimum wage in 2003. I also drop observations with a high hourly wage for respondents who looked likely to have confused annual weeks and months, or weekly and daily hours (the heaping patterns suggest such confusion exists): I drop observations with hourly wages of more than \$100 if weekly hours are nine or less or annual weeks are twelve or less.

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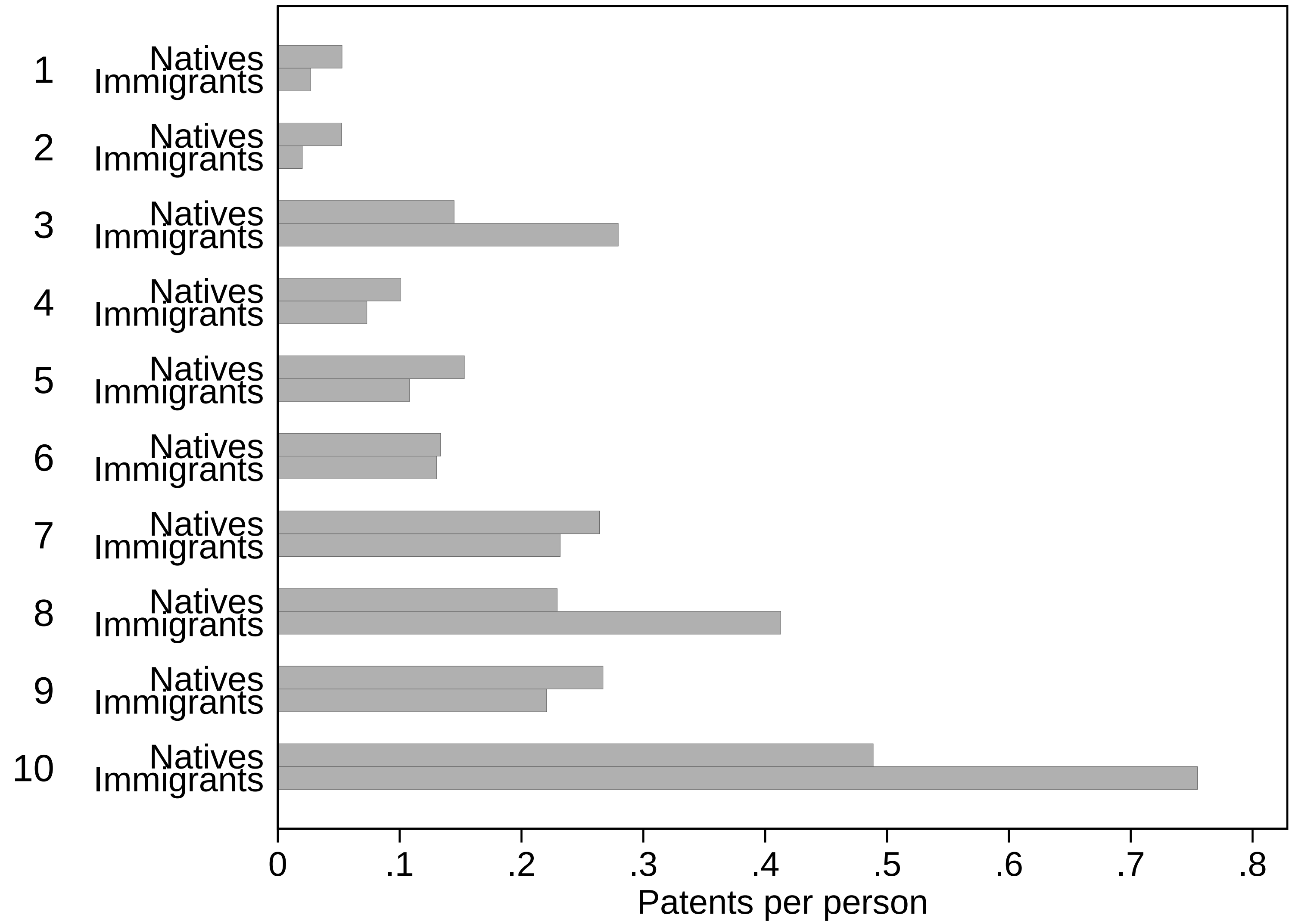
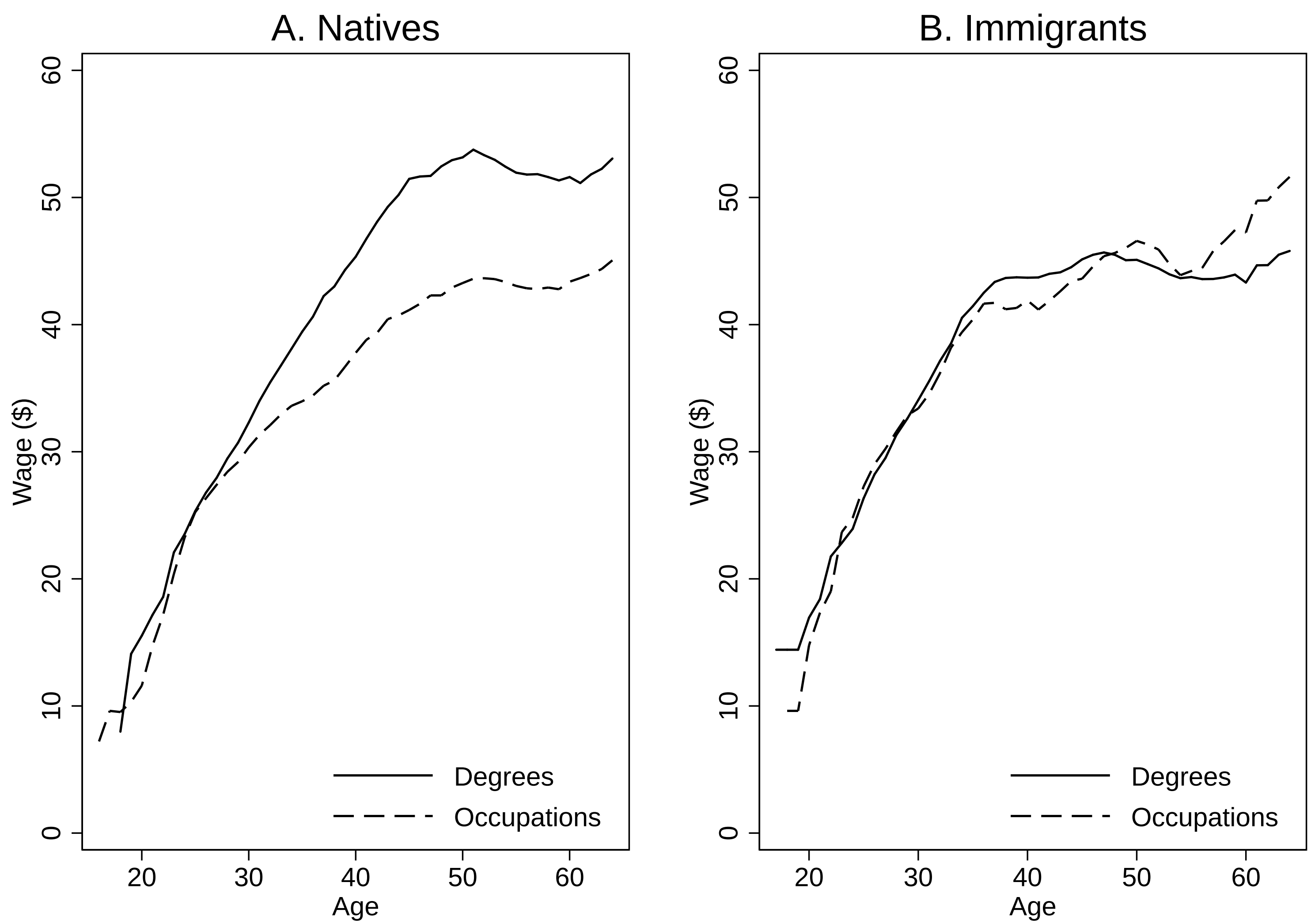
Figure 1: Patenting by wage decile; holders of engineering bachelor's degrees



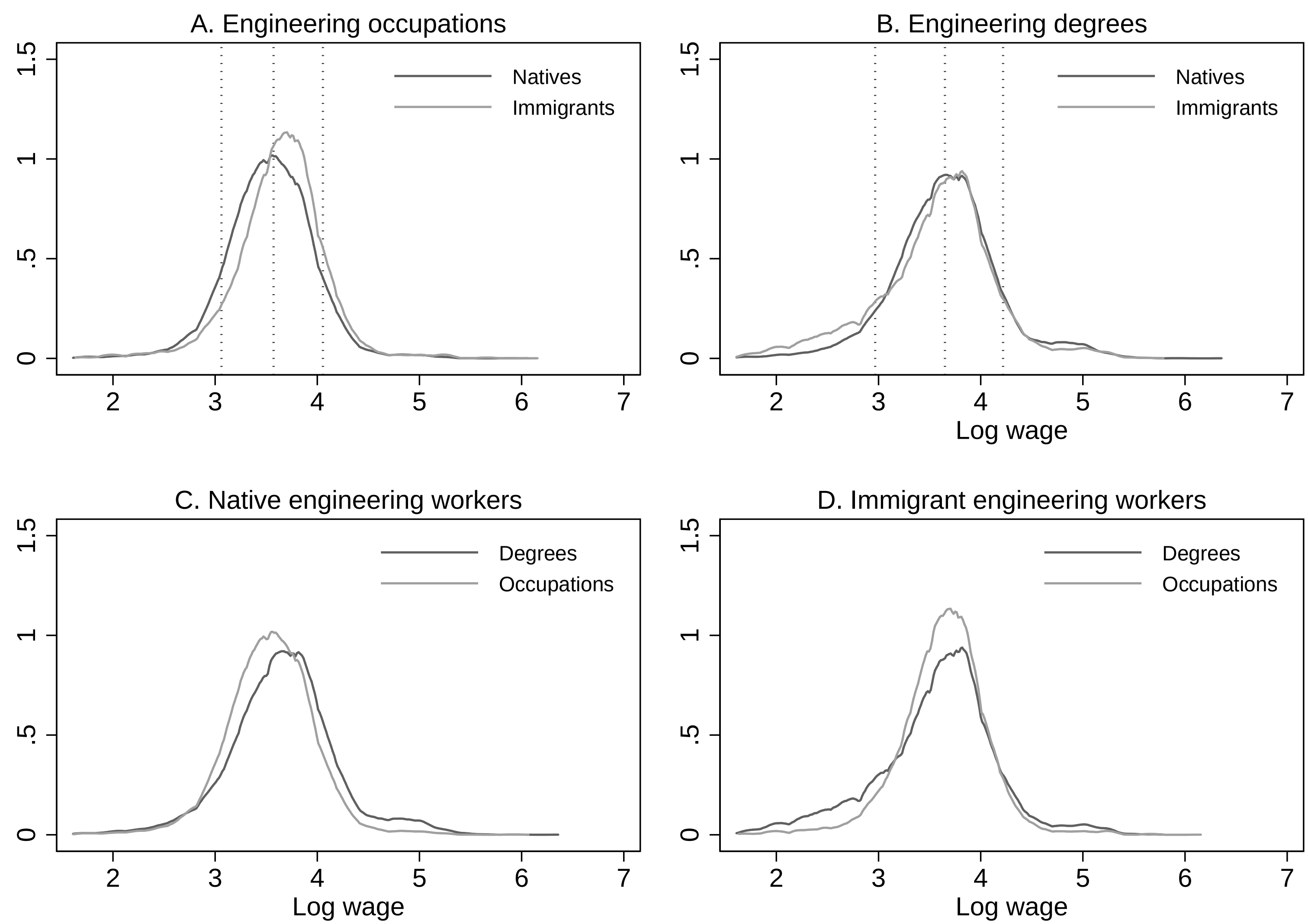
Source: National Survey of College Graduates 2003.
Note: The sample contains workers aged 64 or under, who are not self employed, and hold an engineering bachelor's degree. Deciles are based on hourly wages of pooled immigrants and natives. Calculations are weighted with survey weights.

Figure 2: Age–earnings profiles for engineers



Source: American Community Survey 2009, 2010.
Note: Hourly wages. The sample contains non-enrolled workers ages 18-64, employed full year but not self-employed, who are working in an engineering occupation or hold an engineering bachelor's degree. Data are for 2009 and 2010, and are weighted with survey weights. Age is measured in years and a moving average with one lag and one lead is applied to smooth the series.

Figure 3: Log wage distributions for immigrants and natives



Source: American Community Survey 2009, 2010.

Note: Hourly wage kernel density estimates using an Epanechnikov kernel and a bandwidth of 0.05, weighted with survey weights. The dotted vertical lines indicate the 10th, 50th and 90th percentiles of the wage distribution for the combined immigrant and native sample.

Table 1: Wages and shares of immigrants among engineering workers

	Occupations		Bachelor's degrees	
	Share (%)	Wage ($)	Share (%)	Wage ($)
	(1)	(2)	(3)	(4)
Natives	79.2	37.8	67.1	44.9
Immigrants	19.4	41.7	31.4	41.9
U.S. citizens born abroad	1.1	41.6	1.1	45.4
Born in U.S. territories	0.4	33.1	0.4	39.2
All	100.0	38.6	100.0	43.9
Observations	25,295		47,011	
Immigrants from				
India	3.5	42.6	8.3	45.4
China	2.2	44.2	2.5	43.0
Other East, Southeast, South Asia	5.6	41.7	6.9	40.8
Americas except Canada	2.6	37.1	4.8	33.2
UK, Ireland, Canada, Antipodes	1.3	45.5	1.7	55.7
Western Europe	1.0	44.1	1.5	54.0
Eastern Europe	1.3	38.9	2.5	34.7
Other	2.0	41.3	3.3	40.1
All immigrants	19.4	41.7	31.4	41.9
Immigrants arrived at age				
17 or younger	24.8	39.5	16.8	43.3
18 or older	75.2	42.4	83.2	41.6
All	100.0	100.0	100.0	100.0

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 (columns 1 and 2) or hold an engineering bachelor's degree (columns 3 and 4). Data are for 2009 and 2010. China does not include Hong Kong; Europe is defined as west of the Urals; Eastern Europe is defined as European former Communist countries. The Antipodes include Australia and New Zealand.

Table 2: Education and wages of workers in engineering occupations

	Share (%)		Wage ($)	
	Natives	Immigrants	Natives	Immigrants
	(1)	(2)	(3)	(4)
GED or no high school diploma	0.5	0.0	25.6	21.1
High school diploma or <1 year college	5.9	1.3	28.4	37.5
More than 1 year college, no diploma	6.3	2.5	32.0	33.6
Associate's degree	8.8	3.6	30.8	33.1
Bachelor's degree	55.6	40.3	37.8	38.4
Master's degree	20.2	38.7	44.1	43.5
Professional degree	1.0	1.8	43.4	45.3
Doctoral degree	1.7	11.6	54.5	51.1
All	100.0	100.0	37.8	41.7
Observations	20,316	4640	20,316	4640

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 not included.

Table 3: Education and wages of workers with engineering bachelor's degrees

	Share (%)		Wage ($)	
	Natives	Immigrants	Natives	Immigrants
	(1)	(2)	(3)	(4)
Bachelor's degree	65.7	49.6	41.1	35.7
Master's degree	28.7	38.4	50.5	47.2
Professional degree	2.5	2.3	64.2	45.3
Doctoral degree	3.1	9.7	56.9	51.1
All	100.0	100.0	44.9	41.9
Observations	33,322	13,991	33,322	13,991

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

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

	Share (%)		Wage ($)	
	Natives (1)	Immigrants (2)	Natives (3)	Immigrants (4)
Computer-related	2.6	4.9	42.4	47.2
Engineering, architecture	77.6	84.1	40.6	42.4
Science and mathematics	7.1	6.7	42.5	44.9
Technology	3.9	1.9	34.0	34.6
Business	4.3	1.8	35.7	34.0
None of the above	6.9	2.4	34.4	36.4
All	>100.0	>100.0	39.9	42.3
Observations	15,987	4318	15,987	4318

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 and hold an engineering bachelor's degree. Data are for 2009 and 2010. American citizens born abroad and workers born in U.S. territories are not included. 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: Occupations of workers with an engineering bachelor's degree

	Share (%)		Wage ($)		Patents	
	Natives	Immigrants	Natives	Immigrants	Natives	Immigrants
	(1)	(2)	(3)	(4)	(5)	(6)
Managerial	28.7	23.8	54.1	53.5	0.23	0.52
Engineering, architecture	38.3	25.6	40.6	42.4	0.24	0.35
Computer related	8.3	21.8	43.6	42.8	0.20	0.08
Science, math, technology, health except physician	3.0	4.6	38.5	34.0	0.11	0.22
Education	2.2	3.3	33.2	38.6	0.18	0.18
Lawyer, physician	1.4	0.4	80.3	69.3	0.02	0
Other	18.1	20.5	39.5	28.3	0.07	0.06
All	100.0	100.0	44.9	41.9	0.19	0.22
Observations	32,322	13,991	32,322	13,991	6790	3131

Note: Weighted means from the 2003 National Survey of College Graduates (columns 5 and 6) and the 2009 and 2010 ACS (columns 1-4). Both samples contain workers holding an engineering bachelor's degree who are 64 or under and not self-employed or enrolled; the ACS workers are in addition at least age 18, employed full year. American citizens born abroad and workers born in U.S. territories are not included. Data on patents refer to patents granted in the preceding five years; the NSCG definition of management is narrower than that of the ACS.

Table 6: Occupations of top and bottom 10% of workers with an engineering bachelor's degree

	Top 10% earners		Bottom 10% earners	
	Natives	Immigrants	Natives	Immigrants
	(1)	(2)	(3)	(4)
Managerial	52.8	50.8	14.6	10.0
Engineering, architecture	18.2	17.6	23.7	5.5
Computer related	4.9	13.5	5.5	5.0
Science, math, technology, health except physician	1.7	2.5	5.0	6.0
Education	1.1	3.1	6.6	4.0
Lawyer, physician	6.4	1.8	1.6	0.5
Other	14.8	10.7	43.0	69.1
All	100.0	100.0	100.0	100.0
Observations	3441	1576	3041	1248

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 and hold an engineering bachelor's degree. Data are for 2009 and 2010. American citizens born abroad and workers born in U.S. territories are not included. The top and bottom 10% are calculated separately for natives and immigrants, using weights.

Table 7: Entry visa of engineering bachelor's degree holders

	Full sample (1)	Top 10% earners (2)	Bottom 10% earners (3)
Permanent residence (green card)	33.4	27.7	47.5
Temporary visas			
Work	17.8	18.8	10.3
Study/training	35.4	48.6	23.5
Dependent	7.1	3.1	8.3
Other	6.3	1.7	10.4
Observations	3375	313	249

Note: Weighted means from the 2003 National Survey of College Graduates. Samples contain workers holding an engineering bachelor's degree who are 64 or under and not self-employed and not enrolled. American citizens born abroad and workers born in U.S. territories are not included.

Table 8: English proficiency of immigrant engineering workers

	Occupations		Bachelor's degrees	
	Share (%)	Wage ($)	Share (%)	Wage ($)
	(1)	(2)	(3)	(4)
A. Full samples				
Only English at home	19.6	42.9	15.7	47.9
Speaks English very well	61.6	41.9	62.2	43.9
Speaks English less well	18.9	39.5	22.1	31.8
All	100.0	41.7	100.0	41.9
Observations	4640		13,991	
B. Top 10% earners				
Only English at home	24.0	85.4	24.9	105.0
Speaks English very well	61.6	79.5	64.4	99.2
Speaks English less well	14.3	86.0	10.7	90.4
All	100.0	81.9	100.0	99.7
Observations	540		1576	
C. Bottom 10% earners				
Only English at home	17.8	18.4	8.8	12.0
Speaks English very well	57.5	17.7	41.7	11.7
Speaks English less well	24.7	17.5	49.5	11.3
All	100.0	17.8	100.0	11.5
Observations	407		1248	

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 an engineering occupation (columns 1 and 2) or hold an engineering bachelor's degree (columns 3 and 4). 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 engineering workers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Occupations									
	0.096***	0.003	-0.020***	-0.024***	-0.022***	0.011	0.010	0.003	-0.021**
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.011)	(0.011)	(0.011)	(0.011)
R^2	0.01	0.11	0.15	0.31	0.31	0.31	0.33	0.37	0.40
B. Degrees									
	-0.092***	-0.139***	-0.134***	-0.140***	-0.134***	-0.019*	-0.007	-0.016*	-0.034***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.010)	(0.009)	(0.009)	(0.009)
R^2	0.01	0.06	0.08	0.16	0.17	0.19	0.37	0.42	0.43
Education	--	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field, if bachelor's	--	--	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age	--	--	--	Yes	Yes	Yes	Yes	Yes	Yes
Gender	--	--	--	--	Yes	Yes	Yes	Yes	Yes
English proficiency	--	--	--	--	--	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 25,295 observations (panel A) and 47,011 observations (panel B), weighted with survey weights. Robust standard errors are in parentheses. 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) or three dummies (panels B), field of study 11 dummies (panel B) or a maximum of 38 dummies (panel A), English proficiency two dummies, age 8 dummies, detailed occupation 13 dummies (panel A) or a maximum of 333 dummies (panel B), 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: Wage determinants for engineering workers – 10th and 95th percentiles

	(1)	(2)	(3)	(4)	(5)	(6)
A. Occupations: 95th						
	0.065***	-0.009	0.020	0.017	0.042*	0.031
	(0.015)	(0.016)	(0.015)	(0.015)	(0.022)	(0.022)
R^2	0.00	0.07	0.17	0.17	0.17	0.19
B. Degrees: 95th						
	-0.155***	-0.136***	-0.040**	-0.041**	0.030	0.023
	(0.021)	(0.018)	(0.018)	(0.017)	(0.027)	(0.020)
R^2	0.00	0.06	0.14	0.15	0.15	0.28
C. Occupations: 10th						
	0.110***	-0.039***	-0.088***	-0.082***	0.001	0.002
	(0.012)	(0.012)	(0.012)	(0.011)	(0.016)	(0.016)
R^2	0.00	0.10	0.18	0.18	0.18	0.20
D. Degrees: 10th						
	-0.271***	-0.284***	-0.327***	-0.303***	-0.096***	-0.035***
	(0.012)	(0.010)	(0.012)	(0.012)	(0.016)	(0.013)
R^2	0.02	0.06	0.09	0.10	0.12	0.28
Education, field	--	Yes	Yes	Yes	Yes	Yes
Age	--	--	Yes	Yes	Yes	Yes
Gender	--	--	--	Yes	Yes	Yes
English proficiency	--	--	--	--	Yes	Yes
Detailed occupation	--	--	--	--	--	Yes

Note: The table reports the immigrant dummy coefficient from quantile regressions on 25,295 observations (panels A and C) and 47,011 (panels B and D), weighted with survey weights. 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: Effect of English proficiency on hourly wages

	(1)	(2)	(3)	(4)	(5)
A. Occupations, mean					
Speaks English very well	-0.027**	-0.014	-0.003	-0.003	--
	(0.012)	(0.012)	(0.012)	(0.012)	
Speaks English less well	-0.097***	-0.082***	-0.045**	-0.045**	--
	(0.018)	(0.020)	(0.019)	(0.019)	
B. Degrees, mean					
Speaks English very well	-0.048***	-0.038***	-0.016**	-0.007	-0.018
	(0.011)	(0.011)	(0.011)	(0.010)	(0.011)
Speaks English less well	-0.396***	-0.324***	-0.249***	-0.140***	-0.233***
	(0.016)	(0.016)	(0.016)	(0.014)	(0.016)
C. Degrees, 95th percentile					
Speaks English very well	-0.054*	-0.041	-0.053*	-0.013	-0.009
	(0.028)	(0.028)	(0.029)	(0.022)	(0.024)
Speaks English less well	-0.296***	-0.259***	-0.311***	-0.105***	-0.144***
	(0.037)	(0.038)	(0.040)	(0.031)	(0.033)
D. Degrees, 10th percentile					
Speaks English very well	-0.069***	-0.076***	-0.044**	-0.034***	--
	(0.017)	(0.018)	(0.019)	(0.013)	
Speaks English less well	-0.568***	-0.428***	-0.313***	-0.226***	--
	(0.023)	(0.024)	(0.026)	(0.018)	
Education, field, age, gender	Yes	Yes	Yes	Yes	Yes
Immigrant origin	--	Yes	Yes	Yes	Yes
Age at arrival, quadratic	--	--	Yes	Yes	Yes
Detailed occupation	--	--	--	Yes	--
Managerial dummy	--	-	--	--	Yes

Note: The table reports the immigrant dummy coefficient from least squares regressions (panels A and B) and quantile regressions (panels C and D) on 25,295 observations (panel A) and 47,011 (panels B, C and D), weighted with survey weights. Robust standard errors are in parentheses. 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. See notes to Table 9 for a full description of the covariates.

Table 12: Wage distinctions by origin region – engineering occupations

	(1)	(2)	(3)	(4)	(5)	(6)
Immigrant from						
India	0.130***	-0.047***	0.018	0.020	0.036	0.013
	(0.017)	(0.017)	(0.016)	(0.015)	(0.019)	(0.018)
China	0.183***	-0.038**	-0.035**	-0.027	0.010	-0.021
	(0.018)	(0.017)	(0.017)	(0.017)	(0.020)	(0.019)
Other East, Southeast,	0.108***	0.014	-0.008	-0.005	0.026	-0.033**
South Asia	(0.013)	(0.012)	(0.011)	(0.011)	(0.016)	(0.015)
Americas	-0.064**	-0.102***	-0.095***	-0.094***	-0.074***	-0.083***
except Canada	(0.027)	(0.026)	(0.025)	(0.025)	(0.026)	(0.025)
UK, Ireland, Canada,	0.177***	0.124***	0.101***	0.101***	0.103	0.066***
Antipodes	(0.024)	(0.025)	(0.023)	(0.023)	(0.023)	(0.022)
Western Europe	0.139**	0.048	0.019	0.020	0.035	0.006
	(0.034)	(0.031)	(0.029)	(0.029)	(0.030)	(0.029)
Eastern Europe	0.039	-0.095***	-0.136***	-0.127***	-0.096***	-0.094***
	(0.027)	(0.025)	(0.023)	(0.023)	(0.025)	(0.024)
Other	0.081***	-0.040*	-0.075**	-0.075**	-0.057**	-0.075***
	(0.025)	(0.024)	(0.024)	(0.024)	(0.025)	(0.024)
R^2	0.02	0.16	0.31	0.32	0.32	0.40
Education, field	--	Yes	Yes	Yes	Yes	Yes
Age	--	--	Yes	Yes	Yes	Yes
Gender	--	--	--	Yes	Yes	Yes
English proficiency	--	--	--	--	Yes	Yes
Other covariates	--	--	--	--	--	Yes

Note: The table reports the immigrant dummy coefficient from least squares wage regressions on 25,295 observations. Robust standard errors are in parentheses. 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. China does not include Hong Kong; Europe is defined as west of the Urals; Eastern Europe is defined as European former Communist countries; the Antipodes comprise Australia and New Zealand.

Table 13: Wage distinctions by origin region – engineering bachelor's degrees

	(1)	(2)	(3)	(4)	(5)	(6)
Immigrant from						
India	0.046***	-0.008	0.063***	0.063***	0.126***	0.037***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.013)	(0.012)
China	0.002***	-0.133***	-0.141***	-0.113***	0.028	-0.034**
	(0.016)	(0.017)	(0.016)	(0.017)	(0.020)	(0.015)
Other East, Southeast,	-0.111***	-0.129***	-0.165***	-0.162***	-0.047***	-0.065***
South Asia	(0.012)	(0.012)	(0.012)	(0.012)	(0.015)	(0.012)
Americas	-0.384***	-0.375***	-0.398***	-0.394***	-0.271***	-0.148***
except Canada	(0.018)	(0.017)	(0.017)	(0.017)	(0.018)	(0.015)
UK, Ireland, Canada,	0.191***	0.178***	0.141***	0.142***	0.145***	0.057***
Antipodes	(0.022)	(0.022)	(0.021)	(0.021)	(0.021)	(0.018)
Western Europe	0.146***	0.058**	0.037	0.035	0.089***	0.046**
	(0.026)	(0.026)	(0.024)	(0.024)	(0.025)	(0.022)
Eastern Europe	-0.284***	-0.316***	-0.367***	-0.339***	-0.189***	-0.107***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.022)	(0.018)
Other	-0.156***	-0.198***	-0.229***	-0.226***	-0.158***	-0.104***
	(0.019)	(0.019)	(0.019)	(0.018)	(0.020)	(0.016)
R^2	0.04	0.10	0.19	0.20	0.22	0.44
Education, field	--	Yes	Yes	Yes	Yes	Yes
Age	--	--	Yes	Yes	Yes	Yes
Gender	--	--	--	Yes	Yes	Yes
English proficiency	--	--	--	--	Yes	Yes
Other covariates	--	--	--	--	--	Yes

Note: The table reports the immigrant dummy coefficient from least squares hourly wage regressions on 47,011 observations. Robust standard errors are in parentheses. 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. China does not include Hong Kong; Europe is defined as west of the Urals; Eastern Europe is defined as former Communist countries; the Antipodes comprise Australia and New Zealand.

Table 14: 10th and 95th percentile wage distinctions by origin region

	(1)	(2)	(3)	(4)
	95th percentile		10th percentile	
	Occupations	Bachelor's degrees	Occupations	Bachelor's degrees
Immigrant from				
India	0.071**	-0.169***	0.198***	0.157***
	(0.035)	(0.033)	(0.026)	(0.017)
China	0.046	-0.254***	0.251***	0.000
	(0.044)	(0.058)	(0.032)	(0.031)
Other East, Southeast, South Asia	0.036	-0.232***	0.136***	-0.239***
	(0.029)	(0.036)	(0.021)	(0.019)
Americas except Canada	-0.011	-0.295***	-0.116***	-0.722***
	(0.040)	(0.043)	(0.030)	(0.022)
UK, Ireland, Canada, Australia, New Zealand	0.260***	0.415***	0.218***	0.157***
	(0.055)	(0.071)	(0.041)	(0.037)
Western Europe	0.176***	0.387***	0.118**	0.012
	(0.065)	(0.074)	(0.048)	(0.039)
Eastern Europe	-0.019	-0.352***	0.066	-0.462***
	(0.056)	(0.058)	(0.042)	(0.031)
Other	0.123***	-0.171	-0.065	-0.393***
	(0.046)	(0.050)	(0.078)	(0.027)
R^2	0.00	0.01	0.01	0.06
Observations	25,295	47,011	25,295	47,011

Note: The table reports the immigrant dummy coefficient from quantile regressions. All regressions also include a dummy for 2010 and dummies for American born abroad and born in U.S. territories. China does not include Hong Kong; Europe is defined as west of the Urals; Eastern Europe is defined as European former Communist countries.

Appendix Table: 1 Specific occupations of workers in engineering occupations

	Share (%)		Wage ($)	
	Natives (1)	Immigrants (2)	Natives (3)	Immigrants (4)
Architecture	6.9	5.9	35.0	39.3
Aerospace	8.1	6.9	44.0	44.8
Biomedical, agricultural	0.7	0.8	39.2	35.8
Chemical	3.3	3.4	43.9	44.6
Civil	15.9	14.1	36.6	40.4
Computer hardware	2.4	5.0	39.0	44.2
Electrical	11.9	16.1	39.5	43.3
Environmental	2.0	1.5	37.1	37.2
Industrial	10.4	7.4	32.7	34.6
Marine, naval architecture	0.7	0.4	36.1	29.5
Materials	18	1.9	33.3	36.2
Mechanical	12.3	10.3	34.0	35.9
Mining	1.7	1.4	52.3	54.1
Nuclear, miscellaneous	21.9	25.1	39.3	45.0
All	100.0	100.0	37.8	41.7
Observations	20,316	4640	20,316	4640

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

	Share (%)		Wage ($)	
	Natives (1)	Immigrants (2)	Natives (3)	Immigrants (4)
General	9.7	14.0	44.5	36.5
Aerospace	3.2	1.2	48.4	42.4
Biological	0.9	1.2	36.8	31.4
Agricultural	0.5	0.3	36.4	32.3
Biomedical	0.8	0.5	47.8	42.9
Chemical	6.8	6.5	51.1	45.6
Civil	12.3	9.5	43.3	39.8
Computer	4.6	8.5	42.2	41.4
Electrical	21.9	30.3	47.8	45.6
Engineering mechanics	0.9	0.8	47.5	42.2
Environmental	0.9	0.4	39.5	38.2
Geological, geophysical	0.3	0.1	48.6	49.9
Industrial, manufacturing	5.0	3.5	43.4	40.2
Materials	1.0	0.9	41.7	48.1
Mechanical	19.8	16.2	45.0	43.3
Metallurgical	0.5	0.7	47.0	43.4
Mining, mineral	0.4	0.3	46.8	45.0
Marine, naval architecture	0.5	0.3	48.5	33.3
Nuclear	0.6	0.3	53.6	51.7
Petroleum	0.6	0.4	77.2	52.7
Miscellaneous	2.0	1.5	41.8	30.0
All	~100.0	~100.0	44.9	41.9
Observations	32,322	13,991	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 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: Means for engineering workers not given elsewhere

	Occupations		Bachelor's degrees	
	Native	Immigrants	Native	Immigrants
	(1)	(2)	(3)	(4)
Age	43.0	43.6	42.9	42.4
	(11.0)	(10.0)	(10.6)	(9.8)
Female	0.13	0.17	0.13	0.17
Private for profit firm	0.85	0.87	0.81	0.86
Not for profit firm	0.02	0.02	0.04	0.04
Federal employee	0.07	0.04	0.08	0.03
State government employee	0.04	0.04	0.04	0.05
Local government employee	0.03	0.04	0.04	0.04
Unpaid family worker	0.00	0.00	0.00	0.00
Age at arrival	--	23.3	--	25.6
		(10.2)		(10.0)
Observations	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 an engineering occupation (columns 1 and 2) or hold an engineering bachelor's degree (columns 3 and 4). Data are for 2009 and 2010.

Appendix Table 4: Effect of English proficiency on wages, engineering bachelor's degree holders

	Mean		95th percentile		
	(1)	(2)	(3)	(4)	(5)
Speaks English very well	0.035	0.008	0.293***	0.076	0.138**
	(0.030)	(0.027)	(0.078)	(0.062)	(0.070)
× age	-0.0012*	-0.0004	-0.0082***	-0.0024*	-0.0037**
	(0.0007)	(0.0006)	(0.0018)	(0.0014)	(0.0016)
Speaks English less well	-0.171***	-0.167***	-0.268**	0.102	0.158
	(0.054)	(0.045)	(0.131)	(0.105)	(0.118)
× age	-0.0019	0.0006	-0.0124***	-0.0052**	-0.0077***
	(0.0012)	(0.0010)	(0.0029)	(0.0023)	(0.0026)
Education, field, age, gender	Yes	Yes	Yes	Yes	Yes
Immigrant origin	Yes	Yes	Yes	Yes	Yes
Age at arrival, quadratic	Yes	Yes	Yes	Yes	Yes
Detailed occupation	--	Yes	--	Yes	--
Management dummy	--	--	--	--	Yes
English very well	-0.003	-0.003	0.047	0.003	0.025
at age 30	(0.013)	(0.012)	(0.034)	(0.027)	(0.031)
English very well	-0.028**	-0.011	-0.116***	-0.046*	-0.050*
at age 50	(0.014)	(0.012)	(0.032)	(0.026)	(0.029)
English less well	-0.227***	-0.149***	-0.104*	-0.053	-0.072
at age 30	(0.022)	(0.019)	(0.055)	(0.044)	(0.049)
English less well	-0.264***	-0.136***	-0.353***	-0.156***	-0.226***
at age 50	(0.019)	(0.016)	(0.043)	(0.035)	(0.039)

Note: The table reports coefficients from weighted least squares (columns 1 and 2) and 95th percentile quantile (columns 3-5) regressions with 47,011 observations. 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.