Earnings Gap Dynamics Between Highly Educated Immigrants and US-Born counterparts: The Role of Entry Visa

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Abstract

Using the rich and under-explored National Survey of College Graduates (NSCG), this paper studies the wage gap between natives and immigrants who hold baccalaureate or higher university degrees. I compare natives with all immigrants and also with different groups of immigrants based on their first entry visa to the United States. Additionally, this paper explores the difference between cohorts of immigrants who entered the United States in different decades. Other than analyzing the whole sample (including all fields of education), due to the booming demand for computer and IT degrees in the past couple of decades, I also run my model on those with computer or IT, degrees specifically. My results show that upon arrival, immigrants in general have a 30%-40% wage premium over U.S. natives, but the gap narrows with each year that passes. In the computer and IT field, however, although I do not find a significant wage premium for immigrants at entry, for the 30 years following entry, their wages grow higher than those of natives at about 1% per year. Finally, my results show that while it exists in some, arrival-cohort-based wage difference does not exist among the majority of immigrant groups.

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Introduction

Immigration has been a controversial topic among economists for a long time. The issue became more important to researchers as immigrant inflows were significantly increased (Card, 2009). The question of an earnings gap between immigrants and natives and the question of economic assimilation of immigrants go back more than 40 years, when labor economists first started this line of research. A big part of this literature is studying the adjustment of immigrants in the labor market of the host country (e.g. Chiswick, 1978; Borjas, 1985, 1994, 1999; Card, 2005). Immigrants move to host countries with different skills and human capital. However, there is no guarantee that the human capital that they bring with them to the host country (mainly education and experience) matches the human capital sought in the host country's labor market. Therefore, logically, the longer they stay in the host country (assuming that their time in the host country is spent either going to school or working), the more they acquire and accumulate the human capital that is appreciated by the host country's labor market. Cultural adjustments (such as getting used to the common work ethics in the host country) and proficiency in the host country's language will also increase over time[1]. Such cultural adjustments and improved language proficiency can also positively impact immigrants' job market outcomes (Borjas, 2015).[2]

The main objective of this paper is to study the wage gap between natives and different groups of immigrants based on the first entry visa[3]. This gap is studied upon immigrants' arrival and also during immigrants' years of residence in the United States. I am interested in exploring how the type of visa immigrants first use to enter the United States can potentially affect the native-immigrant wage gap and its dynamics. Additionally, this paper seeks to

[1]Cultural and language differences vary, depending on an immigrant's country of origin. People who migrate to the United States from English speaking countries, especially, Canada, the United Kingdom, Australia, New Zealand, and South Africa might have an important advantage in this capacity (Borjas, 2015).

[2]For instance, Chiswick (1993) finds that for Soviet Jewish immigrants in the United States, lower English proficiency correlated to lower income. Yao and van Ours (2015) find that in the Netherlands, language barriers have significant negative effects on female immigrants' hourly wages.

[3]This research studies only highly educated individuals who hold a bachelor's degree or higher. Immigrants are categorized in four groups based on the type of visa on which they entered the United States for the first time: immigrant visa entry, temporary work visa entry, study or training visa entry, and dependent visa entry.

find evidence on the existence or nonexistence of significant differences between immigrants who arrived during different decades within each group (cohort differences).[4]

Since there has been an increased demand for computer and IT workers in the past couple of decades due to the emergence of tech companies, I run all of the aforementioned analyses specifically on natives and immigrants who hold a degree in computer or IT-related fields, as well as on how their results differ compared to those of the sample at large.

My results show that, in general, immigrants who arrived over different decades have about 30%-40% premium over their native counterparts, at arrival. This wage gap, however, tends to slowly narrow at a 0.04% rate one year after arrival, getting to 0.3% after 30 years of residence in the United States. On the other hand, focusing on those with a degree in computer or IT, although I find no significant wage gap between immigrants and natives at entry, regardless of immigrants' arrival cohort, I find that immigrants' wages tend to gradually diverge from (become higher than) those of natives with a rate of almost 1.1% one year after arrival, slowing down to 0.7% after 30 years of U.S. residence. Additionally, although I find statistically significant wage differences (up to about a 0.08 log point difference) between all arrival cohorts of immigrants at large, I find no evidence of any statistically significant wage difference between arrival cohorts of immigrants (all immigrants combined) when I focus on the computer and IT fields.

Comparing immigrants with different entry visas and natives led to distinct results. Including all fields of education, I find that immigrants who arrived on an immigrant visa in the year 2000 or after, upon arrival, have about a 0.5 log point (approximately 50%) wage premium over natives and over immigrants who arrived before 2000. On the contrary, immigrants who first came to the United States on a temporary work visa or a dependent visa show no significant wage difference among different arrival cohorts or when compared to natives. However, I find a large and statistically significant wage gap between natives

[4] I divide immigrants into six cohorts of arrival to the United States based on the following arrival decades: <=1969, 1970s, 1980s, 1990s, 2000s, and >=2010. I run my models on the full sample and also on the following sub-samples: (a) natives plus immigrants who migrated to the United States on an immigrant (permanent residence) visa, (b) natives plus immigrants who migrated to the United States on a temporary work visa, (c) natives plus immigrants who migrated to the United States on a study or training visa, and (d) natives plus immigrants who migrated to the United States on a dependent visa.

and immigrants with study or training first entry visas. Depending on the cohort of arrival, upon arrival, such immigrants have a 1-1.24 log point wage premium over natives. Results also show up to a 0.25 log point wage difference between arrival cohorts.

Focusing on computer and IT, I get completely different results. I find that although immigrants who first came to the United States on an immigrant visa, a study or training visa, or a dependent visa show no significant wage difference among their different arrival cohorts or when compared to natives, those who first arrived to the United States on a temporary work visa have a large wage premium over natives and show evidence of significant arrival cohort wage differences among them.

With respect to assimilation, for the whole sample, I find that the wages of immigrants who arrived on an immigrant visa keep diverging from (getting higher than) those of natives for at least 15 years from arrival (1.6% after one year, 1.4% after 5 years, 1.1% after 10 years, and 0.8% after 15 years)[5]. For computer and IT, I find that the immigrant visa entry group's average wage goes above that of natives at a 5% rate at the end of first year going down to 2% after 30 years of residence. The average wage of those who arrived on a work visa, however, gets further from those of natives in the first 10 years of residence in the United States; but the gap starts to narrow after that[6].

These results are in general interesting because when highly educated people who migrate to the United States are being paid a premium over their U.S.-born counterparts, one reason could be that the U.S. labor market demand for these workers is greater than the supply. This suggests that developing a merit-based immigration program to ease the immigration rules for such workers could help domestic industries be more productive and may prevent companies from moving jobs overseas. Another policy implication is that the United States government should encourage U.S.-born natives to pursue training and education that meets the needs of the U.S. labor market.

While the majority of existing studies use datasets that represent all groups of immi-

[5]For immigrants with other entry visas, the estimated coefficient of the YSM is not statistically significant at 10% or higher.

[6]For immigrants with study or dependent entry visas, the estimated coefficient of the YSM is not statistically significant at 10% or higher.

grants, I identify earnings gaps and assimilation rates for a highly educated population. In addition, I compare immigrants to natives based on their first type of visa by which they migrated to the United States. While detailed education and immigration information is not available in many of the datasets, one advantage of this work compared to existing studies is employing very rich data with detailed information about education, employment, and demographics of each individual.

Chiswick (1978) was the first to introduce the concept of "years since migration" for immigrants, and brought it into the Mincer (1974) wage equation with the explanation that the effect of years spent on education or on gaining experience in the home country of immigrants could be different from the effect of time spent in the destination country. Chiswick applies this to find the number of years needed to close the earnings gap between white male immigrants and white US-born men to be filled, employing a cross-sectional approach. After his 1978 paper, many studies used similar methodology and calculated the earnings gap between natives and immigrants and the "assimilation rate" for different population groups in different countries (e.g. Chiswick, 1978; Borjas, 1985, 1994, 1999; Card, 2005; Chiswick and Miller, 2011; Borjas, 2015; Rodríguez-Planas and Vegas, 2014). Most of these researchers have used single or multiple cross-section(s) and have found an earnings gap against immigrants at entry time and a rate at which immigrants catch up to natives in wages and close the gap. It is argued in most of the cases that the earnings convergence can be caused by immigrants being more able, more motivated, and/or more hardworking than natives. However, most of these characteristics cannot be observed and controlled for.

There have always been debates in the immigration literature on how to interpret findings gained from a cross-sectional approach. Borjas (1985, 1989, 1995) argues that more recently arrived immigrant cohorts might have lower or higher destination job-market-specific skills than earlier cohorts and he shows the presence of some remarkable "cohort effects." Therefore, accounting for these cohort effects in wage levels is crucial (Borjas, 2015).

Data and Descriptive Statistics

This paper uses the National Survey of College Graduates (NSCG). The NSCG is conducted by the U.S. Census Bureau (under the auspices of the National Science Foundation). The National Survey of College Graduates is a biennial survey that provides data on the nation's college graduates. The program has been conducted since the 1970's. The survey sample individuals who are living in the United States during the survey reference week, have at least a bachelor's degree, and are under the age of 76.

The 2010, 2013, 2015, 2017, and 2019 cycles of the NSCG are used in this study as a pooled sample. NSCG is a unique source for examining various characteristics of college-educated individuals, including occupation, salary, the three highest university degree levels along with the majors, whether each degree was earned in the United States, the type of entry visa for immigrants, and detailed demographic information (National Science Foundation, 2019).

While many administrative datasets do not provide researchers with a variety of characteristics (e.g., in most cases detailed education-related information is not a part of them), the NSCG provides much in-detail information for each individual, especially regarding their education and employment.

My pooled sample includes 448,996 observations. For this study, I keep only those individuals who are living and working inside the United States during survey reference weeks and are 65 years old or younger. Hourly wage of each individual is calculated using the reported annual salary, number of weeks worked per year, and number of hours worked per week. I keep only those observations with hourly wages equal to or above the federal minimum wage in 2010-2019 ($7.25/hour). Additionally, in order to avoid bias in my estimates, I drop all of the observations who claim their current residency status to be "study or training visa," "dependent visa," or "other visa." Due to legal limitations, there is a high probability that such individuals work at pay rates that are lower than market rates. For instance, those who are working on study or training visas are limited to either apprentice-type jobs or lower-paying post-doctoral positions.[7] Dropping observations that do not meet the criteria explained above and also removing observations with conflicts, errors, or missing information, leaves me with 339,257 observations in the pooled data, about 22% of which are immigrants.

Table 1 presents descriptive statistics for the pooled sample using survey weights. As can be seen in Table 1, immigrants, on average, have a higher hourly wage compared to natives, while the average ages of immigrants and natives are quite similar. According to Table 1, within immigrants, those who entered the United States on work visas have the highest hourly wages compared to those who entered on other types of visa. With respect to education level, as is evident in Table 1, immigrants, on average, have higher levels of education compared to natives, and understandably, within immigrants, those who arrived on a student visa have the highest level of education. Additionally, while the majority of natives have their education in non-science and engineering fields, the majority of immigrants have studied in a science and engineering-related discipline. As can be seen in Table 1, within immigrants, the work visa entry group (followed by the study or training visa entry group) has the highest percentage of education in "computer and IT" and also generally in science and engineering related fields.

Finally, as reported in Table 1, more than 50% of immigrants in the pooled sample are male, while more than half of the native observations are female. Also, compared to natives, a larger portion of immigrants are married and have children.

Tables 2, 3, and 4 report the weighted descriptive statistics on some of the important variables exploited in my analysis based on the cohort of arrival for the immigrant visa entry group, work visa entry group, and study or training visa entry group, respectively. As can be seen in Table 2, among immigrants who migrated to the United States on an immigrant visa, the cohorts that arrived during the more recent decades, on average, have lower levels of education and fewer degrees from U.S. universities. However, a higher percentage of them have degrees in science and engineering or related fields. The average hourly wage (adjusted

[7] This category includes visas such as the F-1 student visa, Optional Practical Training (an extension to the F-1 that enables international students to work for a certain period of time after graduation in the United States), the M-1 visa for vocational schools, and the J-1 visa for exchange students

to 2019 prices) of more recent cohorts is lower than those who arrived before and have been working for a longer time. It should be noted that people who arrive to the United States on an immigrant visa, receive their U.S. permanent residency document (green card) soon after their arrival, which gives them access to job opportunities similar to those of natives.

Table 3 shows a lot of fluctuations in the wages of different arrival cohorts of the work visa entry group, which does not seem to follow any trend. However, among those who came to the United States on a temporary work visa, the share with computer and IT as their field of education has been increasing significantly, especially since the 1990s. Almost 30% of those who arrived to the United States on a work visa after 2010 have a degree in computer or IT-related fields and almost 30% of those are in engineering. This shows the shift in the type of skills demanded in the United State's labor market. Regarding the level of education, a master's is the most common graduate degree among all cohorts, including about 41% of the last arrival cohort.

The story of those whose first visa to the United States was a student visa is slightly different. The majority of such immigrants join the labor market after graduation. In order to be eligible to work in the United States after using up their short study visa extension allowance, they need to either have a permanent residency document or obtain a temporary work permit. As I show in Table 4, the level of education keeps getting better by moving to later cohorts. About 60% of the last cohort hold a master's degree, and it is noticeable how non-science and engineering degrees change to science and engineering disciplines, especially computer, IT, and engineering fields in the later cohorts. This shows the change in what the U.S. labor market is requiring over decades.

`[Tables 1-4 about here]`

Limitations of the NSCG data

Although NSCG is uniquely rich and offers some detailed immigration- and education-related information that cannot be easily found in other datasets, it has some shortcomings as well. The main shortcoming of the NSCG (and many other datasets) is the lack of variables that can help with improving the selection bias problem. Although in the model I control for all human-capital-related, socioeconomic, and demographic characteristics available in the rich NSCG data, the problem of not being able to capture and control for unobservables such as ability and motivation of individuals is still a big issue. After all, as mentioned earlier, immigrants are a selected group that can potentially be more able and more motivated than the average native, yet such individuals are being compared with a sample of host country's natives that represents the whole population. Such unobserved characteristics can affect wages through productivity. Therefore, even after controlling for the maximum number of characteristics available in the data, any significant difference found between wages of different groups of people might be (at least in part) due to the differences in unobservable characteristics such as abilities and incentives.

Methodology and Results

As described in the literature (e.g. Chiswick, 1978; Borjas, 1999), immigrants and natives have different human-capital earnings functions:

$$\log\, w_n = \beta_0 + \boldsymbol{X_n \beta_1} + \beta_2 A_n + \beta_3 A_n^2 + \varepsilon_n \tag{1}$$

$$\log\, w_i = \alpha_0 + \boldsymbol{C_i \alpha_1} + \boldsymbol{X_i \alpha_2} + \alpha_3 A_i + \alpha_4 A_i^2 + \alpha_5 YSM_i + \alpha_6 YSM_i^2 + \phi_i \tag{2}$$

where w is wage (could be annual, monthly, weekly, or hourly), $\boldsymbol{X}$ is the vector of socioeconomic and demographic characteristics (including education, gender, marital status, region of employment, etc.), A is the age, and YSM counts the number of years that the immigrant has resided in the host country. Index n is used for natives, and index i is used for immigrants.

Borjas (1985) argues that other than the socioeconomic and demographic characteristics mentioned above, the arrival cohort should also be controlled to capture the differences in the skills and characteristics of different cohorts of immigrants who entered the host country over different time periods. $\boldsymbol{C}$ in Equation 2 is the matrix that controls for the arrival cohort of each immigrant.

According to Borjas (1999), one of the reasons for disagreement in the empirical literature over the relative economic status of immigrants in the United States is that different studies use different controlling variables. As a result, the base group differs drastically from study to study. For example, many studies include a worker's education (as years of schooling or highest degree level) in the vector X, and consequently, different effects are measured relative to native workers who have the same schooling. As Borjas discusses, a part of the adaptation process experienced by immigrants might include the acquisition of additional schooling. Therefore, by controlling for the schooling level observed at the time of the survey, the analysis might undermine an otherwise larger wage convergence between immigrants and natives (Borjas, 1999). In this study, since the individuals presented by the data are highly educated, it is very important to standardize the education level and compare immigrants and natives with the same level and quality of education.

Since Equation 2 controls for age and age-squared of immigrants, coefficients α_5 and α_6 measure the differential value that the host country's labor market attaches to the time spent in the host country in contrast to the time spent in the home country (Borjas, 1999). It is important to let immigrants and natives take different coefficients for age and age-squared because of the notion of specific human capital. "After all, it is very unlikely that a year of pre-migration "experience" for immigrants has the same value in the host country's labor market as a year of experience for the native population" (Borjas, 1999).

The rate of wage convergence/divergence between immigrants and natives is defined as follows (CR stands for convergence rate):

$$CR = \frac{\partial \log w_i}{\partial time} - \frac{\partial \log w_n}{\partial time} = \alpha_3 + 2\alpha_4 \bar{A}_i + \alpha_5 + 2\alpha_6 YSM_i - \beta_2 - 2\beta_3 \bar{A}_n \tag{3}$$

where $\bar{A}_i$ and $\bar{A}_n$ are average ages of immigrants and natives, respectively(Borjas, 1999).

I use the following least squares model with robust standard errors for my cross-sectional analysis to study the earnings difference between natives and different groups of immigrants at entry, and also to calculate the economic convergence/divergence rate between them:

$$\log w_j = \gamma_0 + \boldsymbol{I_j \gamma_1} + \boldsymbol{X_j \gamma_2} + \gamma_3 A_j * Nat_j + \gamma_4 A_j^2 * Nat_j + \\ \gamma_5 A_j * Imm_j + \gamma_6 A_j^2 * Imm_j + \gamma_7 YSM_j + \gamma_8 YSM_j^2 + f_t + \delta_j \tag{4}$$

where $\boldsymbol{I}$ is a matrix containing six dummy variables for the six groups of immigrants (based on the arrival cohort) present in my data. One and only one of these dummies will take one for each immigrant individual in the sample under study, and they will all take zeros when it comes to a native. Hence, the estimated coefficient on the indicator (dummy) variable of any above-mentioned immigrant cohort (if significant) represents the log earnings difference between U.S.-born (native) workers and that group of immigrants.

Using the number of hours worked per week and number of weeks worked per year for each observation, the hourly wages were calculated from the annual salaries reported. So the dependent variable of the model is the log of hourly wage for individual j (adjusted to 2019 prices). $\boldsymbol{X}$ is a matrix that includes the following socioeconomic and demographic attributes of individuals in the sample: the highest degree level (bachelor's degree, master's degree, doctorate, or professional degree), whether the highest degree was earned in the United States, field of study of the highest degree, gender, race, birthplace, whether the individual is from an English-speaking country[8], marital status, whether the individual has children, employment sector, employment location/region, employer size, full-time/part-time status, and physical disability indicator. Recall that YSM is the number of years since migration to the United States and takes zero for natives.

In order to take advantage of all of the observations in all five cycles, observations of the five cycles are pooled and, using the consumer price index (CPI) reported by the Bureau of Labor Statistics (BLS), the hourly wages of all observations in the pooled data are recalculated in 2019 prices[9]. So Equation 4 is run as a pooled OLS. To control for and capture the differences in year-specific economic effects (like national and international

[8] Similar to Borjas (2015), this dummy variable is made based on the country of origin of immigrants. The dummy variable takes one if the immigrant is born in an English-speaking country and zero otherwise. It takes one for U.S.-born natives.

[9] According to the BLS, CPI in 2010, 2013, 2015, 2017, and 2019 are 218.1, 233.0, 237.0, 245.1, and 255.7, respectively (Bureau of Labor Statistics, 2019).

macroeconomic shocks) on earnings between years 2010, 2013, 2015, 2017, and 2019, f_t is used in the model as the year fixed effect[10].

Friedberg (1992) argues that the above-mentioned generic wage model ignores the important role of age at arrival in the host country, while United States data suggest a negative correlation between age-at-arrival and earnings at entry. Because perfect collinearity exists between age, years since migration, and age at arrival, or among age at arrival, years since migration, and year of observation, in order to bring age at arrival into the model (besides arrival cohort), one needs to impose an additional restriction. One possible restriction is to assume that the coefficients of age and age-squared variables are the same for immigrants and natives. The problem, however, is that such an assumption is very restrictive, and as Borjas (1999) argues, contradicts the notion of specific human capital. As mentioned earlier, it is very improbable that one year of premigration experience for immigrants has the same value in the host country's labor market as a year of experience for natives. Although, it does not solve the underlying collinearity concept, an alternative approach to address such an identification problem is modeling the age-at-arrival effect as a step function (using a categorical variable). Individuals who migrate when they are very young encounter more opportunities in the host country than those who migrate at an old age (Borjas, 1999).

The categorical variable for age at arrival was first included in the $\boldsymbol{X}$. However, after running the model, I did not find significant estimates for the age at arrival either in the main model or in any of the auxiliary regressions. Next, I ran the model without controlling for age at arrival and found no significant change in other estimates. The R-squared did not show a noticeable change either. So, I decided not to include age at arrival in the $\boldsymbol{X}$ for my analysis.

[10]To resolve the potential identification problem caused by collinearity between calendar year of the cycle, arrival cohort, and years since migration, I keep the year fixed effect (f_t) the same for both immigrants and natives (Borjas, 1994).

All Fields of Education

Table 5 reports the results of running Equation 4 on the pooled sample at large along with the four sub-samples for all fields of education[11]. Column 1 of Table 5 shows the results of running the model on the whole pooled sample, and columns 2-5 show the results of running the model on all natives and the migrants with an immigrant visa entry, work visa entry, study or training visa entry, and dependent visa entry, respectively.

As shown in column 1, immigrants in general have a wage premium over natives, at arrival. Depending on what cohort of arrival they belong to, the premium can be between 0.331 and 0.405 log points. This also shows a maximum wage difference of 0.074 log points between different immigrant arrival cohorts. This means that immigrants who arrived in the United States in different decades, like what Borjas (1985) discusses, seem to have distinct qualities.

Existence of positive selection among the immigrant group(s) can be an important justification for immigrants' wage premium. After all, those individuals who could successfully go through the complicated immigration and adaptation process (from leaving everything behind in their homelands and migrating to the United States, to assimilating fully into the U.S. economy and finding a job in the U.S. labor market), should be motivated and capable people. Therefore, it is safe to assume that these individuals have above-average qualifications and abilities[12].

Focusing on specific entry visas, I find that among those who arrived on an immigrant visa[13], only 2000's and 2010's cohorts have significant wage premiums over natives, which shows that those who arrived later have higher qualifications than the previous cohorts. For the temporary work visa entry group, surprisingly, I find no wage difference compared to natives and no cohort-based wage difference. This can be due to the fact that U.S. law establishes certain standards in order to protect similarly employed U.S. workers from being

[11]Due to limited space, I am not reporting all of the estimates in Table 5. The complete, detailed version of Table 5 can be found as Table A1 in the online appendix.

[12]Unfortunately, there is no information available in the NSCG data that can help me control for ability and motivation of individuals. So in this study, they are considered unobservables.

[13]An explanation of the different types of immigrant visas can be found online through the U.S. State Department's Bureau of Consular Affairs: https://travel.state.gov/content/travel/en/us-visas/visa-information-resources/all-visa-categories.html.

adversely affected by the employment of the non-immigrant workers, as well as to protect the non-immigrant temporary workers. Employers must attest to the Department of Labor that they will pay wages to the temporary workers that are at least equal to the actual wage paid by the employer to other workers with similar experience and qualifications for the job in question, or the prevailing wage for the occupation in the area of intended employment, whichever is greater (U.S. Department of Labor, 2024).

Although, like the work visa entry group, the dependent visa entry group also shows no wage gap at entry when compared to natives and no cohort-based wage difference, I notice a large wage premium for the study or training visa entry group over natives and also a large range of arrival cohort-based wage difference among them[14]. An important difference in this group of immigrants compared to the rest is that they do not join the U.S. labor market right after arrival. They first go through some education or training in the United States before they join the labor market, so by the time they do enter the labor market, they have experienced some assimilation.

According to Table 5, earning one's highest academic degree from a university in the United States has a positive impact on salary. However, that is not the case for those who arrived on a temporary work visa. The explanation can be based on the nature of such visas. When a non-native person is hired while outside the United States, it means that they already have the required knowledge and skills to do the job for which they are hired. Therefore, getting a degree from a U.S. school (that on average offers a higher quality education) might not add much to the productivity of such an individual.

After exploring the wage difference between natives and different groups of immigrants at arrival, it would be interesting to estimate how immigrants' salaries would change relative to those of natives after a certain number of years of living and working in the United States. I use Equation 3 and the estimated coefficients reported in Table 5 to forecast immigrants'

[14] *A plausible anecdote:* Those who migrate as students (on a student visa) must navigate a competitive route to achieve employment in the United States: After earning their degrees from reputable U.S. schools, they enter the job market and start applying. Many employers prefer to avoid the costly and risky process of sponsorship for those who do not at least hold permanent resident status. Therefore, immigrants need to compete for jobs that accept applicants with no green card. If they get an offer, the next step is obtaining a work visa, which is a risky and complicated process, considering the annual visa cap. Those who manage to pass all of these steps are potentially better qualified than others and get higher salaries.

wage convergence/divergence rate (CR) relative to natives' wages. Table 6 demonstrates this rate 1, 5, 10, 15, and 30 years after arrival to the United States, and Figure 1 shows the assimilation profiles of immigrants from the point of entry until 30 years later[15].

Because the estimates of the YSM or YSM-squared coefficients in the work visa, study or training visa, and dependent visa entry groups are not statistically significant at 10% or less, no strong evidence exists that points to changes in the upon-entry native-immigrant wage gap after living and working in the United States for a certain number of years. As can be seen in Figure 1, the wages of the immigrant visa entry group, however, grow more distant (higher) from those of natives at a rate of 1.6% one year after arrival. This rate stays positive for about 30 years but declines to 1.4%, 1.1%, 0.8%, and almost zero after 5, 10, 15, and 30 years from arrival, respectively. One reason for this can be that while individuals on a work visa might not be able to get promoted above a certain point, U.S. permanent residents (green card holders) do not have any limitations on that capacity.

Considering all immigrants as a whole, as shown in Table 6 and Figure 1, the initial native-immigrant wage gap upon entry narrows over time. Although one year after arrival to the United States immigrants' wages are getting closer to those of natives at the rate of 0.04%, this rate increases to 0.08% after 5 years, 0.12% after 10 years, 0.17% after 15 years, and finally 0.31% after 30 years from arrival. The process, however, is very slow and will not close the gap even after 30 years.

`[Tables 5-6 about here]`

`[Figure 1 about here]`

Computer and IT

Since a couple of decades ago and along with the technology boom in the United States, the demand for a labor force with education and skills in computer and IT-related fields has increased. Therefore, as a part of this study, I decided to focus on natives and immigrants who have their highest degrees in computer, IT, and related disciplines and see whether the

[15] This is similar to Figure 2.1 in Borjas (2014).

results will differ when compared to the general results discussed in the previous section. Table 7 reports the results of comparing natives and immigrants who have their education in computer and IT fields (including computer engineering).[16] Table 7 is similar to Table 5 in how it is set up; the only difference is that Table 7 only includes individuals with such fields of education. As can be seen in Table 7, out of the five columns, the only group of immigrants who show significant wage premiums over natives along with wage differences between different arrival cohorts is the work visa entry group. This means that other than work visa entry group, no arrival cohort within other groups has any wage advantage against natives after controlling for the mentioned observables. Those who are hired from outside the United States on a work visa, however, seem to have unobservable advantages over their native counterparts–advantages that cause a large wage premium over them even after going through the above-mentioned Department of Labor process. After all, computer skills are not as correlated with a university degree as other skills might be. It can also be noted that a large margin of difference exists between the average wages of different arrival cohorts, which can be due to the very different demand-based skills that each cohort brought with them into the United States.

Table 8 and Figure 2 show[17] the estimated assimilation rates and the assimilation profiles for all immigrants and specific groups for up to 30 years after migration to the United States. Due to statistically insignificant YSM or YSM-squared coefficient estimates, I cannot find any evidence that strongly points to any type of assimilation for the study or training visa and dependent visa entry groups. Considering all immigrants with computer and IT degrees, my results show that their wages rise above those of their native counterparts at a 1.08% rate one year after arrival. This rate rises to 1.02% after 5 years, 0.96% after 10 years, 0.89% after 15 years, and to 0.69% 30 years after arrival. Therefore, in the field of computer and IT, as presented in Figure 2, although natives and immigrants have no significant wage difference at arrival, a premium develops and increases with years of immigrants' residence in the United States.

[16]Due to limited space, I am not reporting all of the estimates in Table 7. The complete, detailed version of Table 7 can be found as Table A2 in the online appendix.

[17]This is similar to Figure 2.1 in Borjas (2014).

As can be seen in the second column of Table 8 and in Figure 2, those who arrive on an immigrant visa follow a similar pattern only with a significantly larger divergence rate. So although those who come to the United States on an immigrant visa and have education in the computer and IT fields have no significant wage difference compared to natives at arrival, a wage premium for them develops at a fast rate and increases with years of residence in the United States. Even after 30 years, their wage premium is still growing at a rate of more than 2%.

As reported in the third column of Table 8, during the first 10-15 years of living and working in the United States, the already large wage premium of the work visa entry group at arrival (compared to natives) increases even further. The wage gap grows at the rate of around 3% one year after arrival but the rate decreases to less than 1% after 10 years. Fifteen years after entry, however, the rate narrows the gap at 0.1%, and 30 years after arrival this narrowing rate is increased to more than 3%. This assimilation process can be seen in Figure 2. One reason for this result can be that work visa holders might not be able to reach high managerial ranks in tech companies after a certain point, while natives can get promoted to high-paying managerial positions.

[Tables 7-8 about here]

[Figure 2 about here]

Conclusion

Using a pooled sample of 2010, 2013, 2015, 2017, and 2019 cycles of the National Survey of College Graduates (NSCG), this study analyzes the dynamics of the earnings gap between highly educated U.S.-born natives and immigrants who migrated to the United States over the course of different decades and on different visas (immigrant visa, work visa, study or training visa, or dependent visa). Besides running the models on the whole sample (all fields of study), I also focus on individuals who hold their highest degrees in computer and IT-related disciplines to see whether I find distinct results.

My results on all immigrants (regardless of the entry visa) show that upon entry, they have about a 30%-40% wage premium over their native counterparts. This wage gap, however, tends to slowly narrow at a 0.04% rate one year after arrival, before increasing to 0.3% after 30 years of residence in the United States.

Focusing on computer and IT professionals, although I find no significant wage gap between immigrants at entry and natives (regardless of immigrants' arrival cohort), I find that immigrants' wages tend to gradually grow higher than those of natives with a rate of almost 1.1% one year after arrival, slowing down to 0.7% after 30 years of U.S. residence.

My results show some mild but statistically significant wage gaps (up to about 0.08 log point difference) between different cohorts of immigrants, regardless of their field of education or their entry visa type. However, I find no statistically significant wage difference between arrival cohorts of immigrants when I only focus on computer and IT.

Comparing natives and immigrants who migrated to the United States on different entry visas leads to various results. All fields of education included, I find that immigrants who arrived on an immigrant visa in the year 2000 or after, upon arrival, have about a 0.5 log point wage premium over natives and those who arrived before 2000. On the other hand, immigrants who first came to the United States on a temporary work visa or a dependent visa show no significant wage difference among different arrival cohorts or when compared to natives. However, I find a large and statistically significant wage gap between natives and immigrants with study or training first entry visas. Depending on the cohort of arrival, upon arrival, such immigrants have a 1-1.24 log point wage premium over natives. Results also show up to a 0.25 log point wage difference between their arrival cohorts.

In computer and IT fields, the results are different. Although immigrants who migrated to the United States on an immigrant visa, a study or training visa, or a dependent visa show no significant wage gaps across their different arrival cohorts or when compared to natives, members of the work visa entry group have a large wage premium over natives and show evidence of significant arrival cohort wage difference among them.

With respect to assimilation, I find that the wages of immigrants who arrived on an immigrant visa keep getting higher than those of natives for at least 15 years from arrival

(1.6% after one year, 1.4% after 5 years, 1.1% after 10 years, and 0.8% after 15 years). For computer and IT, I find that the immigrant visa entry group's average wage goes above native's wages at a 5% rate at the end of first year; this rate goes down to 2% after 30 years of residence. The average wage of those who arrived on a work visa, however, gets further from that of natives in the first 10 years of residence in the Unite states, but the gap starts to narrow down after that.

It should be mentioned that, although in my model I control for all human-capital-related, socio-economic, and demographic characteristics available in the NSCG data—these are truly rich data, providing a variety of information that cannot be found all at the same time in most of the other datasets—the problem of not being able to capture and control for unobservable characteristics such as ability and motivation of individuals is still a big issue. Some datasets provide information about the job and salary of immigrants right before migration, or information about some exam grades or rankings that can be used as a weak proxy of ability. Controlling for such variables can potentially reduce the selection bias in the estimated coefficients, but unfortunately, the NSCG data provide no information about immigrants before migration or any other information that could be used as a means to deal with this important and potentially misleading issue.

The immigrants' wage premiums that I find in this study might be suggesting that the demand for these workers outweighs the supply. If highly educated professionals who have migrated to the United States are being paid a premium over their U.S.-born counterparts because the U.S. labor market demands more highly trained workers than there is supply for, then this would suggest that easing immigration rules for such workers[18] may prevent companies from moving jobs overseas. Another policy implication is that United States needs to encourage native-born workers to pursue training and education that meets the needs of its labor market.

[18] For instance, one solution might be to develop a merit-based immigration program like the Federal Skilled Worker program of Canada or a similar program in Australia.

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Table 1: Summary Statistics for the Pooled Sample (Survey Weights Assumed)

	Natives		All Immigrants		Immigrant Visa Entry		Work Visa Entry		Study/Training Visa Entry		Dependent Visa Entry	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Hourly wage (in 2019 $)	49.51	159.00	57.43	266.99	54.89	407.74	65.23	108.73	61.35	116.55	52.19	101.61
Current residency status (%)												
Native	100	-	-	-	-	-	-	-	-	-	-	-
Naturalized citizen	-	-	67.31	-	86.83	-	36.73	-	53.13	-	70.95	-
Permanent resident	-	-	23.22	-	13.17	-	34.95	-	30.33	-	24.82	-
Work visa	-	-	9.47	-	-	-	28.32	-	16.54	-	4.22	-
Highest degree (%)												
Bachelor's	64.35	-	55.12	-	67.78	-	57.60	-	26.53	-	57.40	-
Master's	26.79	-	30.75	-	22.47	-	33.04	-	46.32	-	28.84	-
Doctorate	2.76	-	8.09	-	2.69	-	6.83	-	21.63	-	4.04	-
Professional	6.10	-	6.05	-	7.07	-	2.53	-	5.52	-	9.72	-
Highest degree from a US college/university (%)	99.53	-	59.54	-	67.63	-	17.03	-	78.93	-	62.89	-
Field of study (%)												
Computer and IT	3.36	-	9.80	-	6.51	-	17.18	-	11.68	-	9.88	-
Mathematics and statistics	1.04	-	2.00	-	1.47	-	1.93	-	2.98	-	2.22	-
Biological, agricultural, and environmental life sciences	4.36	-	5.67	-	5.02	-	3.58	-	8.14	-	6.66	-
Physics and related sciences	1.49	-	2.56	-	1.68	-	2.90	-	4.74	-	1.79	-
Social and related sciences	11.18	-	8.72	-	9.86	-	6.29	-	6.50	-	11.36	-
Engineering (w/o computer and IT)	5.44	-	14.91	-	10.71	-	23.84	-	19.19	-	9.86	-
Other science and engineering-related	13.49	-	17.18	-	20.26	-	16.31	-	13.20	-	17.69	-
Non science and engineering	59.66	-	39.17	-	44.50	-	27.97	-	33.57	-	40.54	-
Age	43.02	11.61	43.51	10.32	43.71	10.99	43.55	9.17	43.38	10.06	41.42	9.87
Years since migration	-	-	21.27	12.39	24.87	12.91	13.69	9.03	19.65	10.51	23.39	13.56
Male (%)	47.76	-	54.21	-	48.37	-	69.25	-	62.47	-	36.41	-
Married (%)	70.39	-	77.20	-	72.41	-	86.36	-	80.41	-	74.66	-
Have child(ren) (%)	48.21	-	59.41	-	57.86	-	66.10	-	58.01	-	56.71	-
Employer's sector (%)												
Educational institution	22.22	-	14.26	-	13.72	-	7.98	-	17.64	-	16.19	-
Government	10.84	-	8.57	-	12.69	-	2.22	-	6.85	-	7.22	-
Business/industry	66.94	-	77.17	-	73.60	-	89.80	-	75.51	-	76.59	-
Academic job (%)	6.89	-	7.58	-	5.76	-	4.14	-	13.59	-	8.37	-
Self-employed (%)	17.46	-	19.4	-	20.04	-	18.16	-	18.45	-	19.41	-
Physical disability (%)	9.58	-	9.23	-	11.06	-	7.06	-	7.48	-	7.87	-
English mother tongue (%)	-	-	11.82	-	13.1	-	18.5	-	7.86	-	9.27	-
Number of observations	264,966	-	74,305	-	23,293	-	12,219	-	24,976	-	9,150	-

Table 2: Summary Statistics by Cohort of Arrival: Immigrant Visa Entry (Survey Weights Assumed)

	<= 1969		**1970s**		**1980s**		**1990s**		**2000s**		**>= 2010**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Hourly wage (in 2019 $)	66.11	128.56	75.22	1036.04	67.44	223.98	44.84	104.73	41.87	83.71	34.80	85.05
Age	56.36	5.41	48.87	7.84	44.97	10.51	41.11	10.78	40.35	10.58	36.81	9.42
Years since migration	50.66	5.51	39.09	3.94	30.63	4.36	20.77	4.22	11.78	4.16	4.59	2.17
Highest degree (%)												
Bachelor's	64.03	-	60.56	-	65.60	-	67.82	-	73.34	-	77.39	-
Master's	20.84	-	24.90	-	23.92	-	22.39	-	21.54	-	17.22	-
Doctorate	6.77	-	2.55	-	2.93	-	2.37	-	2.30	-	0.65	-
Professional	8.36	-	12.00	-	7.55	-	7.41	-	2.82	-	4.73	-
Highest degree from a U.S. college/university (%)	94.51	-	87.92	-	81.36	-	69.88	-	42.81	-	14.86	-
Field of study (%)												
Computer and IT	3.54	-	5.39	-	6.57	-	8.43	-	6.12	-	5.01	-
Mathematics and statistics	1.47	-	1.33	-	1.29	-	1.85	-	1.60	-	0.65	-
Biological, agricultural, and environmental life sciences	3.46	-	4.79	-	4.61	-	4.30	-	6.71	-	6.55	-
Physics and related sciences	1.31	-	1.38	-	1.83	-	1.42	-	2.07	-	1.95	-
Social and related sciences	11.78	-	8.66	-	10.67	-	10.43	-	8.50	-	8.90	-
Engineering (w/o computer and IT)	7.32	-	11.67	-	11.24	-	10.89	-	9.67	-	12.12	-
Other science and engineering-related	16.75	-	18.17	-	17.00	-	20.83	-	27.22	-	18.61	-
Non science and engineering	54.36	-	48.61	-	46.80	-	41.85	-	38.11	-	46.22	-
Number of observations	1533	-	3387	-	6208	-	7041	-	4014	-	1110	-

Table 3: Summary Statistics by Cohort of Arrival: Work Visa Entry (Survey Weights Assumed)

	<= 1969		**1970s**		**1980s**		**1990s**		**2000s**		**>= 2010**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Hourly wage (in 2019 $)	35.36	23.08	84.05	153.34	57.67	57.25	70.49	136.38	63.65	111.88	64.06	68.40
Age	61.25	4.29	57.02	8.02	54.82	6.51	46.78	7.38	41.78	7.90	36.46	6.50
Years since migration	48.15	5.54	39.25	4.50	29.50	4.16	18.70	4.29	10.49	4.22	4.00	2.01
Highest degree (%)												
Bachelor's	33.12	-	70.69	-	58.02	-	58.30	-	59.84	-	50.83	-
Master's	26.42	-	26.72	-	26.95	-	31.44	-	32.10	-	40.60	-
Doctorate	28.36	-	1.60	-	14.19	-	6.81	-	5.19	-	7.09	-
Professional	12.10	-	0.99	-	0.84	-	3.45	-	2.87	-	1.48	-
Highest degree from a U.S. college/university (%)	84.95	-	53.24	-	41.15	-	21.90	-	11.89	-	6.54	-
Field of study (%)												
Computer and IT	1.42	-	3.85	-	4.52	-	16.52	-	16.11	-	27.52	-
Mathematics and statistics	2.53	-	0.00	-	1.00	-	2.62	-	1.55	-	2.46	-
Biological, agricultural, and environmental life sciences	5.45	-	1.19	-	2.66	-	4.28	-	4.12	-	2.15	-
Physics and related sciences	6.81	-	1.67	-	2.53	-	2.93	-	2.24	-	4.48	-
Social and related sciences	4.30	-	7.33	-	7.19	-	4.25	-	7.84	-	5.19	-
Engineering (w/o computer and IT)	29.46	-	5.14	-	10.74	-	25.62	-	24.45	-	27.98	-
Other science and engineering-related	41.84	-	23.32	-	29.37	-	22.19	-	12.82	-	9.02	-
Non science and engineering	8.19	-	57.50	-	42.00	-	21.59	-	30.87	-	21.20	-
Number of observations	34	-	148	-	1013	-	4045	-	5043	-	1928	-

Table 4: Summary Statistics by Cohort of Arrival: Study or Training Visa Entry (Survey Weights Assumed)

	<= 1969		**1970s**		**1980s**		**1990s**		**2000s**		**>= 2010**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Hourly wage (in 2019 $)	94.44	261.91	68.57	93.82	70.61	163.96	63.23	96.99	52.65	73.43	57.69	170.05
Age	58.78	6.39	57.64	5.63	52.04	6.28	44.33	6.56	36.47	6.41	32.45	5.99
Years since migration	46.75	4.16	38.32	3.64	29.59	4.29	20.21	4.21	11.71	3.73	5.56	2.13
Highest degree (%)												
Bachelor's	64.71	-	39.94	-	28.17	-	26.33	-	23.56	-	17.37	-
Master's	21.29	-	44.11	-	43.97	-	43.22	-	48.10	-	59.48	-
Doctorate	7.99	-	12.34	-	22.76	-	22.99	-	23.57	-	18.58	-
Professional	6.02	-	3.60	-	5.10	-	7.46	-	4.78	-	4.57	-
Highest degree from a U.S. college/university (%)	95.35	-	88.86	-	86.75	-	77.58	-	75.53	-	68.64	-
Field of study (%)												
Computer and IT	2.39	-	3.75	-	13.62	-	10.81	-	12.14	-	17.85	-
Mathematics and statistics	1.42	-	3.13	-	2.09	-	2.86	-	3.67	-	2.66	-
Biological, agricultural, and environmental life sciences	1.69	-	5.60	-	6.98	-	9.27	-	9.26	-	5.89	-
Physics and related sciences	3.12	-	7.17	-	4.54	-	5.06	-	4.03	-	4.45	-
Social and related sciences	8.60	-	6.68	-	7.42	-	7.07	-	5.82	-	4.87	-
Engineering (w/o computer and IT)	29.50	-	18.86	-	19.55	-	15.08	-	21.91	-	21.34	-
Other science and engineering-related	6.86	-	9.74	-	15.23	-	13.29	-	13.08	-	13.45	-
Non science and engineering	46.43	-	45.08	-	30.57	-	36.56	-	30.08	-	29.49	-
Number of observations	189	-	1819	-	4394	-	6949	-	9483	-	2140	-

Table 5: Earnings of Immigrants Relative to Natives: Role of Entry Visa

	All Immigrants	**Immigrant Visa Entry**	**Work Visa Entry**	**Study/Training Visa Entry**	**Dependent Visa Entry**
Cohort of Arrival to the U.S.					
<= 1969	0.352**	0.381	0.028	1.245***	-0.365
	(0.175)	(0.248)	(0.648)	(0.379)	(0.378)
1970s	0.331**	0.306	0.746	1.140***	-0.280
	(0.162)	(0.236)	(0.568)	(0.307)	(0.374)
1980s	0.323**	0.362	0.586	1.119***	-0.270
	(0.153)	(0.221)	(0.485)	(0.301)	(0.353)
1990s	0.347**	0.356	0.656	1.106***	-0.108
	(0.152)	(0.221)	(0.487)	(0.301)	(0.331)
2000s	0.370**	0.449**	0.631	1.044***	-0.026
	(0.146)	(0.216)	(0.470)	(0.297)	(0.319)
>= 2010	0.405***	0.517**	0.705	1.012***	-0.004
	(0.144)	(0.219)	(0.470)	(0.289)	(0.320)
Age - natives	0.052***	0.052***	0.052***	0.052***	0.051***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age squared - natives ($\times$100)	-0.046***	-0.045***	-0.045***	-0.045***	-0.044***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age - immigrants	0.048***	0.029***	0.047**	0.010	0.064***
	(0.007)	(0.010)	(0.022)	(0.015)	(0.015)
Age squared - immigrants ($\times$100)	-0.054***	-0.035***	-0.053**	-0.015	-0.077***
	(0.007)	(0.011)	(0.023)	(0.016)	(0.017)
Years since migration	0.012***	0.031***	0.007	0.010	0.013
	(0.004)	(0.006)	(0.010)	(0.009)	(0.010)
Years since migration squared ($\times$100)	-0.005*	-0.027***	0.003	0.000	0.005
	(0.007)	(0.010)	(0.028)	(0.018)	(0.016)
Highest degree from the U.S.	0.064***	0.148***	0.047	0.047*	0.128***
	(0.017)	(0.026)	(0.029)	(0.027)	(0.034)
No. of observations					
Natives	264,966	264,966	264,966	264,966	264,966
Immigrants	74,291	23,293	12,211	24,974	9,148
Total	339,257	288,259	277,177	289,940	274,114
R-squared	0.211	0.211	0.214	0.213	0.210

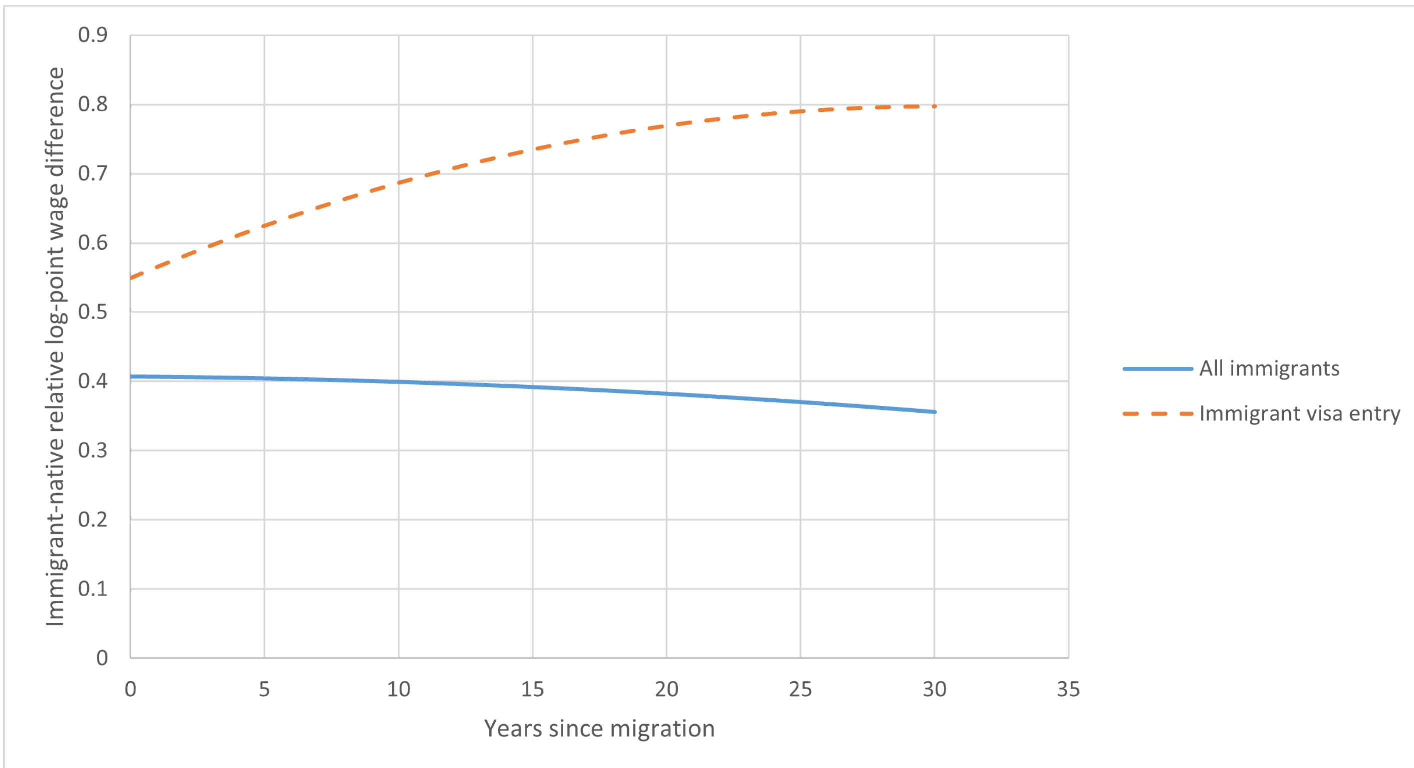
Note. *** p<0.01, ** p<0.05, * p<0.1; numbers in parentheses are robust standard errors; coefficients are estimated using OLS weighted by survey weights; log of hourly wage adjusted to 2019 dollars is the dependent variable; U.S.-born natives are the base group for cohort of arrival; other independent variables that exist in regressions but are not reported are as follows: highest degree, field of education, male, married, children, English-speaking, race, place of birth, physical disability, employer sector, employer size, employer region, self-employed, and year fixed effect (survey year).

Table 6: Assimilation (Convergence/Divergence) Rate for Different Groups of Immigrants (Based on Entry Visa Type)

	All Immigrants	**Immigrant Visa**	**Work Visa***	**Study/Training Visa***	**Dependent Visa***
CR for immigrants 1 year after arrival	-0.00041	0.01594	-0.00531	-0.00569	0.00113
CR for immigrants 5 years after arrival	-0.00078	0.01375	-0.00511	-0.00569	0.00153
CR for immigrants 10 years after arrival	-0.00124	0.01101	-0.00485	-0.00569	0.00203
CR for immigrants 15 years after arrival	-0.00170	0.00827	-0.00460	-0.00569	0.00253
CR for immigrants 30 years after arrival	-0.00308	0.00004	-0.00383	-0.00568	0.00403

Note. CR stands for Convergence Rate; all values in this table are computed by putting Table 5 estimates in Equation 3.
*The estimate of YSM coefficient is not statistically significant at 10% or below (see Table 5).

Figure 1: Assimilation Profiles: All Fields of Education



Source. Regression coefficients reported in Table 5.
Note. The relative earnings profiles in the figure give the log (adjusted) hourly wage gap between immigrants and natives (immigrants minus natives), holding all other factors constant. No assimilation profile can be drawn for other immigrant groups (other entry visas) because we do not find statistically significant estimated coefficients for YSM or YSM^2 in those groups.

Table 7: Earnings of Immigrants Relative to Natives (in Computer and IT): Role of Entry Visa

	All Immigrants	Immigrant Visa Entry	Work Visa Entry	Study/Training Visa Entry	Dependent Visa Entry
Cohort of Arrival to the U.S.					
<= 1969	-0.063	-0.739	2.058***	0.288	-0.795
	(0.370)	(0.708)	(0.661)	(0.444)	(0.690)
1970s	0.018	-0.576	1.029	0.174	-0.624
	(0.340)	(0.693)	(0.773)	(0.408)	(0.670)
1980s	0.133	-0.398	1.252***	0.230	-0.649
	(0.321)	(0.658)	(0.451)	(0.391)	(0.659)
1990s	0.192	-0.314	1.048**	0.245	-0.485
	(0.321)	(0.646)	(0.416)	(0.398)	(0.643)
2000s	0.294	0.092	1.087***	0.260	-0.623
	(0.317)	(0.606)	(0.395)	(0.395)	(0.623)
>= 2010	0.396	0.318	1.134***	0.315	-0.278
	(0.317)	(0.586)	(0.395)	(0.408)	(0.673)
Age - natives	0.044***	0.040***	0.040***	0.041***	0.038***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Age squared - natives ($\times$100)	-0.043***	-0.039***	-0.039***	-0.039***	-0.037***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Age - immigrants	0.032**	0.007	-0.008	0.024	0.080***
	(0.015)	(0.029)	(0.019)	(0.020)	(0.027)
Age squared - immigrants ($\times$100)	-0.039**	-0.013	0.003	-0.024	-0.109***
	(0.016)	(0.032)	(0.022)	(0.021)	(0.032)
Years since migration	0.018**	0.064***	0.042***	0.016	0.013
	(0.008)	(0.023)	(0.012)	(0.013)	(0.019)
Years since migration squared ($\times$100)	-0.007*	-0.053*	-0.105***	-0.036	-0.006
	(0.014)	(0.033)	(0.037)	(0.025)	(0.040)
Highest degree from the U.S.	-0.032	0.038	-0.085	-0.058	0.081
No. of observations					
Natives	13,143	13,143	13,143	13,143	13,143
Immigrants	8,772	2,013	2,272	3,101	1,035
Total	21,915	15,156	15,415	16,244	14,178
R-squared	0.222	0.215	0.239	0.236	0.223

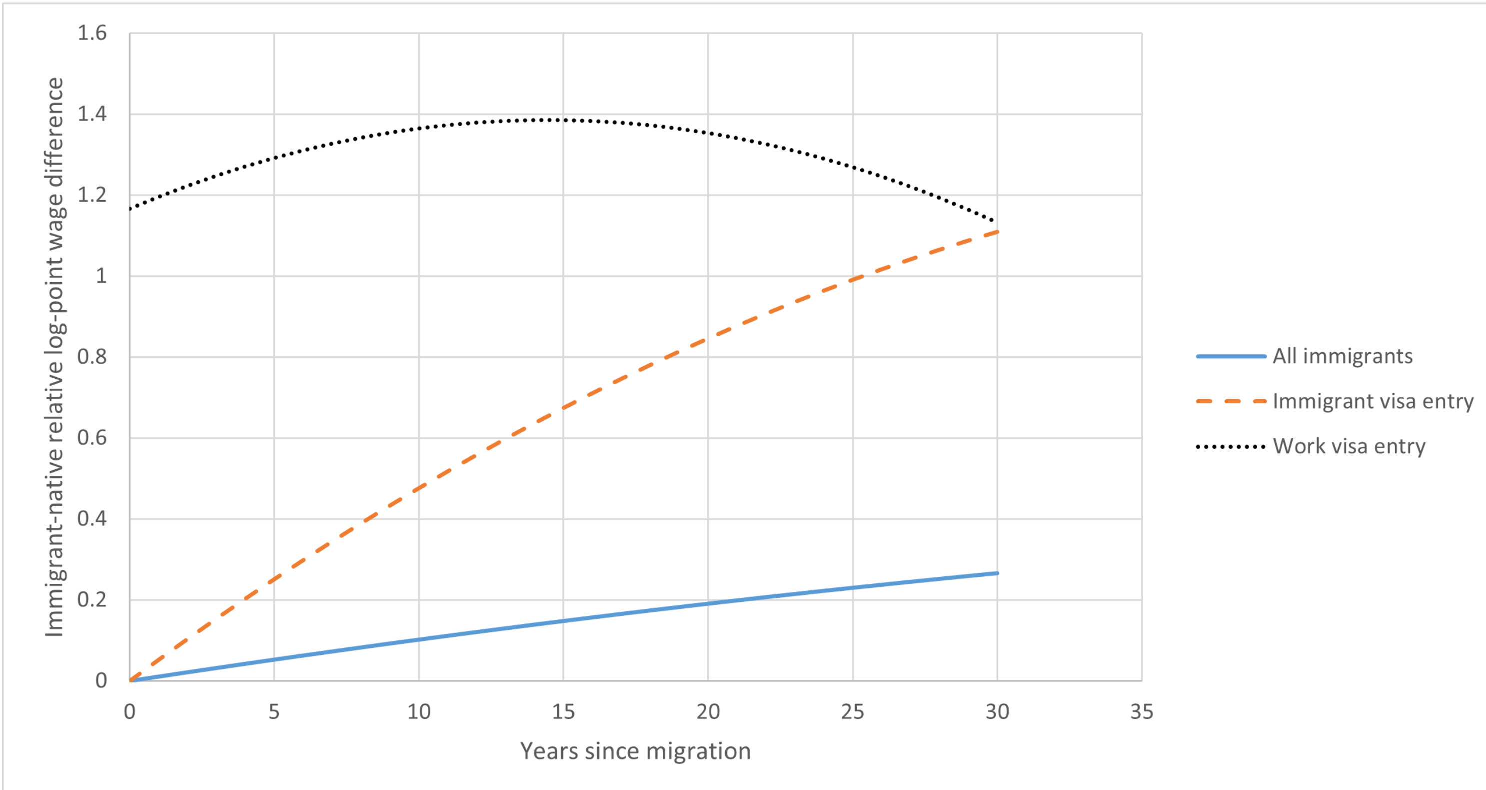
Note. *** p<0.01, ** p<0.05, * p<0.1; numbers in parentheses are robust standard errors; coefficients are estimated using OLS weighted by survey weights; log of hourly wage adjusted to 2019 dollars is the dependent variable; U.S.-born natives are the base group for cohort of arrival; other independent variables that exist in regressions but are not reported are as follows: highest degree, male, married, children, English-speaking, race, place of birth, physical disability, employer sector, employer size, employer region, self-employed, and year fixed effect (survey year).

Table 8: Assimilation (Convergence/Divergence) Rate for Different Groups of Immigrants (Based on Entry Visa Type): Computer and IT

	All Immigrants	**Immigrant Visa**	**Work Visa**	**Study/Training Visa***	**Dependent Visa***
CR for immigrants 1 year after arrival	0.01077	0.05189	0.02814	0.01239	-0.00097
CR for immigrants 5 years after arrival	0.01023	0.04763	0.01978	0.00950	-0.00146
CR for immigrants 10 years after arrival	0.00956	0.04231	0.00932	0.00590	-0.00207
CR for immigrants 15 years after arrival	0.00889	0.03699	-0.00113	0.00230	-0.00269
CR for immigrants 30 years after arrival	0.00687	0.02102	-0.03248	-0.00850	-0.00452

Note: CR stands for Convergence Rate; all values in this table are computed by putting Table 6 estimates in Equation 3.
*The estimate of YSM coefficient is not statistically significant at 10% or below (see Table 7).

Figure 2: Assimilation Profiles: Computer and IT



Source. Regression coefficients reported in table 7.

Note. The relative earnings profiles in the figure give the log (adjusted) hourly wage gap between immigrants and natives (immigrants minus natives), holding all other factors constant. No assimilation profile can be drawn for other immigrant groups (other entry visas) because we do not find statistically significant estimated coefficients for YSM or YSM^2 in those groups.