# Education-Occupation Mismatch Among Immigrants: Evidence from the National Survey of College Graduates

by

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# Abstract

Using the National Survey of College Graduates, I examine the probability of immigrants being mismatched in their job with their education compared to native-born workers, and the earnings penalty experienced by mismatched immigrants versus mismatched natives. Male immigrants are less likely to be mismatched compared to male natives; however, controlling for education level and field of study explains most of the gap. Female immigrants are as likely to be mismatched as female natives, but controlling for various characteristics, female immigrants are slightly more likely to be mismatched than female natives. By looking at entry visas, immigrants who arrive as permanent residents are more likely to be mismatched than those who arrive on a temporary work visa. Immigrants face a larger earnings penalty from mismatch than natives due partly to immigrants tending to be in fields of study where mismatch is relatively costly.

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# 1. Introduction

Students attend college and choose majors largely with the expectation of future financial returns on their education. One measure of labor market success is the return on educational investment (Robst, 2007). However, workers sometimes end up in jobs that are not closely related to the field of study of their degree, i.e., experience “mismatch”. One type of education mismatch – “horizontal mismatch” - occurs when an individual works in an occupation that is not related to their field of study. Workers may work in positions unrelated to their field of study (e.g., a worker with a degree in Statistics working as a web design technician) for a number of reasons, including being unable to find a matching job or family obligations. Empirical results have shown that workers in an occupation which does not match their education tend to earn lower wages compared to workers who are well matched (Robst, 2007; Kinsler and Pavan, 2015; Cassidy and Gaulke, 2024).

The U.S. economy addresses labor market demands in the digital age by attracting foreign talent (Hanson and Slaughter, 2016). An important question to ask, therefore, is how do immigrants perform in terms of educational matching compared to native workers? On the one hand, immigrants may be more likely to be mismatched than natives due to a lack of language proficiency, policy barriers (e.g., occupational licenses and recertification of foreign professionals) (Cassidy and Dacass, 2021; Rabben, 2013), employer bias, lack of familiarity with the labor market, and difficulty in getting foreign credentials recognized. On the other hand, immigrants also may be less likely to be mismatched because work-related immigrant visas usually require immigrants to be employed in jobs that match their education.

In this paper, I consider two questions. First, are college-educated immigrants more or less likely than college-educated natives to be well matched in terms of their job and their field of study? Second, do immigrants face a different earnings penalty than natives for being mismatched? I use the dataset from the National Survey of College Graduates (NSCG) 2019 to test the probability of being mismatched between immigrants and natives, and the earnings effect for immigrants in mismatched jobs.[1] Critically, the survey asks individuals whether their principal job is related to the field of study of their highest degree.

Regression results show male immigrants are 3.7 percentage points, or 20.56%, less likely to be mismatched than male natives, but this difference is driven largely by degree level and field of study. Controlling for these and other covariates, I find little difference in the mismatch rate between immigrant and native men. Overall, female immigrants and natives are equally likely to be mismatched. After controlling for various characteristics, while female immigrants are more likely to be mismatched, the difference is small and not statistically different from zero.

This paper also explores how immigrant visa is related to the probability of mismatch. Permanent resident visa holders have a higher probability of mismatch relative to temporary resident visas holders (e.g., H-1B visa holders), and the mismatch rate for work and study visas is much lower than for immigrants who arrived as dependents or for other reasons. The higher mismatch rate for non-temporary visa holders may be because immigrants who first come to the U.S. with permanent resident status have no working restriction. There is also the potential for selection bias, as immigrants who arrive as permanent residents differ in observable and unobservable was from those who arrive, for example, on temporary work visas. It is not surprising

[1] 2019 NSCG is the most recent one that does not have an issue with the visa question. Also, 2019 NSCG is pre-Covid, which helps to avoid potential issues related to Covid and data collection.

that the mismatch rate for temporary study and work visas is low since visas such as H-1B require employer sponsorship and a degree related to occupation, making mismatch unlikely.

Next, I compare whether there are differences between natives and immigrants in the earnings penalty from being mismatched. For natives, I find a penalty of 0.211 log points for male natives, and 0.269 log points for female natives. For immigrants, the penalty is much higher: for men, it is 0.333 log points higher than the penalty for mismatched native men, while for women, it is 0.270 log points higher than the penalty for mismatched native women. Field of study explains about 20% of the earnings mismatch penalty gap between natives and immigrants, which means immigrants tend to have degrees in fields of study where working in an unrelated job is relatively costly. However, most of the greater mismatch penalty faced by immigrants relative to natives remains unexplained. Recently arrived male immigrants face a slightly larger earnings penalty relative to native men than overall male immigrants, but the earnings penalty relative to native women for recently arrive female immigrants is smaller than overall female immigrants. The difference is marginally statistically significant for male immigrants and statistically insignificant for female immigrants.

My evidence suggests that the earnings penalty from mismatch for immigrants is much higher than natives. Efforts to bring in educated and skilled immigrants should carefully consider how to mitigate mismatches among immigrants. For example, helping immigrants acquire U.S.-specific human capital.

The structure of this paper is as follows. In section 2, I discuss the existing literature. In section 3, I discuss the data I use in my analysis. Section 4 discusses the results of the probability of mismatch analysis. Section 5 discusses the results of the earnings penalty analysis. Section 6 concludes.

## 2. Existing Literature

Educational mismatch occurs when the educational credentials of workers do not match their jobs requirements. Educational mismatch can be vertical, where the workers' education level is higher ("over-educated") or lower ("under-educated") relative to the requirements of their job. Ren and Miller (2010) use the China Health and Nutrition Survey and find that in the Chinese rural labor market, the returns to correctly matched education are much higher for women than for men, the wage penalty for workers who are under-educated in their jobs is significant for women, but relatively minor for men. Chiswick and Miller (2009) find that over-education is common in the U.S. high-skilled labor market, both for immigrants and native-born workers. They also note that the magnitude of over-education decreases with time since migration for immigrants, as high-skilled immigrants obtain jobs commensurate with their educational credentials.

Educational mismatches also can be horizontal when an employee works in a position that is not closely related to their field of study (e.g., a microbiology major working as an insurance agent). There are several papers that have studied horizontal mismatches using different datasets. Robst (2007) uses the 1993 NSCG and the same mismatch question as in this paper and finds that mismatched workers earn less than matching workers with the same field of study. Robst (2007) also finds that some majors teach many field-specific skills that are not transferable to other fields, leading to a negative wage effect of working outside the degree field. On the other hand, some degree fields have a large amount of generalized capital that is transferable to other fields, leading to a smaller negative wage effect from mismatch. He also notes that horizontal mismatches are more likely to occur in degree fields that provide general skills (e.g., non-STEM majors such as liberal arts and English) than in degree fields that provide specific occupational skills (e.g., STEM majors such as engineering and computer science). Manuel (2021) suggests that some degrees that are often considered “specific” produce graduates with highly generalized skills. Cassidy and Gaulke (2024) use four different years of the NSCG to show that the wage penalty from mismatch increased by 56% between 1993 and 2019.

Kinsler and Pavan (2015), using the Baccalaureate and Beyond Longitudinal Study (B&B), find that workers in science majors who are working in jobs unrelated to their field of study are paid about 30% less than those working in related jobs. They also observe that when deciding on a college major, individuals are uncertain about their future productivity.

Next, some articles have examined the impact of employer bias, occupational licensing, and recertification of foreign qualifications on immigration. Employers may show a bias against foreign education to reduce uncertainty, especially in countries with relatively low average quality of tertiary education, and place a higher value on domestic qualifications, which are more readily associated with productivity in the domestic labor market (Li and Yao 2023). Immigrants need to spend time, money, and effort to regain accreditation, for example, by taking exams and certifying overseas qualifications. Chapman and Iredale (1993), using data compiled by the Australian Federal Government, find that around 39% of skilled migrants choose to have their overseas qualifications assessed locally, with 42% of these qualifications found to be equivalent to their Australian counterparts, and that migrants from non-English-speaking countries receive lower incremental pay for their overseas qualifications compared to those with Australian qualifications. Rabben (2013) notes that obtaining a medical license is extremely time-consuming, expensive, and complex, which makes it unattainable for many foreign physicians who lack sufficient financial resources or time to study for and take the USMLE exam, or to apply and practice for an extended period. Occupational licenses and English proficiency have a negative effect on immigrants' ability to find suitable work. Cassidy and Dacass (2021) use data from the Current

Population Survey and the Survey of Income and Program Participation and find that immigrants are significantly less likely to be licensed than natives, and that this disparity is largest among males, the most educated workers, and non-naturalized immigrants.

# 3. Data

I use data from the National Science Foundation's 2019 National Survey of College Graduates (NSCG). The NSCG is a biennial survey that collects data on college graduates from any country who (1) have earned at least a bachelor's degree, (2) reside in the United States or Puerto Rico, and (3) are younger than 76 years old. The NSCG sample is drawn from college educated participants of the American Community Survey. The NSCG is sponsored by the National Science Foundation and administered by the Census Bureau.

My estimation sample is restricted to individuals aged 20-75 who are currently working full time and report a positive annualized salary and are not enrolled in any courses. The estimation sample includes 63,847 observations, and all results use the NSCG-provided weights to create a nationally representative sample.

The survey question I use to assess mismatch is: “To what extent was your work on your principal job related to your highest degree?” The answer options for this question are: (1) “Closely related”; (2) “Somewhat related"; (3) “Not related". Note that this question asks for the respondent's subjective self-report of whether their principal job is related to their degree field. This paper focuses on complete mismatches, where I consider those who answered (1) or (2) to this question as matched and those who answered (3) as mismatched. Individuals who answered a complete mismatch were also asked about the most important reasons for working in a job unrelated to the field of their highest degree. In a robustness test where I consider those who answered (1) are considered matched and those answered (2) or (3) are considered mismatched, the results are very similar (see Appendix A).

Mismatch rate may vary depending on whether the individual received at least some education in the U.S. Individuals report the location of school awarding their most recent degree, which I use to create a dummy variable that indicates if a worker has U.S. educational credentials. Mismatch may also differ depending on whether the individual's field of study is STEM-related. I consider a worker to be "STEM" if the field of study for their highest degree is STEM-related.[2]

I use citizenship status to classify immigrants and natives. Foreign born are classified as immigrants and individuals who report being born in the United States and born abroad of U.S. citizen parent(s) are natives. Non-citizens indicate their visa as of February 1, 2019, including either permanent resident visa (and the year in which it was obtained) or a temporary resident visa. Both naturalized citizens and non-U.S. citizens also answer as to the type of visa they held when they first traveled to the U.S. for six months or more, with possible answers being (1) U.S. Permanent Resident Visa (Green Card), (2) Temporary Work Visa, (3) Temporary Study or Training, (4) Temporary Visa as a Dependent, and (5) Other Temporary Resident Visa, please specify.

**Table 1: Summary Statistics**

| | Men | | Women | |
|---|---|---|---|---|
| | Immigrant | Native | Immigrant | Native |
| Variable | Mean | Mean | Mean | Mean |
| **Mismatch** | | | | |
| Closely related | 0.614 | 0.513 | 0.595 | 0.576 |
| Somewhat related | 0.237 | 0.301 | 0.241 | 0.255 |
| Not related | 0.149 | 0.186 | 0.164 | 0.168 |
| STEM | 0.618 | 0.343 | 0.439 | 0.237 |
| Age | 44.979 | 44.558 | 43.534 | 42.311 |
| Married | 0.774 | 0.687 | 0.701 | 0.564 |
| **Race** | | | | |
| Asian | 0.495 | 0.030 | 0.513 | 0.031 |

[2] I consider the following fields to be STEM: Computer and information sciences, Mathematical sciences, Agricultural and food sciences, Biological sciences, Environmental life sciences, Chemistry, except biochemistry, Earth science, Geology, and oceanography, Physics and astronomy, Other physical sciences, Aerospace and related engineering, Chemical engineering, Civil and architectural engineering, Electrical and related engineering, Industrial engineering, Mechanical engineering, Other engineering, Health-related fields, and Technology and Technical Fields.

| | | | | |
|---|---|---|---|---|
| American Indian | 0.001 | 0.004 | 0.001 | 0.007 |
| Black | 0.096 | 0.058 | 0.078 | 0.100 |
| White | 0.383 | 0.879 | 0.373 | 0.825 |
| Native Hawaiian | 0.008 | 0.004 | 0.012 | 0.002 |
| Multiple Race | 0.018 | 0.025 | 0.024 | 0.034 |
| Hispanic | 0.153 | 0.068 | 0.207 | 0.083 |
| **Highest degree type** | | | | |
| Bachelor's | 0.490 | 0.663 | 0.553 | 0.601 |
| Master's | 0.332 | 0.231 | 0.320 | 0.319 |
| Doctorate | 0.122 | 0.036 | 0.077 | 0.032 |
| Professional | 0.056 | 0.070 | 0.051 | 0.048 |
| Observations | 10,527 | 27,227 | 5,909 | 20,184 |

*Source: 2019 National Survey of College Graduates.*

Table 1 shows summary statistics of my sample, separately for men and women, as well as separately for immigrants and natives. Male immigrants are 10 percentage points more likely to be *closely related* to their occupation than male natives. Female immigrants are only around 2 percentage point more likely to be *closely related* than female natives.

Compared to natives, immigrants are more likely to have a higher education level, such as a master’s or a Doctorate. Immigrants are also more likely to have a field of study in STEM: male immigrants are 27 percentage points more likely to have a STEM education than male natives, while female immigrants are 20 percentage points more likely to have a STEM education than female natives.

Natives are about 47 percentage points more likely to be Whites than immigrants and immigrants are 46 percentage points more likely to be Asian than natives. The average age of immigrants is slightly higher than natives. Immigrants are 11 percentage points more likely to be married than natives.

**Table 2: Most important reason for working outside field of highest degree**

| Most important reason for working outside field of highest degree | Male | | Female | |
|---|---|---|---|---|
| | Immigrant | Native | Immigrant | Native |
| Pay, promotion opportunities | 35.23 | 34.60 | 12.16 | 30.11 |
| Working conditions | 6.93 | 11.09 | 12.03 | 10.61 |

| | | | | |
|---|---|---|---|---|
| Job location | 3.65 | 8.16 | 5.36 | 7.79 |
| Change in career or professional interests | 14.61 | 18.29 | 18.88 | 18.16 |
| Family-related | 14.85 | 5.52 | 21.20 | 11.85 |
| Job in highest degree field not available | 18.11 | 15.76 | 16.97 | 15.44 |
| Other reason | 6.62 | 6.57 | 13.39 | 6.03 |
| Total | 100.00 | 100.00 | 100.00 | 100.00 |

*Source: 2019 National Survey of College Graduates.*

Table 2 shows the distribution of the most important reasons for being mismatched, separately for men and women, as well as separately for immigrants and natives, among mismatched workers. Women are more likely than men to be mismatched for *family-related* reasons while men are more likely to report mismatch due to *pay, promotion opportunities*. Both male and female immigrants are more likely to be mismatched for *family-related* reasons than natives, especially male immigrants, who are nearly three times as likely as male natives to be mismatched for *family-related reasons*. Male natives are more likely than male immigrants to be mismatched due to *change-in-career* and *working conditions*, while female natives are more likely than female immigrants to be mismatched due to *pay, promotion opportunities*. The dataset does not record the answers for *other reason*, and it is not clear why female immigrants are twice as likely as natives to answer *other reason*.

# 4. Results: Probability of Mismatch

Table 1 indicates that male immigrants are less likely to be mismatched than male natives, while the overall mismatch rate is similar between native women and immigrant women. However, these overall percentages do not adjust for characteristics such as age, race, degree level, and degree field, and Table 1 also indicates large differences in these characteristics between immigrants and natives. I use the following linear probability model to test for a difference in mismatch rate between natives and immigrants, adjusting for these characteristics:

$$Mismatch_i = \beta_X X_i + \beta_{Immigrant} Immigrant_i + \beta_{STEM} STEM_i + \beta_{US\ degree} US\ degree_i + \varepsilon_i \quad (1)$$

where $Mismatch_i$ equals one if individual $i$ reports that their principal job is not related to their highest degree, and zero otherwise. $X_i$ includes a vector of demographic variables including age, marital status, race, and highest degree type. The dummy variable $Immigrant_i$ equals one if person $i$ is an immigrant, and zero otherwise. $STEM_i$ is a dummy variable that equals one if person $i$ degree field is in STEM, and zero otherwise. $US\ degree_i$ is a dummy variable that equals one if person $i$ received most recent degree in the U.S., and zero otherwise.

**Table 3: Probability of Mismatch**

| | (1)<br>Model 1 | (2)<br>Model 2 | (3)<br>Model 3 | (4)<br>Model 4 | (5)<br>Model 5 |
|---|---|---|---|---|---|
| **Panel A: Men** | | | | | |
| Immigrant | -0.037** | -0.016 | 0.005 | 0.025 | 0.011 |
| | (0.013) | (0.017) | (0.017) | (0.017) | (0.019) |
| Master's | | -0.125*** | -0.131*** | -0.111*** | -0.110*** |
| | | (0.011) | (0.011) | (0.011) | (0.011) |
| Doctorate | | -0.178*** | -0.154*** | -0.215*** | -0.212*** |
| | | (0.015) | (0.014) | (0.017) | (0.017) |
| Professional | | -0.204*** | -0.192*** | -0.217*** | -0.216*** |
| | | (0.011) | (0.011) | (0.022) | (0.022) |
| STEM | | | -0.107*** | | |
| | | | (0.010) | | |
| U.S. degree | | | | | -0.034 |

| | | | | | |
|---|---|---|---|---|---|
| | | | | | (0.021) |
| Demographics | No | Yes | Yes | Yes | Yes |
| Degree field | No | No | No | Yes | Yes |
| Observations | 37,754 | 37,754 | 37,754 | 37,754 | 37,754 |
| Probability of mismatch | 0.180 | 0.180 | 0.180 | 0.180 | 0.180 |

| | | | | | |
|---|---|---|---|---|---|
| **Panel B: Women** | | | | | |
| Immigrant | -0.005 | 0.019 | 0.026 | 0.026 | 0.015 |
| | (0.016) | (0.020) | (0.020) | (0.020) | (0.022) |
| Master's | | -0.143*** | -0.145*** | -0.119*** | -0.117*** |
| | | (0.011) | (0.011) | (0.012) | (0.012) |
| Doctorate | | -0.210*** | -0.195*** | -0.223*** | -0.221*** |
| | | (0.011) | (0.011) | (0.012) | (0.012) |
| Professional | | -0.181*** | -0.167*** | -0.164*** | -0.163*** |
| | | (0.015) | (0.015) | (0.019) | (0.019) |
| STEM | | | -0.058*** | | |
| | | | (0.011) | | |
| U.S. degree | | | | | -0.037 |
| | | | | | (0.030) |
| Demographics | No | Yes | Yes | Yes | Yes |
| Degree field | No | No | No | Yes | Yes |
| Observations | 26,093 | 26,093 | 26,093 | 26,093 | 26,093 |
| Probability of mismatch | 0.168 | 0.168 | 0.168 | 0.168 | 0.168 |

*Robust standard errors in parentheses*
*Source: 2019 National Survey of College Graduates. Dependent variable is probability of mismatch. Demographics (for all models) are age, age squared, marital status, race/ethnicity.*
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3 shows the results for probability of mismatch for men and women. Panel A shows the results for men, with model 1 including only the immigrant dummy variable as a control. I find that male immigrants are 3.7 percentage points, or 20.56% (0.037 divided by overall mismatch rate of 0.180), less likely to be mismatched than natives. Adding controls for demographics and educational degree (model 2) reduces the magnitude on the immigrant dummy variable coefficient to only 0.016 percentage points, due largely to immigrants being more likely to have a higher degree and mismatch rate decreasing with education level. Model 3 adds a control for STEM, and the coefficient on the immigrant dummy variable becomes positive (0.005) but is statistically insignificant. The coefficient on STEM indicates male workers with a field of study in STEM are 10.7 percentage points, or 59.44%, less likely to be mismatched relative to male workers with a degree from a non-STEM field. This result is consistent with Robst (2007) who finds that mismatches are less likely to occur in majors which provide specific occupational skills. Model 4 replaces STEM with degree field minor group that provide more detail on field of study, and the immigrant dummy variable coefficient increased to 0.025 but remains statistically insignificant. Model 5 adds control for U.S. degree, the coefficient shows male workers with U.S. educational credentials are 3.4 percentage points, or 18.89%, less likely to be mismatched, though the coefficient is insignificant.

Panel B shows the regression results for women. Adding more controls makes immigrants more likely to be mismatched for both men and women. However, the overall rate starts negative for men, and for women it starts close to zero. The baseline model shows female immigrants are equally likely to be mismatched as natives, as the summary statistics table already showed. After controlling for demographics and educational level, the immigrant coefficient is now 0.019. Adding STEM (model 3) further increases the immigrant coefficient to 0.026 but it is only marginally statistically significant. Controlling for degree fields instead of STEM (model 4), the immigrant coefficient remains the same. Model 5 shows female workers with U.S. educational credentials are 3.7 percentage points, or 22.02%, less likely to be mismatched, but the coefficient is only marginally significant. Furthermore, controlling for U.S. degree receipt, the immigrant coefficient shrinks to 0.015, and is no longer even marginally statistically significant.

**Table 4: Decomposition**

| | (1)<br>Men | (2)<br>Women |
|---|---|---|
| Immigrant | | |
| Demographics | 0.014 | -0.005 |
| | (0.010) | (0.012) |

| | | |
|---|---|---|
| Degree | -0.026$^{***}$ | -0.011$^{***}$ |
| | (0.003) | (0.003) |
| Degree Field | -0.049$^{***}$ | -0.016$^{***}$ |
| | (0.004) | (0.005) |
| U.S. degree | 0.014 | 0.013 |
| | (0.009) | (0.010) |
| Total change | -0.047$^{**}$ | -0.020 |
| | (0.015) | (0.015) |
| Observations | 37,754 | 26,093 |

*Robust standard errors in parentheses*
*The results in this table were created with the Stata program b1x2, written by Gelbach (2016).*
$^{*}$ *$p < 0.05$,* $^{**}$ *$p < 0.01$,* $^{***}$ *$p < 0.001$*

Adding the covariates sequentially and interpreting the change in the immigration coefficient before and after the addition of each group of covariates can produce misleading results because it does not account for correlations between covariates (e.g., demographics and field of study) and is sensitive to the order in which these covariates are added. Instead, I use the methodology from Gelbach (2016) to decompose the change in the immigrant coefficient attributable to each group of covariates between the baseline model (model 1) and the full model (model 5). The results are shown in table 4, with the results for men in column 1 and the results for women in column 2. As column 1 shows, of the -0.047 change in the immigrant coefficient for men between models 1 and 5, degree field explains -0.049 and highest degree explains -0.026. Since male immigrants are more likely to have a field of degree in STEM and higher education, these two factors combined explain why male immigrants are more likely to be well matched than natives. The U.S. degree dummy variable explains 0.014 of the -0.047 change which means that controlling for U.S. degree expands the immigrant coefficient (i.e., makes it more negative). Including demographic controls have little influence (only 0.014) on the immigrant coefficient.

As shown in column 2, the immigrant coefficient for women changes by only -0.020 between the baseline model and full model. Of this, degree field explains -0.016 and highest degree type explains -0.011, while demographics explain -0.005. However, like men, adding a control for

U.S. degree expands the immigrant coefficient for women by 0.013. Overall, the results are similar for women as for men, though more muted.

It is possible that mismatch among immigrants might differ depending on the type of immigration. For example, limitations on temporary work visas mean that immigrants need to be matched with a position to obtain a visa, which helps to offset the increased rate of mismatches due to the previously mentioned barriers. By using the entry visa type, I can test whether the mismatch rate of immigrants is related to their entry visa.

**Figure 1: Distribution of first visa types for overall and recently arrived immigrants**

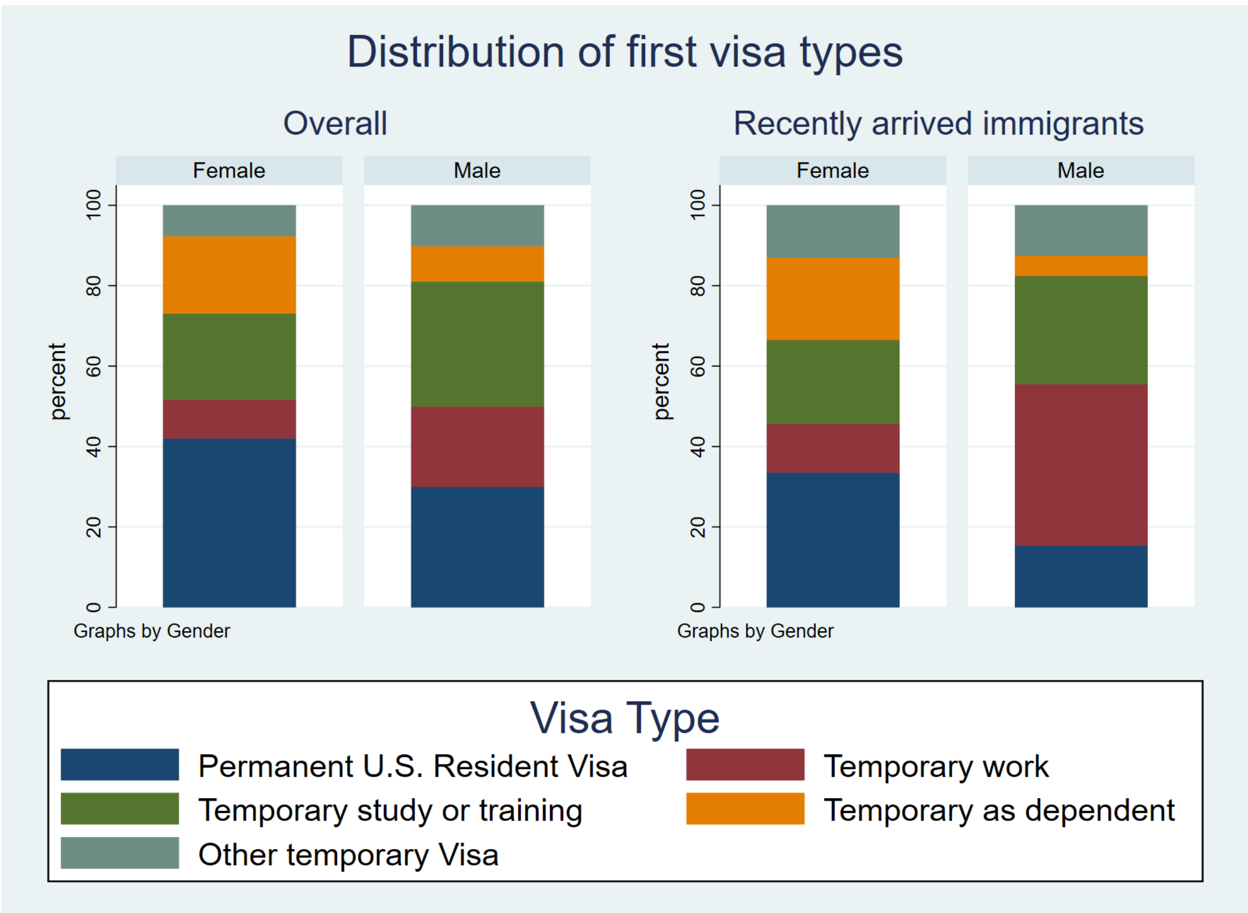


Figure 1 shows the distribution of immigrant visa, both for overall immigrants and recently arrived immigrants, where recently arrived means the number of years since they first came to the

United States for six months or longer is less than or equal to five. The proportion of men that came to the U.S. as a permanent resident or on a temporary study visa are about the same, followed by temporary work, dependent and other temporary visa. Female immigrants are more likely to enter the U.S. as a permanent resident, potentially because they have a sponsor from family or spouse in the U.S. instead of getting sponsor from an employer and entering on a temporary work visa. Women are also more likely to come in as dependent than men if their family members are studying or working in U.S.

The right side of the graph shows recently arrived immigrants only. Male immigrants more likely than female immigrants to come to U.S. on a study and working visa, while men are less likely to come in as a dependent. The highest proportion of recently arrived female immigrants are permanent residents, followed by dependent and study visas. The proportion of other temporary visa are about the same for both recently arrived female and male immigrants.

**Table 5: Probability of Mismatch and First Visa type**

| | (1)<br>Men | (2)<br>Men | (3)<br>Women | (4)<br>Women |
|---|---|---|---|---|
| Permanent U.S. Resident Visa | 0.024 | 0.030 | 0.053 | 0.047 |
| | (0.023) | (0.025) | (0.029) | (0.030) |
| Temporary work | -0.110*** | -0.062** | -0.087*** | -0.044 |
| | (0.017) | (0.021) | (0.021) | (0.027) |
| Temporary study or training | -0.106*** | -0.024 | -0.088*** | 0.002 |
| | (0.017) | (0.021) | (0.022) | (0.025) |
| Temporary as dependent | 0.038 | 0.065 | -0.042 | 0.001 |
| | (0.046) | (0.043) | (0.024) | (0.027) |
| Other temporary Visa | 0.075 | 0.055 | 0.101 | 0.081 |
| | (0.051) | (0.047) | (0.072) | (0.069) |
| Demographics | No | Yes | No | Yes |
| Highest degree type | No | Yes | No | Yes |
| Degree field | No | Yes | No | Yes |
| Observations | 37,714 | 37,714 | 26,062 | 26,062 |

| | | | | |
|---|---|---|---|---|
| Probability of mismatch | 0.180 | 0.180 | 0.168 | 0.168 |

*Robust standard errors in parentheses*
*Source: 2019 National Survey of College Graduates. Demographics (for all models) are age, age squared, marital status, race/ethnicity.*
$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

I repeat my estimations results from Table 3, but where instead of controlling for an immigrant dummy variable, I control for first visa type among immigrants. Results are shown in Table 5, where for brevity, I show only the baseline model (model 1) and full model (model 5), but again separately for men (columns 1 and 2) and women (columns 3 and 4). For both men and women, mismatch rates are lower for first-time arrivals in the United States on temporary work and study or training visas, relative to the omitted group of natives. However, permanent residents and other temporary visas have higher mismatch rates than natives, especially among female immigrants. Permanent residents may accept mismatched jobs because family sponsorship (e.g., by parents) eliminates the need for employer-sponsored visas. There is also likely selection bias, as permanent residents differ from those who arrive on temporary work visas. Work or training visa holders need to be sponsored by an employer to obtain a visa, meaning that they are very likely to work in a position related to their field of study for the duration of their sponsorship or they will not be able to obtain a visa. Study visa holders may undertake optional practical training after graduating from college and may continue to work in the U.S. if they find an employer willing to sponsor them and win a temporary work visa lottery, all of which will involve being more likely to work in a matching job. Dependent mismatches may be because the spouse is more restricted in their job search, leading to higher incidences of mismatch. The dataset does not record the specific visa type for other temporary U.S. resident visa, and the reasons why they are more likely to be mismatched are ambiguous.

**Table 6: Probability of Mismatch First Visa type for Recently Arrived Immigrants and Native**

| | (1) Men | (2) Men | (3) Women | (4) Women |
|---|---|---|---|---|
| Permanent U.S. Resident Visa | 0.223* | 0.248** | 0.128 | 0.101 |
| | (0.101) | (0.092) | (0.147) | (0.148) |
| Temporary work | -0.115** | -0.070 | -0.153*** | -0.091** |
| | (0.035) | (0.039) | (0.017) | (0.031) |
| Temporary study or training | -0.036 | 0.059 | -0.103** | 0.042 |
| | (0.105) | (0.089) | (0.038) | (0.043) |
| Temporary as dependent | -0.130*** | -0.149** | -0.063 | 0.011 |
| | (0.038) | (0.052) | (0.067) | (0.075) |
| Other temporary Visa | 0.202 | 0.155 | -0.007 | -0.024 |
| | (0.174) | (0.151) | (0.126) | (0.124) |
| Demographics | No | Yes | No | Yes |
| Highest degree type | No | Yes | No | Yes |
| Degree field | No | Yes | No | Yes |
| Observations | 28,037 | 28,037 | 20,582 | 20,582 |
| Probability of mismatch | 0.186 | 0.186 | 0.168 | 0.168 |

*Robust standard errors in parentheses*
*Source: 2019 National Survey of College Graduates. Demographics (for all models) are age, age squared, marital status, race/ethnicity.*
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 1 shows that the distribution of entry visa for recently arrived immigrants is different from overall immigrants. Male immigrants are more likely to enter the U.S. on a temporary study or work visa, and female immigrants are more likely to enter the U.S. as a permanent resident or dependent. As immigrants accumulate length of stay in the United States, their visa status may change. For instance, from temporary visa to permanent resident or from permanent resident to naturalized citizen. I test recently arrived immigrants and compare them to natives to determine whether the mismatch rate of recently arrived immigrants and visa status transitions impact the mismatch rate of overall immigrants. Table 6 is identical to Table 5, but where I restrict my sample to natives and recently arrived immigrants. Comparing recently arrived immigrants with natives, immigrants who arrive as permanent residents are more likely to be mismatched relative to overall immigrants. The higher overall mismatch rate for permanent residents may be due to recent arrivals and those who have adjusted their status from permanent residence. 86.62% of immigrants who first arrived in the United States as permanent residents have become naturalized citizens. Temporary work and study visa holders are more likely to be matched than permanent residents for both men and women, but this difference is due largely to demographics, degree and field of study. 28.40% of immigrants who first came to U.S. as temporary work and 24.99% of immigrants who first came to U.S. as temporary study or training have obtained permanent resident status. Female immigrants arriving as other temporary visa recently are more likely to be matched than natives, but the explanation for why is unclear.

## 5. Results: Mismatch penalty

Robst (2007) found that mismatched workers face a wage penalty compared to well-matched workers with the same degree field, and the penalty is larger for majors that teach a substantial number of specific skills that are not transferable to other fields. Section 4 indicates that male immigrants are more likely than natives to be well matched in terms of their job and their field of study, and these differences are due largely to field of study and degree level. But are there differences in the earnings penalties that immigrants face for being mismatched compared to native workers? I use the following model to test whether there is a difference in earnings penalties between immigrants and natives due to mismatch, and if so, what variables might help to explain this difference:

$$Y_i = \beta_X X_i + \beta_{Mismatch} Mismatch_i + \beta_{Immigrant} Immigrant_i + \beta_{STEM} STEM_i + \beta_{US\ degree} US\ degree_i + \beta_{Mismatch \times Immigrant} Mismatch_i \times Immigrant_i + \beta_{Mismatch \times STEM} Mismatch_i \times STEM_i + \beta_{Mismatch \times US\ degree} Mismatch_i \times US\ degree_i + \varepsilon_i \tag{2}$$

where $Y_i$ is log annualized salary for individual $i$. The dummy variables $Mismatch_i$, $Immigrant_i$, $STEM_i$, and $US\ degree_i$ are defined as in the previous section, as is the vector of demographic variables $X_i$. The term $Mismatch_i \times Immigrant_i$ tests if the earnings penalty of working in a job unrelated to field of degree differs between immigrants and natives.[3] $Mismatch_i \times STEM_i$ tests whether mismatch penalty is greater for workers with a STEM degree working in a job not related to their field, compared to non-STEM majors. $Mismatch_i \times US\ degree_i$ tests if the mismatch

[3] I briefly discuss the results from the three-category mismatch: closely related, somewhat related, and not related, see Appendix B.

penalty is greater for a worker whose most recent degree was received in the U.S. versus those who received their most recent degree outside the U.S.

**Table 7: OLS Regression, Log Annualized Salary**

| | (1) Model 1 | (2) Model 2 | (3) Model 3 | (4) Model 4 | (5) Model 5 | (6) Model 6 |
|---|---|---|---|---|---|---|
| **Panel A: Men** | | | | | | |
| Mismatch | -0.392*** | -0.275*** | -0.211*** | -0.255*** | | |
| | (0.027) | (0.026) | (0.027) | (0.031) | | |
| Immigrant | 0.136*** | 0.062* | 0.018 | 0.059* | 0.010 | 0.052 |
| | (0.023) | (0.028) | (0.028) | (0.028) | (0.028) | (0.029) |
| Mismatch × Immigrant | -0.345*** | -0.306*** | -0.333*** | -0.291*** | -0.264** | -0.242* |
| | (0.085) | (0.076) | (0.075) | (0.078) | (0.080) | (0.120) |
| STEM | | 0.156*** | | 0.168*** | | |
| | | (0.016) | | (0.017) | | |
| Mismatch × STEM | | | | -0.084 | | |
| | | | | (0.049) | | |
| U.S. degree | | | | | | 0.104** |
| | | | | | | (0.034) |
| Mismatch × U.S. degree | | | | | | 0.033 |
| | | | | | | (0.123) |
| Demographics | No | Yes | Yes | Yes | Yes | Yes |
| Highest degree type | No | Yes | Yes | Yes | Yes | Yes |
| Field of degree minor group | No | No | Yes | No | Yes | Yes |
| Mismatch × Field of degree | No | No | No | No | Yes | Yes |
| Observations | 37,754 | 37,754 | 37,754 | 37,754 | 37,754 | 37,754 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Panel B: Women** | | | | | | |
| Mismatch | -0.269*** | -0.176*** | -0.173*** | -0.143*** | | |
| | (0.031) | (0.033) | (0.032) | (0.036) | | |
| Immigrant | 0.186*** | 0.016 | -0.014 | 0.012 | -0.026 | 0.052 |
| | (0.030) | (0.033) | (0.033) | (0.033) | (0.033) | (0.031) |
| Mismatch × Immigrant | -0.315*** | -0.284*** | -0.270*** | -0.261** | -0.208* | -0.166 |
| | (0.083) | (0.079) | (0.081) | (0.081) | (0.082) | (0.104) |
| STEM | | 0.158*** | | 0.183*** | | |
| | | (0.021) | | (0.023) | | |
| Mismatch × STEM | | | | -0.187** | | |
| | | | | (0.057) | | |
| U.S. degree | | | | | | 0.268*** |
| | | | | | | (0.047) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Mismatch × U.S. degree | | | | | | 0.049 |
| | | | | | | (0.121) |
| Demographics | No | Yes | Yes | Yes | Yes | Yes |
| Highest degree type | No | Yes | Yes | Yes | Yes | Yes |
| Field of degree minor group | No | No | Yes | No | Yes | Yes |
| Mismatch × Field of degree | No | No | No | No | Yes | Yes |
| Observations | 26,093 | 26,093 | 26,093 | 26,093 | 26,093 | 26,093 |

*Robust standard errors in parentheses*
*Source: 2019 National Survey of College Graduates. Dependent variable is log annualized salary. Demographics (for all models) are age, age squared, marital status, race/ethnicity.*
$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Table 7 shows the earnings penalty due to being mismatched for immigrants and natives, separately for men (panel A) and women (panel B). Without any additional controls, and consistent with previous literature, I find a mismatch penalty for natives of 0.392 log points for men and 0.269 log points for women.

I find that the mismatch penalty for immigrants is significantly larger than for natives. In model 1, where I only include controls for immigrant status, mismatch, and mismatch interacted with immigrant status, the earnings penalty for male immigrants is 0.345 log points larger than male natives and for female immigrants is 0.315 log points larger than female natives. Model 2 adds controls for demographics and STEM, which reduces the overall earnings penalty significantly. However, while the gap in the mismatch penalty between immigrants and natives decreases, the change is modest for both men and women. Model 3 adds controls for all fields of study, and again the overall mismatch penalty decreases, but the mismatch penalty gap between immigrants and natives expands slightly for men and contracts slightly for women. Thus, even with a rich set of controls, I find that immigrants face a substantially higher mismatch penalty than otherwise-similar natives.

To explore the reasons why immigrants have a higher mismatch penalty than natives, I test whether the higher mismatch penalty is due to immigrants being more likely to be in the fields of study where mismatch is more heavily penalized. Model 4 adds the mismatch and STEM interaction term which allows the earnings penalty to differ between STEM and non-STEM fields of study. The coefficient on the mismatch interacted with STEM in model 4 is -0.084 log points for men and -0.187 log points for women. The difference in the mismatch penalty for STEM versus non-STEM degrees is statistically significant for both men and women. Moving from model 3 to model 4, the mismatch interacted with immigrant coefficient decreases 0.042 log points for men and 0.009 log points for women. These changes mean the mismatch penalty between immigrants and natives is slightly reduced due to the penalty differing between STEM and non-STEM degree and immigrants being more likely to be in STEM majors. Model 5 replaces STEM with fields of study code to allow the mismatch penalty to vary across all fields of study, and not just STEM versus non-STEM. Comparing model 4 and model 5, the mismatch interacted with immigrant coefficient decreases 0.027 log points for men and 0.053 log points for women. These change shows that immigrants being more likely to be in the fields of study where mismatch is relatively more penalized is part of the reason that immigrants face a greater mismatch penalty than natives.

Model 6 includes controls for U.S. degree and U.S. degree interacted with mismatch. The earnings penalty for workers with U.S. educational credential is 0.033 log points lower (less negative) for men and 0.049 lower for women, though both coefficients are not statistically different from zero. By comparing model 5 and model 6, the mismatch interacted with immigrant coefficient reduces 0.022 log points for men and 0.042 for women which become marginally statistically significant. These changes indicate the mismatch penalty is different for immigrants with U.S. educational credential versus those who with non-U.S. educational credential. However, there is still a substantial earnings mismatch penalty gap between immigrants and natives which the model can't explain.

**Table 8: OLS Regression, Log Annualized Salary for Natives and Recently Arrived Immigrants**

| | (1) Men | (2) Women |
|---|---|---|
| Mismatch | -0.420$^{*}$ | -0.564$^{*}$ |
| | (0.213) | (0.231) |
| Recently arrived immigrants | -0.021 | -0.144$^{**}$ |
| | (0.048) | (0.053) |
| Mismatch × Recently arrived immigrants | -0.292 | -0.114 |
| | (0.174) | (0.199) |
| U.S. degree | 0.084 | 0.152$^{**}$ |
| | (0.054) | (0.056) |
| Mismatch × U.S. degree | -0.068 | -0.101 |
| | (0.181) | (0.205) |
| Demographics | Yes | Yes |
| Highest degree type | Yes | Yes |
| Field of degree minor group | Yes | Yes |
| Mismatch*Field of degree | Yes | Yes |
| Observations | 29754 | 21470 |

*Robust standard errors in parentheses*
*Source: 2019 National Survey of College Graduates. Dependent variable is log annualized salary. Demographics (for all models) are age, age squared, marital status, race/ethnicity.*
$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

The earnings penalty may differ among immigrants who are new to the U.S. versus those who have been in the country for some time. Work experience in the U.S. might result in a different mismatch penalty, as immigrant workers become more familiar with the U.S. labor market and acquire U.S.-specific human capital.

I repeat my estimations results from Table 7, but where I restrict the sample to natives and recently arrived immigrants. The results are shown in Table 8, where for brevity, I only show the full model (model 6), but again separately for men (column 1) and women (column 2). The mismatch penalty when controlling for various characteristics for recently arrived male immigrants is 0.292 log points greater than male natives and for recently arrived female immigrants is 0.114

log points greater than female natives. Comparing the differences in the earnings penalty between immigrants and natives among all immigrants versus only recent immigrants, I find that the earnings penalty is 0.050 log points greater for recently arrived men, but 0.052 log points less for recently arrived women. Recently arrived male immigrants face slightly larger earnings penalty results from mismatch than overall male immigrants, which is consistent with time since migration mitigating the higher cost of mismatch among immigrants, though recently arrived women have a smaller mismatch penalty than natives, relative to overall female immigrants.

# 6. Conclusion

This paper explores two questions. First, how does the probability of college-educated immigrants being mismatched in their job with their field of study differ from natives? Second, do immigrants and natives experience different earnings penalty from mismatch? I find that educational level and field of study are the main reasons why male immigrants are more likely to be well-matched than male natives. Compared with natives, immigrants tend to have higher educational degree and field of study in STEM field, both of which help to reduce the mismatch rate. Immigrant women have a similar mismatch rate as native women. Controlling for demographics, education degree, and field of study, I find that female immigrants are slightly more likely to be mismatched than female natives. Regression results show master's, Doctorate degree, and professional degree are less likely to be mismatched than bachelor's degree, and STEM degree holders are less likely to be mismatched than non-STEM.

By looking for the type of visa on which immigrants first entered the United States, the results show immigrants who entered the U.S. on a temporary work visa like H-1B are less likely to be mismatched than permanent residents. The requirements for H-1B, being an employer-sponsored visa that require your occupation to align with your education, mean these immigrants are very likely to work in a position related to their field of study to obtain their work visa. Permanent residents, however, are not subject to work restrictions. Recently arrived immigrants and adjustments in visa status contribute to the higher mismatch rate for permanent residents and lower mismatch rate for temporary work visa. There is likely selection bias, as permanent residents differ from those who arrive on temporary work visas.

I find that immigrants face greater earnings penalty from mismatch than natives. For both male and female immigrants, part of the higher mismatch penalty faced by immigrants can be attributed to immigrants being more likely to have fields of study, e.g., STEM-related fields, where mismatch is more costly. However, even controlling for field-specific mismatch penalty, immigrants face a substantially higher mismatch penalty than natives. Recently arrived male immigrants experience slightly larger earnings penalty relative to men native than overall male immigrants, while the earnings penalty relative to women native for recently arrived female immigrants is smaller than overall female immigrants.

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**Appendix A A.1Appendix B A.1**

# Appendix A - Probability of Mismatch Under Alternative Definition

**Table 9: Probability of Mismatch**

| | (1)<br>Model 1 | (2)<br>Model 2 | (3)<br>Model 3 | (4)<br>Model 4 | (5)<br>Model 5 |
|---|---|---|---|---|---|
| **Panel A: Men** | | | | | |
| Immigrant | -0.100*** | -0.050** | -0.023 | -0.013 | -0.022 |
| | (0.015) | (0.018) | (0.018) | (0.019) | (0.020) |
| Master's | | -0.188*** | -0.196*** | -0.162*** | -0.161*** |
| | | (0.014) | (0.014) | (0.015) | (0.015) |
| Doctorate | | -0.367*** | -0.337*** | -0.385*** | -0.384*** |
| | | (0.018) | (0.017) | (0.019) | (0.019) |
| Professional | | -0.484*** | -0.468*** | -0.420*** | -0.419*** |
| | | (0.015) | (0.015) | (0.027) | (0.027) |
| STEM | | | -0.138*** | | |
| | | | (0.012) | | |
| U.S. degree | | | | | -0.021 |
| | | | | | (0.023) |
| Demographics | No | Yes | Yes | Yes | Yes |
| Degree field | No | No | No | Yes | Yes |
| Observations | 37,754 | 37,754 | 37,754 | 37,754 | 37,754 |
| Probability of mismatch | 0.469 | 0.469 | 0.469 | 0.469 | 0.469 |
| **Panel B: Women** | | | | | |
| Immigrant | -0.019 | 0.025 | 0.044 | 0.025 | 0.023 |
| | (0.021) | (0.025) | (0.024) | (0.024) | (0.025) |
| Master's | | -0.243*** | -0.248*** | -0.164*** | -0.164*** |
| | | (0.016) | (0.016) | (0.016) | (0.016) |
| Doctorate | | -0.379*** | -0.342*** | -0.364*** | -0.363*** |
| | | (0.019) | (0.020) | (0.020) | (0.020) |
| Professional | | -0.368*** | -0.333*** | -0.294*** | -0.294*** |
| | | (0.025) | (0.024) | (0.026) | (0.026) |
| STEM | | | -0.152*** | | |
| | | | (0.014) | | |
| U.S. degree | | | | | -0.009 |
| | | | | | (0.035) |
| Demographics | No | Yes | Yes | Yes | Yes |
| Degree field | No | No | No | Yes | Yes |
| Observations | 26,093 | 26,093 | 26,093 | 26,093 | 26,093 |
| Probability of mismatch | 0.421 | 0.421 | 0.421 | 0.421 | 0.421 |

*Robust standard errors in parentheses*

*Source: 2019 National Survey of College Graduates. Dependent variable is probability of mismatch. Demographics (for all models) are age, age squared, marital status, race/ethnicity.*
$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Table 9 shows the results for probability of mismatch using alternative definitions where only *closely related* responses are considered as matched for men (panel A) and women (panel B). The qualitative and quantitative of the results are very similar to table 3.

# Appendix B - Earnings mismatch penalty with categorical variable

**Table 10: OLS Regression, Log Annualized Salary**

| | (1) Model 1 | (2) Model 2 | (3) Model 3 | (4) Model 4 | (5) Model 5 | (6) Model 6 |
|---|---|---|---|---|---|---|
| **Panel A: Men** | | | | | | |
| Somewhat related | -0.158*** | -0.066** | -0.093*** | -0.052 | | |
| | (0.026) | (0.023) | (0.022) | (0.030) | | |
| Not related | -0.450*** | -0.304*** | -0.252*** | -0.280*** | | |
| | (0.029) | (0.028) | (0.028) | (0.033) | | |
| Immigrant | 0.145*** | 0.094** | 0.040 | 0.086** | 0.029 | 0.041 |
| | (0.025) | (0.030) | (0.029) | (0.030) | (0.030) | (0.031) |
| Somewhat related × Immigrant | -0.085 | -0.115* | -0.087 | -0.104* | -0.082 | 0.028 |
| | (0.053) | (0.047) | (0.045) | (0.048) | (0.046) | (0.053) |
| Not related × Immigrant | -0.355*** | -0.335*** | -0.353*** | -0.317*** | -0.282*** | -0.229 |
| | (0.086) | (0.076) | (0.076) | (0.079) | (0.081) | (0.121) |
| STEM | | 0.149*** | | 0.174*** | | |
| | | (0.016) | | (0.021) | | |
| Not related × STEM | | | | -0.090 | | |
| | | | | (0.050) | | |
| U.S. degree | | | | | | 0.026 |
| | | | | | | (0.036) |
| Not related × U.S. degree | | | | | | 0.112 |
| | | | | | | (0.123) |
| Demographics | No | Yes | Yes | Yes | Yes | Yes |
| Highest degree type | No | Yes | Yes | Yes | Yes | Yes |
| Field of degree minor group | No | No | Yes | No | Yes | Yes |
| Somewhat related × Field of degree minor group | No | No | No | No | Yes | Yes |
| Not related × Field of degree minor group | No | No | No | No | Yes | Yes |
| Observations | 37,754 | 37,754 | 37,754 | 37,754 | 37,754 | 37,754 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Panel B: Women** | | | | | | |
| Somewhat related | -0.141*** | -0.048 | -0.110** | -0.033 | | |
| | (0.036) | (0.034) | (0.035) | (0.039) | | |
| Not related | -0.312*** | -0.194*** | -0.218*** | -0.157*** | | |
| | (0.031) | (0.034) | (0.034) | (0.038) | | |
| Immigrant | 0.215*** | 0.046 | 0.016 | 0.037 | 0.006 | 0.058 |
| | (0.029) | (0.033) | (0.033) | (0.034) | (0.033) | (0.032) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Somewhat related × Immigrant | -0.109 | -0.089 | -0.091 | -0.077 | -0.096 | -0.002 |
| | (0.077) | (0.075) | (0.072) | (0.076) | (0.075) | (0.072) |
| Not related × Immigrant | -0.344*** | -0.310*** | -0.294*** | -0.284*** | -0.233** | -0.166 |
| | (0.083) | (0.079) | (0.081) | (0.081) | (0.081) | (0.105) |
| STEM | | 0.150*** | | 0.189*** | | |
| | | (0.021) | | (0.025) | | |
| Not related × STEM | | | | -0.193*** | | |
| | | | | (0.058) | | |
| U.S. degree | | | | | | 0.188*** |
| | | | | | | (0.041) |
| Not related × U.S. degree | | | | | | 0.129 |
| | | | | | | (0.119) |
| Demographics | No | Yes | Yes | Yes | Yes | Yes |
| Highest degree type | No | Yes | Yes | Yes | Yes | Yes |
| Field of degree minor group | No | No | Yes | No | Yes | Yes |
| Somewhat related × Field of degree minor group | No | No | No | No | Yes | Yes |
| Not related × Field of degree minor group | No | No | No | No | Yes | Yes |
| Observations | 26,093 | 26,093 | 26,093 | 26,093 | 26,093 | 26,093 |

*Robust standard errors in parentheses*
*Source: 2019 National Survey of College Graduates. Dependent variable is log annualized salary. Demographics (for all models) are age, age squared, marital status, race/ethnicity.*
$^{*}$ *p < 0.05,* $^{**}$ *p < 0.01,* $^{***}$ *p < 0.001*

In table 10, I define mismatch as a categorical variable so the earnings mismatch penalty can differ between *somewhat related* and *not related* for immigrants and natives. Without any additional controls, I find a mismatch penalty of 0.158 log points and 0.141 log points relative to the omitted group *closely related* for native men and women who report themselves working in jobs that are somewhat related to the fields of study of their degree. The earnings mismatch penalty for native workers who are in jobs not related to the field of study of their degree relative to *closely related* are 0.450 log points for men and 0.312 log points for women.

I find that the mismatch penalty for immigrants who are *not related* is significantly larger than for natives. When I only control for immigrant status, *somewhat related*, *not related*, and mismatch interacted with immigrant status, the earnings penalty for immigrants who are *somewhat related* relative to *closely related* is 0.085 log points greater for immigrant men relative to native men and 0.109 log points greater for immigrant women relative to native women. For immigrants who are *not related* relative to *closely related*, the mismatch penalty is 0.355 log points greater for immigrant men compared to native men and 0.344 log points greater for immigrant women compared to native women.