Wage Dynamics in U.S. STEM: The Role of Immigration Status and Policy

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Abstract

This paper investigates the long-term wage differential between U.S. natives and foreign-born STEM graduates. Applying Oaxaca-Blinder decomposition on U.S. data from 2003 to 2021, I find that naturalized citizens and permanent residents earn more than U.S. natives, a gap not fully explained by predictors like job roles, education level, or STEM employment. Factors such as labor market laws, characteristics of foreign-born STEM workers, and limited visa availability — which intensify competition and filter for highly-skilled individuals — significantly contribute to the 'unexplained' wage gap between U.S. natives and foreign-born workers of two immigration statuses: naturalized citizens and permanent residents. This paper shows wage effects of changes in two factors on the persistence of the wage differentials, the requirement of employer sponsorship and the the restrictiveness of labor market entry - visa approval rate. I employ a worker-level pooled 2SLS model to demonstrate how changes in immigration status — specifically, naturalization and obtaining permanent residency — lead to an increase in wages for foreign-born STEM workers. This increase is likely due to the reduction in labor market barriers such as requirements of employer sponsorship that these workers face. Moreover, I analyze the causal effects of a significant policy change using a Difference-in-Differences (DID) model. Following the 'Buy American and Hire American' executive order issued in 2017, there was an observed 11% wage increase for temporary workers in the U.S. STEM sector, likely resulting from a lower acceptance rate of worker H1B visa applications.

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1 Introduction

Foreign nationals form a significant part of the U.S. workforce, with many receiving their college education domestically. The U.S. is a popular destination for advanced tertiary education. Upon graduating, numerous foreign nationals pursue employment in this country. Since the 1990s, foreign-born workers joining the U.S. workforce, especially those in STEM fields (Science, Technology, Engineering, and Mathematics), often followed a work-sponsored path to permanent residency and citizenship. The existing economic research on high-skilled migration and the influx of foreign-educated graduates primarily focuses on their impact on economic growth, human capital increase, and industry development in the U.S. labor market.

In this paper, I explore the long-term wage differences between U.S. natives and foreign-born workers in STEM fields. Some preliminary pooled OLS estimates show that there is substantial wage differences associated with STEM workers' immigration status. I use the Oaxaca-Blinder approach to break down this wage gap into two parts: an 'explained' component, which can be accounted for by factors like education and experience, and an 'unexplained' component, which includes factors not easily measured. This analysis aims to understand the deeper reasons behind the wage differential in these groups. The 'unexplained' portion of this differential, both between U.S. natives and naturalized citizens, and U.S. natives and permanent residents, is statistically significant for each year from 2003 to 2021[1]. This approach is used in studying the gender wage gap over different time periods in Blau and Kahn (2000, 2017) and many others. My analysis further explores two primary reasons for the wage differences between natives and foreign-born workers. These include labor market restrictions faced by foreign-born workers. These restrictions encompass the requirements for sponsorship, which can change due to shifts in immigration status, and the visa acceptance rate. The sponsorship requirement limits worker mobility across different employers, thereby reducing their bargaining power. Conversely, the visa acceptance rate influences labor market competition. A lower rate means lower supply in the short-run and it would lead to increased competition and a higher equilibrium wage, while a higher rate theoretically should have the opposite effect. I find that changes in visa status correlate with increased wages, likely because of the removal of certain labor market barriers. After a 2017 U.S. government policy directive, the acceptance rate for worker visas declined. This led to higher wages for foreign-born workers holding temporary visas. The likely cause of this wage increase is the reduced supply of temporary visa workers in STEM fields, a gap that U.S. natives did not immediately fill.

Many experts suggest that high-skilled migrants have made an important contribution to U.S. economic development especially those who are specialized in R&D roles (Jones, 2002). U.S. states and regions that historically attracted more high-skilled foreign labor see faster growth rates in labor productivity (Hunt and Gauthier-Loiselle, 2010, Peri, 2012). Kerr and Lincoln (2010) show that ethnic Chinese and Indians, a large portion of whom

[1] In professions within the STEM fields, I observe that, based on how mean $ln(wage)$ trends, the groups of permanent residents and naturalized citizens surpass U.S. natives in earnings, whereas temporary workers generally report the lowest income levels.

are foreign-born, are responsible for rising shares of U.S. patents in computers, electronics, medical devices, and pharmaceuticals. When the U.S. Congress expanded the H1-B visa program for guest workers between 1999 and 2003 temporarily, U.S. metropolitan areas that employed more H-1B workers enjoyed larger "bumps" in patenting. These "bumps" can be disproportionately attributed to inventors of Indian and Chinese descent.

A strand of labor market literature study the labor market outcomes of foreign workers who are subject to labor market entry and mobility restrictions the natives do not face. Foreign nationals face various barriers in changing employers after arrival which has given rise to the concern that firms hold monopsony power over temporary foreign-origin workers. The resultant effects of such firm-level monopsony power are reduction in workers' power of bargaining, lower wages, and worse working conditions which impedes innovation, entrepreneurship, and economic growth (Wadhwa, 2012; Wasem, 2016; Hunt and Xie, 2019). Although this paper does not seek to quantify the effect of firms' monopsony power through their sponsor role, the average wage differential would be greater in absolute value in its absence.

Hunt and Xie (2019) find that the voluntary job-changing rate is similar for temporary work visa holders and the U.S. natives when their characteristics are similar which changes when temporary workers obtain permanent resident status. Their findings show that due to the shift in this immigration status, the job changing rate spikes for the new permanent residents. Moreover, they also examine the differential mobility across immigrant source countries. Wang (2021) shows that the shift in immigration status for temporary workers causes a surge in job mobility. He shows that attaining permanent residency requiring work-sponsorship dampens the possibility of job mobility of temporary workers[2]. Their analysis identifies short-term changes at job and temporary visa types. This paper shows that in STEM fields foreign-born workers earn higher on average than natives and changing immigration status - naturalization and gaining permanent residency - boosts wage. The increase in wage is at least partially due to increased mobility.

This paper complements the findings in some prior work. Hanson and Slaughter (2016) showed that most of the foreign-origin workers in STEM jobs arrived in the U.S. at the age of 21 or older[3]. While examining the wage differences between the native and foreign-born workers, they found that foreign-born workers earn substantially less than native-born workers in non-STEM occupations. The native versus foreign-born earnings differences in STEM fields are much narrower. Moreover, they show that the foreign-born workers achieve earnings parity with native workers much more quickly in STEM fields than they

[2]Kandilov et al. (2007), Mukhopadhyay and Oxborrow (2012), and Depew et al. (2017) also address job-mobility of temporary workers. Depew et al. (2017) analyze inter-firm mobility among H-1B workers within the United States and find that these IT workers of Indian origin exhibit a significant degree of mobility. Hunt and Xie (2019) and Wang (2021) provide evidence of a boost in average income due to the shift from temporary worker status to permanent resident status. The findings of this paper carefully deals with self-selection bias and estimates the effect of naturalization and gaining permanent residency on $ln(wage)$, completing previous work that studied the relationship between worker mobility and other outcomes following immigration status change. On the other hand, Kandilov et al. (2007) and Mukhopadhyay and Oxborrow (2012) analyze the monetary returns to an EB green card using difference-in-differences with propensity score matching methods.

[3]They use data from the IPUMS 5% samples of the 1980, 1990 and 2000 U.S. population censuses and 1% combined samples of the 2010-2012 American Community Survey (ACS).

do in non-STEM fields. In this paper, I track the average change in wage differentials over time between U.S. natives and foreign-born college graduates with different immigration status and provide a more accurate picture of it.

The second major issue addressed in this paper is the change in average earnings of STEM workers when their immigration status changes. For example, does becoming a permanent resident from a temporary worker status increase their earnings? To explore this, I compare the earnings of those initially on a temporary worker visa, who still hold such a visa, with those who entered the U.S. as temporary workers and later became permanent residents. This study is motivated by the fact that H-1B visas are disproportionately issued to STEM-educated workers, many of whom are employed in IT services (Torres, 2017). Temporary workers face several restrictions, including the need for employer sponsorship, which limits them to work only for the sponsor, and the uncertainties of the H-1B lottery. Becoming a permanent resident, however, removes these barriers, allowing foreign-origin workers to work unrestricted hours and change employment without employer sponsorship. This could potentially increase worker mobility across firms within an industry. My findings indicate that shifting from a temporary worker to a permanent resident status does lead to an increase in average wage. An appropriate selection bias correction method, as explained in Semykina and Wooldridge (2010), is used in this analysis. Overall, the findings indicate that temporary workers encounter significant employment barriers and generally earn less compared to those without these barriers. A change in immigration status, from temporary to permanent residency or from permanent residency to naturalized citizen, results in a notable increase in $ln(wage)$. These wage boosts following an immigration status change may be attributed to an increase in the worker's bargaining power, the elimination of the need for sponsorship, and enhanced mobility across different employers[4].

This research paper contributes to understanding the effect of labor market entry restrictions for foreign-born workers by quantifying the causal effect of the "Buy American and Hire American" executive order on the wages of temporary workers in the STEM field. By introducing a government policy treatment, we examine the subsequent wage changes. The executive order was followed by an increase in temporary worker visa rejection rate, a plausibly exogenous treatment the temporary workers received. Our analysis reveals that the tightening of labor market restrictions led to a discernible wage increase for temporary STEM workers who were already part of the US workforce before the implementation of the policy in 2017. The observed wage increase, averaging 11%, is primarily attributed to the diminished supply of temporary workers in the market, which consequently increased the equilibrium wage. This finding sheds light on the significance of labor supply factors in wage determination and offers empirical evidence, robust to various model specifications,

[4]Permanent residents and naturalized citizens both have the option to change employers, but their experiences differ. While naturalized citizens, like U.S. natives, face no restrictions in changing jobs, permanent residents encounter some challenges when they attempt to change employers, especially before their permanent residency is fully confirmed (U.S. Citizenship and Immigration Services, 2024). Furthermore, the transition from a temporary worker to a permanent resident is often a costly process. This can involve staying with the same employer or not changing jobs for a considerable amount of time. Although work mobility isn't something that can be quantified directly, we can observe its impact by examining the mean wage differences associated with these varying levels of mobility.

about the economic consequences of stringent immigration policies on the STEM labor market.

The next section discusses different visa categories that allow foreign workers to work in the U.S. especially in STEM fields and review some of the labor market research works done in this area. Section 3 discusses the data source I used to study historical wage differentials in STEM fields and the wage effect of change in visa status. Section 4 and 5 respectively discuss the empirical methods and analysis of the results. Section 6 concludes.

2 Economic Perspectives on Visa Categories

The U.S. has adopted many temporary workers' visa programs. The most prominent of them is the H-1B program which allows U.S. entities to employ high-skilled foreign workers in specialized occupations. This visa program requires prospective foreign-origin employees to have at least a bachelor's degree. L-1 (intra-company transferees), E-1, E-2 (Treaty Trader and investor), O-1 (persons with extraordinary abilities), and TN (skilled workers from NAFTA countries) are among other temporary visa categories[5]. Canadians and Mexicans are issued TN status for a particular job with a certain employer for three years, but obtaining a new visa for a new employer is easier for Canadians (Citizenship and Services, 2022). H-1B and L-1, L-2 holders cannot be self-employed. The artists, entertainers, and athletes receiving O-1 visas and treaty investors, are the only ones who may be self-employed. Compared to these visa categories, H-1B stands out as the largest visa program. A yearly cap of 65,000 accepted visa applications is in place to restrict the number of H-1B workers since 2004[6]. Over 200 thousand applicants apply every year for H-1B visas, and the lottery system lends a 32% chance of acceptance[7]. The number of L-1 and O-1 visas issued each year is far less than that of H-1B and usually are not under scrutiny by policymakers. All these visa categories provide a path toward permanent residency in the U.S. Other visa categories like spouse visa also provide a path to permanent residency, but H-1B, L-1, and O-1 are drivers of foreign employment of college graduates in the U.S. (Amuedo-Dorantes et al., 2020).

Labor experts provide evidence that shows employment restrictions on temporary or guest workers such as H-1B caps have both intended and unintended consequences, some of which we have already discussed in the previous section. Mayda et al. (2018) demonstrate that the cap reduction on H-1B in 2004 significantly reduced the hiring of new H-1B holders in for-profit firms. They found that the reduction was concentrated at the top and bottom quintiles for the wage distribution. However, the cap did not lead to a reduction

[5] Under the L-1 category, intra-company transferees in the United States are required to have worked for their company for at least one year abroad, and they must be managers or executives (L-1A) or have specialized knowledge of the firm (L-1B).

[6] In the fiscal year (FY) 2004 the annual quota or cap on H-1B issuances available for new foreign workers fell drastically from 195,000 to 65,000 per year. This reduction did not uniformly apply to all types of occupation. Employees of colleges, universities, and non-profit research institutions had been exempted from this cap since 2001. In the 2008-09 period, the total demand for H-1B status spiked and more than 150 thousand applications were filed in the first week of the filing periods. The U.S. government adopted a lottery system in response to distribute all cap-subject H-1Bs for these years (Mayda et al., 2018).

[7] Details on H-1B visa cap and visa processing is discussed in "H-1B Specialty Occupations and Fashion Models: H-1B Cap Season."

in hiring new H-1Bs from India, in IT-related positions, or at firms that used the H-1B program intensively. The new cap did not apply to old H-1B status holders. The more intensive-user firms responded to the cap by employing more old H-1B status holders[8]. Although H-1B employees can change employers, sometimes the process is lengthy and the workers cannot change employers without beginning a new application. Barriers to inter-firm movement like this give rise to the monopsony power of firms (Hunt and Xie, 2019).

When studying the labor market outcomes of foreign-origin workers, authors primarily focus on H-1B visa holders. A few papers have utilized the changes in employment restrictions as an exogenous treatment to the temporary workers subject to them. For example, Kato and Sparber (2013) show that the overall quality of international undergraduate students fell after the quota on H-1B visas was put in place. Shih (2016) find that the reduction of quota on H-1B visas led to a decline in undergraduate enrollment of students from countries with higher expected returns to working in the United States. Amuedo-Dorantes et al. (2018) show that the quota on H-1B visas altered the career choices of foreign students as they substituted away from private sector firms and toward research institutes. Peri et al. (2015) examine multiple cities in the U.S. to study the effect of the 1% increase in a city's foreign STEM workforce leads to a 7-8% wage growth for native college-educated workers and 3-4% for non-college-educated natives, with no significant impact on their employment.

For foreign-born students studying in U.S. colleges, the expected ability to work in the United States after graduation is also likely to play a strong role in their choice of specialization (Ryoo and Rosen, 2004; Amuedo-Dorantes et al., 2020). Rosenzweig et al. (2006) and Bird and Turner (2014) claim that foreign-born students pursue educational opportunities that are not available in their native countries. Kato and Sparber (2013) and Bound et al. (2015) emphasize the foreign students' desire to live and work in the United States after completion of their academic degrees as the main motive driving their choice to study in the United States. Bound et al. (2015) concludes that STEM degrees can be necessary entry points for foreign-born students to work in the U.S. IT labor market. STEM-related occupations, especially those in IT fields offer attractive wage premiums (Clemens, 2013). Besides H-1B, some other less prominent and less debated temporary worker visa types are discussed in the next section[9]. Temporary work visas are often the focus of intense political debates. Foreign-born temporary or guest workers are criticized for displacing U.S. native workers due to their willingness to work for low wages (Hira, 2010). Critics of the H-1B program have accused it to be a gateway to Indian firms such

[8]U.S. immigration rules allow H-1B workers to change employers. The worker may change employers as soon as the prospective new employer has petitioned U.S. Citizenship and Immigration Services to have the status transferred from their existing employers. The workers can join the new firms without waiting for the petition to be approved. See more in "H and L [visa] ... for a Non-immigrant Worker".

[9]Optional Practical Training (OPT) program allows international students to practice their skills by working in the United States for up to 12 months during or after their academic programs (Brier, 2020). Optional Practical Training (OPT) is temporary work that is directly related to an F-1 student's major area of study. F-1 students can apply to receive up to 12 months of OPT before completing their academic studies (pre-completion) and/or after completing their academic studies (post-completion). See more in "Optional Practical Training - OPT for F-1 students"

as Wipro and Infosys, that set up “low-wage programming shops” in the United States (Matloff, 2013). On the other hand, some authors like Dorning and Fanning (2012) express concern that foreign workers are in some cases subject to very poor working conditions and exploitation. Banerjee (2006) and Chakravartty (2006) document how IT workers from India on a temporary visa are at times forced to accept exploitative work conditions, wage cuts, deduction of commissions from hourly wages, lack of benefits, and frequent relocation.

Although the U.S. receives a wide range of foreign talent in its labor force each year and that the issues related to the impact of having foreign workers competing with natives are the subject of intense political debates, studies were done on the comparison of wage earnings of natives versus foreign-born are limited. In the previous and this section, I have discussed the majority of the prominent works that examine foreign-born workers' labor-economic outcomes and related issues.

2.1 The Impact of Increase in Visa Application Rejection

This paper also focuses on the causal link between a policy directive that resulted in higher temporary worker visa application rejection rate. On April 18, 2017, President Donald Trump enacted the ‘Buy American and Hire American’ Executive Order to increase wages and employment for U.S. workers and ensure rigorous enforcement of immigration laws, particularly focusing on ensuring H-1B visas are granted to highly skilled or well-compensated individuals (U.S. Citizenship and Immigration Services, 2017a). A large number of foreign-born temporary workers who are specialized in different STEM fields access the U.S. labor market with H1B visa. The implementation of this directive was followed by an increase in the number of visa application rejections. According to a study by the National Foundation for American Policy, the State Department's ineligibility determinations leading to visa refusals rose by 39% for immigrant visa applicants and 5% for nonimmigrant (temporary visa) applicants between fiscal years 2017 and 2018. Concurrently, the issuance of temporary visas saw a 7% decrease, and immigrant (permanent resident) visas experienced a 5% decline over the same timeframe (National Foundation for American Policy, 2019). Moreover, data published by USCIS shows that H1B approval number dropped from 348,162 in FY 2016 to 197,129 in FY 2017 (U.S. Citizenship and Immigration Services, 2017b). In January, 2021, the executive order was revoked (The White House, 2021).

3 Data

3.1 Data Source

The empirical analysis in this paper draws on 2003, 2010, 2013, 2015, 2017, and 2021 waves of the National Survey of College Graduates (NSCG). NSCG is conducted by National Science Foundation (NSF)[10]. The survey draws from the universe of individuals with

[10] A detailed description of this survey can be found here: ‘National Survey of College Graduates/About the survey’..

a bachelor's degree or above, residing in the United States during the survey reference period, and are 76 years old or younger. This survey covers information on labor market participation, work history, demographic identities, and immigration of the respondents. The major focus of this survey is on the individuals who are working in STEM fields.

NSCG draws stratified random samples from college-educated respondents from the American Community Surveys[11]. Within each sampling strata, the NSCG uses systematic random sampling techniques to select the NSCG sample. The strata are defined by demographic identities, highest degree types, occupational fields and bachelor's degree field[12]. The first survey was conducted in 1993, which I exclude. From 2010, NSCG implemented a rotating panel survey design, which consists of drawing a new panel of respondents from each survey year to participate in three biennial follow-up interviews before rotating out of the survey. This process allows building individual panels from 2010 with two or three observations per person. Usefulness of individual panels covering multiple periods are discussed in the Section 4.

The empirical analysis utilizes both a pooled cross-sectional and panel structure of the surveys. The pooled cross-sectional structure is necessary for observing wage gaps. In this paper, I use National Surveys of College Graduates (NSCG) for 2003, 2010, 2013, 2015, 2017, and 2021 to examine the wage gap in STEM and non-STEM fields between natives and foreign-origin workers and the change in average earnings for foreign-origin workers when their immigration status changes from temporary worker to permanent resident. The NSCG asks about visas, which are needed only for entering the U.S., and immigration status when the survey was conducted. This feature allows researchers to identify if the immigration status has changed for an individual[13].

As the NSCG waves are from 2 to 3 years apart, OPT users with non-immigrant student visas (F-1) who did not or could not manage work sponsorship dropped out after their first wave if there were any in the data. Moreover, transfer workers in L-1A and L-1B are limited in number compared to H-1B holders, and the majority of L-1 holders have limited-time tenure in the U.S. The majority of the temporary workers who participate in the three waves are presumably H-1B holders.

3.2 Analytical Sample

Table 1 provides the statistical description of the key variables used in the analysis of this paper. The first column shows the means of the variables for the full sample. Table 1 and Table 2 show that foreign-born samples have higher proportions of doctorate and master's degrees, working more in STEM fields. Activities like research (applied and product development), engineering, and computer and math have higher proportions of foreign-

[11] From the 2019 cycle, the NSCG's target population was modified to exclude residents of U.S. territories. This change, according to National Science Foundation, was made to better cover the NSCG sampling frame, the American Community Survey (ACS). The ACS coverage includes residents of the 50 states, the District of Columbia, and Puerto Rico. Since 2019, thus, sample members living in the U.S. territories other than Puerto Rico were not considered part of the target population.

[12] Since 2013, NSCG over-samples young graduates.

[13] In each wave, the NSCG asks whether the respondent has changed employer in a recent two-year window, and if so, for what reason. This module of the survey is utilized in the job-mobility research by Hunt and Xie (2019) and Wang (2021)

born workers. These associations will likely predict higher wages. In the analytical sample, as Table 2 shows, Males are over-represented in the temporary visa workforce, Asian is the smallest group in the sample while Whites are the largest, and most respondents who were born outside the U.S. were born in Asia. Annualized salary (inflation adjusted, 2003 prices) was higher for naturalized and permanent residents compared to natives and temporary workers.

3.3 Average Earning Trends

In this section, I discuss the trends in average earnings for respondents with different immigration statuses and major occupational categories: STEM or non-STEM. In this paper, data from the year 2003 to 2021 are used. The timeline is not divided into equal intervals; nevertheless, the patterns in the graphs discussed here would not be much different if the intervals were equal. The intervals, if were equal, would change the "slopes" between two points in time than what they are in the graphs discussed in this section. The main point of interest is not dependent on the slopes of the trend lines but the vertical distance from one trend line to another in a single graph. Figure 1 provides the trends of average log salaries for respondents of different immigration statuses working in various occupational categories. In all panels, in Figure 1, the "dip" in the earning trends during the global financial crisis of 2007-08 is prominent. In the occupational category of "Accounts/Finance/Contracts", the plunge in earnings due to the global financial crisis was not seen for temporary workers. When the earnings of the natives, permanent residents, and naturalized citizens plunged, temporary workers' earnings sky-rocketed. In occupational activity categories of 'product development research', 'computer programming', and 'basic/applied research', naturalized and permanent resident mean wage trends higher than U.S. natives.

Figure 2 provides a comprehensive overview of earnings patterns over the years, offering a clearer understanding of the data. In occupations related to science, technology, engineering, and mathematics (STEM), permanent residents and naturalized citizens, on average, earn more than U.S. native counterparts, while temporary workers tend to earn the least. However, in non-STEM occupations, the average wage trajectories of U.S. natives and individuals in foreign-born categories of temporary visa workers and permanent workers intersect, with none of these three groups consistently surpassing the others in average earnings over time. Among non-STEM occupations, naturalized citizens consistently earn the highest average earnings almost always over the presented timeline.

4 Empirical Methods

This paper aims to understand the depth of the wage differences between college graduate U.S. natives and foreign-born workers. The initial empirical analysis shows permanent residents and naturalized citizens on average earn higher than U.S. natives. I discuss the wage effect of the change in immigration status for foreign-born college graduates working in the U.S. in a separate analysis. Lastly, I check how a policy directive restricting foreign worker entry by lowering visa approval rates affected the earnings of temporary visa workers. The primary analysis of this paper begins with a simple model that observes the association of citizenship status or immigration categories with wages. Next, I empirically estimate the wage differentials and decompose them between two parts - unexplained and explained using a counterfactual approach, Oaxaca-Blinder decomposition popular in the wage-gap literature. The explained part of the wage differential is considered to be the effect of the observable factors or independent variables. The unexplained portion of the wage differential, highlighting differences in average wages between natives and foreign-born worker groups, could be attributed to two main factors: (a) the selection of foreign-born individuals based on their unobserved academic factors—those beyond measurable academic qualifications—and intrinsic talents, and (b) structural barriers that foreign-born workers face in switching jobs and entering the job market.

4.1 The Mincerian Wage Model

The Standard approach of average wage analysis is using Mincer (1974)'s wage equation. In this equation, the wage is modeled on schooling and experience.

$$lnW(s,x) = \alpha + \zeta_s S + \beta_0 x + \beta_1 x^2 + \epsilon \tag{1}$$

where W means annual salary at principal job, s, and x respectively mean schooling and experience. ϵ is an error term and $E(\epsilon|s,x) = 0$. The primary goal of Mincer's wage equation is to estimate ζ_s, which is the "rate of returns to schooling". I extend Equation 1 to

$$ln\ W(s,x) = \alpha + \zeta_s S + \beta_0 x + \beta_1 x^2 + \delta\, C + \boldsymbol{L'\psi} + \epsilon \tag{2}$$

Where C is a factor variable reflecting whether the respondent is a U.S. native, a naturalized citizen, a permanent resident, or a temporary visa worker[14]. The vector $\boldsymbol{L}$ contains other important control variables and interaction terms. Moreover, I replace S with a wide range of variables that cover educational attainment of the individuals. Such variables are highest degrees, most recent degrees, and other education-related control variables such as the number of degrees, year, and month of degree attainment. I have not added extra controls in the model to differentiate between degrees obtained from foreign institutions and those from U.S. institutions, under the assumption that if there is a significant mismatch between U.S. educational standards and those of the foreign-born individuals' home country institutions, these individuals would likely be unable to enter the U.S. labor market or attend U.S. universities and colleges.

Degree majors or areas have rates of return in the labor market which are driven by market demand, market supply, technological changes, government policies and a lot of other factors. However, rates of return are heterogeneous based on skills one possesses. I include various post-graduate controls in Equation 2 which are discussed later. Individ-

[14] In the regression analysis, I treat U.S. natives as the reference group mostly. U.S. natives have not labor market entry restrictions, making this group's average wage as a benchmark to understand the effect of labor market entry restrictions foreign-born workers face. U.S. natives and foreign-born are two mutually exclusive categories.

ual intrinsic capabilities can make rates of return heterogeneous. The rate of returns to education is thus heterogeneous due to individual differences. Mincer (1974) adopted a random-coefficients model to address the individual-level heterogeneity.

Returns to education, ζ_s is heterogeneous, but is not the main parameter of interest in this analysis. The main coefficient of interest is δ in Equation 2. Using a wide range of interaction terms reflecting degree types, degree majors and occupation, and others that are discussed later, I allow ζ_s to vary in different specifications. The paper also includes the individual fixed-effects estimation of Equation (2) which removes the unobserved effects that are invariant *within* the respondent.

4.2 Sample Selection Bias Correction

A portion of respondents in the sample were not working at the time of the interview. The error term in the wage equation might be correlated with both the decision to be employed, citizenship/work permit, the level of education and other factors. For instance, unobserved factors such as motivation, ability, or health might influence both the wages and the likelihood of being employed. Furthermore, selecting individuals for employment based on worker characteristics can introduce selection bias. This sample selection bias effectively creates an omitted variable problem, as it may exclude relevant variables that influence both the likelihood of being employed and the outcomes of interest. To correct for selection bias, I apply the widely-used Heckman (1979) or 'Heckit' method to address that wage is truncated due to selection bias. This bias could be based on reservation wage, entry restrictions in state and federal organizations, union contracts, and other unobserved factors. For the remainder of this paper, 'selection bias' refers to potential biases in regression estimates that may arise from the truncation of the wage variable. The Heckman (1979) correction approach requires modeling the selection process and outcome process separately and then combining them to correct for the bias. The selection equation includes three variables that reflect martial status, $1[\textit{respondent has children}]$ and respondents' parental educational attainment [15].

The 'Heckit bias correction' model typically consists of two parts: the selection equation

$$\begin{aligned} S^* &= z\gamma + u \\ S &= 1[z\gamma + u \geq 0] \\ P(S = 1|z) &= \phi(z\gamma) \\ \hat{\lambda}_i = \lambda(z_i\hat{\gamma}) &= \frac{\phi(z_i\hat{\gamma})}{\Phi(z_i\hat{\gamma})} \end{aligned} \tag{3}$$

which models the probability of being included in the sample, Φ is the cumulative distribution function, ϕ is the probability density function, and z is the predictor of the selection model. S^* represents the latent (unobservable) variable that determines the

[15] These three variables convey information about employment selection that are not observable to employers due to Title VII (U.S. Equal Employment Opportunity Commission, 2024).

propensity or inclination for an observation to be selected into the employed sample[16] The outcome equation is

$$ln\ W = \alpha + \zeta_s S + \beta_0 x + \beta_1 x^2 + \delta\, C + \boldsymbol{L'\psi} + \beta_\lambda \lambda(Z\gamma) + \epsilon \tag{4}$$

where $\lambda(\cdot)$ represents the Inverse Mill's Ratio, which is derived from the selection equation (3) and added to the outcome equation to correct for the selection bias. When employing Maximum Likelihood Estimation (MLE) for the Heckman correction, all parameters, including those of the selection and outcome equations, are estimated simultaneously. MLE is preferred for its statistical properties, including efficiency and consistency under certain conditions.

4.3 Decomposition of Wage Differentials

In the labor market discrimination literature, Gender wage gaps are decomposed with a counterfactual analysis named the Oaxaca-Blinder decomposition method. I utilize this popular method developed by Kitagawa (1955), Blinder (1973), and Oaxaca (1973) that is used to explain the wage gap at the mean. Primarily, two distinct groups of workers – U.S. natives and foreign-born – experience wage differential. I use two-fold Oaxaca-Blinder decomposition to examine the wage gaps between U.S. natives and each of the foreign-born categories. In addition, I also examine the wage differential between permanent residents and temporary workers. Permanent residents, although foreign-born, receive unrestricted right to work in the U.S. The graduation from temporary worker to permanent resident status leads to a wage effect generated from the removal of the barriers to change jobs which is a focus of this study.

In the sample, there are two distinct groups of workers: U.S. natives and foreign-born, US and FB. The mean $ln(wage)$ difference between these two groups of workers:

$$R = E(W_{US}) - E(W_{FB})$$

where $E(W)$ denotes the expected value of the outcome variable, is accounted for by group differences and in the independent variables or predictors. Based on the simplified linear model,

$$\begin{aligned} W_i &= Q_i'\beta + \epsilon_i, \\ E(\epsilon_i) &= 0, \\ i &\in (US.FB) \end{aligned}$$

where Q is a vector containing the predictors and a constant, β contains the slope parameters and an intercept term. The mean outcome difference is expressed as the difference

[16] The latent nature of this variable is that it is not directly observed within the data; rather, it is an underlying factor that influences the observable selection. The actual observed outcome is typically a binary indicator derived from the latent variable S^*.

in the linear prediction at the group-specific means of the regressors. That is,

$$R = E(W_{US}) - E(W_{FB}) = E(Q_{US})'\beta_{US} - E(Q_{FB})'\beta_{FB}$$

because

$$E(W_i) = E(Q_i'\beta_i + \epsilon_i) = E(Q_i'\beta_i) + E(\epsilon_i) = E(Q_i)'\beta_i$$

where $E(\beta_i) = \beta_i$ and $E(\epsilon_i) = 0$ by assumption. In a two-fold decomposition of R,

$$R = \chi + \upsilon$$

where the first component,

$$\chi = E(W_{US}) - E(W_{FB})'\beta^*$$

is the part of the wage differential that is explained by the group differences in the predictors. This part is called the "quantity effect" (Jann, 2008). Suppose there is a coefficient vector β^* that reflects no differences in the wage effect of citizenship or immigration status. I calculate β^* as $0.5\beta_{US} + 0.5\beta_{FB}$ which Reimers (1983) and others suggest. The second component is

$$\upsilon = E(W_{US})'(\beta_{US} - \beta^*) - E(W_{FB})'(\beta^* - \beta_{FB}) \tag{5}$$

This is the unexplained part that is composed of the differential experiences and qualifications that exist between the U.S. natives and foreign-born individuals.

The NSCG sample includes individuals in multiple waves between 2003 and 2021. As there is a time dimension to it, the change in unexplained wage differential can be tracked over time. Blau and Kahn (2000, 2017) use Oaxaca-Blinder decomposition to track unexplained wage differentials over a period of time. Similar to them, the main results of the decomposition of wage differentials between U.S. natives and foreign-born categories are decomposed into explained and unexplained parts quantified in log points (as the outcome is $ln(wage)$) for each year of the survey and presented as trends.

4.4 Impact of Change in Immigration Status

Some foreign-born individuals in the sample report changes in their immigration status. For example, some report naturalization in a later wave after reporting permanent residents as immigration status in their first wave. Similarly, some report the change in the immigration status from temporary worker to permanent resident.

Imposing a panel model would change the main equation of our analysis, Equation 2.

$$ln\, W_{it} = \alpha + \eta_i + \omega_t + \zeta_s\, S_{it} + \beta_0\, x_{it} + \beta_1\, x_{it}^2 + \delta\, C_{it} + \boldsymbol{L}'\Psi + \epsilon_{it} \tag{6}$$

Equation 6 presents a standard panel model, where η_i represents the individual fixed effects, ω_t represents the time fixed effects, and ϵ_{it} is the panel error. S_{it} expresses schooling, for individual i it does not vary a lot for the across periods t. [17]. Equation (6) is not

[17] In the empirical model, schooling is measured in terms of two binary variables "respondent's highest

without selection bias. However, a Heckman (1979) bias correction is inapplicable here. Even if the individual fixed effects control for the individual level unobserved effects, there remains the threat of selection bias.

I apply the Heckman-style bias-correction with a pooled 2SLS approach that Semykina and Wooldridge (2010) developed. They show that one can consistently estimate δ with a flexible 2SLS approach that does not impose strong assumptions about the error structure of Equation 6 like Fixed-effects Panel data model does. Suppose, the selection equation is the one below:

$$S_{it} = 1[z_{it}\gamma + \overline{z_i}\xi_t + u_{it} \geq 0] \tag{7}$$

$\overline{z_i}\xi_t$ individual average of z_i interacting with a time dummy. The observed outcome of employment and its determinants vary within individual i and over time t, u_{it} is normally distributed, u_{it} and ϵ_{it} in Equation (6) share constant correlation across different time periods, $E(\epsilon_{it} \mid u_{it} = \rho u_{it})$. The two required steps are first, estimating $P(S_{it} = 1 \mid z_i) = \Phi(z_{it}\gamma + \overline{z_i}\xi_t)$ and using the results to get $\lambda_{it} = \lambda(z_{it}\hat{\delta_t} + \overline{z_i}\hat{\xi_t})$, then second, use Fixed-effects 2SLS to estimate the following:

$$ln\,(W_{it}) = \alpha + \eta_i + \omega_t + \zeta_s\, S_{it} + \beta_0\, x_{it} + \beta_1\, x_{it}^2 + \delta\, C_{it} + \boldsymbol{L}'\Psi + \rho\hat{\lambda_{it}} + \sum_{d=1}^{T}\theta\lambda_{it}t + \epsilon_{it} \tag{8}$$

$\theta_1\hat{\lambda}_{it}$, ... $\theta_T\hat{\lambda}_{it}$ are time dummies. The asymptotic variance of $\hat{\beta}_1$ needs to be corrected for general heteroskedasticity and serial correlation, as well as first-stage estimation of the coefficient of $\hat{\lambda}_{it}$. For this purpose, Semykina and Wooldridge (2010) suggests producing panel bootstrap standard errors by resampling the cross-section units. In the empirical analysis, I apply this method only on the foreign-born sample that are present in at least two periods[18] Equation (8) permits arbitrary correlation between z_{it} and individual-level unobserved effects, let us call it c_i. The Panel Fixed-effects estimator is consistent if the selection process is strictly exogenous conditional on c_i, which is unlikely and that means the individual-errors are serially correlated. In comparison, the pooled 2SLS is consistent if $E(\epsilon_{it} + c_i \mid z_{it}, S_{it}) = 0$, which is easier to achieve and it allows for arbitrary relation between selection S and ϵ_{it}. c_i can be $c_i = f(z_i) + r_i$, where $f(.)$ is a known linear function and $E(r_i \mid z_i) = 0$. Therefore, $E(c_i) = E(z_{it}) + 0 = h\overline{z}$. So, the second-stage can be the

degree is bachelor's = 1" and "respondent's highest degree is master's = 1" with "respondent's highest degree is above master's/professional/doctorate" as the reference group.

[18] I conduct three tests to check wether bias-correction is needed for the model in Equation (8). Verbeek and Nijman (1992) suggests a test which requires adding s_{t-1} and s_{t+1} to Equation (8) alternatively, estimate the equation using standard Panel Fixed-effects techniques and do t test for the statistical significance of their coefficient estimates. If the coefficient estimates are statistically significant, then it warrants a selection bias correction for the model. The second and the third tests I apply are from Wooldridge (1995) and Semykina and Wooldridge (2010), respectively. The second test requires estimating Equation (8) where the $\lambda(z\gamma)$ is estimated separately for each wave or year and then appended together into a single variable. The researcher needs to conduct a t-test for the estimated coefficient of λ ($H_0 : \lambda = 0$); a statistically significant estimated coefficient of λ would mean bias correction is necessary. The third test is similar to the second test; one needs to add interaction terms between time dummy variables and λ and conduct a Wald test for the joint significance of the coefficients of these interaction terms. A rejection of the null that these interaction terms are all equal to zero will necessitate a bias correction approach. The second and the third test shows that sample-selection bias correction was necessary.

following.

$$ln\, W_{it} = \alpha + h\overline{z_i} + \omega_t + \zeta_s\, S_{it} + \beta_0\, x_{it} + \beta_1\, x_{it}^2 + \delta\, C_{it} + \mathscr{L}'\Psi + \rho\hat{\lambda_{it}} + \sum_{d=1}^{T} \theta\lambda_{it}t + \epsilon_{it} \quad (9)$$

$\mathscr{L}$ includes additional interaction terms such as means of first-stage variables $\times$ means of second-stage variables such as S_{it}, C_{it}, x_{it} and other control variables $\boldsymbol{L}$ included in Equation (8).

4.5 Difference-in-Differences Model

Difference-in-differences (DID) estimation with repeated cross-sectional data assesses the causal impact of a treatment by comparing the outcome differences before and after an intervention across treated and control groups (Angrist and Pischke, 2009). I study the effect of "Buy American and Hire American Executive Order" in 2017 that was followed by a work visa acceptance rate lower than the previous years which affected the number of temporary workers who gained entry into the U.S. labor force. This policy directive is considered in this analysis a binary treatment variable. Difference-in-differences (DID) estimates effect of a binary treatment by fitting a linear model with time and group fixed effects. In this analysis, groups are worker categories: permanent residents and temporary workers. I create additional groups by creating interaction terms between the immigration statuses with workers' occupational characteristics and apply group fixed effects into the model to check robustness of the treatment effect.

The DID model for repeated cross-sectional data is given by

$$ln(W)_{ist} = \gamma_s + \gamma_t + \boldsymbol{Q}_{ist}\beta + D_{st}\delta + \epsilon_{ist} \quad (10)$$

where i is the respondent index, s is the group-level index, and t is the time index. ϵ_{ist} is the error terms. D_{st} is the binary treatment that varies across groups and over time. $\boldsymbol{Q}$ contains all the other regressors on the right-hand side of Equation 4.

I conduct tests for parallel trends and Granger causality (Angrist and Pischke, 2009). For parallel trend test, I augment Equation (10) by adding two additional terms.

$$ln(W)_{ist} = \gamma_s + \gamma_t + \boldsymbol{Q}_{ist}\beta + D_{st}\delta + w_i d_{t,0} t\eta_1 + w_i d_{t,1} t\eta_2 + \epsilon_{ist} \quad (11)$$

$d_{t,0}$ is a variable indicating pre-treatment time periods and $d_{t,1}$ indicates post-treatment time periods. w_i is also a binary variable, it takes on the value 1 if the individual is in the treatment group and 0 otherwise. t is the time period dummy. With this specification I do a Wald test of η_1 against 0 to assess whether linear trends are parallel before treatment. The null hypothesis is that the linear trends in pre-treatment periods are parallel. Then I conduct a Granger test to check whether the anticipation of the treatment drives the outcome. In this context, the Granger causality testing is a checking whether policy effects are observed prior to policy implementation (Angrist and Pischke, 2009).

$$ln(W)_{ist} = \gamma_s + \gamma_t + \boldsymbol{Q}_{ist}\beta + \sum_{j=1}^{3} w_{s,t-j}\zeta_j + D_{st}\delta + \epsilon_{ist} \tag{12}$$

Equation (10) is augmented into (12) include pre-treatment year dummy variables ($w_{s,t-j}$) and the augmented version regresses these three dummy variables on the outcome. Then a Wald test is done to check if ζ_js are jointly 0. $w_{s,t-j}$ is allowed three lags because three pre-treatment waves considered in the analysis[19].

5 Results

5.1 Baseline Regression

The baseline regression is the most parsimonious model. Table 3 includes one education related control in the specification corresponding each column. Naturalized citizens and permanent residents on average earn higher than natives and temporary workers on average earn less than natives, as the evidence shows. Males earn higher than females, and STEM-related occupation, degrees in STEM are associated with higher wages. Interestingly, Asian identity is associated with higher wages but Asian×Male is associated with wage negatively. Black and Hispanic respondents earn less on average than White respondents. These identities in interaction with the male identity are also associated with lower wages.

The results, corrected for selection bias and presented in Table 4, indicate some changes in the coefficient estimates for immigration status post-correction. Interaction terms between STEM occupation and certain Occupational Activity Dummies, notably Computer Programming and Product Development Research, demonstrate a positive association with wages. The reference category for work activity in this analysis was managerial and leadership work. Extending the results by adding more control variable to the regression model - cohort dummies, reference year dummies, current employer location dummies - do not change the main coefficient estimates of interest by any considerable margin (Table 5). I further extend the model by adding Year×worker characteristics fixed effects in Table 6. These effects are meant for controlling the year- and industry-specific unobserved frictions the workers may have encountered in certain years. Another exercise on the bias-corrected pooled model is checking whether foreign-born workers from certain regions see variation in the immigration status effect because of their birth locations. Table 7 shows that being temporary worker or permanent resident from Europe gives the worker an advantage in terms of wage size. On the other hand, the main effect of being born in Africa is not statistically significant[20]. Lastly, by including some additional interaction terms between immigration status and worker characteristics, Table 8 results show that the effect of

[19]The three waves of the National Survey of College Graduates (NSCG) - conducted in 2010, 2013, and 2015 - fell within the Obama administration period, from 2008 to 2016. During this time, the H1B visa approval rate remained relatively stable. To calculate this approval rate, the number of petitions approved is divided by the number of petitions filed, and then the result is multiplied by 100.

[20]Other birth regions (e.g., Latin America) had no statistically significant effect on wages when interacting with foreign-born statuses, so they are not discussed in this section.

immigration status remains very robust.

5.2 Decomposition of Wage Differential

In Section 4.3, the Oaxaca-Blinder decomposition has been discussed. I apply two-fold Oaxaca-Blinder decomposition of wage differential which includes a Heckman (1979) style selection bias correction. Heckman's bias correction has been applied to Oaxaca-Blinder decomposition following methods provided in Jann (2008). The decomposition results in Table 9 pulls data from all survey waves and provides an overall picture of the wage differential between U.S. natives and each of the foreign-born categories. Table 9 description outlines the variables present in the main equation and selection equation specifications used for the results. For wage differential decomposition depicted in Figures 3 to 5, the same specifications as Table 9's has been used. The unexplained portion of the wage differential could mean labor laws that are meant to protect U.S. native employment to some degree – leading to the entry of a lot of foreign-born workers who are highly qualified and whose wage earnings are usually in the right tail of wage distribution of all STEM industries combined. These labor market restrictions at the same time limit mobility of temporary workers across firms, restricts their traveling across borders, quotas that limit their numbers, and subject them to delays and long waiting periods before giving work permit[21]. Table 9 shows permanent residents earn more than temporary workers, and naturalized citizens, permanent residents earn more than U.S. natives partially due to "unexplained" factors. In addition to labor market selectivity and entry restrictions, the unexplained factors also can be barriers to the entry labor market in the U.S. and job mobility, and also average level of intrinsic talents, attitudes, and values in certain groups that are over-represented in the foreign-born categories.

The year-wise cross-sectional decomposition of wage differentials are depicted in Figures 3 to 5. The result of interest is mainly the unexplained portion of the two-fold wage differential decomposition. Figure 3 and Figure 4 show that the naturalized citizens and the permanent resident workers in STEM fields earn significantly higher than the natives, this differential is driven by not just predictors, but also unobserved factors. However, temporary workers do not enjoy the same advantage. The unexplained portion of the wage gaps in Figure 5 is not statistically significant for the years 2013, 2017, 2019, and 2021. The unexplained portion can also mean wage discrimination, lower bargaining power of the foreign worker due to their dependence on employer sponsorship, and the various disadvantages the foreign-born workers may face. These unobserved negative factors could be affecting temporary workers more than permanent residents because temporary workers lack job mobility and need employer sponsorship to stay in the U.S. labor force. Interesting, both naturalized and permanent resident workers see the biggest wage difference compared to natives in the 2010 wave which is the first post-global financial crisis wave in the data. Moreover, labor laws that draw in foreign-born workers, limit mobility across firms, restricts traveling across borders, quotas that limit the number of workers, and subject

[21] In the analysis, labor market restrictions is a leading candidate explanation for unexplained wage differences between U.S. Natives and foreign-born college graduates. Social customs, country-specific capitals, different forms of discrimination are also possible explanation for the unexplained wage differential.

foreign-born workers to delays and waiting periods before giving work permit; these factors also drive the unexplained portion of the wage differentials.

5.3 Wage Impact of Immigration Status Change

The pooled-2SLS model discussed in Section 4.4 show us if a permanent resident becomes naturalized and if a temporary worker becomes a permanent resident, what changes in wage they observe. Results produced by estimating Equation 9 with the Semykina and Wooldridge (2010) approach are provided in Table 10 and Table 11[22]. Gaining permanent residency increases $ln(wage)$ by approximately 0.08 to 0.1 log points (8.8% to 11.3%); the variation in this change is due to using different occupational controls across the columns in Table 10. Naturalization of permanent residents generates (Table (11) statistically significant increase in wages. Including of different STEM occupational controls in the specifications presented in Column 1 to Column 5 in Table (11) causes greater variation in the estimated effect of naturalization compared to that of gaining permanent residency. $ln(wage)$ sees an increase between 0.092 to 0.12 log-point increase equivalent to 9.6% to 12.98% increase in wage due to naturalization. Although immigration status change is endogenous, these results show how wage changes when certain labor restrictions are removed. Permanent residency increases wage by a considerable margin allowing the worker greater job mobility and hence greater bargaining power.

5.4 Impact of "Buy American and Hire American"

This section discusses the estimated causal effect of the "Buy American and Hire American" policy on STEM labor force wages, focusing on changes in labor market restrictions for temporary workers. The methodology is detailed in Section 4.5. The analysis excludes 2021 due to the directive's revocation in 2021 and COVID-19 impacts.

Findings consistent with parallel trends and Granger causality are presented in Tables 12 and 14, with wage trends depicted in Figure 6. Permanent residents and temporary workers of foreign origin share similar characteristics; STEM workers who gained permanent residency were subject to similar labor market restrictions when they held temporary worker visa status. The policy directive is intended to affect only the temporary workers, not the permanent residents. Both permanent residents and temporary workers in STEM share similar characteristics. Therefore, I consider the permanent residents in STEM as the control group. The analysis specifically targets workers aged 35-50. This focus is due to the observed high employer turnover rates among younger temporary workers, which complicates direct comparisons with permanent residents due to non-parallel pre-

[22] In this analysis, the 'permanent resident' variable is crucial and its value changes for individuals whose immigration status changes between two NSCG waves. Specifically, when an individual's status shifts to a permanent resident, this variable's value changes from 0 to 1. To avoid multicollinearity—a statistical issue where variables are too highly correlated—in our model, we do not include a separate indicator for temporary worker status. In Table 10, the coefficient for the 'permanent resident' status shows the impact of this change from 0 to 1. For those who are already permanent residents and whose status does not change between waves, this variable remains 1 in both waves. Therefore, the variation in the 'permanent resident' variable arises solely from individuals who transition from being temporary workers to permanent residents. The variable 'naturalized' in Table 11 is coded also in the same way.

treatment trend in $ln(wage)$. Within the analytical sample, it is notable that a significant number of STEM workers, particularly in their early twenties and specializing in IT fields, tend to work in the U.S. for short periods before leaving. In contrast, permanent residents, who form the control group, generally engage in the U.S. labor market with long-term objectives, unlike some of these temporary workers. The decision to concentrate on the 35-50 age group is further supported by the likelihood of both temporary and permanent STEM workers in this bracket seeking more stable employment in the U.S. Furthermore, in this age range, workers from both categories have, on average, similar duration of employment with their current employers, as per the time of the survey.

A set of straightforward regressions presented in Table A.2, using parsimonious models, reveals that the estimated effects for permanent residents and temporary workers are more similar within the 35-50 age group compared to those outside this age range and the full sample. This suggests that the 35-50 age group provides a more comparable basis for analyzing differences between permanent residents and temporary workers. Table 13 shows that when the sample is split between male and female categories, the estimated average treatment effect is slightly higher for the female sample, which is an interesting result.

Table 12 suggests that temporary workers in the U.S. STEM sector, present before 2017, experienced wage increases during the treatment period, likely due to reduced worker supply. According to Table 14, which shows robustness of the $ATET$ in extended specifications with additional interaction terms between worker characteristics and temporary worker status, the average wage increase for temporary workers post-policy was robust, ranging from 11 to 12% (0.10-0.11 log points). The results in Table 14 show when the DID specification is augmented by adding interaction terms as controls, the estimated effect remains nearly the same as those in Table 12. In the first specification of Table 14, as shown in Column (1), we include interaction terms between being a temporary worker (denoted as $1[Temporary\ Worker]$) and the fields of major for the highest degree obtained by the individuals. Moving to the second specification in Column (2), the model adopts interaction terms between Temporary Worker status and Primary Work Activity Indicators, capturing the specific nature of job roles undertaken by these workers. The third specification, outlined in Column (3), examines the interaction between temporary worker status and broad categories of highest degree fields, allowing highest degree field effects to vary by respondent temporary worker status. Finally, in the fourth specification, presented in Column (4), the interaction of Temporary Worker status is explored with an indicator of whether the highest degree obtained is in a STEM field (1[Highest Degree in STEM]).

For further robustness checks, Table 15 introduces additional interaction terms allowing employer characteristics vary by years. Dummy indicators for Employer sectors, employer locations, and employer size interact with years in these interaction terms. The estimated average treatment effect remains at around 0.12% in these robustness checks.

The 'Buy American and Hire American' executive order, resulting in a lower acceptance rate for visas, appears to have led to an increase in $ln(wage)$ for temporary STEM workers due to a likely supply shortage. This executive order may have influenced these workers to consider changing their industry of employment. Notably, compared to academic positions in STEM, there is greater employment availability in the business or industrial sectors. To analyze the association of temporary worker status with transitions to academia or non-academic jobs during 2017 and 2019, I employ a Probit model with Heckman's bias correction for employment selection. Table A.3 presents this analysis, where $1[Academic]$ and $1[Business]$ denote holding academic and "industry" or "business" jobs, respectively, for individuals who worked in the opposite sector in the previous wave. This analysis focuses solely on temporary workers and permanent residents.

The Probit model results, indicated by negative coefficients in Column 1 and positive in Column 2, suggest varied employment trends. The academic job market, known for its security due to tenured positions and the absence of H1B visa cap (Amuedo-Dorantes and Furtado (2016)), contrasts with the highly competitive nature of STEM academic jobs with dwindling openings since the 1990s (National Center for Science and Engineering Statistics, 2021). Column 1 in Table A.3 shows that the main effect of being a temporary worker is statistically significant and positive, while the effect for business sector employment is negative. However, the interaction effect of the 2017-2019 period with temporary worker status appears to partially offset these main effects. This could be interpreted as increased employment uncertainty for temporary workers due to the drop in visa approval rates, which likely leads them to work non-academic jobs more and academic jobs less during this period. Column 3 shows the effect of temporary worker status on holding jobs in the federal and state government agencies, which is not statistically significant. This is expected as in many instances, government agencies require applicants to be either citizens or permanent residents.

6 Conclusion

This paper examines the wage differential between U.S. natives and foreign-born college graduates in the U.S., utilizing data from seven waves of the National Survey of College Graduates from 1993 to 2019. It investigates the wage effects experienced by foreign-born individuals, categorizing them as naturalized citizens, permanent residents, and temporary workers. The paper also aims to quantify the wage impact of the barriers faced by temporary workers. Graphical analysis of the average $ln(wage)$ trends (annualized, in 2003 base prices) reveals that naturalized citizens and permanent residents typically earn more than U.S. natives in STEM fields. In contrast, temporary workers consistently earn less than both natives and other foreign-born statuses. Permanent residents, unlike temporary workers, do not face restrictions such as visa sponsorship, which limits job mobility due to factors like U.S. labor department licensing, yearly visa caps, work permit delays, difficulties in changing firms, potential discrimination, and employment restrictions. These factors likely contribute to the 'unexplained' wage differential observed in the two-fold Oaxaca-Blinder decomposition between permanent residents and temporary workers, a gap that appears to be narrowing over time. Furthermore, estimating the causal effect of the 'Buy American and Hire American' executive order, which introduced a plausibly exogenous shock to the foreign-born STEM labor force, sheds light on the wage implications of changing labor market restrictions for temporary workers. I find that gaining permanent residency and naturalization were associated with increase in wages. Following the executive order, there was a notable increase in visa application rejection rates in 2017 and 2019. The analysis shows that temporary workers who entered the U.S. STEM workforce before 2017 experienced wage increases during this period, attributed to a decreased supply in the temporary STEM workforce and a resultant increase in the equilibrium wage. This wage increase, averaging 11%, remained robust even after accounting for additional fixed effects.

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Tables

Table 1: Analytical Sample Means of Key Variables

Variables	(1) Native	(2) PR	(3) Temp.	(4) Naturalized	(5) Total
Highest Degree					
Bachelor's	0.348	0.345	0.368	0.539	0.355
	(0.476)	(0.475)	(0.482)	(0.498)	(0.479)
Master's	0.0621	0.137	0.218	0.176	0.0837
	(0.241)	(0.344)	(0.413)	(0.381)	(0.277)
Doctorate	0.0503	0.0411	0.0182	0.00982	0.0461
	(0.219)	(0.199)	(0.134)	(0.0986)	(0.210)
1[Highest Degree in STEM]	0.514	0.659	0.694	0.816	0.553
	(0.500)	(0.474)	(0.461)	(0.387)	(0.497)
1[STEM-related Occupation]	0.497	0.563	0.611	0.779	0.521
	(0.500)	(0.496)	(0.487)	(0.415)	(0.500)
1[Most Recent Degree STEM]	0.514	0.656	0.692	0.815	0.552
	(0.500)	(0.475)	(0.462)	(0.388)	(0.497)
Work Activity					
Teaching	0.140	0.0990	0.0977	0.0763	0.130
	(0.347)	(0.299)	(0.297)	(0.266)	(0.337)
Professional Services	0.179	0.132	0.0882	0.0435	0.163
	(0.383)	(0.338)	(0.284)	(0.204)	(0.370)
Production to Marketing	0.156	0.165	0.149	0.0726	0.154
	(0.363)	(0.371)	(0.356)	(0.260)	(0.361)
Human Resource	0.206	0.189	0.158	0.0878	0.197
	(0.405)	(0.391)	(0.365)	(0.283)	(0.398)
Computer Programming	0.0667	0.112	0.160	0.267	0.0844
	(0.250)	(0.315)	(0.367)	(0.442)	(0.278)
Designing	0.0635	0.0686	0.0659	0.0719	0.0646
	(0.244)	(0.253)	(0.248)	(0.258)	(0.246)
Product Dev. Research	0.0465	0.0605	0.0735	0.0764	0.0508
	(0.211)	(0.238)	(0.261)	(0.266)	(0.220)
Basic/Applied Research	0.0901	0.108	0.158	0.281	0.103
	(0.286)	(0.310)	(0.364)	(0.449)	(0.303)
Accounts/Finance/Contracts	0.0512	0.0665	0.0503	0.0241	0.0523
	(0.220)	(0.249)	(0.218)	(0.153)	(0.223)
Computer & Math Sci.	0.0942	0.144	0.208	0.325	0.115
	(0.292)	(0.351)	(0.406)	(0.468)	(0.318)
Bio, Agro, Life Sci.	0.0370	0.0439	0.0710	0.0908	0.0414
	(0.189)	(0.205)	(0.257)	(0.287)	(0.199)
Physical Sci.	0.0307	0.0263	0.0347	0.0586	0.0313
	(0.172)	(0.160)	(0.183)	(0.235)	(0.174)
Engineers	0.135	0.148	0.136	0.183	0.138
	(0.341)	(0.355)	(0.343)	(0.386)	(0.345)
Sci.& Engieering related	0.200	0.201	0.161	0.122	0.196
	(0.400)	(0.401)	(0.368)	(0.328)	(0.397)
Observations	386.298	67,386	23,658	17,514	494,856

Standard Deviations in parentheses.
PR = Permanent Resident. Temp = Temporary Workers. STEM = STEM Occupation.
Non-STEM = Non-STEM occupation.

Table 2: Analytical Sample Means of Key Variables - Educational Characteristics

Variables	(1) Native	(2) PR	(3) Temp.	(4) Naturalized	(5) Total
Asian	0.0792	0.0725	0.0510	0.0304	0.0752
	(0.270)	(0.259)	(0.220)	(0.172)	(0.264)
Black	0.0908	0.152	0.123	0.0872	0.101
	(0.287)	(0.359)	(0.328)	(0.282)	(0.301)
Hispanic, no-race	0.0501	0.527	0.491	0.716	0.160
	(0.218)	(0.499)	(0.500)	(0.451)	(0.366)
White	0.740	0.232	0.324	0.161	0.630
	(0.439)	(0.422)	(0.468)	(0.367)	(0.483)
Male	0.550	0.597	0.619	0.694	0.565
	(0.497)	(0.490)	(0.486)	(0.461)	(0.496)
Born in Asia	0.00620	0.572	0.519	0.755	0.134
	(0.0785)	(0.495)	(0.500)	(0.430)	(0.341)
Born in Europe	0.00715	0.144	0.203	0.0801	0.0377
	(0.0842)	(0.351)	(0.402)	(0.271)	(0.190)
Born in Africa	0.00114	0.0317	0.0770	0.0372	0.0102
	(0.0338)	(0.175)	(0.267)	(0.189)	(0.101)
Born in South America	0.00104	0.0671	0.0607	0.0481	0.0146
	(0.0322)	(0.250)	(0.239)	(0.214)	(0.120)
Observations	386.298	67,386	23,658	17,514	494,856

Standard Deviations in parentheses.

PR = Permanent Resident. Temp = Temporary Workers. STEM = STEM Occupation. Non-STEM = Non-STEM occupation. U.S. citizens who were born to U.S. citizen parents outside the U.S. are also considered U.S. natives.

Table 3: Baseline Pooled Regression - The Effect of Immigration Status

	(1)	(2)	(3)	(4)
	ln(wage)	*ln(wage)*	*ln(wage)*	*ln(wage)*
Naturalized	0.0354***	0.0308***	0.0315***	0.0389***
	(0.00555)	(0.00559)	(0.00559)	(0.00555)
Permanent Resident	0.0274***	0.0301***	0.0295***	0.0241***
	(0.00791)	(0.00797)	(0.00797)	(0.00790)
Temporary Worker	-0.147***	-0.129***	-0.128***	-0.137***
	(0.00845)	(0.00847)	(0.00847)	(0.00849)
Asian Non-Hispanic	0.0862***	0.0797***	0.0801***	0.159***
	(0.00544)	(0.00547)	(0.00547)	(0.00770)
Black, Non-Hispanic	-0.110***	-0.126***	-0.127***	-0.0104
	(0.00634)	(0.00638)	(0.00639)	(0.00845)
Hispanic, any race	-0.0657***	-0.0826***	-0.0828***	-0.00813
	(0.00517)	(0.00519)	(0.00519)	(0.00761)
Male	0.344***	0.358***	0.359***	0.396***
	(0.00327)	(0.00329)	(0.00329)	(0.00414)
Age	0.121***	0.123***	0.123***	0.122***
	(0.00116)	(0.00117)	(0.00117)	(0.00116)
Age^2	-0.00130***	-0.00133***	-0.00133***	-0.00131***
	(0.0000133)	(0.0000134)	(0.0000134)	(0.0000133)
STEM Occupation	0.283***			0.282***
	(0.00323)			(0.00322)
Highest Degree STEM		0.191***		
		(0.00336)		
Most Recent Degree in STEM			0.189***	
			(0.00337)	
Asian Non-Hispanic × Male				-0.128***
				(0.00891)
Black, Non-Hispanic × Male				-0.214***
				(0.0127)
Hispanic, any race × Male				-0.107***
				(0.0100)
Observations	494856	494856	494856	494856
Adjusted R^2	0.093	0.083	0.083	0.094

Standard Errors in Parentheses. Standard errors clustered at the individual level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
"U.S. Natives" is the reference group among the variables of Immigration Status. Female is the reference gender identity. Whites are the reference racial group. Specification of each column includes survey year dummy variables.

Table 4: Baseline Pooled Regression: Selection-Bias-Corrected Effect of Immigration Status

	(1) $ln(wage)$	(2) $ln(wage)$	(3) $ln(wage)$	(4) $ln(wage)$
Naturalized	0.111***	0.0778***	0.0809***	0.0812***
	(0.00546)	(0.00552)	(0.00553)	(0.00553)
Permanent Resident	0.0617***	0.0475***	0.0505***	0.0508***
	(0.00792)	(0.00781)	(0.00781)	(0.00781)
Temporary Worker	-0.150***	-0.158***	-0.151***	-0.151***
	(0.00844)	(0.00838)	(0.00842)	(0.00842)
STEM Occ.	0.207***	0.179***	0.180***	0.182***
	(0.0208)	(0.0207)	(0.0207)	(0.0207)
STEM Occ. × Basic/Applied Research	-0.0509**	-0.0345	-0.0358	-0.0353
	(0.0244)	(0.0243)	(0.0243)	(0.0243)
STEM Occ. × Product Dev. Research	0.289***	0.267***	0.265***	0.265***
	(0.0301)	(0.0300)	(0.0300)	(0.0300)
STEM Occ. × Designing	0.0794**	0.0655**	0.0626*	0.0627*
	(0.0331)	(0.0331)	(0.0331)	(0.0331)
STEM Occ. × Computer Programming	0.218***	0.216***	0.215***	0.215***
	(0.0311)	(0.0310)	(0.0310)	(0.0310)
STEM Occ. × Human Resource	0.0318	0.0347	0.0332	0.0333
	(0.0214)	(0.0212)	(0.0212)	(0.0212)
STEM Occ. × Production to Marketing	0.251***	0.263***	0.262***	0.262***
	(0.0222)	(0.0221)	(0.0221)	(0.0221)
STEM Occ. × Teaching	0.0421*	0.0481**	0.0463**	0.0465**
	(0.0220)	(0.0219)	(0.0219)	(0.0219)
STEM Occ. × Professional Services	-0.0805***	-0.00928	-0.00875	-0.00789
	(0.0222)	(0.0220)	(0.0220)	(0.0220)
Black, Non-Hispanic	-0.156***	-0.111***	-0.0301***	-0.0302***
	(0.00634)	(0.00633)	(0.00844)	(0.00844)
Hispanic, any race	-0.100***	-0.0629***	-0.0296***	-0.0296***
	(0.00520)	(0.00513)	(0.00753)	(0.00753)
Asian Non-Hispanic	0.0136**	0.0516***	0.102***	0.102***
	(0.00547)	(0.00542)	(0.00764)	(0.00764)
Male		0.288***	0.326***	0.326***
		(0.00341)	(0.00431)	(0.00431)
Age		0.00328***	0.00328***	0.00328***
		(0.000157)	(0.000157)	(0.000157)
Age^2		-0.00133***	-0.00133***	-0.00131***
		(0.0000134)	(0.0000134)	(0.0000133)
Observations	494,856	494,856	494,856	494,856

Standard Errors in Parentheses. They are clustered at the level of the respondent.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
"U.S. Natives" is the reference group among the variables of Immigration Status. Male is the reference gender identity. Whites are the reference racial group. "Accounting/Finance/Contracts" is the reference primary activity. Column 1 does not include a variable for gender identities, Column 2 includes the binary variable "male", Column 3 includes interaction terms between race/ethnicity binary variables and male variable. Column 4 estimates are produced by adding a binary variable for most recent degree type (1 if STEM) in the specification of Column 3. Main effects of job activities are not reported. Table A.1 for the selection equation estimates.

Table 5: Checking Robustness of Selection-Bias-Corrected Effect of Immigration Status

	(1) $ln(wage)$	(2) $ln(wage)$	(3) $ln(wage)$	(4) $ln(wage)$
Naturalized	0.119***	0.0873***	0.0873***	0.0904***
	(0.00540)	(0.00546)	(0.00546)	(0.00546)
Permanent Resident	0.0590***	0.0456***	0.0456***	0.0485***
	(0.00776)	(0.00766)	(0.00766)	(0.00766)
Temporary Worker	-0.120***	-0.131***	-0.131***	-0.124***
	(0.00836)	(0.00830)	(0.00830)	(0.00835)
Male		0.283***	0.283***	0.318***
		(0.00338)	(0.00338)	(0.00426)
Age		0.00294***	0.00294***	0.00293***
		(0.000157)	(0.000157)	(0.000157)
Asian Non-Hispanic	0.0204***	0.0558***	0.0558***	0.102***
	(0.00542)	(0.00537)	(0.00537)	(0.00757)
Black, Non-Hispanic	-0.143***	-0.102***	-0.102***	-0.0238***
	(0.00624)	(0.00624)	(0.00624)	(0.00827)
Hispanic, any race	-0.0972***	-0.0628***	-0.0628***	-0.0312***
	(0.00511)	(0.00505)	(0.00505)	(0.00740)
Highest Degree STEM	0.136***	0.116***	0.116***	0.115***
	(0.00359)	(0.00356)	(0.00356)	(0.00355)
STEM Occ.	0.207***	0.179***	0.180***	0.182***
	(0.0208)	(0.0207)	(0.0207)	(0.0207)
Highest Degree STEM × Highest degree Master's	0.181**	0.106	0.106	0.106
	(0.0805)	(0.0760)	(0.0760)	(0.0760)
Highest Degree STEM × Highest degree Doctorate	0.195	0.0339	0.0339	0.0337
	(0.124)	(0.130)	(0.130)	(0.130)
Highest Degree STEM × Highest degree professional	0.211**	-0.106	-0.106	-0.106
	(0.0978)	(0.115)	(0.115)	(0.115)
Male × Asian Non-Hispanic				-0.0829***
				(0.00876)
Male × Black, Non-Hispanic				-0.170***
				(0.0124)
Male × Hispanic, any race				-0.0587***
Observations	494,856	494,856	494,856	494,856

Standard Errors in Parentheses. They are clustered at the level of the respondent.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

"U.S. Natives" is the reference group among the variables of Immigration Status. Female is the reference gender identity. Whites are the reference racial group. "Accounting/Finance/Contracts" is the reference primary activity. Column 1 does not include a variable for gender identities, Column 2 includes the binary variable "male", Column 3 includes interaction terms between race/ethnicity binary variables and male variable. Column 4 estimates are produced by adding a binary variable for most recent degree type (1 if STEM) in the specification of Column 3. Second-stage variables not reported here: main effects of job activities: Basic/Applied Research, Product development research, designing, computer programming, human resources, production to marketing, teaching, professional services. Table A.1 for the selection equation estimates.

Table 6: The Effect of Immigration Status: Year × Worker Characteristics Interaction Terms

	(1)	(2)	(3)	(4)	(5)
	ln(wage)	*ln(wage)*	*ln(wage)*	*ln(wage)*	*ln(wage)*
Highest Degree = STEM	0.157***	0.202***	-0.000880	0.116***	0.115***
	(0.00614)	(0.0346)	(0.00424)	(0.00356)	(0.00356)
Naturalized	0.119***	0.0873***	0.0890***	0.0898***	0.0894***
	(0.00540)	(0.00546)	(0.00543)	(0.00546)	(0.00546)
Permanent Resident	0.0581***	0.0454***	0.0512***	0.0498***	0.0495***
	(0.00777)	(0.00766)	(0.00763)	(0.00765)	(0.00765)
Temporary Worker	-0.121***	-0.131***	-0.132***	-0.114***	-0.116***
	(0.00837)	(0.00831)	(0.00831)	(0.00834)	(0.00834)
Asian Non-Hispanic	0.0207***	0.0557***	0.0614***	0.103***	0.103***
	(0.00542)	(0.00537)	(0.00535)	(0.00756)	(0.00756)
Black, Non-Hispanic	-0.143***	-0.102***	-0.0874***	-0.0192**	-0.0193**
	(0.00623)	(0.00623)	(0.00620)	(0.00826)	(0.00826)
Hispanic, any race	-0.0962***	-0.0630***	-0.0499***	-0.0266***	-0.0265***
	(0.00511)	(0.00505)	(0.00504)	(0.00740)	(0.00740)
Male		0.283***	0.274***	0.318***	0.318***
		(0.00338)	(0.00337)	(0.00426)	(0.00426)
Age		0.00294***	0.00330***	0.00211***	0.00212***
		(0.000157)	(0.000155)	(0.000160)	(0.000160)
Age^2	0.000234	0.000220	0.000219	0.000218	0.000217
	(0.000164)	(0.000165)	(0.000165)	(0.000165)	(0.000165)
Primary Job Activity					
Primary Activities: Accounting, finance, contracts	-0.325***	-0.301***	-0.253***	-0.297***	0.318***
	(0.00871)	(0.00861)	(0.00862)	(0.00861)	(0.0120)
Research for gaining scientific knowledge	-0.556***	-0.537***	-0.576***	-0.531***	0.0821***
	(0.00997)	(0.00983)	(0.00987)	(0.00982)	(0.0130)
Applied Research for scientific knowledge	-0.309***	-0.287***	-0.331***	-0.281***	0.333***
	(0.00663)	(0.00657)	(0.00661)	(0.00656)	(0.0108)
Developing knowledge for production purposes	-0.190***	-0.196***	-0.240***	-0.191***	0.423***
	(0.00732)	(0.00727)	(0.00730)	(0.00726)	(0.0113)
Designing equipments, processes, structures	-0.144***	-0.176***	-0.245***	-0.173***	0.441***
	(0.00596)	(0.00595)	(0.00604)	(0.00596)	(0.0104)
Computer Applications, Programming, etc.	-0.100***	-0.118***	-0.199***	-0.115***	0.500***
	(0.00561)	(0.00558)	(0.00571)	(0.00557)	(0.0102)
Human resources	-0.348***	-0.292***	-0.252***	-0.289***	0.326***
	(0.0117)	(0.0116)	(0.0116)	(0.0116)	(0.0143)
Observations	494,856	494,856	494,856	494,856	494,856

Standard Errors in Parentheses. They are clustered at the level of respondent. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. "U.S. Natives" is the reference group among the variables of Immigration Status. Female is the reference gender identity. Whites are the reference racial group. "Managing or supervising people or projects" is the reference primary activity. Primary acitivity categories not reported here: "Production, operations, maintenance", "Professional Services (healthcare, financial services, legal services, etc.", "sales, purchases, marketing", "Quality or productivity management", "Teaching", "Other activity". Secondary activities. Table A.1 for the selection equation estimates. Other covariates in second-stage estimation: **Binary variables:** 1[Highest Degree was in STEM], Year Dummy Variables in all columns. **Interaction Terms as additional Controls**: 1[Highest Degree was in STEM]×Years in Column (1), 1[Most Recent Degree was in STEM]×Years in Column (2), 1[Current Occupation is in a STEM field]×Years in Column (3), Cohort ID × Years in Column (4), and Primary Activity Dummy Indicators × Years in Column (5).

Table 7: The Effect of Immigration Status: Year × Worker Characteristics Interaction Terms

	(1) $ln(wage)$	(2) $ln(wage)$	(3) $ln(wage)$	(4) $ln(wage)$
Naturalized	0.116***	0.128***	0.122***	0.122***
	(0.00591)	(0.00714)	(0.00563)	(0.00563)
Permanent Resident	0.0373***	0.0745***	0.0680***	0.0680***
	(0.00860)	(0.0109)	(0.00797)	(0.00797)
Temporary Worker	-0.133***	-0.0667***	-0.115***	-0.115***
	(0.00876)	(0.0155)	(0.00848)	(0.00848)
Born in Europe	0.00941			
	(0.0233)			
Permanent Resident × Born in Europe	0.0791***			
	(0.0302)			
Temporary Worker × Born in Europe	0.0778**			
	(0.0375)			
Born in Asia		0.0498**		
		(0.0217)		
Naturalized × Born in Asia		-0.0825***		
		(0.0233)		
Permanent Resident × Born in Asia		-0.0980***		
		(0.0258)		
Temporary Worker × Born in Asia		-0.140***		
		(0.0277)		
Born in Africa			-0.0397	-0.0397
			(0.0542)	(0.0542)
Temporary Worker × Born in Africa			-0.0397	-0.0397
			(0.0542)	(0.0542)
Naturalized × Born in Africa			0.0185	0.0185
			(0.0570)	(0.0570)
Permanent Resident × Born in Africa			-0.122*	-0.122*
			(0.0643)	(0.0643)
Temporary Worker × Born in Africa			-0.0910	-0.0910
			(0.0732)	(0.0732)
Observations	494,856	494,856	494,856	494,856

Standard Errors in Parentheses. They are clustered at the level of respondent. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

"U.S. Natives" is the reference group among the variables of Immigration Status. Female is the reference gender identity. Whites are the reference racial group. "Managing or supervising people or projects" is the reference primary activity. Primary acitivity categories not reported here: "Production, operations, maintenance", "Professional Services (healthcare, financial services, legal services, etc.", "sales, purchases, marketing", "Quality or productivity management", "Teaching", "Other activity". Secondary activities. Table A.1 for the selection equation estimates. Other covariates in second-stage estimation: **Binary variables:** 1[Highest Degree was in STEM], Year Dummy Variables in all columns. **Interaction Terms as additional Controls**: 1[Highest Degree was in STEM]×Years in Column (1), 1[Most Recent Degree was in STEM]×Years in Column (2), 1[Current Occupation is in a STEM field]×Years in Column (3), Cohort ID × Years in Column (4), and Primary Activity Dummy Indicators × Years in Column (5).

Table 8: The Effect of Immigration Status: Year × Worker Characteristics Interaction Terms

	(1)	(2)	(3)	(4)	(5)	(6)
	$ln(wage)$	$ln(wage)$	$ln(wage)$	$ln(wage)$	$ln(wage)$	$ln(wage)$
Highest Degree = STEM	0.157***	0.202***	-0.000880	0.116***	0.115***	
	(0.00614)	(0.0346)	(0.00424)	(0.00356)	(0.00356)	
Naturalized	0.0788***	0.0838***	0.0821***	0.0852***	0.106***	0.0852***
	(0.00563)	(0.00563)	(0.00562)	(0.00570)	(0.00567)	(0.00570)
Permanent Resident	0.0293***	0.0324***	0.0329***	0.0435***	0.0616***	0.0435***
	(0.00793)	(0.00791)	(0.00791)	(0.00798)	(0.00801)	(0.00798)
Temporary Worker	-0.185***	-0.171***	-0.178***	-0.114***	-0.0966***	-0.114***
	(0.00871)	(0.00872)	(0.00868)	(0.00864)	(0.00868)	(0.00864)
Asian Non-Hispanic	0.124***	0.130***	0.126***	0.104***	0.132***	0.104***
	(0.00783)	(0.00784)	(0.00783)	(0.00800)	(0.00793)	(0.00800)
Black, Non-Hispanic	-0.0199**	-0.0172**	-0.0207**	-0.0620***	-0.0473***	-0.0620***
	(0.00852)	(0.00853)	(0.00852)	(0.00867)	(0.00860)	(0.00867)
Hispanic, any race	-0.0252***	-0.0255***	-0.0263***	-0.0446***	-0.0579***	-0.0446***
	(0.00764)	(0.00765)	(0.00763)	(0.00787)	(0.00773)	(0.00787)
Male	0.355***	0.381***	0.357***	0.429***	0.429***	0.429***
	(0.00435)	(0.00422)	(0.00434)	(0.00421)	(0.00422)	(0.00421)
Major Occupations						
Computer & Math Sci.	0.318***		0.393***			
	(0.00843)		(0.00465)			
Bio, Agro, Life Sci.	0.120***		0.133***			
	(0.0145)		(0.00651)			
Physical Sci.	0.198***		0.182***			
	(0.0150)		(0.00722)			
Social Sci.	0.115***		0.121***			
	(0.0173)		(0.00815)			
Engineers	0.341***		0.423***			
	(0.00839)		(0.00410)			
Male × Asian Non-Hispanic	-0.105***	-0.105***	-0.105***	-0.100***	-0.105***	-0.100***
	(0.00906)	(0.00909)	(0.00906)	(0.00918)	(0.00920)	(0.00918)
Male × Black, Non-Hispanic	-0.200***	-0.208***	-0.200***	-0.219***	-0.222***	-0.219***
	(0.0128)	(0.0128)	(0.0128)	(0.0129)	(0.0130)	(0.0129)
Male × Hispanic, any race	-0.0766***	-0.0799***	-0.0759***	-0.0773***	-0.0800***	-0.0773***
	(0.0101)	(0.0101)	(0.0101)	(0.0102)	(0.0102)	(0.0102)
Age	0.00234***	0.00203***	0.00232***	0.000743***	-0.000247	0.000743***
	(0.000158)	(0.000158)	(0.000158)	(0.000161)	(0.000165)	(0.000161)
Observations	494,856	494,856	494,856	494,856	494,856	494,856

Standard Errors in Parentheses. They are clustered at the level of respondent. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. "U.S. Natives" is the reference group among the variables of Immigration Status. Female is the reference gender identity. Whites are the reference racial group. Table A.1 for the selection equation estimates. Other covariates in second-stage estimation: Besides estimated effect of Major Occupational Categories in Columns (1) and (3), these regression specifications corresponding these two columns also include interaction terms between the occupational categories and year dummy variables. Regression specifications of Column (4) and (6) results included employer location dummy variables, and Column (5) included cohort dummy indicators.

Table 9: Oaxaca-Blinder Decomposition of the Wage Differentials

	(1)	(2)	(3)
	$ln(wage)$	$ln(wage)$	$ln(wage)$
U.S. Native	10.85***	10.85***	10.85***
	(0.00217)	(0.00217)	(0.00217)
Foreign-born	**Naturalized**	**Permanent Resident**	**Temporary Worker**
	11.23***	11.46***	10.88***
	(0.0156)	(0.0416)	(0.0127)
	-0.380***	-0.610***	-0.0275**
	(0.0158)	(0.0417)	(0.0129)
explained	-0.0368***	-0.0180***	0.121***
	(0.00119)	(0.00293)	(0.00820)
unexplained	-0.343***	-0.592***	-0.149***
	(0.0159)	(0.0418)	(0.0151)
Observations	259911	224940	222487

Robust Standard Errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Table A.1 for the selection equation estimates.
Main Equation RHS Variables: experience, experience squared, STEM occupation indicator, whether highest degree in STEM, employer geographical location, survey year, cohort dummies, age groups, primary activities, highest degree types.

Table 10: The Impact of Change in Immigration Status: Temporary Worker Status to Permanent Residency

	(1)	(2)	(3)	(4)
Permanent Resident	0.0892^{**}	0.107^{***}	0.0844^{**}	0.0978^{**}
	(0.0449)	(0.0394)	(0.0393)	(0.0437)
Occupation:				
Computer and Math Scientist	0.195^{***}			
	(0.0551)			
Engineer		-0.00967		
		(0.0513)		
Physical, Biological, Agro and Life Scientist			0.0168	
			(0.0414)	
Highest Degree = STEM				0.158
				(0.100)
Observations	49733	49733	49733	49733

Standard Errors in Parentheses. They are clustered at the level of respondent.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
This table present Equation (9) estimates. The occupational categories are the only variables different across Columns 1 to 4. Analytical Sample is restricted to naturalized citizens and permanent residents. Permanent residents are the reference group. The coefficient estimate of Naturalized shows the increase in $ln(wage)$ when a permanent resident becomes naturalized. Selection equation covariates: includes age, age^2, 1[Respondent's Highest Degree is in STEM], and number of years since the respondent last worked. age, age^2 are added to the selection equation as within-respondent these two variables had little variation, they are more useful in determining whether the repondent gets highered. Second-stage pooled model covariates: Occupational categories, number of years since the last degree was attained.

Table 11: The Impact of Change in Immigration Status: Naturalization

	(1)	(2)	(3)	(4)
Naturalized	0.122***	0.0973***	0.0924***	0.100***
	(0.0282)	(0.0307)	(0.0313)	(0.0247)
Occupation:				
Computer and Math Scientist	0.148***			
	(0.0456)			
Engineer		0.0357		
		(0.0457)		
Physical, Biological, Agro and Life Scientist			0.0128	
			(0.0388)	
Expert in Social Sciences, Humanities				-0.223**
				(0.0941)
Observations	112644	112644	112644	112644

Standard Errors in Parentheses. They are clustered at the level of respondent. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

This table presents Equation (9) estimates. The occupational categories are the only variables different across Columns 1 to 4. Analytical Sample is restricted to naturalized citizens and permanent residents. Permanent residents are the reference group. The coefficient estimate of Naturalized shows the increase in $ln(wage)$ when a permanent resident becomes naturalized. Selection equation covariates: includes age, age^2, 1[Respondent's Highest Degree is in STEM], and number of years since the respondent last worked. age, age^2 are added to the selection equation as within-respondent these two variables had little variation, they are more useful in determining whether the respondent gets hired. Second-stage pooled model covariates: Occupational categories, number of years since the last degree was attained.

Table 12: Impact of "Buy American and Hire American" on Temporary Worker Wage

	(1) $ln(W)$	(2) $ln(W)$
ATET	0.1018**	0.1029**
	(0.0413)	(0.0394)
Controls:		
Male	0.203***	0.203***
	(0.0302)	(0.0307)
Asian	0.0409	0.0439
	(0.0292)	(0.0294)
Black	-0.277***	-0.289***
	(0.0856)	(0.0866)
Hispanic No-race	0.145***	0.144***
	(0.0384)	(0.0387)
Observations	6179	6179

Clustered Robust Standard Errors in Parentheses. Cluster level: Employer Sector × Region × Year.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

ATET = Average Treatment Effect on the Treated. Treatment Group: Temporary workers between 35 and 50 years old working in the U.S. in STEM fields in the years: 2017 and 2019. Control Group: Permanent residents in between 35 and 50 years old working in the U.S. in STEM fields in the years: 2017 and 2019. Pre-treatment years: 2010, 2013, 2015. Group Fixed Effects: Column 1 - Immigration Status: Natives, Naturalized Citizens, Permanent Residents, and Temporary Workers. Column 2 - Fixed Effects generated by interacting Immigration Status × Employer Sectors. Employer Sectors: four-year educational institute, 2-year educational institute, Business for-profit, self-employed or not-incorporated, Business non-profit, Federal Government, State Government. Control Variables: Highest degree types (Bachelor's, Master's, Professional, Doctorates), STEM Occupational Categories, Primary Activity Indicators, Employer Location Indicators, Year Dummies.

Table 13: Impact of "Buy American and Hire American" on Temporary Worker Wage - Male vs Female

	(1) $ln(W)$	(2) $ln(W)$
ATET	0.108**	0.197**
	(0.0438)	(0.0837)
Controls:		
Asian non-Hispanic	0.106*	0.0912
	(0.0569)	(0.0954)
Black, non-Hispanic	-0.295***	-0.163
	(0.101)	(0.144)
Hispanic, Any race	0.0444	-0.0199
	(0.0469)	(0.0895)
Observations	4488	1691
Sample	Male	Female

Clustered Robust Standard Errors in Parentheses. Cluster level: Employer Sector × Region × Year.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

ATET = Average Treatment Effect on the Treated. Treatment Group: Temporary workers between 35 and 50 years old working in the U.S. in STEM fields in the years: 2017 and 2019. Control Group: Permanent residents in between 35 and 50 years old working in the U.S. in STEM fields in the years: 2017 and 2019. Pre-treatment years: 2010, 2013, 2015. Group Fixed Effects: Column 1 - Immigration Status: Natives, Naturalized Citizens, Permanent Residents, and Temporary Workers. Column 2 - Fixed Effects generated by interacting Immigration Status × Employer Sectors. Employer Sectors: four-year educational institute, 2-year educational institute, Business for-profit, self-employed or not-incorporated, Business non-profit, Federal Government, State Government. Control Variables: Highest degree types (Bachelor's, Master's, Professional, Doctorates), STEM Occupational Categories, Primary Activity Indicators, Employer Location Indicators, Year Dummies.

Table 14: Impact of "Buy American and Hire American" on Temporary Worker Wage - Additional Fixed Effects

	(1) $ln(wage)$	(2) $ln(wage)$	(3) $ln(wage)$	(4) $ln(wage)$
ATET	0.112***	0.116***	0.109***	0.107***
	(0.0404)	(0.0397)	(0.0402)	(0.0401)
Controls				
White	0.154***	0.146***	0.157***	0.147***
	(0.0448)	(0.0447)	(0.0455)	(0.0446)
Black	-0.205**	-0.226***	-0.215***	-0.230***
	(0.0832)	(0.0806)	(0.0819)	(0.0828)
Asian	0.0454	0.0436	0.0478	0.0434
	(0.0346)	(0.0325)	(0.0332)	(0.0331)
Male	0.190***	0.208***	0.201***	0.211***
	(0.0403)	(0.0366)	(0.0371)	(0.0359)
Observations	6179	6179	6179	6179

Clustered Robust Standard Errors in Parentheses. Cluster level: Employer Sector × Region × Year.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

ATET = Average Treatment Effect on the Treated. Treatment Group: Temporary workers between 35 and 50 years old working in the U.S. in STEM fields in the years: 2017 and 2019. Control Group: Permanent residents in between 35 and 50 years old working in the U.S. in STEM fields in the years: 2017 and 2019. Pre-treatment years: 2010, 2013, 2015.

Fixed Effects: 1[Temporary Worker]× Fields of Major for Highest Degree in Column (1) specification, 1[Temporary Worker]× Primary Work Activity Indicators in Column (2) specification, 1[Temporary Worker]× Broad categories of highest degree fields in Column (3) specification, 1[Temporary Worker]× 1[Highest Degree is in STEM] (4) specification.

Control Variables: Highest degree types (Bachelor's, Master's, Professional, Doctorates), STEM Occupational Categories, Primary Activity Indicators, Employer Location Indicators, Year Dummies.

Table 15: "Buy American and Hire American" Additional Interaction Terms as Controls

	(1) $ln(wage)$	(2) $ln(wage)$	(3) $ln(wage)$
Panel A			
ATET	0.119***	0.113***	0.120***
	(0.0390)	(0.0408)	(0.0392)
Panel B			
ATET	0.121***	0.116***	0.118***
	(0.0378)	(0.0379)	(0.0377)
Panel C			
ATET	0.118***	0.115***	0.117***
	(0.0377)	(0.0391)	(0.0389)
Panel D			
ATET	0.124***	0.118***	0.119***
	(0.0383)	(0.0384)	(0.0380)
Observations	6179	6179	6179

Clustered Robust Standard Errors in Parentheses. Cluster level: Employer Sector × Region × Year.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
ATET = Average Treatment Effect on the Treated. Treatment Group: Temporary workers between 35 and 50 years old working in the U.S. in STEM fields in the years: 2017 and 2019. Control Group: Permanent residents in between 35 and 50 years old working in the U.S. in STEM fields in the years: 2017 and 2019. Pre-treatment years: 2010, 2013, 2015.
Control Variables: Highest degree types (Bachelor's, Master's, Professional, Doctorates), STEM Occupational Categories, Primary Activity Indicators, Employer Location Indicators, Year Dummies.
Fixed Effects: 1[Temporary Worker]× Fields of Major for Highest Degree in Panel A specifications, 1[Temporary Worker]× Primary Work Activity Indicators in Panel B specifications, 1[Temporary Worker]× Broad categories of highest degree fields in Panel C specifications, 1[Temporary Worker]× 1[Highest Degree is in STEM] in Panel D specifications.
Additional Interaction Terms: For Column 1 specifications: Employer Sector Dummies (Business, Academic, Government) × Year. For Column 2 specifications: Employer Location Dummies (New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Atlantic, West South Atlantic, Mountain, Pacific, U.S. Territories) × Year. Column 3 specifications: Employer size dummies (10 or fewer, 11-24, 25-99, 100-499, 500-999, 1000-4999, 5000-24999, 25000 or above) × Year.

Figures

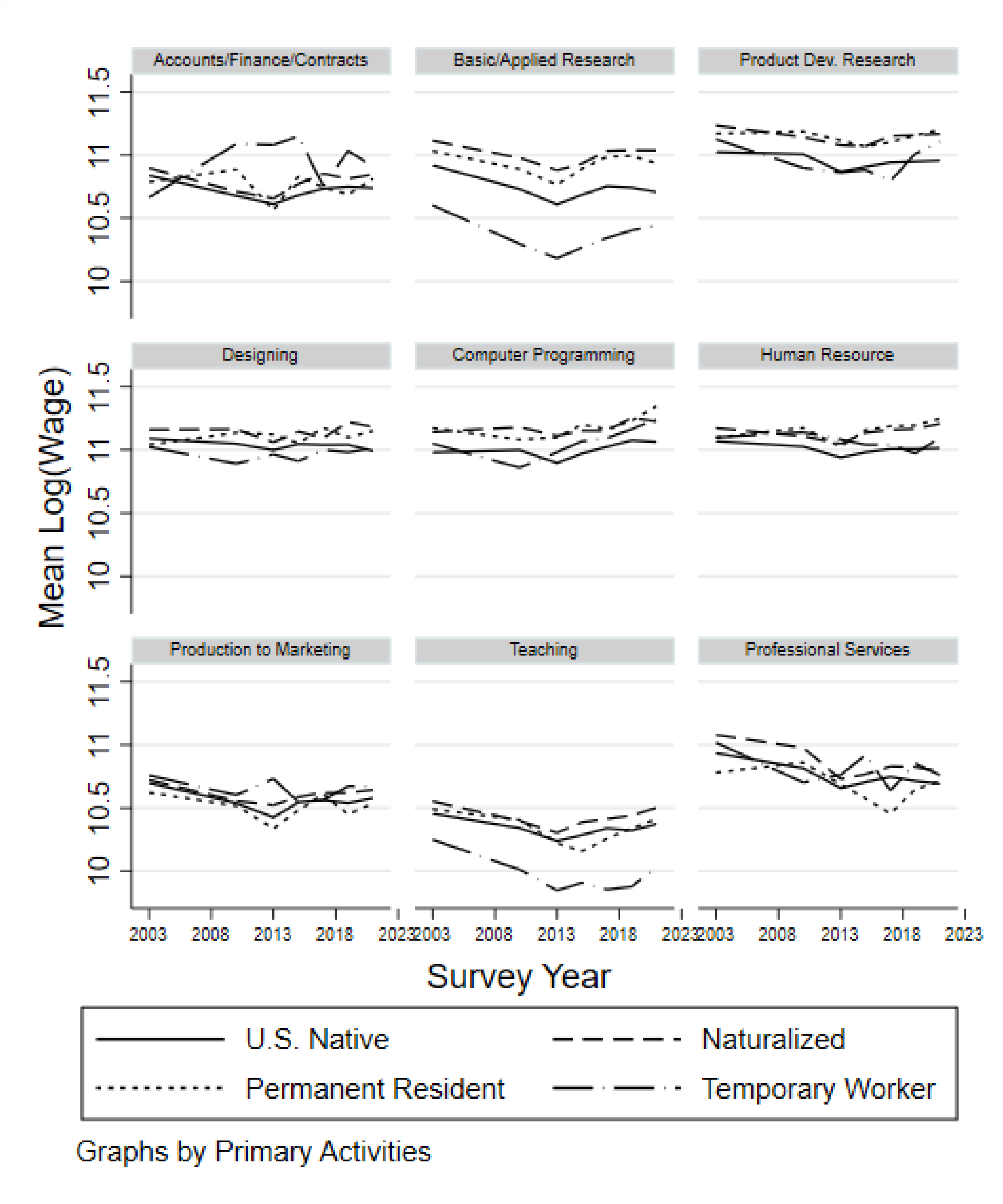

Figure 1: Mean Salary by Primary Activities

*The primary activities in NSCG are combined and shortened into compact headings in Figure 1[23].

[23]**Basic and Applied Research** combines two activities: "basic research or study to gain scientific knowledge primarily for its own sake" and "applied research or study to gain scientific knowledge to meet recognized need". **Product dev. research** = developing knowledge from research for the production of materials and devices. **Designing** = design of equipment, processes, structure, models. **Computer Programming** = Computer applications, programming, systems development. **Human Resources** = human resources, including recruiting, personal development, training, and managing or supervising people or projects. **Production to Marketing** = production, operations, maintenance (e.g. chip production);

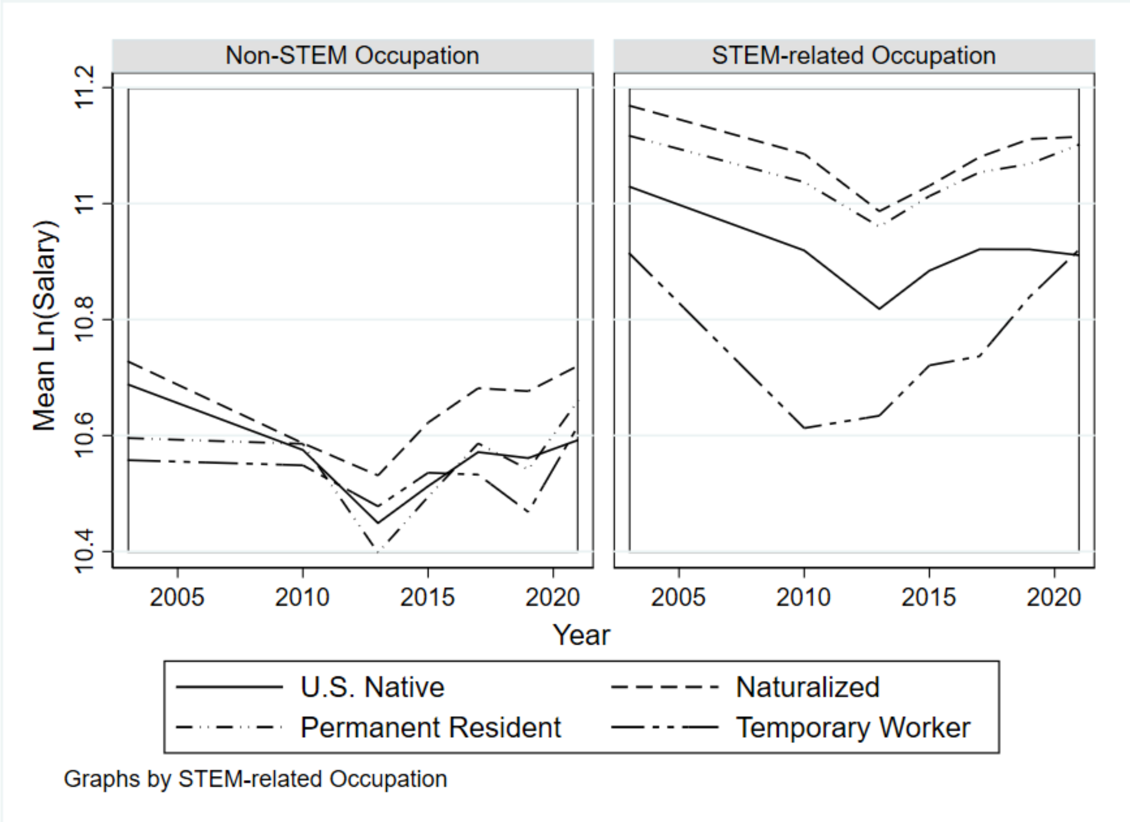

Figure 2: Trends of mean $ln(wage)$ for Workers of Different Immigration Statuses.

sales, purchasing, marketing; quality or productivity management. **Professional Services** = Professional services like healthcare, financial services, legal services, etc.

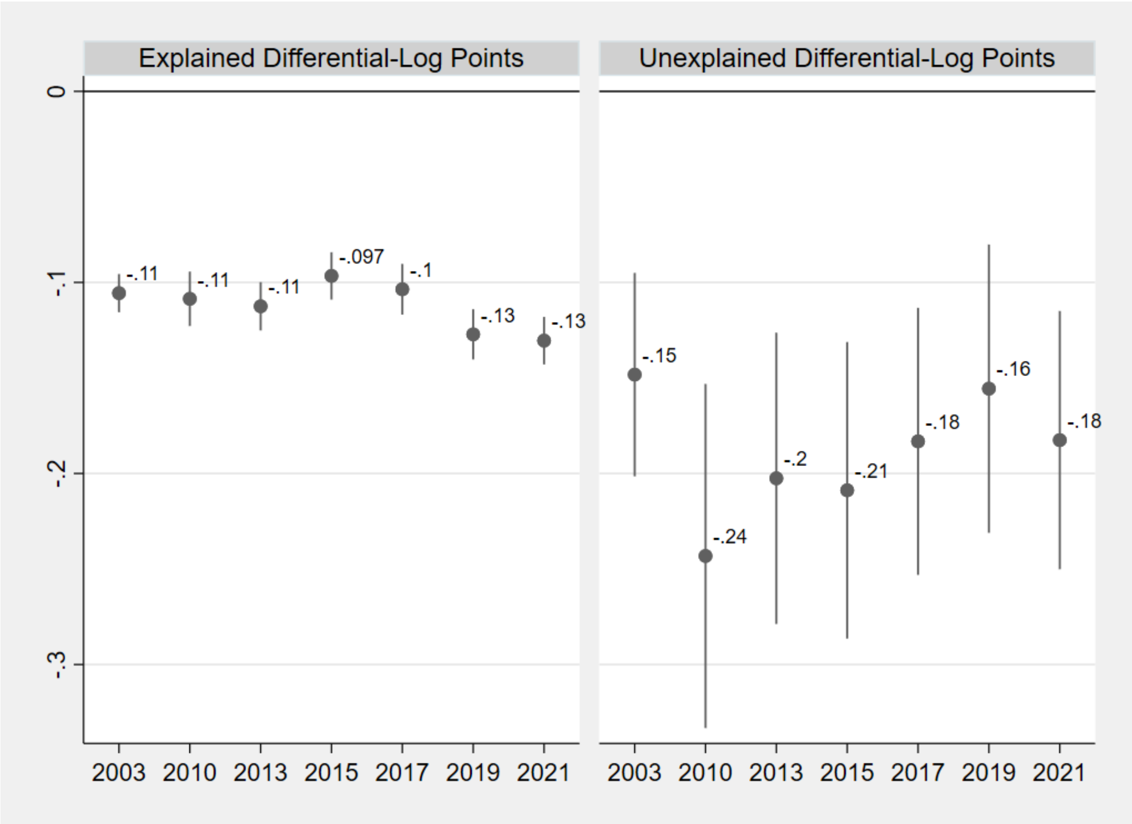

Figure 3: STEM Wage Differential. Mean Wage of U.S. Natives - Mean Wage of Naturalized Citizens

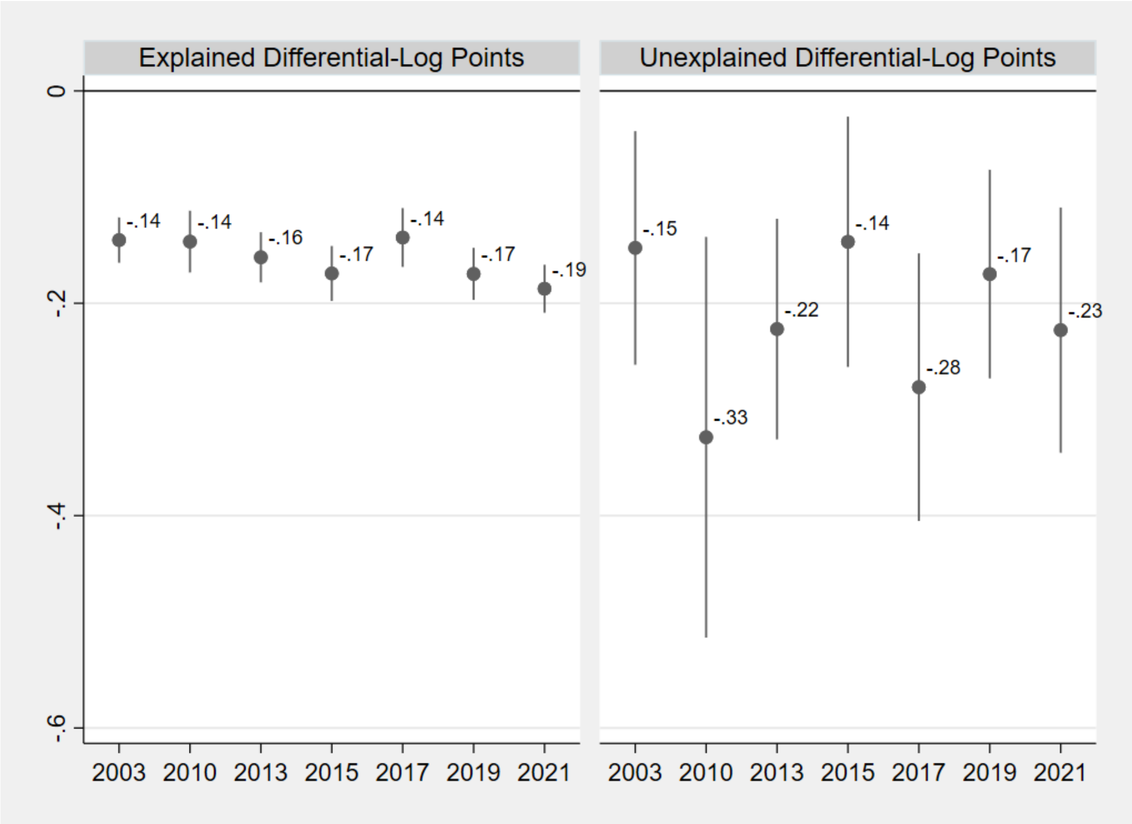

Figure 4: STEM Wage Differential. Mean Wage of U.S. Natives - Mean Wage of Permanent Residents

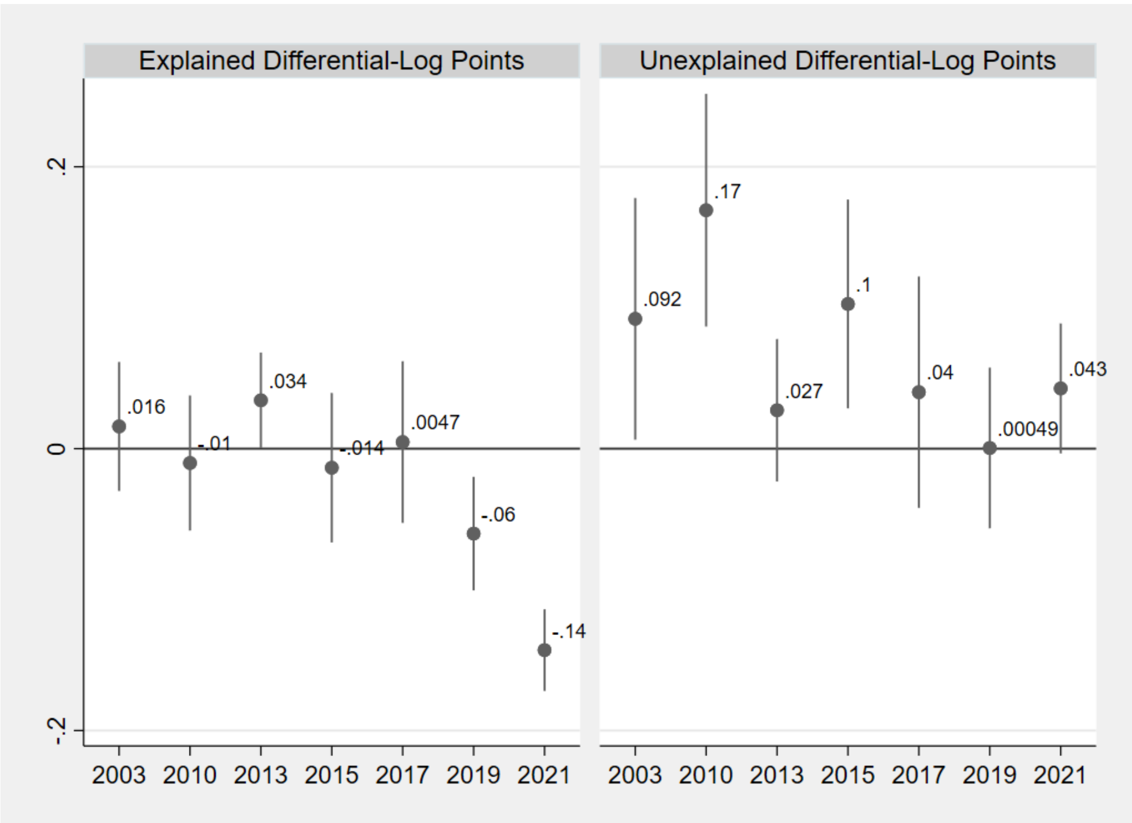

Figure 5: STEM Wage Differential. Mean Wage of U.S. Natives - Temporary Workers

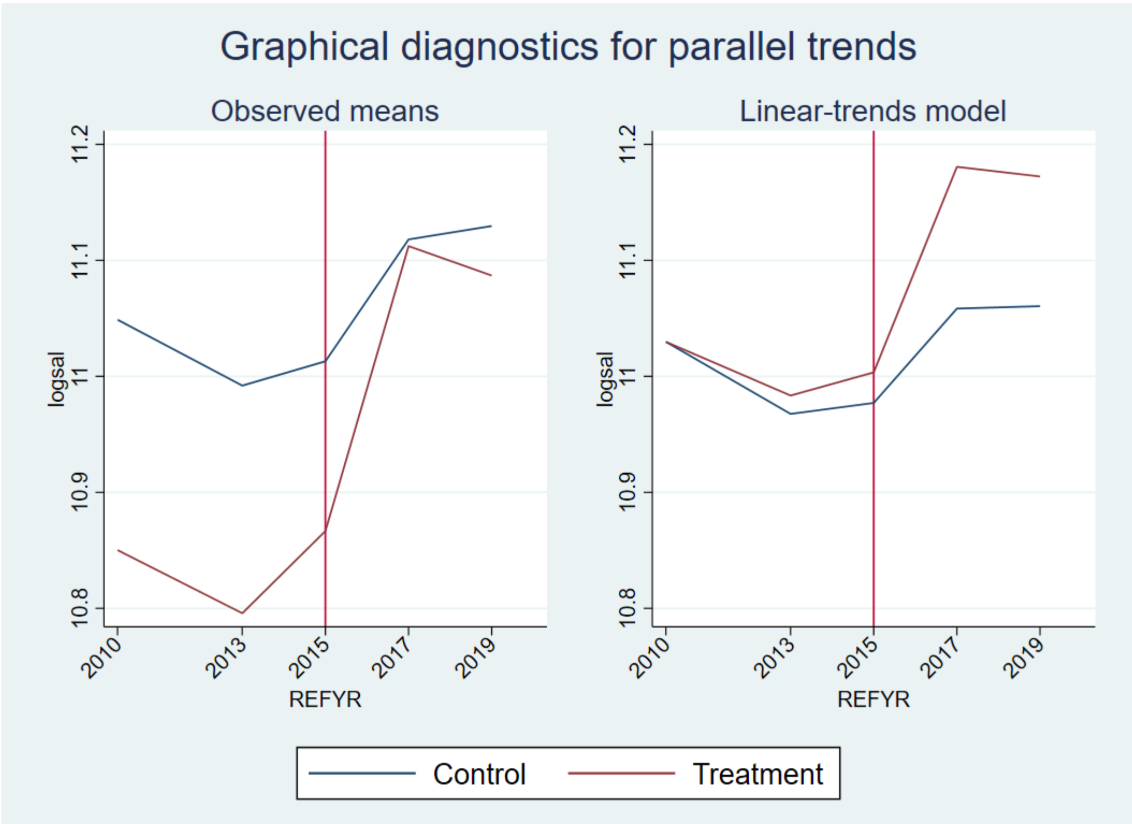

Figure 6: The pre- and post-treatment trends in the $ln(wage)$

Appendix

Table A.1: The Selection Equation for Bias Correction for the Pooled OLS Model

	(1) Working = 1
Male	0.356***
	(0.00420)
Asian Non-Hispanic	-0.0991***
	(0.00591)
Black, Non-Hispanic	-0.0398***
	(0.00778)
Hispanic, any race	-0.00275
	(0.00731)
Highest Degree STEM	0.103***
	(0.00415)
Highest degree is Bachelor's	0.175***
	(0.00832)
Highest degree is Master's	0.326***
	(0.0110)
One parent has bachelor's degree	0.139***
	(0.00800)
One parent has master's degree	0.200***
	(0.00747)
One parent has doctoral degree	0.188***
	(0.00790)
Living with Children	-0.266***
	(0.00458)
Married	-0.0328***
	(0.00494)
Observations	621991

Standard Errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

- Unreported variables: Year highest degree attainment fixed effects, Year fixed effects, highest degree major categories

Table A.2: Duration of Employment with the Current Employer and Immigration Status

	(1) *Years*	(2) *Years*	(3) *Years*
Permanent Resident	-1.467***	-2.877***	-2.222***
	(0.0557)	(0.0772)	(0.0488)
Temporary Worker	-2.035***	-4.430***	-3.640***
	(0.0712)	(0.0577)	(0.0417)
Male	1.216***	2.906***	2.576***
	(0.0745)	(0.0697)	(0.0522)
Asian Non-Hispanic	-0.0478	-1.245***	-0.841***
	(0.0658)	(0.0845)	(0.0574)
Black, Non-Hispanic	-0.783***	-1.332***	-1.121***
	(0.116)	(0.145)	(0.0998)
Hispanic, any race	-0.0764	-1.099***	-0.705***
	(0.0915)	(0.115)	(0.0784)
Inverse Mill's Ratio	7.090***	13.33***	13.63***
	(0.468)	(0.273)	(0.249)
Constant	4.676***	4.221***	3.663***
	(0.131)	(0.123)	(0.0915)
Observations	46995	66025	113020
Adjusted R^2	0.026	0.109	0.074
Age groups	35-50	Below 30 and above 50	full sample

Standard Errors in Parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The inverse Mill's ratio is from employment selection bias correction using Heckman (1976)'s method. Control variables in the first-stage regression for employment selection bias correction: Gender, Race, 1[$HighestDegreeisinSTEM$], Parents' Schooling years, 1[respondent has children in the household], 1[respondent married], Year of attaining highest degree indicators.

Table A.3: Do Temporary Workers Change Industry in Response to Lower Visa Application Acceptance Rate?

Probit Model with Heckit Bias Correction	(1) $1[Academic]$	(2) $1[Business]$	(3) $1[Government]$
Asian Non-Hispanic	0.158*	-0.242***	0.248**
	(0.0893)	(0.0870)	(0.118)
Black Non-Hispanic	0.0430	0.00315	-0.143
	(0.0588)	(0.0579)	(0.0953)
Hispanic, any race	-0.107***	0.128***	-0.110**
	(0.0382)	(0.0374)	(0.0562)
Male	-0.584***	0.585***	-0.535***
	(0.0334)	(0.0329)	(0.0630)
Year 2017 & 2019	0.0198	-0.00368	-0.0798
	(0.0306)	(0.0313)	(0.0521)
Temporary Worker	0.255***	-0.247***	0.0196
	(0.0431)	(0.0435)	(0.0661)
Temporary Worker × Year 2017 & 2019	-0.187***	0.192***	-0.0284
	(0.0650)	(0.0659)	(0.105)
Male	0.626***	0.643***	0.789***
	(0.0443)	(0.0446)	(0.0450)
Observations	7481	7481	7481

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The above results show Selection-bias corrected results of Probit regressions. Selection Bias correction method based on Heckman (1976).
The inverse Mill's ratio is from employment selection bias correction using Heckman (1976)'s method. Control variables in the first-stage regression for employment selection bias correction: Gender, Race, $1[HighestDegreeisinSTEM]$, Parents' Schooling years, 1[respondent has children in the household], 1[respondent married], Year of attaining highest degree indicators.