Do Foreigners Crowd Natives out of STEM Degrees and Occupations? Evidence from the U.S. Immigration Act of 1990*

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Abstract

This paper examines effects of the U.S. Immigration Act of 1990 on STEM (science, technology, engineering, and mathematics) education and labor market outcomes for native-born Americans. The Act increased the inflow and stock of foreign STEM workers in the U.S., potentially altering the relative desirability of STEM fields for natives. The authors examine effects of the policy on STEM degree completion, STEM occupational choice, and employment rates separately for black and white men and women. The novel identification strategy measures exposure to foreign STEM workers of age-18 native cohorts immediately before and after the policy change via geographic dispersion of foreign-born STEM workers in 1980, which predicts subsequent foreign STEM flows. The Act affected natives in three ways: (1) black male students moved away from STEM majors; (2) white male STEM graduates moved away from STEM occupations; and (3) white female STEM graduates moved out of the workforce.

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Increasing the science, technology, engineering, and mathematics (STEM) workforce is widely viewed in the United States as vital for innovation, economic growth, well-being, and national security (National Academies (National Academy of Sciences, National Academy of Engineering, and Institute of Medicine), 2010; President's Council of Advisors on Science and Technology (PCAST), 2012). One potential way to grow the STEM workforce is through increased high-skilled immigration. However, an increased number of foreign-born STEM workers might impact STEM education and employment of natives overall, and especially among groups historically underrepresented in STEM. The extant literature is small, and much is still unknown.

In this paper, we use a novel identification strategy to examine effects on the education and employment outcomes of native-born Americans of a U.S. policy that dramatically increased the number of foreign-born skilled workers over a short period of time. Specifically, we examine whether the U.S. Immigration Act of 1990 (IA90) altered STEM graduation rates and STEM employment rates of native-born Americans. We also study whether the policy had different effects on different demographic subgroups.

We estimate reduced-form effects of increased foreign-born STEM workers on U.S. native STEM degree completion and employment by using policy changes from IA90 as a natural experiment. We employ an identification strategy using variation in natives' exposure to foreign STEM workers in two dimensions: (1) those who turned 18 immediately before and after the policy; and (2) cross-state foreign-born shares of STEM workers in 1980, which precedes IA90 and predicts subsequent foreign STEM flows to state and local areas.

It is important to understand both the costs and benefits of increased high-skilled immigration on the U.S. economy. While there are likely numerous benefits to the U.S. from admitting high-skilled foreigners into the country, high-skilled immigration may also impose costs on some

Americans. Knowing who bears the costsand what the size of the costs areis important for crafting policies to maximize welfare. Our study sheds light on how high-skilled immigration affects the human capital investment and utilization of native workers and has important implications for both immigration and human capital policy.

1 Policy Background and Literature Review

The U.S. Immigration Act of 1990 was passed by Congress on October 27, 1990 and was signed into law by President George H.W. Bush on November 29, 1990. The law became effective October 1, 1991the start of the U.S. government's 1992 Fiscal Year. The Act constituted a comprehensive immigration reform that both increased immigration overall and placed greater emphasis on admitting skilled immigrants. President Bush (1990) called it "the most comprehensive reform of our immigration laws in 66 years."

The Act was designed to increase skilled immigration in two distinct and important ways. First, occupation-based immigrant visas available per year increased from 54,000 to 140,000 and placed increased emphasis on education and work skills (Greenwood and Ziel, 1997). Recipients of these visas immediately obtained green cards and became permanent residents. Second, IA90 also substantially revised the temporary work visa program by creating the widely publicized H-1B program for temporary work visas in specialty occupations, many of which were STEM-related. The H-1B program also significantly reduced barriers for skilled workers on temporary visas to pursue permanent residency (Lowell, 2001).[1]

[1]The H-1B program was initially capped at 65,000 visas per year. This cap was raised to 115,000 in 1998 and then to 195,000 in 2000 before being reduced to 85,000 in 2004 (with exemptions for academic, non-profit, and governmental research institutions). STEM occupations are heavily represented among H-1B visas and the program has played a major role in growing the foreign STEM workforce in the U.S (Kerr and Lincoln, 2010).

Over time, the various policy changes from IA90 significantly increased the foreign-born STEM workforce in the U.S., and this has been found to have increased innovation and economic growth (Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010; Winters, 2014; Peri, Shih, and Sparber, 2015). The increase in the foreign STEM workforce was especially driven by China and India, which had previously experienced considerable excess demand and long waiting lists for green cards (see Kerr, 2008, , Figure 3). The large increase in Chinese STEM immigrants was also connected to the Chinese Student Protection Act (CSPA) signed in 1992, which allowed Chinese students in the U.S. since the Tiananmen Square incident in 1989 to transition to permanent resident status during 1993–1994. Excess green cards under CSPA were deducted from Chinese quotas in subsequent years, so IA90 is still the binding legislation.[2]

The post-IA90 foreign STEM inflow was not equal across the U.S. The foreign STEM workforce increased the most in areas that previously had large numbers of foreign STEM workers (Peri, Shih, and Sparber, 2015). Newly arriving foreigners tend to locate in areas where persons from the same national origin reside to take advantage of social networks and cultural and linguistic similarity (Card, 2001). This pattern continued after IA90. States with previously high levels of foreign STEM workers, like California, New York, and Washington, received some of the largest inflows of foreign STEM workers after 1990. However, such states also experienced growing demand for STEM workers, especially related to the information and communication technology (ICT) revolution. Thus, examining effects of increased foreign STEM workers on natives requires careful consideration.

There is considerable debate and conflicting empirical evidence about whether increases

[2]The influx of foreign STEM workers also included immigrants from former Soviet republics after 1992, especially among academic mathematicians, as noted by Borjas and Doran (2012).

in foreign workers actually constitute adverse labor market shocks (Card, 1990, 2001; Borjas, 2003, 2017; Bound et al., 2015; Bound, Khanna, and Morales, 2017; Kerr, 2013; Peri, Shih, and Sparber, 2015; Llull, 2017). Theory suggests that an increase in foreign-born skilled labor supply will adversely affect labor outcomes for natives who are easily substitutable with the skilled foreigners, consistent with a downward-sloping demand curve for a particular type of labor. However, skilled foreigners may be complementary with other native workers and increase their productivity. The net effect is thus theoretically ambiguous. Similarly, an increased supply of foreigners with particular skills may encourage natives to alter their human capital investments toward skills that are less substitutable and more complementary with foreigners (Peri and Sparber, 2009, 2011; McHenry, 2015; Jackson, 2016; Hunt, 2017).

A large influx of foreign-born STEM workers has the potential to alter college major decisions and post-graduation outcomes of natives. Minorities and women, who are already considerably underrepresented in STEM fields (Weise and Guynn, 2014; Bidwell, 2015; Neate, 2015; Lowe, 2016; Vara, 2016), may be especially affected (Orrenius and Zavodny, 2015). A broad literature finds that minorities tend to be the most severely harmed by adverse labor market shocks (Couch and Fairlie, 2010; Hoynes, Miller, and Schaller, 2012; Hirsch and Winters, 2014). Borjas, Grogger, and Hanson (2010) suggest that labor market outcomes of black men are especially harmed by immigration. Similarly, women and minorities might be the most likely to shift away from STEM degrees or STEM occupations by increases in foreign STEM workers.

The research literature on the effects of foreigners on native STEM education is thin, comprising just two studies. Orrenius and Zavodny (2015) find that increases in same-age foreigners during school ages reduce STEM education for native women but not men. Anelli, Shih, and Williams (2017) examine administrative data for one large public university in California and find that foreign student shares in undergraduate math classes crowd natives out of STEM and into a similarly high-paying subset of social science majors. In contrast, our approach examines how increases in foreign-born competition in the labor market affects STEM education and employment among natives.

2 Empirical Framework

This section outlines our data, identifying assumptions and empirical strategy for estimating the impact of IA90 on native skill investments and utilization. We use nationally representative microdata with annual variation based on year age 18. Our approach allows for a distinct break in the timing of the treatment. We also measure native foreign STEM exposure by state of birth instead of current residence to account for possible out-migration in response to foreign inflows.

2.1 Data

Our primary data come from the 2009–2016 American Community Survey (ACS) microdata extracted from IPUMS (Ruggles et al., 2017). The ACS annually surveys 1% of the U.S. population and includes individual information on age, sex, race, ethnicity, state of birth, occupation, employment, education level, and undergraduate field of study for those completing a bachelor's degree or higher. College major was first asked in the 2009 ACS, which limits the start period for our sample. We define ACS college majors as STEM majors based primarily on definitions used by U.S. Immigration and Customs Enforcement. The full list of ACS majors coded as STEM is in Appendix Table A1. Some graduates report double majors. We classify them as STEM graduates if either their first or second major is a STEM field.

Along with college major, we are interested in whether STEM graduates work in STEM occupations and in measuring the extent of foreign presence in STEM occupations. Our main definition for STEM occupations includes persons working as engineers, mathematicians, natural scientists, computer scientists, and computer software developers, but we also examine robustness to considering a broader definition with health-diagnosing occupations (and STEM college instructors in 1980). The list of STEM occupations is in Appendix Table A2.

2.2 Identifying Assumptions

An important issue for our analysis is deciding which individuals were most exposed to the increased inflow of skilled foreign-born workers. Following existing literature, we measure the timing of increased foreign STEM shocks from IA90 for natives based on the year they were 18 years of age. We compute the year age 18 as the ACS calendar year minus age at the time of the survey plus 18.[3] We do not observe in the data when someone graduated high school, attended college, or chose their college major, but we follow previous literature and assume that individuals graduate high school, begin college, and choose their major at age 18 (Dynarski, 2008; Malamud and Wozniak, 2012; Orrenius and Zavodny, 2015; Sjoquist and Winters, 2014, 2015). To isolate the effects of IA90, we restrict our main analysis to persons who were age 18 in the four years prior to and following 1990 (i.e. 1986–1994); these persons were ages 33–48 in 2009–2016. We assume that persons age 18 in 1986–1989 made their educational decisions independent of IA90, while persons age 18 in 1991–1994 were potentially affected by IA90. We exclude persons age 18 in 1990 because they may be partially affected, but likely not as strongly as later cohorts. Their

[3]For example, someone surveyed in 2010 at age 36 would have been 18 in year 1992.

inclusion would likely increase measurement error in the treatment from IA90.[4] By including year 1991 in the treatment, we allow for both the announcement and implementation of IA90 to affect the outcomes we analyze. Examining a longer time period might cause other policy changes and economic shocks to confound the analysis. However, we also present results with moderate expansions in the time period examined.

One might wish to measure the actual presence of foreign STEM workers by year across geographic areas, but we do not take this approach for two main reasons. First, using contemporaneous measures for foreign STEM presence and native STEM education would likely cause the relationship to be confounded by unobserved demand shocks for STEM workers that ceteris paribus increase both native STEM education and foreign STEM inflows. Second, there is no annual data on foreign STEM workers during this time period. Decennial census data are available for 1980, 1990, and 2000, but intercensal population estimates do not include occupation. Another potential data source, the Current Population Survey (CPS), is conducted annually and includes occupation information but not citizenship or foreign birth status prior to 1994 and cannot be used to confidently construct measures of foreign STEM workers for our study. CPS sample sizes for individual states are also relatively small and would produce noisy estimates even if foreign-born persons were identifiable.

We measure a state's foreign STEM exposure as the share of college-educated STEM workers ages 25–59 who are foreign born in that state using the 1980 census 5% microdata file from IPUMS (Ruggles et al., 2017).[5] The foreign STEM share is measured for 1980 instead of 1990 so that it is determined before our 1986–1989 control group cohorts make initial higher

[4]The 1986–1989 cohorts could have been partially affected also. If so, assuming that they are unaffected would induce measurement error in the treatment from IA90 and attenuate pre- and post-IA90 differences toward zero.

[5]In the 1980 Census, we define college education as completing four years of college or more. In the 1990 and 2000 Censuses and the ACS, we define college education as holding a bachelors degree or advanced degree.

education decisions at age 18, and so that it precedes the ICT revolution that increased demand for STEM skills.

The motivation for using the 1980 foreign STEM share is that previous research inclines us to expect IA90 to increase the foreign STEM workforce the most in areas that already had large numbers of foreign STEM workers (Kerr and Lincoln, 2010; Peri, Shih, and Sparber, 2015). This relationship is illustrated in Figure 1. We compute the foreign STEM share by state in 1990 and 2000 using the decennial census 5% files and then compute 1990–2000 changes. Regressing the 1990–2000 change in the foreign STEM share on the 1980 foreign STEM share yields a positive coefficient of 0.467 that is statistically significant at the 1% level with an R^2 of 0.338. Areas with already high foreign STEM shares in 1980 saw especially large increases in foreign STEM shares during the 1990s following IA90. As noted above, data limitations prevent us from constructing measures of annual growth in the foreign STEM share. However, we expect that the college major decisions of native-born Americans would be affected both by the actual increase in the foreign STEM workforce during their college years as well as their expectations about future increases.

We use state of birth to measure differential exposure to increased levels of foreign STEM workers across states. The ACS does not report the location where someone attended high school or college, but state of birth has been used as a proxy for these by previous researchers (Dynarski, 2008; Malamud and Wozniak, 2012; Orrenius and Zavodny, 2015; Sjoquist and Winters, 2014, 2015). Sjoquist and Winters (2014) report that in 1990, roughly three-fourths of persons ages 15–17 resided in their state of birth. Since some young people do move out of their birth state before finishing high school and starting college, the birth-state exposure assumption will induce some degree of measurement error, which is likely to attenuate coefficient estimates toward zero.

One threat to our identification strategy is the adoption of merit-based scholarship programs. Sjoquist and Winters (2015) find that state adoption of "strong" merit-based scholarship programs causes students to shift away from STEM majors. Georgia is the only state to adopt a strong merit aid program during the 1986–1994 period, but Arkansas, Missouri and North Dakota also adopted weaker programs during this period. To avoid potential confounding effects, our primary analysis excludes these four merit states, but results are robust to including them.

2.3 Empirical Strategy

We now detail our empirical strategy for examining effects of increased foreign STEM inflows. One approach for estimating effects of foreign STEM exposure on native STEM outcomes would be to compare natives born in states that were differentially exposed to foreign STEM workers, before and after the policy, with a binary treatment dummy. Assuming a linear probability model (LPM) gives a classic difference-in-differences regression equation:[6]

$$P\left(Y_{isc}=1\right)=\alpha_0+\alpha_1 post_c+\alpha_2 exposed_s+\theta post_c \times exposed_s \tag{1}$$

where $post_c$ indicates year-age-18 cohorts c that began college after 1990, and $exposed_s$ indicates individuals born in states s where foreign STEM exposure was high. θ is the difference-in-differences estimate, which gives the effect of the policy.

In our setting, however, treatment is continuous rather than binary, so we modify the basic model to allow for dosage effects:

[6] We estimate linear probability models instead of probit or logit models for simplicity and ease of interpretation. LPM is very common in the policy evaluation literature when models include high dimensional fixed effects and facilitates easier interpretation of marginal effects.

$$P\left(Y_{isc}=1\right)=\alpha_0+\alpha_1 post_c+\alpha_2 exposure_s+\theta post_c\times exposure_s \tag{2}$$

where $exposure_s=\frac{N_{1980,STEM,s,foreign}}{N_{1980,STEM,s}}$ measures foreign STEM exposure in the individual's state of birth on a scale of zero to one. $N_{1980,STEM,s}$ refers to the total number of college-educated workers (age 25-59) in state s in 1980 working in STEM occupations, while $N_{1980,STEM,s,foreign}$ is the number of college-educated workers (age 25-59) in state s in 1980 working in STEM occupations and who were not born in the United States.

We are also interested in controlling for additional sources of heterogeneity, such as birth cohort, birth state, year of survey, age at survey, and time-varying birth-state characteristics. Our preferred specification is thus:

$$\Pr\left(Y_{iscta}=1\right)=\theta\text{ForeignSTEMexposure}_{sc}+\Gamma_s+\Pi_c+\Psi_t+\Omega_a+\beta Z_{sc}+\delta_s T_{sc}, \tag{3}$$

where $ForeignSTEMexposure_{sc}$ is our measure of foreign STEM exposure, equal to $post_c\times exposure_s$ in (2), and t indexes ACS survey year while a indexes age at which the ACS survey was taken. Birth state fixed effects, Γ_s in (3), replace the $exposure_s$ variable from (2), while year-age-18 cohort fixed effects, Π_c, replace the $post_c$ dummy. Other studies with dosage effects in a difference-in-differences framework include Acemoglu, Autor, and Lyle (2004) and Stevenson (2010), among others.

The model also includes survey year effects (Ψ_t) and age effects (Ω_a). Because we observe cohorts at ages 33–48 and include year-age-18 cohort dummies, these effects control for aggregate business cycle variation during the ACS survey years and variation in the time duration between age 18 and the time of the survey.

Additionally, our models include time-varying state-level control variables (Z_{sc}) measured at year age 18 in one's birth state and birth-state by year-age-18 linear time trends (T_{sc}). The Z_{sc} variables include log cohort size at age 18 from U.S. Census Bureau intercensal population estimates, the state unemployment rate from the U.S. Bureau of Labor Statistics, and the log of median household income computed from the Current Population Survey. State-specific time trends account for other unobservable factors, e.g., increased relative demand for STEM skills.

We primarily examine three separate outcomes in which Y_{iscta} equals one for persons meeting the following conditions: (1) graduating with a bachelor's degree in a STEM field; (2) working in a STEM occupation during the 2009–2016 ACS reference period; and (3) working in any occupation during the 12 months prior to their 2009–2016 ACS survey. We also discuss results for additional related outcomes. We estimate the models separately for native-born black and white men and women.[7] All estimates use sample weights. Standard errors are clustered by birth state.

Birth-state fixed effects and cohort effects control for time-invariant differences across birth states and aggregate time differences across cohorts, respectively. Thus, identifying variation comes from differences across cohorts within states, while subtracting out aggregate time effects. More specifically, our analysis compares the pre- and post-IA90 within-state changes in native STEM outcomes across states with differing treatment intensities. If IA90 caused foreign STEM workers to crowd natives out of STEM fields, we would expect this to be most pronounced in

[7]Throughout this study, we refer to white and black individuals as those who are not Hispanic. We do not examine Hispanics or Asians because native Hispanics and Asians are often the children or grandchildren of immigrants and parental birthplace is unobserved in our data; assimilation differences across cohorts and states are unobserved and likely affect our outcomes. Other racial groups are also not examined because they yield small ACS samples that prevent precise inferences.

states receiving the largest dose of treatment. This would induce a negative coefficient for θ.

Our identification strategy assumes that the within-state variation across cohorts in the foreign STEM exposure variable is conditionally correlated with the outcomes we consider only through the effects of IA90. For college major decisions, this assumes that there were no other major changes in policy or economic conditions systematically related to the 1980 foreign STEM share at the same time as young people were making college major decisions. We have extensively searched the literature and found no such policy changes that could significantly affect the results. However, we do have some concern that the ICT revolution could have increased demand for STEM skills the most in states with previously high shares of foreign STEM graduates, which could bias results toward zero. We discuss in a later section sensitivity analyses that attempt to address this concern.

For the ACS employment outcomes, we hypothesize at least two factors that could affect our estimates. First, the post-IA90 inflow of foreign-born STEM workers could affect the ACS employment outcomes of pre-IA90 cohorts, meaning that the control group receives treatment also. Second, the post-IA90 inflow of foreign-born STEM workers could cause native workers interested in STEM employment to move away from high $ForeignSTEMExposure_{sc}$ states and into low-exposure ones, which would effectively increase exposure in low-exposure states. In general, both concerns would likely attenuate estimates toward zero relative to the true effects. However, we do expect our estimation strategy to detect at least some differences in recent employment outcomes.

3 Empirical Results

In this section, we present summary statistics of our data and discuss the empirical estimates of equation (3). We focus on three separate outcomes: (1) STEM bachelor's degree completion of natives; (2) native employment in STEM occupations; and (3) native employment in any occupation.

3.1 Summary Statistics

Before discussing estimates of our empirical strategy, we present summary statistics on exposure and outcomes for the groups in our data. Table 1 panel A reports weighted summary statistics for the 1991–1994 cohorts for the foreign STEM exposure measure, separately by race-sex combination. By construction, the measure equals zero for the 1986–1989 cohorts. The 1980 foreign STEM share has weighted mean of 0.121 and 0.118 for blacks and whites respectively, with no observable difference by sex.[8] For all groups, the standard deviation is 0.057, the min is 0.018, and the max is 0.216. For ease of interpretation, all regression results in this section scale up the foreign STEM share explanatory variable by a factor of 10, so that the variable ranges from 0 to 10 and a one-unit increase corresponds to a 10-percentage-point increase in the foreign STEM share, or about 1.75 standard deviations of the unscaled variable. Table 1 panel B reports race-sex means for the 1986–1989 cohorts for the main outcome variables we consider. Finally, Table 1 panel C reports race-sex means for the 1991–1994 cohorts. The outcome means across the two groups are similar.

[8]If we look at the foreign STEM share for the 1986–1989 cohorts (not interacted with the post-1990 dummy), we get a weighted mean of 0.122 for blacks and 0.121 for whites, indicating that the place-of-birth distribution over this time period was stable with respect to foreign STEM exposure.

3.2 College Major Choice

We first examine whether the Immigration Act of 1990 influenced college major decisions for natives. We estimate equation (3) where the dependent variable is an indicator for if the individual graduated college with a major in a STEM field. Panel A of Table 2 shows the effect of birth-state foreign STEM exposure on native STEM degree attainment, unconditional on education level; i.e., the sample includes all education levels and is not restricted to those completing a bachelor's degree. Our most notable finding is that black men are much less likely to major in a STEM field as a result of the policy.[9] The coefficient of -0.017 is statistically significant at the 5% level and large in magnitude. It indicates that a 10-percentage-point (1.75-standard-deviation) increase in foreign STEM exposure reduces STEM degree completion for black men by 1.7 percentage points. This is roughly 40% of the pre-IA90 mean STEM degree rate for black men of 0.041 reported in Table 1 Panel B. In contrast, black women and white men appear unaffected by the policy change. White women have a small positive coefficient of 0.004 that is marginally significant at the 10% level (p-value = 0.099).

Panels B and C of Table 2 help assess whether the negative effect for black men in Panel A is driven by decreased bachelor's degree attainment or decreased STEM attainment conditional on bachelor's attainment. Panel B shows that bachelor's degree attainment was unaffected, while Panel C reports that IA90 caused black male college graduates to be much less likely to major in a STEM field, with a coefficient of -0.085 that is statistically significant at the 5% level. This

[9] While not our focus, the much smaller sample size for black men than black women is consistent with census population estimates and vital statistics showing disturbingly high mortality rates for black men. The ACS includes samples of the institutionalized population and they are included in our analysis. However, our results are not affected by controlling for the size of black male cohorts or non-institutionalized cohorts. Higher mortality and institutionalization are unlikely to affect marginal STEM graduates in ways correlated with our foreign STEM exposure measure.

indicates that a 10-percentage-point increase in foreign STEM exposure reduced STEM major rates by 8.5 percentage points for black male college graduates, or 34% of the pre-IA90 mean of 0.249 in Table 1.

The other demographic groups examined are not significantly affected in either of the separate dimensions in Panels B and C of Table 2. This includes white women, which had a small coefficient in Panel A significant at the 10% level. The implied relative magnitude for the white female Panel A coefficient corresponds to less than 10% of the pre-IA90 mean, which is relatively modest. Given the modest magnitude, marginal significance in Panel A, and lack of significance in Panel C, we do not interpret the results to indicate a meaningful effect of IA90 on white female STEM education.

To further illustrate the effects of IA90 on STEM education, Figure 2 presents cohort trends in STEM major rates for college graduates, separately for our four race-sex groups. We split states into two groupshigh-exposure and low-exposurebased on whether their 1980 foreign STEM share exceeds 0.120, which marks the top tercile of the exposure distribution.[10] Figure 2 is consistent with the results in Panel C of Table 2 despite lacking regression controls. Specifically, we see a large drop in black male STEM major rates in high-exposure areas, starting around 1990. In contrast, STEM major rates for black men in low-exposure states appear to have increased slightly after 1990. The large differences as early as 1990 suggest that the policy had strong announcement effects as well as implementation effects on STEM degree completion of black men. Furthermore, we observe apparent pre-1990 upward trends in both low- and high-exposure states, possibly because of the growing demand for STEM skills related to the ICT revolution. This reinforces

[10]We focus on the top tercile of the distribution because our results indicate that the response to IA90 was concentrated among the states that were most exposed (see Table B7). The graph looks similar if we use the mean or median as the cut point defining high exposure. Ambiguity about how best to define "high" motivates our use of a continuous treatment in our model.

the importance of controlling for state-specific time trends in our main analysis.

For other demographic groups, we see similar increases in STEM education rates post-1990 for both high-exposure and low-exposure states, possibly due to expectations of increased employer demand for technical skills more broadly. Thus, Figure 2 indicates no meaningful difference in STEM education trends between high and low foreign STEM exposure states for white men, white women, and black women. Black men are clearly unique in this regard, consistent with the results in Table 2.

The results lead one to wonder if black men disproportionately switched into certain non-STEM majors, or if they disproportionately switched out of certain STEM majors. Tables 3 and 4 report estimates similar to Panel C of Table 2, but where instead the dependent variable is graduation in a specific non-STEM major in Table 3 or a specific STEM major in Table 4.

Table 3 suggests that popular destination majors for black men included business, liberal arts, and social sciences, but specific effects are imprecisely estimated, and we cannot reject uniformity in the distribution of destination field switches. The spread across non-STEM fields suggests that black men moved out of STEM fields much more than they moved into any particular non-STEM field. This supports our contention that IA90 was primarily a shock to STEM fields and that the effects we estimate are due to this IA90 shock to STEM. That is, we are not simply capturing some unobserved change that directly altered preferences for other majors and affected STEM education indirectly.

Table 4 shows consistently negative coefficients for STEM major sub-fields for black men. Computer science, biological sciences, physical sciences, and math were the majors that black men switched away from at the highest rates, but only the math coefficient is statistically significant at conventional levels. These results suggest that the shock to black male STEM majors was spread across several sub-fields and not driven by any single one.

3.3 STEM Occupation Employment

We now examine the effect of IA90 on the probability of being employed in a STEM occupation during the reference week of the 2009–2016 ACS. We report in Figure 3 the raw differences in STEM occupation employment among STEM BA degree holders between high- and low-exposure states, by cohort. For most demographic groups, there is a sharp decline in high-exposure states in 1990 or 1991. While informative of broad trends, our regression estimates are more informative of IA90's effects because the estimates correct for persistent state-specific differences and state-specific trends and allow for treatment to be continuous rather than discrete.

Regression results are reported in Table 5 for three education samples. Panel A includes all college graduates, while Panels B and C include STEM graduates and non-STEM graduates, respectively. In both Panels A and B, white men move out of STEM occupations in response to higher foreign STEM exposure, with coefficients significant at the 1% level. The effect magnitudes are also sizable. A 10-percentage-point increase in foreign STEM exposure reduces white male STEM employment by 2.0 percentage points across all college graduates and by 5.8 percentage points among STEM graduates. These effect magnitudes correspond to roughly 17% and 20% of the respective pre-IA90 means for white male graduates and STEM graduates.

For the other demographic groups, there are no significant effects in Table 5 Panel A for the samples of all college graduates. However, conditioning on STEM degree completion in Panel B yields a negative coefficient of -0.036 for white women that is significant at the 5% level; this effect corresponds to 27% of the pre-IA90 mean.[11] Black men and women both have

[11] In Table B8, we also separated STEM occupations into 1) engineers, 2) computer scientists and software

relatively large but noisily estimated coefficients in Panel B, with the black male coefficient having a positive sign. While this may seem counter-intuitive to the results in Table 2 documenting reduced STEM graduation for black men, we emphasize that IA90 potentially altered the composition of black male STEM majors in high-exposure areas in terms of ability and STEM attachment. Thus, results that condition on STEM or non-STEM major for black men should be interpreted with caution. Panel C reports no significant effect of IA90 on STEM employment for graduates in non-STEM fields.

3.4 Any Employment

We also examine previous year employment as an outcome. Figure 4 displays the raw differences in employment for STEM BA degree holders by demographic group, state exposure, and cohort. The results in Figure 4 are much noisier than their counterparts in Figures 2 and 3. Most striking is the drop in white female employment in 1991 in high-exposure states relative to low-exposure states, as well as a drop in black male employment in 1991–1992 in low-exposure states compared to high-exposure states. While noisy, the results are in line with our regression results, which we discuss below.

Table 6 reports effects of IA90 on employment in any occupation during the 12 months prior to the 2009–2016 ACS survey. We examine the same three education samples as Table 5 and include all graduates regardless of stated labor force participation, so the results are akin to employment-population ratios. Across all three panels, the estimates for black men and black

developers, and 3) mathematicians and natural scientists. The first two groups combine to account for more than 80% of STEM graduates in STEM occupations in our sample and account for a great majority of the negative effect of IA90 on STEM occupations of white STEM graduates reported in Table 5. Additionally, results in Table B12 examine recent (rather than current) employment in a STEM occupation and mirror the results of Table 5.

women are relatively noisy and prevent strong inferences.

For white men, the coefficient is positive and significant in Panels A and C but virtually zero in Panel B. Thus, it appears that foreign STEM exposure increases the work probability of white male non-STEM graduates but has no effect on the work probability of white male STEM graduates. Combined with Table 5, this suggests that the white male STEM graduates who moved out of STEM occupations shift toward work in non-STEM occupations and not out of the workforce. The positive employment effect of white male non-STEM graduates is consistent with complementarities between foreign STEM graduates and native non-STEM graduates (Llull, 2017).

For white women, foreign STEM exposure has a negative coefficient in all three panels of Table 6, but the effect is only significant for STEM graduates in Panel B. The coefficient of -0.037 for white female STEM graduates is very similar to the corresponding effect on current STEM employment in Table 5, suggesting that white female STEM graduates who move out of STEM occupations appear to exit the workforce altogether.

We also examine several other related outcomes, with results in the online appendix. We look at whether STEM graduates worked at all in any occupation in the past five years and find similar results as Table 6 (see Panel C of Table B9). We also investigate employment during the ACS reference week (Table B13), unemployment, and labor force non-participation (Table B9). We examine log annual earnings in the ACS and find noisily estimated negative coefficients for native STEM graduates and for black male college graduates (Table B14).

In summary, we find that IA90 had three main effects that differ by race-sex group: (1) it caused black male college graduates to move out of STEM majors; (2) it caused white male STEM graduates to move out of STEM occupations; and (3) it caused white female STEM graduates to move out of the workforce.

3.5 Treatment of pre-1990 Cohorts

Due to the nature of the policy and the outcomes we measure, it is possible that the pre-1990 cohorts (our control group) were treated. For example, older students might have delayed graduation because of the policy, so they could switch majors, or those who were in the workforce after college may have had to compete with skilled foreigners later in their careers, even if treatment happened after their initial labor market entry.

We assess the degree to which our control groups were treated in two ways. First, we estimate cross-sectional regressions similar to equation (3) separately for pre- and post-1990 cohorts. To identify the coefficient on Foreign STEM Exposure, we exclude the birth state fixed effects and birth state cohort trends from the model. Second, we expand the window of our analysis to include the 1982-1985 year-age-18 cohorts. We treat these oldest cohorts as the new control group and estimate separate treatment effects for the 1986-1989 and 1991-1994 cohorts.

The cross-sectional analyses corresponding to our main findings are included in Table 7 (abbreviated results) and Table B15 (complete results). There appears to be relatively little treatment of the pre-1990 cohorts. For post-1990 cohorts, negative effects on STEM graduation for black men and STEM employment for white men continue to hold, albeit in smaller magnitudes. The employment effect for white women disappears. While these results are somewhat informative about whether pre-1990 cohorts received treatment, we emphasize that they exclude state fixed effects and state cohort trends which are essential to properly capture unobservable state characteristics that are correlated with immigration.

The results of our second approach are included in Online Appendix Table B11. We find that employment outcomes for white women in the 1986-1989 cohorts appear to have been treated, but there is no significant effect on STEM employment for white men in the 1986–1989 cohorts. Results for black male STEM degree completion are noisily estimated by this approach, but the 1986–1989 cohorts have an insignificant *positive* coefficient, which makes negative effects among black men in the 1991–1994 cohorts starker.

3.6 Instrumental Variables

To help further illustrate effect magnitudes, we estimate two-stage least squares (2SLS) regressions, with estimates for the primary findings in Table 8; additional results are in the online appendix (see Tables B16-B18). The second-stage explanatory variable of interest is the 1990–2000 change in the foreign STEM share, and the instrument is the 1980 foreign STEM share; both are interacted with the post-1990 dummy and scaled upwards by a factor of 10 to facilitate comparison with earlier results. Figure 1 illustrates the unconditional relationship for the first stage. However, the first stage for Table 8 includes the control variables and is estimated separately for each sample. The second-stage dependent variables and control variables are the same as in Table 2 Panel C for black male college graduates, Table 5 Panel B for white male STEM graduates, and Table 6 Panel B for white female STEM graduates.

This 2SLS approach makes strong assumptions, so results should be interpreted with caution. For example, it assumes that the actual treatment was the 1990–2000 increase in the foreign STEM share and assumes no treatment from post-2000 high-skilled immigration expansion. It also assumes that college major and employment decisions made before year 2000 were made in anticipation of the growth in the foreign STEM share to year 2000. If these assumptions fail, this 2SLS procedure does not provide causal estimates. Still, it is a useful exercise for illustrating magnitudes under stronger assumptions.

As expected, first-stage results strongly indicate that 1990–2000 foreign STEM share growth was larger in states with high foreign STEM shares in 1980. The first-stage F statistics are well above the Stock and Yogo (2005) critical value for 10% maximal IV size, indicating that weak instrument issues are not a concern. The first-stage coefficient on the instrument is 0.49 for black men, 0.50 for white men, and 0.49 for white women. Because the excluded instrument here is the same as the reduced form explanatory variable in prior tables, a first-stage coefficient of about one-half means that we should expect the second-stage coefficient to be about twice as large as the corresponding reduced form coefficient. This is indeed what we find, suggesting that effect magnitudes are quite largepotentially even larger than suggested by the reduced form.

3.7 Sensitivity Analysis

In results in the online appendix, we estimate effects of IA90-induced foreign STEM exposure on our main outcomes using several alternative specifications. These include:

- Excluding state-specific time trends, or using the model selection techniques of Belloni, Chernozhukov, and Hansen (2014) (see Table B1)
- Expanding the pre- and post-IA90 year-age-18 sample window to five or six years on either side of the policy change (see Table B2)
- Including cohorts age 18 in 1990 in the control group (see Table B2)
- Separately excluding California, Florida, Illinois, New York, Texas, and Washington, which have very high immigration levels and may be potential outliers (see Table B3, panels A-F)

- Including the four excluded merit states in the analysis (see Table B3, panel G)
- Excluding states with population of less than 1 million in 1980, which may be more prone to measurement error in the exposure variable (see Table B3, panel H)
- Adding a time-varying state control for the 1980 (or 1990) share of native college graduates in the state employed in STEM occupations interacted with the post-IA90 dummy to account for possible ICT effects related to past STEM employment (see Table B4, panels A and B)
- Excluding state control variables (see Table B4, panel C)
- Using the expanded definition of STEM occupations in Table A2 to measure foreign STEM exposure (see Table B5, panel A)
- Measuring exposure to skilled foreign-born workers as the share of college educated workers who are foreign-born (regardless of occupation), rather than the share of college educated STEM workers who are foreign-born; or as the share of college educated non-STEM workers who are foreign-born (see Table B5, panels B and C, respectively)[12]
- Using the expanded definition of STEM occupations in Table A2 for the native STEM occupation outcome (see Table B6)
- Discretizing our continuous measure of exposure into terciles and estimating a classic difference-in-differences model (see Table B7)

[12]The foreign STEM and non-STEM shares are very highly correlated, so that the non-STEM foreign-born share variable in Table B5 picks up a significant effect. We appeal to economic theory to infer that foreign STEM graduates are the primary treatment adversely affecting native STEM graduates because they are the ones with the most substitutable skills.

- Estimating a placebo in which we set 1985 (instead of 1990) as the year of the policy and examining year age 18 cohorts 1981–1989 (instead of 1986–1994) (see Table B10)

The employment results for white female STEM graduates are not significant for alternative specifications in the first two bullet points. We prefer the baseline specification, *a priori*, so our best guess is that there is a negative effect of foreign STEM exposure on employment of female STEM graduates. However, the sensitivity to specification choices moderates our confidence in this effect.

The black male STEM major result is significantly negative except for when we exclude New York from the sample, in which the coefficient is still large and negative but the p-value is only 0.13 and thus not significant at the 10% level. However, we interpret this as a weak test and are not surprised that the significance is moderately sensitive to one large state. Combining either of the first two bullet point alternatives (dropping state trends or expanding the length of the policy window) with excluding New York returns the black male STEM effect to significance at the 5% level (see Panels I and J of Table B3).

We consistently find significant negative effects on STEM occupation employment for white male STEM graduates. The greatest sensitivity occurs from excluding state trends; the p-value is 0.104 and thus not significant at the 10% level, but the coefficient estimate is negative and of non-trivial magnitude. Furthermore, we believe that the trend variables are warranted, so our preferred specification includes them. As further evidence that trends should be included, our use of Belloni, Chernozhukov, and Hansen's (2014) model selection approach ends up selecting many trend variables and yields large and significantly negative effects.

4 Discussion

We next discuss potential pathways through which our main findings may operate and then place our findings in the context of the broader literature on impacts of skilled immigration.

4.1 Black Men Switching out of STEM Majors

Our most surprising result is the unique shift of black men out of STEM degrees. In considering potential reasons for this, we think it useful to consider prominent explanations in prior literature for why STEM degree rates are so low among black men to begin with (Austen-Smith and Fryer, 2005; Griffith, 2010; Price, 2010; Arcidiacono, Aucejo, and Spenner, 2012; Card and Giuliano, 2015; Arcidiacono, Aucejo, and Hotz, 2016). We find five common explanations: (1) worse pre-college academic resources and preparation that result in poor student-campus matches for STEM persistence; (2) lack of similar role models in STEM; (3) cultural norms that deride academic effort and achievement as "acting white"; (4) negative perceptions and low expectations for them by others (teachers, family, community members, etc.); and (5) low self-confidence in their own STEM abilities and chances for future STEM success. We also reviewed a separate literature suggesting that black men may be especially sensitive to immigrant presence in the labor market, perhaps due to cultural conflict, network effects, or employer discrimination (Chang, 1993; Kaufman, 1995; Waldinger, 1997; Borjas, Grogger, and Hanson, 2010).

After reviewing these literatures, we suggest that the most likely channel through which IA90 lowers black STEM degree completion is via negative student expectations about future success in STEM fields resulting from increased inflows of skilled foreign-born workers. The descriptive data in Figure 2 suggest large announcement effects for the earliest treated cohorts, even before foreign inflows were likely to have large impacts on STEM labor markets. This result is consistent with research studying how students form expectations about their majors (Zafar, 2011; Long, Goldhaber, and Huntington-Klein, 2015; Wiswall and Zafar, 2015; Weinstein, 2017). What is unclear, however, is which information students would have used to modify their beliefs about future success. The information may have originated from family members, students' own media consumption, or high school and university guidance counselors, creating important links between the mechanisms noted above. Similarly, black men may have been especially pessimistic about their post-IA90 STEM prospects because of past cultural and labor market conflicts between blacks and immigrants. Furthermore, limited resources, preparation, role models, and peer discouragement could have made some black men especially sensitive to STEM labor market shocks on their choice of college major.

4.2 White Men Less Likely to Work in STEM Occupations

Second, we find that white male STEM graduates were less likely to be employed in STEM occupations during the ACS period. This falls in line with related research showing that immigration shifts natives to fields in which they have a comparative advantage (Peri and Sparber, 2009, 2011; Llull, 2017). Our finding is consistent with this literature if white STEM graduates are less prepared to work in STEM jobs or more prepared to work in complementary fields (e.g. management and marketing) than their foreign-born counterparts. Furthermore, the timing of foreign inflows likely influences which natives are most affected. STEM graduates age 18 in the early 1990s faced much greater labor market exposure to foreign STEM workers than those age 18 in the late 1980s. We suggest that IA90 likely reduced initial STEM employment for highly exposed natives and that this had lasting effects observable roughly 20 years later, consistent with persistent effects of entry labor market conditions found in Oreopoulos, von Wachter, and Heisz (2012) and Altonji, Kahn, and Speer (2016).

Unfortunately, the ACS does not facilitate precise estimates of earnings effects for our setting. However, we address this indirectly. Kinsler and Pavan (2015) examine the wage returns to working in a related occupation for STEM majors. They find that working in a related occupation causes STEM graduates to have 30% higher earnings than STEM graduates who are working in unrelated occupations. This is in addition to the sizable wage returns to majoring in STEM that are well documented in the literature.

Interestingly, while black men are less likely to major in STEM as a result of the policy, black men are no less likely to find STEM jobs in the ACS. This may indicate that avoiding STEM majors helped black men avoid occupational mismatch. However, there are likely adverse welfare effects because of the substantial earnings differentials between STEM and non-STEM majors, regardless of occupation relatedness.

4.3 White Female STEM Graduates Less Likely to Work

Third, our results suggest that IA90 made white female STEM graduates less likely to work in a STEM occupation and less likely to work at all, with roughly equal magnitudes. These outcomes appear jointly influenced by increased competition for STEM jobs from foreign-born STEM workers. Entry labor market conditions at graduation can have lasting effects on employment and occupational attachment Kahn (2010); Oreopoulos, von Wachter, and Heisz (2012); Altonji, Kahn, and Speer (2016). Post-IA90 STEM graduates in high foreign STEM exposure states likely experienced especially difficult early labor market outcomes that result in some white female STEM graduates leaving the workforce in the long run. Hunt (2016) suggests that female engineers are more responsive than men to dissatisfaction with pay and promotion opportunities, causing them to exit the profession at higher rates. Similarly, our results suggest that women respond to adverse STEM labor market shocks from foreign inflows in unique ways compared to men.

4.4 Placing Our Findings in the Broader Skilled Immigration Debate

We now place our findings in the broader discussion of skilled immigrant impacts. As is well noted in the literature, skilled immigration generates both costs and benefits for receiving countries. The primary benefits include increased innovation, increased productivity and wages of workers complementary to the immigrants, increased diversity in both culture and product markets, and increased demand for housing. On the other hand, immigration diminishes the wage and employment prospects of substitutable workers, potentially increases cultural conflict, increases housing prices, and, as shown in the present study, reduces the frequency of underrepresented minorities in STEM majors and of STEM-educated white men and women in STEM occupations.

In response to our findings, one might ask whether the adverse effects of high-skilled immigration are large enough to offset a meaningful portion of the benefits. Peri, Shih, and Sparber (2015) document positive wage effects of foreign STEM workers on both native college graduates and non-college graduates. Their estimates imply that a 1-percentage-point increase in foreign STEM growth results in a 7–8 percentage-point increase in the wage growth of native college graduates. For native non-college graduates, the benefits are smaller but still large at 3–4 percentage points. Aside from Peri, Shih, and Sparber (2015), Hunt and Gauthier-Loiselle (2010), Kerr and

Lincoln (2010), Winters (2014), and others have shown that, on aggregate, immigration has improved the U.S. economy through the pathways discussed in the previous paragraph.[13]

While growth in the STEM workforce has been shown to result in higher wages overall, our findings suggest that STEM growth reduced the number of black men graduating in STEM majors and the number of white male and female STEM graduates working in STEM occupations. We also document in Table B14 earnings losses of about 3%–6% among STEM graduates of all groups, although they are imprecisely estimated.

Combining our results, we perform a back-of-the-envelope calculation of these welfare losses compared to the benefits shown in other studies (see Table B19). The key issue is that the welfare losses we document in this study fall on a small group of workers. STEM graduates comprise less than 10% of the entire workforce. For example, a wage gain of 1% that accrues to 90% of the workforce generates a total gain of 0.9%, while a wage loss of 1% accruing to 10% of the workforce generates a total loss of 0.1%. Similarly, black male college graduates' flight from STEM may be a welfare loss, but this group is a small portion of the overall U.S. population. Combining coefficient estimates, population weights, and 1990–2010 changes in foreign STEM exposure, we estimate that the adverse effects we find equate to 1.2% of average wages across native workers.[14] We also use coefficient estimates in Peri, Shih, and Sparber (2015) along with population weights and 1990–2010 changes in foreign STEM exposure to estimate the corresponding net benefits implied by their study to equal 2.7% of average wages across native workers; this is a net effect which already includes the negative effects for substitutable workers. The gross

[13] Winters (2014) combines domestic and foreign STEM graduates and estimates that a 1-percentage-point increase in STEM graduates results in about 1%–2% higher wages for workers in the same metropolitan area. The explanatory variable in Winters (2014) differs from Peri, Shih, and Sparber (2015) with the former examining effects of STEM graduates and the latter examining effects of STEM occupation workers. Accounting for the different scaling and dispersion across areas, the implied estimates from the two studies are more similar.

[14] See online Appendix Table B19 for further details. Numerous assumptions are required for these calculations.

positive effect can be recovered by subtracting the negative effects from the net effect, i.e., the gross effect is 3.9% of average wages. Thus, our back-of-the-envelope calculations suggest that the negative effects we uncover account for roughly one-third of the gross benefits.

The net benefits are positive as indicated in Peri, Shih, and Sparber (2015), but the adverse effects we find are still important. We also note that our derived estimates are based on wages, whereas there are many other dimensions to welfare than just money. Immigration generates winners and losers. Under the status quo, the winners do not compensate the losers. We thus argue in favor of policies that return lost surplus to the affected groups. Such policies could include income tax credits or student loan forgiveness for native STEM graduates impacted by increased immigration. Policies to compensate black men who left STEM may be more difficult to implement. If the cause of black men's flight from STEM is reduced expectations as we speculate, then policy responses may involve efforts to build self-efficacy via increased resources devoted to preparation, mentorship, coaching, and networking in STEM education and careers for underrepresented minorities. Further research is needed to better understand the appropriate policy responses.

5 Conclusion

Increasing the STEM workforce is vital for national economic performance and individual well-being. Meeting the growing demand for STEM workers in the U.S. has been achieved in recent decades largely by increased inflows of high-skilled foreign-born workers. Furthermore, many businesses, researchers, and policymakers have called for further increases in the foreign STEM workforce, e.g., by "stapling green cards to diplomas" for foreign-born STEM graduates educated in the U.S. (Viser, 2012; Smith, 2015). High-skilled foreigners provide considerable benefits to receiving countries, but may also create unintended consequences by altering the human capital investment and utilization of natives. Growing the foreign STEM workforce through immigration may crowd natives out of STEM fields during college and out of STEM occupations later in their careers. Adverse effects may also be disproportionately felt by women and minorities.

We examine effects of foreign STEM workers on native STEM education and employment by utilizing the Immigration Act of 1990 as a natural experiment and exploiting both spatial and temporal variation in foreign STEM exposure. We find that IA90 did not significantly reduce STEM education among early cohorts for most groups of natives examined, which is good news. The net effect of IA90 has been to substantially increase the STEM-educated workforce of the U.S., fueling innovation and economic growth.

However, we do find that some natives with high exposure to foreign STEM workers were adversely affected by IA90 in three different ways: (1) black male students shifted away from STEM degrees; (2) white male STEM graduates shifted away from STEM occupations; and (3) white female STEM graduates were less likely to participate in the workforce at all.

STEM majors are among the highest paying degree fields, so displacement of black men out of STEM degrees is a troubling result. While increasing the foreign STEM workforce likely benefits the U.S. overall, it imposes unique costs on black men, so that net gains/losses are not equally distributed. Black men, who are already disadvantaged in the labor market in many dimensions, bear a disproportionate burden.

We do not find shifts away from STEM degrees for other groups, but our focus is on early post-IA90 cohorts and does not rule out the possibility that later cohorts of other groups would alter their education decisions. For example, IA90 appears unlikely to have significantly altered native higher education access to STEM degrees for early cohorts, but public institutions may adjust emphases over time to cater to foreign students who pay out-of-state tuition, which might induce later cohort natives to leave STEM (Bound et al., 2016).

Our results also suggest likely welfare losses for white male STEM graduates, through lower earnings in occupations less related to their college major. White female STEM graduates may be especially burdened by permanently exiting the labor force. Black female STEM graduates may also be adversely affected, but results for them are not precisely estimated.

Our findings highlight important considerations and implications for policy proposals to further increase the foreign STEM workforce. While there may be broader national benefits of increased STEM inflows, there are important costs as well that are disproportionately borne by natives with high labor market exposure to foreign STEM graduates. Substantially increasing the stock of foreign STEM workers, e.g., by “stapling green cards to diplomas” would likely have unintended consequences that harm some natives. Our results may also justify additional policy efforts to shield women and underrepresented minorities from being disproportionately burdened.

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Figures and Tables

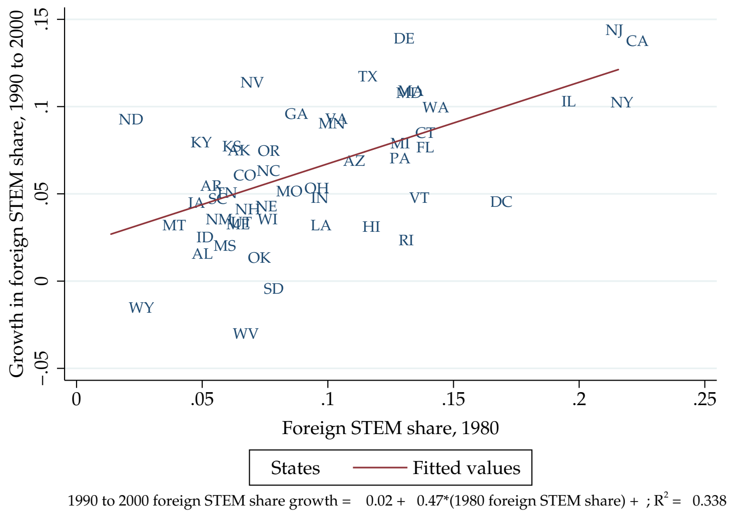
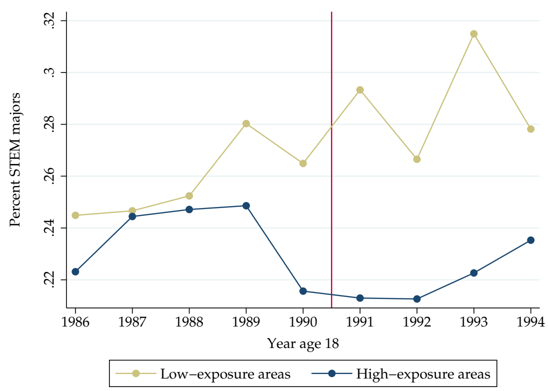


Figure 1: Relationship between Foreign Worker Inflows and 1980 Foreign Worker Shares



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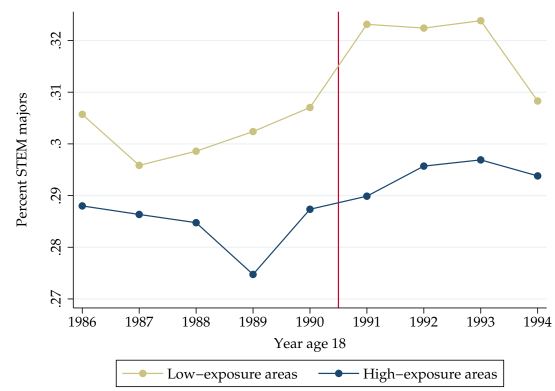

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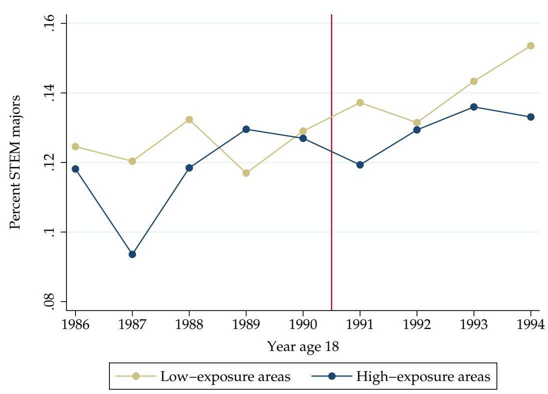

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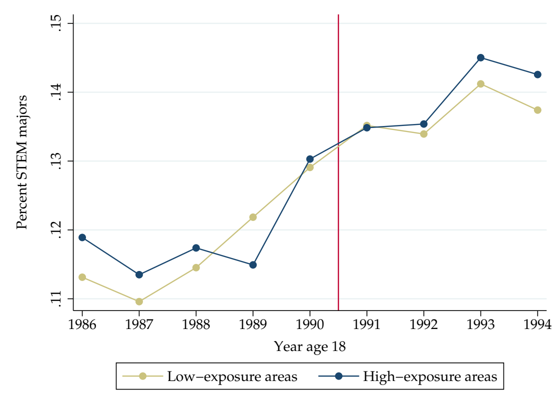
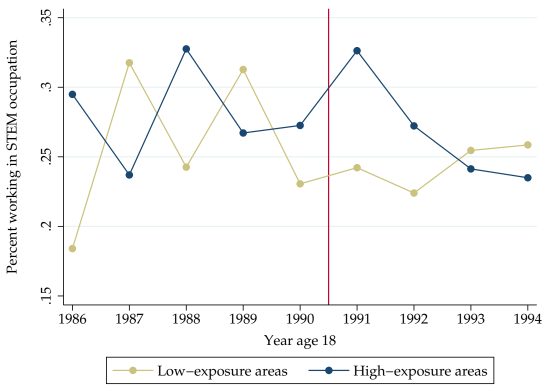
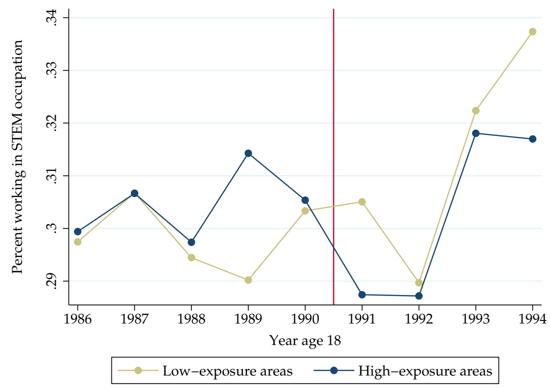


(d) White women

Figure 2: STEM major frequencies (conditional on BA) by year age 18



(a) Black men



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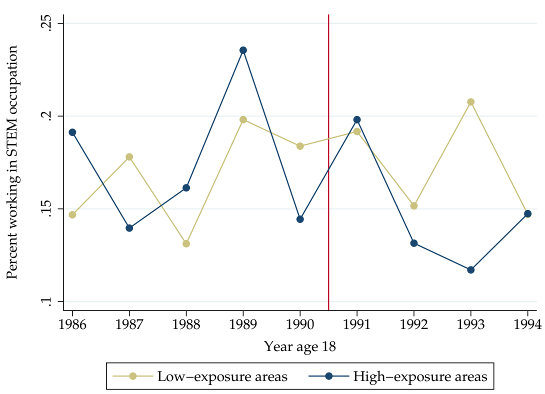
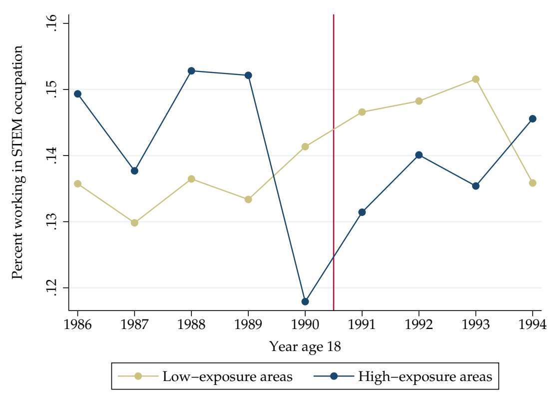
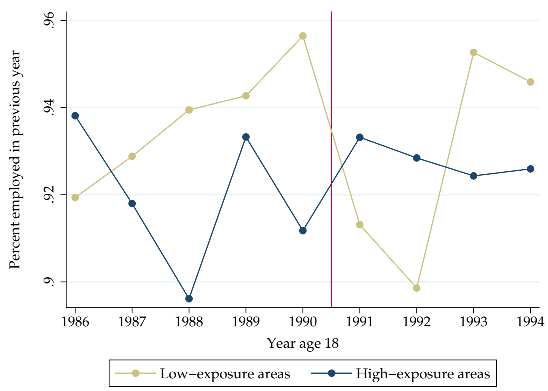


(c) Black women

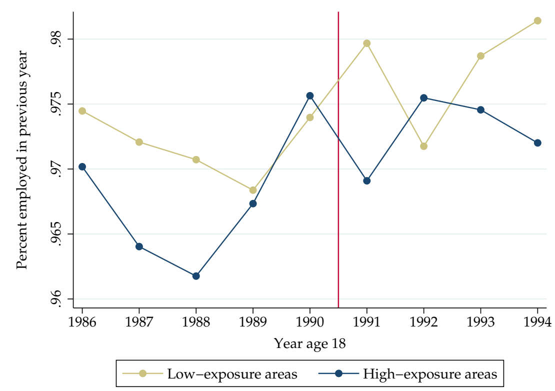


(d) White women

Figure 3: STEM employment frequencies (conditional on STEM BA) by year age 18



(a) Black men



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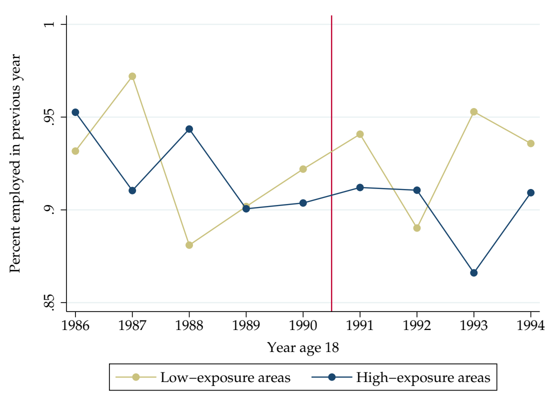
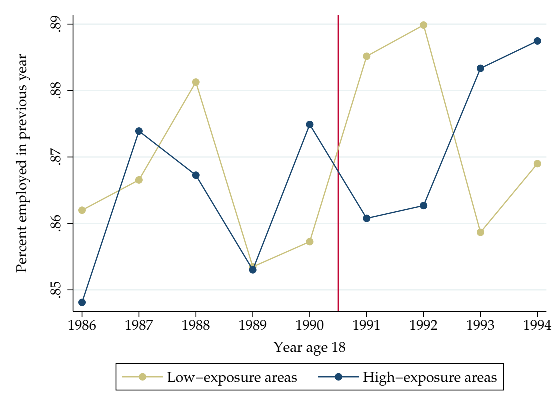


(c) Black women



(d) White women

Figure 4: Employment frequencies (conditional on STEM BA) by year age 18

Table 1: Weighted Summary Statistics of Outcome and Explanatory Variables

Panel A: Foreign STEM Exposure Summary Statistics for 1991–1994 Cohorts

Group	Mean	Std. Dev.	Min	Max
Black Men	0.121	0.057	0.018	0.216
Black Women	0.121	0.057	0.018	0.216
White Men	0.118	0.057	0.018	0.216
White Women	0.117	0.057	0.018	0.216

Panel B: Sample Means of Dependent Variables for 1986–1989 Cohorts

Variable	Black Men	Black Women	White Men	White Women
Main Education Variables				
STEM Degree Unconditional on Education Level	0.041	0.029	0.101	0.045
Bachelor's Degree Completion in Any Field	0.164	0.241	0.348	0.391
STEM Degree Conditional on Bachelor's Completion	0.249	0.119	0.291	0.116
Current STEM Employment				
Conditional on Bachelor's Completion	0.090	0.034	0.120	0.030
Conditional on Bachelor's in STEM Field	0.260	0.159	0.292	0.131
Conditional on Bachelor's in Non-STEM Field	0.033	0.017	0.050	0.016
Prior Year Employment				
Conditional on Bachelor's Completion	0.929	0.913	0.965	0.854
Conditional on Bachelor's in STEM Field	0.927	0.922	0.968	0.863
Conditional on Bachelor's in Non-STEM Field	0.930	0.912	0.963	0.852

Panel C: Sample Means of Dependent Variables for 1991–1994 Cohorts

Variable	Black Men	Black Women	White Men	White Women
Main Education Variables				
STEM Degree Unconditional on Education Level	0.041	0.034	0.107	0.057
Bachelor's Degree Completion in Any Field	0.163	0.251	0.349	0.413
STEM Degree Conditional on Bachelor's Completion	0.253	0.135	0.306	0.138
Current STEM Employment				
Conditional on Bachelor's Completion	0.090	0.036	0.127	0.032
Conditional on Bachelor's in STEM Field	0.239	0.151	0.300	0.130
Conditional on Bachelor's in Non-STEM Field	0.040	0.018	0.050	0.016
Prior Year Employment				
Conditional on Bachelor's Completion	0.934	0.925	0.971	0.859
Conditional on Bachelor's in STEM Field	0.928	0.915	0.975	0.875
Conditional on Bachelor's in Non-STEM Field	0.937	0.926	0.969	0.857

Notes: By definition, the foreign STEM exposure variables in panel A all equal zero for the 1986–1989 cohorts. Means in panel B are useful for quantifying the relative magnitudes of the effects that we examine. A comparison of panels B and C is useful for gauging overall time differences in outcomes during our analysis window.

Table 2: Birth-State Foreign STEM Exposure and STEM Degree Completion

Effect	Black Men	Black Women	White Men	White Women
Panel A: STEM graduation, unconditional of education level				
Foreign STEM Exposure	-0.017**	0.000	-0.001	0.004*
	(0.008)	(0.005)	(0.005)	(0.002)
Control mean	[0.041]	[0.029]	[0.101]	[0.045]
N	93,505	102,128	685,261	687,311
Panel B: BA graduation				
Foreign STEM Exposure	-0.003	-0.001	0.000	-0.005
	(0.013)	(0.014)	(0.006)	(0.006)
Control mean	[0.164]	[0.241]	[0.348]	[0.391]
N	93,505	102,128	685,261	687,311
Panel C: STEM graduation, conditional on BA graduation				
Foreign STEM Exposure	-0.085**	-0.001	-0.007	0.008
	(0.036)	(0.022)	(0.014)	(0.006)
Control mean	[0.249]	[0.119]	[0.291]	[0.116]
N	14,354	26,274	241,807	283,569
Additional controls included in each regression:				
Demographic characteristics	Yes	Yes	Yes	Yes
State characteristics	Yes	Yes	Yes	Yes
State-specific year age 18 trends	Yes	Yes	Yes	Yes

Notes: Dependent variable is an indicator for either *(a)* graduating in a STEM field, unconditional on education level; *(b)* graduating with a bachelor's degree in any field; or *(c)* graduating with a bachelor's degree in a STEM field. Foreign STEM Exposure denotes the effect of a 10 percentage point increase in the share of foreign STEM workers on the dependent variable. Each coefficient is estimated from a separate linear probability model. The mean of the dependent variable for the control group is reported in brackets. *Statistically significant at the .10 level; ** at the .05 level.

Table 3: Foreign STEM Exposure and Non-STEM Degree Completion for Black Men

Effect	Business	Education	Health	Liberal Arts	Social Sciences	Other Majors
Foreign STEM Exposure	0.018	0.000	0.009	0.025	0.023	0.009
	(0.026)	(0.028)	(0.013)	(0.033)	(0.025)	(0.015)
Control mean	[0.258]	[0.067]	[0.023]	[0.161]	[0.211]	[0.029]
N	14,354	14,354	14,354	14,354	14,354	14,354

Notes: Dependent variable is an indicator for graduating with a given non-STEM major, conditional on college graduation. The mean of the dependent variable for the control group is reported in brackets. Note that the bracketed control-group means sum to 100% across columns of Tables 3 and 4 *combined*. See notes in Table 2 for further details.

Table 4: Foreign STEM Exposure and STEM Degree Sub-fields for Black Men

Effect	Computer Science	Engineering	Technology	Biological Sciences	Physical Sciences	Mathematics	All Other STEM
Foreign STEM Exposure	-0.019	-0.003	-0.010	-0.012	-0.013	-0.018***	-0.010
	(0.020)	(0.018)	(0.008)	(0.019)	(0.013)	(0.005)	(0.017)
Control mean	[0.063]	[0.078]	[0.015]	[0.033]	[0.025]	[0.010]	[0.027]
N	14,354	14,354	14,354	14,354	14,354	14,354	14,354

Notes: Dependent variable is an indicator for graduating with a given STEM major, conditional on college graduation. The sum of the coefficients in this table equals the coefficient reported in the first column of Table 2 Panel C. See notes in Table 2 for further details.
***Statistically significant at the .01 level.

Table 5: Birth-State Foreign STEM Exposure and Current Employment in a STEM Occupation

Effect	Black Men	Black Women	White Men	White Women
Panel A: Conditional on college graduation in any field				
Foreign STEM Exposure	0.008	0.001	-0.020***	-0.001
	(0.029)	(0.014)	(0.005)	(0.003)
Control mean	[0.090]	[0.034]	[0.120]	[0.030]
N	14,354	26,274	241,807	283,569
Panel B: Conditional on college graduation in a STEM field				
Foreign STEM Exposure	0.063	-0.050	-0.058***	-0.036**
	(0.079)	(0.086)	(0.014)	(0.016)
Control mean	[0.260]	[0.159]	[0.292]	[0.131]
N	3,679	3,495	72,933	36,519
Panel C: Conditional on college graduation in a non-STEM field				
Foreign STEM Exposure	0.007	0.006	-0.003	0.003
	(0.018)	(0.006)	(0.004)	(0.002)
Control mean	[0.033]	[0.017]	[0.050]	[0.016]
N	10,675	22,779	168,874	247,050

Notes: Dependent variable is an indicator for current employment in a STEM occupation, conditional on various educational outcomes. See notes in Table 2 for further details. **Statistically significant at the .05 level; *** at the .01 level.

Table 6: Birth-State Foreign STEM Exposure and Prior Year Employment Probability

Effect	Black Men	Black Women	White Men	White Women
Panel A: Conditional on college graduation in any field				
Foreign STEM Exposure	0.028	0.015	0.009***	-0.008
	(0.018)	(0.017)	(0.003)	(0.006)
Control mean	[0.929]	[0.913]	[0.965]	[0.854]
N	14,354	26,274	241,807	283,569
Panel B: Conditional on college graduation in a STEM field				
Foreign STEM Exposure	0.048	-0.022	-0.001	-0.037**
	(0.053)	(0.040)	(0.005)	(0.016)
Control mean	[0.927]	[0.922]	[0.968]	[0.863]
N	3,679	3,495	72,933	36,519
Panel C: Conditional on college graduation in a non-STEM field				
Foreign STEM Exposure	0.020	0.022	0.014***	-0.004
	(0.021)	(0.019)	(0.004)	(0.006)
Control mean	[0.930]	[0.912]	[0.963]	[0.852]
N	10,675	22,779	168,874	247,050

Notes: Dependent variable is an indicator for being employed in the prior year, conditional on various educational outcomes. See notes in Table 2 for further details. **Statistically significant at the .05 level; *** at the .01 level.

Table 7: Separate Cross-Section Regressions for Pre- and Post-1990 Cohorts

Effect	Black Male STEM BA	White Male STEM Occ.	White Female Prior Yr Empl.
Panel A: 1986–1989 Cohorts			
Foreign STEM Exposure	-0.001	0.000	-0.007
	(0.013)	(0.010)	(0.006)
Control mean	[0.249]	[0.292]	[0.863]
N	7,694	38,791	17,856
Panel B: 1991–1994 Cohorts			
Foreign STEM Exposure	-0.032*	-0.030***	0.003
	(0.017)	(0.011)	(0.009)
Control mean	[0.253]	[0.300]	[0.875]
N	6,660	34,142	18,663

Notes: This table presents cross-sectional versions of our main estimates, separately for pre- and post-1990 cohorts. To enable identification of the foreign exposure measure for each group, we drop the state fixed effects and state time trends from the model. Table B15 reports a broader set of results from this same specification. *Statistically significant at the .10 level; *** at the .01 level.

Table 8: Instrumental Variable Estimates for Main Findings

Effect	Black Male STEM BA	White Male STEM Occ.	White Female Prior Yr Empl.
Panel A: First-Stage Results			
1980 Foreign STEM Exposure	0.489***	0.502***	0.493***
	(0.071)	(0.069)	(0.069)
F-statistic	47.457	53.060	50.874
Stock-Yogo critical value for 10% maximal IV size	16.38	16.38	16.38
Panel B: Second-Stage Results			
2000–1990 Change in Foreign STEM Exposure	-0.174*	-0.115***	-0.075**
	(0.089)	(0.025)	(0.034)
Control mean	[0.249]	[0.292]	[0.863]
N	14,354	72,933	36,519

Notes: The second-stage explanatory variable is the predicted 1990-2000 change in the foreign STEM share, and the instrument is the 1980 foreign STEM share, both interacted with the post-1990 dummy. The unconditional relationship for the first-stage is illustrated in Figure 1. The dependent variables and control variables are the same as Table 2 Panel C for black men, Table 5 Panel B for white men, and Table 6 Panel B for white women. *Statistically significant at the .10 level; ** at the .05 level; *** at the .01 level.

Appendix A

Table A1: List of STEM Majors and ACS codes

ACS code	Description	ACS code	Description
1103	Animal Sciences	2504	Mechanical Engineering Related Technologies
1104	Food Science	2599	Miscellaneous Engineering Technologies
1105	Plant Science and Agronomy	3600	Biology
1106	Soil Science	3601	Biochemical Sciences
1301	Environmental Science	3602	Botany
1302	Forestry	3603	Molecular Biology
2001	Communication Technologies	3604	Ecology
2100	Computer and Information Systems	3605	Genetics
2101	Computer Programming and Data Processing	3606	Microbiology
2102	Computer Science	3607	Pharmacology
2105	Information Sciences	3608	Physiology
2106	Computer Information Management & Security	3609	Zoology
2107	Computer Networking and Telecommunications	3611	Neuroscience
2400	General Engineering	3699	Miscellaneous Biology
2401	Aerospace Engineering	3700	Mathematics
2402	Biological Engineering	3701	Applied Mathematics
2403	Architectural Engineering	3702	Statistics and Decision Science
2404	Biomedical Engineering	3801	Military Technologies
2405	Chemical Engineering	4002	Nutrition Sciences
2406	Civil Engineering	4003	Neuroscience
2407	Computer Engineering	4005	Mathematics and Computer Science
2408	Electrical Engineering	4006	Cognitive Science and Biopsychology
2409	Engineering Mechanics, Physics, & Science	5000	Physical Sciences
2410	Environmental Engineering	5001	Astronomy and Astrophysics
2411	Geological and Geophysical Engineering	5002	Atmospheric Sciences and Meteorology
2412	Industrial and Manufacturing Engineering	5003	Chemistry
2413	Materials Engineering and Materials Science	5004	Geology and Earth Science
2414	Mechanical Engineering	5005	Geosciences
2415	Metallurgical Engineering	5006	Oceanography
2416	Mining and Mineral Engineering	5007	Physics
2417	Naval Architecture and Marine Engineering	5008	Materials Science
2418	Nuclear Engineering	5098	Multi-disciplinary or General Science
2419	Petroleum Engineering	5102	Nuclear, Industrial Radiology, & Biol. Tech.
2499	Miscellaneous Engineering	5901	Transportation Sciences and Technologies
2500	Engineering Technologies	6106	Health and Medical Preparatory Programs
2501	Engineering and Industrial Management	6108	Pharmacy, Pharmaceutical Sciences, & Admin.
2502	Electrical Engineering Technology	6202	Actuarial Science
2503	Industrial Production Technologies	6212	Management Information Systems and Statistics

Table A2: List of STEM occupations and ACS codes

Occ1990 code	Description	Main Definition	Expanded Definition
44	Aerospace engineer	Yes	Yes
45	Metallurgical and materials engineers	Yes	Yes
47	Petroleum, mining, and geological engineers	Yes	Yes
48	Chemical engineers	Yes	Yes
53	Civil engineers	Yes	Yes
55	Electrical engineer	Yes	Yes
56	Industrial engineers	Yes	Yes
57	Mechanical engineers	Yes	Yes
59	Not-elsewhere-classified engineers	Yes	Yes
64	Computer systems analysts & computer scientists	Yes	Yes
66	Actuaries	Yes	Yes
67	Statisticians	Yes	Yes
68	Mathematicians and mathematical scientists	Yes	Yes
69	Physicists and astronomers	Yes	Yes
73	Chemists	Yes	Yes
74	Atmospheric and space scientists	Yes	Yes
75	Geologists	Yes	Yes
76	Physical scientists, n.e.c.	Yes	Yes
77	Agricultural and food scientists	Yes	Yes
78	Biological scientists	Yes	Yes
79	Foresters and conservation scientists	Yes	Yes
83	Medical scientists	Yes	Yes
229	Computer software developers	Yes	Yes
84	Physicians		Yes
85	Dentists		Yes
86	Veterinarians		Yes
87	Optometrists		Yes
88	Podiatrists		Yes
89	Other health and therapy diagnosing occupations		Yes
96	Pharmacists		Yes
113	Earth, environmental, and marine science instructors		Yes
114	Biological science instructors		Yes
115	Chemistry instructors		Yes
116	Physics instructors		Yes
127	Engineering instructors		Yes
128	Math instructors		Yes

Appendix B (for online publication)

Table B1: Remove time trends

Effect	Black Male STEM BA	White Male STEM Occ.	White Female Prior Yr Empl.
Panel A: Baseline result			
Foreign STEM Exposure	-0.085**	-0.058***	-0.037**
	(0.036)	(0.014)	(0.016)
Control mean	[0.249]	[0.292]	[0.863]
N	14,354	72,933	36,519
Panel B: No state trends			
Foreign STEM Exposure	-0.047***	-0.016*	0.005
	(0.017)	(0.009)	(0.007)
Control mean	[0.249]	[0.292]	[0.863]
N	14,354	72,933	36,519
Panel C: Model selection of linear & quadratic state trends			
Foreign STEM Exposure	-0.052***	-0.026*	0.005
	(0.017)	(0.013)	(0.010)
Control mean	[0.249]	[0.292]	[0.863]
N	14,354	72,933	36,519

Notes: Panel A reproduces the estimates from column 1 of Table 2 Panel C, the column 3 of Table 5 Panel B, and the column 4 of Table 6 Panel B. Panel B presents estimates without state trends. Panels C and D presents estimates using the model selection method of Belloni, Chernozhukov, and Hansen (2014) and implementation by Ahrens, Hansen, and Schaffer (2018), where the model selects among linear and quadratic state trends. *Statistically significant at the .10 level; ** at the .05 level; *** at the .01 level.

Table B2: Robustness of length of time horizon

Effect	Black Male STEM BA	White Male STEM Occ.	White Female Prior Yr Empl.
Panel A: Five years before and after			
Foreign STEM Exposure	-0.101***	-0.054***	-0.019
	(0.032)	(0.013)	(0.013)
Control mean	[0.252]	[0.291]	[0.864]
N	17,752	91,515	46,043
Panel B: Six years before and after			
Foreign STEM Exposure	-0.116***	-0.050***	-0.015
	(0.022)	(0.011)	(0.012)
Control mean	[0.257]	[0.290]	[0.863]
N	21,293	110,192	55,794
Panel C: Five years before (including 1990) and four years after			
Foreign STEM Exposure	-0.051**	-0.034***	-0.039***
	(0.025)	(0.009)	(0.011)
Control mean	[0.247]	[0.293]	[0.864]
N	16,204	81,872	41,203

Notes: This table presents sensitivity of our results as we change the number of birth cohorts in the sample. Panel A includes those turning 18 between 1985 and 1995 (excluding 1990). Panel B includes year age 18 cohorts between 1994 and 1996 (excluding 1990). Panel C includes those turning 18 between 1986 and 1994, including 1990. *Statistically significant at the .10 level; ** at the .05 level; *** at the .01 level.

Table B3: Robustness of exclusion or inclusion of various states

Effect	Black Male STEM BA	White Male STEM Occ.	White Female Prior Yr Empl.
Panel A: Excluding California			
Foreign STEM Exposure	-0.087**	-0.041***	-0.043**
	(0.042)	(0.012)	(0.018)
N	13,360	67,091	33,614
Panel B: Excluding Florida			
Foreign STEM Exposure	-0.081**	-0.058***	-0.037**
	(0.037)	(0.014)	(0.016)
N	13,632	71,027	35,590
Panel C: Excluding Illinois			
Foreign STEM Exposure	-0.079**	-0.057***	-0.044***
	(0.040)	(0.016)	(0.015)
N	13,310	68,529	34,453
Panel D: Excluding New York			
Foreign STEM Exposure	-0.058	-0.061***	-0.031*
	(0.038)	(0.016)	(0.018)
N	12,701	66,228	33,033
Panel E: Excluding Texas			
Foreign STEM Exposure	-0.085**	-0.058***	-0.038**
	(0.035)	(0.014)	(0.016)
N	13,453	69,227	34,689
Panel F: Excluding Washington			
Foreign STEM Exposure	-0.085**	-0.057***	-0.038**
	(0.036)	(0.014)	(0.016)
N	14,269	71,651	35,876
Panel G: Including merit states			
Foreign STEM Exposure	-0.078**	-0.053***	-0.036**
	(0.035)	(0.015)	(0.015)
N	15,722	77,088	38,585
Panel H: Excluding 13 smallest states			
Foreign STEM Exposure	-0.087**	-0.056***	-0.031*
	(0.036)	(0.015)	(0.016)
N	13,687	69,293	34,586
Panel I: Exclude NY and state trends			
Foreign STEM Exposure	-0.048***	-0.015	0.010
	(0.018)	(0.011)	(0.007)
N	12,701	66,228	33,033
Panel J: Exclude NY, lengthen policy window			
Foreign STEM Exposure	-0.097**	-0.056***	-0.012
	(0.038)	(0.015)	(0.014)
N	15,712	83,087	41,664

Notes: This table presents estimates of our three primary findings under various sample selection alternatives. We sequentially exclude the most popular immigrant destinations, as well as the 13 smallest states (each of which had population of less than 1 million in 1980). We also include the merit states and present sensitivity analyses for when New York is excluded. Due to space constraints, we exclude reports of the control group's average outcome. *Statistically significant at the .10 level; ** at the .05 level; *** at the .01 level.

Table B4: Robustness of specification of state controls

Effect	Black Male STEM BA	White Male STEM Occ.	White Female Prior Yr Empl.
Panel A: Adding 1980 share BA working in STEM			
Foreign STEM Exposure	-0.081**	-0.055***	-0.038***
	(0.036)	(0.014)	(0.015)
Control mean	[0.249]	[0.292]	[0.863]
N	14,354	72,933	36,519
Panel B: Adding 1990 share BA working in STEM			
Foreign STEM Exposure	-0.081**	-0.058***	-0.037**
	(0.037)	(0.014)	(0.016)
Control mean	[0.249]	[0.292]	[0.863]
N	13,632	71,027	35,590
Panel C: Excluding state control variables			
Foreign STEM Exposure	-0.079**	-0.057***	-0.044***
	(0.040)	(0.016)	(0.015)
Control mean	[0.249]	[0.292]	[0.863]
N	13,310	68,529	34,453

Notes: Panel A adds as an additional control the 1980 share of native college graduates in the state employed in STEM occupations interacted with the post-IA90 dummy. Panel B adds as an additional control the 1990 share of native college graduates in the state employed in STEM occupations interacted with the post-IA90 dummy. Panel C excludes all time-varying state control variables. *Statistically significant at the .10 level; ** at the .05 level; *** at the .01 level.

Table B5: Alternative definitions for foreign STEM exposure

Effect	Black Male STEM BA	White Male STEM Occ.	White Female Prior Yr Empl.
Panel A: Alternate definition of STEM occupations			
Foreign STEM Exposure	-0.087***	-0.042***	-0.033**
	(0.028)	(0.013)	(0.014)
Control mean	[0.249]	[0.292]	[0.863]
N	14,354	72,933	36,519
Panel B: 1980 share college of graduates instead of 1980 share of STEM workers			
Foreign STEM Exposure	-0.132***	-0.068***	-0.053***
	(0.041)	(0.022)	(0.019)
Control mean	[0.249]	[0.292]	[0.863]
N	14,354	72,933	36,519
Panel C: 1980 share of non-STEM workers instead of 1980 share of STEM workers			
Foreign STEM Exposure	-0.137***	-0.068***	-0.055***
	(0.041)	(0.023)	(0.019)
N	14,354	72,933	36,519

Notes: This table presents estimates using alternative definitions of foreign STEM exposure. Panel A considers a broader set of STEM occupations (see Table A2). Panel B considers using the 1980 share of college graduates rather than the 1980 share of college graduates working in STEM occupations. Panel C uses the 1980 share of college graduates working in non-STEM occupations. *Statistically significant at the .10 level; ** at the .05 level; *** at the .01 level.

Table B6: Additional analysis for STEM occupational outcomes using broader definition

Effect	Black Men	Black Women	White Men	White Women
Panel A: Works in STEM occupation, conditional on BA graduation				
Foreign STEM Exposure	0.001	-0.015	-0.022***	-0.000
	(0.024)	(0.014)	(0.007)	(0.003)
Control mean	[0.133]	[0.053]	[0.150]	[0.049]
N	14,354	26,274	241,807	283,569
Panel B: Works in STEM occupation, conditional on STEM BA graduation				
Foreign STEM Exposure	0.048	-0.130*	-0.063***	-0.027
	(0.078)	(0.078)	(0.013)	(0.019)
Control mean	[0.347]	[0.251]	[0.368]	[0.243]
N	3,679	3,495	72,933	36,519
Panel C: Works in STEM occupation, conditional on non-STEM BA graduation				
Foreign STEM Exposure	0.004	0.001	-0.003	0.002
	(0.020)	(0.008)	(0.005)	(0.003)
Control mean	[0.048]	[0.024]	[0.061]	[0.024]
N	10,675	22,779	168,874	247,050

Notes: This table presents results similar to Table 5, but where current STEM occupation is more broadly defined (see Table A2). *Statistically significant at the .10 level; ** at the .05 level; *** at the .01 level.

Table B7: Discrete Treatment Based on Exposure State Groups

Effect	Black Male STEM BA	White Male STEM Occ.	White Female Prior Yr Empl.
Medium Foreign STEM Exposure	0.049	-0.015	-0.045*
	(0.044)	(0.019)	(0.025)
High Foreign STEM Exposure	-0.105**	-0.068***	-0.052*
	(0.045)	(0.023)	(0.026)
Control mean	[0.249]	[0.292]	[0.863]
N	14,354	72,933	36,519

Notes: This table estimates our main regression model using a discretized version of exposure. States are classified as low-, medium-, or high-exposure based on terciles of the exposure distribution. The coefficients reported represent the change in the outcome variable by moving across exposure terciles (either from low to medium or from low to high). *Statistically significant at the .10 level; ** at the .05 level; *** at the .01 level.

Table B8: Detailed STEM occupation employment for STEM graduates

	Engineering	Computers	Math & Science
Panel A: White Men			
Foreign STEM Exposure	-0.026**	-0.037***	0.002
	(0.011)	(0.012)	(0.006)
Control mean	[0.123]	[0.137]	[0.034]
N	72,933	72,933	72,933
Panel B: White Women			
Foreign STEM Exposure	-0.012	-0.014	-0.012
	(0.011)	(0.010)	(0.013)
Control mean	[0.036]	[0.060]	[0.038]
N	36,519	36,519	36,519

Notes: This table decomposes the effects reported in Panel B of Table 5 for white men and women. Here, each dependent variable is a dummy for being employed in a specific STEM occupation (rather than any STEM occupation as considered in Table 5). The sum of the coefficients across columns equals the coefficient reported in Panel B of Table 5. *Statistically significant at the .10 level; ** at the .05 level; *** at the .01 level.

Table B9: Employment outcomes, conditional on graduation in a STEM field

Effect	Black Men	Black Women	White Men	White Women
Panel A: Unemployment, conditional on STEM BA graduation				
Foreign STEM Exposure	0.002	-0.039	0.009	0.001
	(0.036)	(0.025)	(0.006)	(0.008)
Control mean	[0.035]	[0.042]	[0.022]	[0.024]
N	3,679	3,495	72,933	36,519
Panel B: Not in Labor Force, conditional on STEM BA graduation				
Foreign STEM Exposure	-0.065**	0.072	0.003	0.027*
	(0.031)	(0.069)	(0.007)	(0.016)
Control mean	[0.049]	[0.106]	[0.030]	[0.152]
N	3,679	3,495	72,933	36,519
Panel C: Worked at all in last five years, conditional on STEM BA				
Foreign STEM Exposure	0.039	0.045	0.000	-0.041***
	(0.028)	(0.033)	(0.005)	(0.012)
Control mean	[0.976]	[0.937]	[0.987]	[0.911]
N	3,679	3,495	72,933	36,519

Notes: Dependent variable is an indicator for either *(a)* unemployment; *(b)* not participating in labor force; or *(c)* working at all in the previous five years. All samples are conditional on graduation in a STEM field. *Statistically significant at the .10 level; ** at the .05 level; *** at the .01 level.

Table B10: Placebo results

Effect	Black Male STEM BA	White Male STEM Occ.	White Female Prior Yr Empl.
Foreign STEM Exposure	0.062	-0.005	0.010
	(0.047)	(0.011)	(0.023)
Control mean	[0.261]	[0.284]	[0.863]
N	15,393	83,917	38,585

Note: This table presents results from a placebo setting where we consider individuals who turn 18 years old between 1981-1989, and where we consider 1985 as the year the policy was instituted. Individuals turning 18 in 1986-1989 are considered to be treated, while those turning 18 in 1981-1984 serve as controls. The reported estimates should be compared with those reported in the first column of Table 2 Panel C, the third column of Table 5 Panel B, and the last column of Table 6 Panel B.

Table B11: Treatment of pre-1990 cohorts

Effect	Black Male STEM BA	White Male STEM Occ.	White Female Prior Yr Empl.
Foreign STEM Exposure, 86-89 cohorts	0.021	-0.009	-0.026**
	(0.035)	(0.010)	(0.012)
Foreign STEM Exposure, 91-94 cohorts	-0.023	-0.037*	-0.053**
	(0.060)	(0.022)	(0.022)
Control mean	[0.268]	[0.285]	[0.861]
N	21,865	115,843	56,205

Note: This table presents results from a setting where we consider individuals who turn 18 years old between 1982-1994, with 1990 as the year the policy was instituted. Individuals turning 18 in 1986-1989 are considered to be one treatment group, those turning 18 in 1991-1994 as a different treatment group, and those turning 18 in 1982-1985 serve as controls. The reported estimates should be compared with those reported in the first column of Table 2 Panel C, the third column of Table 5 Panel B, and the last column of Table 6 Panel B.

Table B12: Birth-State Foreign STEM Exposure and Recently Holding a STEM Occupation

Effect	Black Men	Black Women	White Men	White Women
Panel A: Conditional on college graduation in any field				
Foreign STEM Exposure	-0.001	0.001	-0.021***	-0.001
	(0.029)	(0.016)	(0.005)	(0.003)
Control mean	[0.096]	[0.037]	[0.124]	[0.032]
N	14,354	26,274	241,807	283,569
Panel B: Conditional on college graduation in a STEM field				
Foreign STEM Exposure	0.042	-0.064	-0.060***	-0.039***
	(0.075)	(0.087)	(0.014)	(0.015)
Control mean	[0.274]	[0.176]	[0.301]	[0.142]
N	3,679	3,495	72,933	36,519
Panel C: Conditional on college graduation in a non-STEM field				
Foreign STEM Exposure	0.005	0.007	-0.004	0.003
	(0.019)	(0.006)	(0.004)	(0.002)
Control mean	[0.037]	[0.018]	[0.052]	[0.018]
N	10,675	22,779	168,874	247,050

Notes: Dependent variable is an indicator for recently holding a STEM occupation, conditional on various educational outcomes. Compare with Table 5. **Statistically significant at the .05 level; *** at the .01 level.

Table B13: Birth-State Foreign STEM Exposure and Current Employment Probability

Effect	Black Men	Black Women	White Men	White Women
Panel A: Conditional on college graduation in any field				
Foreign STEM Exposure	0.008	0.000	0.002	-0.013
	(0.023)	(0.020)	(0.003)	(0.008)
Control mean	[0.894]	[0.873]	[0.938]	[0.808]
N	14,354	26,274	241,807	283,569
Panel B: Conditional on college graduation in a STEM field				
Foreign STEM Exposure	0.063	-0.033	-0.012	-0.028
	(0.055)	(0.062)	(0.008)	(0.019)
Control mean	[0.895]	[0.878]	[0.947]	[0.824]
N	3,679	3,495	72,933	36,519
Panel C: Conditional on college graduation in a non-STEM field				
Foreign STEM Exposure	-0.014	0.006	0.009	-0.011
	(0.025)	(0.021)	(0.005)	(0.008)
Control mean	[0.893]	[0.873]	[0.934]	[0.806]
N	10,675	22,779	168,874	247,050

Notes: Dependent variable is an indicator for being currently employed, conditional on various educational outcomes. Compare with Table 6.

Table B14: Birth-State Foreign STEM Exposure and Log Earnings

Effect	Black Men	Black Women	White Men	White Women
Panel A: Conditional on college graduation in any field				
Foreign STEM Exposure	-0.101	0.001	-0.016	0.013
	(0.083)	(0.050)	(0.023)	(0.022)
Control mean	[10.923]	[10.679]	[11.272]	[10.620]
N	13,278	24,096	234,168	242,328
Panel B: Conditional on college graduation in a STEM field				
Foreign STEM Exposure	-0.039	-0.057	-0.053	-0.030
	(0.137)	(0.118)	(0.032)	(0.063)
Control mean	[11.096]	[10.893]	[11.406]	[10.865]
N	3,407	3,218	70,972	31,794
Panel C: Conditional on college graduation in a non-STEM field				
Foreign STEM Exposure	-0.102	0.015	0.004	0.019
	(0.094)	(0.064)	(0.023)	(0.024)
Control mean	[10.865]	[10.650]	[11.217]	[10.588]
N	9,871	20,878	163,196	210,534

Notes: Dependent variable is the log of total earned income from the year prior to the survey, conditional on various educational outcomes. See notes in Table 2 for further details.

Table B15: Separate Cross-Section Regressions for Pre- and Post-1990 Cohorts

Effect	Black Men	Black Women	White Men	White Women
Panel A: STEM Major, 1986–1989 Cohorts				
Foreign STEM Exposure	-0.001	-0.006	-0.017***	-0.001
	(0.013)	(0.007)	(0.006)	(0.003)
Control mean	[0.249]	[0.119]	[0.291]	[0.116]
N	7,694	13,652	131,919	151,652
Panel B: STEM Major, 1991–1994 Cohorts				
Foreign STEM Exposure	-0.032*	-0.003	-0.031**	-0.005
	(0.017)	(0.008)	(0.014)	(0.005)
Control mean	[0.253]	[0.135]	[0.306]	[0.138]
N	6,660	12,622	109,888	131,917
Panel C: STEM Occupation given STEM BA, 1986–1989 Cohorts				
Foreign STEM Exposure	-0.013	-0.008	0.000	-0.002
	(0.027)	(0.026)	(0.010)	(0.008)
Control mean	[0.260]	[0.159]	[0.292]	[0.131]
N	1,938	1,693	38,791	17,856
Panel D: STEM Occupation given STEM BA, 1991–1994 Cohorts				
Foreign STEM Exposure	0.016	-0.047*	-0.030***	-0.026**
	(0.031)	(0.028)	(0.011)	(0.011)
Control mean	[0.239]	[0.151]	[0.300]	[0.130]
N	1,741	1,802	34,142	18,663
Panel E: Worked Last Year given STEM BA, 1986–1989 Cohorts				
Foreign STEM Exposure	0.001	0.024	-0.007*	-0.007
	(0.013)	(0.016)	(0.004)	(0.006)
Control mean	[0.927]	[0.922]	[0.968]	[0.863]
N	1,938	1,693	38,791	17,856
Panel F: Worked Last Year given STEM BA, 1991–1994 Cohorts				
Foreign STEM Exposure	-0.013	-0.051**	-0.002	0.003
	(0.018)	(0.023)	(0.004)	(0.009)
Control mean	[0.928]	[0.915]	[0.975]	[0.875]
N	1,741	1,802	34,142	18,663

Notes: This table is a more detailed version of Table 7. See Table 7 for further details.
*Statistically significant at the .10 level; ** at the .05 level; *** at the .01 level.

Table B16: Instrumental Variable Effects of Birth-State Foreign STEM Exposure on STEM Degree Completion

Effect	Black Men	Black Women	White Men	White Women
Panel A: STEM graduation, unconditional of education level				
Foreign STEM Exposure	-0.034*	0.000	-0.002	0.007
	(0.018)	(0.010)	(0.010)	(0.005)
Control mean	[0.041]	[0.029]	[0.101]	[0.045]
N	93,505	102,128	685,261	687,311
Panel B: BA graduation				
Foreign STEM Exposure	-0.007	-0.003	0.001	-0.009
	(0.026)	(0.028)	(0.011)	(0.011)
Control mean	[0.164]	[0.241]	[0.348]	[0.391]
N	93,505	102,128	685,261	687,311
Panel C: STEM graduation, conditional on BA graduation				
Foreign STEM Exposure	-0.174*	-0.003	-0.014	0.016
	(0.089)	(0.046)	(0.030)	(0.012)
Control mean	[0.249]	[0.119]	[0.291]	[0.116]
N	14,354	26,273	241,807	283,569

Notes: Dependent variable is an indicator for either *(a)* graduating in a STEM field, unconditional on education level; *(b)* graduating with a bachelor's degree in any field; or *(c)* graduating with a bachelor's degree in a STEM field. Each coefficient is estimated from a different linear probability model using two-stage least squares, where 1990-2000 foreign STEM growth is instrumented by 1980 foreign STEM exposure. *Statistically significant at the .10 level.

Table B17: IV Effects of Birth-State Foreign STEM Exposure on Current Employment in a STEM Occupation

Effect	Black Men	Black Women	White Men	White Women
Panel A: Conditional on college graduation in any field				
Foreign STEM Exposure	0.016	0.003	-0.041***	-0.001
	(0.057)	(0.030)	(0.012)	(0.005)
Control mean	[0.090]	[0.034]	[0.120]	[0.030]
N	14,354	26,273	241,807	283,569
Panel B: Conditional on college graduation in a STEM field				
Foreign STEM Exposure	0.130	-0.103	-0.115***	-0.073*
	(0.154)	(0.170)	(0.025)	(0.040)
Control mean	[0.260]	[0.159]	[0.292]	[0.131]
N	3,676	3,492	72,933	36,519
Panel C: Conditional on college graduation in a non-STEM field				
Foreign STEM Exposure	0.014	0.013	-0.007	0.007
	(0.036)	(0.012)	(0.009)	(0.005)
Control mean	[0.033]	[0.017]	[0.050]	[0.016]
N	10,673	22,778	168,874	247,050

Notes: Dependent variable is an indicator for current employment in a STEM occupation, conditional on various educational outcomes. See notes in Tables 2 and 5 for further details. *Statistically significant at the .10 level; *** at the .01 level.

Table B18: IV Effects of Birth-State Foreign STEM Exposure on Prior Year Employment Probability

Effect	Black Men	Black Women	White Men	White Women
Panel A: Conditional on college graduation in any field				
Foreign STEM Exposure	0.058	0.032	0.019***	-0.016
	(0.037)	(0.037)	(0.006)	(0.011)
Control mean	[0.929]	[0.913]	[0.965]	[0.854]
N	14,354	26,273	241,807	283,569
Panel B: Conditional on college graduation in a STEM field				
Foreign STEM Exposure	0.098	-0.045	-0.001	-0.075**
	(0.109)	(0.084)	(0.009)	(0.034)
Control mean	[0.927]	[0.922]	[0.968]	[0.863]
N	3,676	3,492	72,933	36,519
Panel C: Conditional on college graduation in a non-STEM field				
Foreign STEM Exposure	0.040	0.046	0.029***	-0.009
	(0.042)	(0.044)	(0.009)	(0.012)
Control mean	[0.930]	[0.912]	[0.963]	[0.852]
N	10,673	22,778	168,874	247,050

Notes: Dependent variable is an indicator for being employed in the prior year, conditional on various educational outcomes. See notes in Tables 2 and 6 for further details. ** Statistically significant at the .05 level; *** at the .01 level.

Table B19: Back-of-the-Envelope Calculations

	Coefficient Estimate	1990–2010 Change in Treatment Variable	Group Effect	Population Weight	Weighted Average Wage Effect
Current Study's Negative Effects					
Wage of Black Male College Graduates	-0.101	1.487	-0.150	0.015	-0.002
Wage Effect from Non-Employment of Female STEM Graduates	-0.037	1.487	-0.055	0.050	-0.003
Wage of Other STEM Graduates	-0.053	1.487	-0.079	0.092	-0.007
Subtotal					**-0.012**
Peri, Shih, and Sparber (2015) Net Positive Effects					
Wage of College Educated	0.080	0.530	0.043	0.3	0.013
Wage of Non-College	0.038	0.530	0.020	0.7	0.014
Subtotal					0.027
Gross Average Positive Effect					**0.039**

Notes: Population weights for negative effects are chosen somewhat as upper bounds since STEM education by women and minorities may be historically below the steady-state that would occur in the absence of discrimination and other barriers.
Specifically, the population weights are computed from a number of simplifying assumptions as follows:
· Black male college graduates: 6% of population is black men; 25% of this group graduate from college. (.06 * .25 = .015)
· Female STEM graduates: 10% of population is STEM graduates; 50% of this group (should be) women. (.10 * .50 = .05)
· Other STEM graduates: 10% of the population is STEM graduates; don't double count black men (6%) or women who left the labor force (3.7% of 50%). ([1-0.06-0.037*0.50]*0.10 = .092)
Coefficient estimates for the current study respectively come from the following sources:
· Table B14, Panel A
· Table 6, Panel B
· Table B14, Panel B
Coefficient estimates for Peri, Shih, and Sparber (2015) come from Table 5, Row 1 of that study.

Change in treatment variable for the current study is computed by the authors. Change in treatment variable for Peri, Shih, and Sparber (2015) is taken from Tables 2 and 3 of that study.