The Impact of Temporary Student Visa Extensions on Patenting: Evidence From STEM OPT

By Seungmin Yoo

Questrom School of Business, Boston University

smyoo@bu.edu

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Abstract

Can foreign students at U.S. universities, with a brief work extension, become inventors without displacing native talent? This paper examines one of the most significant recent U.S. immigration policy changes, the 2008 STEM Optional Practical Training (OPT) extension, which gives international STEM graduates an additional 17 months of work authorization. I show a 59.9%–86.8% increase in the number of first-time ethnic inventors and a 16.9%–23.4% increase in the share of first-time ethnic inventors in geographic areas near R1 universities relative to other areas after the policy change. I find no evidence of first-time native inventors being displaced.

1 Introduction

Skilled immigration's impact on the economy of a host country has become a central topic in current policy debates. Proponents argue that these immigrants bring unique talents that fuel innovation, ultimately boosting the economy (Bloom et al., 2019). In the United States, for instance, President Donald Trump recently floated a proposal to retain talented workers by issuing green cards to all foreign graduates of U.S. colleges, substantially departing from his original view on immigration. Conversely, concerns persist about potential displacement of native workers, exemplified by a recent bill introduced by U.S. Representative Paul Gosar to eliminate the Optional Practical Training (OPT) program, a temporary work program for foreign college graduates, citing its negative impact on American graduates' job prospects.

Although the literature on skilled immigration has extensively examined these arguments for professionals, evidence regarding the impact of international students on innovation remains scarce. Narrowing this gap is particularly important, given the significant share of immigrant STEM workers who first arrive as students and the increasing policy focus of major host countries on attracting international students, alongside recent attempts to reverse this trend (Ganguli and MacGarvie, 2024).

How immigration policy affects the inventing activities of immigrant and native inventors in a host country is unclear a priori when the host country offers work extensions to foreign university students. Giving international students extra time to work in their host country might not help them become inventors—most have little work experience, and innovation takes time. Meanwhile, the evidence in the literature that native innovators are being displaced by immigrant innovators is based on competition between more experienced and specialized innovators, and the results are mixed (Kerr and Lincoln, 2010; Borjas and Doran, 2012; Doran et al., 2022). This makes it hard to predict whether a short extension for foreign university students would hinder the employment of native inventors. Thus, an evaluation of such a policy would provide policymakers with a reference point for designing better immigration policies.

In this paper, I analyze the U.S. government's implementation of the STEM OPT extension in 2008 to examine the impact of an immigration policy that offers a short work extension to foreign university students on the inventing activities of immigrant and native inventors. The OPT extension gave international STEM graduates an additional 17 months to work without a work visa.[1] Although the policy is in effect nationwide, its impact should be felt disproportionately near research-intensive universities. This is because students tend to find employment near their universities and because the inventing activity of recent graduates tends to be related to their academic studies.[2]

The policy's unique feature—targeting recent graduates—generates cross-region variation, enabling causal inference to evaluate the effects of the policy. I therefore adopt a difference-in-differences (DiD) empirical strategy that focuses on trends in patenting by first-time inventors (who are plausibly recent graduates) with ethnic names in locations near R1 universities compared to more distant locations. To my knowledge, this is the first paper to offer evidence on the impact of the STEM OPT extension on innovation.

The OPT program allows every international student on an F-1 visa who has attended an American postsecondary institution for at least one academic year as a full-time student to work in the United States for 12 months. There is no cap on the number of OPT program participants. Although the program does not require a work visa or employer sponsorship, it does require that participants' employment be related to their major field of study. The policy change in 2008 allowed STEM graduates to apply for an additional OPT period of 17 months. Participants must also be employed by an employer enrolled in the E-Verify program.

[1] The policy was changed in 2016, extending the period to 24 months, but I don't examine this policy change in this paper.

[2] In Section 5.2, I will provide evidence for the stickiness of graduates near universities.

The target population of the STEM OPT policy is distinctive in three dimensions: career level, skills, and ability. First, participants are likely early in their careers. As recent graduates, they likely have less work experience than immigrants affected by other policies (e.g., the H-1B program) and, therefore, are more likely to have low-level positions in their firms. Second, participants' skills are concentrated in STEM occupations and are closely aligned with U.S. firms' innovation activities. Since the OPT extension targets STEM graduates and requires them to perform job duties related to their major field of study, participants are more likely to be employed in STEM occupations than immigrants under other visa programs. Furthermore, their U.S. education equips them with skills that are likely better suited to the specific needs of U.S. firms' R&D compared to immigrants with foreign degrees, such as J-1 visa holders. Third, participants go through less-selective labor markets than workers who are subject to other immigration policies.

Because the OPT program does not require employer sponsorship and has no cap on the number of participants, the policy helps firms avoid incurring administrative costs for employer sponsorship and bearing the hiring uncertainty of other policies (e.g., the H-1B program). The lack of employer sponsorship requirement lowers the bar for immigrants to enter the labor market and enables them to use their STEM OPT periods to demonstrate their ability in order to proceed to a more advanced visa. Given these characteristics, the STEM OPT extension is expected to increase the supply of relatively less-competitive early-career immigrant workers who likely fill STEM occupations and provide their employers with skills that are relevant to their innovation needs.

The context of the STEM OPT extension is important because it is one of the most significant U.S. immigration policy changes in the past 20 years. By lifting restrictions on the supply of foreign skilled workers without a cap on participants, the policy change has substantially influenced the immigrant pool. Data from the U.S. Immigration and Customs Enforcement (ICE) show that the number of OPT program participants for all majors grew from 78,000 in 2004 to 257,000 in 2016; for STEM majors in particular, the number has grown from 33,000 to 172,000. As a result, the OPT program surpassed the H-1B program, the largest visa program for temporary workers in the U.S., in terms of the number of initial application approvals in the years 2010, 2014, 2015, and 2016 (Ruiz and Budiman, 2018).

The substantial growth of the OPT program alleviated severe labor-market frictions experienced by firms and foreign skilled workers due to the H-1B cap reduction in 2004, which made it harder for firms to hire foreign skilled workers.[3] The STEM OPT extension lessened its effects by allowing firms to employ recent STEM graduates for a certain period without the inherent uncertainty of the visa lottery process. Furthermore, the policy change allowed

[3]See Glennon (2023) for the impact of the H-1B cap reduction on firms.

foreign skilled workers to apply more than once for an H-1B (if denied the first time) and gave them more time to find an employer willing to sponsor them for an H-1B.

To estimate the impact of the STEM OPT extension on the inventing activities of immigrant and native inventors, I use patent data on first-time inventors from the U.S. Patent and Trademark Office (USPTO) as a proxy for inventors affected by the policy change, between 2000 and 2015, and their name-based ethnicities (Kerr, 2008; Chattergoon and Kerr, 2022). Using inferred ethnicities to categorize inventors as American or foreign, I calculate the number of first-time ethnic and native inventors in each core-based statistical area (CBSA) and year. Also, I calculate the share of first-time ethnic inventors as the ratio of the number of first-time ethnic inventors to the total number of first-time inventors in each CBSA and year. To identify the effect of the policy change, I run DiD regressions at the CBSA level. The treatment status of the CBSAs is determined by whether they had at least one of the 96 R1 universities listed in the 2005 *Carnegie Classification*.[4] That is, CBSAs with at least one R1 university form the treatment group, while others constitute the control group.

My results show that the STEM OPT policy increased the number of first-time ethnic inventors by 86.8% in CBSAs with R1 universities, and that first-time ethnic inventors did not crowd out first-time native inventors. The policy also increased the *share* of first-time ethnic inventors by 16.9% in CBSAs with R1 universities. The first result is robust to matching on demographic and economic covariates, alleviating concerns about the comparability of the treatment and control groups, although the estimated policy effect shrinks to 59.9%.

I also provide mechanisms through which the policy change affects the number of first-time ethnic inventors. First, defining elite universities (the top 30 institutions) by their number of STEM doctorates awarded and their expenditure on science and engineering in 2005, I show that the policy's impact is primarily driven by proximity to these institutions. This result aligns with the expectation that the policy's effect is stronger in areas near elite universities, given the close connection between the inventing activity of recent graduates and their academic studies. Second, I find that the policy change had heterogeneous effects on the number of first-time ethnic inventors depending on the types of organizations their patents are assigned to. The policy's positive effect on the count of these inventors is mainly due to increased patenting in the university, hospital, and government sectors. Third, I find heterogeneity in the policy effect across broad technology fields categorized by the Cooperative Patent Classification section. Specifically, the positive effect of the STEM OPT extension on the number of first-time ethnic inventors is mainly driven by an increase in patenting in Human Necessities (which includes health and pharmaceuticals).

The STEM OPT extension is estimated to have generated 785 additional first-time eth-

[4] https://carnegieclassifications.acenet.edu/

nic inventors in the U.S. between 2008 and 2015, corresponding to a 2.5-percentage-point increase in the share of first-time ethnic inventors during that period.[5] Back-of-the-envelope calculations also show that the policy change produced 1,189 additional issued utility patents filed in the U.S. in their first year by first-time ethnic inventors whose inventing careers began during this period.

This paper demonstrates that foreign university students can become inventors when they are given additional time to work in their host country. Therefore, I contribute to the literature on the contribution of foreign university students to innovation and, more broadly, the effects of university-educated immigrants on innovation (Hunt and Gauthier-Loiselle, 2010; Hunt, 2011; Stuen et al., 2012; Blit et al., 2020; Crown et al., 2020). Although the literature has evidence on the contribution of skilled immigrants to innovation, most existing research shows a general relationship without distinguishing between workers' experience levels or the length of their stay. This paper complements this literature by showing that the additional 17-month OPT duration offered to recent foreign graduates in STEM fields can affect U.S. innovation outcomes. Also, whereas the literature often relies on innovation counts (e.g., patents) to show a relationship between skilled immigration and innovation, this approach aggregates several channels through which immigrants affect innovation, not directly showing skilled immigration's effects on the supply of immigrant inventors. This paper addresses this limitation by directly measuring changes in the number and share of first-time ethnic inventors after the policy change.

This paper also contributes to the literature on the competition between immigrants and natives. Whether natives are displaced by immigrants is an important consideration for policymakers, but the literature provides mixed evidence, even within the same visa program. For example, Kerr and Lincoln (2010) find no evidence of immigrants crowding out natives in their study on H-1B visa reforms; rather, they find some possibility of crowding in. In contrast, Doran et al. (2022) find that obtaining an additional H-1B visa results in the displacement of approximately 1.5 other workers at the firm. These mixed results limit the ability of researchers and policymakers to predict whether immigrant innovators would displace native innovators, and the scarcity of evidence about early-career innovators further complicates the prediction issue for policies targeted at foreign university students. I address this limitation by showing that first-time ethnic inventors do not crowd out first-time native inventors in the same geographically defined labor market after the STEM OPT extension. Indeed, this result is in line with Guo et al.'s (2024) finding that the STEM OPT extension

[5]The first estimate is derived from column 1 of Table 4, my baseline estimate of the effect of the STEM OPT extension on the number of first-time ethnic inventors. For the second estimate, see column 1 of Table 7.

increased local employment of native workers. Together, these findings suggest that whether immigrants displace natives due to an immigration policy depends on the contexts in which the influx of immigrants into a host country takes place.

Finally, I contribute to the literature on human capital supply for innovation. Due to the importance of knowledge workers for economic growth, the literature has focused on ways to increase the supply of STEM workers, such as education programs and childhood exposure to innovation (e.g., Toivanen and Väänänen, 2016; Bell et al., 2019). However, it is often difficult to assess the impact of these policies, including immigration policies, aimed at increasing the supply because they often affect the entire country (Bloom et al., 2019). This paper contributes to this literature by introducing a novel research design that leverages the fundamental properties of the STEM OPT extension to measure the policy's effect on the number of first-time ethnic inventors.

The rest of this paper is organized as follows. Section 2 describes the STEM OPT extension policy, the empirical context of this paper. Section 3 describes the data. Section 4 specifies the identification strategy. Section 5 presents the results of my empirical analysis. Section 6 concludes.

2 The 2008 STEM Optional Practical Training Extension

Established in 1992, the OPT program allows every international student on an F-1 visa (nonimmigrant student) who has completed at least one academic year as a full-time student at a U.S. postsecondary institution to work in the United States for 12 months. Types of employment eligible for the program include paid or unpaid employment, self-employment, and contract work.[6] While the program does not require a work visa or employer sponsorship, it does require that participants' employment be related to their major field of study and that they work at least 20 hours per week. Students are eligible to participate in the OPT program before (precompletion OPT) or after they complete their degree programs (postcompletion OPT). The precompletion OPT period, if used, is deducted from the 12 months available for the postcompletion OPT period. There is no cap on the number of OPT program participants.

In April 2008, the Bush administration expanded the original OPT program to accept STEM OPT applications for international STEM graduates who are employed by an em-

[6]Individuals are eligible to apply for another OPT in their lifetime if their current degree is at a higher level than the previous degree(s) that they already used for their OPT. Students can be self-employed only when they start a business, and self-employed participants must work full-time.

ployer enrolled in the E-Verify program. The STEM OPT policy offered an additional 17 months in the U.S. to STEM graduates, based on the Department of Homeland Security's categorization of STEM majors, increasing their work-eligible period to 29 months.[7] The list of STEM majors has also grown over time.[8]

The continued expansion of the STEM OPT program has increased the number of foreign STEM graduates in the labor market (Ruiz and Budiman, 2018). ICE provides a list of the top 200 employers for STEM OPT students between 2008–2018 with the total number of hires through the STEM OPT program during this period. Table A1 lists the top 30 employers and their STEM OPT hires based on this information, showing that major firms are heavy employers of foreign STEM graduates who work through the OPT program.

This context is useful for examining the impact of an immigration policy that offers a short extension to foreign university students on the inventing activities of immigrant and native inventors, for two reasons. First, while it is often hard to make a causal inference on the effect of such a policy on inventor supply, since a policy aimed at increasing the supply of STEM workers tends to affect the entire country (Bloom et al., 2019), the fundamental properties of the STEM OPT extension help address this issue. Because the policy targets recent STEM graduates who tend to find employment near their universities and because their inventing activity tends to be related to their academic studies, inventors working through the OPT program are likely concentrated near research-intensive universities.

Second, the efficient matching of skills and occupations within the U.S. labor market provides a suitable context for examining how the extension affects the inventor labor market. Even if foreign STEM graduates are given the extra work period, the inventing activities of immigrant inventors might not change significantly if the labor market does not effectively match skills and occupations, which contaminates the estimation of the policy's effect. Indeed, Blit et al.'s (2020) study on Canadian patenting shows that a mismatch between STEM education and non-STEM occupations for immigrant college graduates is responsible for the immigrants' low impact on regional innovation productivity in Canada relative to that in the U.S.

Although the policy change in 2008 was implemented by President Bush, it was not completely exogenous; it was the result of a lobbying campaign. In June 2007, a major immigration reform bill was introduced that included a substantial increase in the number of permitted foreign workers, but it eventually failed in the Senate (Pear and Hulse, 2007). In November 2007, Microsoft started lobbying the Department of Homeland Security, urging

[7]Students must apply for a STEM OPT extension before the end of their one-year OPT period.

[8]This list was expanded in 2011 and 2012, during the study period of this paper. In my analysis, I do not distinguish these expansions from the 2008 STEM OPT extension.

it to extend the length of the OPT program. Microsoft's aim was to relieve the constraints on its highly skilled labor pool caused by the reduction of the H-1B visa cap in 2004. The campaign was joined by multiple interest groups, including the U.S. Chamber of Commerce, Intel, Qualcomm, and various universities. This campaign led to the implementation of the policy in April 2008 (Rosenthal, 2021).

This series of events might raise concerns about potential endogeneity if firm-level analysis is used to identify the impact of the STEM OPT extension on innovation outcomes, because some firms participated in the lobbying campaign for the STEM OPT policy to be implemented (i.e., selection into treatment). However, I mitigate this concern by employing an empirical strategy that uses geographical areas that were determined before the policy change. I will further elaborate on this identification strategy in Section 4.

3 Data & Measurement

3.1 Data

I use issued utility patent data from *PatentsView* to analyze U.S.-based first-time inventors who filed patent applications between 2000 and 2015.[9] Because the patent data do not include an inventor's visa status, I use first-time inventors as a proxy for inventors who were affected by the STEM OPT policy given that the policy targets international students who are likely early in their careers. Also, because neither the nationality nor the visa information of inventors is available, I use first-time inventors' inferred ethnicities as a proxy for their nationalities, as has been done in previous research (Kerr, 2008; Chattergoon and Kerr, 2022).[10] The data have a probability vector over nine ethnicities for each inventor: Anglo-Saxon/English, European, Chinese, Vietnamese, Indian/Hindi/South Asian, Hispanic/Filipino, Japanese, Korean, and Russian.[11] The data cover 96.1% of first-time inventors who filed patent applications between 2000 and 2015 and were in the U.S. at the

[9] I use patent application dates to determine an inventor's first-time inventorship. When an inventor applied for two or more patents on the same day, I use the one that is the earlier when ordered by patent number.

[10] Data on inventor ethnicity was graciously provided by William R. Kerr. The USPTO had collected nationality information of inventors until September 2012 as part of the Declaration of Utility or Design Patent Application. The information for each patent can be purchased on the USPTO's website. I submitted two separate Freedom of Information Act requests to the USPTO to obtain bulk data, but these requests were rejected.

[11] The ethnicities are inferred based on inventors' first and last names as well as geographic information. Differences in inferred ethnicities between inventors of the same names but with different locations are modest. The ethnicities of U.S.-based inventors are generated in a time-invariant way using the ethnicities of local scientists and engineers in the 1990 Census.

time of their applications. Then, I converted the GPS coordinates of inventors to CBSAs.[12]

In addition, I use the GPS coordinates and information on research capacity of 96 R1 universities classified by *Carnegie Classification* in 2005 for analysis. I converted the GPS coordinates of these universities to CBSAs.[13]

Finally, I use the demographic and economic information from the *2000 Decennial Census* for ZIP Code Tabulation Areas (ZCTAs) that correspond to ZIP code areas belonging to CBSAs in my data: population, a share of foreigners, per capita income, and total employment. I use this information to create demographic and economic data at the CBSA level.[14]

I then produced CBSA- and year-level balanced panel data for analysis. The panel data has 902 unique CBSAs between 2000 and 2015. The summary statistics are shown in Table 1.

3.2 Measurement

To create outcome variables, I use Anglo-Saxon/English and European ethnicities as a proxy for American inventors and the other seven ethnicities as a proxy for foreign inventors.

[12]I first used *Google API*, *Open Street Map*, *zipcodeR*, and manual internet searches to convert inventors' GPS coordinates to ZIP codes. Only one first-time inventor with ethnicity information in my data had GPS coordinates that could not be matched with a ZIP code. Using a ZIP code–CBSA crosswalk offered by the U.S. Department of Housing and Urban Development, I matched inventors with CBSAs. There were 42,344 inventors (6.4% of focal inventors) that were not matched with CBSAs because their ZIP codes were not located within a CBSA.

[13]Similar to the inventor-location matching process (described in the preceding footnote), I first converted the GPS coordinates of R1 universities to ZIP codes before matching them to CBSAs via the ZIP code–CBSA crosswalk. There were seven R1 universities whose ZIP codes were not matched with any CBSAs: Florida State University, Georgetown University, University of Connecticut, University of Florida, University of Miami, University of South Florida, and Yale University.

[14]The earliest year that CBSA level data are available on the Census website is 2010. To avoid using covariates observed after the STEM OPT extension in 2008, I decided to aggregate the ZCTA level information in 2000 at the CBSA level. I used the ratio of addresses belonging to a given ZIP code–CBSA pair to the total number of addresses in the ZIP code area for aggregation that was available in the ZIP code–CBSA crosswalk. The Census website says ZCTAs are in most cases the same as ZIP codes, while some areas have ZCTAs that are different from their ZIP codes. The difference occurs when a ZCTA consists of two or more ZIP code areas, but a certain ZIP code occurs most frequently and becomes a ZCTA of the area. Some ZIP codes with very few addresses are not covered by ZCTAs. Because the Census does not provide a crosswalk between ZCTAs and ZIP codes, I used a crosswalk provided by *UDS Mapper* (https://udsmapper.org/zip-code-to-zcta-crosswalk/). Out of 39,490 unique ZIP codes that belong to CBSAs in my data, 33,036 have a one-to-one mapping to ZCTAs, 6,450 have a many-to-one mapping, and four were not matched with a ZCTA. Among the matched ZIP codes, 1,835 were not covered by the Census data. This is likely because those ZCTAs are available in Census data for recent years, but were not in 2000. Therefore, demographic and economic information is not available for the 1,839 ZIP code areas (4.7% of the ZIP code areas belonging to CBSAs in my data). Also, some ZCTAs may change over time. Therefore, there is a potential for error in matching ZIP codes with covariates from the 2000 Census data using the ZCTAs in that data and those in the 2022 UDS report crosswalk.

3.2.1 The Number of Inventors

To count the number of first-time ethnic inventors, a proxy for the supply of immigrant inventors affected by the STEM OPT extension, in each CBSA, I formulate the following variable:

$$Ethnic\ Count_{ct} = \sum_{it \in ct} \sum_{j \notin \{ENG, EUR\}} e_{j(i)}$$

where i indexes an inventor, j an ethnicity, c a CBSA, and t a year. The element $e_{j(i)}$ is the likelihood of an inventor i having an ethnic name of an ethnicity j, and the sum of $e_{j(i)}$'s across all ethnicities for each inventor equals 1. The variable *Ethnic Count* is the sum of inventors' ethnic probabilities for ethnicities that are neither Anglo-Saxon/English nor European for all first-time inventors in a CBSA c and year t.[15]

Similarly, to count the number of first-time native inventors, a proxy for the supply of American inventors affected by the STEM OPT extension, I formulate the following variable:

$$Native\ Count_{ct} = \sum_{it \in ct} \sum_{j \in \{ENG, EUR\}} e_{j(i)}$$

The variable is the sum of inventors' ethnic probabilities for both Anglo-Saxon/English and European across all first-time inventors who are located in a CBSA c and year t. The sum of *Ethnic Count* and *Native Count* equals the number of first-time inventors in a CBSA c and year t.

3.2.2 Ethnic Share

To measure the relative supply of immigrant and native inventors affected by the STEM OPT extension, I create the following variable:

$$Ethnic\ Share_{ct} = (\sum_{it \in ct} \sum_{j \notin \{ENG, EUR\}} e_{j(i)})/N_{it \in ct}$$

The indexes are the same as above. The numerator is *Ethnic Count* and the denominator is the number of first-time inventors in a CBSA c and year t. Therefore, the variable is the ratio of the number of first-time ethnic inventors to the total number of first-time inventors in a CBSA and year. The variable is continuous, with a value between 0 and 1.

The validity of using ethnicity-based variables as a proxy for an inventor's immigrant status

[15] There are inventors whose ZIP code areas belong to several CBSAs. For each ZIP code area, the crosswalk has the ratio of addresses belonging to a given ZIP code–CBSA pair to the total number of addresses in the ZIP code area. I used this ratio to allocate a fractional count of inventors to each CBSA.

is important to this paper's analysis. Using ICE's list of top 200 employers of STEM OPT participants between 2008 and 2018, I identified these employers' issued utility patents that were applied for during this period to compute the ratio of first-time ethnic inventors over total first-time inventors at the assignee-organization and patent levels, respectively.[16] A cross-sectional regression result shows that association with one of the top 200 employers is correlated with an increase in the ratio by 20.5 percentage points (a 90.7% increase relative to the mean) and 19.6 percentage points (a 59% increase relative to the mean) at the assignee-organization and patent levels, respectively. See Appendix A1 for further details.

4 Identification Strategy

To estimate the impact of the STEM OPT extension on the number of first-time ethnic inventors, there is one empirical challenge to be addressed: finding a counterfactual for changes in the outcome in the absence of the policy change. Because immigration policies tend to affect the entire host country, it is difficult to identify specific areas that are affected by such policies to evaluate their effects by causal inference. However, this empirical challenge could be addressed by leveraging the fundamental mechanism of the policy. Specifically, because the STEM OPT extension policy targets graduating students and they tend to find employment near their universities, the geographical distribution of first-time ethnic inventors (a proxy for inventors working through the OPT program) would be correlated with that of the universities they attended. In addition, the inventing activity of recent graduates tends to be related to their academic studies, and universities with high research intensity are likely to produce students who could become inventors. Therefore, areas near research-intensive U.S. universities constitute a treatment group, and other areas a control group. That is, the treatment status indicator is turned on if a CBSA has at least one R1 university and 0 otherwise.

I estimate the following DiD regression at the CBSA level to see the impact of the policy on the number of first-time ethnic inventors in CBSAs with R1 universities:[17]

$$y_{ct} = \alpha + \beta R1_c \times \textit{Post-STEM OPT}_t + \mu_c + \lambda_t + \epsilon_{ct} \tag{1}$$

where c indexes a CBSA and t a year. The equation is estimated on the CBSA- and year-level panel data. The variable *R1* is a treatment status indicator that is turned on if a CBSA has any R1 universities and 0 otherwise, and *Post-STEM OPT* is a postpolicy period

[16] See Table A1 for a list of the top 30 employers of STEM OPT participants and the number of first-time ethnic and native inventors who are associated with each of these employers during this period.

[17] This paper does not estimate a staggered DiD regression.

indicator that is turned on in 2008, the year of the policy change, and onward. CBSA- and year-specific characteristics are, respectively, controlled by μ_c and λ_t. β is a coefficient of interest. I first use *Ethnic Count* as an outcome variable, and β indicates the effect of the policy change on the number of first-time ethnic inventors in CBSAs with R1 universities. Table 2 lists the CBSAs in the treatment group, and a selected subset of CBSAs in the control group used in estimation for *Ethnic Count*.

I also investigate whether an increase in immigrant inventor supply, driven by the policy change, led to a decrease in native inventor employment. If the STEM OPT extension increased the supply of immigrant inventors in CBSAs with R1 universities, competition between immigrant inventors and their native counterparts could increase in those areas, potentially crowding out native inventors. Therefore, I investigate the impact of the policy change on the number of first-time native inventors in CBSAs with R1 universities using Equation 1 where an outcome variable is *Native Count*.

There is a caveat to conducting this exercise. While first-time native inventors are considered treated if they are located in CBSAs with R1 universities at the time of their first patent applications, they were not directly affected by the policy change—they were *indirectly treated* because they were exposed to the influx of first-time ethnic inventors due to the policy change. Still, this exercise allows us to get a general sense of the policy's effects on native inventors.

Lastly, given the potential role of diversity in promoting innovation (Nathan, 2015; Ferrucci and Lissoni, 2019), I analyze changes in the share of first-time ethnic inventors due to the STEM OPT extension using the variable *Ethnic Share*. While some CBSAs lack first-time inventors in certain years, leading to missing *Ethnic Share* values and thus restricting this analysis to a balanced panel of 516 CBSAs (57.2% of the total), this subsample still covers a substantial 98.2% of all first-time inventors with matched CBSAs in my data.

5 Results

5.1 Descriptives and Overview

To assess the impact of the STEM OPT extension on immigrant and native inventors, I first explore changes in both the number and share of first-time ethnic inventors across geographic and temporal dimensions. Figure 1 visualizes the main baseline result of this paper, showing the average of *Ethnic Count*, the number of first-time ethnic inventors, across CBSAs, categorized by the presence of an R1 university. Panels A and B of Figure 1 show the trends in the entire sample and the coarsened exact matching (CEM)-matched sample,

respectively, where *Ethnic Count* is weighted by CEM weights in the latter.[18] The figures suggest that after the STEM OPT extension, CBSAs with R1 universities experienced an increase in the number of first-time ethnic inventors compared to those without.

This positive effect is further supported by a simple tabulation. Specifically, Panel A of Table 3 reports the average number of first-time ethnic inventors (*Ethnic Count*) in CBSAs before and after the STEM OPT extension, comparing those with and without R1 universities in the entire sample. The difference in average counts between CBSAs with and without R1 universities increased from 119.77 to 130.51 following the policy change. This relative increase appears to suggest a positive effect of the policy on the number of first-time ethnic inventors in CBSAs with R1 universities.

Next, I explore changes in the share of first-time ethnic inventors. Panel B of Table 3 shows the average share of first-time ethnic inventors (*Ethnic Share*) before and after the STEM OPT extension, again comparing CBSAs with and without R1 universities in the entire sample. The difference in average shares increased from 0.133 to 0.158 after the policy. This relative increase appears to suggest a positive effect of the policy on the share of first-time ethnic inventors in CBSAs with R1 universities.

Having verified that the STEM OPT extension appears to have increased both the number and share of first-time ethnic inventors, I next examine the policy's impact on immigrant and native inventors using DiD regressions in the following subsections. First, I present baseline results based on three outcome variables: *Ethnic Count*, *Native Count*, and *Ethnic Share*. I then present results on the mechanism of the policy's effects.

5.2 Baseline Results

5.2.1 Did the STEM OPT Extension Increase the Number of First-Time Ethnic Inventors?

To measure the impact of the STEM OPT extension on the number of first-time ethnic inventors in CBSAs with R1 universities, I estimate Equation 1 on the CBSA- and year-level panel for the outcome variable *Ethnic Count* with standard errors clustered at the CBSA level. The results are reported in Table 4. Column 1 shows the estimation result for the entire sample. The coefficient of *ZIP R1 20 Miles* $\times$ *Post-STEM OPT* is significant; it indicates that the policy change increased the number of first-time ethnic inventors by 10.749 in CBSAs with R1 universities. This change implies an 86.8% increase relative to the mean.

Next, I estimate the following event-study model for the same outcome variable with

[18] I will elaborate on how I match CBSAs in Section 5.2.

standard errors clustered at the CBSA level to measure the yearly effect of the STEM OPT extension on the number of first-time ethnic inventors in CBSAs with R1 universities:

$$y_{ct} = \alpha + \sum_{k} \beta_k \mathbb{1}(t - 2008 = k) + \mu_c + \lambda_t + \epsilon_{ct} \tag{2}$$

where c indexes a CBSA and t a year and fixed effects μ_c and λ_t are the same as in Equation 1. The indicator variable $\mathbb{1}(t-2008 = k)$ is turned on for CBSAs with R1 universities in a year t that is k years after 2008 (the year of the policy change) and when k = -1 for the other CBSAs. The coefficients β_k's are coefficients of interest that show the dynamic treatment effects of the STEM OPT extension on the number of first-time ethnic inventors in CBSAs with R1 universities.

Figure 2 shows the result of the event study. The figure shows a very large increase in the number of first-time ethnic inventors in CBSAs with R1 universities beginning three years after the policy change. Before the policy is implemented, the number of first-time ethnic inventors is trending downward in the treated CBSAs. If we assume the downward trend would persist, but for the policy change, then my estimate of the impact of the STEM OPT extension on the number of first-time ethnic inventors in Equation 1 is conservative under the standard assumption of parallel trends.

Although the evidence in Figure 2 suggests that any pretrend is modest compared to the large increase in the number of first-time ethnic inventors after the policy change, a formal test of the hypothesis that all pretreatment coefficients except that of the normalized year (i.e., k = -1) are equal to zero is rejected. Therefore, I use the method proposed by Roth (2022) to assess the plausibility of the assumption of parallel trends using the Stata *pretrends* package. This package allows users to compute the significance level of a violation of parallel trends (i.e., the slope of a linear trend) in their data to detect it at a specified rate corresponding to the desired statistical power. It also computes the likelihood of finding a hypothesized linear trend in the data that violates parallel trends. I used 80% power, which is considered a benchmark for this type of tests (Cohen, 1988). Figure A1 depicts the test, showing a hypothesized linear trend. The result of the test shows that the likelihood ratio of observing the event-study coefficients under the hypothesized trend (as compared to under parallel trends) is 0.09, suggesting that the parallel-trends assumption is reasonable, compared to the model of a linear time trend.

There are two potential reasons why the policy was slow to yield appreciable effects. One is the financial crisis from December 2007 to June 2009, which could have slowed down organizations' investment in R&D and, in turn, the hiring of inventors. The other is the nature of the OPT program: it targets students and it takes time to complete education.

The new policy would have induced more international students to apply for STEM degree programs. Indeed, the literature shows that the policy change led to a higher share of international students earning STEM degrees, and this increase was mainly driven by master's degree holders (Amuedo-Dorantes et al., 2019). Given that it typically takes two years to complete a master's degree in the U.S., and that it takes time to write a patent application, we should expect to see a substantial increase in the number of first-time ethnic inventors three years after the policy change at the earliest. The event-study result shows a pattern that is consistent with this expectation.

While the event-study result alleviates concerns about a pretrend and gives credence to the result of the DiD regression, one potential threat to the identification is that the treatment and control groups in my analysis might not be comparable. For example, many R1 universities are located in large cities, which are usually ethnically diverse, and the observed increase in the number of first-time ethnic inventors could be driven by the agglomeration of ethnic inventors in those cities. To mitigate the concern, I match CBSAs on the pretrend of *Ethnic Count*, the outcome variable, as well as demographic and economic covariates pulled from the *2000 Decennial Census* by CEM.[19]

Table 5 shows the means of *Ethnic Count* in CBSAs in the treatment group and control group and their difference both in the entire sample and in the matched sample, suggesting that their difference becomes smaller after matching. I run Equation 1 again on the matched sample using CEM weights where standard errors are clustered at the CBSA level. Column 2 of Table 4 shows the result. The coefficient of *R1* $\times$ *Post-STEM OPT* is 2.153 and significant; it indicates a 59.9% increase relative to the mean. Although the policy effect in the matched sample shrinks compared to that in the entire sample, the policy effect is still observed in the matched sample. Thus, the results in columns 1 and 2 indicate that the STEM OPT extension increased the number of first-time ethnic inventors by 59.9% to 86.8% in CBSAs with R1 universities.

There may be a concern about using CBSAs with R1 universities as a treatment group to examine changes in the number of first-time ethnic inventors due to the STEM OPT extension, since many graduates could leave their college towns for work. However, Ruiz and Budiman (2018) provide information on a fraction of OPT participants between 2004 and 2016 who stayed in or left each of the top 113 metropolitan areas where they studied (cross-sectional), 106 of which are covered by my data. The weighted average of staying

[19]For the pretrend, I first estimate the following equation for each CBSA during the pretrend period (i.e., 2000–2007): $outcome = \alpha + \beta \times t + \epsilon$ where t is a year. I use β for CEM. For other outcome variables, CEM is done using the pretrend of an outcome variable used in estimation in combination with the demographic and economic covariates.

rates[20] was 62.4%. Therefore, the evidence suggests that the presence of R1 universities in CBSAs provides a reasonable criterion for defining a treatment group, and we can interpret the coefficients of *R1* × *Post-STEM OPT* in Table 4 as the positive effect of the STEM OPT extension on the number of first-time ethnic inventors.

The baseline OLS estimate in column 1 of Table 4 suggests that the STEM OPT extension added 785 first-time ethnic inventors to the U.S. inventor population between 2008 and 2015. I computed this number by multiplying the estimated average effect of the policy change on the number of first-time ethnic inventors in CBSAs with R1 universities (10.749) by the total number of such CBSAs (73). Back-of-the-envelope calculations also show that the policy change led to 1,189 additional issued utility patents filed in the U.S. in their first year by first-time ethnic inventors whose inventing careers began during this period. To estimate this, I computed the average number of issued utility patents filed by first-time ethnic inventors whose inventing careers began between 1996 and 2015 and multiplied the average patenting rate by the increased number of first-time ethnic inventors due to the policy change.[21]

5.2.2 Were First-Time Native Inventors Crowded Out by First-Time Ethnic Inventors?

To investigate whether the increased influx of first-time ethnic inventors into CBSAs with R1 universities after the STEM OPT extension crowded out first-time native inventors, I estimate Equation 1 on the CBSA- and year-level panel for the outcome variable *Native Count* with standard errors clustered at the CBSA level. Table 6 reports the results. Because the event study for the same outcome variable shows a decreasing pretrend between 2000 and 2004 (unreported), I report estimation results on a truncated sample without the pretrend (column 1) and a matched sample for the entire period (column 2), respectively.[22] The *R1* × *Post-STEM OPT* coefficient is positive but insignificant in column 1 and negative but also insignificant in column 2, indicating a lack of statistically significant effect. The coefficient in column 2 is my preferred estimate. Although there is a caveat to interpreting the result as mentioned in Section 4, this result shows that the suspected crowd-out did not take place.

[20] I also computed the weighted average of staying rates separately for CBSAs with R1 universities and those without, which are 64.7% and 51.4%, respectively. For all weighted averages reported, weights are computed by the ratio of OPT participants who studied in each CBSA over total OPT participants across CBSAs included in this analysis. Specifically, for the overall average, the denominator is the total OPT participants across all 106 CBSAs in my data. For the subgroup averages (CBSAs with R1 and those without), the denominator for each is the total OPT participants within that specific group of CBSAs.

[21] I used a simple count of patents, not taking into account author team size. Using a fractional count of patents, this estimate become 432.

[22] The event study on the matched sample does not suggest evidence of a pretrend (unreported).

There are several potential explanations for the lack of crowding-out effects on first-time native inventors. The reduction of the H-1B visa cap in 2004 caused severe constraints in the highly skilled labor pool for U.S. firms, with the strongest impacts on firms' R&D positions (Glennon, 2023). Because the STEM OPT extension was implemented when there was already an excess demand in the labor market for knowledge workers, the increased supply of first-time ethnic inventors after the policy change resolved the supply shortage and did not result in natives being crowded out.

This result is different from that of Borjas and Doran (2012), who show that U.S. mathematicians were crowded out by Soviet immigrants after the collapse of the Soviet Union. This might be because the U.S. labor market for mathematicians was in equilibrium until the collapse, but a sudden, substantial influx of Soviet mathematicians into the U.S. would have caused a severe excess supply of labor leading to natives being crowded out. This pre-shock labor-market condition is in contrast with that of this paper, and the difference suggests that peer effects might depend on the state of the labor market before a shock.

Another factor could be the productivity difference between immigrants and natives. Borjas and Doran (2012) show that the Soviet mathematicians who migrated to the U.S. after the collapse of the Soviet Union were much more productive than their contemporary U.S. mathematicians, and that their migration led to the decreased likelihood of U.S. mathematicians producing a home-run paper. That level of a productivity difference does not exist in the context of this paper, because the STEM OPT extension targeted international STEM graduates who received the same-quality education as native STEM graduates. Even if there existed an ability difference among first-time inventors, the difference was not dramatic enough to crowd out native inventors, likely because their skills and knowledge are relatively standardized. This contrast suggests that whether natives are crowded out by immigrants depends on the magnitude of the productivity gap between the two groups.

Lastly, the distinct nature of first-time inventors could drive the null effect. Compared to more experienced inventors, first-time inventors have less-specialized human capital and can potentially be placed on various types of research projects without too much friction. Therefore, when the influx of first-time ethnic inventors into CBSAs with R1 universities increases after the STEM OPT extension, local first-time native inventors may find opportunities in research projects that are less exposed to the increased supply of inventors, mitigating potential crowding-out effects. The differing levels of specialization between first-time inventors in this paper and mathematicians in Borjas and Doran (2012) is a plausible reason (in addition to the productivity gap between immigrants and natives) for our contrasting results. In sum, the differences between our two contexts imply that whether natives are crowded out by immigrants depends on the context in which the influx of immigrants into a host country

takes place.

5.2.3 Did the Share of First-Time Ethnic Inventors Increase After the STEM OPT Extension?

The results in the previous two subsections show that the number of first-time ethnic inventors increased after the STEM OPT extension but the number of first-time native inventors did not decrease, implying an increase in the *share* of first-time ethnic inventors. To directly examine the change, I estimate Equation 1 on the CBSA- and year-level panel for the outcome variable *Ethnic Share* with standard errors clustered at the CBSA level.

Table 7 shows the results. Column 1 shows the estimation result for the entire sample. The coefficient of *ZIP R1 20 Miles* × *Post-STEM OPT* is significant; it indicates that the policy change increased the share of first-time ethnic inventors by 2.5 percentage points in CBSAs with R1 universities, which translates to a 16.9% increase relative to the mean.

Then, to further examine the dynamic effects of the policy change, I estimate event study for the same outcome variable using Equation 2 with standard errors clustered at the CBSA level. Figure 3 shows the result. The figure shows a modest increase in the share of first-time ethnic inventors in CBSAs with R1 universities beginning three years after the policy change; the timing of the increase is consistent with the pattern in Figure 2. The event-study result also alleviates concerns about a pretrend and gives credence to the result of the DiD regression. Still, to address the potential concern of incomparability between the treatment and control group, I estimate Equation 1 on the matched sample using CEM weights with standard errors clustered at the CBSA level.

Column 2 of Table 7 shows the result. The coefficient of *ZIP R1 20 Miles* × *Post-STEM OPT* rises to 0.030 and is significant; it indicates a 23.4% increase relative to the mean. Thus, the results in columns 1 and 2 indicate that the STEM OPT extension increased the share of first-time ethnic inventors by 16.9%–23.4% in CBSAs with R1 universities. As mentioned in Section 4, this analysis does not cover all of the first-time inventors in my data. Section SA1 in the appendix presents the results of an analogous version of analysis at the inventor level using the entire sample; they are consistent with the results in Table 7.

5.3 Mechanism

5.3.1 Heterogeneity by University Quality

Having confirmed the impact of the STEM OPT extension on the number of first-time ethnic inventors, I now investigate whether there exists any heterogeneity of the policy effect depending on the quality of universities in the CBSAs. Because there is a close relationship

between the inventing activity of recent graduates and their academic studies, students from elite universities are more likely to become inventors than students from other R1 universities, and the policy effect should be greater in CBSAs with those universities. To operationalize this idea, I define elite universities as the top 30 universities as measured by their number of STEM doctorates awarded and their expenditure on science and engineering, per the *Carnegie Classification* in 2005. Table A2 in the appendix displays this list. Then, I estimate the following triple-differences regression on the CBSA- and year-level panel for the outcome variable *Ethnic Count*:

$$\begin{aligned} y_{ct} = \alpha + \beta_1 \textit{Elite University}_c \times R1_c \times \textit{Post-STEM OPT}_t + \\ \beta_2 R1_c \times \textit{Post-STEM OPT}_t + \mu_c + \lambda_t + \epsilon_{ct} \end{aligned} \tag{3}$$

where indexes and variables are the same as in Equation 1 except for the new variable *Elite University*. The variable is a dummy that is turned on if a CBSA has any of the top 30 universities and 0 otherwise. I use the variables *Top-30 STEM Doctorates* and *Top-30 S&E Expenditure*, respectively, for *Elite University* to see whether the result is sensitive to how elite universities are defined. The coefficient β_1 is a coefficient of interest that shows the impact of the STEM OPT extension on the number of first-time ethnic inventors in CBSAs with any elite universities relative to those with other R1 universities.

Table 8 reports the results of the triple-differences regression for *Top-30 STEM Doctorates* (column 1) and *Top-30 S&E Expenditure* (column 2). The coefficient of the triple-interaction term is positive and significant in both columns (albeit at the 10% level). In contrast, the coefficient of *R1 × Post-STEM OPT* is positive but no longer significant in both columns. These results imply that the effect of the STEM OPT extension was mainly driven by CBSAs with elite universities, which is consistent with the expectation about the heterogeneity of the policy effect. Further, these results suggest that the observed increase in the influx of first-time ethnic inventors into CBSAs with R1 universities was due to the STEM OPT extension policy.

5.3.2 Heterogeneity by Assignee Organization Types

Section 5.2 shows that the STEM OPT extension increased the number of first-time ethnic inventors in CBSAs with R1 universities. This raises the question of whether the policy's effect varied across different types of assignee organizations. To explore this, I investigate the heterogeneity of the policy effect by assignee organization type. Specifically, using the dummy for university/hospital/government assignees in Ewens and Marx (2023), I constructed CBSA- and year-level balanced panels for university/hospital/government

and corporate assignees.[23] For each panel, I estimate Equation 1 using the outcome variable *Ethnic Count* clustering standard errors at the CBSA level. Because the university/hospital/government sample shows an increasing pretrend (unreported), I use CEM-matched samples with CEM weights for both types of assignees.

Table 9 shows the regression results. The coefficient of *R1* × *Post-STEM OPT* is significant at the 1% level in the sample of university/hospital/government assignees (column 1); it indicates that the policy change increased the number of first-time ethnic inventors working for those assignees by 1.522 in CBSAs with R1 universities. This change implies a 217.4% increase relative to the mean. The coefficients of the same variable is negative but insignificant in the sample of corporate assignees (column 2). These results suggest that the positive effect of the STEM OPT extension on the number of first-time ethnic inventors in CBSAs with R1 universities was mainly due to an increase in patenting by university/hospital/government assignees. Given that university patents tend to have a higher level of basicness (Trajtenberg et al., 1997), the results imply that the STEM OPT extension's effect is likely concentrated on first-time ethnic inventors who work on patents that are closely related to basic research.

There are two potential explanations for the concentration of the policy effect on university/hospital/government assignees. First, international STEM graduates' skills and knowledge may be more closely related to those used in laboratories at universities and hospitals than those used at firms. Because firms focus more on applied research than academic and medical institutions, the skills and knowledge of recent graduates might be better suited to the needs of these institutions. Second, international STEM graduates could opt to spend their extended OPT period conducting research at academic institutions to further their career development. For example, those graduates might want to apply to more-advanced graduate programs.

The concentration of the policy effect on university/hospital/government assignees might raise a question about the timing of patenting: whether first-time ethnic inventors affected by the STEM OPT extension filed their patents during their academic programs or after graduation. To address this question, I investigated the patenting timing of 100 randomly sampled first-time ethnic inventors relative to their graduation date. I found that a high share of first-time ethnic inventors filed their patents after completing their academic programs: among those whose education background information was available, 63% filed their first patent after graduation and 37% filed before (see Section SA2 in the appendix for details).

This result suggests that the STEM OPT extension can help international STEM students do innovation activities in the U.S. after graduation. But while more than a third of first-time ethnic inventors in the random sample filed patents during their academic pro-

[23] 78.4% of first-time inventors in my data are covered by the assignee–organization type data.

grams, there are other reasons why the STEM OPT extension could lead to more patenting by international STEM students during their academic studies. First, the opportunity to work longer in the U.S. could encourage more international students to enroll in STEM programs, as evidenced by the literature (Amuedo-Dorantes et al., 2019). Holding constant their propensity to file a patent during academic studies, the increased number of international STEM students leads to more patenting during their academic programs. Second, the STEM OPT extension could encourage international STEM students interested in becoming inventors to prioritize patenting during their academic studies, knowing they can defer other lower-priority activities to the extended OPT period. Third, the literature has evidence that the STEM OPT extension has increased the likelihood that international STEM students will transition to work visas (Demirci, 2019). Foreign workers eventually have to get a green card to work in the U.S. without any residency restrictions, and patents can be used as a ground for getting one (e.g., via the EB-1A, Alien of Extraordinary Ability). Therefore, international STEM students might choose to file a patent during their academic programs so that they can apply for a green card afterwards. In sum, the STEM OPT extension can lead to increased patenting by international STEM students through several channels.

5.3.3 Heterogeneity by Broad Technology Fields

Lastly, I explore the heterogeneity of the policy effect by broad technology fields. To operationalize this idea, I use the USPTO's Cooperative Patent Classification (CPC) sections. Table A3 in the appendix shows each section's letter designation, title, and technology subareas.[24] Specifically, for each CPC section, I constructed a CBSA- and year-level balanced panel.[25] I estimate Equation 1 on each panel for the outcome variable *Ethnic Count* with standard errors clustered at the CBSA level. Because some technology fields show a pretrend (unreported), I use CEM-matched samples with CEM weights for all broad technology fields.

Table 10 shows the regression results. The coefficient of *R1* $\times$ *Post-STEM OPT* is significant at the 0.1% level in the sample of Human Necessities (section A); it indicates that the policy change increased the number of first-time ethnic inventors in the field by 0.852 in CBSAs with R1 universities. This change implies a 142.2% increase relative to the mean. The coefficients of the same variable are insignificant in the other samples. Collectively, the regression results show that there exists broad technology-field-based heterogeneity in the effect of the STEM OPT extension on the number of first-time ethnic inventors in CBSAs with R1 universities, and the effect is mainly driven by an increase in patenting in Human

[24] https://www.uspto.gov/web/patents/classification/cpc/html/cpc.html

[25] There are 537 patents in the data with matched CBSAs but without CPC section information; I drop these.

Necessities (which includes health and pharmaceuticals).

6 Conclusion

Many immigrant STEM workers, a significant portion of the global STEM workforce, often first arrive in host countries as students. Many of these countries have made policy changes to attract international students, despite facing growing opposition to this trend (Ganguli and MacGarvie, 2024). However, there is limited evidence about whether granting foreign university students a short work extension helps them become inventors and negatively affects the employment of native inventors. I provide empirical evidence about these issues by examining the STEM OPT extension. Specifically, I show that the STEM OPT extension increased the number of first-time ethnic inventors without crowding out first-time native inventors, resulting in a higher share of first-time inventors in CBSAs with R1 universities. I also show that the increase in the supply of first-time ethnic inventors after the policy change was mainly driven by proximity to elite universities, a rise in patenting by university/hospital/government assignees, and increased patenting in the Human Necessities category.

Although the effects of skilled immigrants on innovation in a host country have been extensively studied, little attention has been paid to the role of international students in innovation (the exceptions include Stuen et al., 2012; Crown et al., 2020). This paper contributes to this literature by showing that international STEM graduates can affect innovation outcomes in a host country, which is consistent with existing evidence. In particular, this paper complements existing research by directly examining changes in the supply of immigrant inventors (instead of changes in innovation counts, e.g., patents) that could be attributed to several channels through which immigrants affect innovation.

The costs and measured benefits of the policy show that even a short work extension of 17 months for recent international STEM graduates could increase the number of ethnic inventors in the host country. This paper suggests that a cost-effective immigration policy like the STEM OPT extension can help a host country reap substantial innovation benefits. Although I focus on a short-term effect of the policy on innovation, future work could delve into its longer-term effect: STEM OPT participants have a higher chance of staying in the U.S. longer by getting a more advanced visa (e.g., H-1B) since the policy change (Demirci, 2019).

Despite its importance to policymakers, the literature on whether immigrant innovators crowd out native innovators is mainly focused on workers at advanced career stages. It does not provide clear evidence about the crowding-out effect, even within the same visa

program (Kerr and Lincoln, 2010; Doran et al., 2022), limiting prediction about the STEM OPT extension's effect on native inventors. This paper fills the gap by showing the lack of crowding-out effects on first-time native inventors by first-time ethnic inventors after the STEM OPT extension, which is consistent with Guo et al.'s (2024) result. Moreover, by examining the STEM OPT context—which contrasts with the post-Soviet mathematician context in Borjas and Doran (2012) in terms of the pre-shock labor-market conditions and the nature of innovators involved in the competition—this paper suggests that the impact of immigrant innovators on native innovators could depend on these aspects. Future research could further investigate this topic using different contexts.

Finally, I contribute to the literature on human capital supply for innovation by directly showing the effectiveness of the STEM OPT extension in increasing the supply of inventors and by providing a research design to evaluate such a policy. Despite the importance of high-quality human capital to innovation and economic growth, evidence of policies' impact on human capital supply is relatively scarce (due to the difficulty of identifying a causal relationship), given such policies' effect on the entire country (Bloom et al., 2019). This paper overcomes this problem by identifying the impact of the STEM OPT extension on the number of first-time ethnic inventors using a research design that leverages the fundamental properties of the policy. The results deepen our understanding of immigration policies' impact on the supply of innovators; the research design could be used in future works to identify individuals affected by policies aimed at increasing the supply of STEM workers.

Tables and Figures

Table 1: Summary Statistics

	Mean	St. Dev.	Min	P25	Median	P75	Max
Ethnic Count	12.386	81.707	0	0	0.003	1.999	1,942.059
Native Count	30.514	125.898	0	0.999	2.999	10.169	1,768.106
Ethnic Share	0.148	0.166	0	0.001	0.115	0.232	1
R1	0.081	0.273	0	0	0	0	1
Post-STEM OPT	0.500	0.500	0	0	0.5	1	1
Top-30 STEM Doctorates	0.030	0.170	0	0	0	0	1
Top-30 S&E Expenditure	0.028	0.164	0	0	0	0	1
Observations	14,432						

Notes: This table shows summary statistics of the CBSA- and year-level panel data between 2000-2015 that are used for estimation. The variable *Ethnic Count* is the sum of ethnic probabilities for all ethnicities except Anglo-Saxon/English and European across all first-time inventors in a CBSA and year. The variable *Native Count* is similarly defined by using the inventors' ethnic probabilities for Anglo-Saxon/English and European. The variable *Ethnic Share* is the ratio of *Ethnic Count* to the sum of *Ethnic Count* and *Native Count* (see Section 3.2 for details on the construction of the ethnicity-based variables). The indicator *R1* is turned on if a CBSA has any R1 universities and 0 otherwise. The indicator *Post-STEM OPT* is turned on in 2008 and onward and 0 otherwise. The indicators *Top-30 STEM Doctorates* and *Top-30 S&E Expenditure* are turned on if a CBSA has any top 30 universities in terms of their number of STEM doctorates awarded and their expenditure on science and engineering, and 0 otherwise. The number of observations is 14,432 for the entire sample, and 8,256 for the sample used for the baseline estimation for *Ethnic Share*.

Table 2: List of Treated and Control CBSAs

Treated CBSAs (unmatched)	**Treated CBSAs (matched)**	**Selected Control CBSAs**	
Ann Arbor, MI	Albany-Schenectady-Troy, NY	Akron, OH	Kingston, NY
Atlanta-Sandy Springs-Roswell, GA	Albuquerque, NM	Allentown-Bethlehem-Easton, PA-NJ	Kiryas Joel-Poughkeepsie-Newburgh, NY
Austin-Round Rock-San Marcos, TX	Ames, IA	Asheville, NC	La Crosse-Onalaska, WI-MN
Boston-Cambridge-Newton, MA-NH	Amherst Town-Northampton, MA	Atlantic City-Hammonton, NJ	Lake Havasu City-Kingman, AZ
Champaign-Urbana, IL	Athens-Clarke County, GA	Augusta-Richmond County, GA-SC	Las Vegas-Henderson-North Las Vegas, NV
Chicago-Naperville-Elgin, IL-IN	Baltimore-Columbia-Towson, MD	Bakersfield-Delano, CA	Logan, UT-ID
Denver-Aurora-Centennial, CO	Baton Rouge, LA	Barre, VT	Louisville/Jefferson County, KY-IN
Detroit-Warren-Dearborn, MI	Birmingham, AL	Bellingham, WA	Mankato, MN
Houston-Pasadena-The Woodlands, TX	Blacksburg-Christiansburg-Radford, VA	Bishop, CA	Milwaukee-Waukesha, WI
Lafayette-West Lafayette, IN	Bloomington, IN	Bloomington, IL	Morgantown, WV
Los Angeles-Long Beach-Anaheim, CA	Boulder, CO	Boise City, ID	Napa, CA
Minneapolis-St. Paul-Bloomington, MN-WI	Bozeman, MT	Burlington, NC	Niles, MI
New Orleans-Metairie, LA	Buffalo-Cheektowaga, NY	Burlington-South Burlington, VT	Oklahoma City, OK
New York-Newark-Jersey City, NY-NJ	Charlottesville, VA	Carbondale, IL	Olympia-Lacey-Tumwater, WA
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	Cincinnati, OH-KY-IN	Cedartown, GA	Orlando-Kissimmee-Sanford, FL
Phoenix-Mesa-Chandler, AZ	Cleveland, OH	Charlotte-Concord-Gastonia, NC-SC	Pittsfield, MA
Providence-Warwick, RI-MA	College Station-Bryan, TX	Chico, CA	Port Angeles, WA
Riverside-San Bernardino-Ontario, CA	Columbia, MO	Dallas-Fort Worth-Arlington, TX	Portland-South Portland, ME
Rochester, NY	Columbia, SC	Dayton-Kettering-Beavercreek, OH	Portland-Vancouver-Hillsboro, OR-WA
Sacramento-Roseville-Folsom, CA	Columbus, OH	Deltona-Daytona Beach-Ormond Beach, FL	Prescott Valley-Prescott, AZ
Salt Lake City-Murray, UT	Corvallis, OR	Eugene-Springfield, OR	Reno, NV
San Diego-Chula Vista-Carlsbad, CA	Durham-Chapel Hill, NC	Fargo, ND-MN	Richmond, VA
San Francisco-Oakland-Fremont, CA	Fort Collins-Loveland, CO	Fayetteville-Springdale-Rogers, AR	Rifle, CO
San Jose-Sunnyvale-Santa Clara, CA	Iowa City, IA	Fresno, CA	Rome, GA
Santa Maria-Santa Barbara, CA	Ithaca, NY	Greensboro-High Point, NC	San Angelo, TX
Seattle-Tacoma-Bellevue, WA	Jefferson City, MO	Greenville-Anderson-Greer, SC	San Antonio-New Braunfels, TX
Trenton-Princeton, NJ	Knoxville, TN	Hagerstown-Martinsburg, MD-WV	San Luis Obispo-Paso Robles, CA
Urban Honolulu, HI	Lansing-East Lansing, MI	Hailey, ID	Santa Fe, NM
Washington-Arlington-Alexandria, DC-VA-MD-WV	Lawrence, KS	Harrisburg-Carlisle, PA	Santa Rosa-Petaluma, CA
	Lebanon-Claremont, NH-VT	Harrisonburg, VA	Savannah, GA
	Lexington-Fayette, KY	Hilton Head Island-Bluffton-Port Royal, SC	Scranton–Wilkes-Barre, PA
	Lincoln, NE	Hot Springs, AR	Sheboygan, WI
	Madison, WI	Huntington-Ashland, WV-KY-OH	Tulsa, OK
	Manhattan, KS	Huntsville, AL	Ukiah, CA
	Nashville-Davidson–Murfreesboro–Franklin, TN	Indianapolis-Carmel-Greenwood, IN	Utica-Rome, NY
	Pittsburgh, PA	Jackson, MS	Virginia Beach-Chesapeake-Norfolk, VA-NC
	Pullman, WA	Kahului-Wailuku, HI	Wildwood-The Villages, FL
	Raleigh-Cary, NC	Kansas City, MO-KS	Winston-Salem, NC
	Santa Cruz-Watsonville, CA	Kapaa, HI	Worcester, MA
	South Bend-Mishawaka, IN-MI		
	St. Louis, MO-IL		
	State College, PA		
	Tucson, AZ		
	Vallejo, CA		

Notes: This table lists the CBSAs that form the treatment and control groups, respectively, in Equation 1. Column 1 lists CBSAs belonging to the treatment group in the entire sample but excluded from the CEM-matched sample for *Ethnic Count*, a main outcome variable in this paper. Column 2 lists CBSAs belonging to the treatment group in both the entire sample and CEM-matched sample. Section 5.2 elaborates on how I matched CBSAs using CEM. Columns 3 and 4 collectively list a representative subset of the CBSAs from the control group that were chosen through nearest neighbor matching. These matched CBSAs are part of the control group used in the entire sample; I provide this subset for illustration due to space limitations. This selection was based on their demographic and economic information, as well as the pretrend of *Ethnic Count*. Each group of CBSAs is alphabetically ordered.

Table 3: Descriptive DiDs: Number and Share of First-Time Ethnic Inventors

A. Descriptive CBSA-Level DiDs: Number of First-Time Ethnic Inventors

	Pre-STEM OPT	*Post-STEM OPT*	*Post - Pre*
With R1 Univ. $(T = 1)$	122.06	132.74	10.68
Without R1 Univ.	2.29	2.23	−0.06
Treated - Control	119.77	130.51	10.74

Notes: Panel A displays the mean of *Ethnic Count* in CBSAs, comparing areas with and without R1 universities and periods before and after the STEM OPT extension. *With R1 Univ. (T = 1)* indicates CBSAs with any R1 universities and *Without R1 Univ.* indicates those without R1 universities. *Pre-STEM OPT* refers to the period before the STEM OPT extension (2000–2007), and *Post-STEM OPT* after the STEM OPT extension (2008–2015).

B. Descriptive CBSA-level DiDs: Share of First-Time Ethnic Inventors

	Pre-STEM OPT	*Post-STEM OPT*	*Post - Pre*
With R1 Univ. $(T = 1)$	0.252	0.293	0.041
Without R1 Univ.	0.119	0.135	0.016
Treated - Control	0.133	0.158	0.025

Notes: Panel B displays the mean of *Ethnic Share* in CBSAs, comparing areas with and without R1 universities and periods before and after the STEM OPT extension. *With R1 Univ. (T = 1)* indicates CBSAs with any R1 universities and *Without R1 Univ.* indicates those without R1 universities. *Pre-STEM OPT* refers to the period before the STEM OPT extension (2000–2007), and *Post-STEM OPT* after the STEM OPT extension (2008–2015).

Table 4: CBSA-Level DiDs: Number of First-Time Ethnic Inventors

	Outcome variable: Ethnic Count	
	(1)	(2)
R1 × Post-STEM OPT	10.749*	2.153*
	(4.805)	(0.911)
Constant	11.951***	9.902***
	(0.194)	(0.034)
Model	OLS	OLS
CBSA Fixed Effect	Y	Y
Year Fixed Effect	Y	Y
Clustered Std. Error	Y (CBSA)	Y (CBSA)
Matching	N	Y (CEM)
Weighting	N	Y (CEM weights)
Observations	14,432	9,456
Time Window	2000–2015	2000–2015
E[Y]	12.386	3.593

Standard errors are in parentheses.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table shows the results from Equation 1 estimated on the CBSA and year-level panel data using *Ethnic Count* as an outcome variable that examines the impact of the STEM OPT extension on the number of first-time ethnic inventors in CBSAs with R1 universities. The standard errors are clustered at the CBSA level. Column 1 shows the result of the equation estimated on the entire sample, and column 2 on the matched sample. Column 2 uses CEM weights.

Table 5: Comparison of the Mean of *Ethnic Count*: CBSAs With and Without R1 Universities

	Sample/Area	R1 CBSAs	Non-R1 CBSAs	Difference
1	Entire Sample	127.40	2.26	125.14
2	CEM-Matched Sample (weighted)	25.63	8.72	16.91

Notes: This table displays the mean of *Ethnic Count* (the number of first-time ethnic inventors) in CBSAs with R1 universities (R1 CBSAs) and those without (Non-R1 CBSAs) as well as their difference. Statistics are shown for the entire sample and for the CEM-matched sample, where the mean is calculated using CEM weights in the latter.

Table 6: CBSA-Level DiDs: Number of First-Time Native Inventors

	Outcome variable: Native Count	
	(1)	(2)
R1 × Post-STEM OPT	3.325	-1.974
	(5.375)	(2.632)
Constant	28.372***	21.832***
	(0.316)	(0.080)
Model	OLS	OLS
CBSA Fixed Effect	Y	Y
Year Fixed Effect	Y	Y
Clustered Std. Error	Y (CBSA)	Y (CBSA)
Matching	N	Y (CEM)
Weighting	N	Y (CEM weights)
Observations	9,922	9,488
Time Window	2005–2015	2000–2015
E[Y]	28.568	12.123

Standard errors are in parentheses.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table shows the results from Equation 1 estimated on the CBSA-level panel data using *Native Count* as an outcome variable that examines the impact of the STEM OPT extension on the number of first-time native inventors in CBSAs with R1 universities. The standard errors are clustered at the CBSA level. Column 1 shows the result of the equation estimated on the truncated sample to exclude the pretrend in early 2000s, and column 2 on the matched sample. CEM weights are used in column 2.

Table 7: CBSA-Level DiDs: Share of First-Time Ethnic Inventors

	Outcome variable: Ethnic Share	
	(1)	(2)
R1 × Post-STEM OPT	0.025***	0.030**
	(0.005)	(0.010)
Constant	0.146***	0.150***
	(0.000)	(0.001)
Model	OLS	OLS
CBSA Fixed Effect	Y	Y
Year Fixed Effect	Y	Y
Clustered Std. Error	Y (CBSA)	Y (CBSA)
Matching	N	Y (CEM)
Weighting	N	Y (CEM weights)
Observations	8,256	4,000
Time Window	2000–2015	2000–2015
E[Y]	0.148	0.128

Standard errors are in parentheses.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table shows the results from Equation 1 estimated on the CBSA and year-level panel data using *Ethnic Share* as an outcome variable that examines the impact of the STEM OPT extension on the share of first-time ethnic inventors in CBSAs with R1 universities. The standard errors are clustered at the CBSA level. Column 1 shows the result of the equation estimated on the entire sample, and column 2 on the matched sample. Column 2 uses CEM weights.

Table 8: CBSA-Level Triple-Differences: Number of First-Time Ethnic Inventors

	Outcome variable: Ethnic Count	
	(1)	(2)
Top-30 STEM Doctorates × R1 × Post-STEM OPT	20.079^{+}	
	(12.063)	
Top-30 S&E Expenditure × R1 × Post-STEM OPT		22.133^{+}
		(12.861)
R1 × Post-STEM OPT	3.323	3.169
	(2.693)	(2.625)
Constant	11.951^{***}	11.951^{***}
	(0.189)	(0.188)
Model	OLS	OLS
CBSA Fixed Effect	Y	Y
Year Fixed Effect	Y	Y
Clustered Std. Error	Y (CBSA)	Y (CBSA)
Observations	14,432	14,432
Time Window	2000–2015	2000–2015
E[Y]	12.386	12.386

Standard errors are in parentheses.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table shows the results from Equation 3 estimated on the CBSA- and year-level panel data using *Ethnic Count* as an outcome variable that examines the university quality-based heterogeneity of the impact of STEM OPT extension on the number of first-time ethnic inventors in CBSAs with R1 universities. The standard errors are clustered at the CBSA level. The dummy *Top-30 STEM Doctorates* is turned on if a CBSA has any top-30 universities in terms of their number of STEM doctorates awarded and 0 otherwise. Similarly, *Top-30 S&E Expenditure* is turned on if a CBSA has any top-30 universities in terms of their expenditure on science and engineering, and 0 otherwise. Column 1 shows the result of the equation estimated on the entire sample using *Top-30 STEM Doctorates*, and column 2 using *Top-30 S&E Expenditure*.

Table 9: CBSA-Level DiDs by Assignee Organization Type: Number of First-Time Ethnic Inventors

	Outcome variable: Ethnic Count	
	(1)	(2)
R1 × Post-STEM OPT	1.522**	-0.683
	(0.582)	(0.880)
Constant	1.306***	6.100***
	(0.029)	(0.036)
Model	OLS	OLS
CBSA Fixed Effect	Y	Y
Year Fixed Effect	Y	Y
Clustered Std. Error	Y (CBSA)	Y (CBSA)
Matching	Y (CEM)	Y (CEM)
Weighting	Y (CEM weights)	Y (CEM weights)
Observations	4,800	7,968
Time Window	2000–2015	2000–2015
Assignee Type	University/Hospital/Government	Corporation
E[Y]	0.700	2.311

Standard errors are in parentheses.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table shows the results from Equation 1 estimated on the CBSA- and year-level panel data for different assignee organization types. The outcome variable is *Ethnic Count*, and the analysis examines the assignee-organization-type-based heterogeneous effect of the STEM OPT extension on the number of first-time ethnic inventors in CBSAs with R1 universities. The equation is estimated on matched samples, and CEM weights are used. The standard errors are clustered at the CBSA level.

Table 10: CBSA-Level DiDs by Broad Technology Fields: Number of First-Time Ethnic Inventors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R1 × Post-STEM OPT	0.852***	0.148	-0.160	0.039	0.021	-0.063	-0.123	0.218
	(0.204)	(0.142)	(0.337)	(0.035)	(0.063)	(0.108)	(0.379)	(0.491)
Constant	1.018***	0.922***	1.390***	0.036***	0.185***	0.439***	1.086***	1.864***
	(0.009)	(0.005)	(0.016)	(0.002)	(0.002)	(0.005)	(0.019)	(0.025)
CPC Section Title & Letter	Human Necessities (A)	Performing Ops. & Transp. (B)	Chemistry & Metallurgy (C)	Textiles & Paper (D)	Fixed Constr. (E)	Mech. Eng. & Related (F)	Physics (G)	Electricity (H)
Model	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
CBSA Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
Clustered Std. Error	Y (CBSA)	Y (CBSA)	Y (CBSA)	Y (CBSA)	Y (CBSA)	Y (CBSA)	Y (CBSA)	Y (CBSA)
Matching	Y (CEM)	Y (CEM)	Y (CEM)	Y (CEM)	Y (CEM)	Y (CEM)	Y (CEM)	Y (CEM)
Weighting	Y (CEM weights)	Y (CEM weights)	Y (CEM weights)	Y (CEM weights)	Y (CEM weights)	Y (CEM weights)	Y (CEM weights)	Y (CEM weights)
Observations	6496	9456	6240	6128	9376	6432	4560	6640
Time Window	2000–2015	2000–2015	2000–2015	2000–2015	2000–2015	2000–2015	2000–2015	2000–2015
E[Y]	0.599	0.344	0.734	0.014	0.070	0.218	0.716	0.796

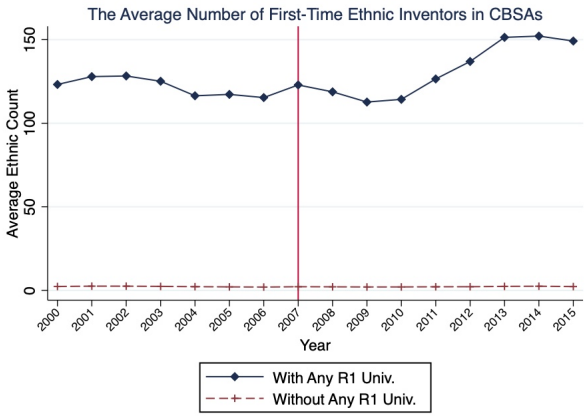
Standard errors are in parentheses.

$+ p < 0.10$, $^{*} p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$

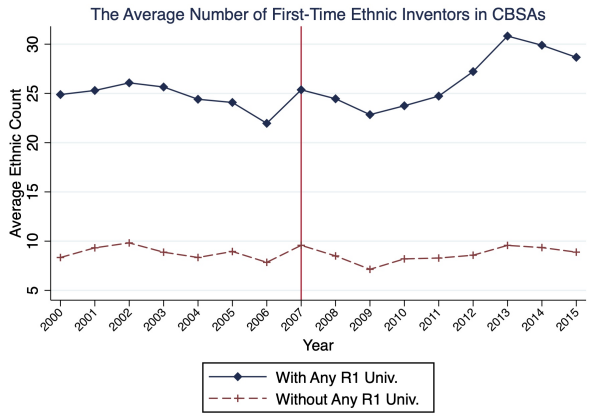
Notes: This table shows the results of Equation 1 estimated on the CBSA- and year-level panel data for broad technology fields. The outcome variable is *Ethnic Count*, and the analysis examines the broad-technology-field-based heterogeneous effect of the STEM OPT extension on the number of first-time ethnic inventors in CBSAs with R1 universities. The equation is estimated on matched samples, and CEM weights are used. The standard errors are clustered at the CBSA level.

Figure 1: Average Number of First-Time Ethnic Inventors in CBSAs, by Proximity to R1 Universities

A. Entire Sample

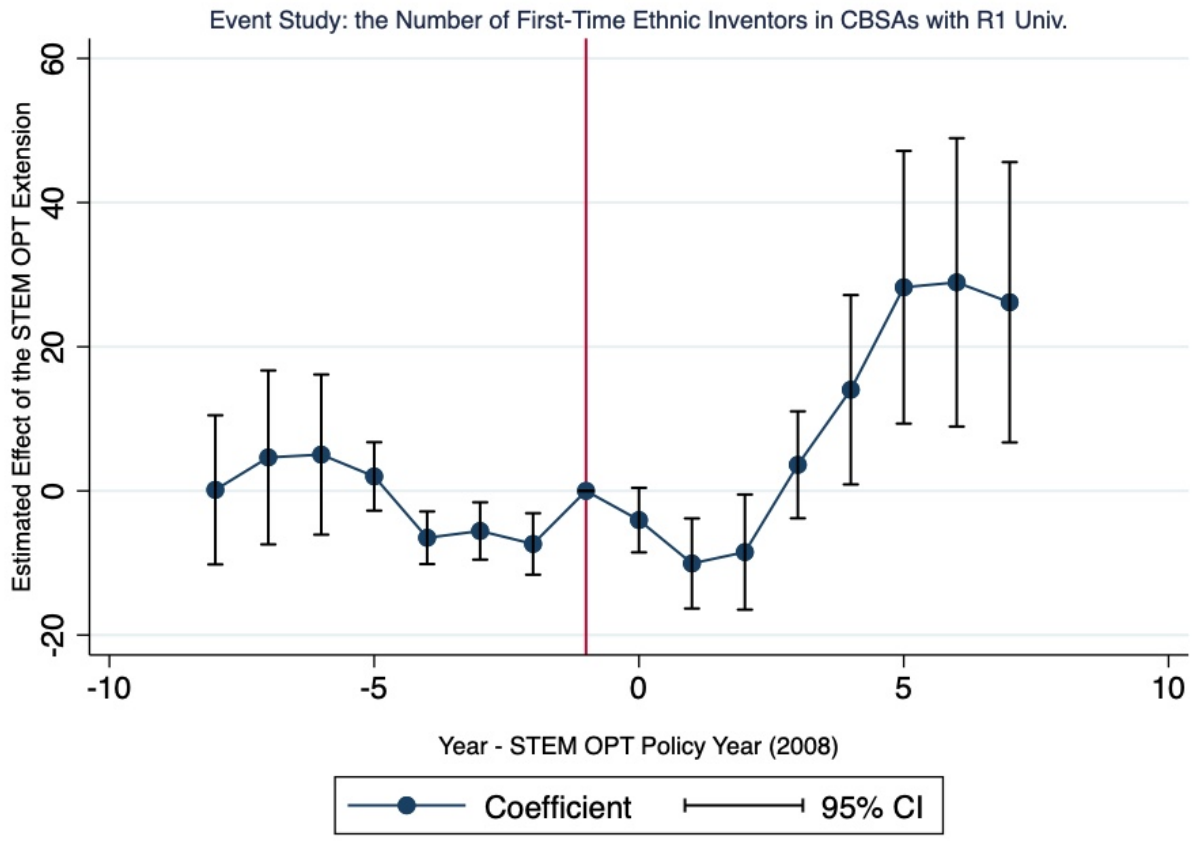


B. CEM-Matched Sample



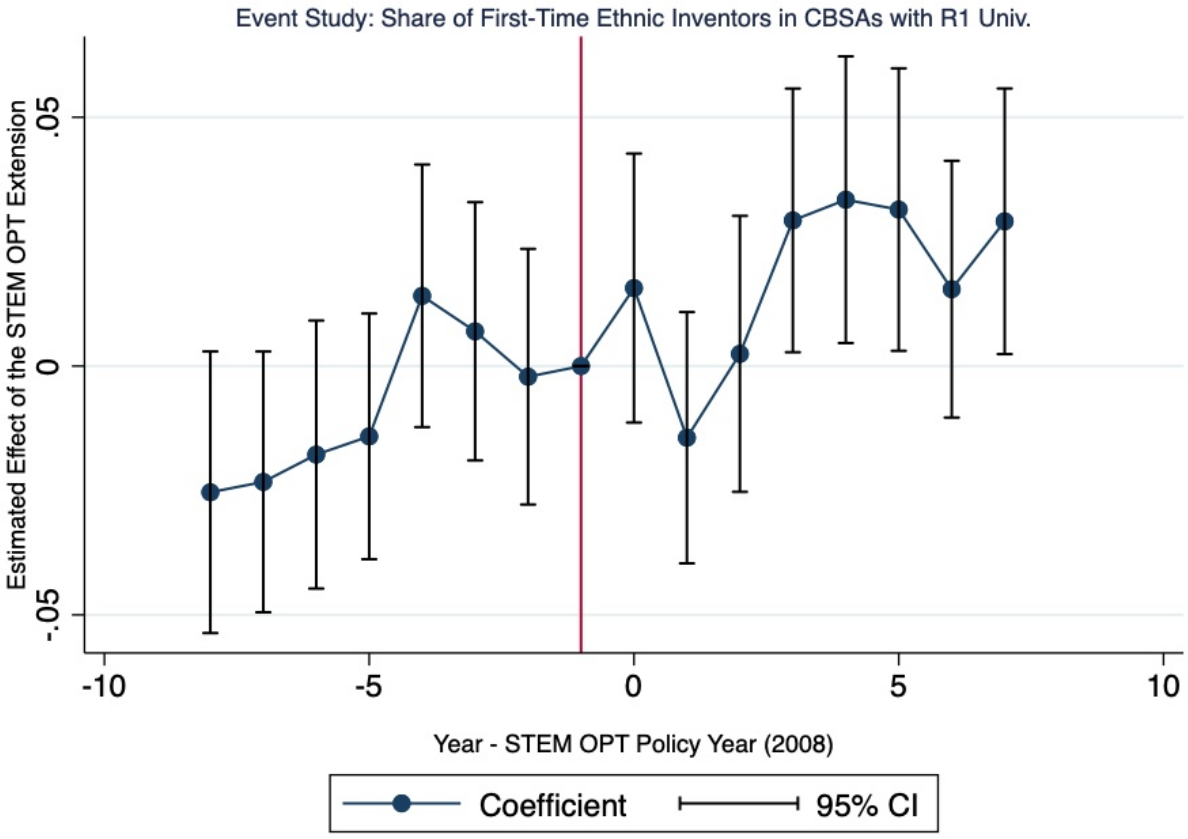
Notes: This figure shows the average of *Ethnic Count*, the number of first-time ethnic inventors, from 2000 to 2015, separately for CBSAs with R1 universities and those without. The vertical line separates the periods before and after the STEM OPT extension in 2008. Panel A shows the trends in the entire sample, and Panel B shows the trends in the CEM-matched sample where the average is calculated using CEM weights in the latter. (Section 5.2 elaborates on how I matched CBSAs.)

Figure 2: CBSA-Level Event Study, 2000–2015: Number of First-Time Ethnic Inventors



Notes: This figure shows coefficient estimates and 95% confidence intervals from Equation 2 estimated on the CBSA- and year-level panel data using *Ethnic Count* as an outcome variable that examines the yearly average treatment effects of the STEM OPT extension on the number of first-time ethnic inventors in CBSAs with R1 universities. The event study is conducted without matching. The standard errors are clustered at the CBSA level.

Figure 3: CBSA-Level Event Study, 2000–2015: Share of First-Time Ethnic Inventors



Notes: This figure shows coefficient estimates and 95% confidence intervals from Equation 2 estimated on the CBSA- and year-level panel data using *Ethnic Share* as an outcome variable that examines the yearly average treatment effects of the STEM OPT extension on the share of first-time ethnic inventors in CBSAs with R1 universities. The event study is conducted without matching. The standard errors are clustered at the CBSA level.

Appendix

A1 Relationship Between Share of First-Time Ethnic Inventors and Being a Top STEM OPT Employer

To investigate the validity of the ethnicity-based variables as a proxy of an inventor's immigrant status, I examine a relationship between a share of first-time ethnic inventors, the ratio of first-time ethnic inventors over total first-time inventors, and association with a top STEM OPT employer at the assignee-organization and patent levels, respectively.

ICE provides a list of top 200 STEM OPT employers between 2008 and 2018, as well as the number of hires by each employer during this period (cross-sectional). I linked these employers with assignee organizations and patents using a crosswalk between the top employers and patent assignee organizations, created using data from Arora et al. (2021) and a manual search for assignee names.

Next, I identify U.S.-based first-time inventors who are associated with each assignee organization[26] and patent, respectively, between 2008 and 2018. Using a link between assignee organizations and first-time inventors during this period, I create the following variable:

$$\textit{Post-Ethnic Share}_a = \Big(\sum_{i(a)} w_{a(i)} \sum_{j \notin \{ENG,EUR\}} e_{j(i)}\Big) \;/\; \sum_{i(a)} w_{a(i)}$$

where a indexes an assignee organization, i an inventor, j an ethnicity. The element $w_{a(i)}$ is the reciprocal of the number of assignee organizations with which an inventor is associated. Therefore, the denominator of the variable is the number of first-time inventors who are associated with an assignee organization a. Also, as in Section 3, I assume Anglo-Saxon/English and European as a proxy for American inventors and the other seven ethnicities as as a proxy for foreign inventors, then I sum inventors' ethnic probabilities for all ethnicities except Anglo-Saxon/English and European. The numerator of the variable is the number of first-time ethnic inventors who are associated with an assignee organization a. Thus, the variable *Post-Ethnic Share*$_a$ is the ratio of first-time ethnic inventors to total first-time inventors who are listed on issued patents that are applied by an assignee organization a between

[26]For a link between first-time inventors and assignees, I assume that US-based inventors are hired by US-based assignee organizations. When some patents have several US-based assignee organizations, I assign an inventor to the closest assignee organization based on GPS coordinates. There are some ties between assignee organizations in terms of their distance to inventors. In such cases, I assign a fraction of an inventor count to each assignee organization. For example, when there is a tie between two assignee organizations for an inventor, I assign a count of 0.5 to each assignee organization. Also, the assignee sample includes U.S.-based assignee organizations only. The patent sample includes only patents by at least 1 U.S.-based assignee organization.

2008 and 2018.

Similarly, using a link between patents and first-time inventors, I generate the following variable:

$$\textit{Post-Ethnic Share}_p = (\sum_{i(p)} \sum_{j \notin \{ENG,EUR\}} e_{j(i)}) \ / \ N_{i(p)}$$

where p indexes a patent and the other indexes are the same as above. The numerator of the variable is the number of first-time ethnic inventors who are listed on a patent p. The denominator $N_{i(p)}$ is the number of first-time inventors listed on the patent. Therefore, the variable $\textit{Post Ethnic Share}_p$ is the ratio of first-time ethnic inventors over total first-time inventors who are listed on an issued patent p that was applied for between 2008 and 2018.

Then, I estimate the following regression:

$$y_u = \alpha + \beta \ \textit{Top STEM OPT Employer}_u \ + \epsilon_u \tag{A1}$$

where u is a unit of analysis that is either a (assignee organization) or p (patent). The endogenous explanatory variable $\textit{Top STEM OPT Employer}_u$ is a dummy that is equal to 1 if u is associated with one of the top 200 STEM OPT employers between 2008 and 2018, and 0 otherwise. Equation A1 is estimated using robust standard errors, and the results are reported in Table A4. Column 1 shows the estimation result of the equation using $\textit{Post-Ethnic Share}_a$ as an outcome variable. The coefficient of $\textit{Top STEM OPT Employer}_a$ is significant; it indicates that association with a top STEM OPT employer is correlated with an increase in the share of first-time ethnic inventors by 20.5 percentage points at the assignee-organization level. This change implies a 90.7% increase relative to the mean. Column 2 shows the estimation result of the equation using $\textit{Post-Ethnic Share}_p$ as an outcome variable. The coefficient of $\textit{Top STEM OPT Employer}_p$ is significant; it indicates that association with a top STEM OPT employer is correlated with an increase in the share of first-time ethnic inventors by 19.6 percentage points at the patent level. This change implies a 59% increase relative to the mean.

These results suggest that the association with a top STEM OPT employer is positively and significantly correlated with the share of first-time ethnic inventors between 2008 and 2018, at both the assignee and the patent levels. Although the results should be interpreted as correlation not causation, this exercise gives credence to the validity of the ethnicity-based variables as a proxy of an inventor's immigrant status.

Table A1: Top-30 Employers of STEM OPT Participants

Employer	STEM OPT Hire	Ethnic Count	Native Count
Amazon	4,658	2,100	2,815
Intel Corporation	2,556	1,754	1,347
Google	2,223	2,050	2,589
Microsoft Corporation	1,737	4,564	4,737
Integra Technologies	1,291	0	0
Deloitte	1,267	3	9
IBM	1,201	2,581	4,454
Qualcomm Technologies	1,171	1,799	742
Facebook	978	825	899
Apple	931	1,431	2,088
Oracle	922	1,172	874
Cerner Corporation	900	39	163
JP Morgan Chase	886	120	269
Cisco Systems	853	1,096	666
Cognizant	820	0	10
Marlabs	789	0	0
eBay or Paypal	695	580	415
Massachusetts Institute of Technology	674	712	919
Ernst & Young	639	0	7
Goldman Sachs	625	12	24
PricewaterhouseCoopers	620	3	5
XCG Design Corporation	613	0	0
Capgemini America	603	0	0
Cummins	594	226	365
Populus Group	570	0	0
Stanford University	569	520	497
Johns Hopkins University	548	408	566
Randstad	530	0	0
Citigroup	524	29	24
Harvard University	518	260	344

Notes: This table lists top 30 employers of STEM OPT participants between 2008 and 2018 and the number of their employees who used an STEM OPT extension during this period. ICE provides a list of top 200 employers of STEM OPT participants and their number of STEM OPT hires between 2008 and 2018. In columns 3 and 4, *Ethnic Count* (the number of first-time ethnic inventors) and *Native Count* (the number of first-time native inventors) are associated with each employer during the same period (rounded), respectively. I use an analogous version of these inventor-count variables computed at the CBSA-year level in the main analysis of this paper. See Section 3.2 for details on the construction of the variables.

Table A2: Elite Universities

Top-30 STEM Doctorates	Top-30 S&E Expenditure
California Institute of Technology	Columbia University
Cornell University	Cornell University
Georgia Institute of Technology	Duke University
Harvard University	Emory University
Johns Hopkins University	Georgia Institute of Technology
Massachusetts Institute of Technology	Harvard University
North Carolina State University	Johns Hopkins University
Northwestern University	Massachusetts Institute of Technology
Ohio State University	Ohio State University
Pennsylvania State University	Pennsylvania State University
Purdue University	Stanford University
Rutgers University–New Brunswick	Texas A&M University
Stanford University	University of Arizona
Texas A&M University	University of California, Berkeley
University of Arizona	University of California, Davis
University of California, Berkeley	University of California, Los Angeles
University of California, Davis	University of California, San Diego
University of California, Los Angeles	University of Florida
University of California, San Diego	University of Illinois Urbana-Champaign
University of Florida	University of Michigan
University of Illinois Urbana-Champaign	University of Minnesota
University of Maryland, College Park	University of North Carolina at Chapel Hill
University of Michigan	University of Pennsylvania
University of Minnesota	University of Pittsburgh
University of North Carolina at Chapel Hill	University of Southern California
University of Pennsylvania	University of Texas at Austin
University of Southern California	University of Washington
University of Texas at Austin	University of Wisconsin–Madison
University of Washington	Washington University in St. Louis
University of Wisconsin–Madison	Yale University

Notes: This table lists elite universities (alphabetically ordered) in terms of *Top-30 STEM Doctorates* (in terms of number of STEM doctorates awarded) and *Top-30 S&E Expenditure* (in terms of expenditure on science and engineering), respectively, based on the *Carnegie Classification* in 2005. I use these variables in Equation 3 to investigate the university quality-based heterogeneity of the impact of the STEM OPT extension on the number of first-time ethnic inventors in CBSAs with R1 universities.

Table A3: CPC Sections

Letter	CPC Section Title	Technology Subareas
A	Human Necessities	Agriculture; Foodstuffs; Tobacco; Personal or Domestic Articles; Health; Amusement
B	Performing Operations; Transporting	Separating; Mixing; Shaping; Printing; Transporting; Microstructural Technology; Nanotechnology
C	Chemistry; Metallurgy	Chemistry; Metallurgy; Combinatorial Technology
D	Textiles; Paper	Textiles or Flexible Materials Not Otherwise Provided For; Paper
E	Fixed Construction	Building; Earth Drilling; Mining
F	Mechanical Engineering; Lighting; Heating; Weapons; Blasting Engines or Pumps	Engines or Pumps; Engineering In General; Lighting; Heating; Weapons; Blasting
G	Physics	Instruments; Information And Communication Technology Specially Adapted For Specific Application Fields; Nucleonics
H	Electricity	Electric Elements; Generation; Conversion or Distribution of Electric Power; Electronic Circuity; Electric Communication Technique; Electric Techniques Not Otherwise Provided For; Semiconductor Devices; Electric Solid-State Devices Not Otherwise Provided For

Notes: This table shows the USPTO's Cooperative Patent Classification (CPC) sections, with letter, section titles, and technology subareas. Technology subareas are either CPC classes or their broader categories.

Table A4: Relationship Between Share of First-Time Ethnic Inventors and Being a Top STEM OPT Employer

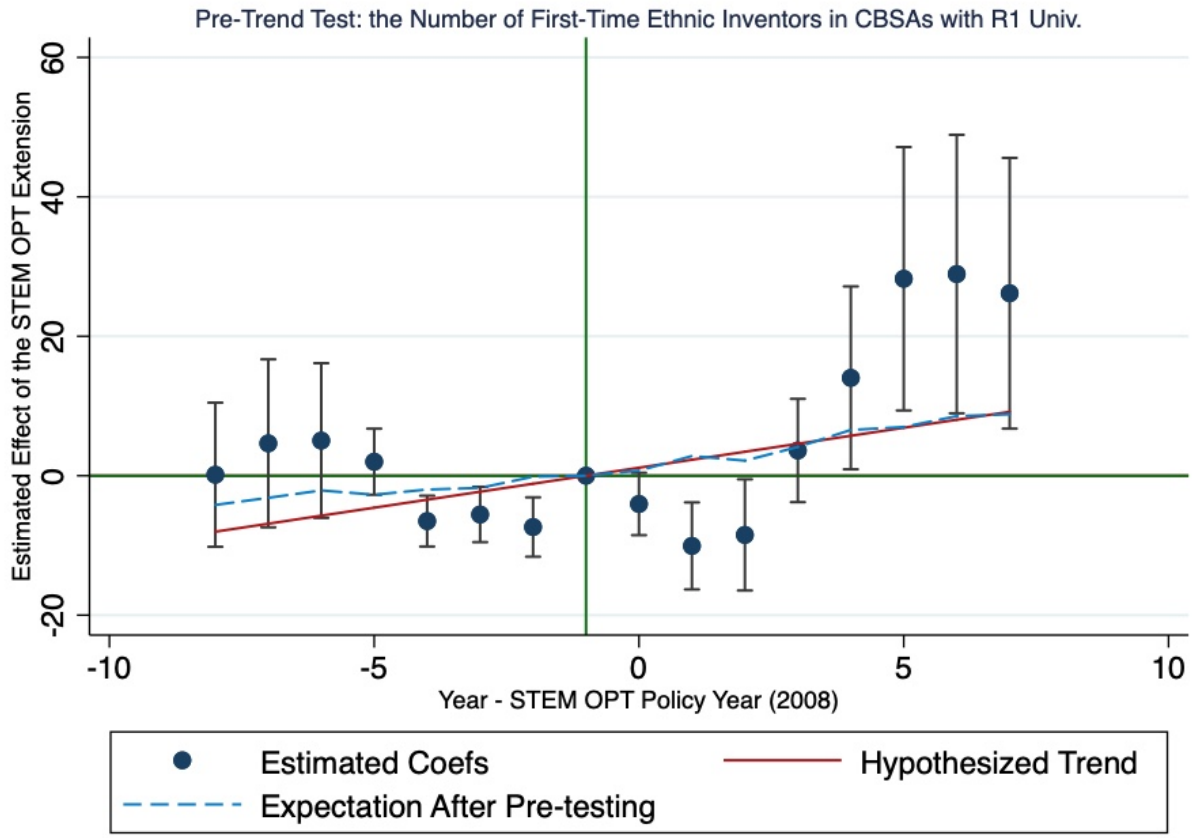
	Outcome variable: Post-Ethnic Share	
	(1)	(2)
Top STEM OPT Employer	0.205***	0.196***
	(0.017)	(0.002)
Constant	0.225***	0.285***
	(0.002)	(0.001)
Model	OLS	OLS
Robust Std. Error	Y	Y
Observations	46,274	230,066
Time Window	2008–2018	2008–2018
E[Y]	0.226	0.332
Unit of Analysis	Assignee	Patent

Standard errors are in parentheses.

. $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table shows the results from Equation A1 estimated using *Post-Ethnic Share* as an outcome variable at the assignee-organization and patent levels, respectively. I use robust standard errors. Column 1 shows the result of the equation estimated at the assignee-organization level, and Column 2 at the patent level.

Figure A1: Pretrend Test: Number of First-Time Ethnic Inventors



Notes: This figure visualizes the pretrend test proposed by Roth (2022) using the event-study result shown in Figure 2. The test is conducted by using the Stata package *pretrends* with 80% power. The solid red line is a hypothesized trend that would be detected 80% of the time. The dashed blue line shows the expected magnitude of the event-study coefficients conditional on finding no significant pretrend when the solid red line is the true trend. Neither of the lines passes through the confidence interval of all coefficients during the prepolicy period.

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Supplemental Appendix

SA1 Inventor-Level Analysis: Relative Supply of Immigrant and Native Inventors

Section 5.2.3 shows an increase in the share of first-time ethnic inventors in CBSAs with R1 universities, but the sample does not cover some of first-time inventors in my sample. To address the limitation of the analysis, I analyze changes in the relative supply of immigrant and native inventors after the STEM OPT extension at the inventor level using the entire cross-sectional data of first-time inventors. Using Anglo-Saxon/English and European ethnicities as a proxy for American inventors, I create the following variable:

$$Ethnic\ Intensity_{it} = \sum_{j \notin \{ENG, EUR\}} e_{j(i)}$$

where i indexes an inventor, and t a year. This is the ethnic intensity of a first-time inventor i who authors a patent in a year t. The variable is constructed by summing up an inventor's ethnic probabilities for all ethnicities except Anglo-Saxon/English and European. The variable is continuous, with a value between 0 and 1, and can be interpreted as the likelihood that a first-time inventor has an ethnic name.

Using the identification strategy described in Section 4, I consider inventors located within 20 miles of any R1 university as treated, and those outside this radius as untreated. The radius is reasonable given that the average daily American round-trip commuting distance is 41 miles (Flynn, 2023). Therefore, I estimate the following equation at the inventor level:

$$\begin{aligned} Ethnic\ Intensity_{it} = \alpha + \gamma_1 R1\ 20\ Miles_i \times \text{Post-STEM OPT}_t + \\ \gamma_2 R1\ 20\ Miles_i + \gamma_3 \text{Post-STEM OPT}_t + \eta_{it} \end{aligned} \tag{SA1}$$

where i indexes a first-time inventor and t a year that the inventor first files a patent. *R1 20 Miles* is a treatment status indicator that turns on if an inventor is located within 20 miles of any R1 universities and 0 otherwise, and *Post-STEM OPT* is a postpolicy-period indicator that is turned on in 2008 and onward. I use robust standard errors. The coefficient γ_1 is a coefficient of interest that indicates the effect of the policy change on the likelihood of an inventor having an ethnic name within a 20-mile radius of R1 universities.

Table SA1 shows the results. Column 1 shows the estimation result for the entire sample. The coefficient of *R1 20 Miles* × *Post-STEM OPT* is significant; it indicates that the policy change increased the likelihood of a first-time inventor having an ethnic name by 1.9 percentage points in areas within 20 miles of R1 universities. This indicates a 6.7% increase

relative to the mean.

Then, I estimate the following event-study model using robust standard errors to measure the yearly effect of the STEM OPT extension on the likelihood of a first-time inventor having an ethnic name in areas within 20 miles of R1 universities:

$$\textit{Ethnic Intensity}_{it} = \alpha + \sum_{k} \beta_k \mathbb{1}(t - 2008 = k) + \gamma R1\ 20\ Miles_i + \lambda_t + \eta_{it} \tag{SA2}$$

where i indexes a first-time inventor and t a year, as in Equation SA1. The variable *R1 20 Miles* is the same as before, and λ_t is a year fixed effect. The indicator variable $\mathbb{1}(t-2008 = k)$ is turned on for first-time inventors in areas within 20 miles of R1 universities in a year t that is k years after 2008 (the year of policy change) and when k = -1 for the other inventors. The coefficients β_k's are coefficients of interest that show the dynamic treatment effects of the STEM OPT extension on the likelihood that a first-time inventor has an ethnic name in areas within 20 miles of R1 universities.

Figure SA1 shows the result of the event study: there exists some pretrend in the early 2000s (i.e., 2000 to 2002) suggesting that the actual policy effect should be smaller than what we see in column 1 of Table SA1. Therefore, I estimated Equation SA1 again on the truncated sample for the years 2003 through 2015; column 2 of Table SA1 shows the result. The coefficient of *R1 20 Miles* × *Post-STEM OPT* becomes smaller at 0.013, but it remains significant. Relative to the mean, this implies a 4.4% increase in ethnic intensity. Thus, the results in both columns 1 and 2 indicate that the STEM OPT extension increased the likelihood of a first-time inventor having an ethnic name in areas within 20 miles of R1 universities—consistent with the results in Section 5.2.3.

SA2 Patenting Timing of First-Time Ethnic Inventors

To examine whether first-time ethnic inventors affected by the STEM OPT extension filed their patents during their academic programs or after graduation, I first collected information on the educational background of 100 randomly sampled first-time ethnic inventors. Specifically, I randomly sampled first-time inventors from the data used in my CBSA-level analysis who satisfy the following criteria: (i) inventors whose sum of ethnic probabilities for ethnicities other than Anglo-Saxon/English and European equals 1; (ii) inventors who show up in my data in 2008 or after; (iii) inventors who were in CBSAs with at least one of the top-30 universities in terms of expenditure on science and engineering, based on the *Carnegie Classification* in 2005; (iv) inventors whose patent was associated with at least one university/hospital/government assignee. The first criterion helps me find inventors who are likely foreigners. The last three criteria are based on this paper's empirical results: the pos-

itive impact of the STEM OPT extension on the number of first-time ethnic inventors was mainly driven by CBSAs with at least one of the top-30 universities and increased patenting by university/hospital/government assignees. I used these four criteria to ensure that the sampled inventors were among those affected by the STEM OPT extension.

Next, I collected information on each inventor's educational background using their name and their assignee organization's name.[27] I collected information on each inventor's degree-granting institution, degree level, graduation year, and country where the degree was granted. Because some inventors' educational background was wholly or partially unavailable, I could collect the complete educational background of only 68 first-time ethnic inventors (68% of the random sample).

For these 68 first-time ethnic inventors, to determine their patenting timing relative to their academic studies, I ascertained each inventor's relevant degree based on their enrollment status at the time of patent filing. If a patent was filed while the inventor was not academically enrolled, I used the degree earned immediately prior. If they were enrolled, I used the degree being pursued. I then created a dummy variable *Post-Grad Patent* that equals 1 if a patent was filed in or after the inventor's graduation year, and 0 otherwise. Thus, inventors with *Post-Grad Patent* equal to 0 are those who filed patents during their academic programs.

Among these 68 first-time ethnic inventors, 59 (87%) earned their relevant degree in the U.S. For the purpose of this analysis, I focused on these 59 inventors. Table SA2 shows the distribution of a relevant degree by level and its timing relative to patenting among these 59 inventors. The table suggests that about two-thirds (37 of 59; 63%) of first-time inventors filed their first patent in or after their graduation year rather than during their academic program. The fraction of first-time inventors filing a patent after graduation is even higher—71.4% at the master's level. These results suggest that a high share of first-time ethnic inventors affected by the STEM OPT extension would have filed their patent after earning their degree.

[27] For each inventor, I searched their patent number on the USPTO website. I then searched for their name in combination with their assignee organization's name. For example, the inventor Anandram Venkatasubramanian, who filed Patent 8718956, had "Georgia Tech Research Corporation" as his assignee. I searched on Google for "Anandram Venkatasubramanian Georgia Tech." Google search results often included links to inventors' LinkedIn page or to their profile page on their academic institution's website, which I could use to get information on an inventor's educational background. I sometimes also used the same keyword on LinkedIn, when Google search results were not satisfactory.

SA3 Did First-Time Ethnic Inventors Start Their Career by Collaborating?

Confirming that the number of first-time ethnic inventors increased, and that this in turn increased a first-time inventor's likelihood of having an ethnic name, I investigate the STEM OPT extension's effect on first-time ethnic inventors by mode of work (i.e., solo vs. collaboration). This is important, because it directly relates to changes in inventors' networks. If most first-time ethnic inventors started their career by working solo after the policy change, this indicates an increase in innovation, but not necessarily changes in the networks among inventors and among the firms employing those inventors. Given that a network is a source of knowledge exchange and creativity (Granovetter, 1973; Burt, 2004), an increase in the number of first-time inventors working solo would be less beneficial to inventors and their employers than an increase in the number of inventors collaborating. To answer the inquiry, I estimate the following triple-differences regression on the inventor-level data:

$$\begin{aligned} \textit{Ethnic Intensity}_{it} = \alpha + \gamma_1 \textit{Collaboration}_i \times \textit{R1 20 Miles}_i \times \textit{Post STEM OPT}_t + \\ \gamma_2 \textit{R1 20 Miles}_i \times \textit{Post STEM OPT}_t + \\ \gamma_3 \textit{Collaboration}_i \times \textit{R1 20 Miles}_i + \\ \gamma_4 \textit{Collaboration}_i \times \textit{Post STEM OPT}_t + \\ \gamma_5 \textit{Collaboration}_i + \gamma_6 \textit{R1 20 Miles}_i + \gamma_7 \textit{Post STEM OPT}_t + \eta_{it} \end{aligned} \tag{SA3}$$

where indexes and variables are the same as in Equation SA1 except for the new variable, *Collaboration*. The variable is a dummy that is turned on if a first-time inventor i collaborates with other inventors, and 0 otherwise.[28] The coefficient γ_1 is a coefficient of interest that shows the impact of the STEM OPT extension on the likelihood of first-time inventors having an ethnic name in areas within 20 miles of R1 universities who collaborate with other inventors relative to those in the same areas who file patents that are solo work.

Table SA3 shows the result of the triple-differences regression. Columns 1 and 2 respectively show the results of the regression estimated on both the entire sample and the truncated sample, as in Table SA1. The coefficient of the triple-interaction term is positive and significant, while the coefficient of *R1 20 Miles* × *Post-STEM OPT* is negative but no longer significant in both columns 1 and 2. The results mean that the effect of the STEM OPT extension was mainly driven by first-time ethnic inventors who collaborated with other inventors. This suggests that the STEM OPT extension policy changed not only the quantity

[28] The dummy is turned on as long as collaboration occurs between a first-time inventor and other inventors, regardless of the collaborators' locations. The regression result is similar when the dummy is turned on only when collaboration occurs between a first-time inventor and other U.S.-based inventors.

of innovation but also the networks among inventors.[29] To alleviate any concerns about the possibility that first-time ethnic collaborating inventors simply put their names on patents without making a noteworthy contribution, Section SA4 further shows that they actually contributed to patenting.

SA4 Did First-Time Ethnic Inventors Actually Contribute to Patenting?

Given that the increase in the number of first-time ethnic inventors after the STEM OPT extension is mainly driven by inventors collaborating with other inventors, it is important to confirm whether those inventors actually contributed to patenting beyond putting their names on patents. If the number of first-time ethnic inventors increased but not the number of patents by those inventors, it would suggest that they did not contribute to patenting, casting doubt on the effectiveness of the STEM OPT extension from an innovation perspective.

It is possible that these inventors authored patents without contributing much. However, their employers and coauthors likely would not want to include them in their patent author teams if those inventors were not expected to contribute to the patents. Employers would have had no economic incentive to hire first-time inventors without expecting them to be able to contribute. Similarly, those coauthors would not have wanted to include anyone on the patent who did not contribute, since patent authors divide any monetary rewards. Therefore, it is unclear a priori whether the increase in the number of first-time ethnic inventors was accompanied by an increase in the number of patents by those inventors.

To verify whether these first-time ethnic inventors actually contributed to patenting, I generate the following outcome variable:

$$Ethnic\ Patenting_{ct} = \sum_{it \in ct} normalized\ patent\ share_{it} \times Ethnic\ intensity_{it}$$

This is the weighted sum of *normalized* patent shares of first-time inventors in a CBSA c in a year t where weights are those inventors' ethnic intensities.[30] Therefore, the variable is

[29] I further investigated whether first-time ethnic inventors collaborated mostly with native or ethnic inventors. To answer this question, I estimate Equation SA3 on the sample of first-time inventors who collaborate with other inventors using a share of native coauthors in the first patent instead of *Collaboration*. In this analysis, I used only first-time inventors whose coauthors' ethnicity information was all available; they accounted for 90.37% of all first-time inventors who collaborated with other inventors. I did not find any significance for the triple-interaction term. This result implies that following the policy change first-time ethnic inventors collaborated with both ethnic and native inventors.

[30] For first-time inventors whose ZIP codes cover multiple CBSAs, I distribute their patents fractionally to each CBSA. The fraction assigned to a specific CBSA is the ratio of addresses in that ZIP code associated

the count of patents by first-time ethnic inventors. To compute a patent share, I use each first-time inventor's first patent application only; an inventor's patent share is a fraction of a patent calculated as 1 divided by the author team size of that inventor's first patent. Each inventor i's patent share in a year t is *normalized* by the average patent share of all inventors who file utility patent applications in the same year where those patent applications involve at least one US-based inventor.[31] Normalization is done because inventors' patent shares decrease over time (unreported) due to an increasing trend in the size of the patent author team (Wuchty et al., 2007). Using the normalized patent share allows me to examine whether first-time ethnic inventors contributed to patenting as much as typical inventors.

Using the outcome variable, I estimate Equation 1 on the CBSA- and year-level panel with standard errors clustered at the CBSA level. The results are reported in Table SA4. Column 1 shows the estimation result on the entire sample. The coefficient of $R1 \times Post\text{-}STEM\ OPT$ is significant; it indicates that the policy change increased the number of patents by first-time ethnic inventors by 10.778 in CBSAs with R1 universities. This change implies an 88.7% increase relative to the mean.

Next, I estimate Equation 2 for the same outcome variable to measure the yearly effect of the STEM OPT extension on the number of patents by first-time ethnic inventors in CBSAs with R1 universities. As in the DiD regression, I cluster standard errors at the CBSA level. Figure SA2 shows the result of the event study. It follows a pattern similar to that in Figure 2, showing that it takes time to see the effect of the policy.

To mitigate a possible concern about the comparability between the treatment and control groups, I match the CBSAs using CEM. Then, I run Equation 1 again on the matched sample using CEM weights where standard errors are clustered at the CBSA level. Column 2 of Table SA4 shows the result. The coefficient of $R1 \times Post\text{-}STEM\ OPT$ is 2.27 and significant; it indicates a 56.6% increase relative to the mean—the policy effect is still observed in the matched sample. The results in columns 1 and 2 indicate that the STEM OPT extension increased the number of patents by first-time ethnic inventors by 56.6%-88.7% in CBSAs with R1 universities. Thus, combined with the results in Table 4, these results show that first-time ethnic inventors following the STEM OPT extension contributed to their patents. This is consistent with evidence in the literature that the influx of foreigners or ethnic diasporas into a host country causes an increase in patenting (Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010). This is also aligned with the result of Crown et al. (2020) that an increase in a regional share of temporary visa-holding international students results

with that CBSA to the total number of addresses in the ZIP code.

[31] I use the authors of patents with at least one US-based inventor as a comparison group since their collaboration patterns are likely to better reflect those of US-based inventors.

in an increase in patenting.

Table SA1: Inventor-Level DiDs: Ethnic Intensity of First-Time Inventors

	Outcome variable: Ethnic Intensity	
	(1)	(2)
R1 20 Miles × Post-STEM OPT	0.019***	0.013***
	(0.002)	(0.002)
R1 20 Miles	0.147***	0.153***
	(0.001)	(0.002)
Post-STEM OPT	0.022***	0.016***
	(0.001)	(0.002)
Constant	0.181***	0.188***
	(0.001)	(0.001)
Model	OLS	OLS
Robust Std. Error	Y	Y
Observations	665,530	521,848
Time Window	2000–2015	2003–2015
E[Y]	0.285	0.295

Standard errors are in parentheses.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table shows the results from Equation SA1 estimated on the inventor-level cross-sectional data using *Ethnic Intensity* as an outcome variable that examines the impact of the STEM OPT extension on the likelihood of a first-time inventor having an ethnic name in areas within 20 miles of R1 universities. I use robust standard errors in the estimation. Column 1 shows the result of the equation estimated on the entire sample, and column 2 on the truncated sample that excludes the pretrend observed in Figure SA1.

Table SA2: Patenting Timing of First-Time Ethnic Inventors

Patenting Timing	Bachelor's	Master's	Doctorate	Row Total
Post-Grad Patent == 1	1 (50%)	5 (71.4%)	31 (62%)	37 (63%)
Post-Grad Patent == 0	1 (50%)	2 (28.6%)	19 (38%)	22 (37%)
Column Total	2	7	50	59

Notes: This table shows the distribution of a relevant degree by level and its timing relative to patenting among 59 randomly sampled first-time ethnic inventors whose complete education background was available and who earned a relevant degree in the U.S. The dummy variable *Post-Grad Patent* equals 1 if a patent was filed in or after the inventor's graduation year, and 0 otherwise. Thus, inventors with *Post-Grad Patent* equal to 0 are those who filed patents during their academic programs. Percentages in parentheses represent the proportion of inventors within each cell relative to its respective column total.

Table SA3: Inventor-Level Triple-Differences: Ethnic Intensity of First-Time Inventors

	Outcome variable: Ethnic Intensity	
	(1)	(2)
Collaboration × R1 20 Miles × Post-STEM OPT	0.022***	0.019**
	(0.006)	(0.007)
R1 20 Miles × Post-STEM OPT	-0.001	-0.004
	(0.005)	(0.006)
Collaboration × R1 20 Miles	0.024***	0.027***
	(0.004)	(0.005)
Collaboration × Post-STEM OPT	0.000	-0.007^{+}
	(0.004)	(0.004)
Collaboration	0.054***	0.062***
	(0.002)	(0.003)
R1 20 Miles	0.124***	0.126***
	(0.003)	(0.004)
Post-STEM OPT	0.021***	0.021***
	(0.003)	(0.004)
Constant	0.138***	0.138***
	(0.002)	(0.003)
Model	OLS	OLS
Robust Std. Error	Y	Y
Observations	665,530	521,848
Time Window	2000–2015	2003–2015
E[Y]	0.285	0.295

Standard errors are in parentheses.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table shows the results from Equation SA3 estimated on the inventor-level cross-sectional data using *Ethnic Intensity* as an outcome variable that examines the impact of the STEM OPT extension on the likelihood of a first-time inventor having an ethnic name in areas within 20 miles of R1 universities by an inventor's work mode. I use robust standard errors in the estimation. The indicator *Collaboration* is turned on if an inventor collaborated with other inventors, and 0 otherwise. Column 1 shows the result of the equation estimated on the entire sample, and column 2 on the truncated sample that excludes the pretrend, as in Table 7.

Table SA4: CBSA-Level DiDs: Patenting by First-Time Ethnic Inventors

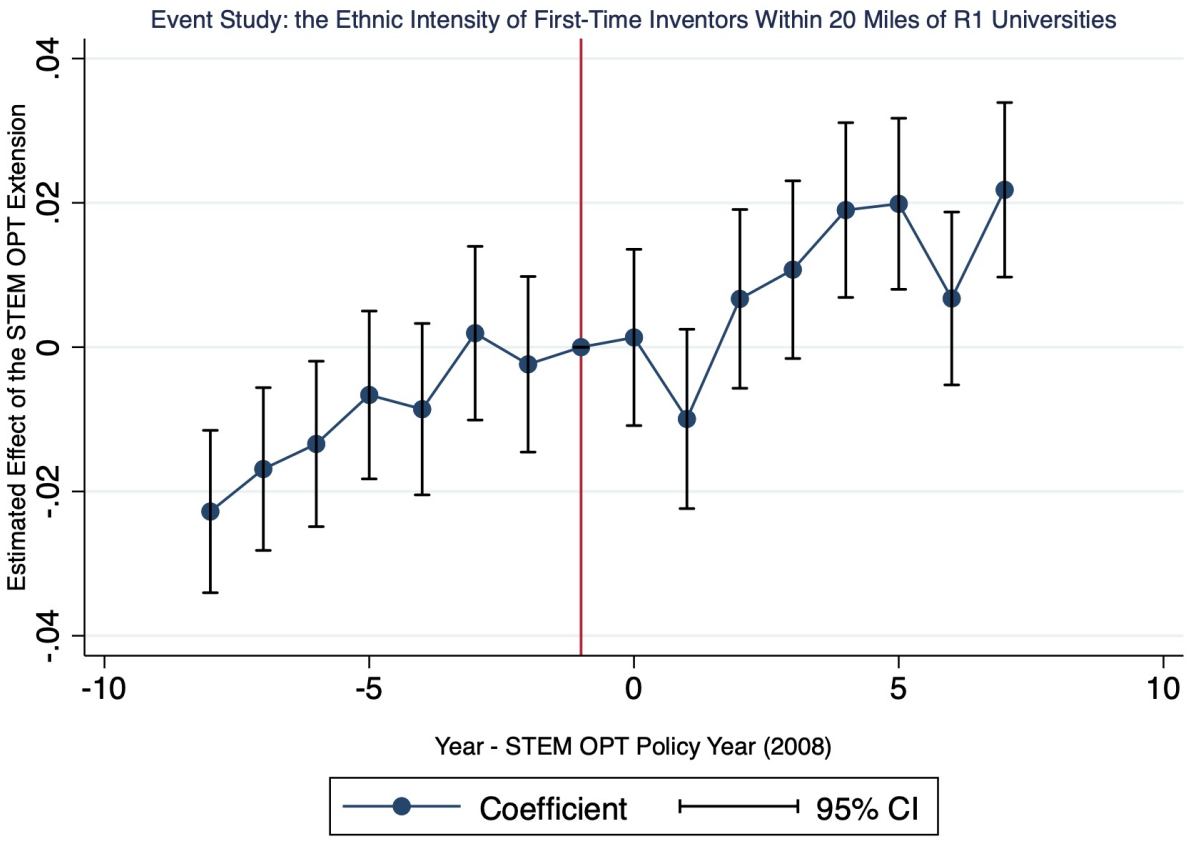
	Outcome variable: Ethnic Patenting	
	(1)	(2)
R1 × Post-STEM OPT	10.778**	2.270*
	(3.863)	(0.940)
Constant	11.720***	9.930***
	(0.156)	(0.039)
Model	OLS	OLS
CBSA Fixed Effect	Y	Y
Year Fixed Effect	Y	Y
Clustered Std. Error	Y (CBSA)	Y (CBSA)
Matching	N	Y (CEM)
Weighting	N	Y (CEM weights)
Observations	14,432	7,984
Time Window	2000–2015	2000–2015
E[Y]	12.156	4.010

Standard errors are in parentheses.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

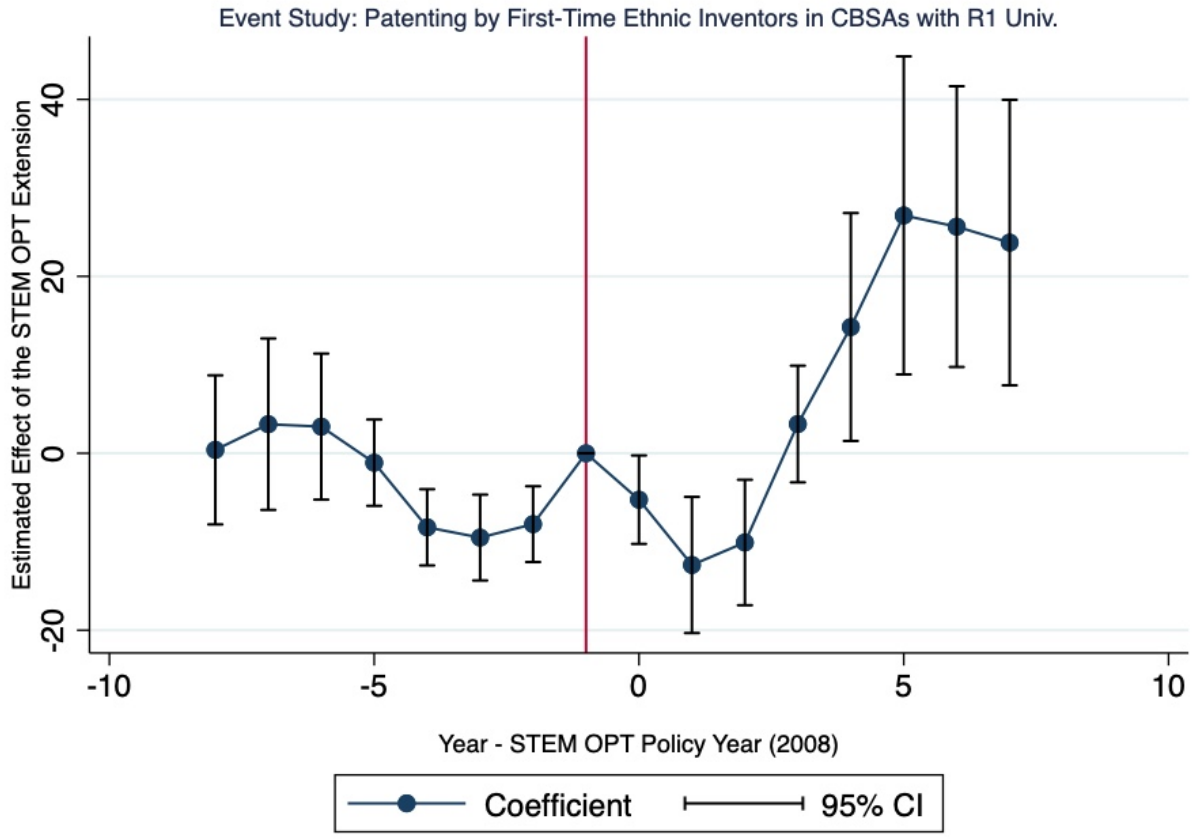
Notes: This table shows the results from Equation 1 estimated on the CBSA- and year-level panel data using *Ethnic Patenting* as an outcome variable that examines the impact of the STEM OPT extension on the number of patents by first-time ethnic inventors in CBSAs with R1 universities. The outcome variable *Ethnic Patenting* is a weighted sum of *normalized* patent shares of first-time inventors in a given CBSA and year where each inventor's *Ethnic Intensity* is used as a weight. The standard errors are clustered at the CBSA level. Column 1 shows the result of the equation estimated on the entire sample, and column 2 on the matched sample. Column 2 uses CEM weights.

Figure SA1: Inventor-Level Event Study, 2000–2015: Ethnic Intensity of First-Time Inventors



Notes: This figure shows coefficient estimates and 95% confidence intervals from Equation SA2 estimated on the inventor-level cross-sectional data using *Ethnic Intensity* as an outcome variable that examines the yearly average treatment effects of the STEM OPT extension on the likelihood of a first-time inventor having an ethnic name in areas within 20 miles of R1 universities. Robust standard errors are used in the estimation.

Figure SA2: CBSA-Level Event Study, 2000–2015: Patenting by First-Time Ethnic Inventors



Notes: This figure shows coefficient estimates and 95% confidence intervals from Equation 2 estimated on the CBSA- and year-level panel data using *Ethnic Patenting* as an outcome variable that examines the yearly average treatment effects of the STEM OPT extension on the number of patents by first-time ethnic inventors in CBSAs with R1 universities. I conducted the event study without matching. The standard errors are clustered at the CBSA level.