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International students and innovation: Evidence from restrictions on US-trained foreign STEM workers

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Abstract

This paper estimates how US policy restrictions on international STEM students affect the production of new, economically valuable technologies. A sudden 2008 expansion of Optional Practical Training (OPT) created a large, plausibly exogenous increase in the supply of US-trained foreign STEM workers across cities. Linking full-universe administrative OPT records to all subsequently granted US utility patents, I find that the evidence is consistent with each additional OPT STEM worker causing roughly 0.21 additional patents per year in the same city. This total effect, including within-city spillovers on the productivity of native inventors, is more than 1.7 times the direct effect of inventions by OPT STEM workers themselves. Weighted results show even larger impacts on influential and high-value patents citing scientific research literature, indicating that OPT STEM workers cause substantial gains in innovation quality.

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1 Introduction

Research-and-development workers produce innovation that drives economic growth (Romer 1990; Jones 1995; Aghion and Howitt 2009). Policy that limits the supply of these workers—such as restrictions on high-skill immigration—can thus constrain productivity (Bloom, Van Reenen and Williams 2019, 180; Kerr and Kerr 2022; Agarwal et al. 2023; Prato 2025). But we have limited evidence about restrictions specific to one of the largest channels of high-skill immigration in the world: international students at US universities. International students are distinct from aggregate high-skill immigrant workers, particularly in science, technology, engineering, and mathematics (STEM). Only a third of high-skill immigrant STEM workers arrived in the US as students, and those who arrived as students innovate relatively more than other high-skill immigrants (Hunt 2011, 427; Amornsiripanitch et al. 2023). International STEM students face binding policy constraints on acquiring work visas and US residency, and most leave the country within a few years of graduation (Glennon 2024; Clemens et al. 2025).[1]

This paper estimates how policy restrictions on international students in STEM affect the invention of new, valuable technologies in the United States. It considers the effects of a large and sudden change in limits to labor force entry by foreign STEM graduates from US universities, limits set by the terms of a post-graduation work permit called Optional Practical Training (OPT). OPT has served as a crucial bridge between international student visas and longer-term work visas (Grogger and Hanson 2015; Amuedo-Dorantes et al. 2019; Beine et al. 2023). A nationwide policy reform extended OPT from 12 to 29 months in 2008 for graduates in STEM fields *only*, then to 36 months in 2016. This policy rule change produced a positive shock of roughly 8–10 percent in the supply of high-skill STEM workers overall, allocated across cities exogenously to post-2008 demand shocks at the national or city level. The analysis links novel, full-universe

[1]For the fraction of high-skill STEM immigrant workers who arrived as students: A flow measure is that 33.4 percent of new H-1B high-skill, employment-based visas in fiscal year 2023 were approved for immigrants changing status from an F-1 or F-2 student visa. The US Dept. of Homeland Security (DHS 2024, 6, 20) approved 118,948 H-1B petitions for initial employment in fiscal year 2023. 55,916 of these requested change-of-status from another nonimmigrant visa, of which 72 percent were F (student) visas. A stock measure is that of all foreign-born workers in the United States whose highest bachelor's, master's, or PhD degree is from a US university in a STEM discipline, in the nationally-representative National Survey of College Graduates (NSF 2025), 33.0 percent (s.e. 0.009) first arrived in the country on a student/trainee visa; for those under age 40, this proportion is 36.5 percent (s.e. 0.014). Approximately 60% of each cohort of international bachelor's, master's, and PhD students in STEM graduating from US universities remains in the United States three years after graduation (Clemens et al. 2025, Fig. 4).

administrative data on OPT workers at US employers from 2004–2022 with full-universe data on utility patent applications granted in the United States, in order to estimate the total direct and indirect influence of these graduates on valuable invention at the city level.

The results are consistent easing policy restrictions on OPT employment causing a substantial rise in the quantity and value of US invention. Each additional international STEM graduate from a US university allowed to remain and work causes 0.23 additional granted utility patents per year in the same city. Because some OPT workers subsequently remain in the US on other visas, this implies that each high-skill foreign worker who originally came to the US as an international STEM student (including those working post-OPT) causes 0.16–1.19 additional patents. This effect rises to 0.25 additional patents per US-trained high-skill foreign STEM worker when weighted by the economic value of the marginal patents (Kogan et al. 2017), suggesting that OPT STEM workers increase the quality and economic value of patenting. The analysis furthermore suggests the importance of considering effects that go beyond additional inventions produced directly by immigrants themselves. The total effect on patenting at the city level—including team-level, organization-level, and city-level spillovers to other R&D workers—exceeds by a factor of 1.7 or more the direct effect of patents filed by current or former OPT workers themselves.

A variety of modern placebo and robustness tests are consistent with the relationship of interest being causal (Adão et al. 2019; Goldsmith-Pinkham et al. 2020; Borusyak et al. 2025). The estimated effect does not reflect unrelated contemporaneous nationwide or regional trends; does not reflect preexisting levels or trends in innovation by city; does not arise only from a handful of the most innovative cities; does not reflect post-2008 shifts in preferences for certain US cities among foreign graduates of US universities in general; does not appear for patents whose subject matter has low relevance to STEM knowledge; and does not reflect city-specific unobserved trends arising from the predetermined industrial structure of each city. The estimates are quantitatively conservative in that the research design inherently cannot account for spillovers in knowledge production from one city to another. The analysis tests for the existence of such spillovers—not their magnitude—and finds that each additional OPT STEM worker allowed to work in one city causes additional citations of patents from inventors in that city by patents from inventors in other cities.

The contribution of this paper lies in its focus on international students, city-level effects that include spillovers, causal identification by a policy shock. Much prior work has highlighted the effects of high-skill foreign H-1B workers (Mahajan et al. 2025), often using by shift-share variation in the supply of H-1B work visas (Kerr and Lincoln 2010; Peri et al. 2015), which are used by both US graduates and overseas graduates, rather than international students specifically. US-trained foreign STEM workers specifically are the focus of a comparatively limited literature (e.g. Hunt and Gauthier-Loiselle 2010; Stuen et al. 2012; Ganguli and Gaulé 2020). A substantial thread of work has focused on innovation by individual firms, laboratories, or even individuals (Stuen et al. 2012; Mahajan et al. 2025; Bernstein et al. 2025); I consider cities in order to capture cross-organization productivity spillovers within innovation hubs. Finally, the strategy for causal identification is a policy rule, distinguishing it from standard shift-share designs and raising the external validity of the findings to inform policy change. That is, this paper estimates the total, policy-relevant treatment effect (Heckman and Vytlacil 2001).

2 Policy-induced supply shock: The OPT extension of 2008

The US federal government sharply reduced employment restrictions on international STEM graduates of US universities in 2008. This produced a supply shock of those graduates to the US labor market, with differential exposure across cities, which I use to examine the effects of international STEM students on innovation. The new policy altered the terms of a work permit for foreign students called Optional Practical Training (OPT).

2.1 Optional Practical Training for foreign graduates of US universities

Starting in 1947, the US Department of Justice began allowing international students to apply for up to 18 months of employment authorization, during their degrees or shortly after completion, "[i]n cases where employment for practical training is required or recommended by the school" (12 FR 5357). In 1992, post-completion employment authorization for international students became possible even without the school's recommendation. The new rule coined the term "Optional Practical Training" and initially limited to 12 months of work in the same field where the student earned his or her degree, whatever that field was, starting within 60 days of

graduation (57 FR 31956).

The OPT permit is not an employment-based visa, but an employment authorization that attaches to a student visa. Thus OPT does not require employers to sponsor the employed students for a work visa, nor to seek foreign labor certification from the Department of Labor. OPT allows foreign graduates from US universities to simply match with an employer and begin work. At the end of the OPT duration those who wish to remain working in the United States must change status from the student visa to a visa that categorically allows employment. This is typically the H-1B high-skill "specialty occupation" visa for nonimmigrant workers, used principally *de facto* for STEM workers. Unlike obtaining a short-term OPT work permit, obtaining an H-1B work visa is difficult. It requires certification from the Department of Labor that suitable American workers and not available. In most years since 2007, it also requires winning a randomized lottery that allocates a tightly-binding quota of visas for private-sector employers.

A central motive for many graduates to remain in the country on OPT is to gain additional chances in the annual H-1B visa lottery (Glennon 2024, 10). This fueled rapid growth of the program. Usage of the OPT work permit crept upward from 11,010 during the 1992–1993 academic year to 41,660 by 2006–2007. OPT usage shot upward after the H-1B lotteries began in 2007, passing 100,000 by six years later and passing 200,000 by ten years later. During the 2024–2025 academic year, 294,253 people worked on OPT (IIE 2025). Some of those unable to obtain a quota-constrained private-sector H-1B visa in the lottery are able to access a quota-exempt H-1B visa to work in the non-profit or academic sectors (Amuedo-Dorantes and Furtado 2019).

OPT has become international students' principal bridge between university studies and the US labor market. Most international STEM students go straight from graduation to OPT, and most US-trained foreign STEM workers who get an H-1B visa did so via OPT. OPT employment authorization was used by 63.7 percent of international STEM students who graduated from US universities between 2018 and 2022. 71 percent of STEM graduates who later changed status to an H-1B visa did so after working on OPT (Clemens et al. 2025, Fig. 3).

2.2 The 2008 extension of OPT for STEM graduates

In 2007, employer demand for H-1B visas rose enough to exhaust the entire quota of private-sector visas for fiscal year 2008 in a single day. Technology companies reliant on the H-1B for STEM hiring petitioned the federal government to extend OPT from 12 months to 29 months, as a way to raise supply of these high-skill immigrant labor absent a politically-infeasible legislative reform to raise the H-1B quota.[2]

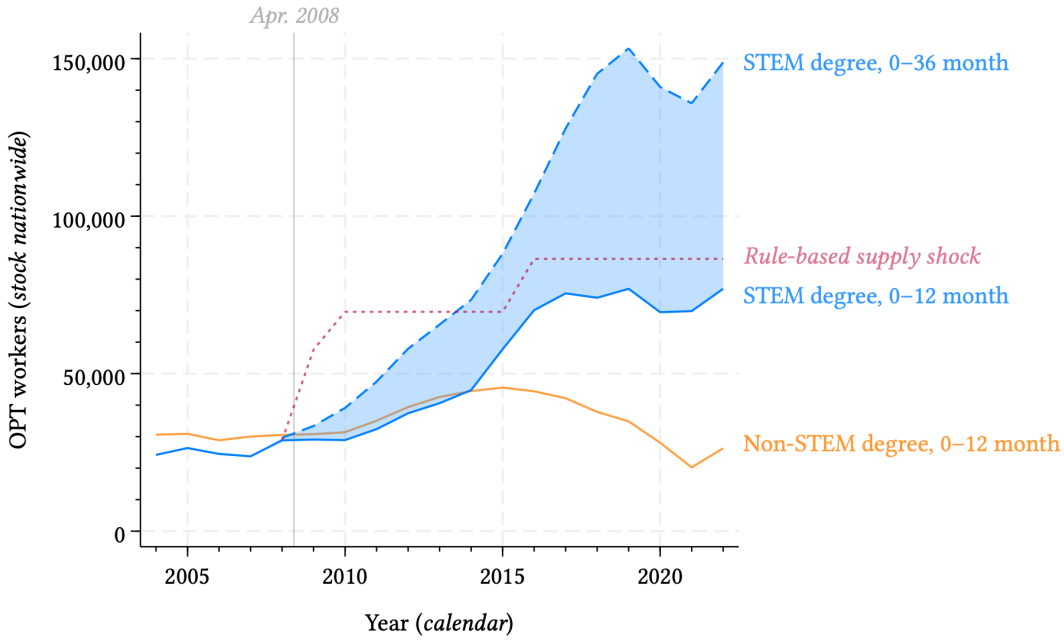
The federal government soon did so, announcing the change on April 2, 2008 and enacting it six days later (73 FR 18944), explicitly referencing employers' unmet demand for high-skill foreign STEM workers.[3] The 2008 rule used authority under existing law to allow graduates with (government defined) STEM degrees to extend the original 12 months of OPT by 17 additional months. This allowed any given STEM graduate to remain on OPT for up to 29 months total. Those without STEM degrees retained access to the original, 12-month OPT. A separate rule in 2016 allowed STEM graduates to further extend OPT by seven additional months, to a total of 36 months (see 80 FR 63376 and 81 FR 13040). Because new annual graduate cohorts could now begin work on OPT while prior cohorts were still working on OPT, the effect of these rules was to raise the stock of OPT workers employed at a given moment.

The federal government changed this rule explicitly to produce a labor supply shock. Figure 1 depicts the shock. The solid blue line shows the nationwide stock of STEM graduates employed on the original 12-month OPT. The solid orange line shows the stock of non-STEM graduates employed on 12-month OPT. The dashed blue line shows the total number of STEM graduates on OPT, both the original 12-month OPT and extended OPT, so that the shaded blue area shows the number of STEM graduates on OPT extended past 12 months.

[2]Tech magnate Bill Gates told a public hearing of the House of Representatives Committee on Science and Technology on March 12, 2008, "Extending OPT from 12 to 29 months would help to alleviate the crisis employers are facing due to the current H-1B visa shortage". Hearing before the House of Representatives Committee on Science and Technology, *Competitiveness and Innovation on the Committee's 50th Anniversary with Bill Gates, Chairman of Microsoft*, Serial No. 110-84, Washington, DC: Government Printing Office. For more on the 2008 OPT extension see Demirci (2019).

[3]In justifying the policy change, the Dept. of Homeland Security wrote, "OPT employees often are unable to obtain H-1B status within their authorized period of stay in F-1 status, including the 12-month OPT period, and thus are forced to leave the country. The inability of U.S. employers, in particular in the fields of science, technology, engineering and mathematics, to obtain H-1B status for highly skilled foreign students and foreign nonimmigrant workers has adversely affected the ability of U.S. employers to recruit and retain skilled workers and creates a competitive disadvantage for U.S. companies" (73 FR 18946).

Figure 1: The OPT-STEM Labor Supply Shock, 2004–2022



Shows the full universe of OPT workers employed for any portion of each calendar year, from the Student and Exchange Visitor Information System (SEVIS). '0–12 month' is the original, one-year OPT. '0–36' month includes both one-year OPT and extended OPT. STEM degrees are defined by the US Dept. of Homeland Security. Sources in Appendix.

OPT-STEM employment was relatively stable in the years leading up to 2008. It rose sharply thereafter. This could arise from either the rule-based shock to labor supply after 2008, or from any shocks to employers' demand to hire new OPT STEM workers after 2008. The dashed red line in Figure 1 shows the magnitude of the post-2008 supply shock *if* demand had remained at its 2008 level.

For example, in 2008, US employers demanded new 28,817 STEM workers on 12-month OPT. Before the 2008 supply shock, if employers' demand in 2009 had remained at its 2008 level, they could only have employed a new cohort of 28,817, because the prior cohort could not stay past one year. But with the supply shock, and without any increase in demand for new hires, they could demand a new cohort of 28,817 in 2009 while continuing to employ the prior 28,817 workers on extended OPT—thus employing a total of 57,634. In 2010, the average employed stock over the course of the year could rise by an additional $\frac{5}{12}$ of the 2008 stock—without any increase in

demand for new hires—as those employed since 2008 on extended OPT stayed the remaining five months between 24 months and the maximum of 29. A further, smaller supply shock occurred with the 2016 revision. The dashed red line thus shows the portion of the post-2008 rise in OPT STEM employment (dashed blue line) that is explained by the policy-rule supply shock rather than post-2008 demand shocks.

2.3 Magnitude of the shock

The rise in high-skill STEM worker employment depicted in Figure 1 accounts for an important portion of rising STEM employment overall during this period. The stock of employed OPT STEM workers rose by about 120,000 between 2008 and 2019. Each additional OPT STEM worker caused about 1.67 additional high-skill foreign STEM workers in the labor force, using estimated rates of stay past the OPT duration by means of the H-1B channel and other minor channels.[4] That is, the rise in STEM OPT workers during this period accounts for an increase in the overall number of high-skill foreign STEM workers by 200,400.

During same years, 2008–2019, the overall stock of foreign-born employed high-skill STEM workers rose by 806,187 in the American Community Survey (ACS). Thus the rise in OPT STEM workers shown in Figure 1 accounts for roughly one quarter of the entire increase in foreign-born, high-skill STEM workers in the US labor force during this period. Because the foreign-born account for 36 percent of growth in the stock of overall high-skill STEM workers in the past two decades, this implies that the rise in OPT STEM employment accounts for roughly 8–10 percent of the growth in the stock of employed high-skill STEM workers in the United States since 2008.[5] This is a major shock by any standard. It suggests that if indeed high-skill foreign STEM workers have an effect on patenting, that effect is plausibly detectable in aggregate data.

[4] Clemens et al. (2025, Fig. 3–4) use the same full-universe SEVIS data to find that the transition rate from OPT STEM to an eventual H-1B visa was approximately 50 percent during this entire period. They furthermore find that approximately one fourth of international STEM graduates from US universities remain in the US in the medium and long-term by non-H1-B channels. This implies that roughly $1+0.5+\frac{1}{4-1}\times 0.5 = 1.67$ high-skill foreign STEM workers entered and remained in the US labor force for every additional OPT STEM worker during this period.

[5] High-skill STEM workers are defined as foreign-born, employed workers with a bachelor's degree or higher. Analysis of the American Community Survey reported by Clemens et al. (2025).

3 Estimating total effects on innovation

Any investigation of the total effect of OPT STEM workers on innovation must account for effects of their own ideas on the production of ideas by others. It was clear to Marshall (1890, 332) that within what we would today call industrial clusters, "*if one man starts a new idea, it is taken up by others and combined with suggestions of their own; and thus it becomes the source of further new ideas.*" It must also choose an empirical specification of innovation.

3.1 Regression framework

For a parsimonious empirical framework to estimate both the direct and indirect effects of OPT STEM workers, consider the Romer (1990)-Jones (1995, 2005) specification for the production of ideas A by research-and-development workers $\mathscr{L}_A$:

$$\dot{A} = \delta \mathscr{L}_A^{\lambda} A^{\phi}, \qquad \phi, \delta > 0; \lambda \leqslant 1. \tag{1}$$

Define R&D workers as a flexible aggregator of foreign and native R&D workers, $\mathscr{L}(L_F, L_N)$, differentiable and homogeneous of degree one. Plugging this into (1), taking logs, approximating by first-order Taylor linearization, and normalizing by the working-age population N gives

$$\frac{\dot{A}}{N} \approx \alpha + \underbrace{\rho\,(1+\theta)}_{\beta} \cdot \frac{L_F}{N}, \tag{2}$$

derived in the Appendix. Here, an increase in foreign R&D workers L_F has a total effect β on ideas production. This includes a direct effect ρ, through foreign workers' own ideas. It has a separate, indirect effect θ by changing the idea-productivity of native R&D workers or the number of native R&D workers L_N. The literature suggests a range of possible channels for such indirect effects, including

- *Spillovers within teams or firms*: Native R&D workers can raise the idea-productivity of native direct collaborators by increasing specialization (Prato 2025). Bernstein et al. (2025) find that this accounts for more than half of the within-team effect foreign inventors on

US patenting.

- *Spillovers across firms in innovation hubs*: Knowledge can diffuse across firms, especially within geographic clusters, by personal contact or job mobility (Kerr and Robert-Nicoud 2020; Moretti 2012).
- *Input or output markets*: Foreign workers can reduce the marginal cost of idea creation by providing inputs (such as supplying shared work-spaces) or expanding the market for new ideas (such as by demanding a more specialized Artificial Intelligence tool).
- *Native crowd-out/crowd-in*: Foreign STEM students and workers can affect the incentives for natives to train in the field and supply R&D labor (Shih 2017; Lin 2019; Bound et al. 2020; Ransom and Winters 2021; Jia et al. 2025).

3.2 Specification of innovation

The measurement of innovative activity is inherently difficult (Kuznets 1962). This analysis specifies innovation as the number of granted utility patents whose principal inventor is located within a given US city. Patents are a heavily-used indicator of innovation (Griliches 1990), and are linked to firm growth and value-added (Farre-Mensa et al. 2020). Patent counts correlate closely, at the city and regional level, with other indicators of innovative activity related to R&D expenditures and business formation (Acs et al. 2002) and future productivity growth (Rothwell et al. 2013).

With the flow of new ideas $\dot{A}$ specified as applications for later-granted patents, a simple city-level regression specification of (2) is

$$p_{mt} = \beta\, o_{mt} + \lambda \mathbb{F}' + \varepsilon_{mt}, \qquad \mathbb{F} \equiv \begin{bmatrix} 1 & \mathbb{1}_m & \mathbb{1}_t \end{bmatrix} \tag{3}$$

where p_{mt} is the flow of new patent applications in year t per working-age population in metropolitan area m; o_{mt} is the stock of employed OPT STEM workers per working-age population; $\mathbb{1}_m$ and $\mathbb{1}_t$ are indicator variables for metropolitan area and year; λ is a 1×3 vector of parameters; and ε_{mt} is an error term. Metropolitan area fixed effects absorb all time-invariant differences in patenting propensity between different cities; time fixed effects absorb any nationwide shocks that raise or lower patenting rates across all cities in a given year. The specification (3) has the

advantage that the economic importance of an estimate $\hat{\beta}$ is transparently interpreted as the number of additional patents associated with one additional OPT worker.

Patents are an imperfect measure of valuable innovation. Many patents are never utilized in production, and many valuable inventions are never patented (e.g. Taalbi 2025). Patent counts best measure valuable innovation when adjusted for influence. Firms' market value rises with patent assignment, but rises even more with highly-cited patents (Trajtenberg 1990; Hall et al. 2005). Thus extensions of the core analysis consider the effects on patenting adjusted for citation-measured impact, or for a direct measure of the economic value of patents due to Kogan et al. (2017) who measure the effect of individual patents on the market value of publicly-traded assignees.

3.3 Policy-disciplined shift-share design

An obvious threat to causal interpretation of any estimate β in the regression (3) is that technology shocks specific to certain city-years could both cause greater patenting and attract OPT STEM workers, so that $\mathbb{E}[o_{mt}\varepsilon_{mt} \neq 0]$.

The policy-determined supply shock in Section 2.2 suggests a strategy to address such bias. The matching of new cohorts of OPT workers with employers and cities is shaped by the persistent networks of their classmates, professors, degree programs, and general locations; thus new cohorts on OPT often work in cities where prior cohorts worked. This allows constructing a shift-share instrumental variable in the tradition of Bartik (1991), but with a key difference: the nationwide shift is fixed by a policy formula, thus cannot be shaped by a few influential shares with high Rotemberg weights (Goldsmith-Pinkham et al. 2020). Define the nationwide shock

$$s_t \equiv \begin{cases} 1 & t \leqslant 2008, \\ \frac{24}{12} & t = 2009, \\ \frac{29}{12} & 2010 \leqslant t \leqslant 2015, \\ \frac{36}{12} & t \geqslant 2016. \end{cases} \tag{4}$$

This represents the relative expansion of the stock of OPT employment in a given employer or

city due only to additional supply from the 2008 rule change. The shift-share $s_t \cdot o_m\big|_{t=2008}$ can then instrument for o_{mt} in (3) with the OPT stock $\widehat{o}_{mt}$ predicted by

$$o_{mt} = \gamma \left(s_t \cdot o_m\big|_{t=2008} \right) + \tilde{\lambda}\mathbb{F}' + \upsilon_{mt}, \tag{5}$$

where γ and the vector $\tilde{\lambda}$ are estimation parameters and υ_{mt} is an error term. This identification strategy has many attractive features: The policy rule changed sharply from one year to the next, immediately and substantially raising OPT supply as prior cohorts were allowed to remain, and the rule exogenously fixed the magnitude of the nationwide share. It thus plausibly identifies effects of OPT supply that are exogenous to post-2008 shocks to the demand for new OPT workers. A key potential drawback of the strategy is that it relies on the assumption of quasi-exogenous baseline shares, as assumption probed with extensive placebo tests below.

4 Data

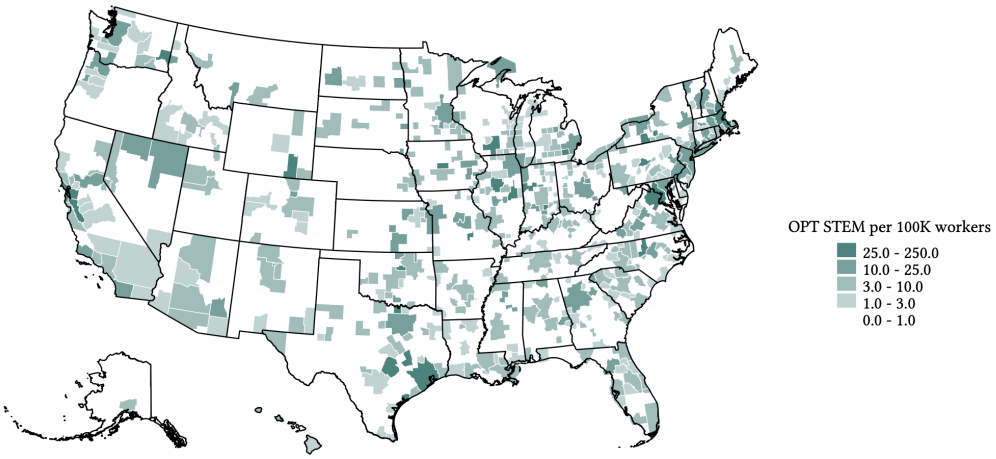
The analysis uses full-universe data on US patenting and OPT worker employment from 2004 through 2022. This time range is fixed by OPT data availability: the OPT data were drawn from US Immigration and Customs Enforcement's Student and Exchange Visitor Information System (SEVIS), which was created in 2003, in an extract obtained under the Freedom of Information Act in late 2023. Thus the data contain no records on OPT workers before 2003 or after 2023, and do not cover all OPT workers during 2003 or 2023.[6] Figure 2a shows the geographic distribution of OPT workers in the baseline year 2008, that determines variation in the instrument across space.

Patent data capture the annual flow of new applications for utility patents that had been granted by April 2025. That is, they exclusively represent ideas whose novelty has been verified by federal patent examiners. Figure 2b shows the geographic distribution of these patent applications in the post-shock years 2009–2022.

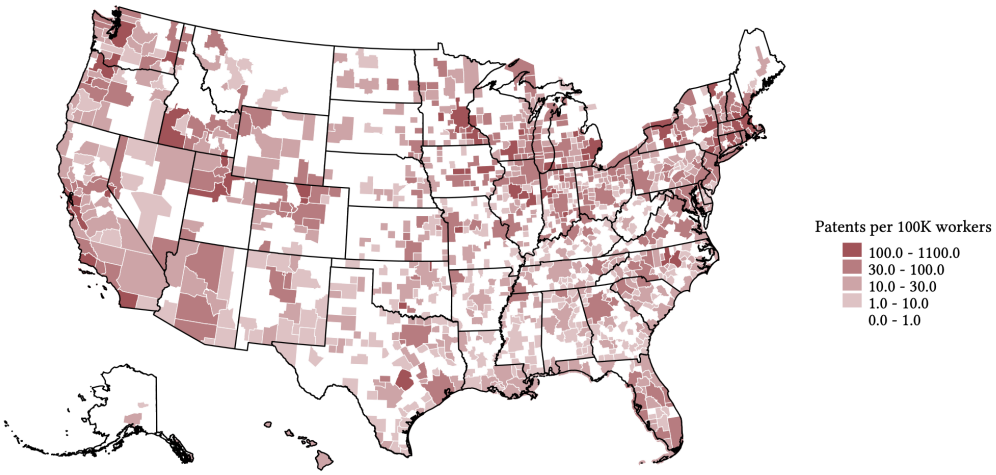
[6] Details are in the Appendix.

Figure 2: Spatial distribution of OPT STEM worker supply shock exposure, and subsequent patenting, by Core-Based Statistical Area (CBSA)

(a) *OPT STEM workers per working-age population (stock), at 2008 baseline*



(b) *Patents per working-age population (flow), average 2009–2022*



OPT workers are the full-universe stock employed in a given year, showing the first employer in a given year to avoid double-counting when individuals change employers within a year. Patents are the flow of the full universe of new applications for utility patents that had been granted by April 18, 2025; location is determined by the principal inventor (listed first on the patent). Core-Based Statistical Areas are perfect supersets of US counties that are designed to approximate city economies, including metropolitan and micropolitan areas. They include only areas with a population of 10,000 or more.

5 Results

This research design is implemented by a series of regressions (3) in a CBSA-year panel, with patents as the dependent variable and OPT STEM workers as the regressor of interest, some of them with OPT STEM workers instrumented as in (5).

5.1 Core estimates

Table 1 presents the core estimation. In column 1, naively regressing patents on OPT STEM workers in the pooled CBSA-year panel gives a coefficient of 0.82. This could naturally arise simply because some CBSAs exhibit more innovation and attract STEM workers. In column 2, adding city and year fixed effects sharply reduces the coefficient on OPT STEM workers to 0.15, implying that most but not all of the correlation in column 1 arises from persistent city-level differences and nationwide trends. Note that city and year fixed effects do not account for all possible correlation of the error term within cities or within years: for example, year fixed effects by themselves do not eliminate the possibility that cities' deviations from a nationwide shock are still correlated with each other—such as if cities with similar characteristics respond similarly to a common shock. For this reason, here and throughout the analysis, standard errors are clustered both by city and by year.

In column 3, the possibly endogenous OPT STEM workers variable is instrumented with the policy-determined shift-share variable (5). The magnitude of the coefficient estimate is consistent with one additional employed OPT STEM worker causing an increase of 0.21 in the number of later-granted utility patent applications per year, in the average city and average post-shock year (2009–2022). The table reports the p-value of the Anderson-Rubin χ^2 test of the null hypothesis that the coefficient on OPT STEM workers is zero, recommended by Moreira (2009), because this test is robust to weak instrumentation (Andrews et al. 2019) that can invalidate traditional t-ratio inference (Lee et al. 2022). The null is rejected at the 1.7 percent level.

A natural concern might be that the coefficient estimate is driven by a few cities with concentrations of high-tech innovation on the west coast, such as San José, California or Redmond,

Table 1: Core results: OPT STEM workers and patents, 2004–2022

	(1)	(2)	(3)	(4)	(5)
Dep. var:	*Patents per 100,000 working-age population*				
Estimator:	OLS		2SLS		
OPT STEM per 100,000 working-age population	0.816	0.152	0.212	0.201	0.183
	(0.180)	(0.089)	(0.065)	(0.064)	(0.094)
Anderson-Rubin p-*val.*	—	—	*0.0169*	*0.0188*	*0.0577*
Sample	Full	Full	Full	Full	∉ top 10
Observations	6,802	6,802	6,802	6,802	6,630
S.E. clustered by city × year	Yes	Yes	Yes	Yes	Yes
City fixed effects	—	Yes	Yes	Yes	Yes
Year fixed effects	—	Yes	Yes	Yes	Yes
Region × year fixed effects	—	—	—	Yes	Yes
Dep. var. mean	51.14	51.14	51.14	51.14	28.49

Robust standard errors clustered by city and year. The "∉ top 10" sample omits the ten cities with the highest baseline exposure to OPT STEM workers, following Peri et al. (2015, S244). Anderson-Rubin p-val. corresponds to the χ^2 test of the null hypothesis that the second-stage coefficient on OPT STEM workers is zero. 'Regions' are the nine regions/divisions of the US Census.

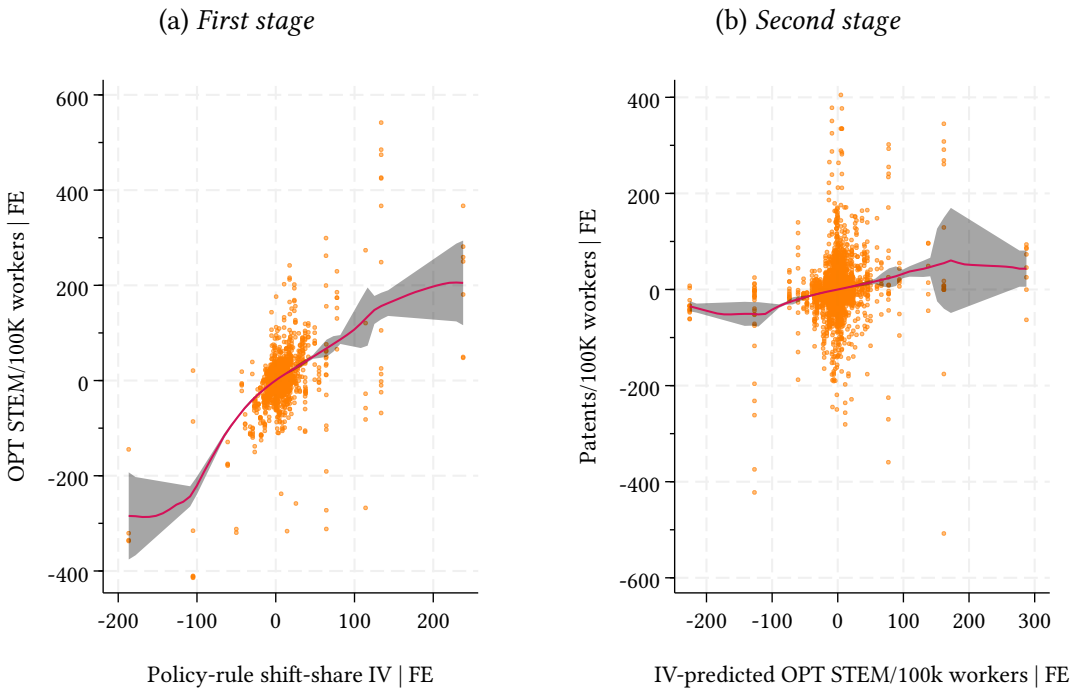
Washington. Column 4 of Table 1 presents the same regression with census region-by-year fixed effects, absorbing all variation between the nine census regions (formally "divisions").[7] The magnitude and statistical significance of the coefficient estimate on OPT STEM workers are highly robust to this change, suggesting that most of the identifying variation is occurring within regions—between cities and over time. Column 5 presents the same regression specification simply truncating the 10 cities most exposed to OPT STEM workers at baseline.[8] The coefficient on OPT STEM workers declines somewhat to 0.18 and the standard error rises so that the Anderson-Rubin test only rejects the null at the 5.8 percent level. But clearly the core result does not arise entirely from a few exceptional cities.

In shift-share designs of this kind, Borusyak et al. (2025, 198) recommend adding further trans-

[7] The nine census divisions ('regions' in Table 1) are: New England (CT, ME, MA, NH, RI, VT); Middle Atlantic (NJ, NY, PA); East North Central (IL, IN, MI, OH, WI); West North Central (IA, KS, MN, MO, NE, ND, SD); South Atlantic (DC, DE, FL, GA, MD, NC, SC, VA, WV); East South Central (AL, KY, MS, TN); West South Central (AR, LA, OK, TX); Mountain (AZ, CO, ID, MT, NV, NM, UT, WY); Pacific (AK, CA, HI, OR, WA).

[8] This is analogous to the robustness check by Peri et al. (2015, S244), who omit only the top five areas most exposed to H-1B workers.

Figure 3: Angrist-Pischke 'Visual IV' plots for Table 1, col. 3

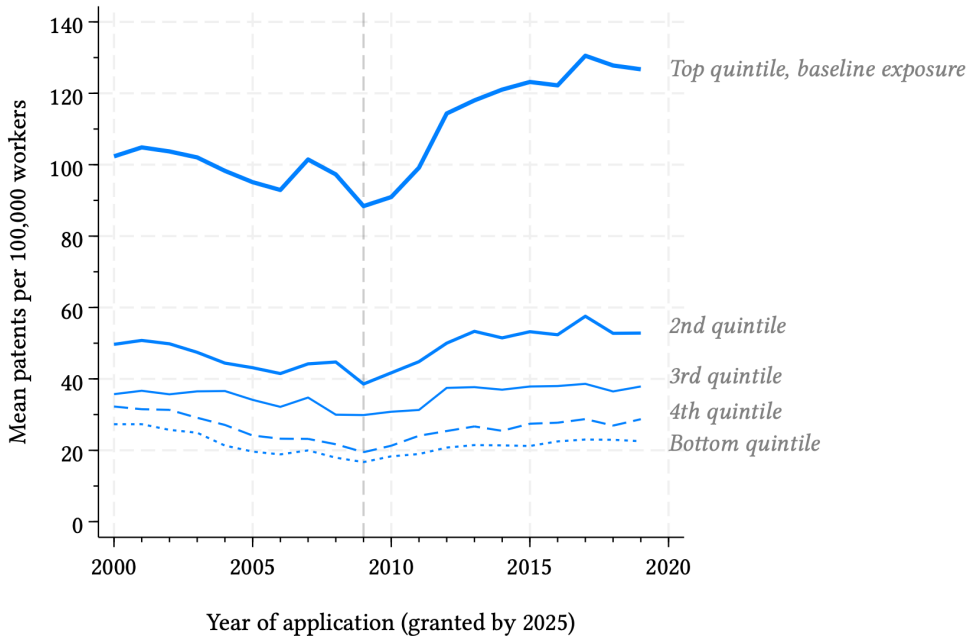


Shows the 'visual IV' plot (Angrist and Pischke 2009, 138–144) corresponding to Table 1, col. 3. Red line shows a local-linear regression, Epanechnikov kernel, bandwidth 50, with shaded area showing the 95% confidence interval on the conditional mean.

parency by presenting Angrist and Pischke's (2009, 138–144) "visual instrumental variables" (VIV) plot. In the present case the VIV plot for the first-stage regression amounts to plotting OPT STEM workers against the shift-share IV, both residualized on city and year fixed effects, shown in Figure 3a. The figure includes a local-linear regression with a bandwidth of 50, that is, whose local slope is not influenced by observations lying outside a window of 100 units on the horizontal axis. The highly significant upward slope of the local linear regression near the center of Figure 3a suggests that the instrument is strong and that its strength does not arise from a few influential, high-leverage observations.

The VIV plot for the second stage is shown in Figure 3b, where the vertical axis is the patents variable and the horizontal axis is the IV-predicted value of the OPT STEM workers variable, both residualized on the fixed effects. Again the local linear regression line has bandwidth 50. The upward slope of that line in the center of the figure thus does not arise from a few influential,

Figure 4: Pre-shock trends in patenting by baseline exposure quintile



Shows the full universe of patents granted by April 2025, by year of application. Quintile are by degree of baseline exposure of each CBSA, that is, OPT STEM workers per 100,000 working-age population in 2008.

high-leverage cities. If anything, the cities that would have the highest leverage on a linear regression fit to the same points would tend to slightly reduce the positive slope of that line and thus the coefficient estimate of interest in Table 1, given that the local linear regression line flattens out at the upper and lower extrema.

5.2 Falsification tests

Recent research has questioned some prior applications of the shift-share methodology, and highlighted the importance of conducting a range of tests for common pathologies in this design. This is a central concern with any causal interpretation of the estimates in Table 1. The section below presents four key tests for the effect of interest under conditions where, if the design is valid, no spurious 'effect' should arise.

1. Pre-trends: The modern literature on shift-share designs has raised important concerns about

hidden potential for bias from endogenous shifts or endogenous shares. The present design avoids the most standard concerns about endogenous shifts because the nationwide shift is fixed by the policy rule (4), rather than being the typical aggregate of area-level shifts. But the research design is quite vulnerable to bias from endogenous shares (Adão et al. 2019; Goldsmith-Pinkham et al. 2020; Borusyak et al. 2025). If the cities demanding the most OPT STEM workers prior to the supply shock were already on trajectories that would have raised their post-shock patenting in the absence of the shock, the core estimates above could be biased as estimators of the causal effect of interest, even severely.

Figure 4 presents a simple visual test for pre-trends. The cities in the sample are divided into quintiles according to their OPT STEM worker employment at baseline (2008). The simple cross-city mean of the patents variable is then plotted over time, by quintile. Although patenting-rate trends in high-exposure cities visibly diverge from those of low-exposure cities after the supply shock, no similar divergence is clearly visible before the supply shock. This test is conducted more formally in Table 2, column 1. This is an OLS regression of the patents variable on the product of baseline exposure by city and a simple linear time trend in the same pre-2008 years shown in Figure 4, with city and year fixed effects. The test fails to reject the hypothesis of no pre-trends. This is finding is inconsistent with substantial bias from cities more exposed to the OPT STEM supply shock possessing unobserved traits that placed them on a higher patenting trajectory pre-shock.

2. Non-STEM OPT workers: The literature places foreign high-skill STEM workers much closer to the patenting process than foreign high-skill non-STEM workers (Kerr and Lincoln 2010; Hunt 2011). Intuitively, OPT workers with degrees in chemistry or engineering might spur more patented innovation than OPT workers with degrees in English literature or physical education. This suggests a natural placebo test: including each CBSA-year's stock of *non*-STEM OPT workers, instrumented with a placebo instrument built as the product of the same shift (4) and the baseline employment of non-STEM OPT workers $\left(s_t \cdot o_m^{\text{non-STEM}}\big|_{t=2008}\right)$. If the core results were contaminated by endogeneity bias arising from the overall attractiveness of innovative CBSAs to inward migration by US-trained foreign workers in general—STEM and non-STEM—then including this placebo control should substantially affect the coefficient estimate of interest.

Table 2: Placebo Tests

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var:	*Patents per 100,000 working-age population*					
Estimator:	OLS	2SLS				
Patent STEM relevance:		All		High	Med.	Low
Pre-trend: $o_m\big\|_{t=2008} \cdot (t - 2007)$	0.016					
	(0.024)					
OPT STEM per 100,000 working-age population		0.218	0.211	0.120	0.081	0.012
		(0.113)	(0.068)	(0.065)	(0.030)	(0.006)
OPT *non*-STEM per 100,000 working-age population		−0.098				
		(1.273)				
Industry growth Bartik			−56.34			
			(85.42)			
Sample	2000–7	Full	Full	Full	Full	Full
Observations	3,648	6,802	6,802	6,802	6,802	6,802
S.E. clustered by city × year	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Dep. var. mean	46.64	51.14	50.65	32.49	8.91	9.74

Robust standard errors clustered by city and year. Anderson-Rubin p-val. corresponds to the χ^2 test of the null hypothesis that the second-stage coefficient on OPT STEM workers is zero. In column 2, the OPT STEM regressor and the OPT non-STEM regressor are instrumented both by the same OPT STEM shift-share instrument used elsewhere, and by the placebo instrument $s_t \cdot o_m^{\text{non-STEM}}\big|_{t=2008}$.

Column 2 of Table 2 presents this test. The coefficient on non-STEM OPT workers is statistically indistinguishable from zero, and the coefficient estimate on OPT STEM workers is materially unaffected. The result is inconsistent with substantial bias from any failure by the shift-share design to purge the coefficient estimate of interest from bias due to some unobserved common factor causing certain CBSAs to become more innovative and causing OPT workers in general to move there for work.

3. Pre-existing industrial structure: Another clear possibility is bias due to cities' differential reaction to unobserved shocks according to their pre-existing industrial structure. For example, cities with larger concentrations of high-tech firms might have responded differently to the overall rise of high-tech employment during the period of interest, and OPT STEM worker at baseline

could correlate with cities' long-term industrial structure. Areas with similar industrial structures can have correlated residuals because nationwide shocks might affect an industry similarly in different cities (Adão et al. 2019).

I therefore construct an industry Bartik (1991) control, following Peri et al. (2015), to control for city-specific shocks driven by cities' industrial structure in the year 2000. This control is $\sum_k (s_{km} \cdot g_{kt})$, where s_{km} is the share of three-digit NAICS industry k in the employment of metropolitan area m in the year 2000, and g_{kt} is the growth of nationwide employment in industry k between the year 2000 and year t. When this control is added to the core regression, in Table 2 column 3, there is no substantial change in the coefficient estimate of interest. This is inconsistent with substantial bias from correlation between baseline OPT STEM exposure and predetermined industrial structure.

4. Effects by patent type: It is plausible that OPT STEM workers have a greater effect on patenting in nuclear physics than in footwear, because patents relying more directly on methods from science and engineering might draw more heavily on the specialized knowledge of STEM workers. A natural placebo test, then, would be to assess whether the putative causal effect of OPT STEM workers on patenting differs across patents in this dimension.

I hand-coded the Cooperative Patent Classification (CPC) two-digit codes by "STEM relevance", that is, a subjective assessment of potential benefit from foreign STEM workers. The category of "high"' benefit represents patents where the process itself is a form of scientific activity, such as nanotechnology or biochemistry. The category of "medium" benefit represents patents where the process is not directly a form of scientific activity, but could clearly benefit from specialized scientific or engineering knowledge, such as metallurgy or aviation. The category of "low" represents patents where patentable innovation might arise from practice without application of specialized scientific or engineering knowledge, such as butchering, headwear, or bookbinding. STEM workers could, of course, contribute to a patent for headwear. But university-level STEM training is essential to the act of patenting in nanotechnology in a way that it clearly is not for patenting in headwear.

The results of separating patents by these types are shown in columns 4–6 of Table 2. The

effect of OPT STEM workers on "low" benefit patents is an order of magnitude smaller than the effect on "high" benefit patents, even accounting for the relatively lower volume of "low" benefit patents (the mean of the dependent variable is at the bottom of the table). The effect on "low" benefit patents is an order of magnitude lower than the effect on "medium" benefit patents, even though the volume of each kind of patent is similar across cities and years. Column 5 offers, in essence, a placebo test of the core result: a large, spurious effect of OPT STEM workers on low-relevance patents would be inconsistent with causal identification in the core results. But no such effect is observed.

5.3 Indirect effects on other inventors

The estimated total, city-level effect of OPT STEM workers on patenting comprises a direct and an indirect effect, as in equation (2). The workers themselves may produce patented ideas—either during their OPT period or, if they remain in the US afterward, while on H-1B or other statuses. They may also cause increased patenting by R&D workers around them, within the same team, organization, cluster, or city. Here I compare the magnitude of the total effects estimated above to estimates of the direct effect from the literature, in order to assess the magnitude of indirect effects at the city level.

Hunt and Gauthier-Loiselle (2010) find that the average high-skill foreign worker in a STEM occupation reported applying for 0.036 later-granted patents per year, in the National Survey of College Graduates (NSCG).[9] I re-analyzed the same survey data to define STEM workers by field of study in their most recent degree, and find the rate to be almost identical at 0.037 patents per high-skill foreign STEM worker per year. Those figures slightly dated, drawn from the NSCG of 2003, the last round of the survey to include questions on patenting. But they are consistent with more recent data from administrative sources and extending through 2016 in Bernstein et al. (2025).[10] I thus consider the Hunt and Gauthier-Loiselle data informative for the post-2008

[9]The average foreign-born worker with a bachelor's degree or higher in a science or engineering field applied for 0.178 patents in the five years leading up to the survey, that is, 0.0356 patents per year (Hunt and Gauthier-Loiselle 2010, Table 1, p. 38). Subsequent waves of the National Survey of College Graduates dropped the question about patenting.

[10]Hunt and Gauthier-Loiselle (2010) found that native and foreign high-skill STEM workers, collectively, apply for 0.0286 later-granted patents per year: Patenting rates over the preceding five years in Hunt and Gauthier-Loiselle (2010, Table 1, p. 38) as an average weighted by the immigrant fraction and annualized by dividing by fives, as $((0.24 \times 0.178) + ((1 - 0.24) \times 0.132))/5 = 0.029$. This closely matches the corresponding rate implied by Bernstein

period of interest here.

The analysis requires an estimate of patenting by US-trained, high-skill foreign STEM workers. Hunt (2011) observes that US-trained foreign STEM workers have much higher patenting rates than those trained abroad, but neither Hunt and Gauthier-Loiselle (2010) nor Hunt (2011) report patenting rates specific to foreign workers who both 1) graduated in a STEM discipline and 2) graduated from a US university. I thus reanalyze the Hunt (2011) data to estimate that the average US-trained, high-skill foreign STEM worker reports being granted 0.0763 patents per year.

Comparing this figure to the analysis above requires noting that US-located patenting by an OPT STEM worker can occur after they have changed to other statuses, typically H-1B. As discussed in Section 2.3, adding one to the ongoing stock of OPT STEM workers in the US workforce typically adds 1.67 to the overall stock of high-skill foreign STEM workers, including those who remain after OPT. That is an upper bound on the number added to the stock within the same city, since some OPT STEM workers who change status to remain in the US could do so by moving to a different city. Taking the coefficient estimate of 0.212 from Table 1, column 3, this implies that each additional high-skill foreign STEM worker in the US workforce caused by the OPT STEM policy supply shock caused more than $\frac{0.212}{1.67} = 0.127$ additional granted utility patents.

The total effect of additional OPT STEM workers on US-based patenting (more than 0.127) thus exceeds the direct effect—patents filed by those foreign STEM workers themselves (0.0763)—by a factor of more than 1.7. This is consistent with the finding of Bernstein et al. (2025) that immigrant inventors' total impact on patenting exceeds the direct impact of their own patents by a factor of 1.35, after accounting for their within-team spillover effects on native inventors they collaborate with directly. The present finding should account for such within-team spillover effects as well as additional within-organization spillovers beyond the team, and within-city spillovers beyond the organization. It implies that at least roughly half of the spillover effects on

et al. (2025) of 0.0295: They find 652,832 inventors with an average of 4.88 patents each (Bernstein et al., Table 1) during the 27 years they study (1990–2016) when there were close to 4 million employed high-skill STEM workers in the United States in the average year based on the American Community Survey (Clemens et al. 2025). Thus $\frac{652{,}832 \times 4.88}{27 \text{ years} \times 4 \text{ million}} = 0.0295$. Bernstein et al. do not consider STEM workers separately, but the vast majority of foreign inventors are STEM workers: In the National Survey of College Graduates used by Hunt (2011), 89.7 percent of immigrants who patent got their degrees in STEM. Furthermore, Hunt and Gauthier-Loiselle find that the immigrant high-skill STEM patenting rate exceeds the corresponding native rate by 35 percent (0.178 versus 0.132 in their Table 1), while the corresponding figure from Bernstein et al. is similar at 43 percent.

other inventors act outside teams but within cities.

6 Innovation quality and productivity

Patents overall do appear to reflect economically valuable innovation on average (Budish et al. 2025). But it is well known that patents do not equate to economically valuable innovation: Many patents are never commercialized, and many economically valuable innovations are never patented. In principle, additional OPT STEM workers could cause a flurry of patenting activity that does not lead to more value-added, even diluting the value of innovation by raising its volume.[11] Bernstein et al. (2025) find that patents filed directly by immigrants and their immediate co-inventors cause greater value-added than those filed only by native inventors, but it is unclear if this result extends to patenting indirectly caused by high-skill foreign STEM workers at the city level.

Thus the analysis proceeds to test whether the core results are robust to tests that place greater weight on more influential and valuable patents. The first column of Table 3 reproduces the core result from Table 1, column 3, for comparison. Column 2 conducts the same regression weighted by total forward citations of patents filed by each CBSA-year, and column 3 weights by 'quick' citations—forward citations within three years of the application date. In both of these tests the coefficient estimate rises relative to the core result in column 1, consistent with OPT STEM workers causing an increase in the quality and influence of patents beyond a pure effect on quantity.

Column 4 weights the regression by the economic value of patents assigned to publicly-traded companies (estimated by Kogan et al. (2017) and updated through 2023 in data publicly available from the authors). Again the coefficient estimate of interest is larger in magnitude than in the core regression. Finally, column 5 shows the regression weighted by backward citations to scientific research papers by each patent, a measure due to Marx and Fuegi (2020). Once more the magnitude of the coefficient estimate exceeds the magnitude in the core regression.

[11] Greater patent productivity correlates with lower quality, across US firms, but quality correlates with firms' market value (Lanjouw and Schankerman 2004).

Table 3: Patent influence and value-added

	(1)	(2)	(3)	(4)	(5)
Dep. var:	*Patents per 100,000 working-age population*				
Estimator:	2SLS				
Weighted by:	*None*	Forward citations, all	Forward citations, 3 years	Value added	Backward citations, sci. lit.
OPT STEM per 100,000 working-age population	0.212	0.329	0.314	0.257	0.239
	(0.065)	(0.086)	(0.056)	(0.043)	(0.068)
Observations	6,802	6,259	5,963	5,112	5,717
S.E. clustered by city × year	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes

Robust standard errors clustered by city and year. Column (1) reproduces Table 1, col. 3. "Forward citations, all" is the number of other patents whose principal inventor is located in the United States that cite the reference patent. "Forward citations, 3 years" is the number of forward citations within three years of the application date of the reference patent. "Value added" is the economic value of the reference patent, estimated by Kogan et al. (2017). "Backward citations, sci. lit." is the number of backward citations by the reference patent to published scientific papers, estimated by Marx and Fuegi (2020, Table 4), using only matches with ⩾91% confidence.

These results are consistent with patents caused by OPT STEM workers taking scientific knowledge and turning it into influential, economically-valuable innovation.

7 Conclusion

This paper documents large aggregate effects of US-trained foreign STEM graduates on the production of new technologies. Using a plausibly exogenous policy shock to OPT duration and full-universe administrative records on both OPT employment and later-granted patents, the analysis is consistent with additional STEM graduates permitted to remain in the US labor market raising local patenting by roughly 0.21 patents per worker per year. Total estimated effects including within-city spillovers exceed direct contributions from foreign inventors by a factor of 1.7 or more, consistent with models in which idea production depends on complementarities across heterogeneous R&D labor. The results hold across extensive falsification tests, persist when weighting patents by forward citations or economic value, and are concentrated in sci-

entific fields where STEM training is most relevant. Together, the evidence is consistent with marginal US-trained foreign STEM workers generating innovation well beyond his or her own output, and short-run constraints on post-study work opportunities substantially reducing the level and value of inventive activity in the United States.

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Online Appendix

International students and innovation: Evidence from restrictions on US-trained foreign STEM workers

Michael A. Clemens — December 2025

This Appendix presents material to supplement the main text.

A1 Data sources

A1.1 Optional Practical Training

I use data on the full universe of OPT employment authorization recipients recorded between 2004 and 2022 in the Student and Exchange Visitor Information System (SEVIS), a database maintained by US Immigration and Customs Enforcement (ICE) within the Department of Homeland Security. The anonymized, individual-level data are part of the public record and were obtained by a request under the Freedom of Information Act by Jeremy Neufeld. The raw FOIA data are spread across 13 different archives available at https://www.ice.gov/foia/library by searching for request ICFO-43657. The earliest entries are from 2004 because SEVIS was created in 2003; the latest entries are from 2022 because the FOIA request was fulfilled in the middle of 2023 and thus does not cover the universe of OPT workers in that year.

A1.2 Granted utility patents

I use data on the full universe of utility patents that had been granted by the US Patent and Trademark Office as of April 18, 2025, accessed via the PatentsView portal on July 22, 2025. The location of the patent is assumed to be the county where the principal inventor (listed first) is located. Only patents whose principal inventor is located within the US are included in the analysis. Forward citations are also counted exclusively for citing patents whose principal inventor is located within the US.

A2 Regression equation derivation

Start from idea production:

$$\dot{A} = \delta \mathscr{L}_A^{\lambda} A^{\phi}, \qquad \phi, \delta > 0,\ \lambda \leq 1. \tag{A.1}$$

Let total R&D labor be a homogeneous-of-degree-one aggregator $\mathscr{L}_A = \mathscr{L}(L_F, L_N)$. Normalize by the working-age population N, define intensities $f \equiv \frac{L_F}{N}$ and $n \equiv \frac{L_N}{N}$, and rewrite using homogeneity:

$$\mathscr{L}_A = N\, \ell(f, n).$$

Substitute and divide by N:

$$\frac{\dot{A}}{N} = \delta N^{\lambda - 1} \ell(f, n)^{\lambda} A^{\phi}. \tag{A.2}$$

Take logs and linearize around a baseline $(\bar{f}, \bar{n})$, with slow changes in the working-age population absorbed into the intercept:

$$\ln\left(\frac{\dot{A}}{N}\right) \approx \alpha_0 + \rho_F f + \rho_N n. \tag{A.3}$$

Let native R&D enter idea production through an effective native input $\tilde{n} \equiv H(n, f)$, where H captures both native productivity and the crowd-in/out response of n to f. Linearize $\tilde{n}$:

$$\tilde{n} \approx \tilde{n}^* + \left.\frac{d\tilde{n}}{df}\right|_{(\bar{f},\bar{n})} f. \tag{A.4}$$

Substitute into idea production and move to levels on the left-hand side with first-order Taylor approximation:

$$\frac{\dot{A}}{N} \approx \alpha^* + \rho_F f + \rho_N \left.\frac{d\tilde{n}}{df}\right|_{(\bar{f},\bar{n})} f. \tag{A.5}$$

Impose $\rho_F \approx \rho_N \equiv \rho$ and define $\theta \equiv \left.\frac{d\tilde{n}}{df}\right|_{(\bar{f},\bar{n})}$, which includes both native productivity spillovers and the marginal effect of f on n. Then the regression form is

$$\frac{\dot{A}}{N} \approx \alpha + \rho(1+\theta)\frac{L_F}{N}. \tag{A.6}$$

A3 CPC classification by benefit from foreign STEM workers

High Benefit Categories

A61	Medical/veterinary	B01	Physical/chem proc.	B81	Microstructural tech	B82	Nanotechnology	C01	Inorganic chemistry
C02	Water treatment	C07	Organic chemistry	C08	Organic macromolec.	C09	Dyes/Paints/Resins	C10	Petroleum/gas
C12	Biochemistry	C23	Coating metallic	C25	Electrolytic processes	C30	Crystal growth	C40	Combinatorial tech
G01	Measuring/Testing	G02	Optics	G05	Controlling	G06	Computing	G09	Crypto/Display
G11	Info storage	G16	ICT applications	G21	Nuclear physics	H01	Basic electric elements	H02	Electric power
H03	Electronic circuitry	H04	Communication	H05	Electric tech n.e.c.	H10	Semiconductors		

Medium Benefit Categories

A01	Agriculture/Forestry	A23	Foods/foodstuffs	B03	Separation solids	B09	Solid waste disposal	B29	Working plastics
B32	Layered products	B33	Additive manufact.	B60	Vehicles general	B64	Aircraft/Aviation	C03	Glass/Mineral wool
C04	Cements/Concrete	C21	Metallurgy iron	C22	Metallurgy/Alloys	F01	Engines general	F02	Combustion engines
F03	Liquid engines	F15	Fluid actuators	F16	Engineering elements	F25	Refrigeration	F27	Furnaces/Kilns
F28	Heat exchange	G03	Photography	G04	Horology	G07	Checking-devices	G08	Signalling
G10	Musical instruments								

Low Benefit Categories

A21	Baking/Doughs	A22	Butchering/Meat	A24	Tobacco/Cigars	A41	Wearing apparel	A42	Headwear
A43	Footwear	A44	Haberdashery/Jewel	A45	Hand/travel articles	A46	Brushware	A47	Furniture/Domestic
A62	Life-saving/Fire	A63	Sports/Games	A99	Subject n.e.c.	B02	Crushing/pulverising	B04	Centrifugal apparatus
B05	Spraying/atomising	B06	Mechanical vibrations	B07	Separating solids	B08	Cleaning	B21	Metal-working
B22	Casting/Powder	B23	Machine tools	B24	Grinding/Polishing	B25	Hand/portable tools	B26	Hand cutting tools
B27	Working wood	B28	Working cement/clay	B30	Presses	B31	Paper articles	B41	Printing
B42	Bookbinding	B43	Writing implements	B44	Decorative arts	B61	Railways	B62	Land vehicles
B63	Ships/vessels	B65	Conveying/Packing	B66	Hoisting/Lifting	B67	Opening bottles	B68	Saddlery/Upholstery
B99	Subject n.e.c.	C05	Fertilisers	C06	Explosives	C11	Oils/fats	C13	Sugar industry
C14	Skins/Leather	D01	Threads/fibres	D02	Yarns/finishing	D03	Weaving	D04	Braiding/Knitting
D05	Sewing/Embroidery	D06	Textile treatment	D07	Ropes/Cables	D21	Paper-making	D99	Subject n.e.c.
E01	Roads/railways	E02	Hydraulic eng.	E03	Water supply	E04	Building	E05	Locks/Keys
E06	Doors/windows	E21	Earth drilling	E99	Subject n.e.c.	F04	Pumps	F17	Storing gases
F21	Lighting	F22	Steam generation	F23	Combustion app.	F24	Heating/Ventilating	F26	Drying
F41	Weapons	F42	Ammunition	G12	Instrument details	Y02	Climate tech	Y04	ICT impact
Y10	Former USPC								