Foreign and Native-Born STEM Graduates and Innovation Intensity in the United States

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Abstract

This paper examines the effects of foreign- and native-born STEM graduates and non-STEM graduates on patent intensity in U.S. metropolitan areas. I find that both native and foreign-born STEM graduates significantly increase metropolitan area patent intensity, but college graduates in non-STEM fields have a smaller and statistically insignificant effect on patenting. These findings hold for both cross-sectional OLS and 2SLS regressions. I also use time-differenced 2SLS regressions to estimate the effects of STEM-driven increases in native and foreign college graduate shares and again find that both native and foreign STEM graduates have statistically significant and economically large effects on innovation. Together these results suggest that policies that increase the stocks of both foreign and native STEM graduates increase innovation and provide considerable economic benefits to regions and nations.

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1. Introduction

Technological innovation is critical for economic growth and development, and many nations and regions are very interested in how they can increase innovation. Skilled labor is widely recognized as an important ingredient in the innovation process (Carlino, Chatterjee, and Hunt 2007), and workers in science, technology, engineering, and math (STEM) fields are believed to be especially important (Atkinson and Mayo 2010). Therefore, many researchers, policymakers, and businesses support various public policies to increase the stock of skilled labor both locally and nationally (Moretti 2013).[1] One way to increase the stock of skilled labor is by increasing human capital levels of current residents, and there are numerous policy efforts intended to do so. However, it is unclear if natives are sufficiently responsive to human capital policies, and many employers and policymakers in advanced economies claim that they are experiencing a shortage of skilled workers especially in STEM fields (National Academies 2010). Areas can also increase human capital stocks via in-migration of persons who acquired the needed skills elsewhere. This latter option has led to considerable debate on high-skilled immigration policy in advanced economies such as the United States.[2] However, there is still much that is unknown about how high-skilled immigration affects receiving areas.[3] Surveying

[1] The local stock of high skilled workers in an area has been shown to increase wages and employment rates for both high and low skilled persons (Moretti 2004; Winters 2013) and increase future employment and population growth (Simon 1998; Simon and Nardinelli 2002; Shapiro 2006).

[2] Much of the debate in the U.S. is centered on the H-1B visa program, which allows employers to apply for temporary visas for skilled foreigners working in specialty occupations. The program began in 1990 and the annual quota has varied considerably since inception. Various stakeholders argue that the quota should be increased, decreased or even reduced to zero. Kerr and Lincoln (2010) provide additional details.

[3] A major concern raised by critics of increased skilled immigration is how such actions affect natives. Traditional models of supply and demand suggest that increasing the supply of skilled labor through in-migration will lower wages for similar natives, and there is some empirical evidence to support this contention (Borjas 2003, 2006). There is also some evidence that increased immigration partially "crowds out" natives in areas receiving large immigrant inflows by encouraging them to migrate to areas receiving smaller immigrant shocks (Borjas 2006; Ali, Partridge and Rickman 2012) and by encouraging them to work in occupations less affected by immigrant labor supply shocks (Levin et al. 2004; Peri and Sparber 2011). However, researchers have also suggested that foreign and native workers may experience considerable complementarities, and some have found wage effects of

the research literature, Kerr (2013) concludes that "the global migration of talented workers … is vastly understudied compared to its economic importance."

There is only a small literature that directly examines the effects of skilled foreigners on innovation.[4] Hunt and Gauthier-Loiselle (2010) and Kerr and Lincoln (2010) examine the effects of immigrants on innovation by looking at patent data.[5] Hunt and Gauthier-Loiselle (2010) first examine the 2003 National Survey of College Graduates (NSCG) to assess individual determinants of patenting. They find that the average foreign college graduate patents at double the rate of the average native graduate but indicate that this effect largely results because foreigners are more likely to have earned degrees in science and engineering fields.[6] Conditional on earning a degree in science or engineering, foreign and native graduates patent at rates that are statistically similar. However, examining individual self-reported data on patenting has some potential limitations: it ignores potential crowds out effects, knowledge spillovers, complementarities between different types of workers, differences in collaboration patterns between natives and foreigners, and the possibility that foreign graduates disproportionately locate in areas that make them more likely to patent.

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immigrants on natives to be small, zero, or even positive (Peri and Sparber 2009; Ottaviano and Peri 2012; Peri, Shih, and Sparber 2014). Kerr (2013) and Lewis and Peri (2014) review recent literature.

[4] A related literature looks at how foreigners compare to natives in various measures of innovation. Much of this literature has examined differences in academic achievements between native and foreign born faculty and graduate students and found mixed results. Levin and Stephan (1999), Stephan and Levin (2001), Corley and Sabharwal (2007), Chellaraj, Maskus, and Mattoo (2008), and Gaulé and Piacentini (2013) find that foreign born academics outperform their native counterparts. However, Stuen, Mobarak, and Maskus (2012) find that foreign and native doctoral students have statistically comparable effects on academic innovation in science and engineering departments at American universities. Gurmu, Black, and Stephan (2010) find that the relative contributions of natives and foreigners to academic innovation vary between graduate students and postdoctoral scholars and also depend on the temporary or permanent visa status of foreigners.

[5] Waldinger (2012) and Moser, Waldinger and Voena (2014) examine the effects of a specific historical immigration shock, Jewish émigrés from Nazi Germany. Both studies find no evidence of knowledge spillovers from émigrés to prior residents. Moser, Waldinger and Voena (2014), however, do find a large positive effect on U.S. chemical innovation due to more researchers working in those fields.

[6] Hunt (2011) also uses the NSCG to examine the effects of immigrants on innovation by entry visa type. She finds that immigrants who were initially admitted as legal permanent residents (such as through family unification) have similar patenting outcomes as natives.

Hunt and Gauthier-Loiselle (2010) also examine the effects of skilled foreigners on regional innovation using 1940-2000 state-level panel data on patents per capita and the stocks of foreign college graduates per capita measured at ten year increments.[7] Their preferred specifications instrument for decadal growth in the skilled immigrant population share using the predicted growth based on state immigrant shares for various origin countries in 1940 and the national growth in the immigrant population from those countries during the decade in question. They find that foreign graduates increase state patent intensity, and the estimated coefficients imply considerable spillovers relative to the effects predicted by individual-level data.

Kerr and Lincoln (2010) exploit the H-1B visa program to identify large annual changes in skilled foreigner inflows across 281 metropolitan areas for the years 1995-2007. They estimate reduced form regressions of the effect of predicted flows of H-1B visa holders on patent intensity. Examining annual changes makes their analysis primarily short-run in nature, and they do not examine the effect of native skill levels on patent intensity. They find that increased predicted H-1B immigrant inflows significantly increases local patenting. They also match patents to ethnic surnames and find that much of the increase is attributable to Indian and Chinese surnames. However, they do find some evidence of increased patenting for Anglo-Saxon surnames due to H-1B inflows, which may suggest positive innovation spillovers from foreigners to natives, i.e., natives may be crowded into innovation instead of crowded out.

The current paper builds on the work of Hunt and Gauthier-Loiselle (2010) and Kerr and Lincoln (2010) by examining the effects of foreign- and native-born STEM graduates and non-STEM graduates on patent intensity in U.S. metropolitan areas.[8] I first use year 2010 data to

[7] Some of their specifications control for the stock of native college graduates in the state, but their analysis treats this variable as exogenous.

[8] Related studies have also considered the effects of various types of skilled workers, including skilled immigrants, on regional innovation in other countries, especially in Europe (e.g., Simonen and McCann 2008; Faggian and

estimate cross-sectional effects via ordinary least squares (OLS). However, my preferred results use instrumental variables (IV) methods to estimate causal effects. I identify the effects of foreign-born STEM graduates using a similar instrument as Hunt and Gauthier-Loiselle (2010) and Peri et al. (2014) based on "shift-share" predicted immigrant inflows. To identify the effects of native STEM and non-STEM graduates, I use instrumental variables based on the predicted flows of native STEM and non-STEM graduates from colleges to metropolitan areas constructed using the 1980 decennial census and the 1980 Integrated Postsecondary Education Data System (IPEDS).

This paper differs from previous literature in several important ways. To my knowledge, this is the first study to estimate causal effects of skilled natives on patent intensity. This is an important contribution that can help policymakers assess the benefits of higher education policies, especially policies intended to affect the domestic production of STEM graduates. Investments in higher education are costly to both individuals and society, and STEM graduates are among the most expensive to educate (Nelson 2008). There is some evidence that college major decisions can be effected by differential tuition and financial aid policies (Stange 2013; Denning and Turley 2013; Sjoquist and Winters 2015a, b). However, there is also evidence that many college students start out pursuing a STEM major but end up switching to less challenging majors because they lack sufficient preparation in math and science skills (Griffith 2010; Arcidiacono, Aucejo and Spenner 2012; Arcidiacono, Aucejo and Hotz 2013; Stinebrickner and Stinebrickner 2014). If there are especially large social benefits from STEM education, then understanding how public policies can affect STEM education outcomes becomes increasingly important.

McCann 2009; Niebuhr 2010; Nathan and Lee 2013; Ozgen, Nijkamp and Poot 2013; Lee 2014; Maré, Fabling, and Stillman 2014; Nathan 2014).

My study also differs from previous literature by focusing on the effects of STEM *graduates* on innovation. Previous literature has focused on the effects of STEM *occupations*[9] rather than STEM *graduate*s, largely because measures of local stocks of STEM graduates have not been available until very recently. STEM graduates and STEM occupations are closely related, but there are differences. Some individuals who report working in a STEM occupation do not have a STEM degree and some have no college degree at all.[10] Similarly, many STEM graduates end up working in non-STEM occupations such as business, management, healthcare, and education. Furthermore, innovation is not always directly related to what one does at work. Many innovations come from persons developing them at home in their spare time; some of these inventors have day jobs that are not in STEM occupations and others may be unemployed or not in the labor force. While there are some differences between STEM occupations and STEM graduates, trying to separate the effects of the two is not the focus of the current study. Instead, I try to identify exogenous increases in the stocks of foreign and native STEM graduates and examine their effects on innovation.[11]

Measuring human capital based on college major allows me to examine the separate effects of STEM graduates and non-STEM graduates on innovation, which more closely aligns with public policies than does looking at occupations. Many researchers and policymakers advocate for increased STEM education based on the expectation that STEM graduates contribute greater benefits to society than non-STEM graduates (National Academies 2010; PCAST 2012). Consistent with that notion, Winters (2014a) examines the extent of human

[9] Researchers have also explored related occupational groupings such as science and engineering, technical, etc.
[10] This may in part result from ambiguous titles of occupations. For example, some workers may refer to themselves as engineers but have completed no higher education and perform duties such as operating machinery and equipment that might incline an outside observer to view them as a technician rather than an engineer.
[11] My study also differs from Hunt and Gauthier-Loiselle (2010) in the time period considered and the geographic unit of analysis.

capital wage externalities created by STEM and non-STEM graduates and finds that STEM graduates have a much larger positive external effect on the wages of non-college graduates in the same metropolitan area. Thus, the general expectation is that STEM graduates will have a greater effect on regional innovation, but it is unclear how different the effects will be. Previous researchers have been unable to offer empirical evidence on this issue because reliable estimates of geographic differences in the densities of STEM and non-STEM graduates across the U.S. have not been available until recently. To my knowledge, this is the first study to exploit newly collected information in the American Community Survey to assess the importance of STEM and non-STEM major college graduates on sub-national innovation.

Previewing the results, I find that both native and foreign-born STEM graduates have statistically significant and economically large effects on metropolitan area patent intensity, but college graduates in non-STEM fields have a smaller and statistically insignificant effect on regional patenting. This result holds for both cross-sectional OLS and two-stage least squares (2SLS) regressions. I also use time-differencing to estimate 2SLS effects of STEM-driven increases in native and foreign college graduate shares and again find that both native and foreign STEM graduates have large statistically significant effects on innovation. These results suggest that policies that increase the stocks of both native and foreign STEM graduates increase innovation and provide considerable economic benefits to regions and nations.

2. Empirical Methods

2.1 Data and Descriptive Methods

This paper examines the effects of foreign and native STEM graduates and non-STEM graduates on patent intensity in U.S. metropolitan areas. Patent intensity is measured as the log of patents per 100,000 population. Patent data are obtained from the U.S. Patent and Trademark Office, and population data are obtained from the U.S. Bureau of the Census.[12] Data on foreign and native STEM and non-STEM graduates come from the 2010 American Community Survey (ACS) accessed from IPUMS (Ruggles et al. 2010). The stock of foreign (native) STEM graduates in each metropolitan area is measured as the number of foreign-born (native) college graduates ages 25 and up with a bachelor's degree in a STEM field divided by the total adult (ages 25 and up) population. The stock of non-STEM graduates is computed as the number of adult college graduates with bachelor's degrees in non-STEM fields relative to the adult population.[13] The ACS began asking college graduates to report their major field of study for their bachelor's degree in 2009. Before 2009 reliable measures of local stocks of STEM and non-STEM graduates were not available. I define college majors as STEM fields based on definitions used by U.S. Immigration and Customs Enforcement (ICE); a full list of STEM majors and corresponding ACS codes is provided in Appendix Table A.

U.S. Census Bureau confidentiality restrictions prevent identification of geographic areas with less than 100,000 people. As a result, the lowest level of geography in the census microdata, PUMAs, often combine parts of metropolitan areas with parts of other nearby metropolitan areas or non-metropolitan areas. I assign a PUMA to a metropolitan area if the majority of the PUMA population is included in the metropolitan area; other PUMAs, including wholly non-metropolitan ones are excluded from the analysis. The 2010 ACS PUMAs are defined based on 1999 Census metropolitan boundaries, and I use the 1999 metro area

[12] The Patent and Trademark Office reports the origin location for each patent based on the residence of the first-named inventor.

[13] I do not differentiate between foreign and native non-STEM graduates for various reasons. First, foreigners make up a much smaller percentage of non-STEM graduates than STEM graduates. Second, STEM fields are expected to have a stronger effect on innovation, so I focus much of the attention on STEM graduates. Third, the instrumental variables methods used become increasingly complicated as the number of endogenous variables and required instruments increases and one becomes more concerned about problems with weak instruments.

boundaries to measure all of the variables included in this study. I can identify 325 metropolitan areas (out of 331) in the 2010 ACS, but the instrumental variables I use below are not available for 18 small metropolitan areas. I exclude these 18 from the OLS analysis to facilitate comparability with the 2SLS results, but including the additional 18 excluded metropolitan areas does not meaningfully affect the OLS estimates presented below. The analytical sample, therefore, includes 307 metropolitan areas.

Figures 1-4 illustrate the bivariate relationship between the four main human capital stock variables in this study and the log of patents per 100,000 population.[14] The four human capital variables are the shares of the adult population that are: 1) STEM graduates, 2) native STEM graduates, 3) foreign STEM graduates, and 4) non-STEM graduates. The second and third human capital variables sum to equal the first one. The figures illustrate a strong positive bivariate descriptive relationship between patent intensity and each of the four human capital variables. To better understand how different types of human capital contribute to innovation, I turn to multivariate regression and experiment with including multiple human capital stock variables simultaneously.

I begin by estimating cross-sectional OLS regressions that include a number of control variables. These include several time-varying metropolitan area characteristics measured as of 2010 including the log of the population, the unemployment rate, the mean age of the adult labor force, the average firm size, and university research expenditures per 100,000 population. I also include three census region dummies (with the Northeast being the omitted region), mean January temperature, mean July temperature, mean precipitation, and the incremental distance to the nearest metropolitan area with a population of at least 250,000, 500,000, and 1,500,000.

[14] Results in this study are robust to measuring patents per capita with a one-year lead, i.e., based on the calendar year one year after the year in which the explanatory variables are measured.

A large literature following Jaffe, Trajtenberg and Henderson (1993) has suggested that knowledge spillovers decline with distance. Larger metropolitan areas are likely to experience greater knowledge spillovers, so log population is included to account for the effects of city size on innovation (Carlino, Chatterjee, and Hunt 2007; Carlino and Kerr 2014). However, agglomeration economies might spill across the urban hierarchy as suggested by Partridge, Rickman, Ali and Olfert (2009, 2010), so also I control for proximity to progressively larger metropolitan areas similarly to Partridge et al. (2009, 2010). The region dummies are intended to account for broad differences in innovative activity across regions. The climate variables are intended to account for local amenities that might be especially attractive to highly skilled workers. The climate variables are measured based on the 2007 County and City Data Book; each metropolitan area is assigned the values of its principal municipality. The unemployment rate measures local labor market conditions and labor utilization, and the mean age of the workforce proxies for worker experience; both are computed using the 2010 ACS. Metropolitan areas with smaller average firm sizes are expected be more entrepreneurial and experience greater innovation and growth (Glaeser, Kerr, and Ponzetto 2010; Glaeser, Kerr, and Kerr 2012; Chatterji, Glaeser, and Kerr 2013). Average firm size is calculated from the Business Dynamics Statistics (BDS) Data Tables produced by the U.S. Census Bureau. University research is expected to increase local innovative activity (Jaffe 1989; Anselin, Varga, and Acs 1997; Adams 2002; Ponds, van Oort, and Frenken 2010; Kantor and Whalley 2014) and is also likely correlated with the primary human capital variables. Therefore, university research expenditures are obtained from the IPEDS and included as a control variable.

Summary statistics for the cross-sectional analysis variables are included in Table 1. A few things are particularly noteworthy. First, non-STEM graduates are generally a substantially larger share of the adult population than are STEM graduates; the mean share for the former is more than three times that of the latter. In fact, no metropolitan area in the U.S. has more STEM graduates than non-STEM graduates. Second, the mean share of native STEM graduates is more than four times the mean share of foreign STEM graduates, indicating that most metropolitan areas rely much more heavily on native STEM graduates than foreign ones despite the influx of foreign graduates in recent years. However, metropolitan areas do differ substantially in their concentration of STEM majors and in their relative dependence on foreign STEM majors. Table 2 reports the population shares for each of the four college graduate variables for the 25 metropolitan areas with the highest shares of STEM graduates. Not surprisingly, San Jose, CA tops the list with an impressive 21.6 percent of the adult population with a STEM degree. San Jose also has the highest foreign STEM graduate population share in the nation and has nearly twice as many foreign STEM graduates as native STEM graduates.[15] Boulder-Longmont, CO has the second highest total STEM graduate share and the highest native STEM graduate share. Furthermore, Boulder-Longmont has more than six times as many native STEM graduates as foreign ones. Table 1 also reports the minimum values for the human capital shares. Tables 1 and 2 together confirm that there is considerable variation in STEM and non-STEM graduate stocks and in relative dependence on domestic and foreign STEM graduates across the country.

Cross-sectional OLS estimates help understand the relationship between various types of human capital stocks and regional innovation, but they may not provide unbiased estimates of causal effects. For example, reverse causality may exist if STEM graduates sort into innovative areas, and omitted variable bias may exist if both innovation and STEM graduate stocks are driven by some unobservable characteristic even after the inclusion of the metropolitan area

[15] Empirical results below are qualitatively robust to excluding outliers such as San Jose.

control variables. Furthermore, the human capital variables are measured using a one percent sample of the population which will lead to some degree of measurement error due to sampling, especially for relatively small areas. Measurement error due to sampling will attenuate coefficients toward zero, and this attenuation bias is likely exacerbated by including multiple related measures and a detailed set of control variables that reduce the signal-to-noise ratio.

2.2 Cross-Sectional Instrumental Variables Methods

The preferred estimates in this study utilize instrumental variables to estimate 2SLS regressions. I identify the effects of foreign-born STEM graduates using an instrument similar to Hunt and Gauthier-Loiselle (2010) and Peri et al. (2014). More specifically, I compute the predicted share of foreign STEM workers in each metropolitan area based on metropolitan area immigrant STEM worker shares for various origin countries in 1980 and the U.S. national growth in the immigrant STEM workforce from those source countries between 1980 and 2010.

I first define a set of workers as STEM workers (more details below) and combine foreign origin countries into 14 groups.[16] I next use the 1980 decennial census 5% PUMS to compute the STEM worker share of each foreign nationality group, n, in each metropolitan area, c, relative to the total adult population of the metropolitan area in 1980,[17] i.e.,

$$STEMShare_{cn,1980} = \frac{\#of\ STEM\ Workers_{cn,1980}}{Total\ Adult\ Population_{c,1980}}\ .$$

I then combine the 1980 5% PUMS with the 2010 ACS to compute the national growth factor in the number of STEM workers from each origin group, i.e.,

[16] I follow Peri et al. (2014) and use the following 14 country groups: Canada, Mexico, Rest of Americas (excluding the U.S.), Western Europe, Eastern Europe, China, Japan, Korea, Philippines, India, Rest of Asia, Africa, Oceania, and Other.
[17] Census microdata geographic boundaries changed between 1980 and 2010, and I can only identify 307 metropolitan areas in 1980 as noted above.

$$GrowthFactor_{n,1980-2010} = \frac{\#of\ STEM\ Workers_{n,2010}}{\#of\ STEM\ Workers_{n,1980}}.$$

Finally, I compute the predicted share of foreign STEM workers in each metropolitan area in 2010 by multiplying the 1980 STEM share for each origin group in each metropolitan area by the national growth factor and adding up across origin groups for each metropolitan area, i.e.,

$$\widehat{STEMShare}_{c,2010}^{Foreign} = \sum_n [STEMShare_{cn,1980} \times GrowthFactor_{n,1980-2010}].$$

This approach computes the predicted foreign STEM worker share that each metropolitan area would experience in 2010 if its origin-specific foreign STEM workforce grew at the national average since 1980.[18] The motivation for this instrument is based on three stylized facts. First, the foreign STEM workforce has historically been disproportionately concentrated in certain areas relative to the native population. Second, there has been a large influx of skilled foreigners to the U.S. since 1980, much of which can be attributed to the H-1B visa program. Third, recently arriving foreigners tend to concentrate in areas that already have a relatively high share of foreigners from their country of origin.

I follow Peri et al. (2014) and choose 1980 as the base year for employment shares for several reasons. First, census microdata geographic identifiers prior to 1980 greatly reduce the number of identifiable metropolitan areas. Second, 1980 precedes the creation of the H-1B visa program, so that base-year STEM shares are not affected by inflows due to the H-1B visa program. Third, 1980 precedes the information and communications technology (ICT) revolution, so that base-year STEM shares primarily reflect initial worker concentrations in other STEM fields.

[18] This IV approach also holds metropolitan area population at its 1980 level, but multiplying the population for each metropolitan area by a common factor to account for national population growth does not affect the 2SLS second-stage results since the first-stage coefficient on the instrument will adjust accordingly. Using actual metropolitan area population growth in the instrument would create concerns that the population growth is endogenous.

There are some caveats about the foreign STEM share instrument. First, the potentially endogenous explanatory variable is the metropolitan area share of foreign STEM *graduates*, and the instrument is the predicted share of foreign STEM *workers*, which is based primarily on occupation. Occupation and college major are not perfectly collinear, but there is likely no better way to instrument for foreign STEM graduates. Fortunately, most workers in STEM occupations have college degrees in STEM fields, so STEM graduates and STEM workers are very closely related. Because I am ultimately intending to measure the effects of STEM graduates on innovation, all measures of STEM workers in this study are restricted to persons who have completed at least a bachelor's degree and are working in a STEM occupation.

A second major caveat is that there is no universally agreed upon definition of STEM occupations. Therefore, I experiment with three measures of STEM occupations for my instrument.[19] My first STEM occupation measure is the most restrictive; it only includes persons employed as engineers, mathematicians, computer scientists, software developers, and natural scientists. The second STEM occupation group includes those in the first group and adds health-diagnosing professionals (physicians, dentists, etc.) and pharmacists since these typically require an undergraduate degree in a STEM field. My third definition of STEM occupations is the most inclusive measure; it includes all occupations in the first two definitions and all other occupations where at least 25% of occupation members in the ACS possessed a bachelor's degree with a major in a STEM field. Examining the robustness to these three different measures should increase confidence in the results.

To identify the effects of native STEM graduates on innovation, I use predicted flows of domestic STEM graduates from U.S. colleges and universities to metropolitan areas based on the

[19] A full list of STEM occupations and corresponding IPUMS occupation codes are included in Appendix Table B.

1980 decennial census and the 1980 IPEDS. I begin by using the 1980 5% PUMS to compute migration flows from each county group origin area o to each of the 307 identifiable metropolitan areas c for native-born college graduates who were ages 23-27 and not enrolled in school at the time of the survey, $RecentGradFlow_{co,1980}$.[20] I treat place of residence five years prior as the place where they earned their bachelor's degree. The 1980 Census did not ask respondents about college major, so I merge the 1980 census flows with data from the IPEDS. Specifically, I use the 1980 IPEDS to compute the number of bachelor's degrees earned in STEM and non-STEM fields in each U.S. county. I then match IPEDS county level degree production to 1980 census county group origin areas. For each county group origin area, I compute the share of all 1980 bachelor's degree graduates who majored in a STEM field, $PCTSTEM_{o,1980}$. I then multiply $RecentGradFlow_{co,1980}$ by $PCTSTEM_{o,1980}$ to predict the number of recent graduates moving from o to c that are STEM graduates. I then sum the predicted STEM flows across origin areas for each metropolitan destination area to compute the predicted native STEM flow to each metropolitan area, i.e.,

$PredictedNativeSTEMFlow_{c,1980} = \sum_o [RecentGradFlow_{co,1980} \times PCTSTEM_{o,1980}]$.

I then divide $PredictedNativeSTEMFlow_{c,1980}$ by the metropolitan area adult population in 1980 to obtain the predicted relative native STEM flow in 1980, which is what I use to instrument for the stock of native STEM graduates in the area in 2010. I construct a similar

[20] County groups are the lowest level of identifiable geography in the 1980 census microdata. They are conceptually similar to PUMAs but the boundaries differ. My sample includes all county group origin areas including non-metropolitan ones, but only the 307 metropolitan areas as destination areas. College graduates in 1980 are defined as persons who report completing at least 4 years of college. This sample also excludes persons who did not reside in the U.S. five years prior to the census and by necessity excludes persons who are not in the migration sample. Only half of the PUMS members were included in the migration sample and asked about their residential location five years prior to the census.

instrument for non-STEM graduates by replacing $PCTSTEM_{o,1980}$ with $PCTNONSTEM_{o,1980}$, the share of all 1980 bachelor's degree graduates who majored in a non-STEM field.

The intuition behind the construction of the native STEM (non-STEM) graduate instrument is that the past flow of STEM (non-STEM) graduates is likely to affect the later stock of STEM (non-STEM) graduates in the area for several reasons.[21] First, some of the past in-migrants will likely still be in the same metropolitan area 30 years later. Second, many of the 1980 in-migrants will have adult children by 2010, and intergenerational transmission of education and college majors will likely further increase the STEM (non-STEM) stock in 2010. Third and perhaps most importantly, population flows tend to be highly persistent. The relative flow of STEM graduates in 1980 is likely highly correlated with the relative flow of STEM graduates in preceding and subsequent years. This persistence is largely driven by proximity to various colleges and universities and the different academic orientations of those institutions. If a given metropolitan area receives a large inflow of STEM (non-STEM) graduates from a nearby college or university or set of higher education institutions that produce a high percentage of STEM (non-STEM) graduates, this will likely be quite persistent.

There are additional considerations in constructing the native STEM and non-STEM instruments worth noting. First, as noted above, census PUMS before 1980 identify far fewer metropolitan areas. Additionally, the 1980 IPEDS is the earliest available source that reports degree production by fields for all colleges and universities in the U.S. Also as noted above, 1980 precedes the ICT revolution, so that the native STEM graduate instrument primarily reflects initial concentrations in other STEM fields.

[21] Previous researchers have investigated a related issue concerning the relationship between the production and stock of college graduates in an area (Bound et al. 2004; Abel and Deitz 2012; Winters 2014b). The relationship likely depends on the level of analysis (states vs. metropolitan areas) and the time period considered, but researchers typically find at least a modest positive correlation between the production and stock of college graduates in an area.

2.3 Time-Differenced Instrumental Variables Methods

There is some concern that the cross-sectional IV estimates might not accurately represent causal effects. In particular, the instruments could be correlated with unobserved time-invariant metropolitan area characteristics that also increase innovation. To address this concern, I next estimate time-differenced 2SLS regressions that account for time-invariant metropolitan area fixed effects. However, there are difficulties with doing so because I am unable to measure metropolitan area stocks of STEM and non-STEM graduates before 2009 when the ACS began asking about college major.

One possible approach would be to utilize short-run variation in the local stocks of STEM and non-STEM graduates between 2009 and 2012 (the most recent year of the ACS available at the time this paper was written). However, I choose not to follow that approach because short run fluctuations in STEM and non-STEM graduate stocks are highly affected by measurement error due to sampling. Each year of the ACS includes only a 1% sample of the U.S. population, so there is some degree of sampling error. Measurement error from sampling is exacerbated by time differencing, especially over very short periods.[22] This is especially problematic for relatively small metropolitan areas. Measurement error causes attenuation bias in OLS estimates and weakens the relationship between the endogenous explanatory variable(s) and the instrument(s) in 2SLS estimates. Thus, short-run time differenced estimates are not credible if measurement error is significant.[23]

[22] A further problem is that PUMA boundaries were changed between 2011 and 2012, which further increases measurement error problems. Of course, one could limit the sample to the 2009-2011 ACS, but that is an even shorter time period.

[23] An additional problem with using short-run differences is that innovations may respond to changes in the stocks of skilled workers with a non-trivial time lag. Once a new skilled worker joins the labor force of a given metropolitan area, it could be a year or more before their efforts results in patentable innovations. Therefore, skilled

This paper uses 10-year time differences by combining the 2010 ACS microdata with the 2000 decennial census 5% PUMS. Unfortunately, college major information is not available in the 2000 census data. Therefore, I cannot use the 2000-2010 time-differenced regressions to directly estimate separate effects of STEM and non-STEM graduates. However, I can use the time-differenced regressions to assess the contributions of STEM-driven increases in foreign and native college graduates on innovation. More specifically, I can indirectly identify the effects of foreign and native STEM graduates by using STEM-motivated instruments and making assumptions about the effects of the instruments on non-STEM graduates. I use similar instruments as in the cross-section analysis. I instrument for the change in the share of foreign-born college graduates using the 2000-2010 predicted change in the foreign STEM worker share:

$$\Delta STEM\widehat{Share}_{c,2000-2010}^{Foreign} = STEM\widehat{Share}_{c,2010}^{Foreign} - STEM\widehat{Share}_{c,2000}^{Foreign}$$

, where $STEM\widehat{Share}_{c,2010}^{Foreign}$ is the cross-sectional instrument defined above and $STEM\widehat{Share}_{c,2000}^{Foreign}$ is constructed similarly for 2000. Using the instrument and interpreting the results as I do assumes that the instrument captures increases in the population share of foreign STEM graduates and is uncorrelated with the time-difference in foreign non-STEM graduates.

I instrument for the change in the share of native-born college graduates using a STEM-motivated instrument in an attempt to estimate the effects of STEM-driven increases in the share of native college graduates on patent intensity. The instrument used is the predicted relative native STEM flow in 1980, which is the same as the instrument used for native STEM graduates in the cross-sectional 2SLS analysis. As explained in more detail later, using the instrument and interpreting the results as I do assumes that the instrument predicts increases in the population

worker increases in one year may affect patenting primarily over the next year or two, which would cause serious problems for short-run time differenced estimates.

share of native STEM graduates but is uncorrelated with changes in the population share of non-STEM graduates. In other words, the analysis assumes that the instrument captures variation in the 2000-2010 change in the native college share that is attributable to STEM graduates and does not capture variation due to increases in non-STEM graduates.

3. Empirical Results

3.1 Cross-Sectional OLS Estimates

Table 3 presents cross-sectional regression results that treat the human capital stock variables as exogenous. The various columns include different combinations of the human capital variables, but all regressions include the full set of control variables listed in Table 1. The first column includes the STEM graduate population share; OLS regression yields a coefficient estimate of 24.40 that is highly statistically significant. The coefficient suggests that increasing the share of the adult population with a STEM degree by one percentage point (i.e., increasing the share by 0.01) would increase log patents per 100,000 population by about 0.244. Since the dependent variable is measured in logs, we can interpret this result as a roughly 24.4 percent increase in patent intensity due to a one percentage point increase in the STEM graduate share. Multiplying the coefficient by the variable standard deviation of 0.029, suggests that a one standard deviation increase in the STEM graduate share would increase patent intensity by just over 70 percent. This is a very considerable magnitude and suggests a very important effect of STEM graduates on innovation as measured by patent intensity. However, assessing the validity of this effect requires further analysis

Column 2 of Table 3 simultaneously includes the STEM graduate population share and the non-STEM graduate population share as explanatory variables. The coefficient for the

STEM graduate share is reduced to 22.11, but the difference from column 1 is not statistically significant. The coefficient estimate for the non-STEM graduate share is 1.797 but is not statistically significant at conventional levels. Thus, though STEM graduates appear to have a considerable effect on innovation, non-STEM graduates do not appear to meaningfully affect patenting intensity. Expectations suggested that STEM graduates would have a greater effect on innovation than non-STEM graduates, but the disparity in the effects is striking. This is a new result that supports policy efforts to increase regional and national stocks of STEM graduates.

I next decompose the STEM graduate share into the native-born and foreign-born components in an attempt to assess their relative contributions to patenting. Columns 3 and 4 separately examine the effects of the native and foreign STEM graduate shares without including any other human capital variables. Column 5 includes the native and foreign STEM graduate shares simultaneously, and column 6 adds the non-STEM graduate share to the specification in column 5. Column 3 reports a coefficient of 30.34 for the native STEM graduate share and column 4 reports a coefficient of 24.80 for the foreign STEM graduate share. However, including the native and foreign STEM graduate share variables simultaneously in column 5 gives coefficient estimates of 28.00 and 18.51, respectively. The reduction from columns 3 and 4 likely suggests that each variable is picking up some of the effect of the other variable when the other is omitted from the regression. Adding the non-STEM graduate share in column 6 again indicates a relatively small and insignificant effect of non-STEM graduates on patenting. Column 6 reports coefficients for the native and foreign STEM graduate shares of 25.69 and 17.33, respectively. Taking these estimates at face value suggests that native STEM graduates have a larger effect on metropolitan area patenting than foreign STEM graduates. Furthermore, the differences in coefficients in columns 5 and 6 are statistically significant at the five percent and 10 percent level, respectively. However, the more important result is likely not the differences between native and foreign STEM graduates, but the indication that both have statistically significant effects on patenting that are large in magnitude.

3.2 Cross-Sectional IV Estimates

Table 4 presents the main results for the cross-sectional 2SLS regressions.[24] First-stage results are included in panel A and second-stage results for the explanatory variables of interest are in panel B. All models again include the control variables listed in Table 1. Column 1 includes the native STEM graduate share as a potentially endogenous explanatory variable and instruments for it with the predicted native STEM graduate relative flow in 1980. The instrument is highly significant in the first stage and the F-statistic greatly exceeds 10, which indicates that weak instrument concerns are very minimal (Stock, Wright and Yogo 2002; Angrist and Pischke 2009). The second-stage regression yields a statistically significant coefficient for the native STEM graduate share of 37.72, which is actually larger than the corresponding OLS estimate in column 3 of Table 3, though the difference is not significant.

Column 2 of Table 4 modifies the specification in column 1 to also include the non-STEM graduate share as a potentially endogenous explanatory variable and adds the predicted relative flow of non-STEM graduates in 1980 as an instrument. The predicted STEM relative flow instrument again has a strong effect on the native STEM graduate share in the first stage, and the predicted non-STEM relative flow instrument also has a strong effect on the non-STEM

[24] In results not shown, I also experimented with instrumenting for the STEM graduate share using the landgrant dummy variable used by Moretti (2004) and others. Doing so yielded a second-stage coefficient for the STEM graduate share of 19.85, which is qualitatively similar and not statistically significantly different from the corresponding estimate in column 1 of Table 3. However, the first-stage F-statistic was only 5.48 which does not reject the possibility that the landgrant dummy is a weak instrument. Furthermore, landgrant institutions appear to increase the stock of both STEM and non-STEM graduates and having only one instrument does not allow me to separate the effects of the two.

graduate share in the first stage. In the second stage, the native STEM graduate share has a significant coefficient estimate of 31.87, which is smaller than in column 1 but the difference is not significant. The second-stage coefficient for non-STEM graduates is 2.47 and not statistically significant. These results are, therefore, qualitatively consistent with the finding from OLS regression that STEM graduates have a large significant effect on patent intensity but non-STEM graduates have a relatively small effect that is statistically indistinguishable from zero.

Column 3 of Table 4 includes the foreign STEM graduate share as the only human capital variable and instruments for it using the predicted foreign STEM occupation share definition 1 (D1). The instrument is highly significant in the first stage, and the foreign STEM graduate share has a significant positive effect on patent intensity in the second stage with a coefficient of 42.28. This coefficient is a bit larger than that for the native STEM graduate share but the difference is not statistically significant.

Column 4 of Table 4 includes the native and foreign STEM graduate shares simultaneously and instruments for them using the predicted relative native STEM flow in 1980 and the predicted foreign STEM occupation share D1. Interestingly, both instruments have a significant positive effect on native STEM graduates in the first stage. The positive effect of the native STEM instrument on native STEM graduates was to be expected, but the positive effect of predicted foreign STEM workers on the native STEM graduate share suggests that areas with high levels of foreign STEM workers also have high levels of native STEM graduates. This suggests that cross-sectional analysis should likely simultaneously account for both native and foreign STEM graduates when examining their effects on regional innovation. Additionally, the predicted foreign STEM instrument has a significant effect on the share of foreign STEM graduates as expected, while the native STEM instrument has a negative but insignificant effect on the share of foreign STEM graduates. First stage F-statistics are both greater than 10. The second-stage results in column 4 suggest that both native STEM graduates and foreign STEM graduates have significant positive effects on patent intensity with coefficients of 34.29 and 28.54, respectively, and the difference is not statistically significant.

Column 5 of Table 4 includes the shares of native and foreign STEM and non-STEM graduates simultaneously and instruments for these using the three variables used previously. Results are largely similar to before. Native and foreign STEM graduates have significant positive effects on patent intensity with coefficients of 30.96 and 28.42, respectively, and non-STEM graduates have a relatively small and statistically insignificant effect on patent intensity with a coefficient estimate of 1.41. These results suggest that both native and foreign STEM graduates considerably increase local innovation but non-STEM graduates have a minimal effect.

Table 5 replicates columns 3-5 of Table 4 using alternative STEM occupational definitions for the foreign STEM instrument. Columns 1-3 of Table 5 use the predicted foreign STEM occupation share definition 2 (D2); columns 4-6 use the predicted foreign STEM occupation share definition 3 (D3). The results are largely similar to those in Table 4, but the coefficient magnitudes change somewhat. Specifically, the coefficient on the foreign STEM graduate share with the native STEM and non-STEM graduate variables included is now “only” 23.09 in column 3 using the D2 instrument and 19.83 in column 6 using the D3 instrument. These coefficients are now a good bit smaller than the native STEM graduate coefficients but the differences are not significant. Rather than debating the merits of the three foreign STEM instruments, I instead focus on the qualitative consistency of the results. Even the most modest coefficient still indicates an economically large effect of foreign STEM graduates on patent intensity. Furthermore, though the coefficients using the alternative foreign STEM instruments are a good bit smaller than the native STEM graduate coefficients, the differences are not statistically significant. Echoing the discussion of the OLS results, the key finding from the cross-section IV results is likely not the differences between native and foreign STEM graduates, but the indication that both have economically large and statistically significant effects on patenting.

3.3 Time-Differenced IV Estimates

I next consider 2000-2010 time-differenced 2SLS regressions. Because time-differencing removes time-invariant metropolitan area characteristics, region dummies are excluded as are the variables for climate (which can vary over time but are measured as averages over time and hence time-invariant) and distance to the urban hierarchy (which is largely time-invariant and only changes due to a nearby area crossing a given threshold).[25] Summary statistics for the variables in the time-differenced regressions are reported in Table 6.

As discussed above, college major information is not available in the 2000 census data, so the explanatory variables of interest are the changes in the population shares of native and foreign college graduates, without differentiating between STEM and non-STEM. However, I can indirectly identify the effects of foreign and native STEM graduates by using the STEM-motivated instruments and assuming that the instruments are correlated with the growth in the college graduate share attributable to STEM graduates and uncorrelated with the growth in the college graduate share due to non-STEM graduates. I am unable to test this assumption, but it

[25] As a practical matter, one can include the excluded time-invariant characteristics in the time-differenced regressions. Doing so weakens the explanatory power of the instruments but gives qualitatively similar second-stage results. Results are available from the author by request.

seems plausible based on the construction of the instruments. However, if this assumption does not hold, non-STEM graduates will affect second-stage results and the direction of the effect depends on 1) the partial correlation between the instrument and the change in the share of non-STEM graduates and 2) the effect of non-STEM graduates on patent intensity. The cross-section results suggest that non-STEM graduates have a zero to small effect on patent intensity. If we also assume that any partial correlation between the instrument and the change in the share of non-STEM graduates is non-negative, which seems likely[26], then any effect of non-STEM graduates on the time-differenced regression estimates would likely be to reduce the estimated coefficient on the change in the share of college graduates relative to the true effect that would result solely from an increase in the share of STEM graduates. However, one should likely use some care in interpreting the time-differenced regression results.

Column 1 of Table 7 reports time-differenced 2SLS estimates for the effect of a STEM-driven increase in native college graduates on patent intensity. The instrument has a strong positive effect on the change in the native college graduate share in the first stage with an F-statistic greater than 10. The second-stage results suggest that a STEM-driven one percentage point increase in the share of native college graduates in an area increases patents per capita by 33.2 percent. This is an economically large effect that is qualitatively similar to the cross-sectional IV estimates.

Column 2 of Table 7 reports time-differenced 2SLS results for the effects of foreign college graduates on patent intensity. The instrument is a strong predictor in the first stage. The second-stage results suggest that a STEM-driven one percentage point increase in the share of

[26]Cross-sectional comparisons suggest that areas with a high share of STEM graduates also have a high share of non-STEM graduates, but I am unable to empirically assess the relationship between the time-changes in the shares of STEM and non-STEM graduates.

foreign college graduates in an area increases patents per capita by 17.4 percent. This effect is a good bit smaller than the effect of natives in column 1 but the differences are not statistically significant. Additionally, this estimate for the effects of skilled foreigners on patent intensity is also within the range of estimates reported by Hunt and Gauthier-Loiselle (2010), despite the differences in variable measures, time period considered, and econometric specification.

Column 3 of Table 7 includes the increase in native and foreign college graduates simultaneously. Both instruments are statistically significant and F-statistics exceed 10 for both first stage regressions. The first-stage results also provide interesting insights on how exogenous inflows of native and foreign STEM graduates affect the net flow of the other. The first-stage regression for the change in native graduates suggests that past native inflows have a positive effect on native inflows but predicted inflows of foreign STEM workers actually reduces native inflows, i.e. inflows of foreign STEM graduates appear to be crowding out native STEM graduates from metropolitan areas. Furthermore, crowd out is a two-way street. The first-stage change in foreign graduates is positively affected by predicted inflows of foreign STEM but is negatively affected by past inflows of native STEM graduates. These crowd out effects are also quite large in magnitude. Finding evidence of crowd out is interesting in itself and fairly novel in the literature.[27] Furthermore, there has been very little investigation of whether natives crowd out foreigners from local labor markets.

The second-stage results for column 3 of Table 7 again suggest that STEM-driven increases in both native and foreign college graduate shares increase innovation. The coefficient

[27]A notable exception for STEM graduates is Orrenius and Zavodny (2014) who find that foreign inflows crowd out native college students from majoring in STEM fields, but they suggest that the magnitudes are relatively small. More generally, Kerr and Lincoln (2010) and Peri et al. (2014) find no evidence that skilled foreigners crowd out employment of skilled natives. Lewis and Peri (2014) conclude that the bulk of previous literature examining the effects of foreigners on the location decisions of natives has found little evidence of crowd out though there are some exceptions noted above.

for natives is reduced slightly from column 1 to 31.3. However, the coefficient for foreign graduates increases from column 2 to 29.1 and is therefore much closer to the native coefficient.

Interpreting these results requires some care. If policymakers are considering policy changes to increase/decrease the stock of foreign graduates in a given local labor market, we are likely more interested in the local total effect rather than the local partial effect. If foreign (STEM) graduates crowd out native (STEM) graduates from local labor markets, then controlling for the change in native (STEM) graduates will give a partial effect and not the total effect. The same is true for interpreting the effects of native graduates on innovation. In such a case, the estimates in columns 1 and 2 are the primary ones of interest. However, interpreting the results at a national level requires understanding what happens to the group that is crowded out. If foreign STEM graduates crowd native STEM graduates out of one local labor market and into another, the crowded out natives will likely increase innovation in the areas in which they are pushed into. If so, the total effects of increased foreign graduates at the national level will exceed the effects at the local level; thus, the estimated effects of STEM-driven increases in foreign graduates in column 2 are likely a lower bound of national level effects.[28] If crowded out natives are just as innovative in their new locations, then the foreign coefficient in column 3 likely gives a reasonable estimate of the national-level effect of foreign STEM graduates on patent intensity.[29] A similar interpretation holds for natives crowding out foreigners except that natives may crowd foreign graduates out of the country, which would reduce the effect on

[28] Global effects, however, might be smaller if foreigners would have created innovations in their origin countries had they located there. Of course, there is good reason to believe that moving to an innovative country like the U.S. would make a skilled foreigner more innovative than they would be in a less innovative origin country if they are combined with more and better resources useful for innovation (Kahn and MacGarvie 2014). In particular, concentrating (foreign and native) STEM graduates in U.S. metropolitan areas increases a skilled immigrants interactions with other skilled workers and is expected to create agglomeration economies such as learning, knowledge spillovers and cross-fertilization of ideas.

[29] However, the Orrenius and Zavodny (2014) finding that foreigners crowd out natives from STEM college majors would reduce national effects.

innovation at the national level. The estimated effect of native graduates in column 3 is actually slightly lower than in column 1 and may provide a reasonable lower bound for the national level effects of native STEM graduates on patent intensity.[30]

Table 8 reports time-differenced 2SLS results that use the alternative definitions of STEM occupations for the foreign STEM instruments. Columns 1-2 of Table 8 use the foreign STEM definition 2 (D2) instrument, and columns 3-4 of Table 8 use the foreign STEM definition 3 (D3) instrument. These results are qualitatively similar to the baseline results in Table 7. All instruments are significant in all first-stage regressions and the first-stage results suggest that predicted foreign graduate inflows crowd out native graduates and past native graduate inflows crowd out foreign graduates. The foreign and native college graduate shares are significantly positive in all second-stage regressions in which they are included. The results in columns 1 and 3 that do not partial out the effect of the change in native graduates give coefficients of 16.9 and 19.8 for the change in foreign graduates. These are similar in magnitude to the corresponding estimate of 17.4 in Table 7. The foreign STEM graduate coefficients increase to 24.0 and 25.9 in columns 2 and 4, respectively, when the change in the share of natives is controlled for. The coefficients for native graduates in Table 8 are very similar to that in column 3 of Table 7.

Overall, the time-differenced IV estimates suggest that STEM-driven increases in both native and foreign STEM graduates have statistically significant and economically large effects on innovation as measured by patent intensity. These results are qualitatively consistent with the cross-sectional 2SLS results, which increases confidence in the general conclusions of the analyses.

[30] Another important benefit of estimating effects of native and foreign graduates simultaneously in column 3 is to ensure that the variables are not capturing the same underlying source of variation. The fact that both instruments are highly significant in the first-stage regressions and both college share variables are highly significant in the second-stage rules out this concern.

4. Conclusion

Technological innovation is widely regarded as a key driver of economic growth both for nations and regions, and human capital is thought to play an important role in fueling innovation. However, some types of human capital may have greater effects on innovation than others. In particular, STEM graduates are typically expected to have greater effects on innovation than non-STEM graduates, but there is relatively little empirical evidence to support this contention. A few researchers and policymakers have also suggested that foreign and native college graduates may have differing effects on innovation. This paper examines differences in patent intensity across U.S. metropolitan areas to assess the importance of different types of human capital on innovation.

Using cross-sectional OLS and cross-sectional 2SLS regressions, I find that both native and foreign-born STEM graduates have statistically significant and economically large effects on innovation as measured by patent intensity. However, the results suggest that non-STEM graduates have little to no effect on patent intensity. Cross-sectional results also suggest a possibly larger effect on innovation from native STEM graduates than foreign STEM graduates but the differences for the 2SLS estimates are not statistically significant.

I also use time-differenced 2SLS regressions to examine the effects of STEM-driven increases in the stocks of native and foreign college graduates. Time-differencing controls for area fixed effects that might be correlated with both skill levels and innovation. The results again suggest that both native and foreign STEM graduates have statistically significant and economically large effects on innovation. The estimates are again somewhat larger for native

STEM graduates than their foreign counterparts but the differences are not statistically significant.

I also find evidence that native and foreign STEM graduates crowd each other out of local labor markets, so the correct interpretation of the results depends on whether one is interested in local or national effects. Using local estimates to infer lower bounds for national effects suggests that a one percentage point increase in the percentage of the nation's population that is a native STEM graduate would increase patenting by 31 percent or more. Similarly, a one percentage point increase in the population share of foreign STEM graduates would increase patenting per capita by 17 percent at the local level and perhaps as much as 29 percent at the national level. Rather than focusing on differences in the effects of native and foreign STEM graduates, I interpret the results to indicate that both have statistically significant and economically large effects on innovation.

Given the importance of technological innovation for economic growth and overall well-being, the results in this study suggest that policies that increase the stock of STEM graduates can provide considerable economic benefits for nations and regions. Increasing the stock of foreign STEM graduates can be achieved at the national level by reducing residence and work restrictions for skilled foreigners, e.g., by "stapling green cards to diplomas" for foreigners earning U.S. graduate degrees in STEM fields. Regions and nations can also benefit from recruiting skilled foreigners to the area and making the area more welcoming and inviting to foreigners. This may also involve expanding graduate programs at local universities and increasing linkages between local industries and local universities to help foreign graduates find suitable jobs locally.

Numerous policies and practices have the potential to affect the production of native STEM graduates. Of course, not everyone should be a STEM graduate. There are numerous individual and societal benefits to producing college graduates in non-STEM fields despite the minimal effects on patenting found in this paper. However, moderate increases in the production of native STEM graduates are likely to be socially beneficial, especially to the extent that there are already additional students interested in pursuing STEM fields. In fact, large numbers of American undergraduates initially declare majors in STEM fields but eventually switch to other majors primarily because of inadequate preparation in math and science prior to college enrollment (Griffith 2010; Arcidiacono, Aucejo and Spenner 2012; Arcidiacono, Aucejo and Hotz 2013; Stinebrickner and Stinebrickner 2014). Thus, increasing production of native STEM graduates likely involves improved K-12 preparation in math and science.

Improving K-12 math and science education is a considerable task with societal implications even beyond the effects on regional and national innovation levels. Unfortunately, there is little consensus on how to best improve K-12 education; more research and experimentation is needed. However, recent research suggests that some practices have considerable potential to improve school effectiveness. In particular, Dobbie and Fryer (2013) find that practices such as high expectations, increased instructional time, high-dosage tutoring, frequent teacher feedback, and using data to guide instruction explain a considerable amount of variation in school effectiveness. If better policies and practices can improve K-12 math and science education, they have the potential to considerably increase the production of native STEM graduates and the resultant benefits to society. In particular, the current study suggests that increasing the production of native STEM graduates would substantially increase technological innovation.

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Figure 1: Bivariate Relationship between Patent Intensity and STEM Graduate Share for 2010

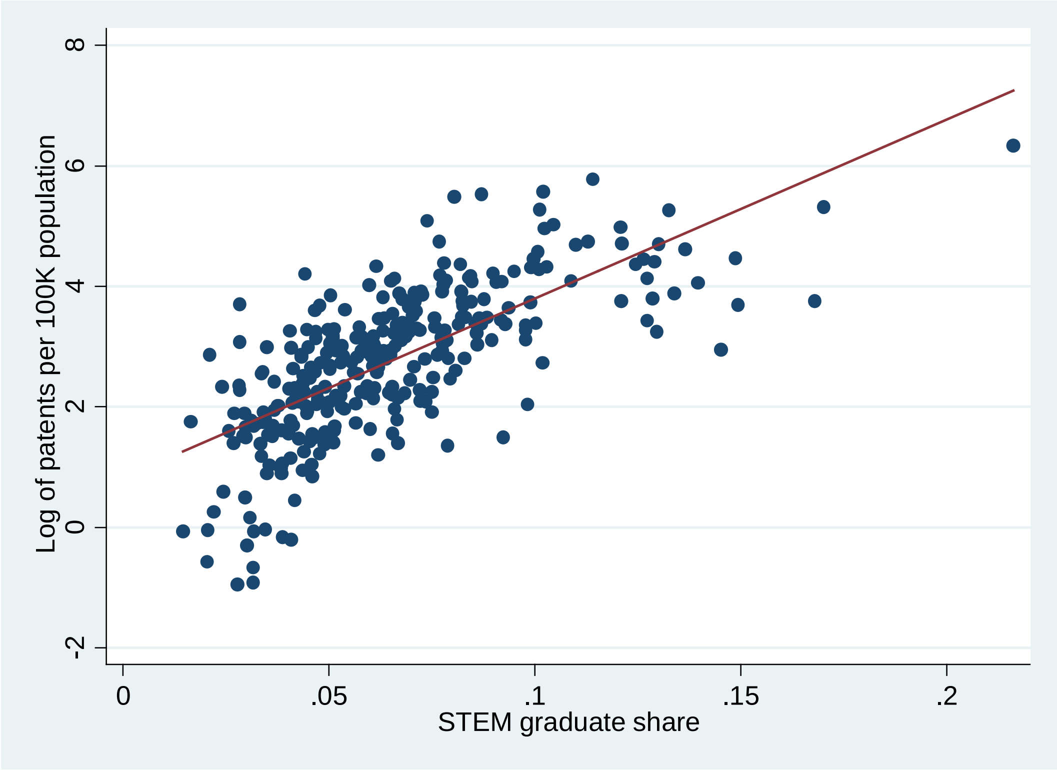

Figure 2: Bivariate Relationship between Patent Intensity and Non-STEM Graduate Share for 2010

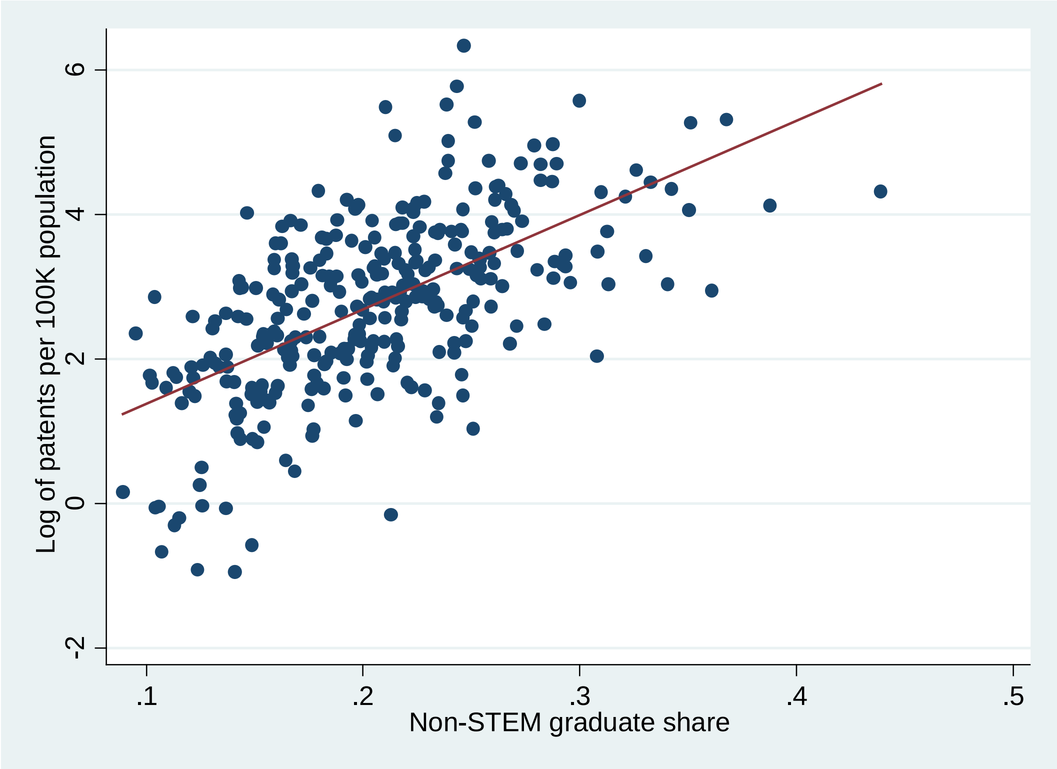

Figure 3: Bivariate Relationship between Patent Intensity and Native STEM Graduate Share for 2010

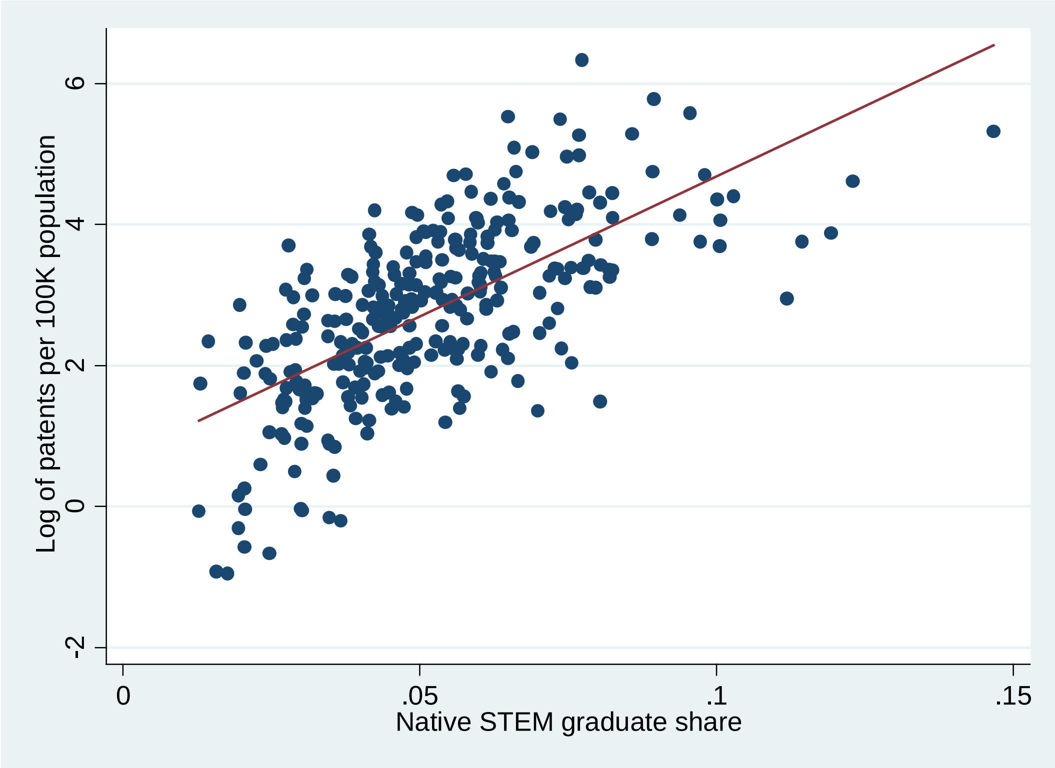

Figure 4: Bivariate Relationship between Patent Intensity and Foreign STEM Graduate Share for 2010

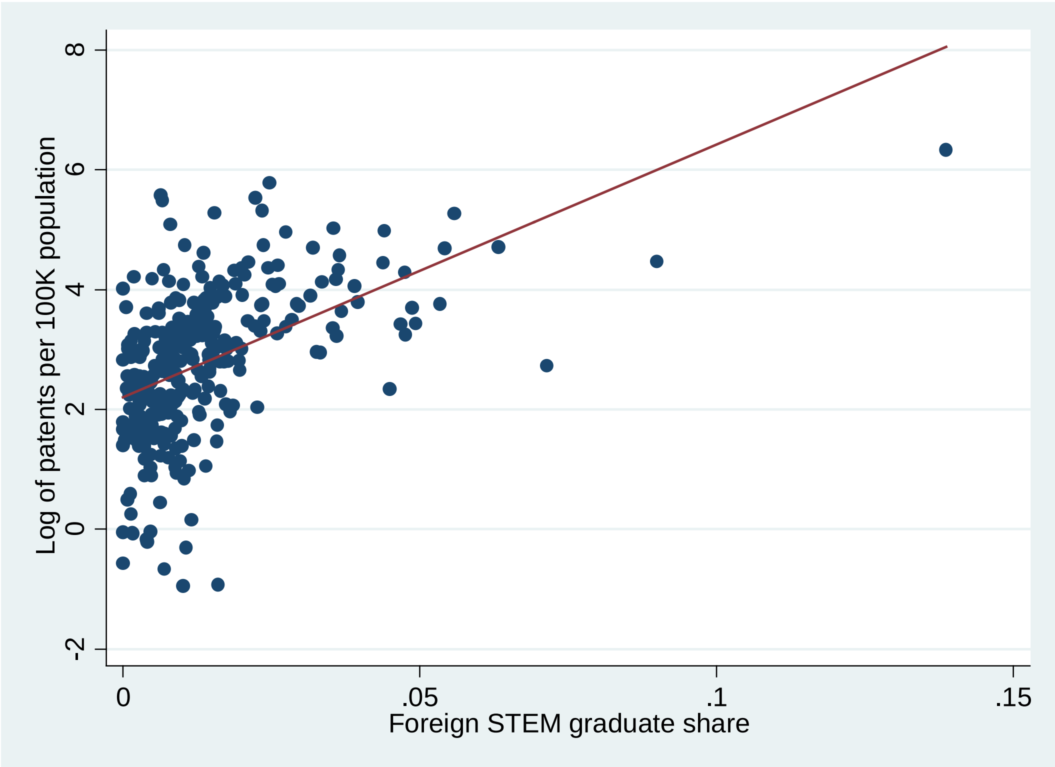

Table 1: Summary Statistics for 2010 Cross-Section Analysis

	Mean	Std. Dev.	Min	Max
Dependent variable				
Log of patents per 100K population	2.765	1.235	-0.949	6.335
Explanatory variables of interest				
STEM graduate population share	0.065	0.029	0.015	0.216
Native STEM graduate share	0.052	0.021	0.013	0.147
Foreign STEM graduate share	0.013	0.015	0.000	0.139
Non-STEM graduate share	0.206	0.058	0.089	0.439
Instruments				
Predicted native STEM graduate relative flow 1980	0.002	0.001	0.000	0.007
Predicted native non-STEM graduate relative flow 1980	0.009	0.004	0.001	0.023
Predicted foreign STEM occupation share D1	0.007	0.009	0.000	0.084
Predicted foreign STEM occupation share D2	0.009	0.009	0.000	0.071
Predicted foreign STEM occupation share D3	0.013	0.012	0.000	0.077
Control variables				
Midwest region dummy	0.244	0.430	0	1
South region dummy	0.381	0.486	0	1
West region dummy	0.192	0.395	0	1
Unemployment rate	0.088	0.025	0.023	0.171
Mean age of adult labor force	44.6	1.1	40.9	47.8
Log metropolitan area population	13.0	1.0	11.3	16.1
Mean January temperature	35.7	13.0	6.8	73.0
Mean July temperature	76.3	5.6	58.4	94.1
Mean precipitation	38.3	13.8	3.0	66.3
Distance to metro w/ pop>250K	25.7	45.7	0.0	384.6
Incremental distance to metro w/ pop>500K	28.8	90.8	0.0	1430.7
Incremental distance to metro w/ pop>1500K	52.1	151.8	0.0	2394.4
Mean firm size (# of Employees)	4618.3	1266.2	2553.4	13935.1
University research expenditure per capita	199.9	504.2	0.0	4750.6

Note: Sample includes 307 metropolitan areas.

Table 2: College Graduate Shares for the Top 25 STEM Graduate Share Metropolitan Areas

MSA/PMSA Name	STEM graduate population share	Native STEM graduate share	Foreign STEM graduate share	Non-STEM graduate share
San Jose, CA PMSA	0.216	0.077	0.139	0.246
Boulder-Longmont, CO PMSA	0.170	0.147	0.024	0.368
State College, PA MSA	0.168	0.114	0.053	0.246
Yolo, CA PMSA	0.149	0.101	0.049	0.223
Middlesex-Somerset-Hunterdon, NJ PMSA	0.149	0.059	0.090	0.282
Columbia, MO MSA	0.145	0.112	0.033	0.361
Champaign-Urbana, IL MSA	0.140	0.101	0.039	0.270
Fort Collins-Loveland, CO MSA	0.137	0.123	0.014	0.326
Huntsville, AL MSA	0.134	0.119	0.015	0.218
San Francisco, CA PMSA	0.133	0.077	0.056	0.351
Raleigh-Durham-Chapel Hill, NC MSA	0.130	0.098	0.032	0.289
Bryan-College Station, TX MSA	0.130	0.082	0.048	0.243
Nashua, NH PMSA	0.129	0.103	0.026	0.263
Gainesville, FL MSA	0.129	0.089	0.040	0.267
Iowa City, IA MSA	0.127	0.094	0.033	0.388
Washington, DC-MD-VA-WV PMSA	0.127	0.080	0.047	0.331
Boston, MA-NH PMSA	0.126	0.082	0.044	0.333
Madison, WI MSA	0.125	0.100	0.024	0.342
Oakland, CA PMSA	0.121	0.058	0.063	0.273
Charlottesville, VA MSA	0.121	0.097	0.024	0.313
Seattle-Bellevue-Everett, WA PMSA	0.121	0.077	0.044	0.288
Rochester, MN MSA	0.114	0.089	0.025	0.243
Ann Arbor, MI PMSA	0.113	0.089	0.024	0.258
Trenton, NJ PMSA	0.110	0.056	0.054	0.282
Lafayette, IN MSA	0.109	0.083	0.026	0.197

Table 3: Cross-Sectional OLS Results

	(1)	(2)	(3)	(4)	(5)	(6)
STEM graduate population share	24.400	22.110				
	(2.223)***	(2.283)***				
Native STEM graduate share			30.344		28.003	25.694
			(3.218)***		(3.220)***	(3.335)***
Foreign STEM graduate share				24.802	18.514	17.330
				(3.916)***	(2.948)***	(3.022)***
Non-STEM graduate share		1.797				1.476
		(1.137)				(1.135)

Notes: Dependent variable is the log of patents per 100K population. All regressions include control variables listed in Table 1. Standard errors in parentheses are robust to heteroskedasticity.
***Statistically significantly different from zero at 1% level.

Table 4: Cross-Sectional 2SLS Results

	(1)	(2)	(3)	(4)	(5)
A. First-Stage Results					
Endogenous Variable: Native STEM graduate share					
Predicted native STEM graduate relative flow 1980	10.296	11.276		9.886	10.946
	(1.159)***	(1.944)***		(1.126)***	(1.879)***
Predicted foreign STEM occupation share D1				0.182	0.185
				(0.084)**	(0.085)**
Predicted native non-STEM graduate relative flow 1980		-0.312			-0.339
		(0.451)			(0.447)
F-statistic	78.94	39.60		40.64	27.31
Endogenous Variable: Foreign STEM graduate share					
Predicted native STEM graduate relative flow 1980				-1.002	-1.612
				(0.763)	(1.064)
Predicted foreign STEM occupation share D1			0.975	0.996	0.995
			(0.189)***	(0.192)***	(0.193)***
Predicted native non-STEM graduate relative flow 1980					0.195
					(0.288)
F-statistic			26.53	14.35	9.58
Endogenous Variable: Non-STEM graduate share					
Predicted native STEM graduate relative flow 1980		-5.233			-6.030
		(5.659)			(5.784)
Predicted foreign STEM occupation share D1					0.445
					(0.371)
Predicted native non-STEM graduate relative flow 1980		9.406			9.340
		(1.356)***			(1.352)***
F-statistic		58.24			40.29
B. Second-Stage Results					
Native STEM graduate share	37.721	31.870		34.286	30.959
	(6.384)***	(8.454)***		(6.477)***	(8.087)***
Foreign STEM graduate share			42.280	28.540	28.421
			(11.763)***	(7.494)***	(7.358)***
Non-STEM graduate share		2.474			1.413
		(2.840)			(2.812)

Notes: The second-stage dependent variable is the log of patents per 100K population. All regressions include control variables listed in Table 1. Standard errors in parentheses are robust to heteroskedasticity.

*Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table 5: Cross-Sectional 2SLS Results Using Alternative Instruments for Foreign STEM

	(1)	(2)	(3)	(4)	(5)	(6)
A. First-Stage Results						
Endogenous Variable: Native STEM graduate share						
Predicted native STEM graduate relative flow 1980		10.006	11.189		9.969	11.022
		(1.150)***	(1.908)***		(1.182)***	(1.950)***
Predicted foreign STEM occupation share D2		0.177	0.184			
		(0.091)*	(0.093)**			
Predicted foreign STEM occupation share D3					0.106	0.109
					(0.083)	(0.084)
Predicted native non-STEM graduate relative flow 1980			-0.380			-0.338
			(0.443)			(0.446)
F-statistic		40.98	27.50		39.68	26.53
Endogenous Variable: Foreign STEM graduate share						
Predicted native STEM graduate relative flow 1980		-0.400	-0.308		-1.209	-1.684
		(0.706)	(0.833)		(0.840)	(1.113)
Predicted foreign STEM occupation share D2	0.994	1.001	1.001			
	(0.209)***	(0.212)***	(0.214)***			
Predicted foreign STEM occupation share D3				0.768	0.795	0.793
				(0.181)***	(0.188)***	(0.189)***
Predicted native non-STEM graduate relative flow 1980			-0.029			0.152
			(0.266)			(0.312)
F-statistic	22.71	12.24	8.21	17.95	9.69	6.88
Endogenous Variable: Non-STEM graduate share						
Predicted native STEM graduate relative flow 1980			-5.502			-6.178
			(5.748)			(5.939)
Predicted foreign STEM occupation share D2			0.567			
			(0.362)			
Predicted foreign STEM occupation share D3						0.405
						(0.320)
Predicted native non-STEM graduate relative flow 1980			9.196			9.310
			(1.335)***			(1.360)***
F-statistic			40.37			40.03
B. Second-Stage Results						
Native STEM graduate share		34.877	31.13		35.271	31.235
		(6.422)***	(8.116)***		(6.386)***	(8.150)***
Foreign STEM graduate share	35.568	23.626	23.094	35.321	20.355	19.825
	(9.597)***	(7.065)***	(6.916)***	(9.570)***	(7.518)***	(7.378)***
Non-STEM graduate share			1.612			1.734
			(2.795)			(2.774)

Notes: The second-stage dependent variable is the log of patents per 100K population. All regressions include control variables listed in Table 1. Standard errors in parentheses are robust to heteroskedasticity.
*Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table 6: Summary Statistics for 2000-2010 Time Difference Analysis

	Mean	Std. Dev.	Min	Max
Dependent variable				
Δ Log patents per 100K population	-0.109	0.500	-2.070	1.414
Explanatory variables of interest				
Δ Native college graduate share	0.024	0.018	-0.021	0.082
Δ Foreign college graduate share	0.010	0.011	-0.008	0.066
Instruments				
Predicted native STEM graduate relative flow 1980	0.002	0.001	0.000	0.007
Predicted Δ in foreign STEM occupation share D1	0.002	0.003	0.000	0.022
Predicted Δ in foreign STEM occupation share D2	0.003	0.003	0.000	0.018
Predicted Δ in foreign STEM occupation share D3	0.004	0.003	0.000	0.021
Control variables				
Δ Unemployment rate	0.046	0.023	-0.016	0.121
Δ Mean age of adult labor force	1.7	0.6	0.1	3.4
Δ Log metropolitan area population	0.1	0.1	-0.1	0.3
Δ Mean firm size (# of Employees)	62.4	524.2	-3964.3	2599.0
Δ University research expenditure per capita	87.9	228.7	-68.0	2376.6

Notes: Sample includes 307 metropolitan areas. Δ indicates change over time.

Table 7: Time-Differenced 2SLS Results

	(1)	(2)	(3)
A. First-Stage Results			
Endogenous Variable: Δ Native college graduate share			
Predicted native STEM graduate relative flow 1980	3.773		5.006
	(1.094)***		(1.104)***
Predicted Δ in foreign STEM occupation share D1			-1.300
			(0.372)***
F-statistic	11.90		13.01
Endogenous Variable: Δ Foreign college graduate share			
Predicted native STEM graduate relative flow 1980			-1.937
			(0.747)***
Predicted Δ in foreign STEM occupation share D1		2.104	2.302
		(0.335)***	(0.335)***
F-statistic		39.35	23.62
B. Second-Stage Results			
Δ Native college graduate share	33.208		31.303
	(12.733)***		(11.957)***
Δ Foreign college graduate share		17.386	29.132
		(4.749)***	(8.585)***

Notes: The second-stage dependent variable is the change in log of patents per 100K population. All regressions include control variables listed in Table 5. Standard errors in parentheses are robust to heteroskedasticity.
Δ indicates change over time.
***Significant at 1% level.

Table 8: Time-Differenced 2SLS Results Using Alternative Instruments for Foreign Graduates

	(1)	(2)	(3)	(4)
A. First-Stage Results				
Endogenous Variable: Δ Native college graduate share				
Predicted native STEM graduate relative flow 1980		4.600		4.809
		(1.099)***		(1.113)***
Predicted Δ in foreign STEM occupation share D2		-0.995		
		(0.440)**		
Predicted Δ in foreign STEM occupation share D3				-0.825
				(0.393)**
F-statistic		9.81		9.91
Endogenous Variable: Δ Foreign college graduate share				
Predicted native STEM graduate relative flow 1980		-1.924		-2.219
		(0.700)***		(0.745)***
Predicted Δ in foreign STEM occupation share D2	2.421	2.611		
	(0.371)***	(0.380)***		
Predicted Δ in foreign STEM occupation share D3			1.738	1.964
			(0.349)***	(0.360)***
F-statistic	42.59	23.59	24.76	15.08
B. Second-Stage Results				
Δ Native college graduate share		31.641		31.517
		(11.946)***		(11.939)***
Δ Foreign college graduate share	16.900	23.964	19.770	25.870
	(4.509)***	(7.649)***	(5.597)***	(8.674)***

Notes: The second-stage dependent variable is the change in log of patents per 100K population. All regressions include control variables listed in Table 5. Standard errors in parentheses are robust to heteroskedasticity.
Δ indicates change over time.
**Significant at 5% level; ***Significant at 1% level.

Table A: List of STEM Majors and ACS Codes

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

Table B: List of STEM Occupations and IPUMS Occ1990 Code for Different Definitions

Occ1990	and Description	STEM Occ D1	STEM Occ D2	STEM Occ D3
44	Aerospace engineer	Yes	Yes	Yes
45	Metallurgical and materials engineers	Yes	Yes	Yes
47	Petroleum, mining, and geological engineers	Yes	Yes	Yes
48	Chemical engineers	Yes	Yes	Yes
53	Civil engineers	Yes	Yes	Yes
55	Electrical engineer	Yes	Yes	Yes
56	Industrial engineers	Yes	Yes	Yes
57	Mechanical engineers	Yes	Yes	Yes
59	Not-elsewhere-classified engineers	Yes	Yes	Yes
64	Computer systems analysts & computer scientists	Yes	Yes	Yes
66	Actuaries	Yes	Yes	Yes
68	Mathematicians and mathematical scientists	Yes	Yes	Yes
69	Physicists and astronomers	Yes	Yes	Yes
73	Chemists	Yes	Yes	Yes
74	Atmospheric and space scientists	Yes	Yes	Yes
75	Geologists	Yes	Yes	Yes
76	Physical scientists, n.e.c.	Yes	Yes	Yes
77	Agricultural and food scientists	Yes	Yes	Yes
78	Biological scientists	Yes	Yes	Yes
79	Foresters and conservation scientists	Yes	Yes	Yes
83	Medical scientists	Yes	Yes	Yes
229	Computer software developers	Yes	Yes	Yes
84	Physicians	No	Yes	Yes
85	Dentists	No	Yes	Yes
86	Veterinarians	No	Yes	Yes
87	Optometrists	No	Yes	Yes
88	Podiatrists	No	Yes	Yes
89	Other health and therapy diagnosing occupations	No	Yes	Yes
96	Pharmacists	No	Yes	Yes
97	Dietitians and nutritionists	No	No	Yes
106	Physicians' assistants	No	No	Yes
154	Subject instructors (HS/college)	No	No	Yes
223	Biological technicians	No	No	Yes
226	Airplane pilots and navigators	No	No	Yes
258	Sales engineers	No	No	Yes