STEM Workers, H-1B Visas, and Productivity in U.S. Cities*

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Abstract

Scientists, Technology professionals, Engineers, and Mathematicians (STEM workers) are fundamental inputs in scientific innovation and technological adoption, the main drivers of productivity growth in the U.S. In this paper we identify the effect of STEM worker growth on the wages and employment of college and non-college educated native workers in 219 U.S. cities from 1990 to 2010. In order to identify a supply-driven and heterogeneous increase in STEM workers across U.S. cities, we use the distribution of foreign-born STEM workers in 1980 and exploit the introduction and variation of the H-1B visa program granting entry to foreign-born college educated (mainly STEM) workers. We find that H-1B-driven increases in STEM workers in a city were associated with significant increases in wages paid to college educated natives. Wage increases for non-college educated natives are smaller but still significant. We do not find significant effects on employment. We also find that STEM workers increased housing rents for college graduates, which eroded part of their wage gains. Together, these results imply a significant effect of foreign STEM on total factor productivity growth in the average US city between 1990 and 2010.

Key Words: STEM Workers, H-1B, Foreign-Born, Productivity, College educated, Wage, Employment.

JEL codes: J61, F22 , O33, R10.

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1 Introduction

Scientists, Technology professionals, Engineers, and Mathematicians (STEM workers) are the main inputs in the creation and adoption of scientific and technological innovation. The important role of STEM innovations in generating economic productivity and growth has been recognized at least since Robert Solow's (1957) seminal work. More recent growth economists, including Zvi Griliches (1992) and Charles I. Jones (1995), have used measures of Scientists and Engineers to identify the main Research & Development (R&D) contribution to idea-production. Advances in STEM, therefore, appear to be important determinants of sustained productivity growth.

Two additional considerations related to ideas and productivity have attracted the attention of economists recently. First, technological innovation during the past 30 years has not increased the productivity of all workers equally. The development of new technologies – especially Information and Communication Technologies (ICT) – significantly increased the productivity and wages of college educated workers. They had a much smaller effect on the demand for non-college educated workers, which has remained rather stagnant.[1]

Second, while technological and scientific knowledge is footloose and spreads across regions and countries, STEM workers are less mobile. Tacit knowledge and face to face interactions still make a difference in the speed at which new ideas are locally adopted. Several studies (e.g. Moretti (2004a, 2004b), Iranzo and Peri (2009)) have shown the importance of concentrations of college educated workers in spurring local productivity. Other studies have shown the tendency of innovation- and idea- intensive industries to agglomerate (Ellison and Glaeser (1999)) and for ideas to remain local and generate virtuous cycles of innovation (Jaffe et al. (1993), Saxenian (2002)).[2]

This paper sits at the intersection of these strands of the literature. We quantify the long-run effect of increases in STEM workers in U.S. cities on the employment and wages of STEM, college educated, and non-college educated native workers. The challenge of the exercise is to identify variation in the growth of STEM workers across U.S. cities that is supply-driven and hence exogenous to other factors affecting wages, employment, and productivity changes. We do this by exploiting the introduction of the H-1B visa in 1990 and the differential effect that these visas had in bringing foreign STEM workers to 219 U.S. metropolitan statistical areas (MSAs)[3] from 1990 to 2010. We then combine a simple production model with our estimated wage and employment effects to infer the effects of STEM growth on changes in total factor productivity (TFP) and skill-biased productivity (SBP) in U.S. cities.

While the variation in STEM workers and foreign STEM workers across U.S. metropolitan areas is likely endogenous to local productivity and employment growth, our identification uses inflows of H-1B visa immigrants to capture more exogenous variation in STEM workers

[1] See Katz and Murphy (1992), Krueger (1993), Autor, Katz, and Krueger (1998), Acemoglu (1998, 2002), Berman, Bound, and Griliches (1994), Autor, Levy, and Murnane (2003), and Autor, Katz, and Kearney (2006) among others.

[2] Recent books by Edward Glaeser (2011) and Enrico Moretti (2012) identify a city's ability to innovate and to continuously reinvent itself as the main engine of its growth.

[3] The official unit of analysis is the metropolitan statistical area. Throughout the text we use the terms "city" and "metropolitan area" interchangeably.

across cities over time. The H-1B visa, introduced with the Immigration and Nationality Act of 1990, allowed college educated specialty professional workers (mostly STEM workers) to enter the country. The policy was national in scope but had differentiated local effects. Foreign STEM workers were unevenly distributed across U.S. cities before the inception of the H-1B visa program. Because of migrant preferences and the availability of information spread by ethnic networks, subsequent inflows of H-1B workers have been more concentrated in areas with large pre-existing foreign STEM presence.

Using the 1980 Census we measure foreign STEM workers as a share of employment in each MSA. This share exhibits very large variation across metropolitan areas. Next, we predict the number of new foreign STEM workers that would end up in each city by allocating the H-1B visas to 14 foreign nationality groups in proportion to the city's 1980 presence of foreign STEM workers of each nationality. This H-1B-driven imputation of future foreign STEM is a good predictor of the actual increase of both foreign STEM and overall STEM workers in a city over subsequent decades. We use this prediction as an instrument for the actual growth of foreign STEM workers in order to obtain causal estimates of the impact of STEM workers growth on wages and employment of native college and non-college educated workers. This identification strategy is rooted in methods used by Altonji and Card (1991) and Card (2001) to identify the wage effect of immigrants. It is also closely related to Kerr and Lincoln's (2010) examination of the impact of foreign scientists on U.S. patent applications.

The 1980 distribution of foreign STEM and the overall inflow of H-1B workers over the period 1990-2010 may be correlated with unobservable city-specific shocks that affect employment and wage growth. Thus, we subject our instrumental variable strategy to tests and falsification checks to reduce potential exclusion restriction violations. We check that the initial (1980) distribution of other types of foreign-born workers (e.g. less educated and manual workers), the initial industry-structure of the metropolitan area, and the subsequent inflow of non-STEM immigrants do not predict growth in foreign STEM workers. We also check that the trends of native outcomes prior to the inception of the H-1B program (1970-1980) were not correlated with the H-1B-driven growth in STEM workers over the 1990-2010 period. Finally, we use a panel of 219 metropolitan areas over 1990-2010, and always adopt a very demanding specification that includes both city and period fixed effects. Our identification relies on changes in growth rates of H-1B-driven STEM workers within metropolitan areas over time.

Our preferred specifications reveal that a rise in the growth of foreign STEM by one percentage point of total employment increases growth in the wages of native college educated workers by a statistically significant 7-8 percentage points. The same change had a smaller but usually statistically significant effect on the wages of native non-college educated workers equal to 3-4 percentage points. No statistically significant effects were found for the growth of native employment. We also find that an increase in foreign STEM growth had a significantly positive impact on growth in housing costs for college educated workers. The increased cost in non-tradable services (housing) absorbed about half of the increase in the purchasing power of college educated wages.

Finally, we use a simple model of city-level production and the estimated wage and employment effects to calculate the effect of STEM on total factor productivity (TFP) and skill-biased productivity (SBP). We find that STEM workers have positive effects on both

TFP and SBP. Aggregating at the national level, inflows of foreign STEM workers may explain between 30 and 50% of the aggregate productivity growth and 4 to 8% of the skill-bias growth that took place in the U.S. between 1990 and 2010.

The rest of the paper is organized as follows. Section 2 briefly presents the empirical specification that we estimate. Section 3 describes the data on STEM workers and H-1B visas, and how we construct the H-1B-driven growth of foreign STEM-workers. In section 4 we test and discuss the power and validity of the constructed H-1B-driven growth variable as an instrument. Section 5 presents the basic empirical estimates of the effect of an increase in STEM workers on wages and employment of native U.S. workers, and also checks the robustness of the estimates, and examines the impact on house rents. In Section 6 we introduce a simple model and combine it with our estimated parameters to calculate the impact of STEM on TFP and SBP across U.S. metropolitan areas. Section 7 concludes.

2 Empirical Framework

Our empirical analysis uses variation in foreign-born STEM workers across U.S. cities (c) and time-periods (t) to estimate their impact on wages, employment, and house rents for native workers. We discuss identification and its challenges in Section 4, and we describe how we use the estimated coefficients to back-out productivity effects in Section 6. The basic specifications we estimate in Section (5) take the form,

$$y_{ct}^{Native,X} = \phi_t + \phi_c + b_{y,X}\frac{\Delta STEM_{ct}^{Foreign}}{E_{ct}} + b_3 Controls_{ct}^{X} + \varepsilon_{ct} \tag{1}$$

The variable $y_{ct}^{Native,X}$ is the period-change in outcome y for the sub-group of natives with skill X (where X includes STEM workers, college educated workers, and non-college educated workers), standardized by the initial year outcome level. The outcomes of interest are average weekly wages, employment, and housing rents (measured as average rent per room) for each group. The term ϕ_t captures period fixed effects, while ϕ_c captures city fixed effects. The variable $\frac{\Delta STEM_{ct}^{Foreign}}{E_{ct}}$ is the change of foreign STEM over a period, standardized by the initial total employment in the city (E_{ct}). The term $Controls_{ct}^{X}$ includes other city-specific controls, and ε_{ct} is a zero-mean idiosyncratic random error. Given this design, we emphasize that identification relies on variation in the growth of foreign STEM workers within cities over time-periods.

We focus our analysis on the period 1990-2010 and choose to partition these two decades into three specific time-periods: 1990-2000, 2000-2005, and 2005-2010. This enables us to take advantage of large variation in national H-1B policy that occurred during the 2000-2005 period relative to the other two. Additionally, as a robustness check, one can abstract from the Great Recession period by removing 2005-2010 from the analysis.[4]

The coefficient $b_{y,X}$, captures the elasticity of outcome y,for worker group X, to an exogenous increase in STEM workers. Interpreting these coefficient estimates as causal requires changes in $STEM_{ct}^{Foreign}$ that are exogenous to productivity shocks and other unobservable

[4]Though not reported, estimates are robust to removing the Great Recession period. Similarly, they remain robust when constructing variables over 1990-2000, and 2000-2010. These are available upon request.

determinants of city-level wage and employment changes. Before turning attention to this challenge, we introduce our data and measures of STEM workers (section 3) and describe the construction of the H-1B-driven Foreign STEM variable and its power as an instrument (section 4).

3 Data: STEM Workers in U.S. Cities

We develop two separate methods of defining STEM occupations. Each method also uses both a more inclusive and a more stringent STEM identification criterion, resulting in four possible STEM definitions. The first method is based on skills that workers use in their occupations. We use the O*NET database (Bureau of Labor Statistics), which associates to each occupation the importance of several dozen skills required to perform the job. We select four O*NET skills that involve STEM use – namely, "Mathematics in Problem Solving," "Science in Problem Solving," "Technology Design," and "Programming." We then compute the average score of each occupation across the four skills and rank the 331 occupations[5] consistently identified in the Census 1980-2010 according to the average STEM skill value defined above. We classify STEM occupations as those employing the top 4% (strict definition) or 8% (broad definition) of workers in that ranking in the year 2010. O*NET 4% (or 8%) STEM workers are the individuals with these occupations.

Our second method for identifying STEM occupations is based on the skills workers possess before employment – namely, the college majors found among workers within occupations. The U.S. State Department recognizes a list of college majors as STEM for the purpose of granting foreign students extended time to work under the Optional Practical Training (OPT) program.[6] We rank occupations based on the percentage, in the 2010 ACS, of individuals with a college degree in a STEM major. We then classify STEM occupations as those employing the top 4% (strict) or 8% (broad) of workers following that ranking in the year 2010. Major-based 4% (or 8%) STEM workers are the individuals within those occupations. Both the O*NET and Major-based strict definitions include mainly Census occupations with "scientist" or "engineer" in the title. The Major-based STEM occupations largely coincide with the O*NET STEM occupations.[7]

3.1 Policy changes to the H-1B Visa Program

The main goal of this paper is to identify the effect of STEM workers on the wages and employment of college educated and non-college educated workers across U.S. cities in the long-run. The ideal experiment would consist of randomly adding different numbers of STEM workers across U.S. cities and then observing the evolution of native wages and employment. As we cannot run such an experiment, we use shifts in national H-1B visa policy, introduced

[5] We make small refinements to the Census Occupational Classification in order to ensure complete time-consistency in the availability of occupations over the 1980-2010 period. A detailed description of both of our STEM definitions, as well as the refinement of occupations is available in the Online Appendix.

[6] There is no direct cross-walk between majors/fields listed under the OPT STEM classification and majors/fields as classified under the 2010 ACS. Thus our list is consistent with, but not exactly identical to, the OPT STEM degree fields.

[7] See the Online Appendix for the full STEM occupation lists and further details.

in 1990, as an exogenous source of variation in the inflow of foreign STEM workers across U.S. cities.

The H-1B visa, introduced in 1990, provides temporary permits[8] for college educated foreign "specialty" workers. Since 1990 the H-1B visa has been a crucial channel of admission for many college educated foreign-born workers, largely employed in STEM occupations.[9] Our analysis exploits large policy-induced fluctuations in the size of the H-1B program over the 1990-2010 period.

Figure 1 shows the maximum number of H-1B visas authorized per year (cap) and the actual number of H-1B visas issued for each year between 1990 and 2010. Set initially at 65,000 H-1B visas annually, the cap rose to 115,000 for fiscal years 1999 and 2000, and then to 195,000 per year for 2001, 2002, and 2003. It reverted back to the original 65,000 per year beginning in 2004. Though the limit officially remains at 65,000, the first 20,000 H-1B visas issued annually to individuals who have obtained a master's (or higher education) degree in the U.S. became exempt from H-1B limits beginning in 2005, effectively raising the cap to 85,000.[10]

Not only has the size of the H-1B program varied greatly since its inception, but the ensuing inflow of foreign STEM workers has been heterogeneously distributed across U.S. cities as well. Certainly part of these cross-city differences were due to varying economic conditions, industrial structures and labor demand that likely influenced native wage and employment growth. Importantly, however, a portion of this variation was also due to persistent immigrant preferences to locate in cities with historical communities of past immigration. The 1980 distribution of STEM workers by nationality proxies for these persistent historical settlements.

Our analysis needs to capture only the heterogeneity in foreign STEM created by this differential initial presence (in 1980) of foreign enclaves by nationality, that are exogenous to other determinants of future wage and employment growth of natives in cities. To do this we construct an H-1B driven instrument which retains only the portion of growth in foreign STEM that was due to national policy fluctuations and removes city-specific factors that may have attracted both foreign STEM and native workers alike. Additionally, we use fixed effects to control for city-specific pre-determined characteristics, such as the industrial and economic structure. We also construct variables that control for future city-shocks. In the following two sections we define the variables in detail, show the importance of H-1B visa entries in determining the net growth of foreign STEM workers, and test the validity of the identifying assumptions, crucial for our approach.

[8] H-1B have a the duration of three years, renewable up to 6, and they give the possibility of applying for permanent residence.

[9] Lowell (2000) notes that 70% of H-1B visas have been awarded to people employed as Computer Analysts, Programmers, Electrical Engineers, University Professors, Accountants, Other Engineers, and Architects. Similarly, Citizenship and Immigration Services (2009) reports that for all years between 2004 and 2011, more than 85% of new H-1B visa holders work in Computer, Health Science, Accounting, Architecture, Engineering, and Mathematics related occupations.

[10] For more discussion of the H-1B visa and its economic effects, see Kerr and Lincoln (2010) and Kato and Sparber (2013).

3.2 The H-1B-Driven Increase in STEM

Our data on occupations, employment, wages, age, and education of individuals comes from the IPUMS 5% Census files for 1980, 1990, and 2000, the 1% American Community Survey (ACS) sample for 2005, and the 2008-2010 3% merged ACS sample for 2010.[11] We only use data on 219 metropolitan areas that can be consistently identified over the period 1980-2010. These span the range of U.S. metropolitan sizes, including all the largest cities in the U.S. (Los Angeles, New York, Chicago, Dallas-Forth Worth, Philadelphia and Houston are the six largest) down to MSAs with close to 200,000 people (Danville, VA, Decatur, IL, Sharon, PA, Waterbury, CT, Muncie, IN and Alexandria, PA are the six smallest). Data on aggregate H-1B flows by nationality and year is publicly available from the Department of State (2011).

We construct a variable which we call the "H-1B-driven increase in STEM workers" in each of 219 U.S. metropolitan areas between 1990 and 2010. This variable captures supply-driven variation in the growth of foreign STEM workers, and we use it as an instrumental variable to estimate variants of equation (1). To create this instrument, we first impute the number of foreign STEM workers in city c and year t, $\widehat{STEM}_{ct}^{FOR}$:

$$\widehat{STEM}_{ct}^{FOR} = \sum_{n=1,14} STEM_{c1980}^{FORn} \left(\frac{\widehat{STEM}_t^{FORn}}{STEM_{1980}^{FOR_n}} \right) \tag{2}$$

The term $STEM_{c1980}^{FORn}$ is the number of foreign STEM workers of nationality n (out of 14 foreign groups[12]) in city c and year 1980, while $\frac{\widehat{STEM}_t^{FORn}}{STEM_{1980}^{FORn}}$ is the growth factor of all foreign STEM workers for each nationality n in the U.S. between 1980 and year t.[13] This is calculated by adding the inflow of STEM workers from each nationality between 1980 and t to its initial 1980 level $\left(STEM_{1980}^{FOR_n}\right)$. For the decades 1990-2000 and 2000-2010 we use the cumulative H-1B visas allocated to nationality n, $\#ofH1B_{1990-t}^{FOR_n}$, as the net increase in $STEM^{FOR_n}$.[14] For the decade 1980-1990 we simply add the net increase in STEM workers from nationality n as recorded in the U.S. Census, $\Delta STEM_{1980-1990}^{FOR_n}$. The imputed growth factor for STEM workers, for each foreign nationality in year $t = 1990, 2000, 2005, 2010$, is therefore:

[11] All of these data were retrieved from Ruggles et al (2010).

[12] The national groups are: Canada, Mexico, Rest of Americas (excluding the USA), Western Europe, Eastern Europe, China, Japan, Korea, Philippines, India, Rest of Asia, Africa, Oceania, and Other.

[13] We choose 1980 as the base year in the imputation of foreign STEM for three reasons. First, it is the earliest Census that allows the identification of 219 metropolitan areas. Second, it occurs well before the creation of the H-1B visa and hence does not reflect the distribution of foreign STEM workers affected by the policy. Third, it pre-dates most of the ICT revolution so that the distribution of STEM workers was hardly affected by the geographic location of the computer and software industries.

[14] Data on visas issued by nationality begin in 1997, and while we know the total number of H-1B visas issued in each year from 1990, we must estimate $\#ofH1B_{n,1990-t}$, the total number of visas issued by nationality between 1990 and 1997, as:

$$\#of\widehat{H1B}_{n,1990-t} = \#ofH1B_{1990-t} \left(\frac{\#ofH1B_{n,1997-2010}}{\#ofH1B_{1997-2010}} \right)$$

where $\frac{\#ofH1B_{n,1997-2010}}{\#ofH1B_{1997-2010}}$ is the share of visas issued to nationality group n among the total visas issued from 1997 to 2010. For t larger than 1997 we have the actual number of yearly visa by nationality $\#ofH1B_{n,t}$.

$$\frac{\widehat{STEM_t^{FORn}}}{STEM_{1980}^{FOR_n}} = \frac{STEM_{1980}^{FOR_n} + \Delta STEM_{1980-1990}^{FOR_n} + \#ofH1B_{1990-t}^{FORn}}{STEM_{1980}^{FOR_n}} \tag{3}$$

The H-1B-driven change in foreign STEM workers that we use as our instrument is the change in $\widehat{STEM_{ct}^{FOR}}$ over the time-periods standardized by the initial imputed city employment, $\widehat{E_{ct}}$, in which natives were also imputed using the 1980 city population and aggregate population growth.[15]

Our identification strategy is closely related to the one used by Altonji and Card (1991) and Card (2001), who exploit the initial distribution of foreign workers across U.S. cities. Our approach differs from theirs in that our strategy is based on the initial distribution of foreign STEM workers across cities rather than all immigrants. In this regard, our methodology is more similar to Kerr and Lincoln's (2010) examination of foreign scientists and engineers and the impact of H-1B flows on innovation. Our approach differs from theirs by using the foreign STEM presence in a city in 1980 (rather than in 1990), and by further distinguishing immigrant presence by nationality (rather than the aggregate foreign STEM presence). We also use a more demanding panel approach that measures variables in growth rates (first differences) while including both city and time-period effects.

Our modeling choices aim to reduce the risk of correlation between the instrument and unobserved determinants of wage and employment growth. To further bolster its validity, we subject our instruments to a series of robustness checks. The possibility that the initial (1980) distribution of foreign STEM is correlated with other shocks may introduce omitted variable bias. The risk that aggregate inflows of H-1B workers may have been driven by a few specific cities raises endogeneity concerns. The presence of measurement error, more likely in cities with small populations, could result in attenuation bias for our estimates. We discuss and address each of these concerns in Section 4. In the next section we describe summary statistics that illustrate the significant foreign-born presence among STEM workers in the U.S. and the numbers of the H-1B program.

3.3 Summary Statistics for Foreign STEM in U.S. Cities

A cursory look at the data shows that foreign-born individuals are particularly over-represented among STEM occupations and that they have contributed substantially to the aggregate growth of STEM jobs in the U.S.[16] Table 1 shows the foreign-born share of five different employment groups for years 1980, 1990, 2000, 2005, and 2010. From left to right we show the percentage of foreign-born in total employment (column (1)), among college educated workers (column (2)), among college educated workers in MSAs (column (3)), among STEM

[15] To avoid endogenous changes in total employment at the city level we also impute city employment by augmenting employment by nativity and skill level in 1980 by the corresponding growth factor in national total employment. Hence, $\widehat{E_{ct}^x} = E_{c1980}^x * (E_t^x / E_{1980}^x)$, where x = native college educated workers, native non-college educated workers, foreign college educated workers, and foreign non-college educated workers. Thus, $\widehat{E_{ct}} = \sum_x \widehat{E^x}$ and the instrument is $\frac{\Delta STEM_{ct}^{H-1B}}{\widehat{E_{ct}}}$.

[16] In the summary statistics and in the empirical analysis we mainly use the O*NET 4% STEM definition, unless we note otherwise.

occupations in MSAs (column (4)), and among college educated STEM workers in MSAs (column (5)). While foreign-born individuals represented about 16% of total U.S. employment in 2010, they counted for almost 30% of college educated STEM workers in the metropolitan sample that we analyze. Also, this percentage has more than doubled since 1980.

Table 2 shows that college educated STEM workers have increased from 2.1% of total employment in 1980 to 3.7% in 2010. The share of college educated foreign STEM workers has grown from 0.3% to 1.1%. Of the 0.81 points increase in college educated STEM as a percentage of employment, between 1990 and 2010, 0.65 percentage points (four fifths of the total) was due to foreigners.

Table 3 shows absolute numbers (in thousands) suggesting that the H-1B program was large enough to drive all or most of the increase in foreign STEM workers. Column (1) reports the net total increase in college educated STEM workers in the U.S. over three decades, and column (2) displays the increase in college educated foreign STEM workers. While before 1990 only one fifth of the net increase in STEM workers was driven by foreigners, in the 1990s and 2000s between half and 90% of the net STEM growth came from foreigners. Column (3) of Table 3 shows the cumulative number of H-1B visas issued during the corresponding decade.

It is clear that in the 1990s H-1B visas were enough to cover the whole growth in college educated foreign STEM workers in the U.S., even accounting for some returnees. Even more remarkably, H-1B issuances were three to four times as large as the net increase in college educated STEM between 2000-2005 and 2005-2010. This implies that many foreign STEM workers, including H-1B recipients, must have left the U.S.[17] Overall, the figures presented emphasize the importance of foreigners for STEM jobs in the U.S. The overall size of the H-1B program was large enough to contribute substantially to the foreign STEM job growth between 1990 and 2010.

4 Identification: Power and Validity of the Instruments

Our identification strategy relies on the H-1B supply-driven instrument whose validity is based on the assumption that the employment share of foreign STEM workers in 1980 varied across cities due to factors related to the persistent agglomeration of foreign communities in some localities. These historical differences – after controlling for an array of other city characteristics and other shocks – affected the change in the supply of foreign STEM workers but were not correlated with omitted shocks that affected the growth of native wages and employment in those cities.

We provide empirical tests of our instrument's validity in this section to address several challenges to our identification strategy raised by the presence of unobservable shocks potentially correlated with our instrument that affect native outcomes. The framework to discuss these issues is the first stage regression of the explanatory variable of our analysis on our instrument:

[17] Depew, Norlander, and Sorensen (2013) provide a detailed analysis of quit and return rates for temporary skilled employees of six large Indian ICT firms. Twenty-nine percent of their sample returned to India during the course of the survey period (2003-2011).

$$\frac{\Delta STEM_{ct}^{FOR}}{E_{ct}} = \phi_t + \phi_c + \beta \frac{\Delta STEM_{ct}^{H-1B}}{\widehat{E_{ct}}} + \varepsilon_{ct} \tag{4}$$

The coefficient β measures the impact of H-1B-driven STEM inflows (our instrument) on the U.S. Census-measured increase in foreign STEM workers (the explanatory variable in regression equation (1)). This coefficient and its power are the main objects of interest in the first stage regressions. The term ϕ_t captures period fixed effects, and ϕ_c represents 219 MSA fixed effects. We include the years $t = 1990$, 2000, 2005, and 2010 so that the changes refer to the periods 1990-2000, 2000-2005, and 2005-2010. ε_{ct} is a zero-mean random error uncorrelated with the explanatory variable.

We tackle several threats to the identification assumptions and begin by showing that the presence of foreign STEM workers in metropolitan areas as of 1980 did not always mirror the presence of native STEM workers. Table 4 shows the estimated coefficient (β) and the partial F-statistic from the first stage regressions (equation 4). The coefficients reported in the first and the second row are the β and the F-statistics of the instrument when using the O*NET 4% definition of STEM for both the endogenous variable and the instrument. Those in the third and fourth row are the corresponding statistics when using the Major-based 4% definition of STEM. The different columns represent different specifications.

Column (1) includes period effects, state effects, and the 1980 employment share of native STEM. Under this specification the imputed H-1B-driven growth of STEM has a highly significant impact on foreign STEM growth. This implies that even controlling for the initial native STEM share the foreign STEM share (used to construct the H-1B imputed STEM growth) has significant explanatory power.[18]

4.1 Basic Specifications and Checks

In column (2) of Table 4 we introduce MSA fixed effects to control for all other initial city-specific conditions, so that our identification relies only on deviations in MSA growth rates from MSA specific trends. We include these in all subsequent specifications. The top two rows of column (2) show the results obtained using the O*NET 4% definition of STEM for the endogenous variable and for the instrument. The following two rows use the Major-based 4% definition for the endogenous variable and for the instrument. Column (3) uses the broader 8% definition of STEM both for the endogenous variable and for the instrument, with the O*NET definition used in the top two rows and the Major-based definition used in the bottom two rows. The power of the instrument in these specifications is stronger (and close to or above 10) than in column (1), emphasizing that our H-1B-based instrument is good at capturing changes in the inflow of STEM workers within cities over time. Moreover,

[18] One reason for the power of foreign STEM after controlling for native STEM is that cities with large native STEM shares in 1980 were associated with traditional sectors that attracted Scientists and Engineers in the 1970s but did not predict the presence of information technology and computer sector that dominated R&D in the 1990s and 2000s. For instance Richland-Kennewick-Pasco, WA was the site of an important nuclear and military production facility in the 1970s; Melbourne-Titusville-Cocoa-Palm Bay, FL had an important aerospace center; Rochester, NY had a very developed office machine industry (Xerox, Kodak). They were all top native STEM but not high foreign STEM cities.

while some small differences exist we find that the two definitions of STEM produce similar results.

Columns (4) and (5) of Table 4 address two important concerns. The first is that the correlation between the instrument and the actual change in foreign STEM could be driven by the large high-tech boom in a few large MSAs, rather than by the exogenous initial distribution of immigrants. If large metropolitan areas drove most of the country's R&D and produced a large increase in demand for foreign H-1B visas and STEM workers, the instrument and the endogenous variable for those large R&D intensive cities could be spuriously correlated.

Alternatively, the presence of a few particular industries (e.g., ICT sector) might have attracted particular types of immigrants whose growth simply proxies for the success of those industries. The current population of foreign STEM workers from India is strongly associated with information technology as most of them are employed in computer, software, and electrical engineering occupations. Moreover, Indians have always accounted for at least 40% of H-1B visas.

Column (4) excludes the five metro areas with the largest number of STEM workers in 1980.[19] Column (5) excludes Indian STEM workers from the calculations of both the actual change and the instrument. The coefficients are still highly significant (although somewhat reduced in column (4) for O*NET STEM), emphasizing that the correlation between H-1B-driven STEM growth and a city's actual foreign STEM growth is not driven by top STEM cities or by a specific nationality group.

An alternative way to check that the predictive power of our instrument is not driven by individual nationality groups, whose specific location preferences may be affected by some industries, is to remove the nationality dimension from the instrument. We construct an instrument similar to the one used by Kerr and Lincoln (2010), by aggregating H-1B visas across nationalities and only exploiting variation in the aggregate number of visas over time, interacted with the initial overall presence of foreign STEM workers. We interact aggregate H-1B visa growth with the 1980 foreign STEM share distribution across cities. First stage results using this instrument are shown in column (6). The estimates remain similar and F-statistics confirm that the instrument maintains its power.

In column (7) we account for another potential weakness of our instrument. The use of 1 to 5% population samples may introduce measurement error in our variables. Aydemir and Borjas (2011) show how measurement error may produce attenuation bias when estimating the causal effect of immigrants on native outcomes. Because of small sample size, it is likely that these cities may actually have small foreign STEM communities that are not captured in Census sampling. In order to see how this measurement error may affect the power of our instrument column (7) shows the first stage estimates when eliminating all metropolitan areas with fewer than 400,000 people. This cut-off eliminates all cities from our sample that have a measured zero foreign STEM (or imputed foreign STEM) employment share.

Although we only retain 118 of the 219 cities, the coefficient estimates remain significant and stable, while the instrument is still reasonably powerful–F-statistics are around 9 for the Major-based STEM definition and well above 10 for the O*NET STEM definition. While we

[19] These are New York, Los Angeles, Chicago, San Jose, San Francisco. Together they account for 24% of STEM workers in our sample.

will discuss the potential impact of measurement error on attenuation bias when presenting the second stage estimates (In Table 6), it is reassuring to notice that the exclusion of the cities where measurement error may be larger does not affect much the power of the instrument and the first-stage estimate of the coefficient.

4.2 Confounding Shocks

Two types of shocks at the MSA level might be correlated with the inflow of STEM workers (and possibly with the instrument) and affect native wages and employment, thereby creating omitted variable bias. The first is a change in the skill distribution of workers related to the inflow of other (non-STEM) immigrants.[20] The second is an industry-driven change in productivity that would affect native employment and wages. Including those shocks directly as controls would introduce endogeneity in regression (1). Instead, we include their predicted values, formed by interacting the 1980 immigrant and industry distribution with national immigrant and industry shocks, respectively.

As STEM immigrants usually possess a college degree, we introduce a control for the imputed number of non-college educated immigrants ($\widehat{NoColl_{ct}^{FOR}}$) based on the distribution of non-college educated immigrants, by nationality, in 1980 across metropolitan areas $\left(NoColl_{c1980}^{FORn}\right)$ and the subsequent aggregate growth of that immigrant population in the U.S. $\left(\frac{NoColl_t^{FORn}}{NoColl_{1980}^{FORn}}\right)$. Using notation similar to (2), we first calculate:

$$\widehat{NoColl_{ct}^{FOR}} = \sum_{n=1,14} NoColl_{c1980}^{FORn} \left(\frac{NoColl_t^{FORn}}{NoColl_{1980}^{FOR_n}}\right) \tag{5}$$

We then construct our control for non-college educated immigrant growth, by taking the change in $\widehat{NoColl_{ct}^{FOR}}$ over time, relative to total initial imputed employment, hence, $\frac{\Delta \widehat{NoColl_{ct}^{FOR}}}{\widehat{E_{ct}}}$.

In column (8) of Table 4 we add the imputed growth of non-college educated immigrants to the basic first stage regression (column (2)). Cities with large communities of less educated immigrants may also have large communities of highly educated immigrants, although usually from different nationalities. Controlling for these flows will also be important to account for complementarity between college and non-college educated workers and their possible effect on wages in the second stage regressions. The results from column (8) show that the imputed H-1B driven instrument maintains its power when controlling for the imputed number of non-college educated immigrants.

To control for the second type of shock – those driven by a city's industrial structure – we construct four variables that predict the growth of wages and employment of college and non-college educated workers in a city based upon its 1980 industrial composition. We use a three-digit industry classification from the census, which, after small refinements for time-consistency, provides a very detailed break-down of the productive structure of cities into the 212 industries/sectors that comprise them.[21]

[20] A change in the skill distribution of natives can also confound the estimates, although it is likely less correlated with 1980 the presence of immigrants. In Table 6, row (i) we include a control for the imputed change in native college educated based on their distribution in 1980 and their national growth.

[21] To give an idea of the detail of the classification sectors as "Computers and related equipment," "Hotel

Let $s_{ic,1980}$ denote the share of total city (c) employment in each sector ($i = 1, 2...212$) in 1980. Then let $\Delta w_t^{i,X}/w_t^{i,X}$ be the percentage change over the decade of the national average of native weekly wages in constant 2010 dollars for group X (=College, No-College) in sector i. Similarly, let $\Delta EMPL_t^{i,X}/TotEmpl_t^i$ be the national growth of native employment of workers of type X in sector i, expressed as percentage of total initial employment in the sector. We define sector-driven wage growth and sector-driven employment growth (respectively) for group X, in city c, and over time-periods beginning in year t with the following expressions:

$$\left(\frac{\Delta w^X}{w^X}\right)_{ct}^{Sector-Driven} = \sum_{s=1,212}\left(s_{ic,1980}\frac{\Delta w_t^{i,X}}{w_t^{i,X}}\right) \quad \text{for } X = Coll, NoColl \tag{6}$$

$$\left(\frac{\Delta E^X}{TotE}\right)_{ct}^{Sector-Driven} = \sum_{s=1,212}\left(s_{ic,1980}\frac{\Delta EMPL_t^{i,X}}{TotEmpl_t^i}\right) \quad \text{for } X = Co, NoColl \tag{7}$$

These two variables measure the average wage and employment growth at the sector level weighted by the share of employment in each sector in the city in 1980. They proxy for the sector-driven changes in demand (wage and employment) in city c based on a very detailed level breakdown of its 1980 industrial composition. These imputed variables are also commonly known as Bartik instruments (from Bartik (1991)).

Column (9) augments the specification shown in column (8) by also adding the employment and the wage Bartik instruments for college educated. The results show that including the Bartik instruments still leaves the H-1B imputed STEM growth instrument with significant, albeit somewhat reduced, explanatory power, especially when using the O*NET definition.

4.3 Falsification and Extensions

Our instrument is predicated on two assumptions. First, the H-1B visa policy significantly and exogenously (from the perspective of each metropolitan area) affected the inflow of foreign STEM workers in the U.S. over the period 1990-2010. Second, the initial distribution of foreign STEM was crucial in determining the subsequent inflow of H-1B immigrants and was not correlated with other city-level shocks that affected native wages and employment. Columns (1)-(4) of Table 5 present some tests of these assumptions.

The aggregate inflow of H-1B workers in the U.S. could simply be a proxy for strong aggregate labor demand growth. This strong demand growth, possibly originating in particular cities or attracting particular nationality of immigrants, may produce a positive correlation between the instrument and the explanatory variable, in spite of the presence of city and period effects. If this was the case, then one could substitute the non-H1-B immigrant flow (or the non-college educated immigrant flow) for the H-1B flow when constructing the instrumental variable and still produce a significant positive first stage correlation. Columns (1) and (2) show that this is not the case by testing the power of such a "falsified" instrument.

and Motels," and "Legal Services" are considered individual sectors. See the online appendix for details on the refinements for time-consistent industries.

No significant relation is generated between the instrument and the explanatory variable (growth of foreign O*NET 4% STEM workers) when we impute the foreign STEM growth by interacting the 1980 distribution of foreign STEM with subsequent non-college immigrant flows (column (1)) or when we augment them with aggregate immigrant flows net of H-1B flows (column (2)), instead of H-1B flows. Hence the aggregate variation of H-1B visas over time is crucial to predict subsequent STEM variation across cities. This is reassuring as aggregate H-1B flows have been driven by policy changes more than by aggregate immigrant inflows.

Column (3) similarly shows that if we substitute the initial presence of foreign workers in manual-intensive jobs (rather than in STEM) across metropolitan areas in the construction of the instrument we do not obtain a significant correlation with the actual STEM growth. Less skilled immigration, therefore, while possibly correlated with STEM immigration, did not drive the explanatory power of the instrument.[22]

Column (4) of Table 5 considers a direct test of the exclusion restriction for the instruments. We show the correlation between the instrument – calculated for the 1990-2000 decade – and the pre-existing growth in native college wages in the period 1970-1980 (and below its F-statistics as check of the coefficient significance). The top two rows show such a test when using the O*NET 4% definition of STEM to build the instrument. The two following rows show the coefficient and F-statistic when using the Major-based 4% definition of STEM. This is a direct test that the instrument is uncorrelated with pre-existing trends in the native outcomes. Of all the outcomes we consider, native college wages are the most significantly affected by increased STEM during the 1990s and 2000s (as we will see in Section 5). It is reassuring, therefore, to see that there is no correlation at all between the H-1B imputed STEM growth after 1980 and the pre-1980 native wage growth.[23]

As a final check in this section, we want to show that H-1B policy has affected the *total* number of STEM workers in the U.S. by attracting more foreign-born workers. That is, metropolitan areas with large foreign STEM inflows have not experienced a substitution of foreign STEM for native STEM, but rather an increase in the overall STEM labor force due to immigration. If this is true, we can consider the H-1B policy as an exogenous shock to assess the impact of STEM workers on native wages, employment, and productivity.

We examine this claim in columns (5) and (6) of Table 5 by regressing total (native plus foreign) STEM worker growth on the H-1B-predicted inflow of foreign STEM (the instrument). The estimated coefficient is even larger than in the basic specification, implying, as we will see below, a positive response of native STEM to foreign inflows. In column (5) we use the stricter 4% STEM definition (based on O*NET in the top rows and on College Major in the two lower rows) for both the endogenous and instrumental variable. In column (6) we use the broader 8% definition of STEM for both endogenous and instrumental variable. The power of the instrument is relatively strong in most cases (except when using the O*NET 8% definition of STEM[24]).

Overall the specifications and falsifications shown in this section demonstrate that our

[22] The details of the construction of these "falsified" instruments are in the Online Appendix.

[23] We also checked the correlation with non-college wages before 1980 and we similarly found no significant coefficient.

[24] For this reason we will in general prefer and use the O*NET 4% definition in the regressions of the next section.

H-1B imputed instrument has significant power in predicting foreign STEM and total STEM growth, that its variation is not driven by top cities or by one ethnic group, and that its power survives the inclusion of city effects, industry controls, and low-skilled immigrants controls. The instrument's predictive power is crucially driven by the H-1B program and by initial distribution of STEM immigrants across cities.

5 The Effect of STEM on Native Outcomes

5.1 Basic Results

The empirical specifications estimated in this section follow the regression described in equation (1) and seek to identify the impact of STEM workers on the wages and employment of different groups of native workers, so as to keep the experiment cleaner since the change in STEM supply is driven by immigrants. The outcomes $\left(y_{ct}^{Native}\right)$ are always measured for native workers, by group X (STEM, college educated, or non-college educated) in city c. The dependent variables measures either growth in outcomes – average weekly wages or employment – for the appropriate native group X. The explanatory variable in each regression is the change in foreign STEM relative to the initial level of total employment, $\frac{\Delta STEM_{ct}^{Foreign}}{E_{ct}}$. All 2SLS regressions use the H-1B driven change in foreign STEM relative to initial imputed employment, $\frac{\Delta STEM_{ct}^{H-1B}}{\widehat{E_{ct}}}$, as an instrument for the actual change (the endogenous explanatory variable).

Tables 6 reports the $b_{y,X}$ coefficients of interest, as defined in equation (1). Each of the six columns reports a different $b_{y,X}$ estimate corresponding to the use of differing outcome variables. The basic specification includes time-period effects, 219 MSA fixed-effects, and the Bartik instruments for the relevant wage (6) and employment (7) changes. We always cluster standard errors at the MSA level.

In column (1) the dependent variable is the percentage change of the weekly wage paid to native STEM workers $\left(\frac{\Delta w_{ST}^{native}}{w_{ST}^{native}}\right)$. In column (2) the dependent variable is the percentage change of the weekly wage of native college educated workers $\left(\frac{\Delta w_{College}^{native}}{w_{College}^{native}}\right)$, and in column (3) it is the percentage change of the weekly wage of native non-college educated workers $\left(\frac{\Delta w_{noCollege}^{native}}{w_{NoCollege}^{native}}\right)$.[25] We define college educated workers as those individuals who completed four years of college, while non-college educated are those who did not. Columns (4), (5), and (6) show the effect of STEM on the employment change of native STEM workers, native college educated workers, and native non-college educated workers, as a percentage of initial total employment (respectively $\frac{\Delta STEM_{ct}^{nat}}{E_{ct}}$, $\frac{\Delta H_{ct}^{nat}}{E_{ct}}$, and $\frac{\Delta L_{ct}^{nat}}{E_{ct}}$).

The different rows of Table 6 represent different specifications to test the robustness of the estimates, mirroring in large part those performed on the first stage of Table 4. Row

[25] Weekly wages are defined as yearly wage income divided by the number of weeks worked. Employment includes all individual between 18 and 65 years old who have worked at least one week during the previous year and do not live in group-quarters. Individual weekly wages are weighted by Census person weights. We convert all wages to current 2010 prices using the BLS Inflation Calculator. See the appendix for full details on the sample selection process.

(a), the baseline specification, shows the results when the O*NET 4% definition of STEM workers is used both for the explanatory variable and the instrument. In row (b) we instead use the Major-based 4% definition of STEM workers and in row (c) we use the broader O*NET 8% definition. Row (d) omits the top five metropolitan areas in terms of STEM employment, from specifications otherwise identical to those in row (a). Row (e) adds to the baseline specification the growth of imputed non-college educated immigrants, as defined in (5), as a control. Row (f) excludes MSAs with populations below 400,000. Row (g) excludes Indian STEM workers from the explanatory variable and instrument. Row (h) uses the instrument constructed using aggregate H-1B flows and the initial foreign STEM distribution, thus removing the nationality dimension. In row (i) we control for growth in native college educated employment by including a shift-share instrument for the growth of native college educated, constructed by interacting the number of native college educated in each city in 1980 with the national growth of native college educated in the population. Finally, row (j) shows the OLS estimates of the basic specification.

We first comment on the main results, which are relatively consistent across specifications, and then discuss some interesting features revealed by the robustness checks. First, there is a positive, large, and significant effect of foreign STEM workers on wages paid to college educated native workers. The estimated effect is significantly different from zero at the 5% significance level in all specifications, and is significant at the 1% level in most. The point estimates from the 2SLS specifications are mostly between 5.6 and 9.3 with some larger values. This implies an increase in college educated wage growth between 5.6 and 9.3 percentage points in response to an increase in foreign STEM growth by 1 percentage point of initial employment.[26]

Second, the estimates of the effects on native STEM wages are comparable to, but less precisely estimated than, the effects on native college educated workers. While we can never rule out the hypothesis that the estimated effect on native STEM wages is equal to the point-estimate of the effects on college educated wages[27], the first effect is only occasionally different from zero at the 5% significance level. As there are fewer STEM natives (about 4% of employment in our sample) than college educated natives (about 25% of employment), measurement error in the average wage of the first group makes the precision of the estimates much smaller.

The third consistent result of Table 6 is that H-1B STEM workers had a positive and usually significant effect on wages paid to non-college educated native workers. The effects, however, are smaller than those for college educated natives. The point estimates are mostly between 2.4 and 4.3 and less significant than those for college educated native wages. This result implies that the productivity effect of STEM workers is positive, but skill-biased: foreign STEM workers are closer substitutes for college educated natives than for non-college educated natives, yet they generate a larger increase in the wages paid to college educated natives than to non-college educated ones.

[26] Let us emphasize that 1 percentage point of employment is a very large increase for STEM workers, comparable to the increase over the whole period 1990-2010 as shown in Table 2.

[27] For instance, a formal test that the estimated coefficient on STEM wages in row (a) is equal to 8.03 (the point estimate for the effect on college educated) has a p-value of 0.76. At no level of confidence can we reject the hypothesis that they are equal. Similarly for the other specifications, we can never reject the hypothesis of equality at the 10% confidence level.

Fourth, the inflow of STEM workers did not significantly affect the employment of any group of workers. The point estimates are mainly positive for native STEM and college educated workers, and mainly negative for non-college educated natives. However, they are usually not significant, even at the 10% level[28]. The weak employment response, especially among college educated workers, who generally tend to be mobile across cities, suggests the potential existence of additional adjustment mechanisms for college educated workers at the metropolitan area level. We explore the possibility of changes in the price of non-tradables (in the form of house rents) as a response to the increase in productivity and wages of college educated workers in Section 5.4.

5.2 Robustness Checks

We now comment on some interesting and reassuring results emerging from the robustness checks performed in Table 6. To mitigate endogeneity concerns discussed earlier, row (d) omits the top five STEM-dependent cities and row (g) removes Indian workers. The estimated effects of STEM on native wages remain stable and even increase in some cases, albeit at the cost of larger standard errors. On one hand, this suggests that the inclusion of fixed effects, the instrumental variable strategy, and the additional controls (Bartik variables) in the baseline model largely address the endogeneity bias. On the other hand, the increase in standard errors indicates that the omitted cities, when included in regressions, afford precision in the estimates due to larger variation in the data.

The introduction of imputed low-skilled immigrants as a control in row (e) also results in an interesting and reasonable small change in the coefficient estimates when compared to row (a). We obtain a somewhat smaller estimate of the effect of STEM on college educated wages (down to 7.00 from 8.03) and a somewhat larger coefficient on non-college educated wages (up to 4.94 from 3.78). This is consistent with the idea that the inflow of less-educated immigrants, as predicted by the MSA composition in 1980, was partially correlated with foreign STEM (although not too strongly) and that less-educated labor inflows complemented college educated natives while substituting for non-college educated ones. Controlling explicitly for such imputed inflows helps to better isolate the effect of STEM, which ends up being more balanced in terms of productivity effects on college and non-college educated natives.

Similarly, a high initial share of foreign STEM might simply proxy for high education levels in a city. If cities with high initial share of college educated natives also experienced high wage and employment growth during periods of large inflows of foreign STEM, this would result in spurious correlation. Hence the inclusion in row (i) of a shift-share predictor of native college-educated growth helps address this issue. The estimated impact of STEM on wage of college educated remains quantitatively similar and is still statistically very significant.

When omitting small cities (row (f)) to examine issues related to measurement error, the point estimates do not change much (relative to row (e)), but the standard errors decrease. Hence, the measurement error that may be present does not seem to importantly affect the explanatory variable or the instrument by inducing bias, but the reduction of measurement

[28] Only the employment effect on native STEM in specification (d) is significantly positive.

error, by focusing only on large MSAs, leads to more precise estimates.

Finally, it is worth commenting on the difference between the OLS estimates (row j) and the corresponding 2SLS (row (e)). Interestingly, while the estimated employment effects have an upward bias in OLS relative to 2SLS, the wage effects have a downward bias. This may be due to the correlation between unobserved shocks and the inflow of foreign STEM over the considered period. It is likely, in fact, that the inflow of foreign STEM is positively correlated with employment growth and with a city's openness to new workers. Hence, the cities endogenously attracting foreign STEM workers could be those with fast inflows of workers in general, which may moderate wage growth. Thus, the correlation between STEM growth and omitted determinants of employment can be positive and the correlation with openness that induces wage growth moderation can drive a negative correlation with wages. This pattern of correlation would result in the observed biases.

Before extending the findings, we provide a sense of the magnitude of the estimated effect. The growth in foreign STEM, measured as a percentage of total initial employment, was only about 0.65% of total employment during the period 1990-2010. Applying the 7.00, 2SLS estimates of row (e) to the national growth in foreign STEM implies that the foreign-driven net growth in STEM increased real wages of college educated natives by around 4.55 percentage points (=7.00 x 0.65) between 1990 and 2010. As a reference, Census data suggests that the cumulative growth of college educated wages in this period equaled around 13 percentage points. Thus, one third of that growth can be attributed to the increased presence of foreign STEM workers. We return to these implications in Section 6 when we analyze the implied productivity and skill-bias effects of STEM.

5.3 Extensions

As shown in columns (5) and (6) of Table 5, the increase in foreign STEM across cities was an important driver of the increase in overall (native plus immigrant) STEM labor. Table 7 generalizes the second-stage results of Table 6 by using the same specifications as those from the first four rows of Table 6, and replacing the explanatory variable with total STEM growth, instead of foreign STEM growth.[29] The estimated effects confirm that STEM workers positively affect wages of college educated natives, and to a smaller extent, wages of the non-college educated as well. STEM workers had a positive and significant effect on wages of college educated natives that equaled around 4 percentage points for each increase in STEM by one percentage point of employment. The effects on wages of non-college natives, on the other hand, is around 2.4.[30] There is no evidence that either group experiences employment effects.

The basic result is robust to using the Major-based definition of STEM (row b), using the broad (8%) definition of STEM (row c), and omitting top STEM cities (row d). Also,

[29] We do not assess native STEM employment outcomes, as employment is subsumed in the explanatory variable itself.

[30] The point estimate of the effect on wages when considering foreign STEM only as explanatory variable (Table 6) is somewhat larger. It is possible that those estimates include a positive effect through the attraction of native STEM (as revealed by Table 6) who, in turn, spur the productivity of college educated workers. Hence an increase in foreign STEM by 1% of employment may imply an increase in total STEM by 1.5%, thereby generating a larger wage effect (by about 50%).

the OLS estimates confirm a positive bias (relative to the 2SLS results) for the effects on employment, and a negative one for the effects on wages. Overall our estimates confirm that the demand for native college educated workers received a significant positive boost from STEM workers and the demand for native non-college educated labor was also positively, but less strongly, affected.

A lot of heterogeneity exists among non-college educated workers. Table 8 explores whether the wage and employment effects of STEM workers are differentiated at different parts of the educational distribution within non-college educated. In particular, we assess whether effects are different among natives without a high school diploma (H.S. dropouts) and with a high school diploma (H.S. graduates). The table presents foreign STEM effects for wages (columns (1) and (2)) and employment (columns (3) and (4)). Rows (a)-(d) present several specifications of the 2SLS regression mirroring those in the corresponding rows of Tables 6 and 7. The main feature of each specification is described by the row headings. Row (e) reports the OLS coefficients.

By distinguishing high school graduates from high school dropouts, we can check whether these two groups are differentiated in their complementarity with college educated labor. This decomposition tests whether STEM workers produced the type of change in labor demand that is commonly called "skill biased" or if their effect appears to be indicative of a "polarization of the labor market." Skill-biased effects (see Acemoglu (1998, 2002)) would imply that productivity growth has been complementary to schooling, hence workers with lower schooling are less positively affected by innovation spurred by STEM workers. College educated workers would be most positively affected, followed by high school graduates, and lastly by high school dropouts. Polarization, instead, implies higher relative labor demand growth at the high and low ends of the educational spectrum at the expense of intermediate-level jobs (e.g. Autor (2010), Autor et al. (2006)). This outcome can be understood in terms of technological progress that may have substituted for intermediate types of skills (e.g., routine cognitive skills) but complemented low end (manual) and high end (analytical) skills.

The estimates of Table 8 show that STEM effects were significant only for high school graduates while dropouts experienced mostly insignificant consequences (typically with smaller point estimates). Neither group had significant employment effects. The basic specification in row (a) shows that STEM workers increased wages paid to native high school graduates by 5.5 percentage points for each percentage point increase in STEM employment. This would be consistent with a claim that STEM-driven technological progress has been skill (or schooling) biased rather than polarizing. The difference between the effects on high school graduates and dropouts is not usually significant, however, due to the lack of precision in estimating the dropout effects. No evidence of polarization as a consequence of STEM growth is found.

5.4 The Effect on Housing Rents

The impact of STEM worker growth on college educated wages is significantly positive. Given that college educated workers are generally mobile across cities (see Malamud and Wozniak (2012), for example), it is interesting that STEM worker growth did not also generate a significant employment response for this group. A plausible explanation, emphasized by

Moretti (2011) and Saiz (2007), is that the cost of non-tradable services, mainly housing rents, increases in the cities experiencing wage growth. Thus, housing prices might absorb some of the college educated wage growth driven by an inflow of STEM workers that we have identified in this paper.

In order to check this adjustment channel, we analyze the effect of STEM workers on native house rents as measured by the U.S. Census in 1990, 2000, 2005, and 2010. We use the data on rents, rather than house values, because they capture more closely the cost of housing services provided by a building or unit, and their changes do not include changes in their asset value (which was subject to large swings during our period of study). We construct average monthly rent per room in constant 2010 dollars by using data on the total number of rooms and monthly rent paid by native workers between 18 and 65 years of age, who rent their house, in the 219 metropolitan areas.[31] In order to identify the specific effect for college and non-college educated rents, we construct the rent per room for the two groups separately. As rental payments are top-coded and in some cities more than 5% of the individuals are subject to the top-code, we also calculate the median value of rent per room in a metro area. We then adopt the growth rate of these rent values as the outcome variable in regression (1), using the same methodology and instrument as in the estimated wage and employment regressions.

Table 9 reports the estimated effects of changes in foreign STEM employment on changes in rents paid by native college (column (1)) and non-college educated workers (column (2)). Each of the six rows of the table correspond to different specifications. Row (a) uses the O*NET 4% definition of STEM (both in the explanatory variable and instrument) and median rent as the dependent variable. In row (b) we use the average rent as dependent variable. Row (c) shows the results obtained using the broader O*NET 8% definition of STEM (both in the explanatory variable and instrument). Row (d) uses the same specification as in row (a), but omits the top five STEM cities. Similarly, row (e) omits Indians in the calculation of STEM workers. Row (f) shows the estimates when we use total (rather than foreign) STEM as the explanatory variable.

Each specification reveals a significant and positive effect (at the 1% level) of STEM growth on growth of rents paid by college educated workers. Point estimates center around 7. Conversely, point estimates of STEM effects on rents paid by non-college educated workers are near zero and are not significant. The inflow of H-1B STEM workers increased the wages of college educated labor and increased their housing costs. These higher wages likely caused college educated natives to bid up the rent price of houses in the parts of cities most desirable to them. This differential increase in rents is therefore due to the more limited supply of desirable locations for college educated labor and the larger increase in their income.

Housing costs are likely to affect the cost of other non-tradable local services as well, and the sum of those effects will influence real wages. The Consumer Expenditure Surveys[32] for college educated workers from 1998-2002 show that housing costs represented 33% of individual expenditures, while 17% of their expenditures were in utilities, health, and entertainment (non-tradable services). Hence, 50% of college educated workers' incomes could easily be spent on non-tradable services.

[31] See Online Appendix for further details on selection criteria.

[32] See the Bureau of Labor Statistics (2005).

If we consider the average estimated price effect (from Table 9) to be around a 7 percentage point increase for each percentage point rise in the STEM share of employment, and the corresponding average effect on native college wages to be around 7 percentage points as well (from the average estimate in Table 6), then the real wage increase for college educated labor, accounting for purchasing power, would be only around 3.5 percentage points. The STEM effect on non-tradables prices, therefore, contributed substantially to absorbing the local effect on college educated wages and helps to explain the small employment response.

6 Deriving Productivity and Skill-Bias Effects

In this final section we sketch a simple model of production in cities that allows us to use the elasticities estimated in Tables 6 and 7 for calculating the long-run effect of STEM on the total factor productivity (TFP) and skill bias of productivity (SBP) in a city. We present the basic assumptions and the intuition of the model, and then we show simulations of TFP and SBP effects for 1990-2010 that can be explained by growth in foreign STEM workers. We present the solution to the model and derive the exact expressions for the three demand conditions used to calculate the effects of STEM on TFP and SBP in the Appendix A.

6.1 Framework

Suppose a city (c) produces a homogeneous, tradable, numeraire product (Y_{ct}) in year t. The economy employs three types of workers: non-college educated (L_{ct}), college educated workers (H_{ct}), and STEM workers (ST_c). Production occurs according to the following long-run production function:

$$Y_{ct} = \left[A(ST_{ct}) \left(\beta(ST_{ct}) K_{ct}^{\frac{\sigma_H - 1}{\sigma_H}} + (1 - \beta(ST_{ct})) L_{ct}^{\frac{\sigma_H - 1}{\sigma_H}} \right) \right]^{\frac{\sigma_H}{\sigma_H - 1}} \tag{8}$$

Input K is a composite factor obtained by combining college educated and STEM workers as follows:

$$K_{ct} = \left(ST_{ct}^{\frac{\sigma_S - 1}{\sigma_S}} + H_{ct}^{\frac{\sigma_S - 1}{\sigma_S}} \right)^{\frac{\sigma_S}{\sigma_S - 1}} \tag{9}$$

The parameter $\sigma_H > 1$ captures the elasticity of substitution between non-college and college educated labor. Similarly, $\sigma_S > 1$ is the elasticity of substitution between college educated (non-STEM) and STEM workers.

Physical capital is absent from (8). Instead we assume that capital mobility and the equalization of capital returns imply a constant capital-output ratio in the long run so that capital can be solved out of the production function. In this sense, the comparative static results that we find can be thought of as a comparison between long-run balanced growth paths.

STEM workers are the key inputs in developing and adopting new technologies, which are widely credited for increasing the productivity of college educated workers as well as increasing total factor productivity. Our modeling choices seek to capture these factors.

We follow the literature on human capital externalities[33] and growth of ideas[34] by allowing the level of total factor productivity, $A(ST_{ct})^{\frac{\sigma_H}{\sigma_H-1}} > 0$, to be a function of the number of STEM workers in the city. If $A'(ST_{ct}) > 0$, STEM-driven innovation externalities have a positive effect on TFP. At the same time we allow for skill (college) biased productivity, $\beta(ST_{ct}) \in [0,1]$, to depend upon the number of STEM workers. If $\beta'(ST_{ct}) > 0$, STEM-driven innovation externalities may have a college-biased effect on productivity. Even if STEM and college-educated workers are close substitutes in production ($\sigma_S \approx \infty$), in the described framework STEM workers are uniquely capable of potentially generating ideas, innovation, and externalities that benefit productivity.

The main goal of the model is to identify the effect of STEM workers on TFP $\left(A^{\frac{\sigma_H}{\sigma_H-1}}\right)$ and its college-bias $(\beta/(1-\beta))$ in equilibrium. We proceed as follows. First we derive wages paid to each factor as their marginal productivity, implied by the production function. Then we calculate the total logarithmic (percentage) change in wages for each group (non-college, college educated , and STEM) in response to the changes in the supply of each type of worker (expressed as a percentage of total employment), allowing for mobility of workers and, hence, for changes in each group's supply in response to an exogenous change of STEM workers. Next, we divide each side of the three labor demand conditions (one for each type of worker) by the exogenous change of STEM workers expressed as a percentage of total employment. This gives us three linear conditions[35] relating the elasticity of each group's wage and employment to STEM (i.e., the coefficients $b_{y,X}$ estimated from Equation 1).

The linear expressions also include terms that depend upon the wage and employment share of each worker type and the four unknown parameters σ_H, σ_s, $\phi_A = \frac{\Delta A/A}{\Delta ST/E}$, and $\phi_\beta = \frac{\Delta\beta/\beta}{\Delta ST/E}$. Wage and employment shares can be calculated from Census data. Values for the elasticity of substitution between college and non-college educated labor (σ_H) can be taken from prior literature. The ϕ_A and ϕ_β terms are the elasticity of A and β to changes in STEM (relative to initial employment). These values, in addition to the elasticity of substitution between STEM and college educated labor (σ_s) can be solved for by using the three labor demand conditions derived from the model (which are linear due to the CES structure of production). ϕ_A and ϕ_B allow us to evaluate the impact of STEM on TFP and its skill bias.

The advantage of this approach is that we have an intuitive and standard definition of TFP and SBP based on a city-specific production function. We can use it to infer the productivity impacts of STEM. Moreover, we can calculate these effects without specifying the labor supply-side of the model, which is affected by mobility and labor force participation, as long as we have the equilibrium elasticity for the employment of each factor to the exogenous change in STEM (which we estimated in Tables 6 and 7). The limitations of this approach are its dependence on the specific assumptions on the production structure and on the form of the productive interactions between different types of labor.

[33] See Acemoglu and Angrist (2000), Iranzo and Peri (2009), and Moretti (2004a).
[34] See Jones (1995).
[35] The interested reader can find these conditions as equations 13-15 in Appendix A.

6.2 Estimated Productivity Effects

By substituting the estimated values of $\widehat{b}_{y,X}$ – the elasticity of outcome y for group X to STEM workers – in the equations derived from our model (and described in Appendix A), we can back-up the effects on the growth of TFP and SBP.[36] The literature provides estimates of σ_H that usually range between 1.5 and 2.5.[37] We assume a σ_H value of 2 in our basic simulation, and we use values of 1.75 and 2.25 in two robustness checks. We combine this value with U.S. Census data on the relative wage and employment of college and non-college educated labor to obtain an implied value of β equal to 0.57 (in the basic specification) for the year 2000.[38] We also use the values of the share of STEM workers in total employment (0.04) and in the total wage bill (0.09), plus the college educated share of the wage bill (0.46) as obtained from the 2000 Census data for the aggregate U.S. sample. Changing those parameters to their 2010 or 1990 values has only very marginal effects on the simulations.[39]

Table 10 displays the simulated changes to TFP (column (1)) and SBP (column (2)) over the period 1990-2010 attributed by our model to the average (aggregate) growth in foreign STEM between 1990 and 2010. The change in foreign STEM was equal to an increase by 0.04% of the total employment each year. Actual annual changes in TFP (from Fernald (2010)) is 0.89% and SBP, from our caluclations based on Census data, is 1.75%. Those values are reported in columns (3) and (4). The last two columns then show the proportion of the actual changes explained by the simulated effect of foreign STEM.

The first row of Table 10 reports the simulated effects when we use the elasticities estimated from the basic specification of Table 6, row (a). Row (2) uses the estimates from Table 6, row (f), in which we control for imputed unskilled immigrants and reduce the attenuation bias by including only large cities in the regression. We label this row "Conservative Estimates" because the underlying regression leads to somewhat smaller estimates of the effect of STEM on native wages. In row (3) we use estimates from Table 7 row (a), obtained using total STEM as explanatory variable,[40] which tend to be 40-50% smaller than those obtained with foreign STEM. The fourth and fifth row show the robustness of the estimates to changes in values of the parameter σ_H, using the Basic specification of Row (a).

The estimated elasticities imply that foreign STEM growth can explain between a third

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[36] We also get from our model an estimate of σ_S the elasticity of substitution between STEM and non-STEM college educated in production. That elasticity is always very high and statistically non distinguishable from infinity ($1/\sigma_S$ is not significantly different from 0). This is because our estimates of the elasticity of college educated wages and STEM wages to STEM supply are always very close to each other, implying high substitutability between the two groups.

[37] See Ciccone and Peri (2005) for a review of the estimates. Katz and Murphy (1992), Goldin and Katz (2007), and Ottaviano and Peri (2012) provide some influential estimates of that parameter.

[38] The formula is $\frac{\beta}{1-\beta} = \frac{w_H}{w_L}\left(\frac{H}{L}\right)^{1/\sigma_H}$, where w_H and w_L are the wages of college and non-college educated workers and H and L their respective employment. Using data from year 2000, the term $\frac{\beta}{1-\beta}$ for the US turns out to be 1.07, which implies $\beta = 0.57$.When we change the value of σ_H in the simulations, the value of β changes as well according to the above formula.

[39] These simulations are available upon request.

[40] In this case we used the estimated elasticity of college educated wages (3.96) also for STEM, as the model implies that the elasticity of college educated wages to foreign STEM cannot be smaller than that of native STEM wages.

and a half of the average productivity growth in the period 1990-2010, depending on the particular wage regression coefficients and value of σ_H substituted into the model. Even in the case of the smallest estimates, 30% of the TFP growth of the average U.S. city is explained by foreign STEM. Let us emphasize that the average annual TFP effect implied by our simulations is about 0.44 percentage points per year. This annual growth implies that income per capita of native workers in 2010 was 9.1% larger in the U.S. that it would have been without contributions from foreign STEM. This is a significant effect. We also find an effect on the skill bias, but it seems more modest and it does not explain more than 5 to 8% of the SBP growth over the period.[41]

This macro exercise must certainly be taken with great caution as it is based on very strong assumptions. In particular, we apply parameters that were estimated across cities to calculate national effects of foreign STEM. Simulations will overstate the aggregate effects on productivity if some of the wage effects from the underlying regressions are due to the selection of natives. However, since our regressions only capture the within city productivity effect, we may also be under-estimating the national impact on productivity.

Despite its limitations, the exercise is informative as it provides a reference for the magnitude of productivity effects. It is also reassuring that the simulated effects are closely aligned with the productivity effects of scientists and engineers found by the growth literature. For example, Jones's (2002) very influential paper on aggregate U.S. data found that about 50% of the long-run productivity growth of the U.S. in recent decades could be attributed to growth in scientists and engineers as a share of employment. We find that during the 20 years leading to 2010, between one third and one half of the U.S. productivity growth can be attributed to the growth of foreign STEM workers. As foreign STEM worker growth represented about 80% of the net growth in STEM workers in those decades, our results closely align with Jones (2002). It would be impossible to justify the estimated effects of foreign STEM on native wages by considering them only as an increase in skilled labor supply. However, if they are considered as a source of growth in R&D resources, then their effect is perfectly in line with the previously estimated effects of R&D on productivity growth.

7 Conclusions

In this paper we used the inflow of foreign scientists, technology professionals, engineers, and mathematicians (STEM), made possible by the H-1B visa program, to estimate the impact of STEM workers on the productivity of college and non-college educated American workers over the 1990-2010 period. The uneven distribution of foreign STEM workers across cities in 1980 – a decade before the introduction of the H-1B visa – and the high correlation between the pre-existing presence of foreign-born workers and subsequent immigration flows allows us to use the variation in foreign STEM as a supply-driven increase in STEM workers across metropolitan areas.

We find that a one percentage point increase in the foreign STEM share of a city's total employment increased wages of native college educated labor by about 7-8 percentage points and the wages of non-college educated natives by 3-4 percentage points. We find

[41] Our measure of college bias is the percentage change in the college to non-college labor wage ratio, keeping their relative labor supply constant.

non-significant effects on the employment of those two groups. These results indicate that growth in STEM workers spurred technological growth by increasing productivity, especially that of college educated workers. They also experienced increasing housing rents, which eroded part of their wage gain.

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A A Model to Derive Productivity Effects

In this Appendix we show the details of the calculations performed to obtain the elasticities of TFP and SBP to changes in STEM workers, $\phi_A = \frac{\Delta A/A}{\Delta ST/E}$ and $\phi_B = \frac{\Delta \beta/\beta}{\Delta ST/E}$, used to simulate the effects shown in Table 10 and discussed in Section 6.

A.1 Wages and Labor Demand System

Using a production function as defined in (8) for each city we assume that each group of workers is paid their marginal productivity. Hence, to obtain the wages of each type of worker, we take the first derivative of the production function (8) with respect to the employment of each group. This generates the following expressions (for brevity, we omit the subscripts and the dependence of A and β on ST):

$$w_L = A(1-\beta)Y^{\frac{1}{\sigma_H}}L^{-\frac{1}{\sigma_H}} \tag{10}$$

$$w_H = A\beta Y^{\frac{1}{\sigma_H}}K^{(\frac{1}{\sigma_S}-\frac{1}{\sigma_H})}H^{-\frac{1}{\sigma_S}} \tag{11}$$

$$w_{ST} = A\beta Y^{\frac{1}{\sigma_H}}K^{(\frac{1}{\sigma_S}-\frac{1}{\sigma_H})}ST^{-\frac{1}{\sigma_S}} \tag{12}$$

In equilibrium we observe simultaneous changes in wages and employment of each type of worker. Taking a total logarithmic differential of expressions (10)-(12) and writing all employment changes relative to total employment $E = L + H + ST$, we have the following three equations relating the equilibrium changes in employment and wages for each group of workers (non-college educated, college educated, and STEM, respectively):

$$\begin{aligned}\frac{\Delta w_L}{w_L} &= \left(\phi_A - \frac{\beta}{1-\beta}\phi_B + \frac{s_w^{ST}}{\sigma_H s_E^{ST}}\right)\left(\frac{\Delta ST^{Foreign} + \Delta ST^{Native}}{E}\right) + \\ &\quad \frac{s_w^H}{\sigma_H s_E^H}\frac{\Delta H}{E} + \left(\frac{s_w^L}{\sigma_H s_E^L} - \frac{1}{\sigma_H s_E^L}\right)\frac{\Delta L}{E}\end{aligned} \tag{13}$$

$$\begin{aligned}\frac{\Delta w_H}{w_H} &= \left(\phi_A + \phi_B + \frac{s_w^{ST}}{\sigma_H s_E^{ST}} + \left(\frac{1}{\sigma_S} - \frac{1}{\sigma_H}\right)\frac{s_w^{ST}}{s_w^K s_E^{ST}}\right)\frac{\Delta ST^{Foreign}}{E} + \\ &\quad \left(\frac{s_w^H}{\sigma_H s_E^H} + \left(\frac{1}{\sigma_S} - \frac{1}{\sigma_H}\right)\frac{s_w^H}{s_w^K s_E^H} - \frac{1}{\sigma_S s_E^H}\right)\frac{\Delta H}{E} + \frac{s_w^L}{\sigma_H s_E^L}\frac{\Delta L}{E}\end{aligned} \tag{14}$$

$$\begin{aligned}\frac{\Delta w_{ST}}{w_{ST}} &= \left(\phi_A + \phi_B + \frac{s_w^{ST}}{\sigma_H s_E^{ST}} + \left(\frac{1}{\sigma_S} - \frac{1}{\sigma_H}\right)\frac{s_w^{ST}}{s_w^K s_E^{ST}} - \frac{1}{\sigma_S s_E^{ST}}\right)\frac{\Delta ST^{Foreign}}{E} + \\ &\quad \left(\frac{s_w^H}{\sigma_H s_E^H} + \left(\frac{1}{\sigma_S} - \frac{1}{\sigma_H}\right)\frac{s_w^H}{s_w^K s_E^H} - \frac{1}{\sigma_S s_E^H}\right)\frac{\Delta H}{E} + \frac{s_w^L}{\sigma_H s_E^L}\frac{\Delta L}{E}\end{aligned} \tag{15}$$

These equations have to hold in equilibrium. The terms ϕ_A and ϕ_B, appearing in all expressions, are our main objects of interest. They capture the elasticity of productivity and skill-bias to (foreign-born) STEM workers. Their expressions are:

$$\phi_A = \frac{\Delta A/A}{\Delta ST/E}, \ \phi_\beta = \frac{\Delta \beta/\beta}{\Delta ST/E} \tag{16}$$

We use the equilibrium conditions (13)-(15) and our empirical estimates to calculate ϕ_A and ϕ_B. If we divide both sides of all equations by $\frac{\Delta ST^{Foreign}}{E}$ then the wage and employment elasticity terms obtained are exactly the estimated coefficients $b_{y,X}$ from the empirical equation (1). For instance the elasticity $\frac{\Delta w_L}{w_L}/\frac{\Delta ST^{Foreign}}{E}$ is the coefficient $b_{w,L}$ estimated from regression (1) when the dependent variable is $\left(\frac{\Delta w_L}{w_L}\right)_{ct}$. Similarly, $\frac{\Delta L}{E}/\frac{\Delta ST^{Foreign}}{E}$ is the coefficient $b_{E,L}$ estimated from regression (1) when the dependent variable is $\left(\frac{\Delta L}{E}\right)_{ct}$.

The terms s_w^X and s_E^X, for $X = ST, H, L$, and K represent, respectively, the share of total wage income and employment represented by factor X. For example, s_w^K is the share of total wage income accruing to workers with college education (STEM and non-STEM) and equals $(w_{ST}ST + w_H H)/(w_{ST}ST + w_H H + w_L L)$, while $s_E^{ST} = ST/E$ is the STEM worker share of total employment.

With the equilibrium response of wages and employment of each group to $STEM$ estimated in the text, and using census wage and employment data to calculate the shares s_w^X and s_E^X, equations (13)-(15) only depend on four unknown parameters: ϕ_A, ϕ_B, σ_S, and σ_H. We adopt estimates of the parameter σ_H from the extensive literature that estimates the elasticity of substitution between college and non-college educated, and we use (13)-(15) and our elasticity estimates to obtain values for ϕ_A, ϕ_B and σ_S. The three equations are linear in ϕ_A, ϕ_B and $1/\sigma_S$.

A.2 Solving the Linear System to Obtain TFP and Skill Bias

Our empirical estimates suggest that three employment elasticities – $\widehat{b}_{E,L} = \frac{\Delta L}{E}/\frac{\Delta ST^{Foreign}}{E}$; $\widehat{b}_{H,L} = \frac{\Delta H}{E}/\frac{\Delta ST^{Foreign}}{E}$; and $\widehat{b}_{ST,L} = \frac{\Delta ST^{Native}}{E}/\frac{\Delta ST^{Foreign}}{E}$ – are never statistically different from zero. Hence for simplicity (and without affecting much the simulations) we set them equal to zero. This allows us to simplify the system and obtain the following three equations that identify the remaining three unknown parameters:

$$\phi_A - \frac{\beta}{1-\beta}\phi_B = \widehat{b}_{w,L} - \frac{s_w^{ST}}{\sigma_H s_E^{ST}} \tag{17}$$

$$\phi_A + \phi_B = \widehat{b}_{w,H} - \frac{s_w^{ST}}{\sigma_H s_E^{ST}} - \left(\frac{1}{\sigma_S} - \frac{1}{\sigma_H}\right)\frac{s_w^{ST}}{s_w^K s_E^{ST}} \tag{18}$$

$$\frac{1}{\sigma_S} = s_E^{ST}\left(\widehat{b}_{w,NST} - \widehat{b}_{w,ST}\right) \tag{19}$$

The last equation immediately defines $1/\sigma_S$. This can be substituted into (17) and (18), thereby reducing them to simple linear equations in the two unknown $\phi_A$and ϕ_B. By solving them we obtain the following solutions:

$$\phi_A = \beta T_1 + (1-\beta)T_2 \tag{20}$$

$$\phi_B = (1-\beta)(T_1 - T_2) \tag{21}$$

Where:

$$T_1 = \widehat{b}_{w,H} - \frac{s_w^{ST}}{\sigma_H s_E^{ST}} - \left(\frac{1}{\sigma_S} - \frac{1}{\sigma_H}\right)\frac{s_w^{ST}}{s_w^K s_E^{ST}} \tag{22}$$

$$T_2 = \widehat{b}_{w,L} - \frac{s_w^{ST}}{\sigma_H s_E^{ST}} \tag{23}$$

We use these formulas to calculate the effect of STEM growth on TFP and skill biased growth that we report in Table 10.

Tables and Figures

Table 1:
Summary Statistics, Percentage of Foreign-Born by Group

	(1) % in Total Employment	(2) % Among College Educated Employment	(3) % Among College Educated Employment in 219 MSAs	(4) % Employment in STEM Occupations in 219 MSAs	(5) % Among College Educated Employment in STEM Occupations in 219 MSAs
1980	6.15	6.81	8.01	9.27	12.18
1990	8.82	8.96	10.51	12.63	15.64
2000	13.31	12.80	14.75	19.66	24.74
2005	15.37	14.82	17.10	22.74	28.40
2010	16.37	15.46	17.74	23.95	29.74

Note: The figures are obtained by the authors' calculations using IPUMS Census data from 1980-2010. The relevant population includes only non-institutionalized individuals between age 18 and 65, who have worked at least one week in the previous year and report identified occupations. The statistics exclude those with unknown, unreported, or military occupations, and individuals without a clearly identified birthplace who do not possess U.S. citizenship through parents with U.S. citizenship. STEM occupations are defined according to the O*NET 4% definition. College educated workers have a bachelor degree or higher. The sample is comprised of 219 consistently identified MSAs from 1980-2010.

Table 2:
College Educated STEM Workers as a Percentage of Employment, 219 Metropolitan Areas

	Foreign STEM	Total STEM
1980	0.26	2.11
1990	0.45	2.90
2000	0.87	3.52
2005	1.00	3.52
2010	1.10	3.71

Note: The figures are obtained by the authors' calculations using IPUMS Census data from 1980-2010. The relevant population includes only non-institutionalized individuals between age 18 and 65, who have worked at least one week in the previous year, and report identified occupations. The statistics exclude those with unknown, unreported, or military occupations, and individuals without a clearly identified birthplace who do not possess U.S. citizenship through parents with U.S. citizenship. STEM occupations are defined according to the O*NET 4% definition. College educated workers have a bachelor degree or higher. The sample is comprised of 219 consistently identified MSAs from 1980-2010.

Table 3:
Net Increase in College educated STEM Workers and Cumulative H-1B Visas (Thousands)

	Net Change in Total College Educated STEM	Net Change in Foreign College Educated STEM	Cumulative H-1B Visas Issued
1980-1990	980	204	0
1990-2000	1,114	498	575
2000-2005	254	202	663
2005-2010	269	131	671

Note: The figures are obtained by the authors' calculations on 219 consistently identified MSAs in IPUMS Census data from 1980-2010. The relevant population includes only non-institutionalized individuals between age 18 and 65, who have worked at least one week in the previous year, and report identified occupations. The statistics exclude those with unknown, unreported, or military occupations, and individuals without a clearly identified birthplace who do not possess U.S. citizenship through parents with U.S. citizenship. STEM occupations are defined according to the O*NET 4% definition. College educated workers have a bachelor degrees or higher. H-1B numbers also include TN visas. Data on the total number of H-1B & TN visas issued are from the Department of State (2010).

Table 4:
First Stage: Power and Validity of H-1B-Driven STEM as an IV

Explanatory Variable	Coefficient	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Specification		Strict (4%) Definition of STEM (with State Fixed Effects)	Baseline: Strict (4%) Definition of STEM (with City Fixed Effects)	Broad (8%) Definition of STEM both for endogenous variable and Instrument	As (2), Excluding Top 5 Cities	As (2), Excluding Indians	As (2), Imputation Using Aggregate H-1B Visas (Not by Nationality)	As (2), Excluding Cities with Population <400,000	As (2), Controlling for Imputed Non-College Educated Immigrants	As (8), Controlling for Bartik Employment and Wage Growth
H-1B Driven Growth in Foreign-STEM, O*Net	Coefficient (Standard Error)	0.48*** (0.18)	2.56*** (0.88)	4.06*** (1.28)	1.82** (0.82)	3.51*** (0.90)	3.02*** (0.74)	3.21*** (0.85)	2.47*** (0.90)	2.33*** (0.92)
	F-statistic	6.57	8.51	9.95	4.86	15.20	16.43	14.04	7.59	6.46
H-1B Driven Growth in Foreign-STEM, Major-based	Coefficient (Standard Error)	0.44*** (0.16)	2.83*** (0.84)	4.23*** (0.93)	2.13*** (0.63)	3.59*** (1.00)	3.26*** (1.03)	3.34*** (1.08)	2.79*** (0.86)	2.42** (0.88)
	F-statistic	7.73	11.32	20.53	11.27	12.99	9.86	9.48	10.64	7.50
Fixed Effects:		State & Period	City & Period	City & Period	City & Period	City & Period	City & Period	City & Period	City & Period	City & Period
Number of Observations:		657	657	657	642	657	657	354	657	657
Metro areas:		219	219	219	214	219	219	118	219	219

Note: Each cell shows the coefficient from a different regression. The dependent variable is the growth in foreign STEM as percentage of the labor force. The units of observations are 219 U.S. metropolitan areas over the periods 1990-2000, 2000-2005, 2005-2010. The explanatory variable is the H-1B-driven growth of foreign-STEM jobs, as a percentage of initial employment. Top 2 rows use the O*NET based definition of STEM occupations; Rows 3 and 4 use Major-based STEM definitions. Baseline models use the narrow (4%) definition of STEM. Column (1) also controls for a city's native STEM employment in 1980. Standard errors (in parentheses) are always clustered at the metro area level.
***, **,*= significant at 1%, 5% and 10% level respectively.

Table 5:
First Stage: Falsification and Extensions

Explanatory Variable	**Coefficient**	**(1)** Falsification: Endogenous Variable is Growth of foreign STEM O*NET 4%	**(2)** Falsification: Endogenous Variable is Growth of foreign STEM O*NET 4%	**(3)** Falsification: Endogenous Variable is Growth of foreign STEM Major-based 4%	**(4)** Dependent Variable 1970-1980 College educated Native Wages; Explanatory Variable 1990-2000	**(5)** Dependent Variable: Total STEM Growth (Native + Immigrant), 4% STEM Definition	**(6)** Dependent Variable: Total STEM Growth, 8% STEM Definition
Predicted Foreign-STEM, O*NET definition	Coefficient (Standard Error)				-1.66 (1.02)	5.03*** (1.81)	8.50** (4.40)
	F-statistics				2.62	7.70	3.65
Predicted Foreign-STEM, Major-based definition	Coefficient (Standard Error)				-1.12 (1.09)	5.29*** (1.71)	9.632*** (2.56)
	F-statistics				1.05	9.54	14.05
Predicted Growth in Foreign STEM using Flows of Non-College Immigrants	Coefficient (Standard Error)	0.04 (0.03)					
	F-statistics	2.24					
Predicted Growth in Foreign STEM using Flows of Total Immigrants minus H-1B	Coefficient (Standard Error)		0.04 (0.025)				
	F-statistics		3.08				
Predicted Growth in Foreign STEM using 1980 Distribution of Manual Immigrants	Coefficient (Standard Error)			0.41 (0.27)			
	F-statistics			2.42			
Number of Observations:		657	657	657	116	657	657
Metro areas:		219	219	219	116	219	219

Note: Each cell shows the coefficient from a different regression and below it the F-test of significance. The units of observations are 219 U.S. metropolitan areas over the periods 1990-2000, 2000-2005, 2005-2010. The dependent variable is the growth in foreign STEM in columns (1)-(3), the growth in native college educated wage 1970-1980 in column (4), and total STEM growth in columns (5) and (6). The explanatory variables are described at the beginning of the row. Standard errors (in parentheses) are always clustered at the metro area level.***, **,*= significant at 1%, 5% and 10% level respectively.

Table 6: The Effects of Foreign STEM on Native Wages and Employment

Explanatory Variable: Growth Rate of Foreign–STEM **Instrument:** H-1B Imputed Growth of Foreign-STEM	**(1) Weekly Wage, Native STEM**	**(2) Weekly Wage, Native College educated**	**(3) Weekly Wage, Native Non-College educated**	**(4) Employment, Native STEM**	**(5) Employment, Native College educated**	**(6) Employment, Native Non-College educated**
(a) Baseline 2SLS; O*NET 4% Definition	6.65 (4.53)	8.03*** (3.02)	3.78** (1.75)	0.53 (0.56)	2.47 (4.69)	-5.17 (4.19)
(b) 2SLS; Major-based 4% Definition	6.64 (5.08)	10.94** (4.34)	3.21** (1.67)	0.60 (0.63)	1.04 (3.98)	-7.82 (4.90)
(c) 2SLS; O*NET 8% Definition	7.23** (3.51)	5.64*** (1.95)	2.55** (1.08)	0.53 (0.75)	1.84 (3.20)	-4.13 (3.31)
(d) Omitting Top 5 STEM Cities	11.35 (8.63)	12.78*** (4.99)	5.03 (3.42)	1.64*** (0.53)	8.45 (7.04)	-2.50 (7.45)
(e) Controlling for Imputed Non-College Immigrants	7.94 (5.38)	7.00** (2.98)	4.94** (2.08)	0.76 (0.61)	3.29 (4.84)	-3.39 (4.15)
(f) Dropping Small Cities (pop<400,000)	5.70 (3.51)	7.17*** (2.61)	4.28*** (1.45)	0.34 (0.58)	-0.60 (1.50)	-5.19 (3.18)
(g) Dropping Indians from the IV	3.52 (5.04)	9.33** (4.35)	3.45* (2.07)	0.46 (0.51)	1.29 (3.60)	-6.43* (3.53)
(h) Aggregate H-1B IV	5.76 (4.05)	6.03** (2.75)	4.13*** (1.33)	0.31 (0.48)	1.64 (4.20)	-5.56 (3.63)
(i) Controlling for Imputed College Natives	2.72 (4.68)	7.57** (3.78)	2.39 (1.99)	-0.32 (0.47)	-0.62 (4.18)	-7.28 (5.15)
(j) OLS Version of Specification (e)	3.32 (2.98)	4.10*** (1.86)	1.16 (1.24)	0.91** (0.34)	4.97 (3.68)	2.11 (2.51)

Note: Each cell shows the estimate of the coefficient on the growth in foreign STEM (relative to employment) when the dependent variable is the one described at the top of the column. Each regression includes period effects, metropolitan area effects, and the Bartik for employment or wage of the relevant group. Rows (a) and (d)-(h) are 2SLS regressions using the O*NET 4% definition of STEM. Rows (b) and (c) use alternative definitions of STEM. Row (j) shows the OLS estimates. Standard errors (in parentheses) are clustered at the metro area level. Unit of observations are 219 metro areas over 3 periods, 1990-2000, 2000-2005 and 2005-2010.
***, **,*= significant at 1%, 5% and 10% level respectively.

Table 7: The Effects of Total STEM on Native Wages and Employment

Explanatory Variable: Growth Rate of Total STEM **Instrument:** H-1B Imputed Growth of Foreign-STEM	**(1) Weekly Wage, Native STEM**	**(2) Weekly Wage, Native College educated**	**(3) Weekly Wage, Native Non-College educated**	**(5) Employment, Native College educated**	**(6) Employment, Native Non-College educated**
(a) 2SLS; O*NET 4% Definition	4.50 (2.93)	3.96*** (1.41)	2.43** (1.01)	1.86 (2.31)	-1.67 (2.33)
(b) 2SLS; Major-based 4% Definition	4.89 (3.4)	5.68** (2.41)	2.40** (1.00)	1.15 (2.10)	-2.91 (2.82)
(c) 2SLS; O*NET, 8% Definition	4.55 (3.01)	2.64* (1.43)	2.43** (1.01)	1.45 (1.24)	-1.23 (1.79)
(d) Same as (a), but omitting Top 5 STEM Cities	4.50 (3.38)	4.02** (1.73)	1.97 (1.12)	3.23 (2.37)	-0.27 (2.33)
(e) OLS; O*NET 4% Definition	0.37 (1.08)	0.72 (0.54)	0.75* (0.40)	2.72*** (0.77)	4.59*** (0.79)

Note: Each cell shows the estimate of the coefficient on the growth in total STEM (relative to employment) when the dependent variable is the one described at the top of the column and the instrument is the H-1B driven STEM growth. Each regression includes period effects, metropolitan area effects, the Bartik for employment and wage of the relevant group, and the imputed growth of non-college educated immigrants. Standard errors (in parentheses) are clustered at the metro area level. Unit of observations are 219 metro areas over 3 periods, 1990-2000, 2000-2005 and 2005-2010.
***, **,*= significant at 1%, 5% and 10% level respectively.

Table 8: The Effect of Total STEM on Non College educated Natives

Explanatory Variable: Growth Rate of Total STEM **Instrument:** H-1B Imputed Growth of Foreign-STEM	**(1)** **Weekly Wage, Native HS Graduates**	**(2)** **Weekly Wage, Native HS Dropouts**	**(3)** **Employment, Native HS Graduates**	**(4)** **Employment, Native HS Dropouts**
(a) 2SLS; O*NET 4%	5.54**	3.30	-3.35	-0.03
Definition	(2.33)	(4.26)	(3.72)	(0.54)
(b) 2SLS; Major-based 4%	4.86**	5.97	-5.11	-0.50
Definition	(2.10)	(4.67)	(4.08)	(0.65)
(c) 2SLS; O*NET, 8%	4.10**	2.45	-2.48	-0.02
Definition	(1.70)	(3.01)	(2.88)	(0.40)
(d) Same as (a), but	7.05*	6.28	-1.37	0.50
Dropping Top 5 STEM Cities	(4.29)	(7.58)	(6.65)	(0.96)
(e)	2.73**	1.63	-1.65	-0.01
Explanatory Variable: Total STEM, O*NET 4%	(1.15)	(1.99)	(2.12)	(0.27)

Note: Each cell shows the estimate of the coefficient on the growth in foreign STEM (relative to employment) when the dependent variable is the one described at the top of the column. Each regression includes period effects, metropolitan area effects, the Bartik for employment and wage of the relevant group, and the imputed growth of non-college educated immigrants. Standard errors (in parentheses) are clustered at the metro area level. Unit of observations are 219 metro areas over 3 periods, 1990-2000, 2000-2005 and 2005-2010.

***, **,*= significant at 1%, 5% and 10% level respectively.

Table 9: The Effects of Foreign STEM on Native Rents

Explanatory Variable: Growth Rate of STEM **Instrument:** H-1B Imputed Growth of Foreign STEM	**(1)** **Dep. Var: Rent per Room, Native College Educated**	**(2)** **Dep. Var: Rent per Room, Native non-College Educated**
(a) 2SLS; Expl. Var.: Foreign O*NET 4% Dep. Var.: Median Rent	10.29*** (3.64)	1.64 (2.88)
(b) 2SLS; Expl. Var.: Foreign O*NET 4% Dep. Var.: Average Rent	10.02*** (3.85)	2.73 (2.80)
(c) 2SLS; Expl. Var.: Foreign O*NET 8% Dep. Var.: Median Rent	6.80*** (2.56)	0.04 (2.30)
(d) Same as (a), but Dropping Top 5 Metro areas	13.27* (6.69)	-1.14 (4.05)
(e) Same as (a), but No Indians in the IV	5.33*** (1.92)	2.00 (1.57)
(f) 2SLS; Expl. Var.: Total O*NET 4% Dep. Var.: Median Rent	5.07** (2.04)	0.80 (1.54)

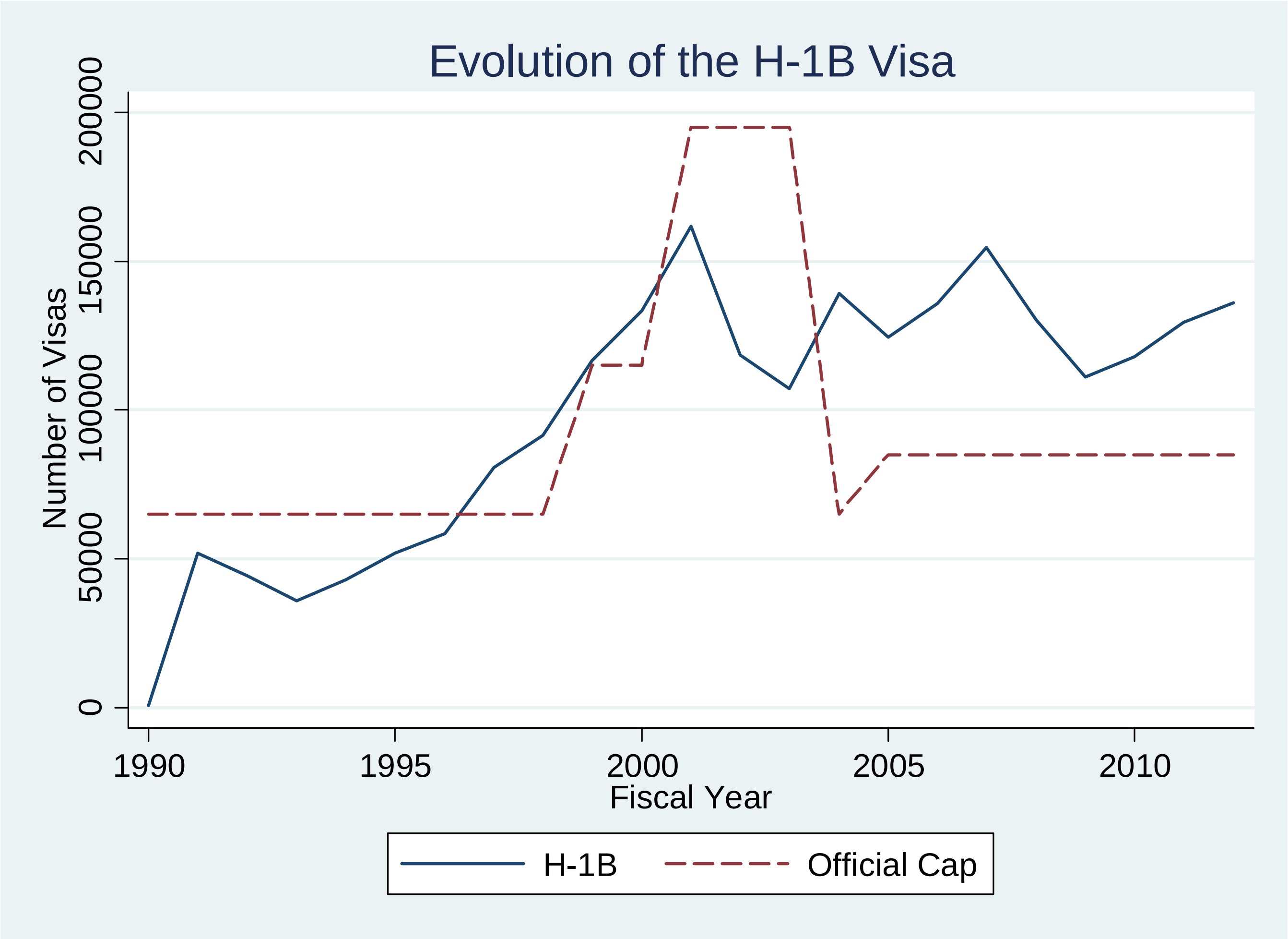
Note: Each cell shows the estimate of the coefficient on the growth in foreign STEM (relative to employment) when the dependent variable is the one described at the top of the column. Each regression includes period effects, metropolitan area effects, the Bartik for wage of the relevant group, and the imputed growth of non-college educated immigrants. Standard errors (in parentheses) are clustered at the metro area level. Unit of observations are 219 metro areas over 3 periods, 1990-2000, 2000-2005 and 2005-2010. Row (a) shows the basic specification with Median rent as dep. Variable. Row (b) uses average rent as dep. var. Row (c) uses the broader O*NET definition of STEM, Row (d) omits the top 5 Metro Area in number of STEM. Row (e) Omits Indians from the instrument construction. Row (f) uses total (native+ foreign) STEM as explanatory variable.
***, **,*= significant at 1%, 5% and 10% level respectively.

Table 10: Simulated Foreign-STEM effects on Yearly Average TFP Growth and SBP Change

	(1) Simulated Foreign STEM Effect on TFP Growth	(2) Simulated Foreign STEM Effect on Skill-Biased Growth	(3) Average U.S. TFP Growth 1990-2010	(4) Average Change in Skill-Biased Productivity 1990-2010	(3)/(1) TFP Growth Explained by Foreign STEM	(4)/(2) Skill Bias Growth Explained by Foreign STEM
(1) Basic Estimates	0.47%	0.13%	0.89%	1.75%	0.53	0.07
(2) Conservative Estimates	0.41%	0.08%	0.89%	1.75%	0.47	0.05
(3) Based on Total STEM	0.27%	0.04%	0.89%	1.75%	0.30	0.04
(4) σ_H=1.75	0.54%	0.13%	0.89%	1.75%	0.61	0.08
(5) σ_H =2.25	0.43%	0.12%	0.89%	1.75%	0.48	0.07

Note: The table uses the formulas in the Appendix to calculate the implied elasticity ϕ_A and $\phi_{?}$. We then use the growth of US foreign-STEM workers as a share of employment to calculate the implied effects on TFP. The average TFP growth is taken from Fernald (2010) and the average skill biased growth is calculated using the average U.S. values for the wages and employment (in hours) of college educated and non-college educated workers from the Census 1990 and 2010. Unless otherwise noted, the elasticity of substitution between college and non-college educated workers is σ_H=2. The STEM share of employment is 0.04, the STEM share of wages 0.09, and the college educated share of wages 0.46. The values are calculated from the 2000 US Census.

Figure 1: Official Cap and Number of H-1B Visas, 1990-2012



Note: The data on H-1B visas and their cap are from the Department of State (2011)