STEM Workers, H1B Visas and Productivity in US Cities*

Giovanni Peri (UC, Davis) Kevin Shih (UC, Davis)
Chad Sparber (Colgate University)

This draft: February, 5th, 2013

Abstract

Scientists, Technology professionals, Engineers, and Mathematicians (STEM workers) are the fundamental inputs in scientific innovation and technological adoption. Innovation and technological adoption are, in turn, the main drivers of productivity growth in the U.S. In this paper we identify STEM workers in the U.S. and we look at the effect of their growth on the wages and employment of college and non-college educated labor in 219 U.S. cities from 1990 to 2010. In order to identify a supply-driven and heterogenous increase in STEM workers across U.S. cities, we use the dependence of each city on foreign-born STEM workers in 1980 (or 1970) and exploit the introduction and variation (over time and across nationalities) of the H-1B visa program, which expanded access to U.S. labor markets for 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 both STEM and non-STEM college-educated natives. Non-college educated show no significant wage or employment effect. We also find evidence that STEM workers caused cities to experience higher housing prices for college graduates, increased specialization in high human capital sectors, and a rise in the concentration of natives in cognitive occupations. The magnitudes of these estimates imply that STEM workers contributed significantly to total factor productivity growth in the U.S. and across cities and – to a lesser extent – to the growth in skill-bias between 1990 and 2010.

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

JEL codes: J61, F22 , O33, R10.

---

*Address: Giovanni Peri, Department of Economics, UC Davis, One Shields Avenue, Davis Ca 95616; gperi@ucdavis.edu; Kevin Shih, Department of Economics, UC Davis, One Shields Avenue, Davis Ca 95616 kyshih@ucdavis.edu; Chad Sparber, Department of Economics, Colgate University, csparber@colgate.edu. This paper is produced as part of the project Temporary Migration, Integration and the role of Policies (TEMPO) funded by the NORFACE Research Programme: Migration in Europe – Social, Economic, Cultural and Policy Dynamics..

1 Introduction

The activities of Scientists, Technology specialists, Engineers, and Mathematicians – STEM workers (or simply STEM for short) – comprise the main inputs in the creation, adaptation, 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 in the field, while more recent growth economists including Zvi Griliches (1992) and Charles I. Jones (1995) have used measures of Scientists and Engineers to identify the main input in idea-production.

While advances in STEM are a clear determinant of sustained productivity growth, two additional considerations related to ideas and productivity have attracted the attention of economists in the last 20 years. First, technological innovation during the past 30 years has not increased 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 by enhancing and complementing their abilities, but left the demand for non-college-educated workers stagnant by substituting for their skills.[1] Second, while technological and scientific knowledge is footloose and spreads across regions and countries, STEM workers are less mobile. Tacit knowledge, face to face interactions, and local mobility seem to still make a difference in the speed at which new ideas are locally available, are adopted, and affect local productivity. Several studies (Rauch (1993), Moretti (2004a, 2004b), Iranzo and Peri (2010)) have shown the importance of having a large concentration of college-educated workers for 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. (1992), Saxenian (2003)). 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 by affecting, in the long-run, productivity, wages, and employment of its residents.

This paper sits at the intersection of these three strands of literature. We quantify the long-run effect of increases in STEM workers in U.S. cities, between 1990 and 2010, on the employment, wages, and specialization of STEM and non-STEM workers with and without a college education. With some assumptions we are able to infer, from wage and employment effects, the effects of STEM growth on total factor productivity (TFP) growth and on changes in Skill-Biased Productivity (SBP). The challenge of the exercise is to identify variation in the growth of STEM workers across U.S. cities that could be considered supply-driven and hence exogenous to other factors affecting wages, employment, and productivity changes in cities. We do this by exploiting the introduction of the H-1B visa in 1990 and the differential

[1] See Katz and Murphy (1992), Krueger (1993), Autor, Katz, and Krueger (1998), Acemoglu (1998, 2002), Berman, Bound, and Griliches (2004), Autor, Levy, and Murnane (2003), and Autor, Katz, and Kerney (2007) among others. Several papers in this literature (e.g. Caselli (1996), Caselli and Coleman (2006), and Goldin and Katz (2008)) emphasize that the large supply of college-educated workers was itself the driver of the development of skill-biased technologies. Beaudry et al. (2010) and Lewis (2011) show the role of skill-supply in the adoption of specific technologies. Other papers (Beaudry and Greene (2003, 2005) and Krusell et al. (2000)) emphasize the role of capital (equipment) in increasing the productivity of highly educated workers.

effect that these visas had in bringing foreign college-educated STEM workers to 219 U.S. metropolitan areas from 1990 to 2010.

The H-1B visa, introduced with the Immigration and Nationality Act of 1990, established temporary renewable visas (up to a maximum of 6 years) for college-educated specialty professional workers, most of whom work in STEM occupations. The policy was national in scope but had differentiated local effects because foreign-STEM workers have long been very unevenly distributed across U.S. cities. Using the 1980 Census, we first construct the degree of dependence (reliance) of each U.S. metropolitan area on foreign STEM workers by measuring the foreign STEM share of employment in each city. We then show that this dependence was not correlated with a city's dependence on STEM workers in general, most of whom were natives in 1980. Rather, the 1980 foreign STEM dependence is correlated with the presence of other foreign-born residents within the city – a characteristic determined by historical settlement patterns of foreign communities and geographical preferences of immigrants that is unlikely to be related to future productivity changes. 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 dependence on foreign STEM workers of each nationality. This H-1B-driven increase in foreign STEM turns out to be a good predictor of the increase in the number of foreign and overall STEM workers in a city in subsequent decades. While this is not the random helicopter drop of STEM workers that we would like to have in order to identify effects on wages, employment, and productivity, this constructed change, accompanied with controls for sector-specific demand and fixed effects, seems to represent a reasonable supply-driven variation of foreign STEM workers. This identification strategy is related to the one used by Card and Altonji (1991) and Card (2001) to identify the wage effect of immigrants, and it is even more closely related to the one used in Kerr and Lincoln (2010) to estimate the effect of foreign scientists on U.S. patent applications.

We find that a 1 percentage-point rise in the foreign-STEM share of total employment would increase the wages of native college-educated workers (both STEM and non-STEM) by 4-6%, while it would have no significant effect on the wages and employment of native non-college-educated workers. We also find that increases in the number of foreign-STEM workers push native college-educated workers toward occupations that use creative problem-solving skills more intensely. They also have a significantly positive impact on the housing costs of college-educated workers, and insignificant effects on the employment and housing costs of high school educated individuals. The increased cost in non-tradable services (housing) absorbed about half of the increase in the purchasing power of college-educated wages. Finally, our estimates allow us to calculate the effect of STEM on total factor productivity and on skill-biased productivity at the national level. We find both effects to be positive, and we provide some simple calculations showing that the growth in foreign-STEM workers may explain between 10 and 25% of the aggregate productivity growth and 10% of the skill-bias growth that took place in the U.S. between 1990 and 2010.

The paper is organized as follows. Section 2 presents a simple framework to interpret the estimation results. Section 3 describes the data on STEM workers and H-1B visas, the construction of H-1B-driven growth of foreign STEM-workers, and characterizes STEM behavior across cities and over time. Section 4 presents the basic empirical estimates of the effect of an increase in STEM workers on wages and employment of U.S. workers. Section

5 extends the empirical analysis, checks the robustness of the estimates, and looks at the impact on other outcomes such as house rents and the specialization of natives. In section 6 we perform some simple calculations of the impact of STEM on productivity and on its skill (college) bias using our previously-estimated wage and employment effects. Section 7 concludes.

2 Theoretical Framework and Productivity Parameters

The empirical analysis developed below uses exogenous variation in foreign-born STEM workers across U.S. cities, c, over decades, t, and estimates their impact on wages, employment, and house rents for native workers. The basic specifications that we will estimate in Section (4) is of the following type:

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

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 non-STEM workers, and non-college-educated workers), standardized by the initial year outcome level. The outcomes of interest are weekly wages, employment, and the price of housing for each group. The term ϕ_t captures year effects, ϕ_s captures state effects, and $\frac{\Delta STEM_{ct}^{Foreign}}{E_{ct}}$ is the exogenous change of foreign-STEM over a decade, standardized by the initial total employment in the city (E_{ct}). The term $Controls_{ct}^{X}$ includes other city-specific controls that affect the outcomes and ε_{ct} is a zero-mean idiosyncratic random error. The coefficients of interest is $b_{y,X}$, which captures the elasticity for worker group X of a specific outcome, y, to an exogenous increase in STEM workers. In order to use these coefficient estimates to obtain a measure of the effect of STEM workers on productivity, we need a simple equilibrium framework that allows for productivity effects as well as for local supply and local price responses to an exogenous change in $STEM_{ct}^{Foreign}$. Before discussing identification of the coefficients, we describe a simple framework that allows us to use the estimates from (1) to calculate the productivity and skill-bias effect of an exogenous increase in STEM. The same framework also allows us to identify the elasticity of local supply and the local price responses to STEM workers.

2.1 Production and Wage Response

The framework we present derives a simple labor demand and labor supply model from a production function and utility function. It is a static framework and it should be thought of as a long-run equilibrium. We perform comparative static analysis to learn about the long-run effects of a change in STEM workers. Consider a small economy such as a city (c), producing a homogeneous and tradable product (output), y_{ct}, in year t. The economy employs three types of workers: non-college-educated, L_{ct}, college-educated doing non-STEM jobs, NST_{ct}, and college-educated doing STEM jobs, ST_c. Production occurs according to the following long-run production function:

$$y_{ct} = \left[A(ST_{ct}) \left(\beta(ST_{ct}) H_{ct}^{\frac{\sigma_H - 1}{\sigma_H}} + (1 - \beta(ST_{ct})) L_{ct}^{\frac{\sigma_H - 1}{\sigma_H}} \right) \right]^{\frac{\sigma_H}{\sigma_H - 1}} \tag{2}$$

In (2) we do not include physical capital and instead assume that capital mobility and the equalization of capital return imply a constant capital-output ratio in the long run so that capital can be solved out of the production function. We also follow the literature on human capital externalities[2] and growth and ideas[3] by allowing the term $A(ST_{ct})^{\frac{\sigma_H}{\sigma_H - 1}}$, which is the level of total factor productivity, to be a function of the number of STEM workers in the city ST_{ct} . If $A'(ST_{ct}) > 0$, then STEM-driven innovation externalities have a positive effect on productivity. At the same time we allow for the term $\beta(ST_{ct})$, which captures the possibility for skill (college) biased productivity, to depend upon the number of STEM workers. If $\beta'(ST_{ct}) > 0$, STEM-driven innovation externalities have a college-biased effect on productivity. The intuition for this simple characterization of productivity and skill-bias is that STEM workers are the key inputs in developing and adopting new technologies, especially information and communication technologies, which are widely credited for increasing the productivity of college-educated workers as well as increasing total factor productivity during the last 30 years. The main goal of our empirical analysis is to identify the effect of STEM workers on total factor productivity $A^{\frac{\sigma_H}{\sigma_H - 1}}$ and on its college-bias, $\beta/(1 - \beta)$.

The parameter $\sigma_H > 1$ captures the elasticity of substitution between non-college-educated labor, L, and a composite factor, H, obtained by combining the two groups of college-educated workers as follows:

$$H_{ct} = \left(ST_{ct}^{\frac{\sigma_S - 1}{\sigma_S}} + NST_{ct}^{\frac{\sigma_S - 1}{\sigma_S}} \right)^{\frac{\sigma_S}{\sigma_S - 1}} \tag{3}$$

The parameter σ_S is the elasticity of substitution between STEM and non-STEM college-educated workers. The assumption is that while both STEM and non-STEM workers can be employed in production, STEM workers are also generating ideas, innovation, and externalities that benefit productivity – possibly with greater benefits for the college-educated.

If the labor factors are paid their marginal productivity, the wages of each type of worker are given by the following expressions in which, for brevity, we omit the subscripts and the dependence of A and β on ST:

$$w_L = A(1 - \beta) y^{\frac{1}{\sigma_H}} L^{-\frac{1}{\sigma_H}} \tag{4}$$

$$w_{NST} = A\beta y^{\frac{1}{\sigma_H}} H^{(\frac{1}{\sigma_S} - \frac{1}{\sigma_H})} NST^{-\frac{1}{\sigma_S}} \tag{5}$$

$$w_{ST} = A\beta y^{\frac{1}{\sigma_H}} H^{(\frac{1}{\sigma_S} - \frac{1}{\sigma_H})} ST^{-\frac{1}{\sigma_S}} \tag{6}$$

In our empirical analysis we identify the responses of the three wages defined above (w_L, w_{NST}, and w_{ST}) and also of the employment levels (L, NST, and ST) to an exogenous

[2]See Acemoglu and Angrist (2000), Iranzo and Peri (2009), Moretti (2004a).
[3]See Jones (1995).

change of STEM workers that we denote as $\Delta ST^{foreign}$. It is important to recognize that workers L, NST, and ST respond to wage changes produced by $\Delta ST^{Foreign}$ (by moving into or out of the city and/or employment). Hence, in equilibrium we observe simultaneous changes in wages and employment. Taking a total logarithmic differential of expressions (4)-(6) and writing all employment changes relative to total employment $E = L+ST+NST$, we have the following three equations relating equilibrium changes in employment and wages for each group of workers (Non-college-educated, college-non-STEM, and college-STEM, respectively):

$$\begin{aligned} \frac{\Delta w_L}{w_L} &= \left(\phi_A - \frac{\beta}{1-\beta}\phi_B + \frac{s_w^{ST}}{\sigma_H s_E^{ST}}\right)\left(\frac{\Delta ST^{Foreign} + \Delta ST^{Native}}{E}\right) + \\ & \frac{s_w^{NST}}{\sigma_H s_E^{NST}}\frac{\Delta NST}{E} + \left(\frac{s_w^L}{\sigma_H s_E^L} - \frac{1}{\sigma_H s_E^L}\right)\frac{\Delta L}{E} \end{aligned} \tag{7}$$

$$\begin{aligned} \frac{\Delta w_{NST}}{w_{NST}} &= \left(\phi_A + \phi_B + \frac{s_w^{ST}}{\sigma_H s_E^{ST}} + \left(\frac{1}{\sigma_S} - \frac{1}{\sigma_H}\right)\frac{s_w^{ST}}{s_w^H s_E^{ST}}\right)\frac{\Delta ST^{Foreign}}{E} + \\ & \left(\frac{s_w^{NST}}{\sigma_H s_E^{NST}} + \left(\frac{1}{\sigma_S} - \frac{1}{\sigma_H}\right)\frac{s_w^{NST}}{s_w^H s_E^{NST}} - \frac{1}{\sigma_S s_E^{NST}}\right)\frac{\Delta NST}{E} + \frac{s_w^L}{\sigma_H s_E^L}\frac{\Delta L}{E} \end{aligned} \tag{8}$$

$$\begin{aligned} \frac{\Delta w_{ST}}{w_{ST}} &= \left(\phi_A + \phi_B + \frac{s_w^{ST}}{\sigma_H s_E^{ST}} + \left(\frac{1}{\sigma_S} - \frac{1}{\sigma_H}\right)\frac{s_w^{ST}}{s_w^H s_E^{ST}} - \frac{1}{\sigma_S s_E^{NST}}\right)\frac{\Delta ST^{Foreign}}{E} + \\ & \left(\frac{s_w^{NST}}{\sigma_H s_E^{NST}} + \left(\frac{1}{\sigma_S} - \frac{1}{\sigma_H}\right)\frac{s_w^{NST}}{s_w^H s_E^{NST}} - \frac{1}{\sigma_S s_E^{NST}}\right)\frac{\Delta NST}{E} + \frac{s_w^L}{\sigma_H s_E^L}\frac{\Delta L}{E} \end{aligned} \tag{9}$$

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:

$$\phi_A = \frac{\Delta A/A}{\Delta ST/E}, \ \ \phi_B = \frac{\Delta\beta/\beta}{\Delta ST/E} \tag{10}$$

We can use the equilibrium conditions (7)-(9) 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 our coefficients $b_{y,X}$ estimated from 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 $\left(\frac{\Delta L}{E}\right)_{ct}$, and so on. The terms s_w^x and s_E^x, for $x = ST, NST, L$, and H represent, respectively, the share of total wage income and employment represented by factor x. For example, s_w^H is the share of total wage income accruing to workers with college education and equals $(w_{ST}ST + w_{NST}NST)/(w_{ST}ST + w_{NST}NST + w_L L)$, 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 $\Delta ST^{Foreign}$ identified, and using wage and employment data to calculate the shares s_w^x and s_E^x, equations (7)-(9) 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 (7)-(9) and our elasticity estimates to obtain values for ϕ_A, ϕ_B and σ_S.

2.2 Labor Supply and Local Price Response

The simple framework described above allows us to translate the equilibrium employment and wage responses to an exogenous change in STEM workers into the productivity effects ϕ_A and ϕ_B by only using conditions (7)-(9). We do not require the full specification of the supply response of each group to a change in STEM, as long as we can estimate the equilibrium employment response to such change. Let us suggest here a simple way to close the model on the labor supply side that provides two further results on the margin of local adjustment to an increase in STEM workers. A simple way to model the employment and consumption of each group is to assume that local households of type i (=L, NST, ST) choose the optimal amount of employment l_i (out of a maximum endowment) and consume a composite basket $C_i = y_i^{1-\alpha} T_i^a$ made of tradable good y purchased at price 1 (numeraire) and non-tradable housing services T (purchased at price p_i) in order to maximize the following utility function:

$$U_i = \theta_c (y_i^{1-\alpha} T_i^a)^{\delta} - \theta_l l_i^{\eta} \tag{11}$$

with the following budget constraint: $y_i + p_i T_i = w_i l_i$. Solving the problem, the optimal consumption conditions imply that $y_i = (1-\alpha) w_i l_i$, $T_i = \alpha w_i l_i / p_i$, $C_i = \alpha^{\alpha}(1-\alpha)^{(1-\alpha)} \frac{w_i}{p_i^{\alpha}} l^i$, and the optimal labor supply is:

$$l_i = \phi \left(\frac{w_i}{p_i^{\alpha}} \right)^{\gamma} \tag{12}$$

where $\phi = \left(\frac{\alpha^{\alpha}(1-\alpha)^{(1-\alpha)} \theta_c \delta}{\theta_l \eta} \right)^{\frac{1}{\eta-\delta}}$ and $\gamma = \frac{\delta}{\eta-\delta}$, which is positive if $\eta > \delta$. Equation (12) implies, very intuitively, that the supply of labor of a certain type may increase if the real wage for that type of labor increases. The wage is divided by the price index (p_i^{α}) which is the price of one unit of consumption and depends positively on the price of housing. The elasticity of labor supply is γ. We have derived equation (12) using utility maximization for a local household, however it can also be justified considering mobility of local households in response to the differential between local wages and average outside wages (assumed as given because of the small economy assumption) with an elasticity γ capturing the degree of mobility of workers. For instance, $\gamma = \infty$ would imply perfect mobility, and hence real wages fixed to the outside level. The equilibrium employment response in that case will be determined to maintain a constant wage. Allowing different types of workers to have different supply elasticities (between zero and infinity), and considering the logarithmic total differential of (12) in response to an exogenous change in STEM workers, we obtain the following equilibrium relations:

$$\frac{\Delta ST^{Native}}{E} = s_E^{ST}\gamma_{ST}\left(\frac{\Delta w_{ST}}{w_{ST}} - \alpha_{ST}\frac{\Delta p_{ST}}{p_{ST}}\right) \tag{13}$$

$$\frac{\Delta NST}{E} = s_E^{NST}\gamma_{NST}\left(\frac{\Delta w_{NST}}{w_{NST}} - \alpha_{NST}\frac{\Delta p_{NST}}{p_{NST}}\right) \tag{14}$$

$$\frac{\Delta L}{E} = s_E^{L}\gamma_{L}\left(\frac{\Delta w_{L}}{w_{L}} - \alpha_{L}\frac{\Delta p_{L}}{p_{L}}\right) \tag{15}$$

The coefficients α_i are measured as the share of income in non-tradable services (housing) for workers of type i. The equilibrium elasticity of housing prices for each group to STEM workers, estimated using such specifications as (1), provide the last term in each of the equations (13)-(15).[4] These may differ due to the segmented housing land supply for college and non-college-educated individuals. Armed with these estimates, equations (13)-(15) allow us to calculate the supply elasticities of different groups and check that they are consistent with mobility of workers in the long run.

3 Data: STEM Workers in U.S. Cities

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, and then to use those effects to calculate the impact of STEM-workers on productivity and skill-bias. Admittedly this exercise only captures productivity effects localized within metropolitan areas. The ideal experiment would consist of exogenously and randomly adding different numbers of STEM workers across U.S. cities and then observing the effects of these random shocks on the wages and employment of other workers. As STEM workers are the main innovators and adopters of new technologies, this exercise would indirectly provide a window to the effects of new technologies on college and non-college labor productivity. As we do not have such experiment, we instead use the H-1B visa policy introduced in 1990 as an exogenous source of variation in foreign-STEM workers across the U.S.

Perhaps the most relevant piece of immigration legislation introduced in the last 22 years, the Immigration Act of 1990 created the H-1B visa to provide temporary visas (for the duration of three years, renewable up to 6, and with the possibility of applying for permanent residence) for college-educated foreign-STEM workers. This change in immigration policy can be reasonably considered as an exogenous source of variation in foreign-STEM workers in the U.S. Since 1990 the H-1B visa has been a crucial channel of admission for many college-educated foreign-born "specialty" workers, a very large majority of which have been STEM workers. Lowell (2000), for example, notes that 70% of H-1B recipients 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 in 2009 (and similarly for all years between 2004 and 2011), more than 85% of new H-1B visa holders work in Computer, Health Science,

[4] One would divide both sides of the equations by $\Delta ST^{Foreign}/E$ and use the estimated elasticity of employment, wages and housing prices in the equation.

Accounting, Architecture, Engineering, and Mathematics related occupations, while less than 5% of are awarded to people working in occupations related to Law, Social Sciences, Art, and Literature.

Figure 1 shows the maximum number (cap) of visas allowed, the actual H-1B labor flows, and the decade-averages for each of those two series for each year between 1990 and 2010.[5] Initially, Congress authorized 65,000 H-1B visas annually. This cap rose to 115,000 for fiscal years 1999 and 2000, and rose again to 195,000 per year for 2001, 2002, and 2003. The cap reverted back to the original 65,000 per year beginning in 2004. Though the limit officially remains at that level, the first 20,000 H-1B visas issued annually to individuals who have obtained a master's degree (or higher education) in the U.S. became exempt from H-1B limits beginning in 2006, effectively raising the cap to 85,000. Our long-run analysis uses changes over decades, and it is important to note that we observe a lower average cap from 1990-2000 than from 2000-2010.[6]

The ensuing inflow of foreign STEM workers was not homogeneously distributed across locations in the U.S. This was because different cities (and the companies located within them) had a varying dependence on foreign-STEM workers before the program was implemented. This variation is due to persistent immigrant preferences to locate in cities with historical communities of past immigration. The H-1B policy, therefore, generated large flows of foreign STEM workers to cities with stronger networks of foreign-born STEM workers that were able and willing to hire new foreign-STEM arrivals, and much smaller flows to other cities. Certainly part of the differences were driven by different economic and labor demand conditions in the cities. We argue, however, that we can use the part of foreign STEM inflows driven by the differential city dependence on foreign STEM workers (of some specific nationalities) as of 1980 (and as of 1970 in a robustness check) as a supply shock. Only those cities with high initial foreign dependence experienced large inflows caused by the H-1B visa policy. Those with low foreign dependence and high reliance on native STEM workers did not experience such a surge. 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 check the validity of some identifying assumptions that are crucial for our approach.

3.1 Construction of the H-1B-Driven Increase in Foreign-STEM Workers

Our data on occupations, employment, wages, age, and education of individuals comes from the IPUMS 5% Census files for 1980, 1990, 2000. We also merge the 2008-2010 three year sample of the American Community Survey to obtain a 3% sample that we call 2010. We only use data on 219 metropolitan areas that can be consistently identified over the period 1980-2010.[7] These areas span the range of U.S. metropolitan sizes and include all the largest

[5]In the years 2005-2010 the total number of visas exceeds the cap because universities and non-profit research facilities hiring college educated foreign workers became exempt from the cap beginning in 2001.

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

[7]In a robustness check we will limit the analysis to the 116 Metropolitan Areas that can be identified since 1970.

metropolises in the U.S. (Los Angeles, New York, Chicago, Dallas-Forth Worth, Philadelphia and Houston are the six largest) down to metropolitan areas with close to 200,000 people (Danville VA, Decatour 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 (2010).

We first construct a variable which we call the "H-1B-driven increase in STEM workers" in each of 219 U.S. metropolitan areas (cities) between 1990 and 2010. We begin by defining a city's dependence on foreign STEM workers from 14 specific foreign nationalities[8] in 1980 as the employment share of foreign-STEM workers of nationality n in city c, $\frac{STEM^{FOR_n}_{c,1980}}{E_{c,1980}}$. The dependence of city c on foreign-STEM workers overall is the sum of the dependence from each specific nationality: $\frac{STEM^{FOR}_{c,1980}}{E_{c,1980}} = \sum_{j=1,14}\left(\frac{STEM^{FOR_n}_{c,1980}}{E_{c,1980}}\right)$. We choose 1980 as a base year 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 the ICT revolution so that the distribution of STEM workers was hardly affected by the geographic location of the computer and software industries.[9] Instead it was nuclear, military, chemical, and traditional manufacturing sectors that were demanding a large amount of science and technology workers. Still, in order to eliminate any impact of the ICT revolution, we also use 1970 as the initial year for a subset of cities as a robustness check.

While the U.S. government has created a list of official STEM college degrees for the purpose of permitting foreign students to work under the Optional Practical Training (OPT) Program, there is no official definition of STEM occupations. This motivates us to consider three alternative criteria to define STEM work. The first is based on the skills used within an occupation. We use the O*NET database provided by the Bureau of Labor Statistics, which associates each occupation, according to its SOC classification, the importance of several dozen skills and abilities required to perform a job. We select four O*NET skills that involve the use of Science, Technology, Engineering, and Math. Namely, we use the importance of "Mathematics in Problem Solving," "Science in Problem Solving," "Technology Design," and "Programming." We consider the average score of each occupation across the four skills and we rank the 333 occupations, identified consistently in the Census 1980-2010, according to the average score among the STEM skills defined above. We identify STEM occupations as those with the highest 10% of STEM skills used by employees in 2000. We call individuals in these occupations O*NET-STEM workers. The list of occupations included in this STEM definition, ranked in decreasing order of STEM-skill importance, is reported in Table A1, Part A in the appendix.

The second STEM definition modifies the occupation selection criteria by restricting it to the top 10% of STEM workers with at least a college degree. While in theory STEM workers need not be college-educated, many of them are. A list of College Educated O*NET-STEM workers, which includes about 4.3% of all workers in 2000, is provided in appendix Table A1,

[8] 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.

[9] While early video-games and computers were introduced in the late seventies, the Personal Computer was introduced in 1981.

Part B. Finally, we use a third definition of STEM occupations based on the percentage of workers who have obtained college degrees in STEM majors, as identified by the American Community Survey of 2009. This third definition recognizes STEM occupations – listed in Table A1, Part C, of the Appendix – as those in which at least 25% of workers have graduated from a STEM major. This definition is more stringent than first definition and selects about 5% of workers. Note that the median occupation has only 6% of workers with a STEM major.[10]

After defining 1980 STEM dependence, we calculate the growth factor of foreign STEM workers for each nationality n in the U.S. between 1980 and year t. We do so by adding the inflow of STEM workers from each nationality to its initial 1980 level $\left(STEM_{1980}^{FOR_n}\right)$ during the period between 1980 and t. 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 $STEM^{FOR_n}$.[11] 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:

$$\frac{\widehat{STEM_t^{FORn}}}{STEM_{1980}^{FOR_n}} = \frac{STEM_{1980}^{FOR_n} + \Delta STEM_{1980-1990}^{FOR_n} + \#ofH1B_{1990-t}^{FORn}}{STEM_{1980}^{FOR_n}} \tag{16}$$

In order to impute the number of foreign-STEM workers in city c in year t, we then multiply the growth factor calculated above for each nationality by the number of foreign-STEM workers of that nationality as of 1980, and then add the figures across all nationalities.

$$\widehat{STEM_{ct}^{FOR}} = \sum_{n=1,14} STEM_{c1980}^{FORn} \left(\frac{\widehat{STEM_t^{FORn}}}{STEM_{1980}^{FOR_n}} \right) \tag{17}$$

The H-1B-driven change in foreign-STEM workers, that we use as our explanatory variable in the main empirical specifications, is the change in $\widehat{STEM_{ct}^{FOR}}$ over a decade standardized by the initial employment in the city E_{ct}[12]:

$$\frac{\Delta STEM_{ct}^{H-1B}}{E_{ct}} = \frac{\widehat{STEM_{ct+10}^{FOR}} - \widehat{STEM_{ct}^{FOR}}}{E_{ct}} \tag{18}$$

[10] The correlation between the STEM dummies defined for each occupation, across the three definition is between 0.4 and 0.6.

[11] Since the data on visas issued by nationality begin in 1997, while we know the total number of visa in each year, we must estimate $\#ofH1B_{n,1990-t}$, the total number of visas issued by nationality between 1990 and 1997, as,

$$\#of\widehat{H1B}_{n,1990-t} = \#ofH1B_{1990-t} \left(\frac{\#ofH1B_{n,1997-201}}{\#ofH1B_{1997-2010}} \right)$$

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 $\#ofH1B_{n,t}$.

[12] To avoid that endogenous changes in total employment in the city level affect the standardization we also use the imputed city employment, obtained using employment in 1980, augmented by the growth factor of national total employment. Hence $E_{ct} = E_{c1980}(E_t^{US}/E_{1980}^{US})$.

This identification strategy is closely related to the one used by Altonji and Card (1991) and Card (2001), based on the initial distribution of foreign workers across U.S. cities. It is also similar to the one used by Kerr and Lincoln (2010) who consider dependence on foreign scientists and engineers and the impact of H-1B on innovation. Our variable, however, is based on foreign-STEM dependence of a city in 1980 or 1970 (rather then in 1990 as done by Kerr and Lincoln (2010)), and uses also the distribution of foreign-STEM across 14 nationalities, rather than only the aggregate one. Hence it should be less subject to correlation with recent economic conditions and more accurate.

Foreign-STEM workers do not coincide exactly with H-1B visas as there are workers entering with other visas or with permanent permits and some of the H-1B workers return to their country after 6 years. Moreover, we need to establish whether our policy-driven variable, mechanically created using the visa issuances and the initial distribution of foreign-STEM, has predictive power on $\frac{\Delta STEM_{ct}^{FOR}}{E_{ct}}$, the change in foreign-STEM workers standardized by total initial employment.

3.2 Summary Statistics for Foreign-born and STEM occupations

Before analyzing how the H-1B-driven variable predicts the change in foreign STEM workers and of STEM workers in general across cities let us present some aggregate statistics. Even a very cursory look at the data shows that foreign-born individuals are particularly over-represented in STEM[13] occupations. Moreover foreigners have contributed substantially, in the aggregate, to the growth of STEM jobs in the U.S.. Table 1 shows the foreign-born share of five different employment groups for each census year from 1980 to 2010. From left to right we show the percentage of foreign-born among all workers, among college-educated workers, among college-educated workers in metropolitan areas, among STEM occupations in metropolitan areas, and among college-educated STEM workers in metropolitan areas. While foreign-born individuals represented 16% of total employment in 2010, they counted for a quarter of college-educated STEM workers in the metropolitan sample that we analyze. Remarkably, this figure has more than doubled since 1980.

Table 2 shows that college-educated STEM workers have increased from 2.7% of total employment in 1980 to 4.5% in 2010. Even more remarkably, the share of college-educated foreign-STEM workers has grown from 0.3% to 1.1%. The 1990s were a period of particularly fast growth in STEM workers relative to other decades in the analysis. The STEM worker share of employment grew by 1.1 percentage points in that decade. Of that increase, 0.4 percentage points were due to foreign-STEM workers. Also remarkably, the first decade of the 2000s saw very little growth in STEM employment (0.2 percentage points), and the growth that did occur was due almost entirely to the increase in foreign-STEM employment.

Was the H-1B program large enough to affect the aggregate number of STEM jobs? Is it likely to have contributed significantly to the growth of foreign STEM workers? 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 STEM workers in the U.S., and column 2 displays the increase in college educated

[13] In the summary statistics and in the empirical analysis we use the O*NET STEM definiton, unless we note otherwise.

STEM workers. Column 3 shows the cumulative number of H-1B visas issued during the corresponding decade. It is clear that in the 1990s the 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 times as large as the net increase in college educated STEM between 2000 and 2010. This implies that many foreign STEM workers, including H-1B recipients, must have left the U.S., while many native STEM workers must have lost their jobs or changed occupations. Overall, the figures presented emphasize the importance of foreigners for STEM jobs in the U.S.. Foreign-born labor is over-represented among STEM workers, and the overall size of the H-1B program was large enough to contribute substantially to the foreign STEM job growth between 1990 and 2010.

3.3 Key to Identification: Foreign-STEM and Native-STEM Dependence of U.S. Cities in 1980

Our identification strategy is based on the assumption that a city's dependence on foreign-STEM workers in 1980 (or in 1970) varied across cites due to a differential presence of immigrants caused by persistent agglomeration of foreign communities. These differences subsequently affected the supply of foreign-STEM workers but were not otherwise correlated with future technological and demand shocks that affected wages and employment. A particular challenge to this assumption is that dependence upon foreign STEM workers in 1980 will predict 1990s and 2000s wage and employment shocks if it is correlated with the productive and industrial structure of the city in terms of its sectoral composition and its scientific and technological base.

We take several steps to partially address these concerns. First, in this section we show that the dependence of metropolitan areas on foreign-STEM workers in 1980 has essentially no correlation with their dependence on native-STEM workers. In 1980, 90% of STEM workers were native-born. This implies that the overall dependence of a city on STEM workers in 1980, though correlated with scientific and technological intensity of production, was not driven by foreign-STEM workers. Instead, foreign-STEM dependence was determined by the overall percentage of foreign-born city residents. We also show that while the dependence on foreign-STEM workers in 1980 is correlated with the H-1B-driven growth in STEM workers between 1990 and 2010, the 1980 dependence on native-STEM workers is not. Second, in section 3.5 we introduce sector-driven changes in college and non-college educated wages and employment at the city level as controls for the changes in productivity driven by the 1980 industrial structure of the city.[14] Including those sector-driven shocks as controls will further go in the direction of isolating the effect of a supply-driven change in STEM. Finally, we estimate very demanding empirical specifications. Our dataset is comprised of a panel of 219 metropolitan areas from 1990-2000, 2000-2005, and 2005-2010. Our models are estimated in first differences so that effects are identified by inter-decade changes in H-1B-driven foreign-STEM supply across cities. This strategy should eliminate error arising from unobserved determinants of the level of our outcome variables. However, we add to the rigor of our models by also including controls for fifty state-specific effects. Thus, identification relies on variation of growth rates across cities in the same state. Further analysis tests an

[14] This is sometimes called a Bartik demand shifter.

even more demanding specification that instead includes 219 city-specific effects. Finally, we also perform robustness checks using foreign-STEM dependence in 1970 to construct the instrument.

The dependence on native and on foreign STEM workers across 219 U.S. metropolitan areas in 1980 varied dramatically and those two variables had very little correlation with each other. Columns 1 through 3 of Table 4 list the ten cities most dependent upon native-STEM supply in 1980, and the share of native STEM workers in total employment for 1980 and 2010. Analogously, columns 4 through 6 display the foreign-STEM shares for the ten most foreign-STEM dependent cities. No city appears on both lists. Several of the top native-STEM cities are in the Midwest and in the East. Most are associated with traditional sectors that attracted many Scientists and Engineers in the 1970s. For instance Richland-Kennewick-Pasco, WA was the site of an important nuclear and military production facility in the 1970s; Rockford, IL had a very developed machine tool and aerospace industry; Racine, WI was the headquarter of S. C. Johnson and S. C. Johnson, A Family Company (Chemicals, detergents, and home products).

In contrast, many of the metropolitan areas with large foreign-STEM dependence were larger and more diversified, with large immigrant communities. Also notice that the native-STEM dependence in 1980 is an order of magnitude larger than foreign-STEM dependence. Even more clearly, Figure 2 and the first two columns of Table 5 show no correlation between foreign- and native-STEM dependence across cities. The OLS correlation obtained after controlling for state effects (Column 1) is negative and insignificant at standard confidence levels (t-statistics are smaller than 1.6). The visual impression of Figure 2 is also clear: there was essentially no correlation between foreign and native-STEM dependence in 1980. This is a hint that foreign-STEM dependence had little to do with STEM intensity of a city in 1980. Column 2 of Table 5 and Figure 3 show that a city's dependence on foreign-STEM workers in 1980 instead had more to do with the presence of other foreign-born residents as a share of the population. When including state fixed effects, the foreign-born population share has an extremely significant association with its foreign-STEM dependence (t-statistics of 10.3). Figure 3 also illustrates that a city's foreign-STEM dependence in 1980 was driven by the presence of the foreign born population.

Figure 4 and column 4 of Table 5 go on to show that the 1980 foreign-STEM dependence has significant power to predict the H-1B-driven increase in STEM across cities (F-statistic of 20.41 and the partial R-squared explained by that variable is 0.39). Figure 5 and column 3 of Table 5 show instead that the 1980 native-STEM dependence has very limited power to predict the H-1B-driven increase in STEM (F-statistic of 4.55 and partial R-squared of 0.03). Cities with larger foreign STEM-dependence in 1980 were not necessarily associated with high shares of STEM workers overall in 1980. However the fact that the H-1B program allowed a significant increase in the highly educated foreign-STEM workers during the 1990s and 2000s allowed these cities to increase the size of their STEM employment. The initial advantage in foreign-STEM dependence made these cities a more likely destination for foreign STEM workers entering with an H-1B visa. The presence of a network, the easier diffusion of information across foreign groups, and the familiarity of firms with foreign STEM workers likely reduced the cost of H-1B visa recipients to locate in these cities.

Finally, let us emphasize that our identification strategy relies upon more than just the overall foreign-STEM dependence. Since we consider H-1B visa by nationality, we also use the

differential location of foreigners across U.S. cities depending on nationality. In particular, a very large share of H-1B visas is awarded to Indian, Chinese, and other Asian workers (see Table A2 in the appendix, showing the percentage of total H-1B visas awarded to each nationality by decade). Hence an initial foreign-STEM dependence on these ethnic groups would produce a particularly large increase in STEM. Our method exploits this variation. In a robustness check, we verify that the location of Indian workers is not the only factor predicting variation of foreign-STEM workers.

3.4 The H-1B Program: Predicting the Increase in Foreign-STEM

The H-1B-driven increase in STEM workers, defined in expression (18), can be considered as an instrument accounting for the effects of the H-1B policy on STEM workers in U.S. cities. Hence we can (and will) use the variable directly to analyze its impact on wages and employment of native college and non-college-educated workers. As it is a constructed variable, however, we want to first establish that it significantly affected the actual increase in foreign-STEM workers across cities. Ultimately, we would like to determine the effect of STEM workers on employment and wages, and hence we will use the H-1B-driven increase in STEM workers as an instrument for the actual increase. The growth of foreign-STEM workers in a city was driven in part by the H-1B program, but also by demand and productivity increases. In this section we analyze how the H-1B-driven increase in STEM affected the net observed increase in foreign-STEM workers across U.S. cities. We estimate the following specification:

$$\frac{\Delta STEM_{ct}^{FOR}}{E_{ct}} = \phi_t + \phi_s + b_1 \frac{\Delta STEM_{ct}^{H-1B}}{E_{ct}} + \varepsilon_{ct} \tag{19}$$

The coefficient of interest is b_1 which measures the impact of H-1B-driven STEM inflows on the actual increase in foreign-STEM workers (as measured from the U.S. Census). The term ϕ_t is a two period fixed effect, and ϕ_s represents 49 state-fixed effects (we will include different effects in alternative specifications). We include $t = 1990, 2000, 2005$ so that the changes Δ refer to the periods 1990-2000, 2000-2005, and 2000-2010. ε_{ct} is a zero-mean random error uncorrelated with the explanatory variable.

In Tables 6 and 7 we show estimates of the coefficient b_1 from different specifications and samples. They provide an idea of the robustness of the H-1B-driven variable in predicting changes in foreign-STEM workers across U.S. metropolitan areas. Columns 1, 2 and 3 of Table 6 show the estimates of the coefficient b_1 in equation (19). In specification (1) we only include the time dummies. In (2) we include also state fixed effects (this is the basic specification), and in (3) we include the very demanding metro-area fixed effects. The effect of H-1B driven STEM is always significant at the 5% level and in the basic specification it is close to 0.7, implying that an H-1B-driven increase in STEM by 1% of employment produces a 0.7% increase in foreign-STEM workers in a city. We can interpret this regression as the first stage in a two stage least squares (2SLS) estimate of the effect of STEM workers. Note that the F-statistic of 17 in the basic specification is well above the critical value for weak instrument tests. Only when we include city-effects does the policy-driven variable (though still significant) become less powerful in predicting foreign-STEM (F-statistic equal to 4.85). Figures 6a and 6b provide the graphical representation of the power of the H-1B-driven

variable in predicting the change in foreign-STEM. Figure 6a shows a clear positive relation (t-statistic equal to 4.3) between the two variables. It also makes clear that there are two outliers – San Jose, CA and Stamford, CT[15] – between 1990 and 2000. Figure 6b shows that the correlation is even stronger without the outliers (t-statistic equal to 6.28), with no other observation being too far from the regression line.

The period 2005-2010 was rather turbulent and unusual because the great recession (2007-2009) produced the largest drop in employment experienced since the great depression. Hence we also limit our analysis to the period 1990-2005. Column 4 of Table 6 shows that ending the sample in 2005 tightens the predictive power (F-statistic 21.9) and increases the coefficient (to almost 0.9) of the H-1B driven variable. In the pre-great recession period, each extra H-1B visa entrant to a metropolitan area increased its foreign-STEM workforce by 0.9 units. In column 5 of Table 6 we explore whether the H-1B policy-driven variable had a significant effect on the total increase in STEM. While less powerful than in predicting foreign-STEM, the H-1B-policy variable has a significant effect (at the 5% level) also on the growth of total STEM workers (as percentage of the employment). The last column of Table 6 tests whether the predictive power of the H-1B policy variable is affected by the inclusion of a control for the 1980 native-STEM dependence of the metro area. We already documented in Table 5 a very weak correlation of native-STEM dependence in 1980 and subsequent foreign-STEM growth. Column 6 of Table 6 confirms that controlling for native-STEM dependence does not change at all the predictive power of the H-1B policy variable.

In Table 7 we perform several robustness checks of the basic specification (19). Columns 1 to 4 show the power of the H-1B-driven growth on foreign-STEM when we use the two alternative definitions of STEM occupations that we described in Section 3.1. In columns 1 and 2 we restrict STEM workers to be only those with college education among those employed in the occupations defined as STEM intensive by O*NET. The definition of the dependent and explanatory variables are both changed accordingly. In columns 3 and 4 we instead use the college-major based definition of STEM, including occupations with 25% or more workers with a STEM degree. In specifications (1) and (3) we include state fixed effects, while in (2) and (4) we include the very demanding metropolitan area effects. In the basic specifications (1) and (3) the H-1B driven variable is a very strong predictor of the change in foreign-STEM. The college-major based definition shows such a strong predictive power of the H-1B-driven variable that even the city fixed effects specification (4) delivers a large F-statistic (19.5).

Column 5 addresses the possibility that the foreign-STEM distribution in 1980 might have been influenced by the very recent computer and information technologies that affected productivity in the 1990-2010 period. Therefore we construct the H-1B driven variable using the STEM dependence of cities as revealed by the 1970 Census. This implies that we can only use the 116 metropolitan areas consistently identified for the whole 1970-2010 period. While the power is reduced (F-statistic of 6.05) we still find that the H-1B driven variable significantly predicts the foreign-STEM growth in the 1990-2010 period. That is, the dependence on foreign-STEM workers in 1970 still significantly impacted the allocation

[15] Because of the extremely large increase in foreign-STEM in San Jose and Stamford that is not explained by the H1B-predictor, it is reasonable to think that sector-specific factors are at play (e.g., the computer industry in San Jose and the financial industry in Stamford). We have run several of the regressions in Table 8-12 without those two outliers and the results are virtually identical.

of H-1B workers twenty years later. Column 6 of Table 7 checks that the location of Indian workers – who account for almost 50% of H-1B visas and are well known to be concentrated in the computer industry – are not responsible for the full explanatory power of the H-1B driven variable. We construct the H-1B driven variable omitting Indian nationals both from the initial STEM distribution and from the H-1B visas. The coefficient and the F-statistic confirm that the H-1B driven variable still has significant explanatory power (albeit with a reduced F-statistic). Finally, column 7 includes L1 visas, which are used for inter-company transfers, in the policy-driven variables. Those visas began to be used to attract STEM workers especially in the late 2000s. However, their inclusion does not significantly change the predictive power of the policy-driven variable.

3.5 Sector-Driven Growth in Employment and Wages

Despite being only weakly correlated with the presence of native-STEM workers, dependence on foreign-STEM workers could still be correlated with a city's productive structure. In particular, the presence of dynamic sectors that employ foreign-STEM workers and were likely to experience larger productivity or employment growth between 1990 and 2010 could bias our results. In order to control for this we construct four variables that predict, based on the 1980 city-composition across 228 industries, the growth of wages and employment of college and non-college-educated workers in the city. We use is the three-digit industry classification from the census, which is consistent across decades, and provides a very detailed break-down of the productive structure of a city.[16]

Let $s_{ic,1980}$ denote the share of total city c employment in each industry $i = 1, 2...228$ 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 $(= 1, 2...228)$. Similarly, let $\Delta EMPL_t^{i,X}/TotEmpl_t^i$ be the national growth of native employment of workers of type X (=College, No-College) in sector i $(= 1, 2...228)$ during the relevant period, expressed as percentage of total initial employment in the sector. We define sector-driven wage growth and sector-driven employment growth (respectively) in city c and decade t for group X with the following expressions:

$$\left(\frac{\Delta w^X}{w^X}\right)_{ct}^{Sector-Driven} = \sum_{s=1,228}\left(s_{ic,1980}\frac{\Delta w_t^{i,X}}{w_t^{i,X}}\right) \quad \text{for } X = Coll, NoColl \tag{20}$$

$$\left(\frac{\Delta E^X}{TotE}\right)_{ct}^{Sector-Driven} = \sum_{s=1,228}\left(s_{ic,1980}\frac{\Delta EMPL_t^{i,X}}{TotEmpl_t^i}\right) \quad \text{for } X = Co, NoColl \tag{21}$$

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 the industry composition in 1980 to a very detailed level of aggregation. We include the relevant sector-driven controls in all our regressions in section 4 below. For instance, when we analyze the

[16] To give an idea of the detail of the classification sectors as "Computers and related equipment", "Hotel and Motels" and "Legal Services" ar considered individual sectors.

effect of H-1B-driven STEM on wages of non-college-educated natives, we control for the 1980 sector-driven growth in wages paid to non-college-educated native. When we analyze the effects on the employment of college-educated workers, we include the sector-driven growth of employment of college-educated labor, and so on.[17]

4 The Effect of STEM on Wages and Employment

4.1 Basic Specifications

In our empirical analysis we estimate two basic specifications with the goal of identifying the impact of STEM workers on the wages and employment of different groups. The outcome variables are measured for native workers so as to keep the experiment cleaner: The exogenous change in STEM is due to the inflow of immigrants and we analyze the impact of this inflow, through supply and productivity effects, on the outcomes of existing native workers. The first specification we estimate is as follows:

$$y_{ct}^{Native,X} = \phi_t + \phi_s + b_{y,X}^{D} \frac{\Delta STEM_{ct}^{H-1B}}{E_{ct}} + b_3 y_{ct}^{Sector-Driven,X} + \varepsilon_{ct} \tag{22}$$

The variable y_{ct}^{Native} is an outcome for native workers of type X (college-STEM, college-non-STEM, or non-college) in city c. In our analysis it measures either a change in wages or in employment. ϕ_t are period fixed effects, ϕ_s are state fixed effects, $y_{ct}^{Sector-Driven,X}$ is the control for the specific sector-driven outcome described in (21) and (20). The term $\frac{\Delta STEM_{ct}^{H-1B}}{E_{ct}}$ is the H-1B-driven growth in foreign-STEM, ε_{ct} is a zero-mean random error, and the coefficient of interest is $b_{y,X}^{D}$. We will call specification (22) the "direct regression" since the H-1B-policy variable enters the regression directly. Alternatively, we also estimate:

$$y_{ct}^{Native} = \phi_t + \phi_s + b_{y,X}^{IV} \frac{\Delta STEM_{ct}^{Foreign}}{E_{ct}} + b_3 y_{ct}^{Sector-Driven,X} + \varepsilon_{ct} \tag{23}$$

Specification (23) is similar to (22) except that it includes the actual change in foreign-STEM, $\frac{\Delta STEM_{ct}^{Foreign}}{E_{ct}}$, as the main independent variable and we use $\frac{\Delta STEM_{ct}^{H-1B}}{E_{ct}}$ as an instrument in the 2SLS estimate. We call this specification the 2SLS or IV specification. The coefficient of interest is $b_{y,X}^{IV}$.

Each cell of Table 8 reports the $b_{y,X}^{IV}$ estimates of the effects of H-1B-driven foreign-STEM. Each of the six columns represents a different outcome estimated with the direct regression of specification (22). 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 each of 219 metropolitan areas over the 1990-2000, 2000-2005, and 2000-2010 periods. 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

[17] All of these variables are significantly correlated with the corresponding employment or wage growth. The initial sector structure is therefore a predictor of employment and wage growth of the city.

workers $\left(\frac{\Delta w_{noCollege}^{native}}{w_{NoCollege}^{native}}\right)$.[18] Columns 4, 5, and 6 show the effect of STEM on the change in employment of native-STEM workers, native college-educated workers, and native non-college-educated workers, as 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 8 represent different specifications and samples. Each includes period effects, state effects, and the sector-driven variable controls. The first row reports results from the basic specification that uses the broad O*NET STEM definition. The second row specification is the same but adds a control the native-STEM dependence of cities in 1980. In the third row we adopt the O*NET-college graduate definition of STEM, while in the fourth row we use the major-based STEM definition. The fifth row specification omits the post-2005 period in order to exclude the great recession from the sample. In the sixth row we include L1 visas in the construction of the policy-variable, and the results in the final row use the 1970-based STEM dependence to construct the H-1B variable.

Four interesting and relatively consistent results emerge. First, there is a positive and significant effect of H-1B STEM workers on wages paid to college-educated workers. The estimated effect is always significantly different from 0 at the 1% significance level, and the point estimates are between 2 and 5 percentage points for each percentage-point increase in the H-1B STEM share of employment. The estimates of the effects on STEM-worker wages are usually larger but more imprecise so that we can never rule out the hypothesis that the effect on STEM wages is equal to the effect on college-educated wages. The second consistent result is that H-1B STEM workers did not have any significant effect on wages of non-college-educated workers. The point estimates are much smaller than those on college-educated wages (usually smaller than one) and never significantly different from zero. Third, the inflow of STEM workers did not significantly affect the employment college-educated natives or the STEM workers among them. While most estimates are positive and several are around one they are never significantly different from zero. Finally, H-1B STEM workers also had no effect on non-college-educated employment. Point estimates of the response are usually negative, but are also imprecise and insignificant. The null effect on non-college-educated workers and the positive wage effect on college-educated together suggest that H-1B STEM increases might have caused skill-biased productivity growth. The weak employment response of college employment might also suggest that adjustment mechanisms beyond the net inflow of college-educated employment were at work at the metropolitan area level. We explore the possibility of changes in the price of non-tradables (in the form of house rents) in the next section.

While the direct regressions are useful to have a sense of the effect of H-1B visa policy, our preferred specification is (23), which uses changes in foreign-STEM employment as the explanatory variable and adopts the H-1B policy variable as an instrument. Cells in Table 9 show the estimated $b_{y,X}^{IV}$ coefficients for the same six dependent variables analyzed in Table 8. Rows are defined by the different samples and specifications described above for Table 8. Columns continue to report coefficients for regressions defined by the dependent variables in

[18] Weekly wages are defined as yearly wage income divided by the number of weeks worked. Employment includes all individual between 18 and 65 who have worked at least one week during the previous year and do not live in group-quarters. Individual weekly wages are weighted by the personal weight in the Census. We convert all wages in current 2010 prices using the CPI deflator provided by IPUMS.

the column headers. A new final column shows the Kleinberger-Paap Wald F-statistic for the first stage regression (essentially identical for all the regressions in the row, as the first stage is the same) to give a sense of the strength of the instruments.

Overall the 2SLS results of Table 9 clearly confirm those of the direct regressions in Table 8. Foreign STEM workers (and STEM workers in general) have a positive and significant effect on the wage of college-educated and native STEM workers. They have no significant effect on the wage of non-college-educated workers and the employment of both college-educated and non-college-educated workers. This last outcome is very imprecisely estimated, however, and the point estimate is often negative and large. Notice that while the estimates and their significance are remarkably consistent across specifications, the power of the 1970-based instrument is rather low. Similarly, the H-1B instrument is rather weak in predicting total STEM workers. While we should not attach very high confidence to the point-estimates of the coefficients in those rows, it is still the case that the only significant effects are those on the wages of college-educated and STEM workers, which confirms all the previous estimates. The point estimates of the effect on college-educated wages in Table 9, usually between 4.3 and 6, is larger than it was the direct regressions of Table 8. We consider the range of estimates in Table 9 to be the preferred ones.

The growth in foreign-STEM is measured as a percentage of total initial employment. Foreign-STEM workers are a small group (about 1 to 3% of employment, depending on how they are measured). Their growth was only about 0.6% of total employment during the 1990s, and 0.2% in the following decade. Applying the 2SLS estimates of Table 9 to the average growth in foreign-STEM nationally implies that the foreign-driven net increase in STEM increased inflation-adjusted wages of college-educated natives between 2.5 and 3.6% between 1990 and 2000, and between 0.8 and 1.2% between 2000 and 2010. We will come back to these implications in Section 6 when we analyze the implied productivity and skill-bias effects of STEM.

Another instructive and important observation can be seen in the last row of Table 9. It shows the OLS correlation of foreign-STEM growth with the dependent variables – that is, the coefficient that we would estimate by using OLS in regression (23). This row shows how largely over-stated the positive effects are – especially for employment and for non-college-educated workers – if we fail to account for the endogeneity of foreign-STEM workers and do not include the sector-driven growth variables. This regression finds positive and significant effects of STEM on all variables. This means that STEM workers are attracted to cities in which employment and wages of all workers are growing. Our instrument, in contrast, allows us to separate the positive effect on demand for college-educated workers from the negative effect on the demand for non-college-educated labor.

5 Extensions

5.1 Robustness Checks

In Table 10 we estimate the 2SLS regressions using the two alternative definitions of STEM workers – we limit the O*NET STEM definition to college-educated workers only in rows 1, 4, and 5, and we used the definition based on college major in rows 2, 3, and 6. We also

modify the H-1B-based instrument accordingly. As already noted in Table 7, the college-major based definition produces more powerful instruments. This is particularly evident in the relatively strong F-test of the first stage in row 3 when we also include 219 metro-area fixed effects. Row 4 focuses on the pre-great-recession period. Also notice that the college-educated O*NET definition produces stronger instruments when we try to predict the change in total STEM workers (in row 5). We report the OLS estimates in the last row, as comparison, using the major-based STEM definition.

The main results of Table 9 (and of Table 8) are clearly confirmed in the robustness checks of Table 10. Only the effect on wages paid to college-educated natives is significantly different from zero in each specification. Estimated for that effect range between 2.8 and 6.8, a bit broader than the previously estimated range, but not far from it. Note also that the estimated effect on STEM worker wages is more variable and less precise than the estimates of Table 9. Changing the definition of STEM workers from a broader definition based on O*NET (row 1 and 4) to a narrower definition based on college-majors (row 2 and 3) seems to affect the estimated coefficient on wages by making them smaller. It is possible that narrower definitions of STEM imply that these foreign-STEM workers still have a productivity effect on, but are less substitutable with, college-educated workers, thereby having an increased competition effect on wages. Let us emphasize that the third row of Table 10 estimates a very demanding specification by including in a differenced panel (with only 3 periods) and a full set of 219 metropolitan areas fixed effects. The coefficients are identified on differences in the growth rates of STEM in a city across periods. The main qualitative characteristics of the coefficients are, however, still consistent with those of the other specifications. Finally the estimated effects on non-college employment are negative but not significant in any specification. The standard errors of those estimates are usually large.

Overall these robustness checks confirm that we do not find any significant positive effect on employment or wages of non-college-educated labor driven by foreign-STEM workers. Also confirmed in Table 10 is the importance of using the 2SLS estimation rather than OLS. Immigrant STEM workers have a positive and significant correlation with almost all native groups (see row 6 of Table 10). Part of this is certainly due to the fact that economic growth of cities increases employment of all workers. Isolating only the H-1B-driven increase in foreign-STEM workers reveals different effects on employment and wages, which are mainly limited to college-educated workers.

5.2 The Effect on Housing Rents

The STEM impact on the employment and wages paid to non-college-educated workers is insignificant. The impact on college-educated wages is significantly positive, though STEM similarly fails to generate a significant employment response for this group. This second result suggests a mystery – why do we not see more college-educated workers move to cities in which STEM workers have increased their productivity? 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 that this is a plausible adjustment channel we analyze the effect of

STEM workers on house rents, as measured by the U.S. Census in 1990, 2000, 2005, and 2010. We construct the monthly rent per room in constant 2010 dollars by using data on the total number of rooms occupied and rent paid by native individuals between 18 and 65 years of age in a metropolitan area (to be consistent with the wage data). In order to identify the specific effect for college and non-college-educated rents we construct the rent per room of those two groups separately. As the 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 these rent values as the y outcome variable in regression (23), using the same methodology and instruments as in our wage and employment regressions. Table 11 reports the estimated effect on a change in rents paid by college and non-college-educated workers caused by changes in foreign-STEM employment. We use the data on rents, rather than house values, because they capture more closely the cost of housing services provided by a building and do not include their asset value. We should caution that, as is well-known, the housing market was exceptionally turbulent between 2007 and 2010. This likely introduced very high variability in the data post 2005 that may cloud the results.

Columns 1 and 2 show the effect on average and median rent paid by college-educated workers, while columns 3 and 4 show the impact on average and median rent of non-college-educated labor. In the first row we show 2SLS estimates of the basic specification. The second row drops post-2005 observations. Specification 3 includes L1 visas in the construction of the instruments, and specification 4 uses the college graduate O*NET definition of STEM. The last row shows the OLS estimates for comparison.

The main result is that all the 2SLS estimates (except one that includes the turbulent post-2005 period) reveal a significant and positive effect (at the 1% level) of STEM on rents paid by college-educated workers. Point estimates center around 5. Conversely, point estimates of STEM effects on rents paid by non-college-educated workers are near -1 and are never significant. The inflow of H-1B STEM workers increased the wages of college-educated labor but also increased their housing costs. This differential increase in rents is probably 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[19] for college-educated workers from 1998-2002 – dates in the middle of our dataset – shows that housing costs represented 33% of individual expenditures, while 17% of their expenditures were in utilities, health, and entertainment (arguably non-tradable services). Hence, 50% of college-educated workers' incomes could easily be spent on non-tradable services. If we consider the average estimated price effect (from Table 11) to be around a 5% increase for each one percentage-point rise in the STEM share of employment, and the corresponding average effect on nominal wages to be around 5% as well (from the average estimate in Table 9), then the real wage increase for college-educated labor, accounting for purchasing power, would be only around 2.5%. With a local labor supply elasticity of 2.5 or more, which would be a quite sizeable response, this would imply a college-educated employment increase of 1% or less – a value in the range of most of our estimates, though our values are insignificant

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

due to standard errors between one and two. The STEM effect on non-tradables prices, therefore, contributes substantially in absorbing the local effect on college-educated wages while also helping to explain the small employment response.

5.3 The Effect on Specific Skills, Industries, and Tasks

Our estimates reveal that the demand for native college-educated workers received a significant positive boost from STEM workers. At the same time, though, the demand for non-college-educated labor was not positively affected. In this section we explore three channels through which STEM workers might have affected the city economy that go beyond the broad groups considered in the previous sections. First we analyze whether the null effect on the demand for non-college-educated labor is concentrated mainly in the very low part of the educational distribution within that group. That is, we assess whether effects are different among individuals with very limited schooling, or are instead experienced uniformly across all non-college-educated labor. Second, we analyze whether STEM growth pushed college-educated native workers toward more human capital (and knowledge) intensive industries – an effect likely to benefit natives. Finally, we analyze whether the inflow of foreign-STEM workers encouraged native college-educated workers to specialize in abilities that complement those of foreign-STEM workers. On one hand, we have already shown that native-STEM workers' productivity increased. However there are other skills important in generating innovation and scientific-technological growth that may have been encouraged by the H-1B-driven STEM increase.

Table 12 shows the effect of foreign-STEM workers on the wages (columns 1 and 2) and employment (columns 3 and 4) of native workers. We separate our analysis into high school dropouts (columns 2 and 4) and high school graduates (columns 1 and 3). In rows 1-5 we run several specifications of the 2SLS regression, each described by the row leaders. Row 6 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. It is also a preliminary test for whether STEM workers produced the type of change in labor demand that has been baptized the polarization of the labor market. This phenomenon implies higher employment growth at the high and low ends of the education spectrum have occurred at the expenses of intermediate-level jobs (e.g. Autor (2010), Autor et al. (2006)). The estimates of Table 12 show that STEM effects on both high school graduates and dropouts are mostly negative and insignificant. The only coefficients sometimes close to significance are those for the employment of high school graduates. The third row (pre-2005 data only) estimates a -4.38 coefficient on STEM for the employment of high school educated labor that is significant at the 10% level. This would be consistent with claims that STEM driven technological progress contributes to labor market polarization by affecting intermediate education groups (high school graduates) more negatively than low education groups (dropouts). The effect, however, is not very robust.

Table 13 shows the employment response to STEM workers for college-educated labor (columns 3 and 4) and all workers (columns 1 and 2) for nine separate sectors. We included all sectors except those that have very small employment shares in some cities (mining, agriculture, and entertainment) and would therefore exhibit rather noisy estimated effects. We arrange sectors in Table 13 in three groups: private sectors with low human capital

intensity, (measured as having a share of college-educated labor smaller than 0.25 in year 2000), private sectors with high human capital intensity (measured as having a college-educated share larger than 0.25 in year 2000), and the public sector (whose employment growth may not be driven by productivity considerations). The coefficients of columns 3 and 4 in Table 13 obtained using the basic specifications (22) or (23) show that the employment of college-educated labor in high human capital sectors increased significantly in response to an inflow of STEM workers in the city. To the contrary, low human capital sectors and the public sector did not experience net college-educated job growth. Hence, cities with high STEM inflows also experienced a reallocation of college-educated workers toward more human capital-intensive sectors. The coefficients of columns 1 and 2 show that while high human capital sectors experienced positive total employment changes (that is, employment increases among workers of all education levels) in response to STEM workers, those effects were not significant.

Previous research has found that foreign-STEM workers increase innovation in the U.S., while other studies have found that U.S. workers respond to the inflow of similarly educated foreign-workers by specializing in complementary type of skills.[20] In Table 14 we explore the possibility that the inflow of foreign-STEM workers encouraged native college-educated labor to specialize in abilities that may complement those of foreign-STEM workers.

Using the O*NET "Ability," "Activity," "Skill," and "Work Characteristic" surveys, we identify variables associated with creativity and with problem solving. We measure their importance in each of the 333 occupation definitions that we can track consistently across census years.[21] Then we associate native college-educated individuals in each city and year to occupations, and hence to the importance of these creative and problem-solving skills. Finally, we use the average abilities (for native college-educated labor) at the city level as outcome variables in specifications (22) and (23). The dependent variables are measured as the change in the average index (ranging from 0 to 1), and both variables have a standard deviation around 0.025.

The coefficients show that H-1B driven growth of foreign-STEM produces a significant shift of native college-educated labor toward occupation that use creative and problem solving skills more intensively. On one hand, this shift could contribute to an increase in the productivity of native college-educated labor beyond increases driven by technological change. On the other hand,. the result confirms the complementarity-specialization effect between STEM workers and other college-educated workers. Even non-STEM workers could take advantage of the presence of STEM labor by specializing in skills that, in the process of innovation and technology, are complementary to science and technology. An increase of foreign STEM by 1% would increase the creative-intensity of native college-educated occupations in the city by 1.3%, and the problem-solving intensity of their occupations by 0.8%. This is about half of the standard deviation of innovative skill growth across cities.

[20] See Kerr and Lincoln (2010), Hunt and Gauthier-Loiselle (2011), and Peri and Sparber (2009, 2011).

[21] The variables that we associate with Creativity are: "Fluency of ideas", "Originality" (among Abilities), "Thinking Creatively" (among Activities), "Innovation" (among work characteristics). The variables that we associate with "Problem Solving" are "Making decisions" and "Solving problems" (among activities), "Critical thinking", "Active learning and Complex Problem Solving" (among skills) and "Analytical Thinking" (among work characteristics).

6 Productivity and Skill-Bias Effects: Macro and City-Implications

Overall, the empirical results presented in Section 4 indicate that in a U.S. metropolitan area, an increase in STEM workers by 1% of total employment over a decade has a positive and significant effect between 4 and 6% on the wage of college-educated workers, and no significant effect on their employment. Non-college-educated workers experience insignificant wage and employment effects, though our results in Table 9 do suggest an imprecise point estimate around -4% for the latter effect. In this section we use the estimated values of $\widehat{b}_{y,X}$ – the elasticity of outcome y for group X to STEM workers – and equations (7)-(9) to translate the wage and employment elasticities into effects on the growth of total factor productivity and its skill-bias. We begin by noting that our results suggest that three elasticities – $\frac{\Delta w_L}{w_L}/\frac{\Delta ST^{Foreign}}{E}$, $\frac{\Delta NST}{E}/\frac{\Delta ST^{Foreign}}{E}$, and $\frac{\Delta ST^{Native}}{E}/\frac{\Delta ST^{Foreign}}{E}$ – are never statistically different from zero. Hence we set them equal to zero, which allows us to simplify the system and obtain the following three equations that identify remaining unknown parameters:

$$\phi_A - \frac{\beta}{1-\beta}\phi_B = \widehat{b}_{E,L}\left(\frac{s_w^L}{\sigma_H s_E^L} - \frac{1}{\sigma_H s_E^L}\right) - \frac{s_w^{ST}}{\sigma_H s_E^{ST}} \tag{24}$$

$$\phi_A + \phi_B = \widehat{b}_{w,NST} - \widehat{b}_{E,L}\frac{s_w^L}{\sigma_H s_E^L} - \frac{s_w^{ST}}{\sigma_H s_E^{ST}} - \left(\frac{1}{\sigma_S} - \frac{1}{\sigma_H}\right)\frac{s_w^{ST}}{s_w^H s_E^{ST}} \tag{25}$$

$$\frac{1}{\sigma_S} = s_E^{ST}\left(\widehat{b}_{w,NST} - \widehat{b}_{w,ST}\right) \tag{26}$$

The last equation immediately defines σ_S. Since most of our results produce noisy estimates of $\widehat{b}_{w,ST}$ that are not statistically different from $\widehat{b}_{w,NST}$, we infer that $\frac{1}{\sigma_S} = 0$. This can be substituted into (24) and (25), thereby reducing them to very simple linear equations in the two unknown $\phi_A$and ϕ_B, provided that we know σ_H and β. Appendix A shows the expression for those variables obtained by solving (24) and (25). The literature provides estimates of σ_H that usually range from 1.5 and 2.5.[22] We assume a σ_H value of 1.75 and combine it 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 0.52 for the year 2000.[23]

We perform two exercises using our assumed parameters above. The first is a macro application. We calculate the aggregate TFP and skill-bias effect for the U.S. due to the growth in foreign-STEM between 1990 and 2010. The second application is for city differences. We take the cities with the highest and lowest inflows of foreign-STEM workers and those with the highest and lowest growth in productivity (as revealed by average wages), and we calculate the percentage of the productivity difference that can be explained by foreign STEM flows.

[22] 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,

[23] 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 $\beta = 0.52$.

Table 15 shows the results from the macro exercise. Columns 2 and 3 report the values of ϕ_A and ϕ_B implied by two sets of estimates. In the upper part of the table we use the average value of 5 for $\widehat{b}_{w,NST}$ and $\widehat{b}_{w,ST}$ from Table 9, and we set all non-significant coefficients equal to zero so that $\widehat{b}_{E,L} = 0$. In the lower part of the table we instead set $\widehat{b}_{E,L}$ equal to -3.5, its average point-estimate from Table 9. Columns 4 and 5 show the implied productivity and on the skill-bias effects caused by average yearly foreign-STEM worker growth (reported in column 1) that we obtain from our estimates and the average growth of foreign-STEM workers for the U.S. in the two decades after 1990. Columns 6 and 7 show the actual productivity growth and skill-biased growth measured in the aggregate U.S. data, and the last two columns show the proportion of productivity and skill-biased growth attributable to the increase in foreign-STEM workers.

The average yearly growth of foreign-STEM workers in the U.S. (as percentage of total employment) was 0.06% in the 1990s and 0.02% in the 2000s. No major differences depend upon whether we set $\widehat{b}_{E,L}$ equal to the average negative point estimates (lower part of the table) or to zero (upper part). The estimated elasticities imply that foreign-STEM growth can explain a quarter of the aggregate productivity growth between 1990 and 2010, and possibly 40% of it in the 1990s. Our calculations attribute 0.30% of TFP growth per year to foreign-STEM in the 1990s and 0.10% in the 2000s. Such annual growth implies that income per capita in 2010 is 4% larger in the U.S. that it would have been without contributions from foreign-STEM contribution. On the other hand, the skill-bias effect implied by the growth in foreign-STEM is only able to explain at most 10% of the growth in skill-bias (college-bias) over the same period.[24]

The macro exercise is based on the very strong assumption that we can apply parameters that were estimated across cities to calculate national effects of foreign-STEM. Nonetheless, the exercise is informative as it provides a reference for the magnitude of those effects. For reference, a very influential paper on aggregate U.S. data (Jones (2002)) found that about 50% of the long-run productivity growth of the U.S. in the last decades could be attributed to growth in the share of scientists and engineers. In our estimates, we emphasize how a significant part of that contribution might have come from foreign-STEM workers between 1990 and 2010.

Table 16 turns to a city-level analysis and shows the implication of differences in foreign-STEM growth across U.S. cities on differences in productivity growth (as measured from average wage growth). In column 1 we report the difference between the cities with the highest and lowest foreign-STEM labor growth from 1990-2000 and 2000-2010.[25] Column 3 shows the effect on differential TFP growth between cities implied by this difference and our estimated coefficients. Column 4 reports the actual difference in TFP growth, as measured by difference in average wage growth, between the slowest and fastest growing cities. The last column displays the fraction of the wage growth differential explained by the foreign-STEM differential. The magnitude is again substantial. Differences in foreign-STEM growth are

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

[25] The city with lowest STEM growth in the 1990s was Terre Haute, IN, while San Jose, CA had the highest foreign-STEM growth. In the 2000s, Wichita Falls, TX and Seattle, WA had the bottom and top position, respectively.

able to explain the whole difference in TFP growth in the 1990s, while they explain about half of it in the 2000s. Foreign-STEM workers seem to play a very important role both in explaining aggregate TFP and its cross-city differences.

7 Conclusions

In this paper we used the inflow of foreign scientists, technology experts, engineers, and mathematicians (STEM) made possible by the introduction of the H-1B visa program to estimate the impact of those types of workers on the productivity of college and non-college-educated American workers. The uneven distribution across cities of foreign-STEM workers 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 allows us to use the variation in foreign-STEM as a supply-driven increase in STEM workers that is unevenly distributed across metropolitan areas. We find that a one percentage point increase in the foreign-STEM share of a city's total employment over a decade increased wages of native college-educated labor by 4-6% with a small effect on their employment. It also had non-significant effects on the wages and employment of non-college-educated labor. These results indicate that growth in STEM workers spurred technological growth by increasing the productivity of (and demand for) college-educated workers. The technologies introduced in the between 1990 and 2010 by STEM workers likely increased total production and even more strongly the productivity of college-educated labor. We also find that college-educated natives responded to the increase of foreign-STEM workers by switching to more human capital intensive sectors of the city economy and by increasing their use of creative skills used in production. They also experienced increasing housing rents, which eroded part of their wage gain.

References

[1] Acemoglu, Daron, and Joshua Angrist. (2000) "How large are human capital externalities? Evidence from Compulsory Schooling Laws." *NBER Macroeconomics Annual*, 2000.

[2] Acemoglu, Daron. (1998) "Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality." *The Quarterly Journal of Economics* 113(4): November 1998, pp. 1055-89.

[3] Acemoglu, Daron. (2002) "Technical Change, Inequality and the Labor Market." *Journal of Economic Literature* 40(1): March 2002, p. 7-72.

[4] Altonji, Joseph G., and David Card. (1991) "The Effects of Immigration on the Labor Market Outcomes of Less-Skilled Natives." In . John M. Abowd and Richard B. Freeman, eds., Immigration, Trade, and the Labor Market. Chicago: University of Chicago Press, 1991, pp. 201–34.

[5] Autor, David H. (2010) "The Polarization of Job opportunities in the U.S. Labor Market" The Hamilton Project, Washington D.C. April 2010.

[6] Autor, David H., Frank Levy, and Richard J. Murnane. (2003). "The Skill Content of Recent Technological Change: An Empirical Exploration," *The Quarterly Journal of Economics* 118(4). November 2003, pp. 1279-1334.

[7] Autor, David, Lawrence Katz and Alan Krueger (1998). "Computing Inequality: Have Computers Changed the Labor Market?" *The Quarterly Journal of Economics* 113(4): November 1998, pp. 1169-1214.

[8] Autor, David H., Lawrence F Katz, and Melissa S. Kearney. (2006). "The Polarization of the U.S. Labor Market." *The American Economic Review* 96(2): May 2006, pp. 189-194.

[9] Beaudry, Paul, Mark Doms and Ethan Lewis. (2010) "Should the PC be Considered a Technological Revolution? Evidence from U.S. Metropolitan Areas." *Journal of Political Economy* 118(5): October 2010, pp. 988-1036.

[10] Beaudry, Paul, and David A. Green. (2003) "Wages and Employment in the United States and Germany: What Explains the Differences?" *The American Economic Review* 93(3): June 2003, pp. 573-602.

[11] Beaudry, Paul, and David A. Green. (2005) "Changes in U.S. Wages, 1976–2000: Ongoing Skill Bias or Major Technological Change?" *Journal of Labor Economics* 23(3), July 2005, pp. 609-648.

[12] Berman, Eli, John Bound and Zvi Griliches. (1994) "Changes in the Demand for Skilled Labor within U.S. Manufacturing: Evidence from the Annual Survey of Manufactures." *The Quarterly Journal Of Economics* 109(2): May 1994, pp. 367-397.

[13] Bureau of Labor Statistics. (2005) " The Consumer Expenditure Survey" year 1999-2002, http://www.bls.gov/cex/home.htm#tables.

[14] Card, David. (2001) "Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration." *Journal of Labor Economics* 19(1): January 2001, pp. 22-64.

[15] Caselli, Francesco. (1999) "Technological Revolutions," *The American Economic Review*, 89(1): March 1999, pp. 78-102.

[16] Caselli, Francesco and Wilbur John Coleman II (2006) "The World Technology Frontier." *American Economic Review* 96(3): June 2006, pp. 499-522.

[17] Ciccone, Antonio and Giovanni Peri. (2005) "Long-Run Substitutability between More and Less Educated Workers: Evidence from U.S. States 1950-1990." *Review of Economics and Statistics* Vol. 87, Issue 4, pp. 652-663

[18] Department of State (2011) "Nonimmigrant Visa Statistics" http://travel.state.gov/visa/statistics/nivstats/nivstats_4582.html" Classes of Nonimmigrants Issued Visas – FY1987-2010 Detail Table.

[19] Ellison, Glenn and Edward L. Glaeser, (1999) "The Geographic Concentration of Industry: Does Natural Advantage Explain Agglomeration?," *American Economic Review*, American Economic Association, vol. 89(2), pages 311-316, May.

[20] Fernald, John (2010) "A Quarterly, Utilization-Adjusted Series on Total Factor Productivity." FRBSF Working Paper.

[21] Ottaviano, Gianmarco I.P. and Giovanni Peri (2012) "Rethinking the Effects of Immigration on Wages" *Journal of the European Economic Association*, vol. 10(1), pages 152-197, 02

[22] Glaeser, Edward (2011) "The Triumph of the City: How Our Greatest Invention Makes Us Richer, Smarter, Greener, Healthier, and Happier" New York: Penguin Press (2011)

[23] Goldin, Claudia, and Lawrence F. Katz. (1998) "The Origins of Technology-Skill Complementarity." *The Quarterly Journal of Economics* 113(3): August 1998, pp. 693-732.

[24] Goldin, Claudia, and Lawrence F. Katz. (2007) "Long-Run Changes in the Wage Stucture: Narrowing, Widening, Polarizing." *Brookings Papers on Economic Activity.* 2007 (2):135-65

[25] Griliches, Z. (1992) "The Search for R&D Spillovers" *Scandinavian Journal of Economics.* Vol. 94(0), pp. 29-47.

[26] Hunt, Jennifer and Marjolaine Gauthier-Loiselle. (2010) "How Much Does Immigration Boost Innovation?" *American Economic Journal: Macroeconomics* 2: April 2010, p. 31-56.

[27] Iranzo, Susana and Giovanni Peri. (2009) "Schooling Externalities, Technology, and Productivity: Theory and Evidence from U.S. States." *Review of Economics and Statistics* 91(2): May 2009, pp. 420-431.

[28] Jaffe, Adam B., Manuel Trajtenberg, Rebecca Henderson. (1993) "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations." *The Quarterly Journal of Economics* 108 (3): August 1993, pp. 577-598.1.

[29] Jones, C. (1995) "Time Series tests of Endogenous Growth Models" *Quarterly Journal of Economics,* Vol.110. pp.495-525.

[30] Jones, C. (2002) "Sources of U.S. Economic Growth in a World of Ideas" *American Economic Review* Vol 92, No

[31] Kato, Takao and Chad Sparber (Forthcoming) "Quotas and Quality: The Effect of H-1B Visa Restrictions on the Pool of Prospective Undergraduate Students from Abroad" *Review of Economics and Statistics*

[32] Katz, Lawrence F. and Kevin M. Murphy. (1992) "Changes in Relative Wages, 1963-1987: Supply and Demand Factors." *The Quarterly Journal of Economics* 107(1): February 1992, pp. 35-78.

[33] Kerr, William and William F. Lincoln. (2010) "The Supply Side of Innovation: H-1B Visa Reforms and U.S. Ethnic Invention." *Journal of Labor Economics* 28(3): 2010, p. 473-508.

[34] Krueger, Alan. (1993) "How Computers Have Changed the Wage Structure: Evidence from Microdata 1984-1989." *The Quarterly Journal of Economics* 108(1), February 1993, pp. 33-60.

[35] Krusell, Per, Lee E. Ohanian, Jose-Victor Rios-Rull, and Giovanni L. Violante. (2000) "Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis," *Econometrica* 68(5), September 2000, pp. 1029-1053.

[36] Lewis, Ethan. (2011) "Immigration, Skill Mix, and Capital-Skill Complementarity", *Quarterly Journal of Economics* 126(2): May 2011, pp. 1029-1069.

[37] Lowell, Lindsay. (2000) "H-1B Temporary Workers: Estimating the Population" Working Paper, Center for Comparative Immigration Studies UC San Diego, http://escholarship.org/uc/item/4ms039dc.

[38] Moretti, Enrico. (2004a) "Estimating the Social Return to Higher Education: Evidence from Longitudinal and Repeated Cross-Sectional Data." *Journal of Econometrics* 121 (1): 2004a, pp. 175-212.

[39] Moretti, Enrico. (2004b) "Workers' Education, Spillovers and Productivity: Evidence from Plant-Level Production Functions." *American Economic Review* 94(3) pp. 656-690.

[40] Moretti, Enrico. (2011) "Local Labor Markets" Volume 4 of the Handbook of Labor Economics, Chapter 14, pp. 1237-1313.

[41] Moretti, Enrico. (2012) "The New Geography of Jobs" Houghton Miffin Harcourt Publishing Company, New York NY.

[42] Peri, Giovanni and Chad Sparber. (2009) "Task Specialization, Immigration and Wages" *American Economic Journal: Applied Economics*, 1:3, July, 2009.

[43] Peri, Giovanni and Chad Sparber. (2011) "Highly-Educated Immigrants and Native Occupational Choice" *Industrial Relations*, Vol. 50 (3): 385-411, July 2011.

[44] Rauch, James E. (1993) "Productivity Gains from Geographic Concentration of Human Capital: Evidence from the Cities," Journal of Urban Economics, Elsevier, vol. 34(3), pages 380-400, November.

[45] Saiz, Albert. (2007) "Immigration and housing rents in American cities," *Journal of Urban Economics*, Elsevier, vol. 61(2), pages 345-371.

[46] Saxenian, Anna Lee. (2002) "Silicon Valley's New Immigrant High Growth Entrepreneurs." *Economic Development Quarterly* 16(1): February 2002, p. 20-31.

[47] Solow, Robert M. (1957) "Technical Change and the Aggregate Production Function" *The Review of Economics and Statistics*, Vol. 39, No. 3. (Aug., 1957), pp. 312-320.

[48] U.S. Citizenship and Immigration Services (2009) "Characteristics of Specialty Occupation Workers (H-1B): Fiscal Year 2009", available at http://www.uscis.gov/portal/site/uscis.

A Appendix: Explicit Solution for ϕ_A and ϕ_B

Solving (24)-(26) with respect to the unknown parameters we obtain the following solutions:

$$\frac{1}{\sigma_S} = s_E^{ST}\left(\widehat{b}_{w,NST} - \widehat{b}_{w,ST}\right) \tag{27}$$

$$\phi_A = \beta A + (1-\beta)B \tag{28}$$

$$\phi_B = (1-\beta)(A-B) \tag{29}$$

Where:

$$A = \widehat{b}_{w,NST} - \widehat{b}_{E,L}\frac{s_w^L}{\sigma_H s_E^L} - \frac{s_w^{ST}}{\sigma_H s_E^{ST}} - \left(\frac{1}{\sigma_S} - \frac{1}{\sigma_H}\right)\frac{s_w^{ST}}{s_w^H s_E^{ST}} \tag{30}$$

$$B = \widehat{b}_{E,L}\left(\frac{s_w^L}{\sigma_H s_E^L} - \frac{1}{\sigma_H s_E^L}\right) - \frac{s_w^{ST}}{\sigma_H s_E^{ST}} \tag{31}$$

We use these formulas to calculate the effect of STEM growth on TFP and skill biased growth in Table 13.

Tables and Figures

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

	Foreign-Born % of Employment	Foreign-Born % of College-Educated	Foreign-Born % of College-Educated in 219 Metro Areas	Foreign-Born % of STEM Occupations in Metro Areas	Foreign-Born % of College Graduates in STEM Occupations in Metro Areas
1980	6.4%	7.0%	8.9%	9.8%	11.1%
1990	9.0%	9.0%	11.8%	13.7%	15.0%
2000	13.2%	12.7%	16.2%	19.5%	21.1%
2005	15.0%	14.3%	18.7%	22.5%	24.6%
2010	16.0%	15.3%	19.4%	24.0%	26.0%

Note: The figures are obtained by the authors from IPUMS Census data. The relevant population includes only non-institutionalized individuals between age 18 and 65 who have worked at least one week in the previous year.

Table 2
College-Educated O*NET-STEM Workers as a Percentage of Employment, 219 Metropolitan areas

	Foreign-STEM	Total STEM
1980	0.3%	2.7%
1990	0.5%	3.2%
2000	0.9%	4.3%
2005	1.0%	4.3%
2010	1.1%	4.5%

Note: The figures are obtained by the authors from IPUMS Census data. The relevant population includes only non-institutionalized individuals between age 18 and 65 who have worked at least one week in the previous year.

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
1980-1990	794	195	0
1990-2000	1,741	543	689
2000-2005	283	220	637
2005-2010	213	106	648

Note: Data on the change in total STEM occupations are from the IPUMS Census. Data on the total number of H-1B visas are from the Department of State (2010).

Table 4

Top 10 Cities in Native and Foreign-STEM Dependence in 1980

Metropolitan area	Native-STEM Dependence	Metropolitan area	Foreign-STEM Dependence
Richland-Kennewick-Pasco WA (Nuclear, Military)	14.7%	Miami, FL	3.1%
Rockford, IL (Machine Tools, Heavy Machinery, Aerospace)	12.5%	Waterbury, CT	2.6%
Lafayette, IN (Education, Purdue University)	11.5%	Los Angeles, CA	2.2%
Waterbury, CT (Clock-making, Metal Machinery)	11.4%	San Jose, CA	2.1%
Galveston-Texas City, TX (University of Texas Medical Branch)	11.3%	Hartford, CT	2.0%
Racine, WI (Detergents, Chemicals)	11.0%	Stamford, CT	1.9%
Jackson, MI (Medical, Recording Industry)	11.02%	New Bedford, MA	1.8%
Fort Collins, CO (Colorado State University)	10.9%	Providence, RI	1.7%
Sheboygan, WI	10.9%	Bridgeport, CT	1.7%
Elkhart-Goshen, IN	10.7%	New York, NY	1.6%

Note: The ranking is among the 219 metropolitan areas that can be followed consistently from 1980 to 2010 in the U.S. Census.

Table 5

Native and Foreign STEM Dependence across Cities in 1980 and the H-1B Predicted STEM Change

Panel of 219 U.S. Metropolitan Areas 1990-2000, 2000-2005, and 2005-2010

	(1) Foreign-Stem Dependence 1980	(2) Foreign-Stem Dependence 1980	(3) H-1B-Predicted STEM Growth	(4) H-1B-Predicted STEM Growth
Foreign-STEM Dependence, 1980				0.54*** (0.11)
Native STEM Dependence, 1980	-0.029 (0.032)		0.040* (0.021)	
Foreign-Born Share of Population, 1980		0.067*** (0.0065)		
Observations	219	219	657	657
F-Statistic	0.83	103.68	4.55	20.41
Year Effects	No	No	Yes	Yes
State Effects	Yes	Yes	Yes	Yes
Partial R-Square ("partialling out" State and Year Effects)	NA	NA	0.03	0.39

Note: Each column represents a separate regression. The dependent variable is written at the top of the corresponding column. Specifications (1) and (2) include 219 metropolitan areas in 1980. Regressions (3) and (4) include the H-1B-predicted change in STEM in 1990-2000, 2000-200,5 and 2005-2010 regressed on the 1980 STEM dependence (foreign or native). The standard errors are heteroskedasticity robust and, when there is more than one observation per metro area, they are clustered at the metro-area level. The STEM definition is based on O*NET skills.
***, **,*= significant at the 1%, 5% and 10% level.

Table 6

Power of H-1B Driven Increase in Foreign-STEM (O*NET Definition) as a Predictor of Foreign-STEM
Panel of 219 U.S. Metropolitan areas 1990-2000, 2000-2005, and 2005-2010

Dependent Variable	**(1) Change in Foreign-STEM as a % of Initial Employment**	**(2) Change in Foreign-STEM as a % of Initial Employment**	**(3) Change in Foreign-STEM as a % of Initial Employment**	**(4) Change in Foreign-STEM as a % of Initial Employment**	**(5) Change in total STEM as a % of Initial Employment**	**(6) Change in Foreign-STEM as a % of Initial Employment**
Other Notes:				*Drop Observations post 2005 (Great Recession)*		*Control for 1980 Native Stem Dependence*
H-1B Driven Growth in Foreign-STEM	0.56*** (0.16)	0.67*** (0.16)	2.61** (1.18)	0.87*** (0.18)	0.77** (0.39)	0.70** (0.17)
Observations	657	657	657	438	657	657
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Effects	No	Yes	No	Yes	Yes	Yes
Metro-Area Effects	No	No	Yes	No	No	No
F-test of the Coefficient	11.93	17.04	4.85	21.92	3.88	16.81

Note: Each column reports coefficients from a separate regression. The units of observations are 219 U.S. metropolitan areas over decades 1990-2000 and 2000-2010. The dependent variable is described at the top of the column. The explanatory variable is always the H-1B-driven growth of foreign-STEM jobs, as a percentage of initial employment.
***, **,*= significant at 1%, 5% and 10% level respectively.

Table 7

Power of H-1B Driven Increase in Foreign-STEM as a Predictor of Foreign-STEM: Alternative Definitions and Data

Panel of 219 U.S. Metropolitan areas 1990-2000, 2000-2005, and 2005-2010

Dependent Variable: Change in Foreign-STEM as a % of Initial Employment	**(1) College-Educated O*NET STEM Definition**	**(2) Same as (1) but with Metro-Area Fixed Effects**	**(3) College-Major Based STEM Definition**	**(4) Same as (3) but with Metro-Area Fixed Effects**	**(5) Same as (3) but with 1970 Based Immigrant Stock (116 Metro Areas)**	**(6) Same as (1), but Excluding Indians from STEM**	**(7) Same as (1), but Including L1 Visas in the Visa-Entry Construction**
H-1B Driven Growth in Foreign-STEM	0.49** (0.12)	2.20** (0.74)	0.89*** (0.13)	3.52*** (0.79)	0.32*** (0.12)	1.22** (0.40)	0.44*** (0.11)
Observations	657	657	657	657	348	657	
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Effects	Yes	No	Yes	No	No	Yes	Yes
Metro Area Effects	No	Yes	No	Yes	No	No	No
F-Test of the Coefficient	15.80	8.72	42.06	19.51	6.05	9.15	14.94

Note: Each column reports coefficients from a separate regression. The units of observations are 219 U.S. metropolitan areas over decades 1990-2000 and 2000-2010. The dependent variable is described at the top of the column. The explanatory variable is always the H-1B-driven growth of foreign-STEM jobs as a percentage of initial employment.

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

Table 8

Direct Regression of H-1B Driven Foreign O*NET STEM on the Wages & Employment of Native Workers

219 U.S. Metropolitan Areas 1990-2000, 2000-2005, and 2005-2010

Explanatory Variable: H-1B Driven Growth in Foreign-STEM	**(1) Growth Rate in Weekly Wage, Native STEM**	**(2) Growth Rate in Weekly Wage, Native College-Educated**	**(3) Growth Rate in Weekly Wage, Native Non-College-Educated**	**(4) Growth Rate in Employment, Native STEM**	**(5) Growth rate in Employment, Native College-Educated**	**(6) Growth Rate in Employment, Native Non-College-Educated**
Basic Specification, O*NET STEM	5.33*** (1.40)	3.31*** (0.80)	-0.31 (0.66)	0.09 (0.36)	1.17 (1.02)	-2.35 (1.83)
Controlling for 1980 Native STEM Dependence	5.83*** (1.46)	3.40*** (0.88)	-0.11 (0.67)	0.14 (0.38)	1.35 (1.15)	-2.34 (1.90)
O*NET College-Educated STEM	5.26** (2.68)	2.31*** (0.74)	0.17 (0.44)	0.18 (0.15)	0.70 (0.90)	-1.58 (1.48)
College-Major STEM	-1.07 (1.24)	2.30*** (0.91)	0.02 (0.57)	0.49 (0.28)	0.14 (0.73)	-2.72 (1.91)
Pre-2005 Only	8.06*** (1.93)	4.45*** (1.39)	-0.19 (0.87)	0.09 (0.50)	1.21 (1.31)	-3.61 (2.42)
Including L1 Visas	3.61*** (1.11)	2.50*** (0.58)	-0.31 (0.44)	0.02 (0.24)	0.70 (0.65)	-1.60 (-1.22)
Imputation Based on 1970 Foreign-STEM	1.25* (0.63)	1.19** (0.58)	0.09 (0.32)	-0.14 (0.18)	-0.39 (0.49)	-1.02 (1.03)

Note: Each cell includes the estimate of the impact of H-1B-driven growth of foreign-STEM on the dependent variable listed at the top of the column. The specification estimated is as (22) in the text. It includes state and year effects and the industry-driven growth in the relevant employment or wage variable at the metropolitan area level (depending on the regression).

***, **, * significant at the 1, 5, 10% level.

Table 9
2SLS Regression of Foreign O*NET STEM on Wages & Employment of Native Workers
219 U.S. Metropolitan Areas 1990-2000, 2000-2005, and 2005-2010

	Dependent variable: Growth rate of						
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**	**K-P Wald F-Statistic of the First Stage**
Basic Specification, O*NET STEM	7.81** (1.93)	4.98*** (1.20)	-0.46 (0.96)	0.14 (0.52)	1.80 (1.52)	-3.51 (2.67)	17.20
Controlling for 1980 Native STEM Dependence	8.47** (1.87)	4.93** (1.21)	-0.17 (0.94)	0.20 (0.53)	1.94 (1.56)	-3.38 (2.75)	17.31
Pre-2005 only	9.26** (2.19)	5.29*** (1.53)	-0.17 (0.97)	0.11 (0.58)	1.38 (1.42)	-4.02 (2.70)	22.3
Including L1 Visas	8.09*** (2.24)	5.80*** (1.59)	-0.71 (1.03)	0.61 (0.53)	1.64 (1.49)	-3.67 (2.67)	15.09
IV Constructed without Indian Immigrants	6.88*** (2.01)	4.72*** (1.26)	-0.36 (0.90)	-0.30 (0.65)	0.29 (1.70)	-4.24 (2.77)	16.41
Imputation of IV-Based on 1970 Foreign-STEM	6.37*** (2.51)	6.08*** (1.98)	0.44 (1.40)	-1.18 (2.09)	-3.26 (5.93)	-6.86 (9.42)	3.17
1970-Based IV, Pre-2005 only	6.58** (3.02)	5.30*** (1.82)	0.68 (1.50)	-1.14 (1.50)	-2.67 (3.64)	-3.22 (7.83)	4.52
Total STEM as Explanatory Variable	7.12*** (2.90)	4.30*** (1.91)	-0.36 (0.92)	N.A.	1.58* (0.82)	-3.03 (3.59)	3.88
OLS, Basic Specification	4.61*** (1.21)	2.83*** (0.70)	1.59*** (0.43)	1.25*** (0.26)	3.73*** (1.35)	4.57*** (1.48)	N.A.

Note: Each cell includes the 2SLS estimate of the impact of growth of foreign-STEM on the dependent variable listed at the top of the column. The instrument used is the H-1B driven growth of foreign-STEM workers. The specification estimated is as (23) in the text. It always includes state and year effects and the industry-driven growth in the employment or wage (depending on the regression). The last row shows the OLS estimate of the Basic Specification. The standard errors are heteroskedasticity-robust and clustered at the metro-area level. ***, **, * significant at the 1, 5, 10% level.

Table 10

2SLS Regression of Foreign-STEM on Wages & Employment of Native workers: Extension and robustness

219 U.S. Metropolitan Areas 1990-2000, 2000-2005, and 2005-2010

	Dependent Variable: Growth Rate of						
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**	**K-P Wald F-Statistic of the First Stage**
O*NET STEM, College-Educated	11.05* (5.92)	4.84*** (1.53)	0.35 (0.84)	0.18 (0.15)	0.70 (0.92)	-1.58 (1.43)	15.32
Major-Based STEM	2.10 (1.64)	2.64*** (0.88)	0.03 (0.61)	0.62 (0.38)	0.17 (1.89)	-3.23 (2.17)	42.70
Major-Based STEM, with Metro-Area Fixed Effects	1.98 (2.40)	6.88*** (1.92)	1.47 (1.42)	0.60 (0.47)	-0.31 (1.79)	-6.78 (3.54)	21.67
O*NET STEM, College-Educated Pre-2005 Only	11.90* (6.30)	5.80*** (2.12)	0.70 (1.01)	0.61 (0.49)	1.54 (2.39)	-4.23 (3.23)	14.95
Total STEM (O*NET, College-Educated) as Explanatory Variable	6.56** (3.27)	2.87*** (0.79)	0.20 (0.47)	N.A.	1.70 (0.90)	-1.71 (2.01)	19.55
OLS, Major-Based STEM Specification	0.62 (1.01)	3.21*** (0.62)	1.52*** (0.40)	1.20*** (0.26)	4.25*** (1.59)	2.90** (1.40)	N.A.

Note: Each cell includes the 2SLS estimate of the impact of growth of foreign-STEM on the dependent variable listed at the top of the column. The instrument used is the H-1B driven growth of foreign- STEM workers. The specification estimated is as (23) in the text. It always includes state and year effects and the industry-driven growth in employment or wage (depending on the regression). The last row shows the OLS estimate of the basic specification not including the industry-driven growth. The standard errors are heteroskedasticity-robust and clustered at the metro-area level. ***, **, * significant at the 1, 5, 10% level.

Table 11

2SLS Regression of Foreign-STEM on House Rental Prices

219 U.S. Metropolitan Areas 1990-2000, 2000-2005, and 2005-2010

Explanatory Variable: Growth Rate of Foreign –STEM **Instrument:** H-1B Imputed Growth of Foreign-STEM	**(1) Average Rent, College-Educated**	**(2) Median Rent, College-Educated**	**(3) Average Rent, Non-College-Educated**	**(4) Median Rent, Non-College-Educated**	**K-P Wald F-Statistic of the First Stage**
Basic Specification, O*NET STEM	2.34 (1.47)	4.11*** (1.29)	-1.76 (1.38)	-1.90 (1.45)	16.46
Pre-2005 only	4.98*** (1.69)	5.16** (1.63)	-1.19 (1.37)	-1.33 (1.30)	22.01
Pre-2005 Including L1 Visas	4.97*** (1.67)	5.30*** (1.86)	-1.37 (1.40)	-1.14 (1.50)	19.86
Pre-2005, O*NET, College-Educated STEM	4.76*** (2.02)	5.89*** (2.13)	-0.33 (1.47)	-0.77 (1.44)	14.99
Basic Specification, OLS	3.56*** (1.03)	3.11*** (0.96)	1.77** (0.68)	0.91 (0.68)	N.A.

.

Note: Each cell includes the 2SLS estimate of the impact of growth of foreign-STEM on the dependent variable listed at the top of the column. The instrument used is the H-1B driven growth of foreign- STEM workers. The specification estimated is as (23) in the text. It always includes state and year effects and the industry-driven growth in employment or wageS (depending on the regression). The last row shows the OLS estimate of the Basic Specification not including the industry-driven growth. The standard errors are heteroskedasticity-robust and clustered at the metro-area level. ***, **, * significant at the 1, 5, 10% level.

Table 12

2SLS Regression of Foreign-STEM on Wages & Employment of Native Workers: Split Non-College into Two groups

219 U.S. Metropolitan Areas 1990-2000, 2000-2005, and 2005-2010

	Dependent Variable: Growth rate of				
Explanatory Variable: Growth Rate of Foreign –STEM **Instrument:** H-1B Imputed Growth of Foreign-STEM	**(1) Weekly Wage, Native HS Graduates**	**(2) Weekly Wage, HS Dropouts**	**(3) Employment, Native HS Graduates**	**(4) Employment, Native HS Dropouts**	**K-P Wald F-Statistic of the First Stage**
Basic Specification, O*NET STEM	-0.50 (1.08)	-4.29 (2.70)	-4.03 (2.80)	0.11 (0.48)	13.44
Controlling for 1980 Native STEM Dependence	-0.17 (1.06)	-4.30 (2.65)	-3.89 (2.83)	0.23 (0.47)	13.34
Pre-2005 only	0.07 (1.04)	-2.26 (2.75)	-4.38* (2.37)	0.22 (0.41)	24.19
Including L1 Visas	-0.90 (1.12)	-3.66 (2.60)	-4.06 (2.99)	0.16 (0.5)	11.80
All STEM as Explanatory Variable	-0.49 (1.21)	-3.06 (2.48)	-4.26 (4.61)	0.28 (0.35)	3.67
Basic Specification, OLS	0.56** (0.13)	0.64* (0.31)	3.23** (0.34)	0.59** (0.10)	N.A.

Note: Each cell includes the 2SLS estimate of the impact of growth of foreign-STEM on the dependent variable listed at the top of the column. The instrument used is the H-1B driven growth of foreign- STEM workers. The specification estimated is as (23) in the text. It always includes state and year effects and the industry-driven growth in employment or wages (depending on the regression). The last row shows the OLS estimate of the basic specification not including the industry-driven growth. The standard errors are heteroskedasticity-robust and clustered at the metro-area level. ***, **, * significant at the 1, 5, 10% level.

Table 13:
Effects of Foreign-STEM on Employment by Industry
219 U.S. Metropolitan Areas 1990-2000, 2000-2005, and 2005-2010

Explanatory Variable: Growth Rate of Foreign–STEM **Instrument:** H-1B Imputed Growth of Foreign-STEM	**(1)** **Dep. Variable: Total Employment 2SLS**	**(2)** **Dep. Variable: Total Employment Direct Regression**	**(3)** **Dep. Variable: College–Educated Employment 2SLS**	**(4)** **Dep. Variable: College–Educated Employment Direct Regression**
		Low Human Capital Private Sectors		
Construction	-0.23	-0.11	0.04	0.02
	(0.35)	(0.18)	(0.05)	(0.02)
Transportation	-0.18	-0.09	0.09	0.04
	(0.24)	(0.12)	(0.06)	(0.03)
Wholesale	-0.19	-0.09	-0.06	-0.03
	(0.16)	(0.08)	(0.05)	(0.03)
Manufacturing	0.55	0.27	0.20	0.098
	(1.16)	(0.55)	(0.32)	(0.15)
Retail	0.05	0.02	0.24	0.12*
	(0.72)	(0.37)	(0.15)	(0.07)
		High Human Capital Private Sectors		
Finance	0.63	0.31	0.63	0.31
	(0.62)	(0.31)	(0.47)	(0.24)
Business	0.44	0.22	0.67***	0.33***
	(0.30)	(0.15)	(0.20)	(0.08)
Professional Services	0.26	0.13	1.30**	0.64*
	(1.16)	(0.59)	(0.79)	(0.35)
		Non-Private Sector		
Public Sector	-0.19	-0.09	0.06	0.03
	(0.29)	(0.15)	(0.10)	(0.05)

Note: Each cell includes the 2SLS estimate of the impact of growth of foreign-STEM on the dependent variable listed at the top of the column, within the sector listed in the row. The instrument used is the H-1B driven growth of foreign- STEM workers. The standard errors are heteroskedasticity-robust and clustered at the metro-area level. ***, **, * significant at the 1, 5, 10% level.

Table 14
Foreign-STEM and "Innovative" Skills of College-Educated Natives

Dependent Variable	(1) Growth in "Creative" O*NET Skills of Native College-Educated	(2) Growth in "Problem Solving" O*NET Skills of Native College-Educated
	Direct Regression	
H-1B-Driven Growth rate of College-Educated Foreign O*NET STEM	1.33*** (0.36)	0.83** (0.36)
	2SLS Regression	
Growth rate College-Educated O*NET STEM	1.30*** (0.46)	0.81** (0.39)
	First Stage	
F-Statistic of Instrument	19.71	19.71

Note: each cell shows the coefficient from a separate regression. The dependent variable is the O*NET intensity index of creative skills and problem-solving skills calculated based on the occupations of the native college-educated workers in the metropolitan area. Observations are 219 metropolitan areas in 1990, 2000, 2005 and 2010. The standard errors are heteroskedasticity robust and clustered by Metro area. ***, **, *= significant at the 1%, 5% and 10% level respectively.

Table 15
Implied Macro Effect of Foreign-STEM Growth on TFP Growth and on Skill-Biased Productivity

	(1) Average Yearly Growth in Foreign-STEM (as a % of Employment)	(2) ϕ_A Elasticity of A to STEM	(3) ϕ_B Elasticity of β to STEM	(4) Implied Effect on Average Yearly TFP Growth	*(5)* Implied Change in Average Yearly Skill-Biased Productivity: $\beta/(1-\beta)$	(6) Actual U.S. TFP Average Yearly Growth, from Fernald (2010)	(7) Change in Average Yearly Skill-Biased Productivity Implied by U.S. Data	(8) Column (4) Divided by Column (6)	(9) Column (5) Divided by Column (7)
Average value of $b_{w,NS}$ from Table 9. Insignificant=0									
1990-2000	0.06%	2.75	3.57	0.38%	0.23%	1.01%	1.7%	0.38	0.14
2000-2010	0.02%	2.75	3.57	0.10%	0.06%	0.77%	1.8%	0.12	0.03
Average	**0.04%**	**2.75**	**3.57**	**0.24%**	**0.14%**	**0.89%**	**1.75%**	**0.27**	**0.08**
Average value of $b_{w,NS}$ from Table 9. Average point estimate of $b_{L,E}$									
1990-2000	0.06%	2.92	4.94	0.41%	0.32%	1.01%	1.7%	0.41	0.19
2000-2010	0.02%	2.92	4.94	0.10%	0.08%	0.77%	1.8%	0.13	0.04
Average	**0.04%**	**2.92**	**4.94**	**0.26%**	**0.20%**	**0.89%**	**1.75%**	**0.29**	**0.11**

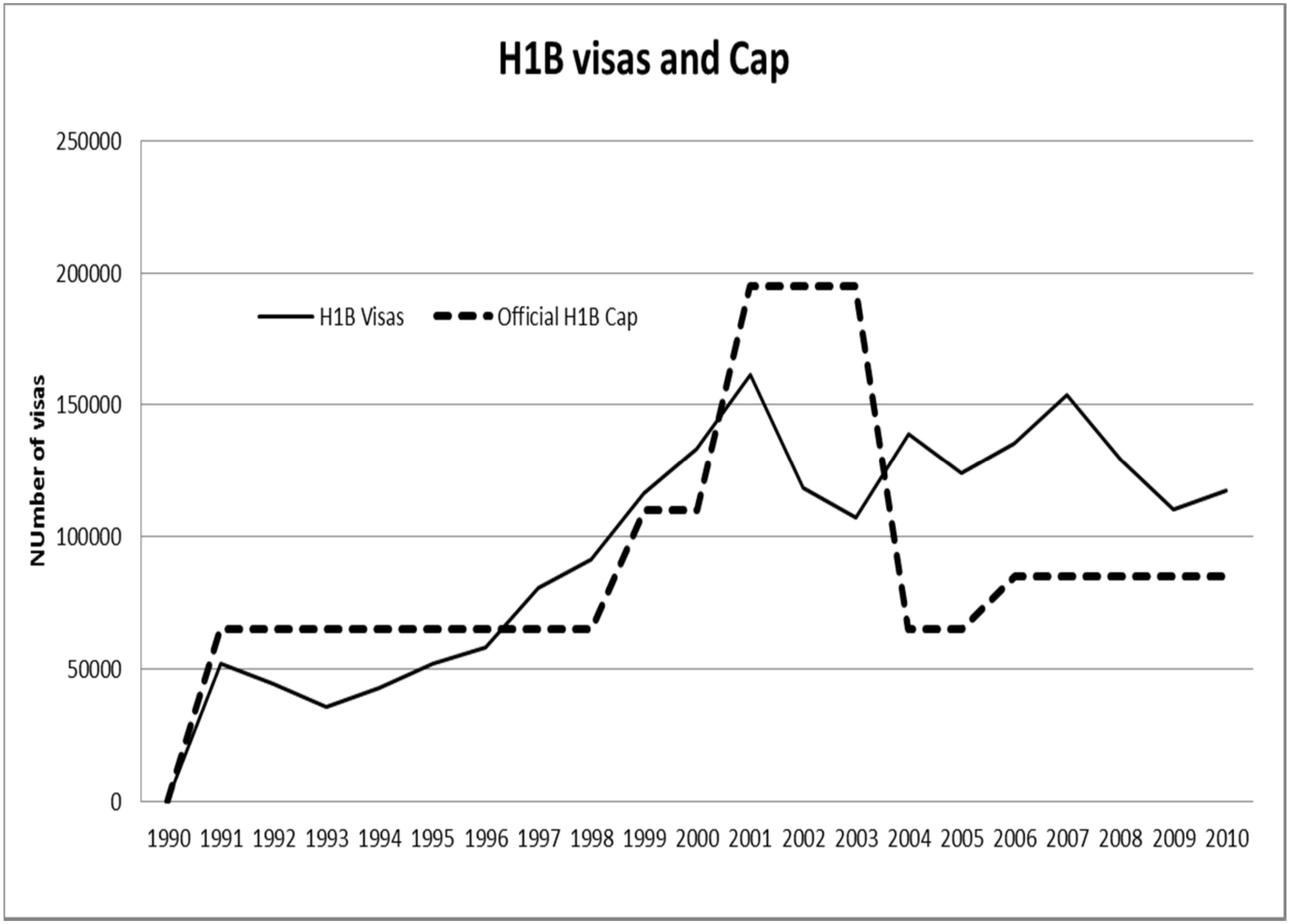
Note: The table uses the formulas in the appendix to calculate the implied elasticity ϕ_A and ϕ_B. We then use the growth of STEM workers as a % of employment to calculate the implied effects on TFP and skill-biased productivity. The figures on actual TFP growth were taken from Fernald (2010) and the figures for the data-implied change in skill-bias were calculated using the census 1980, 1990, 2000 and 2010 data on employment and wages of college and non-college-educated workers and the formula implied by our model in footnote 15 of the text.

Table 16
Implied Min-Max Inter-City Differences in TFP Growth

	(1) Min-Max Intercity Difference in Foreign-STEM Growth (as a % of Employment)	(2) ϕ_A Elasticity of A to STEM	(3) Implied Min-Max Difference in TFP Growth	(4) Actual Min-Max Difference in TFP Growth, from Average Wages	(5) Column (3) Divided by Column (4)
Average Value of $b_{w,NS}$ from Table 9. Insignificant=0					
1990-2000	0.70%	2.75	4.48%	4.40%	1.02
2000-2010	0.26%	2.75	1.67	3.30%	0.50
Average	**0.48%**	**2.75**	**3.08%**	**3.85%**	**0.76**
Average Value of $b_{w,NS}$ from Table 9. Average Point Estimate of $b_{L,E}$					
1990-2000	0.70%	2.92	4.76%	4.40%	1.08
2000-2010	0.26%	2.92	1.77%	3.30%	0.54
Average	**0.48%**	**2.92**	**3.27%**	**3.85%**	**0.80**

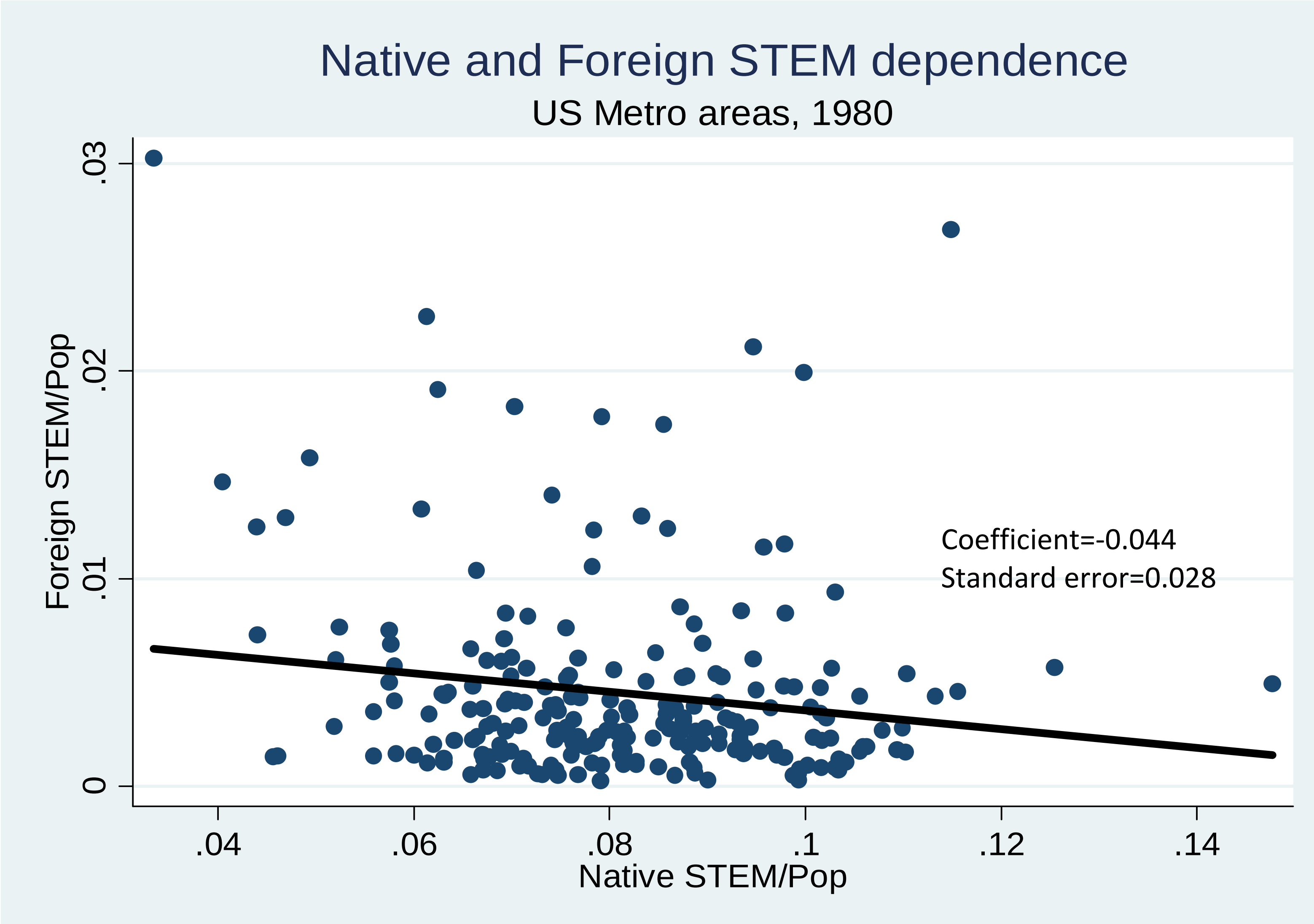
Note: The table uses the formulas in the appendix to calculate the implied elasticity ϕ_A and ϕ_B. We then use the growth of foreign-STEM workers as a % of employment to calculate the implied effects on TFP. The actual TFP min-max difference is obtained as the difference in growth of average wages in cities. Cities with lowest growth of foreign-STEM: Terre Haute, IN (in the 1990s) and Wichita Falls, TX (in the 2000s). Cities with highest foreign-STEM growth: San Jose, CA (in the 1990s) and Seattle-Everett, WA (in the 2000s).

Figure 1



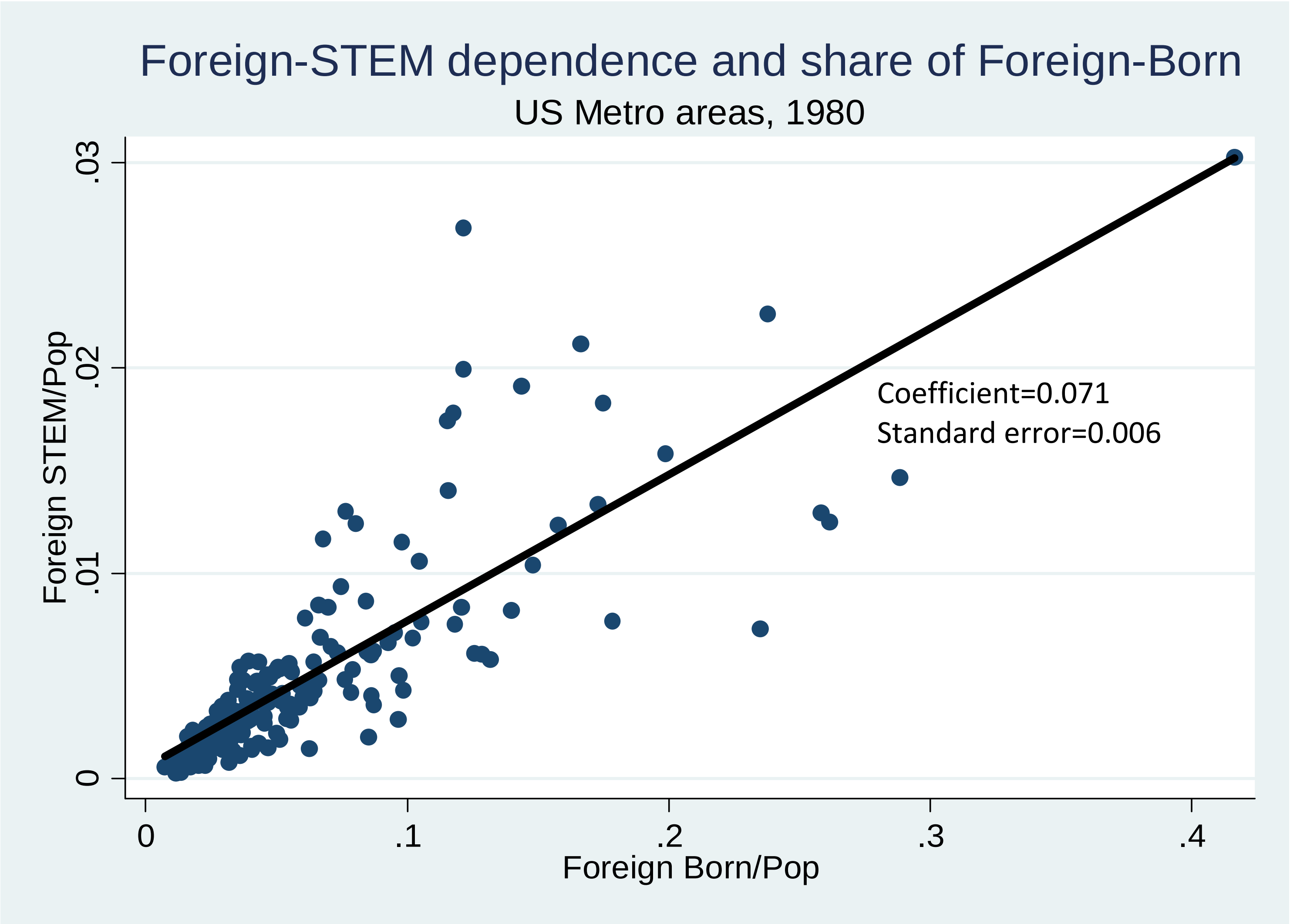
Note: The data on H-1B visas and their cap are from the Department of State

Figure 2



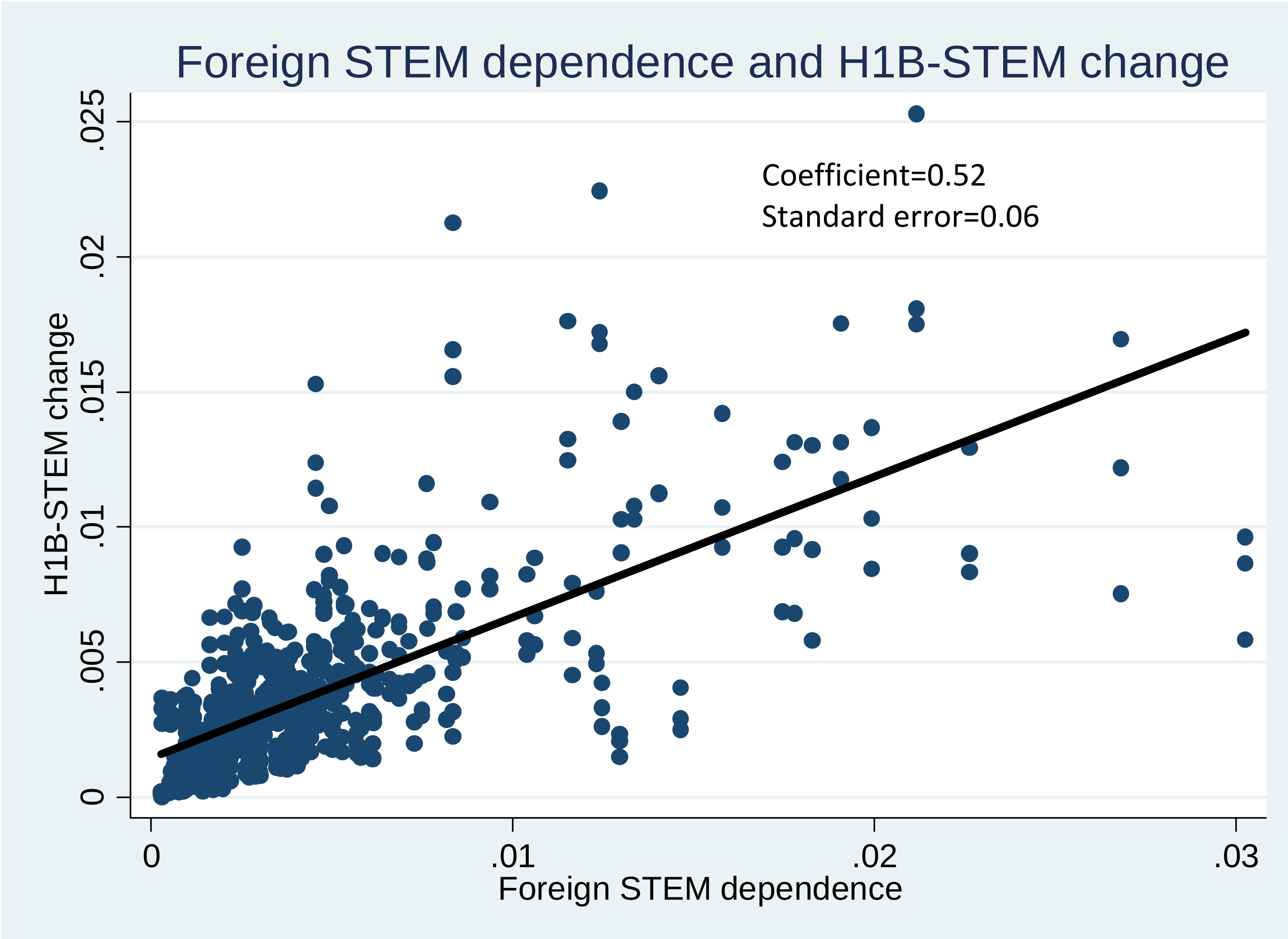
Note: The rates of Foreign and Native STEM dependence are calculated using 1980 Census data for 219 metropolitan areas.

Figure 3



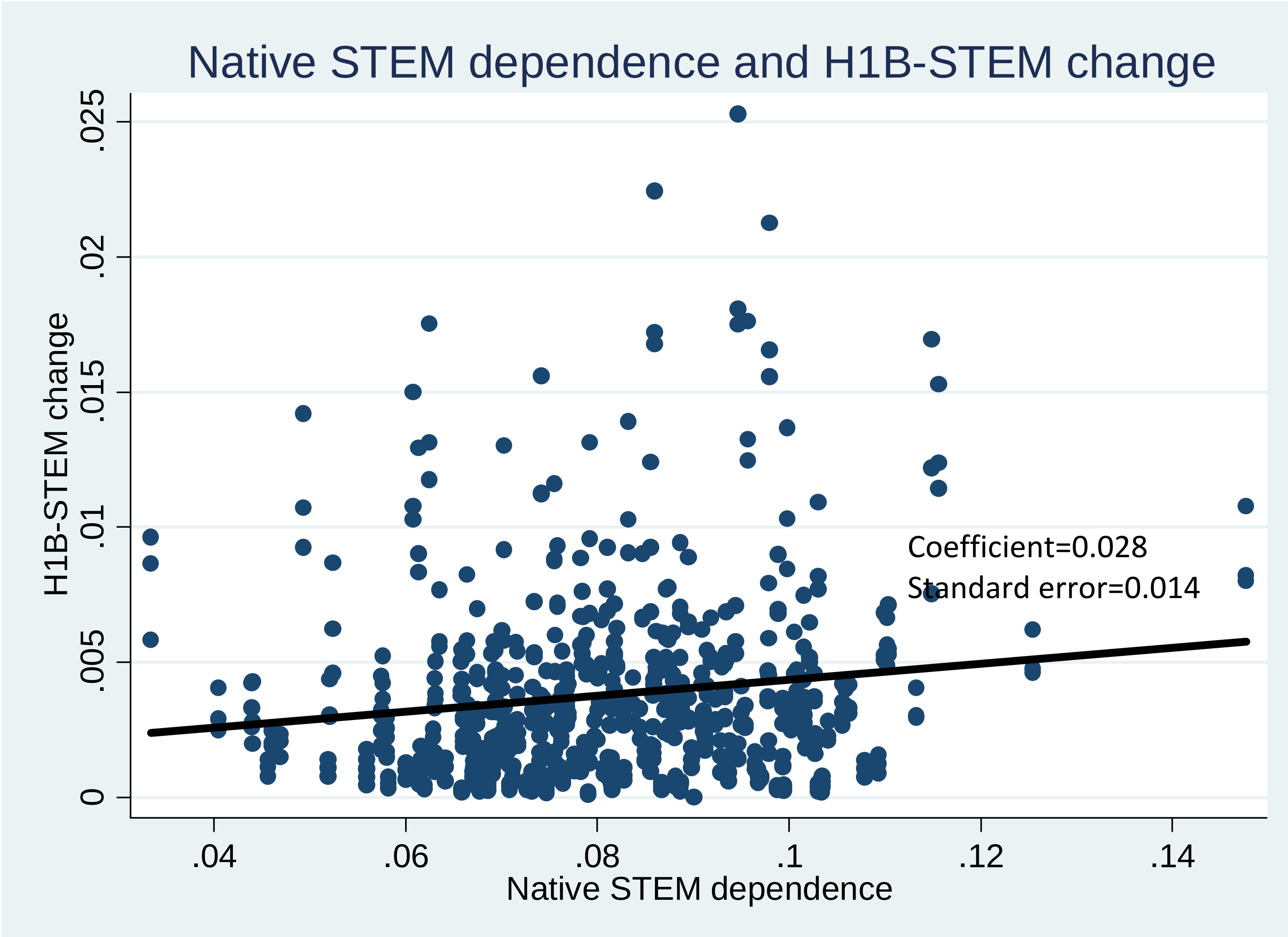
Note: The figures are calculated using 1980 Census data. The population of reference used to calculate the foreign-born share of in a city is the total adult (18-65) non-institutionalized population.

Figure 4



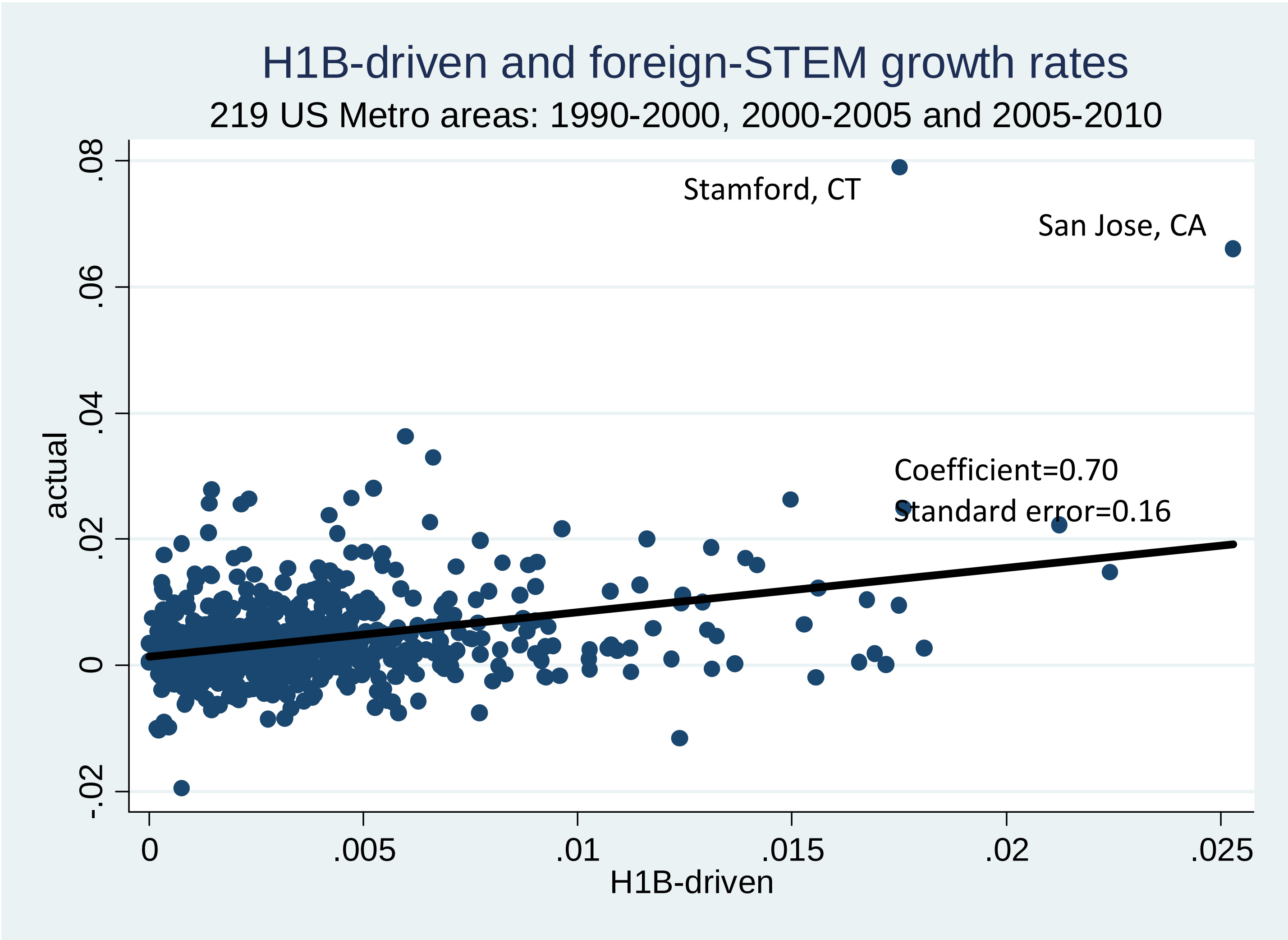
Note: The rates of foreign-STEM dependence are calculated using 1980 Census data. The H-1B induced STEM change is constructed as described in the text.

Figure 5



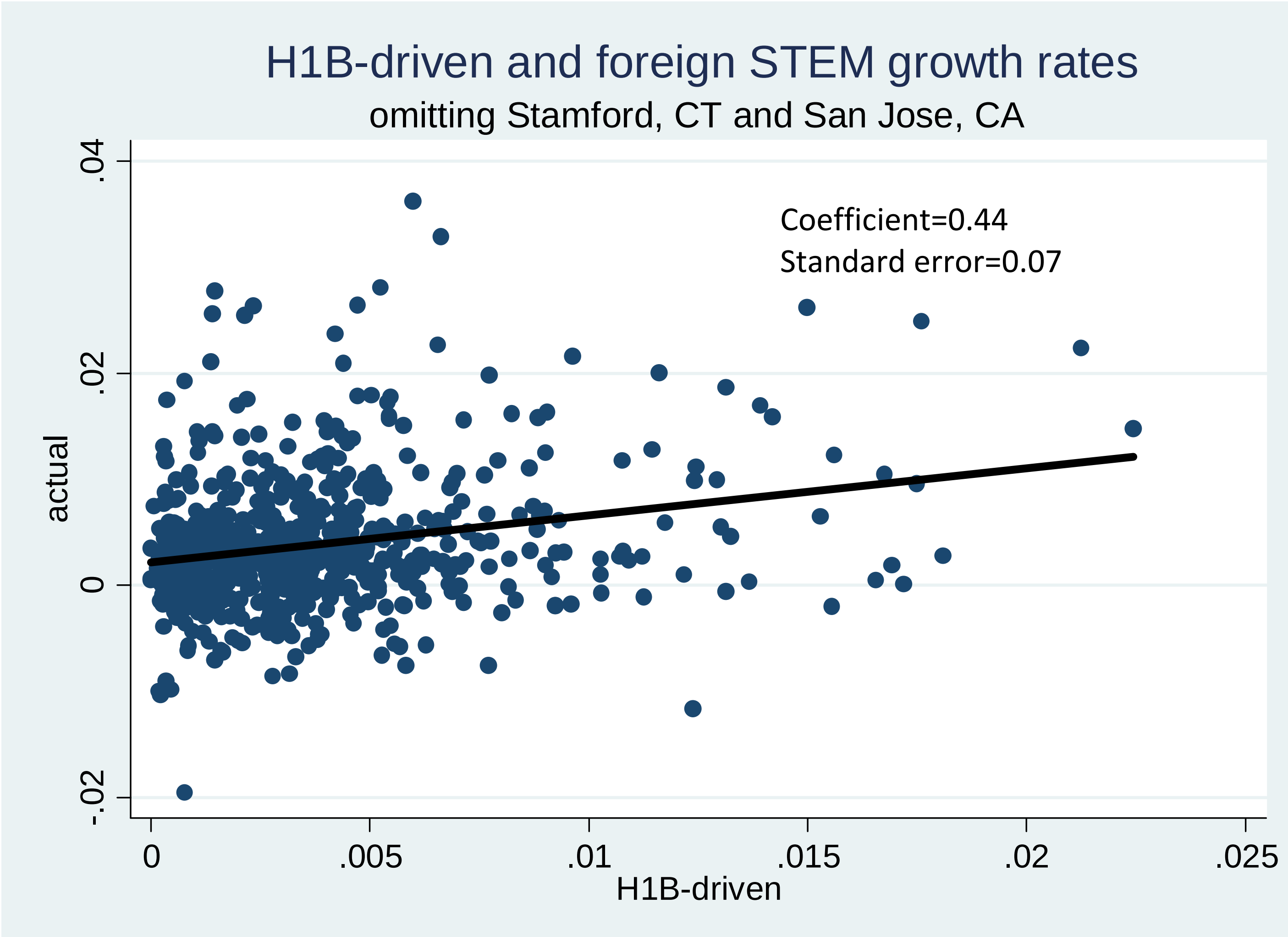
Note: The rates of native STEM dependence are calculated using 1980 Census data. The H-1B induced STEM change is constructed as described in the text.

Figure 6a
Predictive Power of H-1B-Driven STEM



Note: Power of the H-1B driven STEM immigrants in predicting actual growth of STEM immigrants

Figure 6b
Predictive Power of H-1B-Driven STEM, without outliers



Note: Same as figure 6a without Stamford, CT and San Jose, CA

Appendix

Table A1, Part A
Occupations classified as O*NET-STEM, skills at the top 10% of the distribution in 2000

Chemical engineers	**Veterinarians**
Civil engineers	**Programmers of numerically controlled machine tool**
Not-elsewhere-classified engineers	Cementing and gluing machine operators
Physicists and astronomers	**Geologists**
Chemists	**Chemical technicians**
Sales engineers	Supervisors of agricultural occupations
Management analysts	Heating, air conditioning, and refrigeration mechanic
Petroleum, mining, and geological engineers	Carpenters
Licensed practical nurses	Boilermakers
Electrical engineer	Plant and system operators, stationary engineers
Industrial engineers	Chief executives and public administrators
Operations and systems researchers and analysts	**Biological technicians**
Actuaries	**Statistical clerks**
Mathematicians and mathematical scientists	Farm managers, except for horticultural farms
Atmospheric and space scientists	Supervisors of mechanics and repairers
Medical scientists	Machinery maintenance occupations
Surveyors, cartographers, mapping scientists and t	Water and sewage treatment plant operators
Other science technicians	Lathe, milling, and turning machine operatives
Elevator installers and repairers	Drilling and boring machine operators
Plasterers	Construction inspectors
Rollers, roll hands, and finishers of metal	**Biological scientists**
Agricultural and food scientists	Airplane pilots and navigators
Engineering technicians, n.e.c.	Millwrights
Drafters	Drillers of oil wells
Plumbers, pipe fitters, and steamfitters	Explosives workers
Aerospace engineer	Tool and die makers and die setters
Mechanical engineers	Machinists
Computer software developers	Power plant operators
Managers of medicine and health occupations	Machine operators, n.e.c.
Automobile mechanics	Secondary school teachers

Table A1, Part B
Occupations classified as College-Major-STEM, those with more than 25% of workers with a STEM college degree

Pharmacists	Metallurgical and materials engineers, variously p
Chemists	Occupational therapists
Optometrists	Other health and therapy
Chemical engineers	Atmospheric and space scientists
Physicists and astronomers	Computer software developers
Medical scientists	Industrial engineers
Podiatrists	Agricultural and food scientists
Dentists	Physical therapists
Physicians	Sales engineers
Civil engineers	Mathematicians and mathematical scientists
Geologists	Physicians' assistants
Biological scientists	Therapists, n.e.c.
Aerospace engineer	Airplane pilots and navigators
Veterinarians	Clinical laboratory technologies and technicians
Speech therapists	Dietitians and nutritionists
Not-elsewhere-classified engineers	Subject instructors (HS/college)
Petroleum, mining, and geological engineers	Computer systems analysts and computer scientists
Electrical engineer	Vocational and educational counselors
Mechanical engineers	Management analysts
Psychologists	Chemical technicians
Actuaries	Biological technicians

Table A1, Part C
List of College Majors Classified as STEM

Animal Sciences
Food Science
Plant Science and Agronomy
Soil Science
Environmental Science
Computer and Information Systems
Computer Programming and Data Processing
Computer Science
Information Sciences
Computer Information Management and Sec
Computer Networking and Telecommunication
General Engineering
Aerospace Engineering
Biological Engineering
Architectural Engineering
Biomedical Engineering
Chemical Engineering
Civil Engineering
Computer Engineering
Electrical Engineering
Engineering Mechanics, Physics, and Sci
Environmental Engineering
Geological and Geophysical Engineering
Industrial and Manufacturing Engineering
Materials Engineering and Materials Sci
Mechanical Engineering
General Medical and Health Services
Communication Disorders Sciences and Se

Family and Consumer Sciences
Library Science
Biology
Biochemical Sciences
Botany
Molecular Biology
Ecology
Genetics
Microbiology
Pharmacology
Physiology
Zoology
Neuroscience
Miscellaneous Biology
Mathematics
Applied Mathematics
Statistics and Decision Science
Military Technologies
Nutrition Sciences
Mathematics and Computer Science
Cognitive Science and Biopsychology
Physical Sciences
Astronomy and Astrophysics
Atmospheric Sciences and Meteorology
Chemistry
Geology and Earth Science
Miscellaneous Psychology
Transportation Sciences and Technologies

Metallurgical Engineering
Mining and Mineral Engineering
Naval Architecture and Marine Engineer
Nuclear Engineering
Petroleum Engineering
Miscellaneous Engineering
Engineering Technologies
Engineering and Industrial Management
Electrical Engineering Technology
Industrial Production Technologies
Mechanical Engineering Related Technology
Miscellaneous Engineering Technologies
Medical Technologies Technicians
Health and Medical Preparatory Programs
Pharmacy, Pharmaceutical Sciences, and
Treatment Therapy Professions
Geosciences
Oceanography
Physics
Materials Science
Multi-disciplinary or General Science
Nuclear, Industrial Radiology, and Bio
Psychology
Educational Psychology
Clinical Psychology
Counseling Psychology
Industrial and Organizational Psychology
Social Psychology

Table A2: H-1B Visas composition by Nationality

Nationality	Percentage of Total, 1990-2000	Percentage of Total, 2000-2010
Africa	3%	2%
Canada	0%	0%
China	5%	7%
Eastern Europe	5%	4%
India	45%	47%
Japan	3%	3%
Korea	1%	3%
Mexico	3%	4%
Oceania	2%	1%
Philippines	3%	3%
Rest of Americas	5%	8%
Rest of Asia	10%	9%
Western Europe	16%	11%
Other	0%	0%
Total H-1B visas	709505	1321028