STEM workers, H1B Visas and Productivity in US Cities*

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

This draft: January, 29th 2013

Abstract

Scientists, Technology professionals, Engineers and Mathematicians (STEM workers) are the fundamental inputs in scientific innovation and technological adoption which, in turn, the main drivers of the productivity growth in the US. During the last thirty years productivity growth appeared to be "college" biased, in that it increased demand and productivity of college educated much more than that of other workers. In this paper we identify STEM workers in the US and we look at the effect of their growth on the growth of wages and employment of college and non-college educated in 219 US cities during the period 1990-2010. In order to identify a supply-driven and heterogenous increase in STEM workers across US cities we use the "dependence" of each city on foreign-born STEM workers in 1980 (or 1970) and we exploit the introduction and the variation (over time and across nationalities) of the H1B visa program directed specifically to allow access into the US to professoional STEM workers.We find that H1B-driven increases in STEM workers in a city were associated with significant increases in wages of college educated natives, (in general as well as STEM). Non-college educated natives, instead, experienced non significant effects on their wages and on their employment. We also find evidence that STEM workers increased the price of housing for college graduates and the specialization in high human capital sectors and high cognitive occupations in US cities. The magnitudes of these estimates imply that STEM workers contributed significantly to total factor productivity growth in the US and across cities and also, but to a lesser extent, to the growth of the skill biased during the 1990-2010 period.

Key Words: STEM workers, H1B, Foreign-Born, Productivity, College-Educated, Wage, Employment.
JEL codes: J54, 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 kevinyangshih@gmail.com; Chad Sparber, Department of Economics, Colgate University, csparber@colgate.edu. Giovanni Peri gratefully acknowledges partial funding for this research from the Microsoft Corporation.

1 Introduction

The activity of Scientists, Technology specialists, Engineers and Mathematicians, a group that we call STEM workers (or sometimes Scientists and Engineers) is the main input in the creation, adaptation and adoption of scientific and technological growth. That, in turn, has been connected to economic productivity and to its growth since the seminal work in economic growth by Robert Solow (1957). Growth economists, such as Zvi Griliches (1992) and Charles I. Jones (1995, 2002) have used measures of Scientists and Engineers to capture the main input in the idea-production function. Sustained productivity growth is fed by scientific and technological innovation and adoption and STEM workers are the innovators and adopters. Two other considerations related to ideas and productivity have attracted the attention of economists in the last 20 years and are gathering consensus. First, technological innovation during the past 30 years has not helped the productivity of all workers equally. The development of new technologies, especially those known as "Information and Communication Technologies" (ICT), have increased significantly the productivity and wages of college-educated workers by enhancing and complementing their abilities. They have, however left stagnant the demand for non-college educated workers possibly because they act as substitute of their skills (e.g. Katz and Murphy 1992, Krueger 1993, Autor Katz and Krueger 1998, Acemoglu 1998, 2002, Berman Bound and Griliches 2004, Autor, Levy and Murnane 2003, Autor, Katz and Kerney 2007 among others)[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, local mobility seem to still make a difference in the speed at which new ideas are locally available and at which they are adopted and affect local productivity. Several studies (Rauch 1993, Moretti 2004a, 2004b, Iranzo and Peri 2010) have shown the importance of concentration of college educated workers for local productivity. Other studies have shown the tendency of innovation- and idea-intensive industries to agglomerate (Ellison and Gleaser 1999) and for ideas to remain local and generate virtuous cycles of innovation (Jaffe et al 1992, Saxenian 2003). In two very interesting recent books Ed Glaeser (2011) and Enrico Moretti (2012) identify the ability to innovate and to continuously reinvent itself as the main engine of growth for cities affecting, in the long-run, productivity, wages and employment of everybody in it.

This paper sits at the intersection of those three strands of the literature. In it we quantify the long-run effect of increases in STEM workers in US cities, between 1990 and 2010, on the employment, wages and specialization of other workers with and without college education. With some assumptions we are also able to infer, from wage and employment effects, the effects of STEM growth on total factor productivity (TFP) growth and on Skill-Biased productivity (SBP) growth. The challenge of the exercise is to identify variation in growth of STEM workers across US cities that could be considered as 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 H1B visa policies in 1990 and the

[1] Several papers in this literature (e.g. Caselli (1996), Caselli and Coleman (2006), Goldin and Katz (2008)) emphasizes that the large supply of college-educated workers was itself the driver of 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, Krusell et al. 2000) emphasize the role of capital (equipment) in increasing the productivity of highly educated workers.

differential effect that they had in bringing foreign college educated STEM workers to 219 U.S. metropolitan areas during the period 1990-2010.The H1B visa policy, introduced with the Immigration and Nationality Act of 1990 established temporary renewable visas (for a maximum of 6 years) for college educated specialty professional workers, most of whom were in STEM occupations. The policy was national but had differentiated local effects because foreign-STEM workers ended up very unevenly distributed across US cities. Using the 1981 and, in a robustness check, the 1971 censuses we first construct the degree of reliance of each US metropolitan areas on foreign-STEM workers, as the percentage of foreign-STEM in the total employment of the city. We document that this dependence was not significantly correlated with the dependence of the city on STEM workers in general, most of whom were natives in 1980, but rather to the presence of foreign-born in the city, which varied with historical settlements of foreign communities and geographical preferences of immigrants. This distribution as of 1980 (or 1970) is unlikely to be related to productivity changes that took place in the 1990's and 2000's. Then we predict how many new foreign STEM workers would locate in each city, by allocating the H1B visas to each foreign national group in proportion of the 1981 dependence of cities on foreign-STEM workers of that nationality. This H1B-driven increase in foreign STEM turns out to be a reasonably good predictor of the increase in foreign STEM workers in a city and also of STEM workers overall in the city.

While this is not the random "helicopter drop" of STEM workers that we would like to have in order to identify the effect on local wages, employment and productivity this constructed changes, accompanied with controls for sector-specific demand and fixed effects seems to represent a reasonable variation of STEM, largely supply driven. 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 even more closely related to the one used in Kerr and Lincoln (2010) to estimate the effect of foreign scientists on US patent applications.

We find that an increase in foreign STEM workers of 1% of total employment increased the wage of native college educated workers (both STEM and non-STEM) over the period 1990-2000 by 4-6%, while it had no significant effect on wages and employment of native non-college educated workers. We also find that increases in foreign STEM workers moved native college educated workers towards human capital intensive sectors and towards occupations that use more intensively creative, problem-solving skills (according to the O*NET classification). They also had a significant and positive impact on house rental costs of college educated, while they had insignificant effects on employment and housing costs of high-school educated. The increased cost in non-tradable services (housing) absorbed about half of the increase in purchasing power of college educated wages. 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 productivity growth and skill biased growth due to 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 US during the period 1990-2010.

The rest of the paper is organized as flows. Section 2 presents a simple framework to interpret the estimation results. Section 3 describes the data on STEM workers, on H1B visas and describes the construction of H1B-driven growth of foreign STEM-workers and characterizes its 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 US 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 specialization of natives. In section 6 we perform some simple calculations the impact of STEM on productivity and on its skill (college) bias using the estimated wage and employment effects. Section 7 concludes the paper.

2 Framework and Productivity Parameters

The empirical analysis developed below uses exogenous variation in foreign-born STEM workers across US 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 decade-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). The outcomes of interest are weekly wages, employment and price of housing for each group. The term ϕ_t capture year effects, $\phi_s$capture state effects, $\frac{\Delta STEM_{ct}^{Foreign}}{E_{ct}}$ is the decade exogenous change of foreign STEM, 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 from the regressions are the $b_{y,X}$, capturing the elasticity of a specific outcome, y, for worker group X 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 as long-run equilibrium. We preform 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 an 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 and it produces according tho the following long-run production function:

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

In (2) we do not include physical capital, assuming that capital mobility and 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 (Acemoglu and Angrist, 2000, Iranzo and Peri 2009, Moretti 2004a) and that on growth and ideas (Jones, 1995) and we consider the term $A(ST_{ct})^{\frac{\sigma_H}{\sigma_H - 1}}$ which is the level of total factor productivity, as a function of the number of STEM workers in the city ST_{ct} . If $A'(ST_{ct}) > 0$ 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 that the skill (college) bias of productivity also depends on 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, Those, and especially information and communication technologies, are widely credited with 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 L and a composite factor H, obtained by the combination of the two groups of college-educated workers as follows:

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

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, the $STEM$ workers are also generating ideas, innovation and externalities that benefit productivity an possibly benefit college educated more.

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:

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

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

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

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

city or into-out of employment) and hence in equilibrium we observe at the same time change in wages and in 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 in wages for each group of workers (Non-college educated, College-non-STEM and College-STEM)
:

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

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

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

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)-(8) 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 accruing to factor x and the share of employment represented by factor x. Hence, for instance s_w^H is the share of total wage income accruing to workers with college education (H) hence $(w_{ST}ST + w_{NST}NST)/(w_{ST}ST + w_{NST}NST + w_L L)$, while $s_E^{ST} = ST/E$ are STEM workers as share of the total employment.

With the equilibrium response of wages and employment of each group to $\Delta ST^{Foreign}$ and using wage and employment data to calculate the shares s_w^x and s_E^x equations (7)-(8) only depend on four unknown: ϕ_A, ϕ_B, σ_S and σ_H. Given the extensive literature that estimates the elasticity of substitution between college and non-college educated, we adopt estimates of the parameter σ_H from the literature and we use (7)-(8) 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)-(8). 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 which 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 $y_i = (1-\alpha) w_i l_i$, $T_i = \alpha w_i l_i / p_i$ and $C_i = \alpha^\alpha (1-\alpha)^{(1-\alpha)} \frac{w_i}{p_i^\alpha} l^i$ 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 larger than 0 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 be also justified considering mobility of local household 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 wage constant. Allowing different types of workers to have different supply elasticity (between 0 and infinite), 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 specifications as 1 provide the last term in each equation 13-15[2]. Those may differ due to the segmented land supply for housing of college and non-college educated. Armed with those estimates equations 13-15 allow to calculate the supply elasticity of different groups and check that they are consistent with mobility of workers in the long run.

3 Data: STEM workers in US Cities

The main goal of this paper is to identify the effect of STEM workers on productivity of college-educated and non-college educated workers across US cities in the long-run and via the impact of STEM-workers on their wages and employment. Admittedly this exercise only captures productivity effects localized within metropolitan areas. The ideal experiment would consist in adding exogenously and randomly different numbers of STEM workers across US cities observing, then, the effects of these random shocks on wage and employment of other workers. As STEM workers are the main innovators and adopters of new technologies this exercise would indirectly provide a window on the effects of new technologies on college and non-college productivity. As we do not have such experiment, we exploit a policy-change introduced in 1990, the introduction of the dual-intent H1B visa for specialty workers. This change in immigration policy can be reasonably considered as an exogenous factor of variation of foreign STEM workers in the US. The H1B visas introduced with the Immigration Act of 1990. They are temporary visas for the duration of three years, renewable up to 6 and they allow explicitly for the possibility of applying for permanent residence. They have been, since 1990, a crucial channel of admission of many college-educated foreign "specialty" workers. In particular the very large majority of those visas has been given to STEM workers. For instance Lowell (2000) lists 70% of these visas as used in one of the following occupations: Computer Analyst, Programmer, Electrical Engineer, University Professor, Accountant, Other Engineers, Architect. Similarly Citizenship and Immigration Services (2009) reports for year 2009 (and similarly for all years between 2004 and 2011) that more than 85% of new H1B visa holder work in Computer, Health Science, Accounting, Architecture, Engineering and Mathematics related occupations, while less than 5% of them are awarded to people working in occupations related to Law, Social Sciences, Art and Literature.

The policy was probably the most relevant piece of immigration legislation introduced in the last 22 years. The maximum number (cap) of visa allowed each year has changed over time. In our long-run analysis, using changes over five and 10 year intervals, we observe a

[2] 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.

lower average cap in place for the period 1990-2000, resulting in fewer average entries, while a larger cap (as well as exceptions to the cap as in 2006 Universities and non-profit Research facilities were excluded from the cap H1B) in place in the 2000-2005 and 2005-2010 period. Figure 1 shows the numerical value of the cap every year between 1990 and 2010 and the actual flows every year [3].

The ensuing inflow of foreign-STEM workers was not homogeneously distributed across locations in the US. This is because different cities (and the companies in them located) depended on foreign-STEM workers to very different extent, before the policy was put in place. This was due in large part to the preference of immigrants to locate in some cities and to the persistence of historical communities of immigrants in some places. The policy, therefore, generated large flows of foreign STEM workers in some cities, better equipped through networks of foreign-born STEM workers to connect and hire new foreign STEM, and much smaller in others. Certainly part of the differences were driven by different economic/labor demand conditions in the cities. We argue, however, that we can use the part of foreign-STEM inflow driven by the differential city "dependence" on foreign STEM workers by nationality as of 1980 (and as of 1970 in a robustness check) as a supply shock. Those cities with high initial foreign dependence experienced during the 1990-2010 a large inflows allowed by the H1B visa policy. Those with low foreign-dependence and relying on native STEM workers did not experience such surge. In the following two sections we define in detail the variables, we show the importance of H1B visa entries in determining the net growth of foreign STEM workers and we check the validity of some identifying assumptions that are crucial for our approach.

3.1 Construction of the H1B-driven increase in foreign STEM workers

The source of all our data on occupations, employment, wages, rents, age and education of individuals are the IPUMS 5% Census files for 1980, 1990, 2000. We also merge the 2004-2006 and the 2008-2010 three years sample of the American Community Survey to obtain 3% larger samples that we call 2005 and 2010. It is useful to separate the 2000's decade in two, as the second part of it experienced the deep and unusual great recession which may introduce noise in wage and rent behavior. We only use data on 219 metropolitan areas that can be consistently identified over the period 1980-2010[4]. These areas span the range of US metropolitan sizes and include all the largest metropolis in the US (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). The source of the data on aggregate H1B flows, by nationality and year is publicly available from the Department of State (2010). We first construct a variable which we call the "H1B-driven increase in STEM workers" in each of 217 U.S. Metropolitan areas (we will often call them simply "cities"),

[3] In the years 2005-2010 the total number of visas exceeds the cap because universities and non-profit research facilities hiring H1B workers were exempt from the cap.

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

between 1990 and 2010. We begin by defining the "dependence" of a metropolitan area on foreign STEM workers from 14 specific foreign nationalities[5], measured from the Census of 1980. The "dependence" of city c on foreign STEM workers from a specific nationality (n) in 1980 is defined as foreign STEM workers of that nationality as a share of total employment in the city in 1980: $\frac{STEM^{FOR_n}_{c,1980}}{E_{c,1980}}$. The dependence of city c on foreign STEM workers overall is the sum of the dependence from each specific nationality: $\frac{STEM^{FOR}_{c,1980}}{E_{c,1980}} = \sum_{n=1}^{14} \left(\frac{STEM^{FOR_n}_{c,1980}}{E_{c,1980}} \right)$. We choose 1980 because it is the earliest Census that allows the identification of 217 metropolitan areas. It is also well before the H1B visa policy and hence does not reflect distribution of foreign-STEM affected by the policy. Finally it is mostly before the ICT revolution produced a surge in demand for STEM workers. While early video-games and computers were introduced in the late seventies, the Personal Computer was introduced in 1981. The distribution of STEM workers back then was not much affected at all by the geography of the computer and software industries, while nuclear, military, chemical, and traditional manufacturing sectors were demanding a large amount of science and technology workers. Still, in order to eliminate any impact of the IT revolution we also use as initial year 1970, for a subset of cities, in a robustness check.

An important issue is how to define STEM workers. There is no official definition for it and, therefore, we use three alternative criteria to define it. The first is based on the skills used in the occupation. We use the O*NET database provided by the Bureau of Labor Statistics, which associate to each occupation, according to the SOC classification, the importance of several dozens of skills and abilities in performing the job. We select four O*NET skills that involve the use of Science, Technology, Engineering and Math namely "Mathematics in Problem Solving", "Science in Problem Solving", "Use of 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 Censuses 1980-2010, according to the average score in the "STEM" skills defined above. We define as STEM the occupations accounting for the top 10% of employment as of year 2000 in that ranking . We call these the 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 definition of STEM is identical to the first in terms of occupation chosen but we restrict the definition of STEM workers only to people with a college degree or more. While in theory STEM workers need not be college educated many of them are. This second definition, the College Educated O*NET-STEM workers include about 5% of workers in 2000. Finally we use a third definition of STEM occupations based on the percentage of workers with "STEM" degrees in them. The American Community Survey of 2009 reports the occupation of workers as well as the major of their college degree. We consider, therefore as STEM those occupations where at least 25% of workers have graduated from a STEM major. The median occupation has only 6% of workers with a STEM major. The list of STEM college majors is in Table A1, Part C of the appendix, while the list of occupations selected using this STEM definition is shown Appendix Table A1, Part B. This definition is more stringent than first definition and selects about 4% of workers.

[5]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.

We call these the College-Major-based STEM workers[6].

Once we have defined STEM dependence in 1980 we calculate the growth factor of foreign STEM workers for each nationality, n in the US between 1980 and year t. We do so by adding to the initial 1980 level $STEM_{1980}^{FOR_n}$ the inflow of STEM workers from that national group during the period between 1980 and t. For the decades 1990-2000 and 2000-2010 we use the cumulated H1B visa allocated to nationality n, that we call $\#ofH1B_{1990-t}^{FORn}$, to proxy the increase in $STEM^{FOR_n}$[7]. For the decade 1980-1990 we simply add the net increase in STEM workers from nationality n from the US 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 as follows:

$$\frac{\widehat{STEM_t^{FORn}}}{STEM_{1980}^{FOR_n}} = \frac{STEM_{1980}^{FOR_n} + \Delta STEM_{1980-1990}^{FOR_n} + \#ofH1B_{1990-t}^{FORn}}{STEM_{1980}^{FOR_n}} \text{ for } t = 1990, 2000, 2005, 2010 \tag{16}$$

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 we add 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 H1B-driven change in foreign-STEM workers, that we use as our explanatory variable in the main empirical specifications, is the change in $\widehat{STEM_{ct}^{FOR}}$, defined above, over a decade standardized by the initial employment in the city E_{ct}[8]:

$$\frac{\Delta STEM_{ct}^{H1B}}{E_{ct}} = \frac{\widehat{STEM_{ct+10}^{FOR}} - \widehat{STEM_{ct}^{FOR}}}{E_{ct}} \tag{18}$$

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 US 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 H1B 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

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

[7]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 $\#ofH1B_{n,t}$.

[8]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 $E_{ct} = E_{c1980}(E_t^{US}/E_{1980}^{US})$.

Kerr and Lincoln (2010)), and uses 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 H1B visas as there are workers entering with other visas or with permanent permits and some of the H1B workers return to their country after 6 years. Moreover we need to establish whether our policy-driven variable, mechanically created using the visa number and the initial distribution of Foreign STEM, has predictive power on $\frac{\Delta STEM_{ct}^{FOR}}{E_{ct}}$,the change in foreign STEM workers, as measured by Census data, standardized by total initial employment.

3.2 Summary Statistics for Foreign-born and STEM occupations

Before analyzing how the H1B-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[9] occupations. Moreover, foreigners have contributed substantially, in the aggregate, to the growth of STEM jobs in the US. Table 1 shows the percentage of foreign-born individuals in five groups, for each census year from 1980 to 2000 and for 2005 and 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, in STEM occupations and among College educated in STEM occupations. While foreign born individuals represented 16% of total employment in 2010, they counted for 26% (one in four) of College- educated STEM workers in the metropolitan sample that we analyze. Also remarkably, considering the time series, that percentage has more than doubled since 1980 and it has been growing faster than the percentage of foreign-born among college-educated workers. Table 2 shows the growth of STEM workers as share of employment and the particularly fast growth of foreign STEM workers. College-educated STEM workers have increased from 2.7% of total employment in 1980 to 4.4% in 2010. Even more remarkably college educated foreign STEM workers have grown from 0.3% to 1.1% of the total employment. The details by decade make also clear that the 1990's were a period of very fast growth in STEM workers, both relative to the 2000's and to the 1980's. STEM workers as share of employment grew by 1.1 percentage points during the 1990's. Of that increase 0.4 percentage points were due to foreign STEM workers. Also remarkably during the period 2000-2010 there was very small growth of STEM jobs in employment (0.2 percentage points), and this was due almost entirely to the increase in foreign STEM employment.

Was the H1B 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 the absolute numbers (in thousands) of native, foreign STEM workers and H1B visas. Those numbers suggest that the H1B program scale was large enough to drive all or most of the increase in foreign-STEM workers . It reports the net total increase in college-educated STEM workers in the US in Column 1 and the increase in college educated foreign STEM workers in Column 2. Then in column 3 it shows the cumulated number of H1B visas for the

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

corresponding periods. It is clear that in the 1990's the H1B visas were enough to cover the whole growth in college-educated foreign STEM workers in the US, even accounting for some return. Even more remarkably in the period after 2000 the H1B visas were three to four times as large as the net increase in college educated STEM. This implies that many foreign STEM workers left the US, for other countries or to return in their country of origin. Overall the figures presented emphasize that foreign-born were over-represented among STEM workers and that the overall size of the H1B program was large enough to contribute substantially or entirely to the foreign STEM worker growth in the period 1990-2010.

3.3 A key to identification: Foreign-STEM and Native-STEM dependence of US Cities in 1980

Our identification strategy is based on the idea that the dependence on Foreign-STEM workers in 1980 (or in 1970), varied across cites because of persistence of agglomeration of foreign communities. These differences, measured in 1980, affected supply of foreign-STEM workers but were not (significantly) correlated with technological and demand shocks affecting wages and employment of those cities during the period 1990-2010. In particular we are concerned that the dependence on foreign STEM workers in 1980 may predict future wage and employment shocks in the 1990's and 2000's because it is correlated with the productive and industrial structure of the city, with its sector composition, its scientific and technological base. These features may be correlated with future demand and productivity changes. In order to partially address these concerns we do several things. First, in this section we show that the dependence of metropolitan areas on foreign-STEM workers in 1980 has very low correlation with their dependence on native-STEM workers. As in 1980, 90% of STEM workers were natives this implies that the overall dependence of a city on STEM workers, likely to be correlated with the science and technological intensity of production in 1980, was not driven by dependence on foreign-STEM workers. Instead dependence on foreign-STEM was determined by the percentage of foreign-born overall in the city population. We also show that while the dependence on Foreign-STEM workers in 1980 is a very good predictor of the H1B-driven growth in STEM workers between 1990 and 2010, the 1980 dependence on Native-STEM workers is a very poor predictor of that. Second, in section 3.5 we introduce sector-driven changes in wage and employment of college and non-college educated at the city level as controls for the changes in productivity driven by the 1980 industrial structure of the city[10]. Including those sector-driven shocks as controls will further go in the direction of isolating the effect of a supply-driven change in STEM. Third we estimate very demanding empirical specification in which we include the change in H1B-driven foreign STEM across cities (differencing any fixed effect in the level of foreign-STEM workers) in a panel of 217 metropolitan areas and 3 periods 1990-2000, 200-2005 and 2005-2010 and we also include fifty state–specific effects. In the most demanding specification we include 219 city-specific effects. The inclusion of the state fixed effects implies that identification relies on variation of growth rates across cities in the same state. Finally in some robustness check we use the foreign STEM dependence as of 1970 to construct the instrument.

The dependence on native and on foreign STEM workers across 219 US metropolitan areas

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

in 1980 varied dramatically and those two variables had limited correlation with each other. In Table 4, Column 1 and 2, we list the top 10 metropolitan areas and their native-STEM dependence in 1980 (as the percentage of native-STEM workers on total city employment). Columns 3 and 4 of the same Table show the top 10 areas as of foreign-STEM dependence and the value in 1980. We use the O*NET skill based broader definition of STEM workers. No city is in both lists. Several of the top native-STEM cities are in the Midwest and in the East. Most of them are associated to "traditional Sectors" that attracted many Scientists and Engineers in the 1970's. For instance Richland-Kennewick-Pasco, WA was the site of an important nuclear and military production facility in the 1970's. Rockford, IL had very developed machine tool and aerospace industry, Racine, WI was the headquarter of Johnsons & Johsons (Chemicals and home products). Differently, many of the metro area with large Foreign-STEM dependence were more diversified larger metro areas, with large immigrant communities. Also notice that the Native-STEM dependence in 1980 was almost an order of magnitude larger than the Foreign-STEM dependence. Even more clearly, Figure 2 and the first column 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 not significant at any level of confidence (t-statistic smaller than 1.6). The visual impression of Figure 2 is also very 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. But what was the determinant of Foreign-STEM dependence in 1980 then? Column 2 of Table 5 and Figure 3 show that the dependence on foreign-STEM workers of a city had much more to do with the presence of foreign-born as share of the population. Including state fixed effects, the share of foreign born in the city-population has an extremely significant association with its foreign-STEM dependence (t-statistic of 10.3). Figure 3 shows very clearly that foreign-STEM dependence of a city is driven by the presence of foreign born in the population.

Then, figure 4 and Figure 5 and Columns 5 and 6 of Table 5, go on to show that the 1980 Foreign-STEM dependence has a significant power to predict the H1B-driven increase in STEM across cities: the F-statistic is 20.41 and the partial R-squared explained by that variable is 0.39. The 1980 native-STEM dependence, instead, has very limited power to predict the H1B-driven increase in STEM: F-statistics 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 H1B program allowed a significant increase in the highly educated foreign-STEM workers during the 1990's and 2000's allowed these cities to increase the size of their STEM employment. The initial advantage in foreign-STEM dependence made these cities more likely destination for foreign STEM workers entering with an H1B visa. The presence of a network, the easier diffusion of information across foreign groups, the familiarity of firms with foreign STEM workers likely reduced the cost of H1B visa recipients to locate in these cities. Finally let us emphasize that is not only the overall foreign-STEM dependence to drive our identification. As we consider H1B visa by nationality we also use the differential location of foreigners across US cities, depending on nationality. In particular a very large share of H1B was awarded to Indians, and also large shares were given to Chinese and other Asians (see Table A4 in the appendix, showing the percentage of total H1B awarded to each nationality by decade). Hence an initial foreign-STEM dependence on Indians and Asians 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 H1B program: predicting the increase in Foreign-STEM

The H1B-driven increase in STEM workers, defined in expression 18 can be considered as an instrument accounting for the effects of the H1B policy on STEM workers in US 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 establish first that it affected significantly the actual increase in foreign STEM workers across cities. Ultimately we like to determine the effect of STEM workers on employment and wages and hence we will use H1B-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 H1B-driven increase but also by demand and productivity driven increases. In this section we analyze how H1B-driven increase in STEM affected the net observed increase in foreign-STEM workers across US cities. We estimate the following specification:

$$\frac{\Delta STEM_{ct}^{FOR}}{E_{ct}} = \phi_t + \phi_s + b_1 \frac{\Delta STEM_{ct}^{H1B}}{E_{ct}} + \varepsilon_{ct} \tag{19}$$

The coefficient of interest is b_1 which measures the impact of H1B-driven STEM inflows on the actual increase in Foreign-STEM workers (as measured from the US Census). The term ϕ_t are two period fixed effects effect and ϕ_s are 49 state-fixed effects (we will include different effects in some 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 Table 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 H1B-driven variable in predicting changes in foreign-STEM workers across US 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, in (3) we include the very demanding metro-area fixed effects. The effect of H1B driven STEM is always significant at the 5% level and in the basic specification it is close to 0.7, implying that an H1B-driven increase in STEM by 1% of employment produces a 0.7% increase in foreign-STEM workers in a city. If we think of this regression as the first stage in a 2SLS estimate of the effect of STEM workers the F-statistic is 17 in the basic specification, hence well above the critical value for weak instrument tests. Only when we include city-effects, while still significant the policy-driven variable becomes significantly less powerful in predicting foreign STEM (F-statistic equal to 4.85). Figure 6a and 6b provide the graphical representation of the power of the H1B-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[11] in the decade 1990-2000. Figure 6b shows the correlation without the outliers, which is even stronger (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-statistics 21.9) and increases the coefficient (to almost 0.9) of the H1B driven variable. In the pre-great recession period each extra H1B visa to a metropolitan area increased its foreign STEM workers by 0.9 units. In column 5 of Table 6 we explore whether the H1B policy-driven variable had a significant effect on the total increase in STEM in cities. While less powerful than in predicting foreign-STEM the H1B-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 H1B 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 H1B policy variable.

In Table 7 we perform several robustness checks of the basic specification 19.Column (1)to (4) show the power of the H1B-driven growth on foreign-STEM when we use the two alternative definitions of STEM occupations that we described in section 3.1. In column (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 of the explanatory variable are both changed accordingly. In column (3) and (4) instead, we 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 H1B 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 H1B-driven variable so that even in specification (4) with city fixed effects the power is very large (F-statistics of 19.5).

Column (5) addresses the possibility that the foreign STEM distribution in 1980 might have been influenced by the very recent computer/information technologies that affected productivity in the 1990-2010 period. Therefore we construct the H1B driven variable using the STEM dependence of cities as revealed by the 1970 census. This implies that we can only use 116 metropolitan areas, consistently identified for the whole period 1970-2010. While the power is reduced (F-statistics of 6.05) we still find that the H1B driven variable predicts significantly the foreign STEM growth in the 1990-2010 period. The dependence on foreign STEM workers in 1970 still impacted significantly the allocation of H1B workers twenty years later. Column (6) of Table 7 checks that the location of Indian workers, who accounted for almost 50% of the H1B visas and are well known to be concentrated in the computer industry

[11] Because of the extremely large increase in foreign-STEM in St. Jose and Stamford, not explained by the H1B-predictor it is reasonable to think that sector-specific factors are at play (Computer industry in St Jose and 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.

is not responsible for the full explanatory power of the H1B driven variable. We construct the H1B driven variable omitting Indian nationals both from the initial STEM distribution and from the H1B visas. The coefficient and the F-statistic confirm that the H1B driven variable still has significant explanatory power (albeit the F-statistic is reduced). Finally column (7) includes in the policy-driven variables also L1 visas, used for inter-company transfers. Those visas, especially in the late 2000's, began to be used to attract STEM workers. Their inclusion does not change significantly the predictive power of the policy-driven variable.

3.5 Sector-driven growth in employment and wages

In spite of being only weakly correlated with the presence of native STEM workers the dependence on foreign-STEM workers could still be correlated with the city productive structure. In particular the presence of dynamic sectors that employ foreign STEM workers and were likely to experience larger productivity or employment growth in the 1990-2010 period could bias our results. In order to control for that we construct four variables that predict, based on the 1980 city-composition across 228 industries, the growth of wage and employment of college and non-college educated in the city. The industry classification we use is the three-digit classification from the census, which is consistent across decades, and provides a very detailed break-down of the productive structure of a city[12].

Let us denote as $s_{ic,1980}$ the share of total city c employment in each industry $i = 1, 2...228$ as of year 1980. Then we call $\Delta w_t^{i,X}/w_t^{i,X}$ the percentage change over the decade $t, t+10$ of the national native average weekly wage in constant 2010 dollar for group X (=College, No-College) in sector i $(= 1, 2...228)$.Also we denote as $\Delta EMPL_t^{i,X}/TotEmpl_t^i$ 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 as sector-driven wage growth and sector-driven employment growth (respectively) in city c and decade t for group X the following expressions:

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

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

The 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 as of 1980. They proxy for the sector-driven changes in demand (wage and employment) in city c based on the industry composition as of 1980 to a very detailed level of aggregation. We include the relevant sector-driven control in all our regressions in section 4, below. For instance when we analyze the effect of H1B-driven STEM on wages of non-college educated natives we control for the 1980 sector-driven growth in wage of non-college educated native, when we analyze the effects

[12] 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.

on employment of college-educated we include the sector-driven growth of employment of college educated, and so on[13].

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 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:

$$y_{ct}^{Native,X} = \phi_t + \phi_s + b_{y,X}^{D} \frac{\Delta STEM_{ct}^{H1B}}{E_{ct}} + b_3 y_{ct}^{Sector-Driven,X} + \varepsilon_{ct} \tag{22}$$

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 change in wages or in employment. ϕ_t are decade 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 $\frac{\Delta STEM_{ct}^{H1B}}{E_{ct}}$ is the H1B-driven growth in foreign STEM. The term 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" as we enter the H1B-policy variable into the regression, directly. Alternatively we estimate a specification, as 1 introduced at the beginning. More precisely that will be:

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

Specification (23) is similar to (22) except that it includes the actual change in foreign-STEM, $\frac{\Delta STEM_{ct}^{Foreign}}{E_{ct}}$ as dependent variable and we use $\frac{\Delta STEM_{ct}^{H1B}}{E_{ct}}$ as instrument in the 2SLS estimate. We call this specification the 2SLS or IV specification. The coefficient of interest is $b_{y,X}^{IV}$.

Table 8 shows the estimates of the effects of H1B-driven foreign STEM on six outcomes, one per column, using the direct regression of specification (22). In column 1 the dependent variable is the percentage change of the weekly wage of native STEM workers, $\frac{\Delta w_{ST}^{native}}{w_{ST}^{native}}$ 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 during the decade of the weekly wage of native College-educated workers, $\frac{\Delta w_{College}^{native}}{w_{College}^{native}}$ in each of 219 metropolitan areas, over the 1990-2000 and 2000-2010 decade. In column (3) it is the percentage change of the weekly

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

wage of native non-College-educated workers, $\frac{\Delta w^{native}_{noCollege}}{w^{native}_{NoCollege}}$[14].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 $\frac{\Delta STEM^{nat}_{ct}}{E_{ct}}$, $\frac{\Delta H^{nat}_{ct}}{E_{ct}}$ and $\frac{\Delta L^{nat}_{ct}}{E_{ct}}$. The different rows of the table represent different specification and samples. All specifications include period effects, state effects and the sector-driven variable as controls. In the first row we report the basic specification using the broad O*NET STEM definition and including period effects, state effects and industry-driven demand controls. In the second row we continue to use the same definition and we add as 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. In the fifth row we omit the post-2005 period in order to keep the great recession out of the sample. In the sixth row we include L1 visas in the construction of the policy-variable and finally in the last row we use the 1970-based STEM dependence to construct the H1B variable. Four interesting and relatively consistent results emerge from the seven rows. First, there is a positive and significant effect of H1B-STEM workers on wages of 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 increase in H1B-STEM by one percentage 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 H1B-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 0 at any confidence level. The third result is that employment of college educated as well as STEM workers among them, was not significantly affected by the inflow of STEM workers. While most estimates are positive and several are around one they are never significantly different from 0. The last result is that employment of non-college educated workers was also not significantly affected by H1B-STEM. Most of the time the point estimates of the response are negative but imprecise and not significant. The null effect on non-college educated and the positive wage effect on college educated suggests already that H1B-STEM might have caused productivity growth, of the skill-based type. The weak employment response of college employment may also suggest that other adjustment mechanisms, beyond net inflow of college educated, were at work at the metropolitan area level, such as changes in the price of non-tradable, especially house rents. We will explore this possibility in the next section.

While the direct regressions are useful to have a sense of the effect of the H1B visa policy our preferred specification is (23) that uses changes in foreign STEM as explanatory variable and adopts the H1B policy variable as instrument. Table 9 shows the estimated $b^{IV}_{y,X}$ coefficients for the same six dependent variables analyzed in Table 8. Each column reports the coefficient on the regression using the corresponding variable as dependent. We add a last

[14] 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.

column, (7), that shows the Kleinberger-Paap Wald F-statsitic for the first stage regression (essentially identical for all the regressions in the row, as the first stage is the same) and gives a sense of the strength of the instruments. The rows shows estimates for different samples and specifications. In the first row we show our basic specification, using the O*NET STEM definition, including period effects, state effects and industry-driven demand. The second row includes a control for the 1980 native-STEM dependence. The third row omits the period after 2005. The fourth row includes L1 visas in the construction of the instrument, while in the fifth we exclude Indian immigrants from it. The sixth row uses the 1970-based H1B instrument and in the seventh row we exclude the post-2005 period, while still using the 1970-based instrument. In the eight row we use total STEM workers (rather than foreign-STEM only) as explanatory variable, while the instrument is still the H1B-predicted change in STEM. Before commenting on some specific features of the estimates in Table 9, let us notice that overall the results clearly confirm those of the direct regressions. Foreign STEM (and in general STEM) workers have a positive and significant effect on the wage of college educated and of STEM native workers. They have a null effect on the wage of non-college educated and they do not have a significant effect on the employment of college educated and of non-college educated. This last effect is very imprecisely estimated, however, and usually the point estimate is negative and it can be large. Notice that while the estimates and their significance are remarkably consistent across specifications, the power of the 1970 based instrument is rather low, and similarly the H1B instrument is rather weak to predict total STEM worker. While we should not attach very high confidence in the point-estimates of the coefficients of 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 is larger in Table 9 than it was the direct regressions of Table 8. Usually that value is between 4.3 and 6. We consider this range as the preferred one.

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

Very instructive and important is also taking a look at the last row of Table 9. It shows the OLS correlation of foreign STEM growth with the dependent variables, namely the coefficient that we would estimate by using OLS in regression 23. That row shows how largely over-stated are the positive effects, especially for employment and for non-college educated, if we fail to account for the endogeneity of foreign-STEM workers and do not include the sector-driven growth variables. That regression finds positive and significant effects of STEM on all variables. This means that STEM workers are attracted to growing cities in which employment and wages of all workers are growing. Our instrument, however, allows us to separate, instead, the positive effect on demand for college educated from the negative effect on the demand of non-college educated.

5 Extensions

5.1 Robustness Checks

In Table 10 we estimate the 2SLS regressions using the two alternative definitions of STEM workers, namely limiting the O*NET based group to college educated only (in row 1, 4, 5 and 6) and using the Major-based definition (in row 2 and 3). We also modify the H1B-based instrument accordingly. As noticed already 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 noticeable is the fact that the O*NET plus college-graduate 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.

Overall the main results of Table 9 (and of Table 8) are clearly confirmed in the robustness checks of Table 10. The only effect that is significantly different from 0 in each specification is the one on the wages of college educated natives. The estimated range for that effect is between 2.8 and 6.2, a bit broader than the previously estimated range, but not far from it. The other effects on employment and wage of non-college educated are not significantly different from 0. The effects on college educated employment are small and not significant. One feature of the results in Table 10 is 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 to a narrower definition based on college-major, seems to affect the estimated coefficient on their wages, by making them smaller. It is possible that the narrower definition of STEM implies that group still has the productivity effect on college educated but it is less substitutable with them showing a clearer competition effect on wages. While in most of the cases the effects on STEM wages are not statistically different from those on wages of native college educated overall, the estimates from row 3 imply the largest difference. Let us emphasize that the third row of Table 10 estimates a very demanding specification, by including in a difference panel (with only 3 periods) 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 check confirm that we do not find any significant positive effect on employment or wages of non-college educated from foreign STEM workers. Also confirmed in Table 10 is the importance of using the 2SLS estimation, rather than the OLS one. Immigrant STEM workers have in fact a positive and significant correlation with 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 H1B-driven increase in foreign STEM workers reveals a different effect on employment and wages, mainly limited to college educated.

5.2 The effect on housing rents

The impact of STEM on wages of non-college educated is not significant. Consistently with this, there is no significant employment response of that group. The impact on college educated wages, however, is significantly positive but, while mostly positive, the employment response of college educated is not significant. Why don't' more college educated move to work in cities where 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, increase in the cities experiencing wage growth, driven by an inflow of STEM workers in our case, dissipating some of the wage gains. 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 Census in 1990, 2000, 2005 and 2010. We construct the monthly rent per room in 2010 US $, from the data on the rent and total number of rooms paid by native individuals between 18 and 65 years of age (to be consistent with the wage data) in a metropolitan area. In order to identify the specific effect for college and non-college educated rents we construct the rent per room of each 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 that is not affected by the top-code. Then we use these as outcomes y in regression (23) and use the same 2SLS estimation and instrument as for wage and employment. The estimated coefficients of a change in rents paid by college and non-college educated on changes in foreign STEM workers are reported in Table 11. We use the data on rents, rather than house values, because they capture more closely the cost of the housing services provided by a building and do not include their asset value. We should also observe that the housing market had a period of very strong turbulence between 2007 and 2010 and this likely introduced very high variability in the data post 2005 that may cloud the results. Column 1 and 2 show the effect on average and median rent paid by college educated, Columns 3 and 4 show the impact on average and median rent of non-college educated. In the first row we show 2SLS estimates of the basic specification, in the second row we drop the post 2005 period. In specification 3 we include L1 visas in the construction of the instruments and in specification 4 we use the major-based definition of STEM. The last row, as usual, 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 of college educated with a point estimate around 5. To the contrary the effects of STEM on rents of non-college educated are never significant with a point estimate around -1. The inflow of H1B STEM did increase the wages of college educated and it also increased their housing rental costs. This differential increase in rents is probably due to the more limited supply of desirable locations for college educated and the larger increase in their income. We should keep in mind that housing costs are likely to affect the cost of other non-tradable local services as well. What effect did this increase in non-tradable price have on real wages? Considering the Consumer Expenditure Surveys for college educated for year 1998-2002, right in the middle of our sample (Bureau of Labor Statistics 2005) we see that housing costs represent 33% of individual expenditures, plus another 17% of their expenditure were in utilities, health and entertainment (arguably non-tradable services). Hence easily 50% of their income could be spent in non-tradable services by college educated workers. Considering the average estimated effect on price from Table 11 as a 5% increase for each increase in STEM workers by one percentage of employment, and the corresponding average effect on wages to be around 5% as well (from the average estimate in Table 9) we have that the "real wage increase" for college educated, accounting for purchasing power, would be only around 2.5%. With a local labor supply elasticity of 2.5 or more, which implies quite significant response of employment, this would imply an employment response of college educated by 1% or less, which is in the range of most of our estimates of the college employment response. Due to standard errors between 1 and 2 those values are not significant. The effect on price of non tradables, therefore, contributes substantially to absorb the local effect on college educated wages and 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 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/negative effect on the demand for non-college educated is concentrated mainly in the very low part of that skill group involving individual with no schooling or if it impacted uniformly all non-college educated. Second we analyze whether the employment of college educated native workers, which did not change much in the aggregate, was however pushed, by STEM growth, towards more human capital (and knowledge) intensive industries, likely to benefit disproportionately from STEM workers. Finally we analyze whether the inflow of foreign-STEM workers encouraged native college-educated workers to specialize in abilities that may complement those. On one hand we have already shown that native STEM workers' productivity increased. However there are other skills, important to produce innovation and scientific-technological growth, that may have been encouraged by the H1B-driven STEM increase.

Table 12 shows the effect of foreign STEM workers on wages (columns 1 and 2) and employment (columns 3 and 4) of native workers separating high school dropouts (column 2 and 4) and high school graduates (columns 1 and 3). We run several specifications of the 2SLS estimates, described by the header of each row, in rows 1 to 5. In row 6 we report the OLS coefficients. Distinguishing high school graduates from high school dropouts allows us to check whether these two groups are differentiated in their complementarity with college educated. It is also a preliminary test for whether STEM workers produced that type of change in labor demand that has been baptized "polarization of the labor market". That phenomenon implies higher employment growth at the high and low end of the skill spectrum at the expenses of intermediate-skill jobs (e.g. Autor 2010, Autor et al. 2006). The estimates of Table 12 show that for both groups (high school graduates and dropouts) the effects of STEM are mostly negative and in general not significant. The only coefficients sometimes close to significance are relative to the effects on employment of high school graduates. In the third row (pre 2005 period only) we estimate the coefficient of STEM on employment of high school educated to be -4.38, significant at the 10% level. This would be consistent with an idea of STEM driven technological progress contributing to Labor market polarization by affecting intermediate skills (high school graduates) more negatively than low skills (dropouts). The effect is however not very robust.

Table 13 shows the employment response to STEM workers of college educated (columns 3 and 4) and all workers (column 1 and 2) for nine sectors separately. We included all sectors except those that have very small employment shares in some cities (mining, agriculture and entertainment) and hence exhibit rather noisy estimated effects. We arrange sectors in Table 13 in three groups. Private sectors with low "human capital intensity" measured as share of college educated smaller than 0.25 in year 2000. Private sectors with "high human capital" intensity measured as share of college educated larger than 0.25 in year 2000. And the public sector, whose employment growth may not be driven by productivity considerations. The coefficients of Column (3) and (4) in Table 13 obtained using the basic specifications 22, (direct regression) or 23 , (2SLS) show that the employment of college educated in high human capital sectors, such as business and professional services, 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 job growth for college educated. Hence cities with high STEM inflows also experienced a reallocation of college educated workers towards more college-intensive sectors. The coefficients of Columns 1 and 2 show that while high human capital private sectors experienced positive total employment changes in response to STEM workers, those effects were not significant.

Previous studies (Kerr and Lincoln 2010, Hunt and Gauthier-Loiselle 2011) also found that foreign STEM have increased innovation in the US. Other studies have found that US workers respond to the inflow of similarly educated foreign-workers by specializing in complementary type of skills (Peri and Sparber 2009). In Table 14 we explore the possibility that the inflow of foreign-STEM workers encouraged native college-educated workers to specialize in abilities that may complement those.

Using the O*NET dataset we identify in the "Abiliy", "Activity" , "Skill" and "Work Characteristic" variables those associated with Creativity and with Problem Solving and we measure their importance in each of the 333 occupation definitions that we can track consistently across census years[15]. 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 (for native college -educated) at the city level of those creative abilities 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 H1B driven growth of Foreign-STEM produces a significant shift of native college educated towards occupation that use more intensively creative and problem solving tasks. On one hand this shift could contribute (besides technological change) to the increase in productivity of native college educated. On the other 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-workers by specializing in skills that, in the process

[15] 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).

of innovation and technology, are complementary to STEM. 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 in the standard deviation of innovative skill growth across cities.

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

Overall, the empirical results presented in section 4 indicate that in a US metropolitan area, an increase in STEM workers by 1% of total employment over a decade had a positive and significant effect between 4 and 6% on the wage of college-educated workers and no significant effect on their employment. It also had an insignificant effect on wages of non college educated workers and a negative and non significant effects on employment of non-college educated. Although very imprecise and non significant, in most estimates of Table 9, we the point estimates of the effect on employment of non-college educated are sometimes around -4%.

In this section we use the estimated values of $\widehat{b}_{y,X}$ the elasticity to STEM workers of outcome y for group X and equations (7)-(8) to translate the wage and employment elasticities into the impact on the growth of total factor productivity and of its skill-bias. In particular our results suggest that three elasticity are never statistically different from zero, namely$\frac{\Delta w_L}{w_L}/\frac{\Delta ST^{Foreign}}{E}=0$; $\frac{\Delta NST}{E}/\frac{\Delta ST^{Foreign}}{E}=0$ and $\frac{\Delta ST^{Native}}{E}/\frac{\Delta ST^{Foreign}}{E}=0$. Hence we set them to 0 and This allows us to simplify the system obtaining the following three equations that identify the 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 defines immediately σ_S. As in most of our estimates $\widehat{b}_{w,ST}$ is rather noisy and not statistically different from $\widehat{b}_{w,ST}$ we infer that $\frac{1}{\sigma_S}=0$. This can be substituted into (24) and (25) making them very simple linear equations in the two unknown $\phi_A$and ϕ_B provided we know σ_H and β. The appendix A shows the expression for those variables obtained by solving (24) and (25). In our calculations use values of σ_H from the literature and the implied value of β obtained using that σ_H from the relative wage and relative employment of college and non college educated. There are several estimates[16] in the literature of the parameter σ_H which is usually assessed between 1.5 and 2.5. We choose 1.75 as a reasonable

[16] See Ciccone and Peri (2005) for a review of the estimates. Katz and Murphy (1992), Goldin and Katz (2008), Angrist 1995 and Ottaviano and Peri 2012 provide some influential estimates of that parameter,

value. β is equal to 0.52, for year 2000[17]. We use the values of the shares in employment and income from the US census 2000. Using the productivity effects calculated as described we perform two exercises. The first is a "macro" application. Using the whole US and the estimated parameters, what calculate the aggregate TFP and skill-bias effect due to the growth in foreign-STEM in the period 1990-2010. The second application is to city-differences. We consider the city with highest and lowest inflow of foreign STEM workers and those with highest and lowest growth in productivity, as revealed by average wages and we calculate what percentage of the second can be explained by the first.

Table 13 shows the macro exercise. Column (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 consider as 0 all the non-significant coefficients so that, among all the others, also $\widehat{b}_{E,L} = 0$. In the lower part of the table we use the same estimates, but instead of 0 we set $\widehat{b}_{E,L}$ to the average point-estimate for it from Table 9 which equals -3.5. Columns (4) and (5) show the implied effects of the average yearly foreign-STEM worker growth (reported in column 1) on productivity and on the skill-bias obtained using our estimates and the average growth of foreign-STEM workers for the US, in the two decades after 1990. Columns (6) and (7) show the actual productivity growth and skill biased growth measured in the aggregate US data and the last 2 columns show what share of productivity and skill biased growth can be attributed to the increase in foreign STEM workers. The average yearly growth of foreign STEM workers in the US (as percentage of total employment) was 0.06% in the 1990's and 0.02% in the 2000's. Using the actual negative point estimates of the effect on non college employment (lower part of the table) or the 0 effect (upper part) does not imply major differences. The estimated elasticities imply that foreign STEM growth can explain one fourth of the aggregate productivity growth in the 1990-2000 decades, and possibly 40% of it in the 1990's. Our calculation attribute to foreign-STEM a yearly TFP growth by 0.30% per year in the 1990's and by 0.10% in the 2000's. Just to give an idea, such yearly growth implies that income per capita in 2010 is 4% larger in the US that it would have been without foreign STEM contribution[18]. 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[19]. The macro exercise is based on the very strong assumption that we can apply the parameters estimated across cities to the national effects of foreign-STEM. Still the exercise is informative as it provides a reference for the magnitude of the effect. As reference a very influential paper on aggregate US data (Jones, 2002) found that about 50% of the long-run productivity growth of the US in the last decades could be attributed to the growth of share of scientists and engineers. In our estimates we emphasize how a significant part of that contribution might have come from foreign STEM in the period 1990-2010.

Table 16 shows the implication of differences in foreign STEM growth across US cities on

[17] 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 $\beta = 0.52$.

[18] That number, in current dollars would be 615 Billion.

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

the differences in productivity growth, as measured from average wage growth. In column (1) we report the difference between the city with highest and the city with lowest growth of foreign STEM workers in the 1990-2000 and in the 2000-2010 period[20]. Using this difference and the estimated coefficients we obtain, in Column (3) the effect on differential TFP growth between cities. In column (4) we report the actual difference in TFP growth, as measured by difference in average wage growth, between the slowest and fastest city. In the last column we show what fraction of the wage growth differential is explained by the foreign STEM differential. The magnitude is again substantial as in the 1990's differences in growth of foreign STEM are able to explain the whole difference in TFP growth, while in the 2000s they explain about half of it. Both in explaining the aggregate TFP and its cross-city differences foreign STEM workers seem to play a very important role.

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 H1B visa program to estimate the impact of those type of workers on productivity of college and non-college educated American workers. The uneven distribution across cities of foreign STEM workers as of 1980 and its high correlation with the pre-existing presence of immigrants allows us to use the variation in foreign-STEM as an arguably supply-driven increase in STEM workers, unevenly distributed across Metropolitan areas. We find that in a metro area, an increase of foreign STEM workers during a decade by 1% of total employment increased wages of native college educated by 4-6% with small effect on their employment. It also had non significant effects on the wages and employment of non-college educated. These results are indication that growth in STEM workers spurred technological growth by increasing the productivity of (and demand for) college educated. The technologies introduced in the period 1990-2010 by STEM workers, likely increased total production and even more strongly the productivity of college-educated. We also found that college educated natives moved in response to foreign STEM workers to more human capital intensive sectors of the city economy, they increased the "creative" skills used in production and their house rent increased eroding part of their wage gain.

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

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. "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 US 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. "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] 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.

[18] 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.

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

[20] Glaeser Edward (2011). "The Triumph of the City: How Our Greatest Invention Makes Us Richer, Smarter, Greener, Healthier, and Happier"

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

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

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

[24] 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.

[25] 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.

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

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

[28] 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.

[29] 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.

[30] 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.

[31] 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.

[32] 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.

[33] 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.

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

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

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

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

[38] 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.

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

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

[41] 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.

[42] 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

	% of foreign-born in employment	% of foreign born among college educated	% of foreign-born among college educated in 218 metro area	% of foreign-born in STEM occupations in metro-area	% of foreign-born among 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 on 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 percentage of Employment, Total 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 on 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 total cumulated H1B (thousands)

US overall	Net change in Total College-Educated STEM	Net Change in Foreign college-educated STEM	Total Cumulated H1B
1980-90	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 H1B visas are from the Department of State (2010).

Table 4

Top 10 cities in Native- and in Foreign-STEM dependence as of 1980

Metropolitan area	Native STEM dependence, 1980	Metropolitan area	Foreign STEM dependence, 1980
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)	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 (Johnson and Johnson, 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 UC Census.

Table 5

Foreign-Born, Native STEM-dependence across cities in 1980 and the H1B predicted STEM change

Panel of 219 US metropolitan areas 1990-2000, 2000-2005 and 2005-2010

	(1) Foreign-Born Stem dependence 1980	(2) Foreign-Born Stem dependence 1980	(3) H1B-predicted STEM growth	(4) H1B-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-stat	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 H1B-predicted change in STEM in 1990-2000, 2000-2005 and 2005-2010 regressed on the 1980 of STEM dependence (foreign or native). The standard errors are heteroskedasticity robust and, when there is more than one observation per metro areas, 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 H1-B driven increase in Foreign STEM (O*NET definition) as predictor of Foreign STEM

Panel of 219 US metropolitan areas 1990-2000, 2000-2005 and 2005-2010

Dependent Variable	**(1) Change in foreign-born STEM as % of initial Employment**	**(2) Change in foreign-born STEM as % of initial Employment**	**(3) Change in foreign-born STEM as % of initial Employment**	**(4) As (2) pre-2005 (pre-great recession)**	**(5) Change in total STEM as % of initial Employment**	**(6) As (2) Controlling for native STEM dependence in 1980**
H1-B 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 US Metro areas decades over two decades 1990-2000 and 2000-2010.The dependent variable is described at the top of the column. The explanatory variable is always the H1B-driven growth of Foreign-STEM jobs, as a percentage of initial employment.
***, **,*= significant at 1%, 5% and 10% level respectively.

Table 7

Power of H1-B driven increase in Foreign STEM as predictor of Foreign STEM: Alternative definitions and data

Panel of 219 US metropolitan areas 1990-2000, 2000-2005 and 2005-2010

Dependent Variable: Change in foreign-born STEM as % of initial Employment	**(1) Definition of STEM: College Educated and O*NET/STEM**	**(2) As (1) with metro-area fixed effects**	**(3) Definition of STEM: College-Major based**	**(4) As (3) with metro-area fixed effects**	**(5) As (3) with 1970 based foreign-O*NET/STEM, 116 metro areas**	**(6) As (1), Excluding Indians from ONET/STEM**	**(7) As (1), Including L1 visa in the construction of visa-entries**
H1-B 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 US Metro areas decades over two decades 1990-2000 and 2000-2010.The dependent variable is described at the top of the column. The explanatory variable is always the H1B-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 H1-B driven foreign O*NET STEM on wages/employment of native workers

219 US metropolitan areas 1990-2000, 2000-2005 and 2005-2010

Explanatory Variable: H1B-driven Growth rate of 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 H1B-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 as controls 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 US metropolitan areas 1990-2000, 2000-2005 and 2005-2010

	Dependent variable: Growth rate of						
Explanatory Variable: Growth rate of Foreign – STEM **Instrument:** H1B 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	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 H1-B driven growth of foreign- STEM workers. The specification estimated is as (23) in the text. It always includes state and year effects as controls and the industry-driven growth in the relevant 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 US metropolitan areas 1990-2000, 2000-2005 and 2005-2010

	Dependent variable: Growth rate of						
Explanatory Variable: Growth rate of Foreign – STEM **Instrument:** H1B 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	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 H1-B driven growth of foreign- STEM workers. The specification estimated is as (23) in the text. It always includes state and year effects as controls and the industry-driven growth in the relevant 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 US metropolitan areas 1990-2000, 2000-2005 and 2005-2010

Explanatory Variable: Growth rate of Foreign – STEM **Instrument:** H1B 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 H1-B driven growth of foreign- STEM workers. The specification estimated is as (23) in the text. It always includes state and year effects as controls and the industry-driven growth in the relevant 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 12

2SLS regression of foreign STEM on wages/employment of native workers: Split of non-college in2 groups

219 US metropolitan areas 1990-2000, 2000-2005 and 2005-2010

	Dependent Variable: Growth rate of				
Explanatory Variable: Growth rate of Foreign – STEM **Instrument:** H1B 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 H1-B driven growth of foreign- STEM workers. The specification estimated is as (23) in the text. It always includes state and year effects as controls and the industry-driven growth in the relevant 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 13:
Effects of foreign STEM on employment by Industry
219 US metropolitan areas 1990-2000, 2000-2005 and 2005-2010

Explanatory Variable: Growth rate of Foreign –STEM **Instrument:** H1B 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 H1-B 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	
H1B-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-stat 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", "Problem-Solving" skills and STEM Skills calculated based on occupation 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 % 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 US TFP average yearly growth, from Fernald (2010)	(7) Change in average yearly skill-biased productivity implied by the US data	(4)/(6)	(5)/(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**

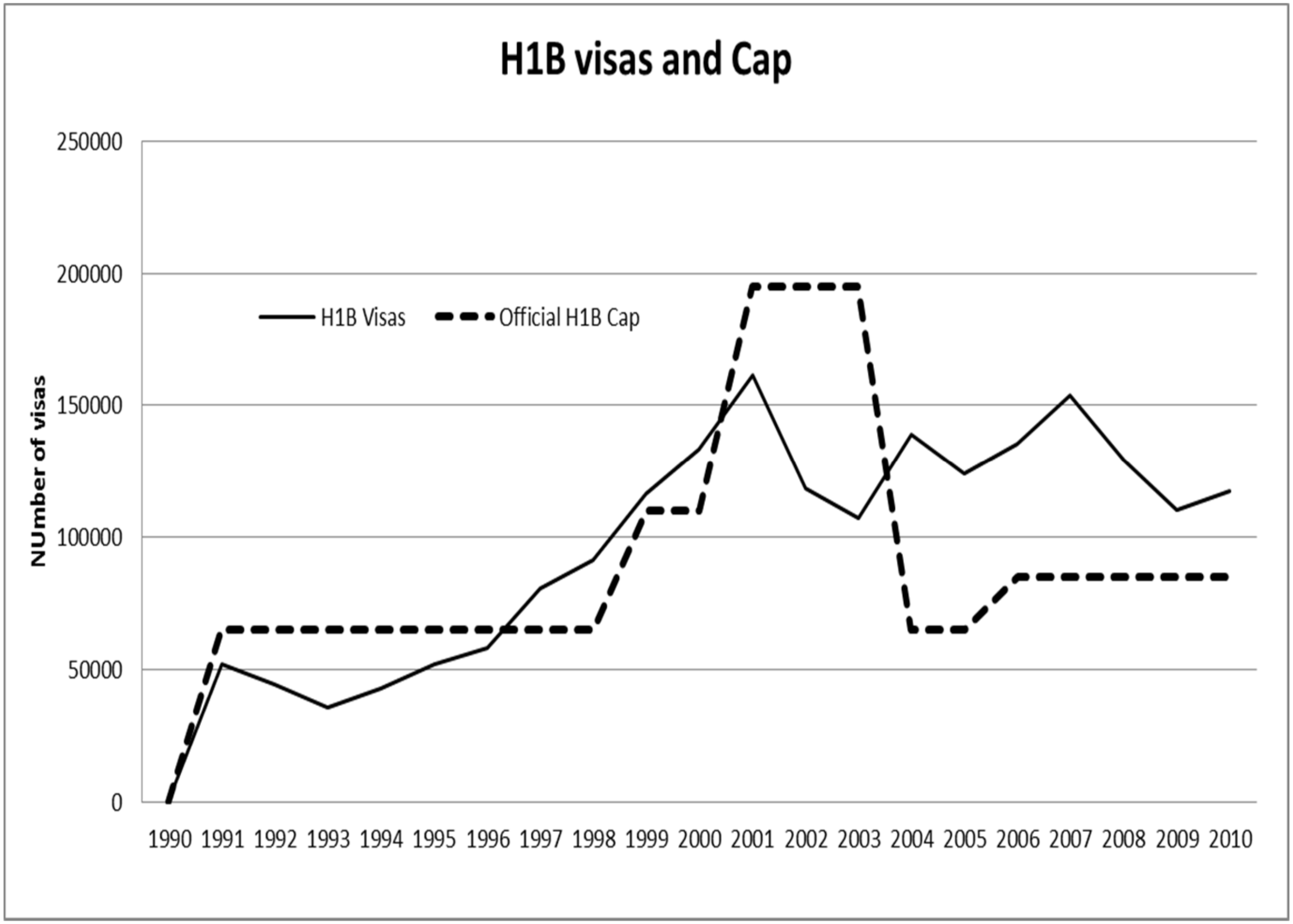
Note: The table uses the formulas in the appendix to calculate the implied elasticity ϕ_A and ϕ_B. We then use the growth of STEM workers as % of the employment to calculate the implied effects on TFP and skill-biased productivity. The figures on actual TFP growth were taken from Fernald (2010) and the 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 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 % of employment)	(2) ϕ_A Elasticity of A to STEM	(3) Implied Min-Max difference in TFP growth	(4) Actual Min-Max Difference TFP growth, from Average Wages	(3)/(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**

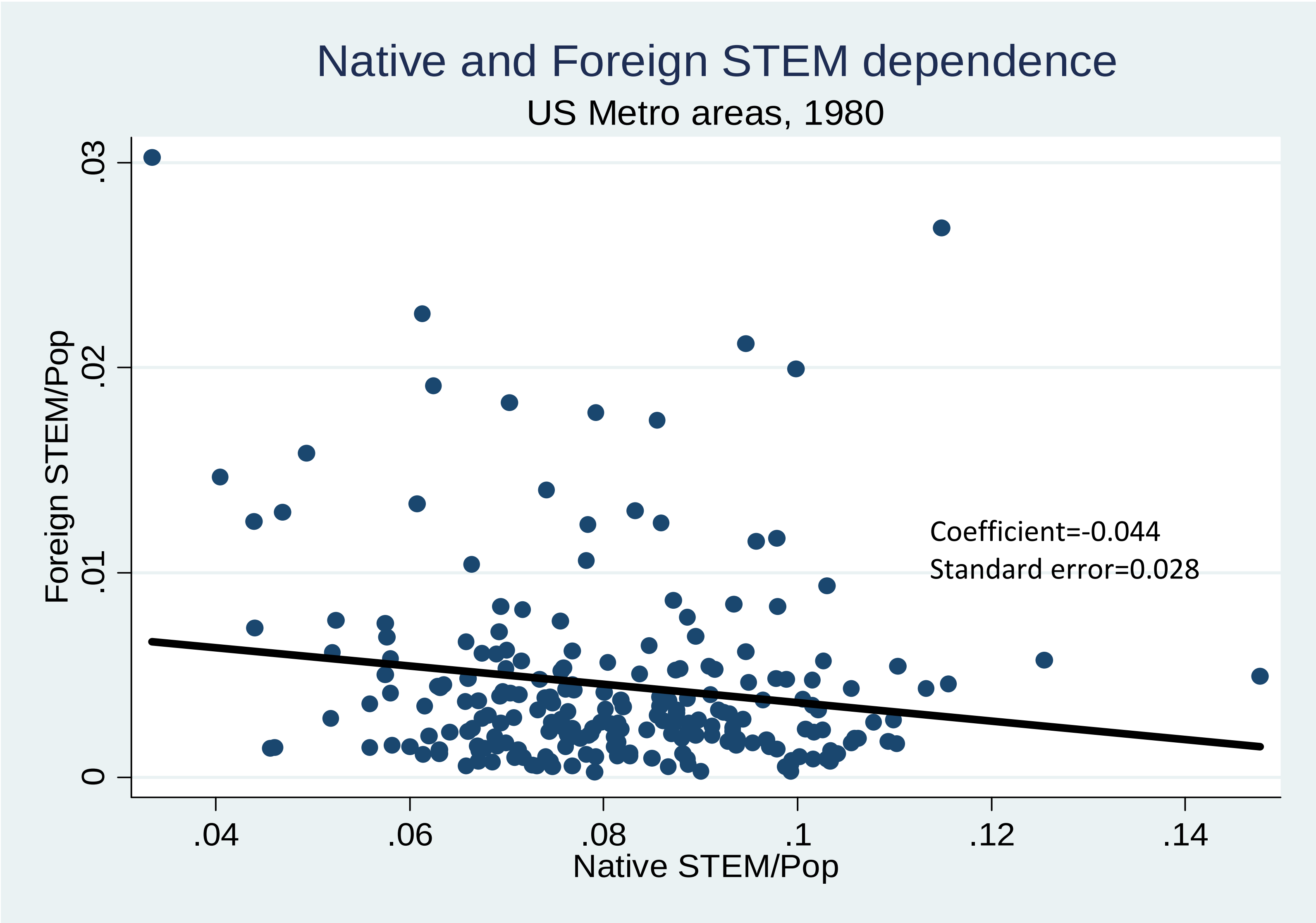
Note: The table uses the formulas in the appendix to calculate the implied elasticity ϕ_A and ϕ_B. We then use the growth of foreign STEM workers as % of the employment to calculate the implied effects on TFP. The actual TFP min-max difference is obtained as the difference in growth of average wages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

Figure 1



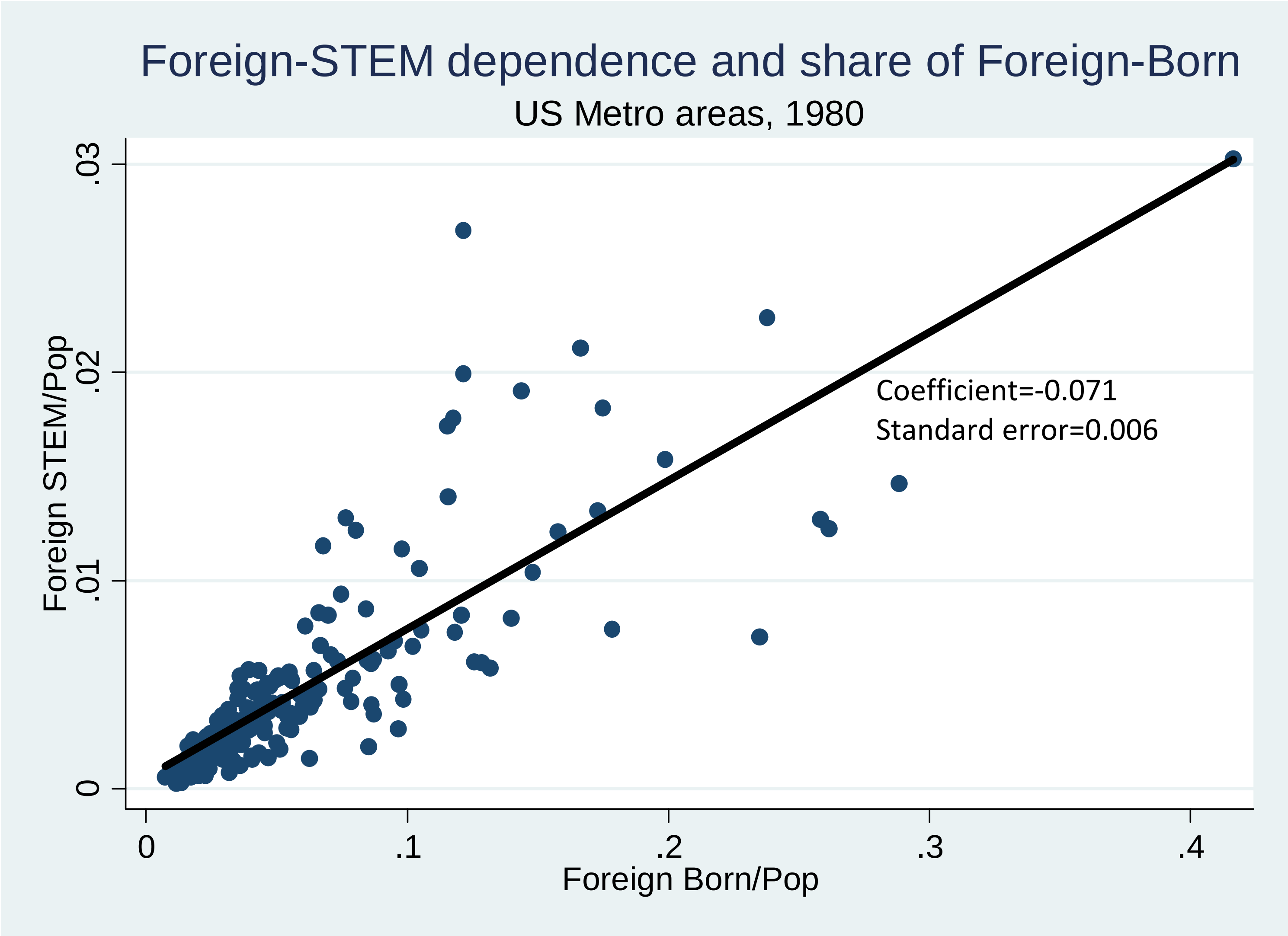
Note: The data on H1B visas and their cap are from the Department of State

Figure 2



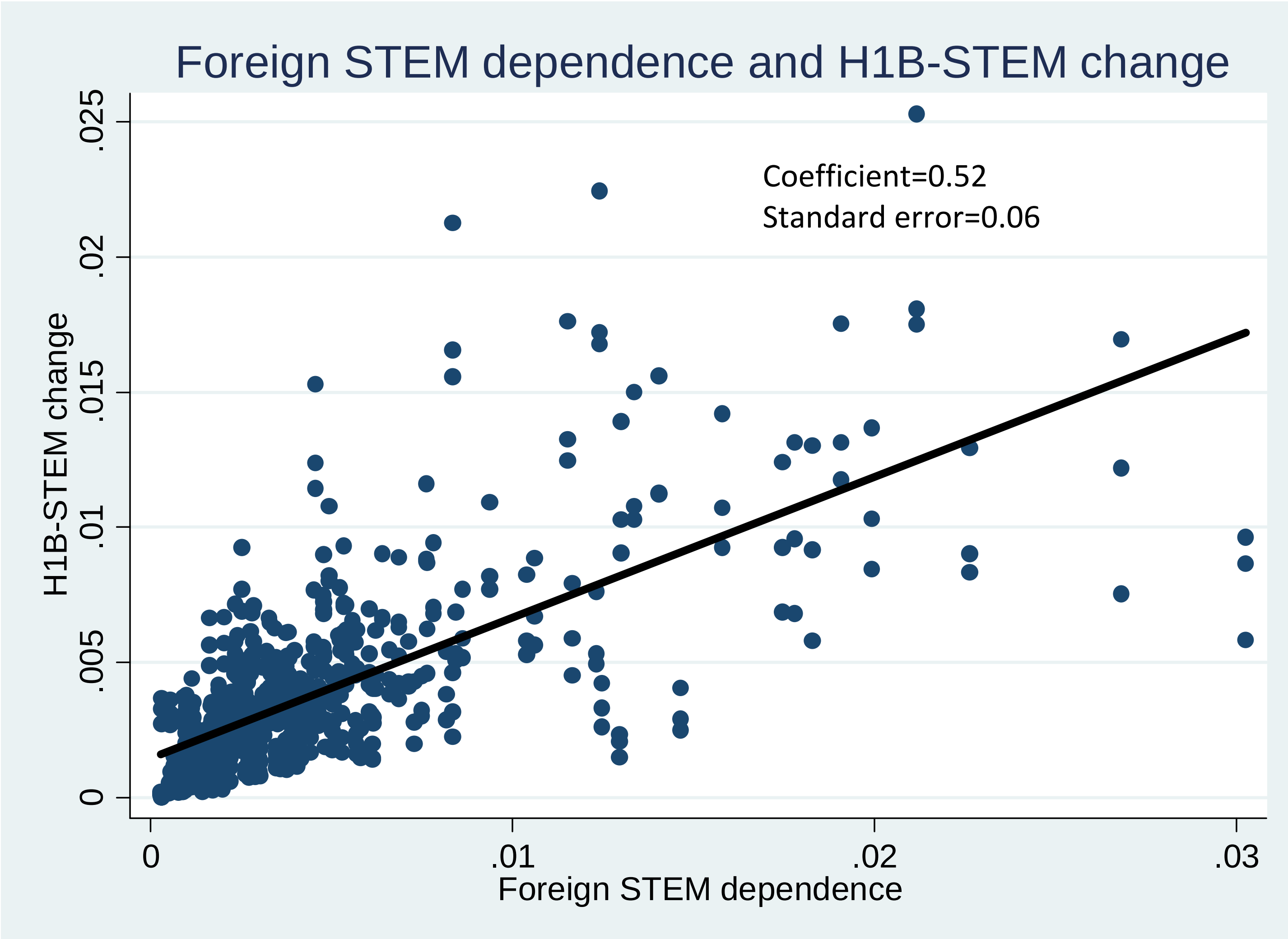
Note: The rates of Foreign and Native STEM dependence are calculated using 1980 Census data for 219 Metro Areas.

Figure 3



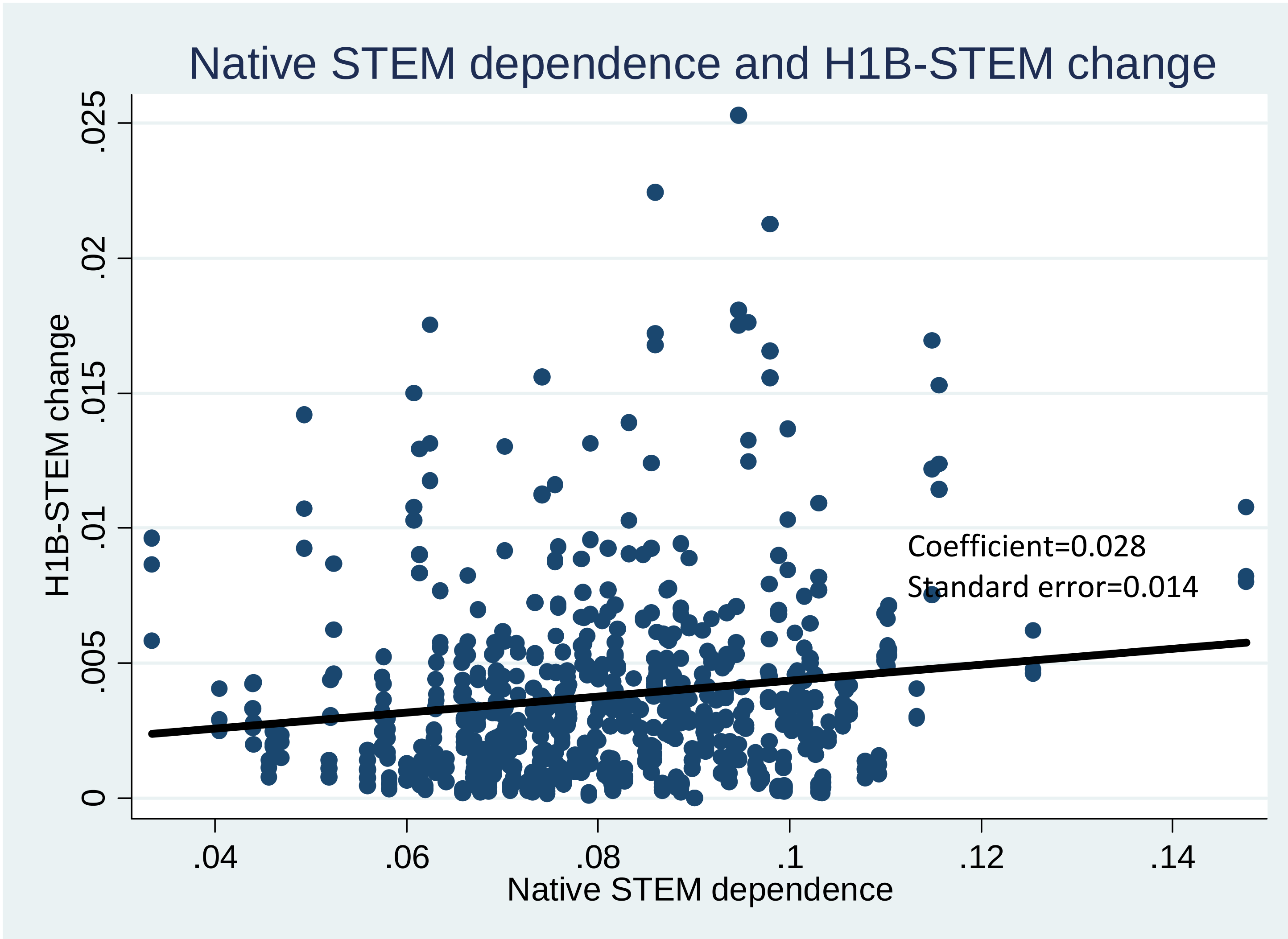
Note: The figures are calculated using 1980 Census data. The population of reference to calculate the share of foreign born in a city is the total adult (18-65) population not institutionalized.

Figure 4



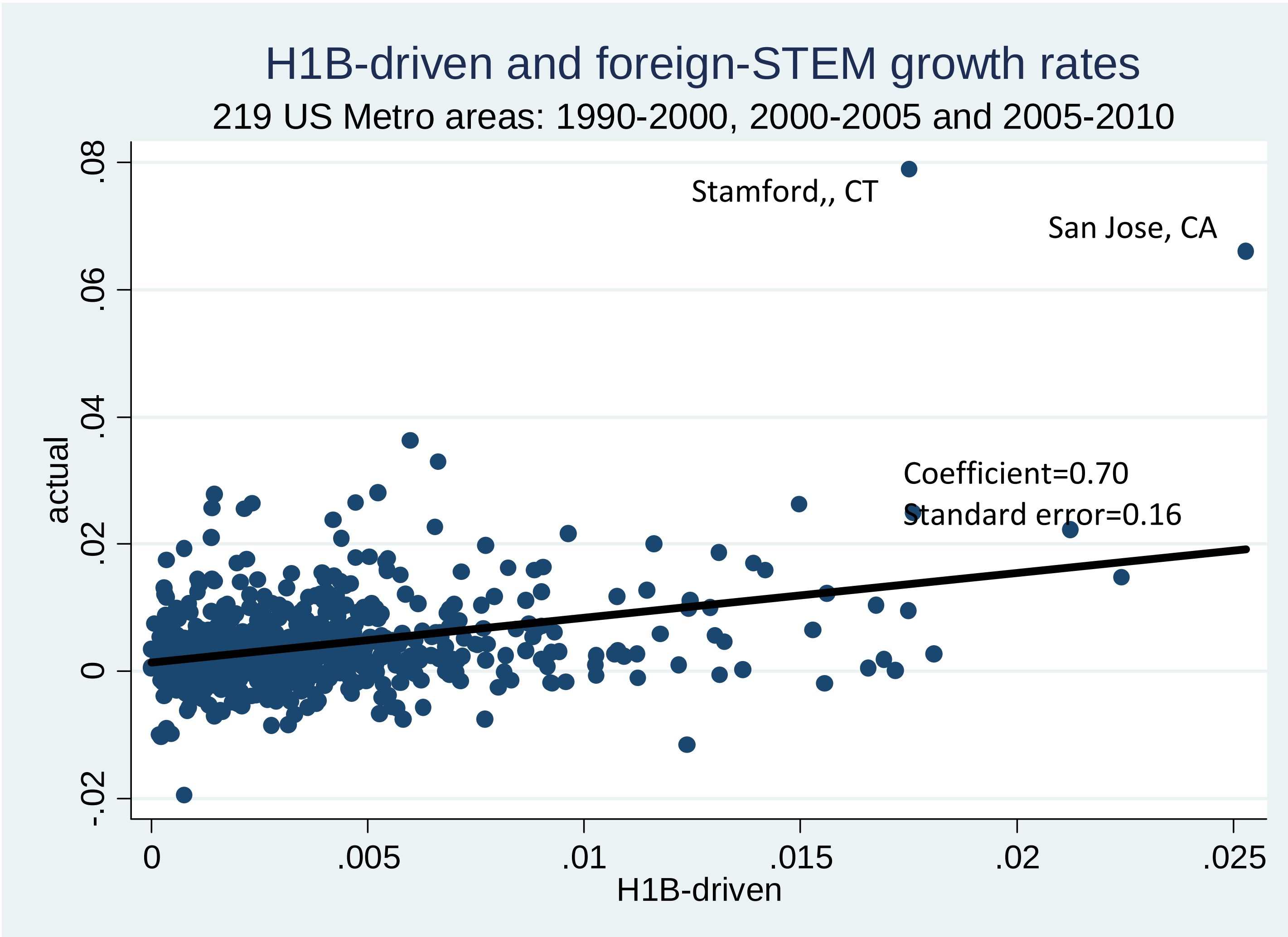
Note: The rates of Foreign STEM dependence are calculated using 1980 Census data. The H1B induced STEM change is constructed as described in the text.

Figure 5



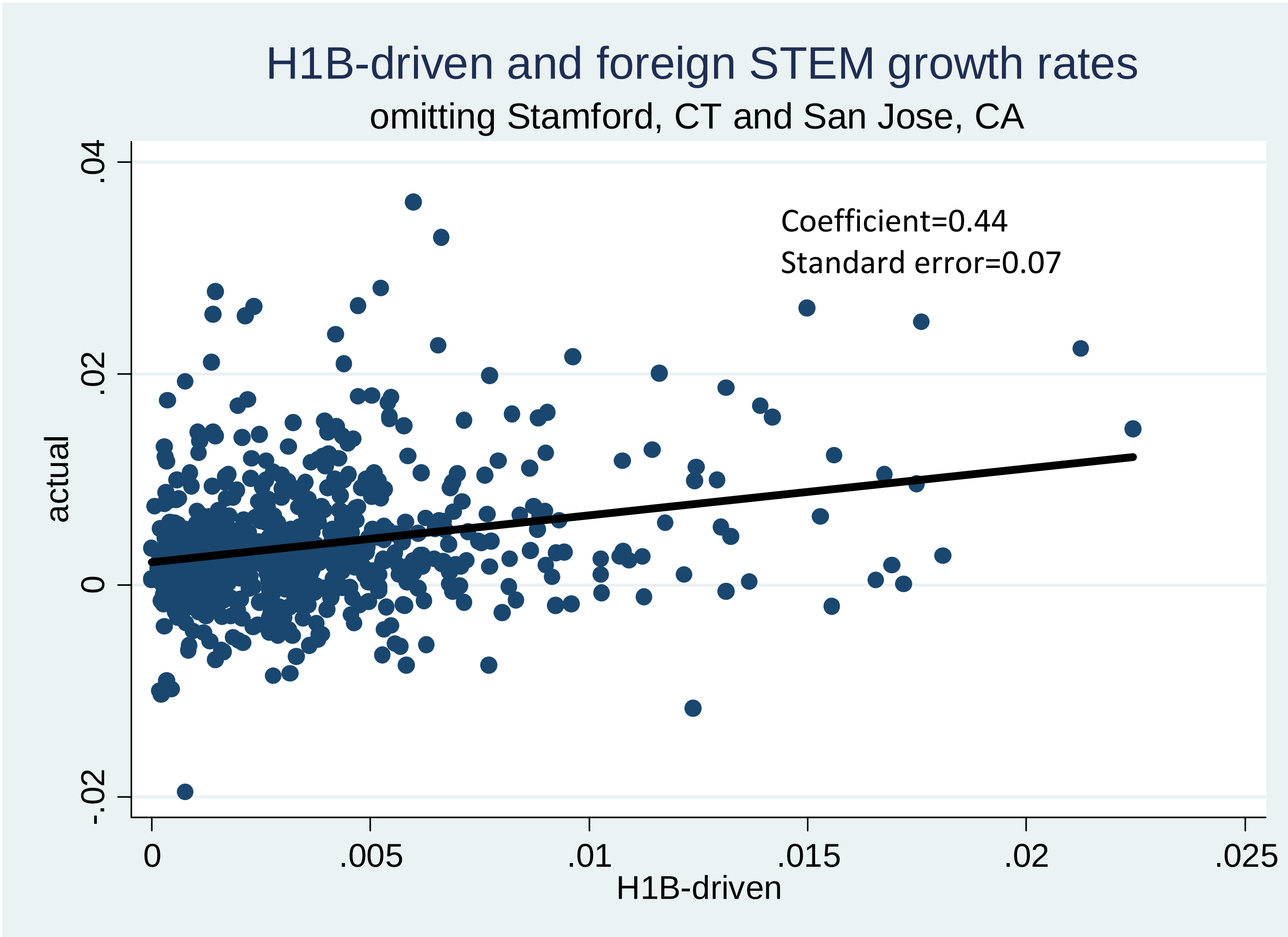
Note: The rates of native STEM dependence are calculated using 1980 Census data. The H1B induced STEM change is constructed as described in the text.

Figure 6a
Predictive Power of H1B-driven STEM



Note: Power of the H1-B driven STEM immigrants in predicting actual growth of STEM immigrants

Figure 6b
Predictive Power of H1B-driven STEM, without outliers



Note: 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, PartC

List of college major 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: H1-B 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 H1B visas	709505	1321028