Online Appendix for "STEM Workers, H-1B Visas, and Productivity in U.S. Cities"

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This appendix provides supplemental clarification about the data, variables, and simulation exercise in "STEM Workers, H-1B Visas, and Productivity in U.S. Cities." Section 1 describes the sample criteria used to construct the dataset. Section 2 outlines how we define demographic groups, industries, occupations, and STEM workers. Such definitions help understanding the variables used in the empirical analysis and, for the interested reader, they also help replicating our results. Section 3 then provides additional details on how we construct the H-1B instrument, control variables, and data used in the paper's falsification and robustness checks. Finally, Section 4 describes our model for deriving productivity and skill-bias effects.

1 Data Selection

The Ruggles et al. (2010) IPUMS dataset provides all information data on wages, employment, occupation, industry, nativity, and education for the analysis. Specifically, we extract samples of workers from the 1970, 1980, 1990, and 2000 Census, the 2005 American Community Survey (ACS), and the 2008-2010 3-Year ACS (which we refer to as 2010). The IPUMS Censuses are 5% random samples of the U.S. population, with the exception of 1970 when we use the Form 1 Metro 1% sample. The 2005 ACS is a 1% sample, and the 3-Year 2008-2010 ACS is a 3% sample. We focus our analysis on 219 Metropolitan Statistical Areas (MSAs) that are consistently identified from 1980-2010, excluding individuals who do not live in identified MSAs. Our dependent variables of interest include measures of employment and wages for native workers.

All measures of employment (e.g. foreign-born STEM workers, total city employment, etc.) are calculated from the "employment sample"˙This sample is restricted to non-institutionalized individuals between ages 18 and 65 (inclusive) who report positive weeks worked over the previous year. We further exclude individuals in military occupations, unidentified occupations, and occupations that cannot be consistently identified over time.[1] Additionally, because we

[1] Section 2.2 describes our efforts to create a time-consistent occupation classification scheme. Only four occupations cannot be subsumed into other larger occupational groupings so as to be identified consistently across our sample time frame.

distinguish natives and immigrants, we exclude individuals who we cannot categorize into either category (see section 2.1 for further clarification). To construct different measures of employment we calculate the weighted count of the number of workers in the appropriate group using IPUMS person weight.

All measures of wages are calculated from our "wage sample"Ṫo construct this sample we begin with the employment sample and only retain individuals who report positive wage and salary income over the previous year. Annual wage and salary incomes are converted to constant 2010 dollars using the BLS Inflation Calculator (`http://www.bls.gov/data/inflation_calculator.htm`). Our dependent variables are constructed by calculating each city's average weekly wages for the appropriate group (e.g. native college-educated, native non-college-educated, etc.). Weekly wages are calculated by dividing each individual's annual wage and salary income by their annual weeks worked. Weighted averages for the appropriate demographic group are taken within each MSA using IPUMS person weights.

2 Defining Groups, Industries, and Occupations

2.1 Demographic Groups

Demographic groups are defined by nativity and educational attainment. We classify workers as natives if they were born in the United States or born abroad to U.S. citizens. Persons born outside the U.S. to non-U.S. citizens are classified as foreign. Individuals that do not fall into these two groups–i.e. those without an identified place of birth–are removed from the analysis. Foreign workers are further classified into one of 14 aggregated foreign nationality groups based upon their country of birth. Those regions 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.

The analysis often groups workers by education level, which we measure according to the highest degree a person has attained. College-educated workers are those with a bachelor's degree or higher, and non-college-educated workers are those without a bachelor's degree. In part of our analysis, we also divide non-college-educated workers into those with less than a high school degree and those with at least a high school degree.

2.2 Time-Consistent Industries and Occupations

IPUMS modifies occupation and industry codes to provide time consistent classification schemes based upon the Census Bureau's 1990 occupation and industry categories. These harmonized codes facilitate data analysis over time. Our analysis requires a few additional adjustments to these codes.

First, we use our employment sample and refine the IPUMS 1990 occupational classification by examining the complete list of occupations available in each year of our analysis. Those occupations appearing in each year are called "time-consistent." Those not identified in all years are "time-inconsistent" and are recoded to the most similar time-consistent occupation. The refinement narrows the IPUMS 1990 occupational classification from 389 occupations to 331 time-consistent ones.

Occupations that are recoded as time-consistent are shown in Table A1. For example, "Mechanical engineering technicians" are only identified prior to 2000, whereas "Engineering technicians, n.e.c." are identified in all years. Thus, we recode "Mechanical engineering technicians" in the 1970, 1980, and 1990 Censuses as "Engineering technicians, n.e.c." There are only four occupations[2] in which no logical time-consistent matches were available, and thus we drop individuals with these occupations from the analysis.

We follow the same procedure for the IPUMS 1990 Industrial Classification. We replace industries that do not appear in all years of the sample with the most similar time-consistent industry code. All time-inconsistent industries are matched with the most similar time-consistent industry. This refinement narrows the number of industries from 243 to 212.

2.3 Defining STEM Occupations

Our key explanatory variable measures changes in foreign STEM workers over periods, standardized by total city employment at the beginning of the period. We use the employment sample and person weights to calculate the number of foreign-born workers in STEM occupations and total city employment (native & foreign) in each of the 219 MSAs. Unfortunately, there is no single definition of STEM occupations. We therefore create four distinct STEM classification schemes – using the employment sample detailed in Section 1 – that attempt to identify occupations that require workers to possess high STEM knowledge or skills. To do this we create two different measures of an occupation's STEM intensity. For each of the two STEM measures, we then choose two different cutoff values at which to separate STEM and non-STEM occupations.

The first measure of the STEM intensity of occupations is derived from the U.S. Department of Labor's O*NET database. O*NET provides a score measuring the importance of several dozen skills and abilities used in performing the job for each Standard Occupational Classification (SOC) occupation. We select four O*NET skills that involve STEM: "Mathematics in Problem Solving," "Science in Problem Solving," "Use of Technology Design," and "Programming."

We crosswalk the STEM skill scores from each SOC code to the more aggregated Census 2010 occupation code. Census occupation O*NET skill values initially represent the unweighted average of each SOC occupation's values within them, but are then rescaled so that values equal percentiles measuring the share of the labor force using less of the particular skill in 2010. We then take the weighted average of these percentiles within our refined time-consistent IPUMS 1990 occupational classification codes. Our ultimate STEM skill score simply equals the average of the four O*NET skill percentile variables discussed above. Finally, we rank occupations according to this STEM skill score and define the occupations comprising the top 4% (strict) or 8% (broad) of employment as STEM. We call these the O*NET 4% and O*NET 8% STEM occupation definitions.

The second measure of STEM occupational intensity is derived from information on college majors in the 2010 ACS (1% sample). For each occupation we calculate the share of all workers with bachelor's degrees in STEM fields. We then rank occupations according to

[2] Those occupations are Adjusters and Calibrators; Other Precision and Craft Workers; Other Telecom Operators; and Supervisors of Guards.

their share of workers with STEM college majors and choose those comprising 4% (strict) and 8% (broad) of employment in 2010 as STEM occupations. We call these the Major-Based 4% and Major-Based 8% STEM occupation definitions.

As there is no single definition of STEM occupations, there is also no single definition of STEM majors. We select a group of majors that are consistent with a list of designated STEM degree programs used by U.S. Immigration and Customs Enforcement (ICE).[3] There is no available crosswalk between ICE classified majors and the majors classified under the 2010 ACS. The list of STEM majors selected from the ACS is shown in Table A3.

3 Constructing the Instrument, Control Variables, and Data for Falsification Tests

3.1 H-1B Instrument

The H-1B driven instrument relies upon data from the U.S. Department of State on non-immigrant visa issuance by country of origin from 1997-2010 and total non-immigrant visa issuance data from 1990-2010. Though we refer to our instrument as an "H-1B-driven" variable, it also accounts for TN visa issuances. Like the H-1B, the TN (or NAFTA treaty) visa is awarded to workers in specialty occupations. However, the TN visa has no cap, is reserved for Canadian and Mexican workers, and has grown in popularity among citizens from those countries since 2004 when the H-1B cap reverted to 65,000 per year.

We use the employment sample to calculate the number of foreign workers in STEM occupations, by nationality, for each city, in 1980. We place individuals into the 14 aforementioned foreign nationality groups (n), each of which represents a source region accounting for a large share of H-1B visa issuances. Additionally, the H-1B issuances by country are also aggregated into the same 14 nationality groups. As detailed in the main paper, we calculate the aggregate growth in foreign STEM workers from 1980 to each year in our sample ($t =$1990, 2000, 2005, 2010) for each nationality. We first add the census inflows of foreign STEM workers of nationality n from 1980-1990 to the total number of H-1B visas issued to those nationalities from $1990 - t$. We then divide this number by the total U.S. stock of STEM workers from nationality n in 1980 to get the growth factor. Data on H-1B and TN visas issued by nationality are available each year beginning in 1997. Since we require total inflows from 1990, we have to impute the total number of visas issued from $1990 - t$, as detailed in the footnotes in Section 3.2 of the main paper.

Our instrument is formed by taking changes in these predicted values over our periods and standardizing by imputed initial city employment. This imputation avoids endogenous changes in total employment at the city level from affecting our instrument. To impute city employment we predict employment in cities for each of four separate demographic groups X (native college, native non-college, foreign college, and foreign non-college workers) using their initial city stocks in 1980 and interacting it with their national growth since 1980. We predict each city's number of workers $\left(\widehat{E_{c,t}^{X}}\right)$ of each demographic group X in years 1990,

[3] The ICE STEM major list is available at available here: http://www.ice.gov/sevis/stemlist.htm.

2000, 2005, and 2010 as $\widehat{E_{c,t}^X} = E_{c,1980}^X \left(\frac{E_t^X}{E_{1980}^X}\right)$, where $E_{c,1980}^X$ is city c's 1980 stock of group X workers, E_t^X is the national total number of workers of group X in year t, and E_{1980}^X is the national total number of group X workers in 1980. Next, we sum the four groups to obtain our imputed city employment $\left(\widehat{E_{c,t}}\right)$, which we then use to standardize changes in our instrument's city-level H-1B-driven predicted foreign STEM.

3.2 Controls and Data Used in Falsification Tests

Foreign Non-College Imputed Growth and Bartik Control Variables

Section 4.2 of the main paper describes the construction of our foreign non-college imputed growth and Bartik control variables. Here, we provide a few additional details. For the imputed growth in foreign non-college-educated workers, the variable is formed by taking changes (over the defined time-periods) in the predictions of non-college workers in cities, standardized by initial imputed city employment, $\widehat{E_{c,t}}$. For the Bartiks, note that they rely on variation in a city's workforce by industry. Bartik employment variables are constructed using the employment sample, and the Bartik wage variables are constructed using the wage sample. Section 2.2 provided further details about how we refined the industrial classification for time-consistency across all years of our sample. In constructing Bartiks we further refine the sample by removing individuals in military and unidentified industries.[4]

Aggregate H-1B Instrument: Kerr & Lincoln (2010)

One of the robustness tests we use to check the validity of our identification strategy is to construct the instrument without relying on variation across nationalities. This is similar to the method used in Kerr and Lincoln (2010). It addresses the concern that individual nationality groups may have specific location preferences that are affected by particular industries. That is, the presence of specific nationality groups and their subsequent growth may simply proxy for the success of particular industries. To avoid this issue, we construct an aggregate instrument by first interacting total foreign STEM in 1980 with H-1B-driven U.S. growth rates as follows,

$$\widehat{STEM_{c,t}^{FOR,agg}} = STEM_{c,1980}^{FOR} \left(\frac{\widehat{STEM_t^{FOR}}}{STEM_{1980}^{FOR}}\right)$$

In the above equation, $STEM_{c,1980}^{FOR}$ is the total number of foreign STEM workers in city c in 1980. This is multiplied by the national growth factor of foreign STEM since 1980, calculated as the ratio of the national H-1B-driven total foreign STEM workforce in year t ($\widehat{STEM_t^{FOR}}$) over the total foreign STEM workforce in 1980 ($STEM_{1980}^{FOR}$). $\widehat{STEM_t^{FOR}}$ is calculated by adding to the total foreign STEM workforce in 1980 ($STEM_{1980}^{FOR}$) the census inflow of total foreign STEM workers between 1980 and 1990, and the cumulative number of aggregate H-1B visas issued from 1990 to year t.

[4] Those in military and unidentified occupations are already omitted from the analysis entirely.

Instrument Falsification: Non-College Immigrant Flows

To check that it is truly fluctuations in H-1B visa policy that drive our instrument and not simply overall growth in labor demand (that itself is possibly driven by particular cities), we construct an instrument that uses aggregate non-college immigrant inflows instead of H-1B flows. We do this by interacting the city distribution of foreign STEM workers by nationality in 1980 with a growth factor that is calculated by adding the census inflow of foreign STEM workers of nationality n from 1980-1990 with the census inflow of non-college immigrants of nationality n from $1990 - t$. Specifically,

$$\frac{\widetilde{STEM}_t^{FORn,noncoll}}{STEM_{1980}^{FORn}} = \frac{STEM_{1980}^{FORn} + \Delta STEM_{1980-1990}^{FORn} + \Delta Noncoll_{1990-t}^{FORn}}{STEM_{1980}^{FORn}}$$

Notice that the above equation is quite similar to the construction of the main H-1B-driven instrument in Equation (3) of the main paper, but it replaces H-1B visas issued a nationality group ($\#ofH1B_{1990-t}^{FORn}$) with $\Delta Noncoll_{1990-t}^{FORn}$, the Census-measured inflow of non-college immigrants of that nationality.

To construct our falsification instrument we then multiply this growth factor by the 1980 distribution of foreign STEM, and sum across nationalities to obtain

$$\widetilde{STEM}_{c,t}^{FOR,nocoll} = \sum_{n=1,14} STEM_{c,1980}^{FORn} \left(\frac{\widetilde{STEM}_t^{FORn,noncoll}}{STEM_{1980}^{FORn}} \right)$$

Our falsification instrument is formed by taking changes of $\widetilde{STEM}_{c,t}^{FOR,nocoll}$ over periods and standardizing by the imputed initial city employment, $\widehat{E_{c,t}}$.

Instrument Falsification: Total Immigrant Flows

To further ensure our instrument is driven by H-1B policy fluctuations and not by overall labor demand growth, we construct another falsification variable that uses total immigrant inflows, net of H-1B inflows, rather than only non-college immigrant inflows. This is done by first calculating total immigrant inflows and netting out the number of H-1B visas issued,

$$\Delta Total_{1990-t}^{FORn,netH1B} = \Delta Total_{1990-t}^{FORn} - \#ofH1B_{1990-t}^{FORn}$$

We then calculate growth factors as before,

$$\frac{\widetilde{STEM}_t^{FORn,tot}}{STEM_{1980}^{FORn}} = \frac{STEM_{1980}^{FORn} + \Delta STEM_{1980-1990}^{FORn} + \Delta Total_{1990-t}^{FORn,netH1B}}{STEM_{1980}^{FORn}}$$

where we have replaced $\#ofH1B_{1990-t}^{FORn}$ in Equation (3) of the paper with $\Delta Total_{1990-t}^{FORn,netH1B}$, the Census-measured inflow of total immigrants of nationality n net of H-1B flows. We multiply this growth factor by the 1980 foreign STEM distribution across cities and sum over nationalities,

$$\widetilde{STEM}_{c,t}^{FOR,tot} = \sum_{n=1,14} STEM_{c,1980}^{FORn} \left(\frac{\widetilde{STEM}_t^{FORn,tot}}{STEM_{1980}^{FORn}} \right)$$

Our falsification instrument is formed by taking changes of $\widetilde{STEM}_{c,t}^{FOR,tot}$ over periods and standardizing by imputed initial city employment, $\widehat{E_{c,t}}$.

Instrument Falsification: 1980 Distribution of Immigrants in Manual Occupations

A third falsification test involves replacing the base year distribution of foreign STEM workers in the instrument with the distribution of foreign workers in manual occupations. We define manual occupations based on a measure of the manual-intensity of occupations used in Peri and Sparber (2009). In particular, Appendix Table A1 of Peri and Sparber (2009) lists 19 O*NET variables used to construct a "Basic Definition" of manual skills. We combine those O*NET variables into a single index of an occupation's manual skill intensity. We then define manual occupations as those among the top 8% manual-intensive occupations.[5]

To construct the instrument, we interact the 1980 city distribution of foreign manual occupation workers, by nationality, with the same national H-1B driven growth factors used to construct the main instrument.

$$\widetilde{STEM}_{c,t}^{FOR,manual} = \sum_{n=1,14} Manual_{c,1980}^{FORn} \left(\frac{\widehat{STEM_t^{FORn}}}{STEM_{1980}^{FORn}} \right)$$

In the above equation, $\left(\frac{\widehat{STEM_t^{FORn}}}{STEM_{1980}^{FORn}} \right)$ is the same as detailed in Equation (3) of the paper, while $Manual_{c,1980}^{FORn}$ is city c's total number of foreign workers of nationality n in a manual occupation in 1980. The instrument is then formed by taking changes of $\widetilde{STEM}_{c,t}^{FOR,manual}$ over periods and standardizing by initial imputed city employment, $\widehat{E_{c,t}}$.

4 A Model for Deriving Productivity and Skill-Bias Effects

4.1 Framework

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

[5] The procedure for defining the dichotomous manual occupation classification is analogous to the STEM occupation classification scheme outlined in Section 2.3.

production function in (1).

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

Input K is a composite factor combining college-educated and STEM workers such that:

$$K_{ct} = \left(ST_{ct}^{\frac{\sigma_S - 1}{\sigma_S}} + H_{ct}^{\frac{\sigma_S - 1}{\sigma_S}} \right)^{\frac{\sigma_S}{\sigma_S - 1}} \tag{2}$$

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

Physical capital is absent from (1). Instead we assume that capital mobility and the equalization of capital returns imply a constant capital-output ratio in the long run so that capital can be solved out of the production function. In this sense, the comparative static results that we find can be thought of as a comparison between long-run balanced growth paths.

STEM workers are the key inputs in developing and adopting new technologies, which are widely credited for increasing the productivity of college educated workers as well as increasing total factor productivity. Our modeling choices seek to capture these factors. We follow the literature on human capital externalities[6] and the growth of ideas (Jones (1995)) by allowing the level of total factor productivity, $A(ST_{ct})^{\frac{\sigma_H}{\sigma_H - 1}} > 0$, to be a function of the number of STEM workers in the city. If $A'(ST_{ct}) > 0$, STEM-driven innovation externalities have a positive effect on TFP. At the same time we allow for skill (college) biased productivity, $\beta(ST_{ct}) \in [0, 1]$, to depend upon the number of STEM workers. If $\beta'(ST_{ct}) > 0$, STEM-driven innovation externalities may have a college-biased effect on productivity. Even if STEM and college-educated workers are close substitutes in production ($\sigma_S \approx \infty$), STEM workers are uniquely capable of potentially generating ideas, innovation, and externalities that benefit productivity.

The main goal of the model is to identify the effect of STEM workers on TFP $\left(A^{\frac{\sigma_H}{\sigma_H - 1}}\right)$ and its college-bias $(\beta/(1 - \beta))$ in equilibrium. We proceed as follows. First we derive wages paid to each factor as their marginal product implied by the production function. Then we calculate the total logarithmic (percentage) change in wages for each group (non-college, college-educated, and STEM) in response to the changes in the supply of each type of worker (expressed as a percentage of total employment), allowing for mobility of workers and, hence, for changes in each group's supply in response to an exogenous change of STEM workers. Next, we divide each side of the three labor demand conditions (one for each type of worker) by the exogenous change of STEM workers expressed as a percentage of total employment. This gives us three linear conditions[7] relating, via the elasticity $b_{y,X}$, each group's wage and employment to supply of STEM (i.e., the coefficients $b_{y,X}$ estimated from Equation (1) in the main text).

[6] See Acemoglu and Angrist (2000), Iranzo and Peri (2009), and Moretti (2004).

[7] Equations (6)-(8) described below.

The advantage of this approach is that we have an intuitive and standard definition of TFP and SBP based on a city-specific production function. We can use it to infer the productivity impacts of STEM. Moreover, we can calculate these effects without specifying the labor supply-side of the model, which is affected by mobility and labor force participation, as long as we have the equilibrium elasticity for the employment of each factor to the exogenous change in STEM (which we estimated in Table 5). The limitations of this approach are its dependence on the specific assumptions on the production structure and on the form of the productive interactions between different types of labor.

4.2 Wages and Labor Demand System

We assume that each group of workers is paid their marginal product. Wages of each type of worker come from the first derivative of the production function (1) with respect to the employment of each group. This generates the following expressions (for brevity, we omit the subscripts and the dependence of A and β on ST):

$$w_L = A(1-\beta)Y^{\frac{1}{\sigma_H}}L^{-\frac{1}{\sigma_H}} \tag{3}$$

$$w_H = A\beta Y^{\frac{1}{\sigma_H}}K^{(\frac{1}{\sigma_S}-\frac{1}{\sigma_H})}H^{-\frac{1}{\sigma_S}} \tag{4}$$

$$w_{ST} = A\beta Y^{\frac{1}{\sigma_H}}K^{(\frac{1}{\sigma_S}-\frac{1}{\sigma_H})}ST^{-\frac{1}{\sigma_S}} \tag{5}$$

In equilibrium we observe simultaneous changes in wages and employment of each type of worker. Taking a total logarithmic differential of expressions (3)-(5) and writing all employment changes relative to total employment $(E = L + H + ST)$, the following three equations relate the equilibrium changes in employment and wages for non-college-educated, college-educated, and STEM workers:

$$\frac{\Delta w_L}{w_L} = \left(\phi_A - \frac{\beta}{1-\beta}\phi_B + \frac{s_w^{ST}}{\sigma_H s_E^{ST}}\right)\left(\frac{\Delta ST^{Foreign} + \Delta ST^{Native}}{E}\right) + \frac{s_w^{H}}{\sigma_H s_E^{H}}\frac{\Delta H}{E} + \left(\frac{s_w^{L}}{\sigma_H s_E^{L}} - \frac{1}{\sigma_H s_E^{L}}\right)\frac{\Delta L}{E} \tag{6}$$

$$\frac{\Delta w_H}{w_H} = \left(\phi_A + \phi_B + \frac{s_w^{ST}}{\sigma_H s_E^{ST}} + \left(\frac{1}{\sigma_S} - \frac{1}{\sigma_H}\right)\frac{s_w^{ST}}{s_w^K s_E^{ST}}\right)\frac{\Delta ST^{Foreign}}{E} + \left(\frac{s_w^{H}}{\sigma_H s_E^{H}} + \left(\frac{1}{\sigma_S} - \frac{1}{\sigma_H}\right)\frac{s_w^{H}}{s_w^K s_E^{H}} - \frac{1}{\sigma_S s_E^{H}}\right)\frac{\Delta H}{E} + \frac{s_w^{L}}{\sigma_H s_E^{L}}\frac{\Delta L}{E} \tag{7}$$

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

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

$$\phi_A = \frac{\Delta A/A}{\Delta ST/E}, \ \phi_\beta = \frac{\Delta\beta/\beta}{\Delta ST/E} \tag{9}$$

We use the equilibrium conditions (6)-(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 the estimated coefficients $b_{y,X}$ from the empirical Equation (1) in the main text. For instance the elasticity $\frac{\Delta w_L}{w_L}/\frac{\Delta ST^{Foreign}}{E}$ is the coefficient $b_{w,L}$ estimated 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 when the dependent variable is $\left(\frac{\Delta L}{E}\right)_{ct}$.

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

With the equilibrium response of wages and employment of each group to $STEM$ estimated in the text, and using census wage and employment data to calculate the shares s_w^X and s_E^X, equations (6)-(8) only depend on four unknown parameters: ϕ_A, ϕ_B, σ_S, and σ_H. We adopt estimates of the parameter σ_H from the extensive literature that estimates the elasticity of substitution between college and non-college-educated, and we use (6)-(8) and our elasticity estimates to obtain values for ϕ_A, ϕ_B and σ_S. The three equations are linear in ϕ_A, ϕ_B and $1/\sigma_S$.

4.3 Solving the Linear System to Obtain TFP and Skill Bias

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

$$\phi_A - \frac{\beta}{1-\beta}\phi_B = \widehat{b}_{w,L} - \frac{s_w^{ST}}{\sigma_H s_E^{ST}} \tag{10}$$

$$\phi_A + \phi_B = \widehat{b}_{w,H} - \frac{s_w^{ST}}{\sigma_H s_E^{ST}} - \left(\frac{1}{\sigma_S} - \frac{1}{\sigma_H}\right)\frac{s_w^{ST}}{s_w^K s_E^{ST}} \tag{11}$$

$$\frac{1}{\sigma_S} = s_E^{ST}\left(\widehat{b}_{w,NST} - \widehat{b}_{w,ST}\right) \tag{12}$$

The last equation immediately defines $1/\sigma_S$. This can be substituted into (10) and (11), thereby reducing them to simple linear equations in the two unknown parameters $\phi_A$and ϕ_B. By solving them we obtain the following solutions:

$$\phi_A = \beta T_1 + (1-\beta) T_2 \tag{13}$$

$$\phi_B = (1-\beta)(T_1 - T_2) \tag{14}$$

Where:

$$T_1 = \widehat{b}_{w,H} - \frac{s_w^{ST}}{\sigma_H s_E^{ST}} - \left(\frac{1}{\sigma_S} - \frac{1}{\sigma_H}\right) \frac{s_w^{ST}}{s_w^K s_E^{ST}} \tag{15}$$

$$T_2 = \widehat{b}_{w,L} - \frac{s_w^{ST}}{\sigma_H s_E^{ST}} \tag{16}$$

4.4 Estimated Productivity Effects

Our simulation alternatively uses σ_H values of 2, 1.75, and 2.25. Note that the literature typically estimates σ_H to fall between 1.5 and 2.5.[8] Our empirical model provides an estimate of σ_S , the elasticity of substitution between STEM and non-STEM college-educated labor in production. That elasticity is always very high and statistically non distinguishable from infinity ($1/\sigma_S$ is not significantly different from 0). This is because our estimates of the elasticity of college-educated wages and STEM wages to STEM supply are always very close to each other, implying high substitutability between the two groups. Finally, by substituting the estimated ($\widehat{b}_{y,X}$) elasticities of outcomes y for group X into the model, we can simulate the effects on the growth of TFP and SBP. These results are presented in Table 8 of the main text.

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

References

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ONLINE APPENDIX TABLES

Table A1: Time-Consistent Occupations

Original (Time-Inconsistent) Occupation	**Replacement (Time-Consistent) Occupation**
Fabricating machine operators, n.e.c.	Assemblers of electrical equipment
Cost and rate clerks (financial records processing)	Billing clerks and related financial records processing
Legislators	Chief executives and public administrators
Tailors	Dressmakers and seamstresses
Electrical and electronic (engineering) technicians	Engineering technicians, n.e.c.
Mechanical engineering technicians	Engineering technicians, n.e.c.
Technicians, n.e.c.	Engineering technicians, n.e.c.
Marine life cultivation workers	Farm workers
Farm managers, except for horticultural farms	Farmers (owners and tenants)
Horticultural specialty farmers	Farmers (owners and tenants)
Managers of horticultural specialty farms	Farmers (owners and tenants)
Water transport infrastructure tenders and crossing guards	Freight, stock, and materials handlers
Stenographers	General office clerks
Production checkers and inspectors	Graders and sorters in manufacturing
Nursery farming workers	Graders and sorters of agricultural products
Private household cleaners and servants	Housekeepers, maids, butlers, stewards, and lodging quarters cleaners
Materials movers: stevedores and longshore workers	Laborers outside construction
Stock handlers	Laborers outside construction
Judges	Lawyers
Postmasters and mail superintendents	Managers and administrators, n.e.c.
Statisticians	Mathematicians and mathematical scientists
Crushing and grinding machine operators	Mixing and blending machine operatives
Shaping and joining machine operator (woodworking)	Nail and tacking machine operators (woodworking)

Duplication machine operators / office machine operators	Office machine operators, n.e.c.
Other precision woodworkers	Other woodworking machine operators
Hand painting, coating, and decorating occupations	Painting machine operators
Information clerks, nec	Receptionists
Office machine repairers and mechanics	Repairers of data processing equipment
Tinsmiths, coppersmiths, and sheet metal workers	Sheet metal duct installers
Sociologists	Social scientists, n.e.c.
Biological science instructors	Subject instructors (HS/college)
Chemistry instructors	Subject instructors (HS/college)
Earth, environmental, and marine science instructors	Subject instructors (HS/college)
Economics instructors	Subject instructors (HS/college)
Education instructors	Subject instructors (HS/college)
Engineering instructors	Subject instructors (HS/college)
History instructors	Subject instructors (HS/college)
Home economics instructors	Subject instructors (HS/college)
Law instructors	Subject instructors (HS/college)
Math instructors	Subject instructors (HS/college)
Physics instructors	Subject instructors (HS/college)
Psychology instructors	Subject instructors (HS/college)
Sociology instructors	Subject instructors (HS/college)
Theology instructors	Subject instructors (HS/college)
Teacher's aides	Teachers , n.e.c.
Photoengravers and lithographers	Typesetters and compositors
Printing machine operators, n.e.c.	Typesetters and compositors
Other precision apparel and fabric workers	Upholsterers
Food counter and fountain workers	Waiter's assistant
Solderers	Welders and metal cutters
Lay-out workers	Wood lathe, routing, and planing machine operators
Adjusters and calibrators	*No clear match*
Other precision and craft workers	*No clear match*
Other telecom operators	*No clear match*
Supervisors of guards	*No clear match*

Table A2: STEM Occupation Classifications

Occupation	ONET 4%	ONET 8%	Major 4%	Major 8%
Accountants and auditors		X		
Actuaries	X	X	X	X
Aerospace engineer	X	X	X	X
Agricultural and food scientists	X	X	X	X
Airplane pilots and navigators				X
Architects		X		
Atmospheric and space scientists			X	X
Biological scientists	X	X	X	X
Biological technicians				X
Chemical engineers	X	X	X	X
Chemical technicians		X		X
Chemists	X	X	X	X
Chief executives and public administrators		X		
Civil engineers	X	X	X	X
Clinical laboratory technologies and technicians				X
Computer software developers	X	X	X	X
Computer systems analysts and computer scientists	X	X		X
Dentists			X	X
Dietitians and nutritionists		X		X
Drafters		X		
Economists, market researchers, and survey researchers	X	X		
Electrical engineer	X	X	X	X
Engineering technicians, n.e.c.	X	X		
Foresters and conservation scientists		X		
Geologists	X	X	X	X
Human resources and labor relations managers		X		
Industrial engineers	X	X	X	X
Management analysts				X
Mathematicians and mathematical scientists	X	X		X
Mechanical engineers	X	X	X	X
Medical scientists	X	X	X	X

Metallurgical and materials engineers, variously phrased	X	X	X	X
Not-elsewhere-classified engineers	X	X	X	X
Occupational therapists			X	X
Operations and systems researchers and analysts	X	X		
Optometrists	X	X	X	X
Other health and therapy			X	X
Other science technicians		X		
Petroleum, mining, and geological engineers	X	X	X	X
Pharmacists			X	X
Physical scientists, n.e.c.	X	X	X	X
Physical therapists			X	X
Physicians			X	X
Physicians' assistants				X
Physicists and astronomers	X	X	X	X
Podiatrists	X	X	X	X
Programmers of numerically controlled machine tools	X	X		
Psychologists			X	X
Respiratory therapists		X		
Sales engineers	X	X	X	X
Social scientists, n.e.c.				X
Speech therapists		X	X	X
Statistical clerks		X		
Subject instructors (HS/college)				X
Supervisors of mechanics and repairers		X		
Surveyors, cartographers, mapping scientists and technicians	X	X		
Therapists, n.e.c.				X
Urban and regional planners		X		
Veterinarians			X	X
Vocational and educational counselors				X

Note: The listed occupations are consistent with the IPUMS variable occ1990, a modified version of the 1990 Census Bureau occupational classification scheme.

Table A3: STEM College Majors, 2010 ACS

Aerospace Engineering	Industrial and Manufacturing Engineering
Animal Sciences	Industrial and Organizational Psychology
Applied Mathematics	Industrial Production Technologies
Architectural Engineering	Information Sciences
Astronomy and Astrophysics	Library Science
Atmospheric Sciences and Meteorology	Materials Engineering and Materials Science
Biochemical Sciences	Materials Science
Biological Engineering	Mathematics
Biology	Mathematics and Computer Science
Biomedical Engineering	Mechanical Engineering
Botany	Mechanical Engineering Related Technologies
Chemical Engineering	Medical Technologies Technicians
Chemistry	Metallurgical Engineering
Civil Engineering	Microbiology
Clinical Psychology	Military Technologies
Cognitive Science and Biopsychology	Mining and Mineral Engineering
Communication Disorders Sciences and Se	Miscellaneous Biology
Computer and Information Systems	Miscellaneous Engineering
Computer Engineering	Miscellaneous Engineering Technologies
Computer Information Management and Security	Miscellaneous Psychology
Computer Networking and Telecommunication	Molecular Biology
Computer Programming and Data Processing	Multi-disciplinary or General Science
Computer Science	Naval Architecture and Marine Engineering
Counseling Psychology	Neuroscience
Ecology	Nuclear Engineering
Educational Psychology	Nuclear, Industrial Radiology, and Biology
Electrical Engineering	Nutrition Sciences
Electrical Engineering Technology	Oceanography
Engineering and Industrial Management	Petroleum Engineering
Engineering Mechanics, Physics, and Sci	Pharmacology
Engineering Technologies	Pharmacy, Pharmaceutical Sciences, and
Environmental Engineering	Physical Sciences
Environmental Science	Physics
Family and Consumer Sciences	Physiology
Food Science	Plant Science and Agronomy
General Engineering	Psychology
General Medical and Health Services	Social Psychology
Genetics	Soil Science
Geological and Geophysical Engineering	Statistics and Decision Science
Geology and Earth Science	Transportation Sciences and Technologies
Geosciences	Treatment Therapy Professions
Health and Medical Preparatory Programs	Zoology