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High-Skilled Immigration, STEM Employment, and Nonroutine-Biased Technical Change

Nir Jaimovich and Henry E. Siu

5.1 Introduction

Immigration has constituted an important source of growth in high-skilled employment, innovation, and productivity in the United States during the past thirty-five years. In this chapter, we study the role of this immigration in accounting for changes in the occupational-skill distribution and wage inequality experienced during this time period.

There is a growing body of empirical work studying the labor market implications of high-skilled immigration. Most of this work focuses on the impact on employment outcomes for other high-skilled workers and, specifically, whether there is "crowding out" or displacement of the native born. Though methodological approaches differ across studies, a rough summary of the literature is that there is mixed or little evidence that such displacement exists.[1] However, as noted by Kerr (2013), much less is known about

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1. See Hunt and Gauthier-Loiselle (2010), Kerr and Lincoln (2010), and Peri, Shih, and Sparber (2015). Kerr (2013) provides a very useful overview of the literature on immigration, high-skilled labor markets, and innovation. In recent work, Doran, Gelber, and Isen (2016) find evidence of crowding out among high-skilled workers at the firm level. It should be noted that firm-level effects do not necessarily extend to the aggregate level that we are interested in here. See also Borjas and Doran (2015) and Bound et al. (2015) for analyses of mathematicians and computer scientists, respectively.

the long-run and general-equilibrium impacts of high-skilled immigration on the US labor market. The aim of this chapter is to contribute on this dimension and provide a quantitative theoretic framework in which such questions can be addressed.

The starting point of our analysis, as documented in section 5.2 and by Hanson and Slaughter (2016), is the fact that high-skilled immigrants represent a large and growing share of employment in *STEM occupations*—fields related to research, development, and innovation which are key to productivity growth and technological progress. As such, these high-skilled immigrants and foreign-born innovators contribute disproportionately to US growth. As we show in section 5.2, the likelihood of high-skilled immigrants working in a STEM occupation has increased over time, while this likelihood has remained essentially constant for the native born. This differential change is not due simply to differences in demographic change between native- and foreign-born workers; rather, relative to native-born, high-skilled workers, the foreign born have either experienced a much larger change in their propensity to work in STEM occupations conditional on (observable) demographic characteristics, or there has been an important change in unobservable characteristics of the foreign born, or both.

During the same time of increased high-skilled immigration, the economy has experienced technical change that is *nonroutine biased*, allowing technology to substitute for labor in performing "routine tasks" during the past thirty-five years.[2] Given this, we present in section 5.3 a unified framework of endogenous nonroutine-biased technical change (NBTC) with both native- and foreign-born workers. In the model, workers face an occupational choice between employment in production or innovation jobs. As such, NBTC is the outcome of purposeful activity, namely, the equilibrium allocation of workers to innovation. These elements of the model provide a framework to simultaneously assess the general-equilibrium implications of high-skilled immigration and changes in occupational sorting documented in section 5.2.

In section 5.4, we discuss the calibration and quantitative specification of the model. We then use the model to quantify the role of high-skilled immigration on nonroutine-biased technical change, its associated polarization of employment opportunities, and the evolution of wage inequality since 1980. We find that, contrary to expectation, high-skilled immigration has contributed to a narrowing of wage inequality.

2. While others have referred to this process as "routine-biased" technical change (see, e.g., Goos, Manning, and Salomons 2014; Autor, Dorn, and Hanson 2015), we depart from the literature and use the term nonroutine biased. This is in keeping with the use of terminology in the literature on skill-biased technical change (see, e.g., Violante 2008) in which recent technological progress has benefited skilled (versus unskilled) workers. As argued here and in the literature on *job polarization* (discussed below), recent technical change has benefited workers in nonroutine (versus routine) occupations.

Table 5.1 **High-skilled employment by occupational group**

	1. Total		2. NRC		3. STEM	
	1980	2010	1980	2010	1980	2010
Foreign born	1,368	7,061	951	4,948	172	1,063
Native born	16,283	34,973	11,933	25,256	1,238	2,653
Foreign-born share						
Employment	0.078	0.168	0.074	0.164	0.122	0.286
Employment growth (%)	23.3		23.1		38.6	

Source: Data from 1980 census and 2010 American Community Survey. See text for details.
Notes: Employment among twenty to sixty-four-year-olds with ≥ four years of college/bachelor's degree, in thousands.

5.2 Empirical Facts

5.2.1 Immigration and High-Skilled Employment

According to the US Census Bureau, the foreign-born share of the population has more than doubled between 1980 and 2010, from 6.2 percent to 12.9 percent (see Grieco et al. 2012). As a result, the foreign-born share of high-skilled employment has increased as well. In table 5.1, we present evidence of this using the 5 percent sample of the 1980 decennial census and the 1 percent sample of the 2010 American Community Survey (ACS), made available by IPUMS (see Ruggles et al. 2010). We restrict attention to the twenty- to sixty-four-year-old (or "working age") population. Given differences in the questionnaire, we define *high-skilled* workers as those with at least four years of college in the 1980 census, and those with at least a bachelor's degree in the 2010 ACS.[3]

Evidently, high-skilled, foreign-born employment increased by 5.7 million workers during this period. As a fraction of total high-skilled employment (*in levels*), the foreign-born share increased from 7.8 percent in 1980 to 16.8 percent in 2010, mirroring the proportional increase in the overall population. The bottom row of column (1), table 5.1 indicates that, of the total *growth* in high-skilled employment, approximately 23 percent is accounted for by the foreign born.

Among high-skilled workers, employment is concentrated within certain occupations. To illustrate this, we adopt the classification system used in the job-polarization literature that documents changes in the occupational-employment distribution since the 1980s (see, e.g., Acemoglu and Autor 2011; Cortes et al. 2015). We delineate occupations along two dimensions—

3. For highly related results to those presented in this subsection and the next, see Hanson and Slaughter (2016) who provide more detailed analysis disaggregated by educational attainment and occupation, analysis of wages and earnings, and discussion on the H-1B visa program and means of entry.

"cognitive" versus "manual" and "routine" versus "nonroutine"—based on the skill content of tasks performed on the job. The distinction between cognitive and manual jobs is based on the extent of mental versus physical activity. The distinction between routine and nonroutine occupations is based on the work of Autor, Levy, and Murnane (2003). If the tasks involved can be summarized as a set of specific activities accomplished by following well-defined instructions and procedures, the occupation is considered routine. If instead the job requires mental or physical flexibility, problem solving, or human-interaction skills, the occupation is nonroutine.

High-skilled employment is concentrated in *nonroutine cognitive* (NRC) occupations. Not surprisingly, these jobs occupy the upper tail of the occupational wage distribution (see, e.g., Goos and Manning 2007; Acemoglu and Autor 2011). This is true of both native- and foreign-born workers. The second set of columns of table 5.1 display these employment figures.[4] Among the foreign born, 951 ÷ 1,368 = 69.5 percent of high-skilled individuals worked in a nonroutine cognitive occupation in 1980. This has held remarkably constant over time, at 70.1 percent in 2010. Similarly, approximately 72 percent of high-skilled, native-born workers work in NRC occupations in both 1980 and 2010.[5]

This occupational concentration, coupled with increasing immigration, implies that the foreign-born share of nonroutine cognitive employment has risen over time. This share increased from 7.4 percent in 1980 to 16.4 percent in 2010, closely mirroring the proportional increase observed in high-skilled employment and population. Of the total increase in nonroutine cognitive employment, approximately 23 percent is accounted for by the foreign born.

While the sorting of high-skilled workers into nonroutine cognitive occupations is similar between the native and foreign born, sorting into jobs *within* this broad occupational group differ in important ways. High-skilled, foreign-born workers tend to work in occupations with a quantitative emphasis, whereas the native born specialize in occupations emphasizing communication and interpersonal skills (see, e.g., Chiswick and Taengnoi 2007; Hunt and Gauthier-Loiselle 2010; Peri and Sparber 2011). This is evident in the native- and foreign-born representation in the subset of nonroutine cognitive occupations related to STEM fields: science, technology, engineering, and mathematics, displayed in the third set of columns of table 5.1.[6]

4. In our analysis, nonroutine cognitive jobs correspond to those under the categories of management, business and financial operations, and professional occupations in the 2010 Standard Occupational Classification. See Cortes et al. (2015) for a more detailed discussion, as well as how occupation codes are linked across the 1980 and 2010 classification systems.

5. Perhaps unsurprisingly, the approximately 30 percent of the high skilled not working in NRC jobs is concentrated in the young. For instance, the fraction of twenty- to twenty-four-year-old high-skilled workers employed in a nonroutine cognitive occupation is only 57 percent.

6. In particular, we define STEM jobs as those listed under computer and mathematical, architecture and engineering, and life and physical science occupations, a subset within the professional occupation category in the 2010 Standard Occupational Classification.

While the foreign born accounted for 7.4 percent of employment in nonroutine cognitive jobs in 1980, they represented 12.2 percent of employment in STEM occupations. In 2010, high-skilled, foreign-born workers account for 28.6 percent of STEM employment, an increase of a factor of approximately 2.5. Of the total increase in STEM employment in the United States between 1980 and 2010, approximately 39 percent is accounted for by the foreign born (see also Kerr and Lincoln 2010).[7] Finally, as discussed in the literature, such occupations are closely related to innovation, research and development (R&D), and thus, technological progress; as such, high-skilled immigration has played an important role in the output of these occupations as indicated by statistics on patenting, high-tech start-ups, and other measures (see, e.g., Hunt and Gauthier-Loiselle [2010]; Hunt [2011]; Peri [2012]; Kerr [2013] and the references therein).

5.2.2 Nativity Differences in STEM Employment

In this subsection, we take a closer look at occupational sorting among high-skilled workers. Our interest is in the tendency to work in STEM occupations—how this differs between the native and foreign born, and how this difference has changed over time. Panel A of table 5.2 presents the fraction of high-skilled workers who are employed in a STEM occupation; panel B presents the fraction, conditional on being employed in a nonroutine cognitive occupation. The basic data are taken from table 5.1.

From the perspective of nativity, it is clear that the foreign born are more likely to work in STEM occupations than the native born. For instance, the fraction of high-skilled workers employed in STEM is 5.0 percentage points greater in 1980 (12.6 percent versus 7.6 percent); similarly, conditional on being a nonroutine cognitive worker, the likelihood of being a STEM worker is 7.7 pp greater. As a point of comparison, the tendency for high-skilled workers born in either India or China to work in STEM is approximately three times that of the native born.

Over time this difference has become more pronounced. Consider the tendency of the high skilled to work in STEM, conditional on either employment in any occupation, or in a nonroutine cognitive occupation. As the third column in table 5.2 makes clear, this tendency has remained essentially constant for the native born between 1980 and 2010. By contrast, the fraction of foreign-born workers in STEM has increased by 2.5 pp in panel A and 3.4 pp in panel B. As such, the foreign-born tendency toward STEM employment is now twice that of native-born workers.[8]

This differential change in tendency is not due simply to differences in

7. Interestingly, about 21 percent of the total increase in STEM employment in the United States is accounted for by the source countries of India and China alone.

8. See also Peri and Sparber (2011), who find that the occupational choice among native-born "job switchers" is affected by the foreign-born worker share. This is consistent with our findings on differential trends in sorting into STEM and Kerr, Kerr, and Lincoln (2013), who study the impact of skilled immigrants on the employment structures of US firms.

Table 5.2 **High-skilled employment in STEM occupations**

	1980	2010	Change	Unexplained
A. Per worker (%)				
Native born	7.6	7.6	+0.0	+0.4
Foreign born	12.6	15.1	+2.5	+5.3
India & China	23.6	30.6	+7.0	+13.7
B. Per NRC worker (%)				
Native born	10.4	10.5	+0.1	+1.1
Foreign born	18.1	21.5	+3.4	+7.2
India & China	30.5	38.0	+7.5	+13.0

Source: Data from 1980 census and 2010 American Community Survey. See text for details.
Notes: Employment among twenty- to sixty-four-year-olds with ≥ four years of college/bachelor's degree, in thousands.

observable demographic change between native- and foreign-born workers. To see this, let π_{it} be a dummy variable that takes on the value of 1 if individual *i* works in a STEM occupation and 0 otherwise (conditional on either employment or employment in a nonroutine cognitive job). We consider a simple linear probability model for working in STEM:

$$\pi_{it} = X_{it}\beta + \varepsilon_{it}, \tag{1}$$

for $t \in \{1980,2010\}$. Here, X_{it} denotes standard demographic characteristics of individual *i* that can be observed in the census and ACS: age, gender, marital status, and an indicator for whether the worker has greater than college education.[9] The fractions of STEM workers presented in the first two columns of table 5.2 are simply the sample averages:

$$\frac{1}{N}\sum_{i}^{N}\pi_{it} = \bar{\pi}_t. \tag{2}$$

As such, the change in tendency reported in the third column of table 5.2, $\bar{\pi}_{2010} - \bar{\pi}_{1980}$, can be decomposed into a component that is "explained" by differences in observables, and an "unexplained" component owing to changes in coefficients, β, over time (see Oaxaca 1973; Blinder 1973). We perform this Oaxaca-Blinder decomposition separately for the native- and foreign-born samples.

The final column of table 5.2 presents the estimated unexplained component.[10] In all cases, the unexplained component is greater than the actual, observed change.[11] As a result, the changes observed in the data are *not* due

9. That is, we control for whether the worker has five or more years of college in the 1980 census and either a master's, professional, or doctoral degree in the 2010 ACS.

10. We implement this from a pooled regression over both time periods. Results in which coefficient estimates are obtained for either the 1980 or 2010 period are essentially unchanged.

11. This is due primarily to the fact that the explained component is dominated by the increasing female share of high-skilled employment. Since men are more likely to work in STEM jobs, this change implies that the contribution of the demographic change is negative.

to the explained component. In addition, as with the observed change in the third column, the native and foreign born differ in terms of the magnitude of the unexplained effect. For instance, in panel A the effect is an order of magnitude larger for the foreign born. Hence, relative to native-born, high-skilled workers, the foreign born have either experienced a much larger change in their propensity to work in STEM occupations or there has been an important change in unobservable characteristics of the foreign born, or both. For instance, conditional on having at least a college education, the quality of immigrants' education or their fields of study or college major may have changed (more than among the native born) over time. Unfortunately, this type of information is not available in the census. Perhaps more importantly, the type of visa with which immigrants first entered the United States may have changed since 1980. This is particularly relevant given the expansion of the H-1B visa program (see Hunt [2011] for further discussion).

To summarize, the tendency of the foreign born to work in STEM occupations has increased since 1980, while the tendency of high-skilled native born has not. Moreover, this relative increase is unexplained by observable demographic change.

5.2.3 Nonroutine-Biased Technical Change

As discussed above, STEM occupations are those involved with R&D, innovation, and technical change. We discuss in this subsection the fact that technical change since the 1980s has been *nonroutine biased* in nature. That is, in the past thirty years, advances in information and communication technology, robotics, and automation has allowed technology embodied in machinery, equipment, and software to substitute for labor in performing routine tasks. A growing body of literature documents the prevalence of nonroutine-biased technical change (NBTC) in the United States and other industrialized economies.[12]

This literature argues that NBTC resulted in a stark change in the occupational-skill distribution of employment. Industrialized economies have experienced *job polarization*: the labor market has become polarized, with employment share shifting away from middle-skill, routine occupations, toward both the high- and low-skill tails of the distribution. To illustrate this, figure 5.1 replicates a figure from Jaimovich and Siu (2012). Each bar represents the percent change in an occupational group's share of total employment. Over time, the share of employment in high-skill (nonroutine cognitive) and low-skill (nonroutine manual) jobs has been growing. This has been accompanied by a hollowing out of the middle-skill, routine occupations. In 1982, routine occupations accounted for approximately 56 per-

12. See, for instance, Autor, Levy, and Murnane (2003), Violante (2008), Firpo, Fortin, and Lemieux (2011), Acemoglu and Autor (2011), Goos, Manning, and Salomons (2014), Levy and Murnane (2014), and Jaimovich and Siu (2015).

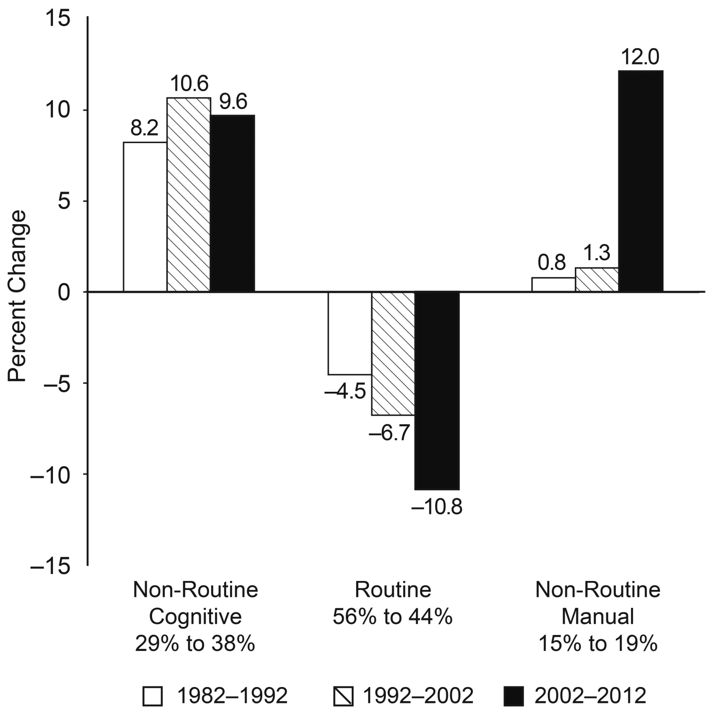

Fig. 5.1 Percent change in employment shares by occupation group
Source: Data from the Current Population Survey, BLS. See Jaimovich and Siu (2012) for details.

cent of total employment; in 2012, this share has fallen to 44 percent. Hence, according to this literature, NBTC has led to a polarization in employment away from routine, middle-skill occupations toward nonroutine cognitive and manual jobs.

5.3 Model

Motivated by the findings of section 5.2, we consider a simple model of endogenous NBTC. Nonroutine-biased technology is modeled as technology that is substitutable with routine labor in production. Advances in this technology are the outcome of employment devoted to innovation activities.

A key element to the model is occupational choice. There are two types of individuals in the economy: low skilled and high skilled. Given the data presented in section 5.2, high-skilled individuals work in nonroutine cognitive occupations. For the sake of exposition, we refer to their choice as either working as *innovators* (in STEM occupations) in the production of technology, or as *managers* (in other nonroutine cognitive jobs) in the production of goods. Low-skilled individuals choose to work in either *routine* or *service* occupations (both of which produce goods).

In section 5.4, we use this model to quantify the impact of high-skilled immigration, and the increasing tendency of immigrants to work in innovation, on the pace of NBTC and labor market outcomes.

5.3.1 Production

Industrial Structure

The model features three sectors of production. In the first sector, perfectly competitive, price-taking firms produce gross output (Y) using a Cobb-Douglas function in "managerial tasks" and "routine tasks." Managerial tasks are derived from labor input of managers, L_M. Routine tasks are derived from routine labor input, L_R, and *automation technology*, A. Specifically,

$$Y = (zL_M)^{\alpha}[\lambda A^{\rho} + (1-\lambda)(zL_R)^{\rho}]^{(1-\alpha)/\rho}, \ \rho < 1. \tag{3}$$

Here, z represents labor-augmenting technology, which grows exogenously at the rate $g \geq 0$. By contrast, growth in the automation technology is endogenous to purposeful innovation activities as described below. The degree of substitutability between automation technology and routine labor is governed by ρ: as $\rho \to 1$, the two factors approach perfect substitutes.

The input of automation technology is composed of intermediate goods, x_i, with measure n, and a fixed factor $\bar{F}$ according to[13]

$$A = \bar{F}^{1-\sigma} \int_0^n x_i^{\sigma} \, di, \ 0 < \sigma < 1. \tag{4}$$

We note that this specification of production is related to other work on nonroutine-biased technical change.[14]

The second sector produces intermediate goods, x. We consider a Romer-style (1990) model in which growth is driven by innovation that expands the variety of intermediate inputs. We assume that the innovator of a specific variety of input owns a permanent patent on the production of its associated intermediate good. Each unit of intermediate good is produced with η units of gross output.

In the third sector, perfectly competitive, price-taking firms produce output as a linear function of labor input into service occupations: L_S units of service labor input produce $w_S L_S$ units of output. Finally, to complete the description of production, we note that gross output is either consumed or used as an input in the production of x.

13. The fixed factor is included simply for technical reasons, namely, to ensure that production of Y is homogeneous of degree one in factor inputs L_M, L_R, $\bar{F}$, and x_i for all $i \in [0,n]$.

14. See, for example, Jung and Mercenier (2014) and Acemoglu and Restrepo (2015), as well as Caselli (2015), who studies the effects of experience-biased technical change.

Optimization

Normalizing the price of output to one, the first-order conditions for profit maximization in the first sector provide expressions for wage rates on managerial and routine labor, the rental rate on the fixed factor, and the price of intermediate inputs, respectively:

(5) $$w_M = \alpha Y L_M^{-1}$$

(6) $$w_R = (1-\alpha) Y \Omega (1-\lambda) z^{\rho} L_R^{\rho-1}$$

(7) $$r = (1-\alpha) Y \Omega \lambda (1-\sigma) \bar{F}^{(1-\sigma)\rho-1} \left[\int_0^n x_i^{\sigma} di \right]^{\rho}$$

(8) $$p_i = (1-\alpha) Y \Omega \lambda \bar{F}^{(1-\sigma)\rho} \left[\int_0^n x_i^{\sigma} di \right]^{\rho-1} \sigma x_i^{\sigma-1},$$

where $\Omega = [\lambda A^{\rho} + (1-\lambda)(zL_R)^{\rho}]^{-1}$.

In the intermediate goods sector, the per-period profit earned by the innovator of input variety i is $\pi_i = (p_i - \eta)x_i$. Substituting in equation (8), the first-order condition (FOC) is given by

(9) $$x_i = \left(\frac{\sigma\Phi}{\eta} \right)^{1/(1-\sigma)},$$

where $\Phi = (1-\alpha) Y \Omega \lambda \bar{F}^{(1-\sigma)\rho} \left[\int_0^n x_i^{\alpha} di \right]^{\rho-1} \sigma$. In a symmetric equilibrium, denote $x_i \equiv x$ for all i. Substituting equation (9) into equation (8) and the definition of profit yields that the price is a constant markup over marginal cost:

(10) $$p_i = \frac{\eta}{\sigma} \equiv p,$$

and that profits are given by

(11) $$\pi_i = (1-\sigma)\Phi^{1/(1-\sigma)} \left(\frac{\sigma}{\eta} \right)^{\sigma/(1-\sigma)} \equiv \pi.$$

In the third sector, given the linearity of the production function, optimizing behavior implies that the productivity parameter in this sector, w_S, is equal to the service-occupation wage. We assume that w_S grows exogenously at the rate g.

Differential Effects of NBTC

Having characterized optimal demand for the various factors of production, we note the following. The marginal product of routine labor (MPL_R) is given by the right-hand side of equation (6). As such,

(12) $$\text{sign}\left(\frac{\partial MPL_R}{\partial A} \right) = \text{sign}(1-\alpha-\rho).$$

Hence, an increase in automation technology shifts the "demand curve" for routine labor *down* whenever $\rho > 1 - \alpha$. This condition captures the effect of the substitution between automation technology and routine labor, and the degree of the diminishing returns to the "routine tasks" composite. To see this, consider the extreme case where production is linear in routine tasks, i.e. $\alpha = 0$: for every $\rho < 1$, an increase in A increases the marginal productivity of routine labor. More generally, when the composite exhibits diminishing returns (when $\alpha > 0$), there is a smaller set of ρ values for which this is true.

Moreover, given the Cobb-Douglas functional form of (3), managerial labor and routine tasks are complementary. Thus, we consider an economy where the effects of automation-technology growth are differential: all else equal, it decreases the marginal productivity of routine workers while increasing the marginal productivity of managers, when $\rho > 1 - \alpha$.

5.3.2 Households

The economy is populated by a representative household. The household is composed of a continuum of individuals, which we refer to as "workers." Each worker supplies one unit of labor inelastically. Within the household, *native-born* workers are of measure μ^{nat}, and *foreign-born* workers are of measure μ^{for}. There are two types of native-born workers: high skilled and low skilled; we let ϕ denote the share of high-skilled native born. For simplicity, given our interest in high-skilled immigration, we assume that all foreign born are high skilled.

Low-skilled workers can be employed in either a routine occupation or a service occupation. Low-skilled workers differ in their routine work ability, u, which is distributed $Y(u)$. By contrast, they are identical in their service-occupation ability, which we normalize to unity. Given the date t wage per unit of (effective) routine labor, w_{Rt}, a worker with ability u earns $u \times w_{Rt}$ employed in the routine occupation. Alternatively, workers earn w_{St} employed in the service occupation, regardless of u. Hence, it is optimal for the household to allocate all low-skilled workers with $u < u_t^*$ to employment in the service occupation, where

$$u_t^* w_{Rt} = w_{St}. \tag{13}$$

All workers with $u \geq u_t^*$ are allocated to routine work. We denote $s_t^{lo} = \Upsilon(u_t^*)$ as the fraction of low-skilled (native-born) workers employed in the service occupation.[15]

15. Note that we have specified workers as supplying labor inelastically; workers do not face a labor-leisure trade-off, nor do they face the possibility of nonemployment. As such, job polarization—generated by our experiments in the following section—is a result of changes in occupational sorting among low-skilled workers. Any decline in routine employment is reflected as a rise in the number of workers allocated to the service occupation. An alternative would be to introduce an explicit possibility of nonemployment for low-skilled workers. See Cortes, Jaimovich, and Siu (2016) for a model of exogenous NBTC where workers choose between nonemployment, employment in service jobs, and employment in routine jobs.

High-skilled workers work either as managers or innovators. While they are identical in their ability as managers (which we normalize to unity), high-skilled workers differ in their innovation ability, a. This ability is distributed $\Gamma(a)$. For simplicity, we assume this is true of both the native and foreign born. A native-born worker with ability a develops $a \times f^{\text{nat}} \times n_t$ new ideas at date t, to which the innovator's household is bestowed a permanent patent. Here, $f^{\text{nat}} > 0$ is a productivity parameter, and n_t represents the externality of the aggregate stock of ideas on an individual's innovative activity, as in Romer (1990). Similarly, a foreign-born worker with ability a develops $a \times f^{\text{for}} \times n_t$ new ideas.

Alternatively, a high-skilled worker earns w_{Mt} employed as a manager, regardless of a. It is optimal for the household to allocate all native-born, high-skilled workers with $a < a_t^{\text{nat*}}$ as managers, where

$$\zeta_t a_t^{\text{nat*}} f^{\text{nat}} n_t = \theta_t w_{Mt}. \tag{14}$$

Here, ζ_t represents the shadow value to the household of an additional idea, and θ_t the shadow value of an additional unit of income, both of which we derive below. Workers with $a \geq a_t^{\text{nat*}}$ are allocated to innovation. Similarly, the foreign-born cutoff, $a_t^{\text{for*}}$, is defined as the value that satisfies

$$\zeta_t a_t^{\text{for*}} f^{\text{for}} n_t = \theta_t w_{Mt}. \tag{15}$$

We denote $s_t^{\text{hi}} = \Gamma\left(a_t^{\text{nat*}}\right)$ and $s_t^{\text{for}} = \Gamma\left(a_t^{\text{for*}}\right)$ as the fraction of high-skilled native- and foreign-born workers employed as managers, respectively.[16]

The household's date τ problem is to maximize

$$\sum_{t=\tau} \beta^{t-\tau}\left[\int_0^{\phi\mu^{\text{nat}}} \log\left(C_{it}\right) di + \int_{\phi\mu^{\text{nat}}}^{\mu^{\text{nat}}} \log\left(C_{jt}\right) dj + \int_{\mu^{\text{nat}}}^{\mu^{\text{nat}}+\mu^{\text{for}}} \log\left(C_{kt}\right) dk\right], \tag{16}$$

subject to the budget constraint

$$\int_0^{\phi\mu^{\text{nat}}} C_{it}\, di + \int_{\phi\mu^{\text{nat}}}^{\mu^{\text{nat}}} C_{jt}\, dj + \int_{\mu^{\text{nat}}}^{\mu^{\text{nat}}+\mu^{for}} C_{kt}\, dk + B_{t+1} \leq R_t B_t + r_t \overline{F} + \tag{17}$$

$$m_t \pi_t + w_{Mt}\left[\mu^{\text{nat}} \phi s_t^{\text{hi}} + \mu^{\text{for}} s_t^{\text{for}}\right] + \left[w_{St} s_t^{\text{lo}} + w_{Rt} \int_{u_t^*}^{\infty} u\, d\Upsilon(u)\right] \mu^{\text{nat}}(1-\phi),$$

and the law of motion for the household's stock of patents

$$m_{t+1} = m_t + n_t\left[\mu^{\text{nat}} \phi f^{\text{nat}} \int_{a_t^{\text{nat*}}}^{\infty} a\, d\Gamma(a) + \mu^{\text{for}} f^{\text{for}} \int_{a_t^{\text{for*}}}^{\infty} a\, d\Gamma(a)\right], \tag{18}$$

for all $t \geq \tau$. In equation (17), B_{t+1} denotes one-period bonds purchased at date t that pay a return of R_{t+1} at date $t+1$.[17] Rental income on the house-

16. Given that $\Gamma(a)$ is identical across nativity, $f^{\text{nat}} \neq f^{\text{for}}$ allows the model to generate differences in occupational sorting across high-skilled native- and foreign-born workers; this is made explicit via equation (29) below. An alternative would be to allow the distributions to differ by nativity.

17. In equilibrium, such bonds are in zero net supply and simply allow us to designate the household's discount factor in the derivations to follow.

hold's fixed factor is given by $r_t\bar{F}$. The second line of equation (17) denotes household labor income earned by workers in management, service, and routine employment.

At date t, the household's stock of ideas is m_t. With symmetry, each idea earns flow profit π_t. Patents do not expire or depreciate, so that equation (18) indicates that m_{t+1} is simply the stock today augmented by new ideas developed by high-skilled workers at date t.[18]

Let θ_t and ζ_t denote the Lagrange multipliers associated with the date t budget constraint (equation [17]) and law of motion (equation [18]), respectively. Given preferences, optimality involves allocating the same consumption level to all workers, regardless of nativity, skill, or occupation: $C_{it} = C_{jt} = C_{kt} = C_t, \forall i, j, k$. As such, our model is suited to the analysis of changes in wage and income inequality; it is not suited to analyzing consumption or welfare inequality.[19] Moreover, optimality implies $\theta_t = 1/C_t$. The FOC for bond holding is

(19) $$\theta_t = \beta\theta_{t+1}R_{t+1}.$$

The FOC for the household's stock of ideas is given by

(20) $$\zeta_t = \beta\zeta_{t+1} + \beta\theta_{t+1}\pi_{t+1}.$$

Iterating forward, this becomes

(21) $$\zeta_t = \beta\theta_{t+1}\pi_{t+1} + \beta^2\theta_{t+2}\pi_{t+2} + \beta^3\theta_{t+3}\pi_{t+3} + \ldots$$

Dividing by θ_t and using equation (19) obtains

(22) $$\frac{\zeta_t}{\theta_t} = \frac{\pi_{t+1}}{R_{t+1}} + \frac{\pi_{t+2}}{R_{t+1}R_{t+2}} + \frac{\pi_{t+3}}{R_{t+1}R_{t+2}R_{t+3}} + \ldots$$

As a result, the cutoff condition (equation [14]) can be rewritten as

(23) $$w_{Mt} = a_t^{\text{nat}*} f^{\text{nat}} n_t \sum_{i=1}^{\infty}\left[\frac{\pi_{t+i}}{\prod_{j=1}^{i} R_{t+j}}\right].$$

That is, occupational choice among high-skilled natives is such that, at $a_t^{\text{nat}*}$, the return to working as a manager (in terms of current wage income) is equated to the present value of future profit that worker would generate from innovation. Obviously, equation (15) can be rewritten in the analogous way, with $a_t^{\text{for}*} f^{\text{for}}$ replacing $a_t^{\text{nat}*} f^{\text{nat}}$ above.

18. For simplicity, we have assumed that patents do not depreciate. Instead, one could assume that patents depreciate at a constant rate δ. This would introduce an additional parameter to calibrate, but importantly, would not qualitatively change the nature of our analysis or results.

19. Addressing these latter issues would require the explicit modeling of heterogeneous agents and tracking the distribution of capital and savings as aggregate state variables. Doing so would muddle the analysis of occupational employment and wage outcomes that are of primary concern, and is therefore beyond the scope of this chapter.

5.3.3 Equilibrium and Balanced Growth

Equilibrium in this model is defined in the usual way. Optimization on the part of firms is summarized by the FOCs equation (5) through (9). Household optimization is summarized by equations (13) through (15), and equation (17) holding with equality.

Since bonds are in zero net supply, $B_t = 0$. Labor market clearing requires

$$L_{St} = \mu^{\text{nat}}(1-\phi)s_t^{\text{lo}}, \tag{24}$$

$$L_{Rt} = \mu^{\text{nat}}(1-\phi)\int_{u_t^*}^{\infty} u\, d\Upsilon(u), \tag{25}$$

$$L_{Mt} = \mu^{\text{nat}}\phi s_t^{\text{hi}} + \mu^{\text{for}} s_t^{\text{for}}. \tag{26}$$

In the ideas market, $m_t = n_t$. Using equation (18), this implies that the growth rate of the aggregate stock of ideas is given by

$$g_{t+1}^n = \frac{n_{t+1} - n_t}{n_t} = \mu^{\text{nat}}\phi f^{\text{nat}} \int_{a_t^{\text{nat}*}}^{\infty} a\, d\Gamma(a) + \mu^{\text{for}} f^{\text{for}} \int_{a_t^{\text{for}*}}^{\infty} a\, d\Gamma(a). \tag{27}$$

Finally, the household budget constraint can be used to derive the aggregate resource constraint:

$$(\mu^{\text{nat}} + \mu^{\text{for}})C_t = Y_t + w_{St}L_{St} - \eta x_t n_t. \tag{28}$$

Equation (27) allows us to consider the determinants of the growth of ideas, that is, nonroutine-biased technical change. For instance, an increase in the productivity of innovation, either f^{nat} or f^{for}, has a direct effect of increasing g^n. In addition, such a change has an effect on occupational choice: the more productive is innovation, the lower is the threshold productivity ($a^{\text{nat}*}$ and $a^{\text{for}*}$) required to equate returns to managerial work and innovation in equations (14) and (15), all else equal. Hence, increases in f^{nat} and f^{for} have an equilibrium effect of inducing greater resources devoted to innovation that reinforce the direct effect.

In addition, increases in the high-skilled population, either $\mu^{\text{nat}}\phi$ or μ^{for}, increase NBTC. That is, our model displays a version of the "scale effect" on growth shared by Romer-style (1990) models; here, the scale effect is in terms of the measure of high-skilled workers (as opposed to total population per se).

Finally, note that changes in the composition of high-skilled workers affect g^n when $a^{\text{nat}*} \neq a^{\text{for}*}$. From equations (14) and (15), it is easy to see that

$$\frac{a_t^{\text{nat}*}}{a_t^{\text{for}*}} = \frac{f^{\text{for}}}{f^{\text{nat}}}. \tag{29}$$

Suppose, for instance, that $f^{\text{for}} > f^{\text{nat}}$ so $a^{\text{nat}*} > a^{\text{for}*}$; given that the distribution, Γ, is identical across nativity, this implies that sorting into the innovation occupation is greater among the foreign born. In this case, a compositional shift toward more foreign-born workers that leaves the total measure of high-skilled workers unchanged has the effect of increasing the growth rate of ideas.

Given this discussion and the characterization of equilibrium, it is possible to consider balanced growth in our economy. In particular, the model admits a balanced growth path (BGP) in which labor allocations are constant ($u_t^* = u^*$, $a_t^{\text{nat}*} = a^{\text{nat}*}$, and $a_t^{\text{for}*} = a^{\text{for}*}$), and the stock of ideas (n_t), labor-augmenting technology (z_t), and the service-occupation wage (w_{St}) all grow at the same, constant rate ($g_{t+1}^n = g^n = g$). It is straightforward to show that along such a BGP the service flow (x_t) and profit (π_t) from each idea is constant; the gross real interest rate (R_t) is constant; and automation technology (A_t), wages (w_{St}, w_{Rt}, w_{Mt}), and consumption (C_t) grow at rate g.

5.4 Quantitative Results

5.4.1 Calibration and Parameter Specification

In this subsection, we discuss how to quantify the model economy to a BGP. This is meant to represent the US economy *prior* to the onset of job polarization. We view the past thirty-five years as a period of "unbalanced" growth, characterized by a declining share of employment in routine occupations due to NBTC; we defer discussion of unbalanced growth/NBTC to subsection 5.4.2.

There are fourteen parameters that need to be specified. To maintain comparability to the literature, we perform a standard calibration when possible. The initial BGP is calibrated to the United States in 1980.

First we normalize $\eta = 1$ and $\overline{F} = 1$. We then set the BGP growth rate of the technology variables (n, z, and w_S) to 2 percent per year. To accord with an annual risk-free rate of 4.6 percent, we set $\beta = 0.975$. We set the nativity and skill shares of the employed population to match those observed in the 1980 census. Normalizing $\mu^{\text{nat}} + \mu^{\text{for}} = 1$, we set $\mu^{\text{for}} = 0.0137$ to accord with the fraction of high-skilled, foreign-born workers in the economy. Of the native born, $\phi = 0.17$ specifies the split between high- and low-skilled workers.

To match the fat right tail of returns to innovation and entrepreneurial activity observed in US data, we specify the $\Gamma(a)$ distribution to be Pareto. This has the computational advantage of introducing only one calibration target, namely the shape parameter, which we denote κ.[20] Recall that we restrict the innovation ability distributions to be identical across the native and foreign born. As a result, nativity differences in sorting across innovation and managerial employment are reflected in the productivity parame-

20. The location parameter of the Pareto distribution is simply a normalization relative to f^{nat} and f^{for}, for the purposes of calibration.

ters f^{nat} and f^{for}. For the sake of consistency, we specify $\Upsilon(u)$ to also be Pareto, with corresponding shape parameter ν.

Given this, we jointly calibrate the following six parameters: the production share parameters α and λ, the shape parameters ν and κ, and the innovation productivity parameters f^{nat} and f^{for} as follows. In order to identify these we specify that along the BGP, the model matches the following six moments from the 1980 census data. First, we match three "quantity moments." Given the results of section 5.2, we calibrate the BGP values $s^{hi} = 0.896$ and $s^{for} = 0.819$ to match the fraction of nonroutine cognitive workers in managerial (i.e., non-STEM) occupations for the native and foreign born, respectively. We set s^{lo} 0.2 to match the fraction of low-skilled workers that work in service (i.e., nonroutine manual) occupations. The remaining three moments relate to prices: (a) a share of total labor income paid to low-skilled (routine and service) labor of 47 percent, (b) a median routine-to-service-occupation wage ratio of 1.75, and (c) a median managerial-to-routine-occupation wage ratio of 1.6.

This leaves the two elasticity parameters in production to be specified. Given the nature of our results, we set $\rho = 0.995$. That is, we set the elasticity of substitution between automation technology and routine labor as close to infinite as (computationally) possible; this allows the model to maximize the negative effect of increased innovation and NBTC on the demand for routine labor. Finally, we set $\sigma = 0.5$. In numerical experiments, we find that our results are extremely robust to the choice of this parameter.

5.4.2 Nature of the Experiments

As discussed above, the period since 1980 is not well characterized as displaying balanced growth. The phenomenon of job polarization has meant that employment allocations have not been constant: the share of employment in routine occupations has been falling, while the shares in nonroutine cognitive and service occupations have been rising. Moreover, inequality between high- and low-skilled wages has increased; more recently, routine- and service-occupation wages have converged (see Acemoglu and Autor 2011).

From the perspective of the model, the past thirty-five years has been a period of unbalanced growth. In particular, NBTC and the accumulation of automation technology has led to an inward shift in the demand for routine labor and an outward shift in the demand for high-skilled labor, all else equal. Moreover, rising educational attainment has meant a shift in the composition of labor supply toward high-skilled workers, and immigration policy has led to a rise in the foreign-born share of the high-skilled population.

As such, we conduct a series of quantitative experiments in the model to *isolate the role of immigration* for the evolution of the economy during this unbalanced growth period. In our experiments we assume the economy was on a BGP in 1980 and then hit by a number of shocks that we specify below.

After the arrival of the shocks, we track the perfect foresight transition path of the economy to a new BGP. We specify that the economy arrives at the new BGP in the year 2070, ninety years after the arrival period of the shock.[21]

Specifically, we assume that in 1980 the economy is hit with two shocks. First, we allow the fraction μ^{for} to increase at a constant rate; this growth is specified so that after thirty years of growth, the fraction of high-skilled, foreign-born workers matches that observed in 2010 in the US data. Given that the high skilled can select into innovation, this increase alone accelerates the growth of automation technology that substitutes for routine labor input.

But as reported in the bottom panel of table 5.2, the tendency of high-skilled, foreign-born workers to work in innovation occupations increased between 1980 and 2010. As discussed in section 5.2, this represents either a true "propensity" change or a change in the unobserved characteristics of foreign-born workers. Hence, we also allow for a one-time increase in the innovation productivity, f^{for}, that causes foreign-born workers to sort more heavily into innovation as opposed to managerial labor that replicates the changes observed in table 5.2.[22]

As discussed in subsection 5.3.3, these two changes (increasing μ^{for} and f^{for}) increase the number of innovators in the economy, and results in an endogenous rise in the growth rate of ideas. Our experiment causes g^n to rise, while leaving the growth rates of labor-augmenting productivity (z) and the service-occupation productivity (w_S) unchanged at their previous BGP value. The new BGP is attained in 2070 when the growth rates of z and w_S make a one-time increase from g to the endogenously determined value of g^n in that period. From 2070 onward, μ^{for} becomes constant.

5.4.3 Results

Figure 5.2 presents the foreign-born population share for the period 1980 to 2010. In all figures, the line with circles indicates the time series under the original BGP, while the line with squares represents the immigration

21. In principle, the results of the experiment depend on the "terminal date" at which the new BGP is attained, since agents in the model operate with perfect foresight. However, in experiments not reported here, we find that the results for the transition path are incredibly insensitive to the choice of this date. For instance, when we set the terminal date to 2010, the results for the period of interest—1980 to 2010—are surprisingly similar to the case reported here, with the terminal date set to 2070. We specify a ninety-year transition period in the baseline experiment in order to better understand the model's implications for the "very long run" (see section 5.4.4 for further discussion).

22. Note that other changes that cause greater equilibrium sorting of the foreign born into innovation in equilibrium are equivalent to increasing f^{for}. For instance, one could argue that the unobservable characteristics of the foreign born have changed over time due to the H-1B visa. This might be reflected as a rightward shift of the distribution, $\Gamma(a)$, of innovation ability of the foreign-born relative to natives. But given our specification of production in innovation, $a \times f \times b_t$, allowing for a change in the location parameter of the Pareto distribution for the foreign born is isomorphic to changing the productivity parameter, f^{for}.

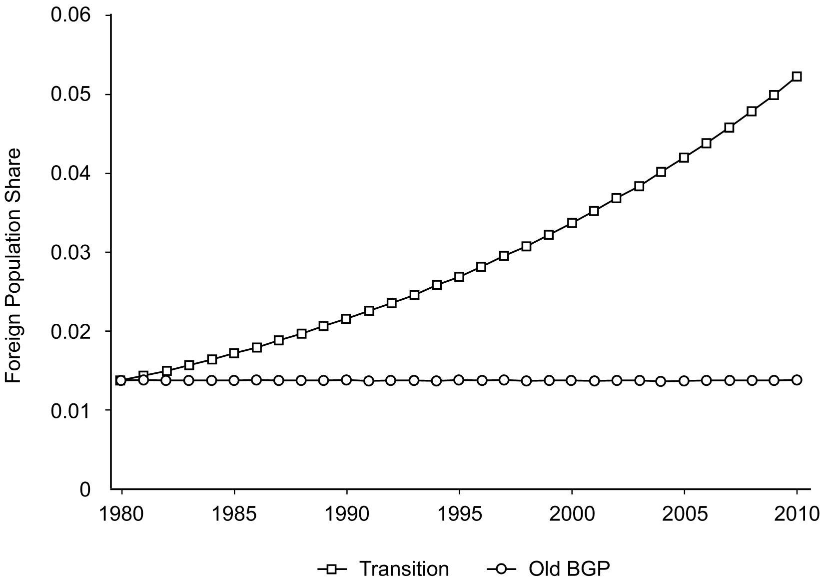

Fig. 5.2 High-skilled immigration experiment, overview

Note: The line with circles indicates the time series under the original balanced growth path; the line with squares represents the immigration experiment. See text for details.

experiment detailed in the previous subsection. By construction, the values for 1980 and 2010 along the experiment's transition path correspond with the values observed in the 1980 census and 2010 ACS data, representing a fourfold increase. Recall that the foreign-born population in the model represents only foreign-born, high-skilled employment.

In the upper-left panel of figure 5.3, we present the fraction of high-skilled workers who sort into innovation ($1 - s^{\text{for}}$) among the foreign born. By construction, this increases as observed in the US data due to the increase in foreign-born innovation productivity. The upper-right panel presents the same variable for the native born. In response to the increase in the number of foreign-born innovators, the fraction of native born who sort into innovation falls.

Though this effect on native-born innovation is quantitatively small, it is instructive to understand the force generating it. Native sorting into innovation falls, despite production of new ideas being linear in the number of innovators; that is, the fall occurs despite innovation productivity of the native born, f^{nat}, remaining unchanged in the experiment. Instead, the fall is due to the general-equilibrium effect on the real interest rate.

Specifically, the increase in high-skilled immigration endogenously increases economic growth. This is evidenced in the middle row of figure 5.3. During the first thirty years of transition, the growth rate of ideas and con-

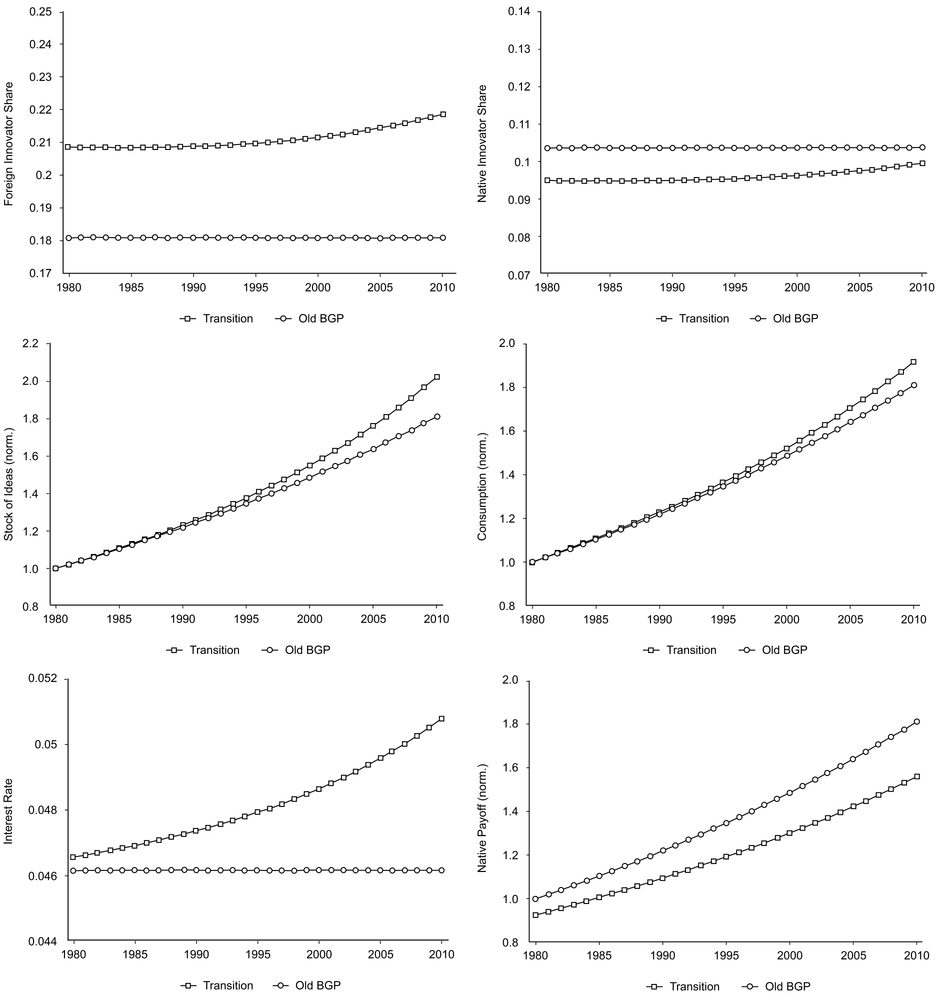

Fig. 5.3 High-skilled immigration experiment, all workers

Note: The lines with circles indicate the time series under the original balanced growth path; the lines with squares represent the immigration experiment. See text for details.

sumption are higher than under the original BGP (both variables are normalized to one in 1980). Because the representative household has concave preferences, it desires to smooth consumption intertemporally and transfer some of the additional future consumption growth forward in time. Obviously, this reallocation of consumption is not possible in equilibrium (of our closed economy model). This necessitates an increase in the real interest rate or return to saving, as displayed in the bottom-left panel of figure 5.3.

The increase in the interest rate, in turn, affects the equilibrium return to innovation. Recall that the payoff to innovation, displayed in the bottom-right panel, is the present value of the future profit stream accruing to the generated ideas. This is summarized by equation (23), which we reproduce here:

$$w_{Mt} = a_t^{\text{nat}^*} f^{\text{nat}} n_t \sum_{i=1}^{\infty} \left[\frac{\pi_{t+i}}{\prod_{j=1}^{i} R_{t+j}} \right].$$

Higher real interest rates mean that future profits are discounted more heavily. All else equal, sorting into innovation becomes more selective; the ability level at which high-skilled, native-born workers are indifferent between working in management and innovation must rise. Since the high-skilled, native-born workers did not experience a shock to their innovation productivity, less of them sort into innovation (though, as stated above, the effect is quantitatively small).

The upper and middle rows of figure 5.4 present the time series for managerial labor. As the population of high-skilled, foreign-born workers increases, so too does the number of foreign-born managers.[23] By 2010, this increase is quantitatively large. The number of native-born managers also increases due to the change in occupational sorting described above, though again, this is quantitatively small. As a result, total employment in the managerial occupation increases by approximately 20 percent over the thirty-year period, as displayed in the middle-left panel, due largely to the foreign-born increase. As a result of this immigration-induced increase in the supply of labor, the managerial wage rate falls relative to the original BGP. This is displayed in the middle-right panel.

The bottom row of figure 5.4 presents the time series for routine labor. Though the effect is quantitatively small, increased high-skilled immigration has the effect of *increasing* employment in routine occupations. That is, during the 1980 to 2010 transition period of our model's experiment, high-skilled immigration has *not* been responsible for a decrease in routine employment among the native born. And as indicated in the bottom-right panel, the increase in the high-skilled, foreign-born workforce has not led to a fall in the wage earned by routine workers. Because the quantitative effect is small, we plot this as a *log* deviation from the original BGP. Nonetheless, the result of the immigration experiment is to *increase* the marginal product of routine labor.

To understand this, note that an increase in high-skilled immigrants has two effects on the demand for routine labor. First, because of the increase in the number of innovators, there is an increase in the growth rate of ideas and an increase in the accumulation of automation technology. Because automation technology and routine labor are substitutes in production, this lowers routine labor demand, as derived in equation (12). However, high-

23. Note that foreign-born managerial labor actually falls slightly in the very first period, relative to the original BGP. This is due to the increased sorting into innovation.

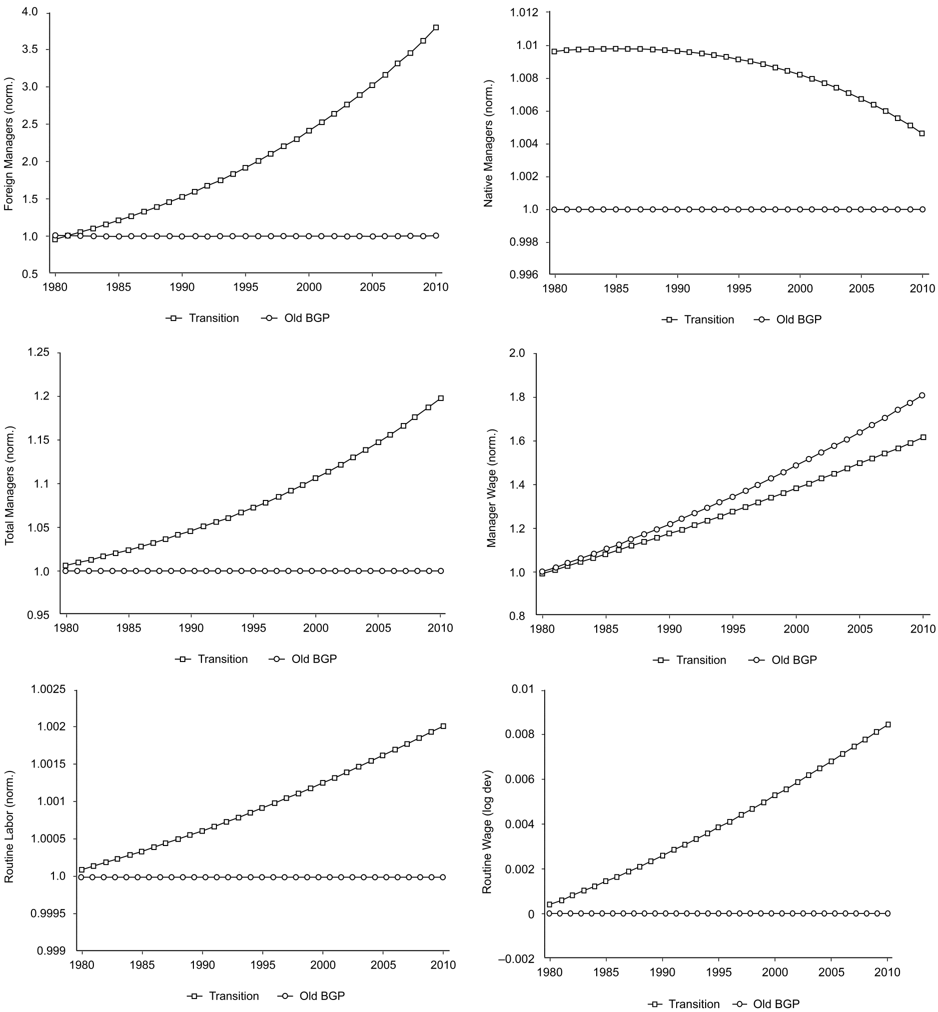

Fig. 5.4 High-skilled immigration experiment, managerial labor

Note: The lines with circles indicate the time series under the original balanced growth path; the lines with squares represent the immigration experiment. See text for details.

skilled immigrants also work as managers. Though the foreign born sort more intensively into innovation relative to the native born, the majority are employed in managerial occupations. Hence, the increase in immigration increases managerial labor. Because managerial labor and routine tasks—and, therefore, routine labor—are complements in production, this raises routine labor demand. This complementarity effect dominates the substitution effect, resulting in an equilibrium increase in employment *and* wages in routine occupations.

As a result, the model predicts that increased high-skilled immigration has led to a *narrowing* of inequality between low- and high-skilled workers. This is displayed in figure 5.5. The upper-left panel plots the ratio of wages between routine and managerial labor; this has been normalized so that its value in the original BGP is one. Evidently, increased immigration causes this ratio to rise, shrinking the wage gap between routine workers and managers.

As an alternative measure of inequality, the upper-right panel displays the ratio of labor income earned by native-born routine workers to managers, specifically,

$$\frac{w_{Rt}\int_{u_t^*}^{\infty} u\, d\Upsilon(u)(1-\phi)}{w_{Mt}\phi s_t^{\text{hi}}}. \tag{30}$$

This differs from the ratio of wages, w_{Rt}/w_{Mt}, in that it accounts for changes in routine and managerial employment among the native born via changes in occupational sorting.[24] While this statistic is conceptually different, it generates decreasing inequality that is quantitatively very similar to that observed in the wage gap.[25]

The lower-left panel displays the ratio of labor income earned by all low-skilled workers to native-born managers. That is, it adds the income earned by service-occupation workers to the numerator of equation (30). Relative to equation (30), this provides greater scope for worsened relative outcomes for the low skilled, as employment gains in routine occupations come out of employment in the service occupation. Nonetheless, the change in this statistic is quantitatively very similar to those discussed above. Finally, the bottom-right panel displays the share of total income accruing to low-skilled (native-born) labor. Between 1980 and 2010, this falls only modestly by about 2 pp; this is primarily a mechanical result of the fact that total low-skilled employment is constant while the experiment adds only high-skilled, foreign-born workers over time.

5.4.4 Further Analysis

In this section, we provide analytical results to illustrate that relative to the 1980 BGP, the increase in high-skilled immigration has a quantitatively small effect on nonroutine-biased technical change. As a result, early in the transition path to a new BGP, the substitution effect of increased automation technology on the demand for routine labor is small.

To see this, consider equation (27) describing the equilibrium growth rate

24. In addition, increases in routine employment are drawn from the lower end of the skill distribution, $\Upsilon(u)$ from workers who previously sorted into the service occupation.

25. In the first two periods of the experiment, the income ratio falls relative to the original BGP; this is due primarily to the larger increase manager employment relative to routine employment among the native born. However, as the transition progresses, this quickly reverses.

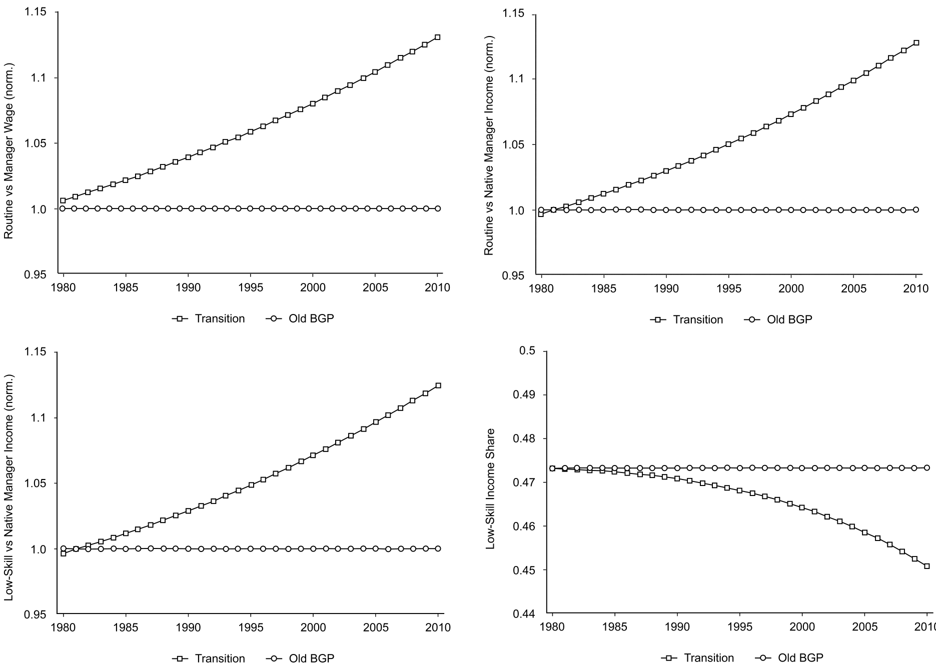

Fig. 5.5 High-skilled immigration experiment, gap between low-skilled and high-skilled workers

Note: The lines with circles indicate the time series under the original balanced growth path; the lines with squares represent the immigration experiment. See text for details

of ideas, where we have used the fact that $\Gamma(a)$ is a Pareto distribution with shape parameter κ:

$$g_{t+1}^{n} = \mu^{\text{nat}}\phi f^{\text{nat}}\bar{\kappa}(a_t^{\text{nat}*})^{1-\kappa} + \mu^{\text{for}} f^{\text{for}}\bar{\kappa}(a_t^{\text{for}*})^{1-\kappa},$$

where $\bar{\kappa} \equiv \kappa/(\kappa - 1)$. Taking a first-order, log-linear approximation to this equation obtains

$$(31)\quad \hat{g}^{n} = \frac{\mu^{\text{nat}}\phi f^{\text{nat}}\bar{\kappa}(a^{\text{nat}*})^{1-\kappa}}{\mu^{\text{nat}}\phi f^{\text{nat}}\bar{\kappa}(a^{\text{nat}*})^{1-\kappa} + \mu^{\text{for}} f^{\text{for}}\bar{\kappa}(a^{\text{for}*})^{1-\kappa}}[\hat{\mu}^{\text{nat}} + \hat{\phi} + \hat{f}^{\text{nat}} + (1-\kappa)\hat{a}^{\text{nat}*}]$$
$$+ \frac{\mu^{\text{for}} f^{\text{for}}\bar{\kappa}(a^{\text{for}*})^{1-\kappa}}{\mu^{\text{nat}}\phi f^{\text{nat}}\bar{\kappa}(a^{\text{nat}*})^{1-\kappa} + \mu^{\text{for}} f^{\text{for}}\bar{\kappa}(a^{\text{for}*})^{1-\kappa}}[\hat{\mu}^{\text{for}} + \hat{f}^{\text{for}} + (1-\kappa)\hat{a}^{\text{for}*}].$$

In our immigration experiment, we leave the measure of high-skilled, native-born workers and native productivity unchanged ($\hat{\mu}^{\text{nat}} = \hat{\phi} = \hat{f}^{\text{nat}} = 0$). Moreover, as displayed in figure 5.3, occupational choice among the native born hardly changes; this implies that the native cutoff ability hardly changes ($\hat{a}^{\text{nat}*} \approx 0$).

As such, we focus our attention on the second term in equation (31), and approximate it as

$$(32)\quad \hat{g}^n \approx \frac{\mu^{\text{for}} f^{\text{for}} (a^{\text{for}*})^{1-\kappa}}{\mu^{\text{nat}} \phi f^{\text{nat}} (a^{\text{nat}*})^{1-\kappa} + \mu^{\text{for}} f^{\text{for}} (a^{\text{for}*})^{1-\kappa}} [\hat{\mu}^{\text{for}} + \hat{f}^{\text{for}} + (1-\kappa)\hat{a}^{\text{for}*}].$$

Under the Pareto distribution, $(a^*)^{-\kappa}$ is the fraction of high-skilled workers who sort into innovation. Using this and equation (29), equation (32) becomes

$$(33)\quad \hat{g}^n \approx \varphi[\hat{\mu}^{\text{for}} + \hat{f}^{\text{for}} + (1-\kappa)\hat{a}^{\text{for}*}],$$

where

$$\varphi \equiv \frac{\mu^{\text{for}} (a^{\text{for}*})^{-\kappa}}{\mu^{\text{for}} (a^{\text{for}*})^{-\kappa} + \mu^{\text{nat}} \phi (a^{\text{nat}*})^{-\kappa}}.$$

Note that φ is simply the foreign-born share of innovators.

Calculated at 1980 BGP values, $\varphi = 0.122$. Hence, to a first-order, log-linear approximation, the impact of high-skilled immigration on the growth rate of ideas—that is, the pace of NBTC—is small. For instance, suppose we were to consider an immediate doubling of the measure of foreign-born workers in 1980 (i.e., $\hat{\mu}^{\text{for}} = 1$); this is large given that it took fifteen years for the model economy to experience the same-sized increase (as displayed in figure 5.2). Using equation (33), this would increase g^n from the original BGP value of 2 percent to 2.224 percent.[26] This illustrates how, during the 1980 to 2010 period under consideration, the substitution effect of automation-technology growth on routine labor demand is dominated by the direct complementarity effect of increased managerial labor supply, brought about by high-skilled immigration.

Note, however, that the relative importance of these substitution and complementarity effects depends on the time horizon under consideration. The strength of each grows at a different rate in our experiment. Consider the complementarity effect of managerial labor. In the long run, the growth rate of managers is bounded above by the (constant) growth rate of high-skilled immigration. By contrast, the substitution effect is governed by the stock of ideas. The growth rate of ideas, displayed in equation (27), depends on the *level* of high-skilled labor, given our Romer-style (1990) specification of technical change. Hence, the direct effect of immigration implies that the growth rate of ideas and automation technology is increasing over time, so that the relative strength of the two effects in the "very long run" is a quantitative question.

26. Of course, the accuracy of this log-linear approximation is compromised for such a large shock, $\hat{\mu}^{\text{for}}$. Note also that our experiment discussed in the previous two subsections also considered a positive shock, $\hat{f}^{\text{for}} > 0$; however, the equilibrium effect of this is to induce an offsetting fall, $\hat{a}^{\text{for}*} < 0$. All things considered, the nature of the result remains that the effect of immigration on NBTC is small.

This is illustrated in figure 5.6, where we plot the ninety-year transition path of the immigration experiment. Recall that the experiment involves growth of the high-skilled, foreign-born workforce at a constant rate (which generates increasing idea growth, g^n), leaving the growth rate of the other forms of technology (specifically, z and w_S) constant. In the ninetieth period, immigration stops and the growth rates of z and w_S make a one-time increase to the endogenous value of g^n so that the economy is forced to enter a new BGP.

As the top row of figure 5.6 makes clear, the stock of ideas exhibits much greater growth than the number of managers in the very long run. The substitution effect of automation technology on routine labor demand can eventually dominate the complementarity effect of increased managerial labor. The middle row displays routine employment and the routine wage. Both display about fifty-five periods of growth during the experiment. However, they begin to decline in about 2035, cross below the values implied by the original BGP in about 2050, and fall thereafter. The bottom row displays two measures of inequality between low- and high-skilled workers. Consider, for instance, the routine-to-manager wage ratio. If high-skilled immigration growth and NBTC were to continue as predicted by the model until 2070, this wage ratio would be approximately one-third of its value in the 1980 BGP.

Hence, the impact of high-skilled immigration on polarization and wage inequality are evident only in the very long run of this numerical exercise. There are many good reasons to question the predictions from this experiment for outcomes fifty to sixty years hence. This is because of the stark assumptions made in the analysis of the specific model experiment. For instance, the experiment assumes constant growth of the high-skilled, foreign-born population over ninety years at the substantial growth rates observed between 1980 and 2010. Future immigration policy is obviously uncertain. In addition, and perhaps more controvertible, it assumes that the *direction* of technical change via innovation remains nonroutine biased over the entire ninety-year period. That is, innovative activity augments automation technology leaving, for instance, the path of labor-augmenting technology unchanged. While this may be a reasonable representation of the job-polarization period of the past thirty years, it may not remain the case for the next sixty. Finally, the model assumes Romer-style (1990) scale effects on the growth of nonroutine-biased ideas. Augmenting the model to diminish or eliminate these scale effects would weaken the long-run substitution of automation technology for routine labor.

As such, we view the predictions of figure 5.6 as uncertain and clearly representing a quantitative theoretic upper bound of the effects of high-skilled immigration on increasing inequality. In terms of the 1980–2010 experience, the model indicates that high-skilled immigration has, in fact, reduced inequality.

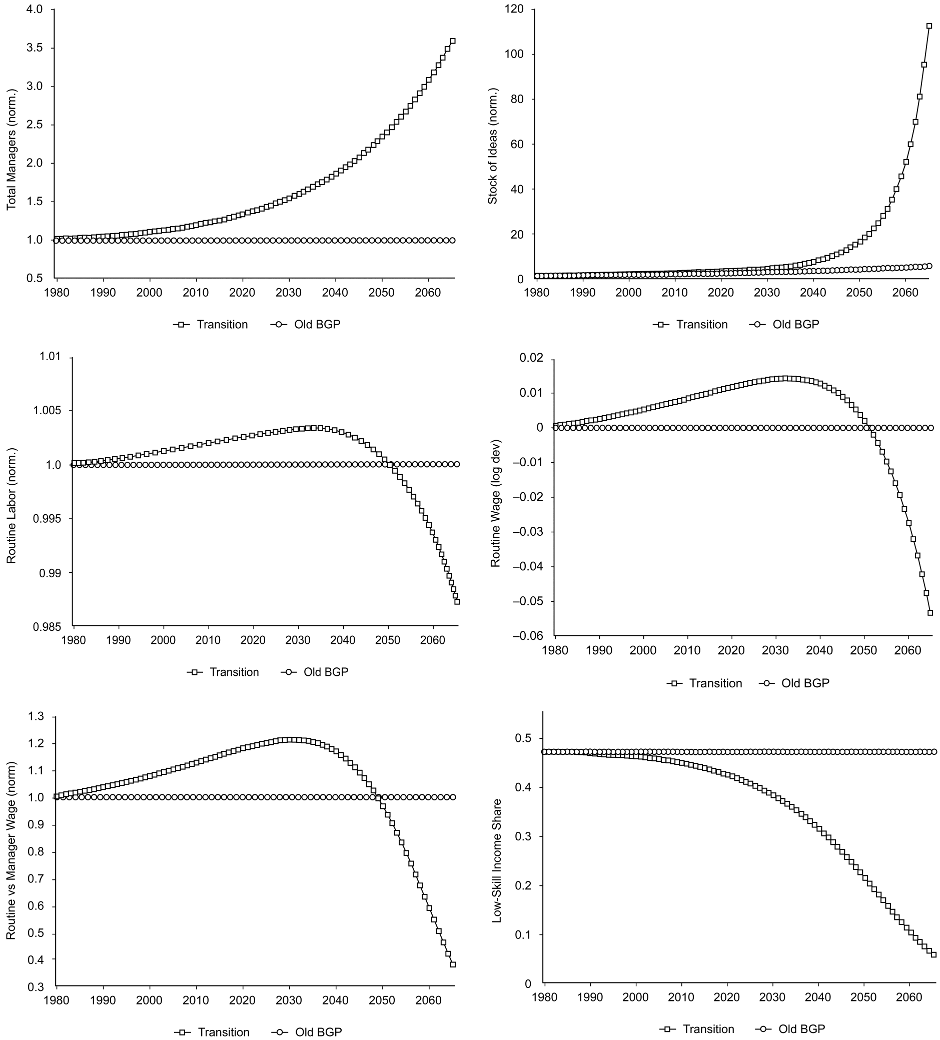

Fig. 5.6 High-skilled immigration experiment, extended

Note: The lines with circles indicate the time series under the original balanced growth path; the lines with squares represent the immigration experiment. See text for details.

5.5 Conclusion

In the last thirty to forty years, immigration has constituted an important source of growth in high-skilled employment, innovation, and productivity in the United States. At the same time, the United States has experienced technical change that is nonroutine biased, allowing technology to substitute for labor in performing routine tasks leading to job polarization and wage polarization in the labor market.

In this chapter, we study the role of high-skilled immigration in accounting for these changes in the occupational-skill distribution and wage inequality. We do so in a general-equilibrium model featuring endogenous nonroutine-biased technical change. We use this model to quantify the impact of high-skilled immigration and the increasing tendency of the foreign born to work in innovation, on the pace of technical change, the polarization of employment opportunities, and the evolution of wage inequality since 1980. We find that high-skilled immigration has led to a narrowing of inequality.

References

Acemoglu, Daron, and David Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings." In *Handbook of Labor Economics*, vol. 4B, edited by Orley Ashenfelter and David Card, 1043–171. Amsterdam: Elsevier.

Acemoglu, Daron, and Pascual Restrepo. 2015. "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares and Employment." Working Paper, Massachusetts Institute of Technology.

Autor, David H., David Dorn, and Gordon H. Hanson. 2015. "Untangling Trade and Technology: Evidence from Local Labour Markets." *Economic Journal* 125:621–46.

Autor, David H., Frank Levy, and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics* 118 (4): 1279–333.

Blinder, Alan. 1973. "Wage Discrimination: Reduced Form and Structural Estimates." *Journal of Human Resources* 8:436–55.

Borjas, George, and Kirk Doran. 2015. "Cognitive Mobility: Labor Market Responses to Supply Shocks in the Space of Ideas." *Journal of Labor Economics* 33 (S1): S109–45.

Bound, John, Breno Braga, Joseph M. Golden, and Gaurav Khanna. 2015. "Recruitment of Foreigners in the Market for Computer Scientists in the United States." *Journal of Labor Economics* 33 (S1): S187–223.

Caselli, Francesco. 2015. "Experience-Biased Technical Change." CEPR Discussion Paper no. 10752, Centre for Economic Policy Research.

Chiswick, Barry, and Sarinda Taengnoi. 2007. "Occupational Choice of High-Skilled Immigrants in the United States." *International Migration* 45 (5): 3–34.

Cortes, Guido Matias, Nir Jaimovich, Christopher J. Nekarda, and Henry E. Siu. 2015. "The Micro and Macro of Disappearing Routine Jobs: A Flows Approach." Working Paper, University of British Columbia.

Cortes, Guido Matias, Nir Jaimovich, and Henry E. Siu. 2016. "Disappearing Routine Jobs: Who, How, and Why?" Working Paper, USC Marshall School of Business.

Doran, Kirk, Alexander Gelber, and Adam Isen. 2016. "The Effects of High-Skilled Immigration Policy on Firms: Evidence from Visa Lotteries." Working Paper, University of Notre Dame.

Firpo, Sergio, Nicole M. Fortin, and Thomas Lemieux. 2011. "Occupational Tasks and Changes in the Wage Structure." Working Paper, University of British Columbia.

Goos, Maarten, and Alan Manning. 2007. "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain." *Review of Economics and Statistics* 89 (1): 118–33.

Goos, Maarten, Alan Manning, and Anna Salomons. 2014. "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring." *American Economic Review* 104 (8): 2509–26.

Grieco, Elizabeth M., Edward Trevelyan, Luke Larsen, Yesenia D. Acosta, Christine Gambino, Patricia de la Cruz, Tom Gryn, and Nathan Walters. 2012. "The Size, Place of Birth, and Geographic Distribution of the Foreign-Born Population in the United States: 1960 to 2010." Population Division Working Paper no. 96, US Census Bureau.

Hanson, Gordon H., and Matthew J. Slaughter. 2016. "High-Skilled Immigration and the Rise of STEM Occupations in US Employment." NBER Working Paper no. 22623, Cambridge, MA.

Hunt, Jennifer. 2011. "Which Immigrants Are Most Innovative and Entrepreneurial? Distinctions by Entry Visa." *Journal of Labor Economics* 29 (3): 417–57.

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

Jaimovich, Nir, and Henry E. Siu. 2012. "Job Polarization and Jobless Recoveries." NBER Working Paper no. 18334, Cambridge, MA.

———. 2015. "Jobless Recoveries." *Third Way NEXT*. http://www.thirdway.org/report/jobless-recoveries.

Jung, Jaewon, and Jean Mercenier. 2014. "Routinization-Biased Technical Change and Globalization: Understanding Labor Market Polarization." *Economic Inquiry* 52 (4): 1446–65.

Kerr, Sari Pekkala, William R. Kerr, and William F. Lincoln. 2013. "Skilled Immigration and the Employment Structures of US Firms." NBER Working Paper no. 19658, Cambridge, MA.

Kerr, William. 2013. "US High-Skilled Immigration, Innovation, and Entrepreneurship: Empirical Approaches and Evidence." NBER Working Paper no. 19377, Cambridge, MA.

Kerr, William, and William Lincoln. 2010. "The Supply Side of Innovation: H-1B Visa Reforms and US Ethnic Invention." *Journal of Labor Economics* 38 (3): 473–508.

Levy, Frank, and Richard J. Murnane. 2014. "Dancing with Robots: Human Skills for Computerized Work." *Third Way NEXT*. content.thirdway.org/publications/714/Dancing-With-Robots.pdf.

Oaxaca, Ronald. 1973. "Male-Female Wage Differentials in Urban Labor Markets." *International Economic Review* 14:693–709.

Peri, Giovanni. 2012. "The Effect of Immigration on Productivity: Evidence from US States." *Review of Economics and Statistics* 94 (1): 348–58.

Peri, Giovanni, Kevin Shih, and Chad Sparber. 2015. "Stem Workers, H-1B Visas, and Productivity in US Cities." *Journal of Labor Economics* 33 (S1): S225–55.

Peri, Giovanni, and Chad Sparber. 2011. "Highly Educated Immigrants and Native Occupational Choice." *Industrial Relations* 50 (3): 385–411.

Romer, Paul M. 1990. "Endogenous Technological Change." *Journal of Political Economy* 98 (5): S71–102.

Ruggles, Steven, J. Trent Alexander, Katie Genadek, Ronald Goeken, Matthew B. Schroeder, and Matthew Sobek. 2010. Integrated Public Use Microdata Series: Version 5.0 [machine-readable database]. Minnesota Population Center, University of Minnesota.

Violante, Giovanni L. 2008. "Skill-Biased Technical Change." In *The New Palgrave Dictionary of Economics*, 2nd ed., edited by Steven N. Durlauf and Lawrence E. Blume. London: Palgrave Macmillan.