Immigration, Wages, and Education: A Labor Market Equilibrium Structural Model

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This paper analyzes the effect of immigration on wages taking into account human capital and labor supply adjustments. Using U.S. microdata for 1967-2007, I estimate a labor market equilibrium model that includes endogenous decisions on education, participation, and occupation, and allows for skill-biased technical change. Results suggest important labor market adjustments that mitigate the effect of immigration on wages. These adjustments include career switches, labor market detachment and changes in schooling decisions, and are heterogeneous across the workforce. The adjustments generate substantial self-selection biases at the lower tail of the wage distribution that are corrected by the estimated model.

Keywords: *Immigration, Wages, Human Capital, Labor Supply, Dynamic Discrete Choice, Labor Market Equilibrium*

JEL Codes: *J2, J31, J61.*

How do human capital investments react to immigration? Would U.S. natives have spent fewer years in school without the massive inflow of foreign workers over the last four decades? Would they have participated more in the labor market? Would they have chosen to work in different occupations? These questions are crucial to understand the wage consequences of immigration. Most of the literature, however, does not take them into account.

During the last forty years, 26 million immigrants of working-age entered the

United States. These immigrants differ from natives in terms of skills and occupations. Whether and to what extent this increase harmed labor market opportunities of native workers has concerned economists and policy makers for years. Such a huge worker inflow might have affected not only average wages, but also the skill premium. As a result, human capital and labor supply decisions may have been affected as well. Failing to take these adjustments into account may produce misleading estimates of wage effects of immigration.

In this paper, I propose and estimate an equilibrium structural model of a labor market with immigration. In the model, labor supply and human capital investment decisions are explicitly taken into account. The estimated model is then used to compute the effect of four decades of large scale immigration on labor market outcomes in the United States.

The labor market consequences of immigration are analyzed through different lenses. First, I compute the effect of immigration on average wages. The structure of the model allows me to separately identify the initial effect of immigration (i.e. when human capital and labor supply are not allowed to adjust), and the one when the equilibrium adjustments are allowed for. Findings suggest that equilibrium adjustments tend to mitigate wage effects of immigration, as they alleviate the initially negative effect on blue collar workers and increase downward pressures on white collar wages. This result is the combination of some individuals leaving the labor market, and others switching occupations.

Second, I analyze equilibrium adjustments in detail. More specifically, I examine individual adjustments in terms of education, career choices, and labor supply. Results suggest that a large fraction of individuals change their behavior as a consequence of immigration. In particular, when immigrants come in, blue collar workers are more likely to either switch to a white collar career, or to leave the labor market; some white collar workers leave the labor market as well, given initial downward wage pressures in both occupations. Regarding human capital investments, particularly education (but also experience), individuals face a new trade-off as a result of immigration: on the one hand, initial downward wage pressures reduce future expected return to human capital investments; on the other hand, the initial increase in the white collar relative wage (compared to blue collar) make individuals more likely to take a white collar career, which increases the future expected return to education (as its white collar return is larger than the blue collar one). On aggregate, the first channel seems to dominate, especially for individuals who reduce their attachment to the labor market, but for the workers who switch careers (from blue collar to white collar) the second one prevails.

Finally, I look at the effect over the distribution of wages. The model is able to correct for self-selection into working when computing wage effects over the

distribution of wages. The individuals that are pushed out from the labor market by immigrants are not a random sample. Instead, least productive workers will be more likely to abandon the labor force. As a result, wage effects at the the lower tail of the distribution will be underestimated if we compare accepted wages with and without immigration. The model, however, allows me to compare wage offers instead of accepted wages, thus correcting this downward bias in a very natural way. Results suggest important biases for all quantiles below the median, which become especially severe below the 20th percentile.

The framework builds on the equilibrium models described in Heckman, Lochner and Taber (1998), Lee (2005), and Lee and Wolpin (2006, 2010). The supply side of the model is similar to Keane and Wolpin (1997), which I extend to accommodate immigrant and native workers separately. Individuals live from age 16 to 65 and make yearly forward looking decisions on education, participation and occupation. Human capital accumulates throughout the life-cycle both because of investments in education, and because learning-by-doing on the job leads to accumulation of (occupation-specific) work experience.

On the demand side, blue collar and white collar labor is combined with capital to produce a single output. Labor is defined in skill units, which implies that workers have heterogeneous productivity depending on their education, occupation-specific experience, place of birth, gender, foreign experience and unobservables. I assume a nested Constant Elasticity of Substitution (CES) production function that accounts for skill-biased technical change through capital-skill complementarity (as in Krusell, Ohanian, Rios-Rull and Violante, 2000). Skill-biased technical change is important because it is considered as an alternative mechanism for the rise in the skill premium over the last four decades. Hence, not taking it into account may potentially lead to attribute its effect on wages to immigration.

I fit the model to U.S. micro-data data from CPS and NLSY for the period 1967-2007. I then use the estimated parameters to quantify the effect of immigration on labor market outcomes. In order to do so, I define a counterfactual world without large scale immigration in which the immigrant/native ratio is kept constant to 1967 levels. Then, I compare counterfactual wages, human capital, and labor supply with baseline simulations using the estimated parameters.

There is a large literature studying the effect of immigration on wages. The first and the most prolific strand of the literature is the so-called spatial correlations approach.[1] The approach exploits the fact that immigrants cluster in a small number of geographic areas, generating a large cross-city variation in immigrant

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[1] This strand of the literature was pioneered by Grossman (1982) and Borjas (1983), and notably followed by Card (1990, 2001), Altonji and Card (1991), LaLonde and Topel (1991), Goldin (1994), Card and Lewis (2007), Saiz (2007), and Cortés (2008) among many others.

incursion. This variability can be used to identify how immigration relates to wages. The key assumption is that metropolitan areas constitute closed labor markets that are exogenously penetrated by immigrants. Borjas, Freeman and Katz (1997), however, claim that natives may respond to the inflow of immigrants by moving their labor to other cities until wages are equalized across areas.[2]

Closer to the approach used in the present paper, a more recent strand of the literature changes the unit of analysis to the national level. Borjas, Freeman and Katz (1992, 1997) put forward the "factor proportions approach" which has evolved substantially in subsequent years. This methodology compares a nation's actual supply of workers in a particular skill group to counterfactual supply in the absence of immigration. Initial studies borrowed elasticities of substitution between different types of labor from the literature whereas in more recent studies, beginning with Card (2001) and Borjas (2003), these elasticities are estimated.[3]

This literature typically assumes that labor supply is perfectly inelastic. As a result, counterfactual labor supplies of workers in each skill group are predicted by simply removing immigrants from each cell. However, this assumption is rather restrictive. Recent evidence suggests native responses to immigration. Hunt (2012) uses cross-state variation to provide evidence that native children might be encouraged to complete high school in order to avoid competing with immigrant high school dropouts in the labor market. Smith (2012) finds that immigration of low educated workers led to an important reduction of native employment, particularly severe for native youth. Peri and Sparber (2009) find that natives specialize in language intensive tasks (occupations) to compensate by the competition induced by immigrants in manual intensive occupations.

In the model presented below, individuals are allowed to adjust their human capital and labor supply decisions. The structure of the model allows me to compute more realistic counterfactual labor supplies taking individuals back to the decisions they would have made without immigrants. Equilibrium adjustments will tend to mitigate wage effects, and not taking them into account in the counterfactuals may produce misleading results.

Dustmann, Frattini and Preston (2013) exploit variation at the regional level to

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[2] Borjas (2003) finds that negative effects of immigration on wages are smaller at the state than at the national level, and Cortés (2008) finds state-level effects to be more sizable than those across metropolitan areas. Both conclude that negative effects are attenuated at the local level by native migration responses. Borjas et al. (1997), Card and DiNardo (2000), Card (2001), and Borjas (2006) analyze how immigration affects the joint determination of wages and internal migration behavior. The magnitude of these responses, however, is a subject of controversy that is out of the scope of this paper. Differentials in capital adoption are suggested by Lewis (2011) as an alternative mechanism.

[3] More recent papers using this approach include Friedberg (2001), Card (2009), Ottaviano and Peri (2012), Manacorda, Manning and Wadsworth (2012), and Llull (2013) among others.

study the effect of immigration along the native wage distribution. Immigrants are assumed to compete with individuals that are in a similar position in the distribution. This redefinition of worker competition is important because the authors find significant evidence of immigrant downgrading upon arrival. Given this, their approach provides a better identification of which natives experience a more intense competition by immigrants.

The framework presented in this paper allows for immigrant downgrading upon arrival, and labor market competition is specified in terms of observable and unobservable skills, as in Dustmann et al. (2013). The model below, however, additionally corrects for biases generated by the self-selection into labor market participation as described above, which is an important contribution of the paper.

The rest of the paper is organized as follows: Section I provides some descriptive evidence; Section II presents the labor market equilibrium structural model with immigration; Section III briefly introduces the solution and estimation algorithm; in Section IV, I present parameter estimates and some validation exercises; Section V presents the results for the counterfactual exercises. And Section VI concludes.

I.   Exploring U.S. mass immigration

According to Census data, the U.S. labor force was enlarged by about 26 millions of working-age immigrants during the last four decades, an increase of almost 0.7 millions per year. This section aims to compare the evolution of the skill composition of immigrants with that of natives, and to establish some correlations between immigration, schooling, and occupational choice. These facts serve as a motivation for the modeling decisions taken in subsequent sections.

According to Table 1, the share of immigrants in the population of working-age increased from 5.7 to 16.6 percent over this period. The skill and occupational composition of the immigrant inflow also changed substantially. The share of immigrants among the less educated has increased faster than among any other group (6.8% to 33.7%). And immigrants are increasingly more clustered in blue collar jobs (6% to 24%, much larger than the 5.7% to 16.6% overall increase). This blue collar concentration holds as well conditional on educational levels. For example, the share of immigrants among dropout blue collar workers increased from 7.2 to 55.5 percent, whereas it only increased from 6.8 to 33.7 percent for the overall high school dropouts group.

These facts are analyzed in more depth in Appendix A. Three important extensions are shown there. First, the fact that immigrants are increasingly less educated than natives is the result of a slower increase (as opposed to a reduction) in their education compared to natives. Second, the pattern of clustering

TABLE 1—SHARE OF IMMIGRANTS IN THE POPULATION (%)

|	1970	1980	1990	2000	2008
A. Working-age population	**5.70**	**7.13**	**10.27**	**14.62**	**16.56**
B. By education:					
High school dropouts	6.84	9.60	17.93	29.02	33.73
High school graduates	4.32	5.14	7.94	12.04	13.27
Some college	5.14	6.63	7.92	9.96	11.65
College graduates	6.48	8.02	10.60	14.59	16.92
C. In blue collar jobs:					
All education levels	*6.03*	*7.83*	*11.21*	*17.53*	*24.07*
High school dropouts	7.18	12.18	23.75	41.03	55.45
High school graduates	4.19	4.94	7.57	12.47	17.30
Some college	5.95	6.14	7.26	9.82	14.07
College graduates	9.53	9.52	12.14	17.89	23.82

Note: Figures in each panel indicate respectively the percentage of immigrants in the population working-age, in the pool of individuals with each educational level, and among blue-collar workers. *Sources*: Census data (1970-2000) and ACS (2008).

in blue collar occupations holds at a more disaggregate level; therefore, although sometimes the blue/white collar classification is seen as too broad and heterogeneous (especially for a long period of time), in this case it seems enough to describe the differential supply shock across occupations. And, third, the national origin composition of the immigrant stock changed gradually over the period: from a majority of Western immigrants during 1960s and 1970s to a majority of Latin Americans later on, and a substantial increase in immigration from Asia/Africa in recent years. These changes in the national origin of immigrants can explain most of the slower increase in education by immigrants.

Borjas (2003) compares immigration and wages in different education-experience cells (see Borjas, 2003, Secs. II-VI). He considers four education groups and eight (potential) experience categories to define cells that are then treated as closed labor markets. As the incidence of immigration varies across skill groups, he uses this variation to identify the effect of immigration on wages in regressions that include different combinations of fixed effects. With this approach, he finds a sizeable negative correlation between immigration and wages. I replicate his results using 1960-2000 Censuses and 2008 ACS in Panel A from Figure 1. The figure shows that the correlation between the share of immigrants in a skill cell and the average wage of native males in that cell (net of fixed effects) is negative. In particular, a one percentage point increase in the share of immigrants is associated with a 0.41 (s.e. 0.044) percent decrease in the average hourly wage.

Given the research question of this paper, it is worthwhile to look at the correlation between immigration and education. Panel B in Figure 1 compares school enrollment rates and immigrant shares, following an analogous approach to the

A. Wages   *B. School Enrollment*   *C. Occupation Transitions*
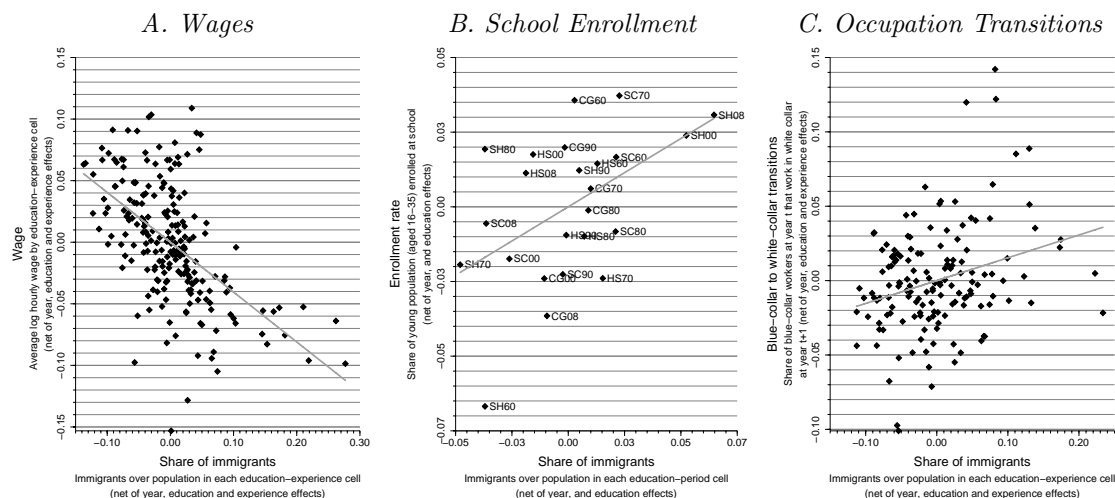
Note: Each observation corresponds to an education-experience cell and a particular survey year (education-year in the central figure). Horizontal axes plot the immigrant share in each cell, net of education, experience, and period fixed effects. Vertical axes depict average log hourly wage of the cell (left), enrollment rate for individuals that already completed the indicated education (center), and the probability of working in a white-collar occupation in year $t+1$ conditional on working in blue-collar in year t (right), all of them net of fixed effects. Education is grouped in four categories: high school dropouts, high school graduates, some college, and college graduates; potential experience (age minus education) is categorized into 9 five-year groups. Samples include full time male workers (more than 20 hours per week, more than 40 weeks per year) aged 16-65 years old (left and right), and individuals aged 16-35 still in school (center). Plotted lines represent fitted regressions. *Sources:* Census data (1960, 1970, 1980, 1990, and 2000), ACS (2008), and March Supplements of CPS (1970-71, 1980-81, 1990-91, 2000-01, and 2007-2008 matched supplements).

one described for wages. In particular, I correlate the share of immigrants in a particular education group with enrollment rates of individuals aged 16-35 who exactly achieved that educational level (net of education and time fixed effects). The intuition behind this exercise is as follows: an individual who has just completed, say, high school, will decide whether to enroll for one additional year or not depending on how tough is the labor market competition for high school graduates. The figure suggests a positive correlation. Specifically, a one percentage point increase in the share of immigrants in a particular group is associated with a 0.46 (s.e. 0.125) points increase in the enrollment rate at that educational level.

Older natives or those who already left education are less likely to go back to school to differentiate themselves from immigrants. A more natural mechanism for them is switching occupations. Peri and Sparber (2009) find evidence that natives tend to specialize in language intensive occupations to benefit from their comparative advantage in language skills, whereas immigrants tend to work in manual occupations. If immigrants cluster in blue collar jobs, the accumulation of white collar experience may additionally act as an insurance mechanism to prevent immigrant-induced increases in labor market competition. Panel C in Figure 1 is suggestive of the extent to which this is observed in the data. In this graph,

immigrant shares in education-experience cells are related to one year blue collar to white collar transition probabilities in an analogous way to Panel A. The fitted regression suggests that a percentage point increase in the share of immigrants in a cell is associated with a 0.15 (s.e. 0.045) percentage points increase in the one year blue collar to white collar transition probability. This effect is sizable, as it suggests that the increase in immigration of the last decades would explain more than a 10% of the observed increase in blue collar to white collar transitions. The result is in line with the findings of Peri and Sparber (2009), and indicative of the importance of taking into account occupational choice in the analysis.

The correlations presented in Panels B and C from Figure 1 are suggestive of natives making adjustments to immigration in terms of human capital and labor supply. However, career paths and human capital investments are forward looking decisions that are difficult to asses through reduced form approaches. For this reason, the model below describes the behavior of forward looking agents making such decisions, within an equilibrium framework that links the effect of immigration to native decisions through changes in relative wages.

II. A labor market equilibrium model with immigration

In this section, I present a labor market equilibrium model with immigration. The model, estimated with U.S. data, is then used to quantify the effect of the last four decades of immigration on wages, human capital, and labor supply of incumbent workers (natives and previous immigrants).[4] The main contribution of this approach is to explicitly model labor supply and human capital decisions. It also takes into account skill-biased technical change (considered as an alternative hypothesis for the increase in wage dispersion in the U.S. in recent decades).

A. Career decisions and the labor supply

Native individuals enter in the model at age $a = 16$, and immigrants upon arrival in the United States. They decide every year (until the age of 65 when they die with certainty) among four mutually exclusive alternatives to maximize their lifetime expected utility. The alternatives are: to work in a blue collar job, $d_a = B$; or in a white collar job, $d_a = W$; to attend school, $d_a = S$; or to stay at home, $d_a = H$. There are L types of individuals that differ in skill endowments and preferences, as described below. These types are defined based on observable characteristics. Natives differ by gender (males and females). Immigrants additionally differ in the region of birth (Western countries, Latin America, and

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[4] In order to make the text shorter and easier to read, I often use "native adjustments" indistinctly to refer to adjustments by native individuals and adjustments by natives and previous immigrants. The specific meaning in each case is easily identifiable from the context.

Asia/Africa). Hence, I assume six types of immigrants and two types of natives.

Immigrants enter the U.S. exogenously and with a given skill endowment. This assumption is standard in the literature.[5] Attempting to endogenize migration in this model is not feasible for computational reasons, and because it would require information on immigrants before and after migration, which is not available.[6]

At every point in time t, an individual i of type l and age a solves the following dynamic programming problem:

$$V_{a,t,l}(\Omega_{a,t}) = \max_{d_a} U_{a,l}(\Omega_{a,t}, d_a) + \beta E\left[V_{a+1,t+1,l}(\Omega_{a+1,t+1}) \mid \Omega_{a,t}, d_a, l\right], \quad (1)$$

where the terminal value is $V_{65+1,t,l} = 0 \; \forall l, t$.[7] β is a subjective discount factor, and Ω_a is the information set of individual i at age a and time t (state variables are listed below). The instantaneous utility function is choice-specific, $U_{a,l}(\Omega_a, d_a = j) \equiv U_{a,l}^j$ for $j = B, W, S, H$. Workers are not allowed to save and, hence, they are not able to smooth consumption; as a result, I prevent them from having incentives to smooth by assuming a linear utility function.

Working utilities are given by

$$U_{a,t,l}^j = w_{a,t,l}^j + \delta_g^{BW} \mathbb{1}\{d_{a-1} = H\} \quad j = B, W, \quad (2)$$

where $w_{a,t,l}^j$ are individual wages in occupation $j = B, W$, $\mathbb{1}\{A\}$ denotes the indicator function, which takes the value of one if condition A is satisfied and zero otherwise, and δ_g^{BW} is a gender-specific search cost that individuals have to pay to get a job if they were not working (and not in school) in the previous period.[8]

Wages are defined as the product of the number of individual skill units times their market price: $w_{t,a,l}^j \equiv r_t^j \times s_{a,l}^j$. Market prices of skill units, r_t^j, are obtained in equilibrium, and individual skill units are defined by the individual-specific component of a fairly standard Mincer equation (Mincer, 1974):

$$w_{a,t,l}^j = r_t^j \exp\{\omega_{0,l}^j + \omega_{1,is}^j E_a + \omega_2^j X_{Ba} + \omega_3^j X_{Ba}^2 + \omega_4^j X_{Wa} + \omega_5^j X_{Wa}^2 + \omega_6^j X_{Fa} + \varepsilon_a^j\}., \quad (3)$$

where

$$\begin{pmatrix} \varepsilon_a^B \\ \varepsilon_a^W \end{pmatrix} \sim i.i.\mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} (\sigma_g^B)^2 & \rho^{BW}\sigma_g^B\sigma_g^W \\ \rho^{BW}\sigma_g^B\sigma_g^W & (\sigma_g^W)^2 \end{bmatrix}\right).$$

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[5] A recent exception to this is Llull (2013), who exploits exogenous variation from origin countries together with distance (using a two-sample two-stage least squares approach).

[6] Computational complexity and data requirements for the estimation of structural models of migration decisions are discussed in Kennan and Walker (2011) and Lessem (2013).

[7] For notational simplicity, I omit the individual subindex i, which should be present in all individual variables throughout the paper. I do not include time subindex t in individual-specific variables as long as, for a given individual i, t and a are perfectly collinear.

[8] I assume that transitions from school into work are costless. Equivalently, new immigrants have to pay this search cost unless they were at school in their home country in the previous period, i.e. if their foreign potential experience is strictly greater than zero.

The exponential part of equation (3) is the individual production function of skill units, $s_{a,l}^j$. All ω^js, interpreted as technology parameters, represent the return to each observable characteristic in terms of productivity in occupation j. Therefore, education E_a, blue collar and white collar effective experience in the U.S. X_B and X_W, and (potential) experience abroad X_F, affect workers' productivity. The return to education, $\omega_{1,is}^j$, is allowed to differ for immigrants and natives ($is = nat, immig$).[9] Equation (3) also includes a type-specific constant, $\omega_{0,l}^j$, and an i.i.d. unobserved shock, ε_a^j, with gender-specific variance σ_g^{j2}, and (gender invariant) correlation between the shocks for the two working alternatives ρ^{BW}. When individuals decide to work in occupation j they accumulate occupation-specific work experience, $X_{ja+1} = X_{ja} + \mathbb{1}\{d_a = j\}$, which produces a return in the future in the form of additional productivity and, hence, wages.

Skill prices r_t^j are only identified up to a multiplying constant in equation (3). Therefore, I impose the normalization $\omega_{0,male,nat}^j = 0$. Given this normalization, a skill price is interpreted as the average wage in occupation j of native male workers that have zero years of education and zero years of experience at time t.

Equation (3) allows for *assimilation* of immigrants. LaLonde and Topel (1992) define assimilation as the process whereby, between two observationally equivalent immigrants, the one with greater time in the U.S. earns more. According to this definition, immigrants assimilate as they accumulate some skills in the U.S. that they would not have accumulated in their home country (Borjas, 1999). In terms of the present model, assimilation would be provided by a different (larger) return to one year of U.S. experience compared to one year of experience abroad.[10]

Individuals who decide to attend school face a monetary cost, which is different for undergraduate (τ_1), and graduate students ($\tau_1 + \tau_2$). Additionally, they get a non-pecuniary utility with a permanent component $\delta_{0,l}^S$, a disutility of coming back to school if they were not in school in previous period $\delta_{1,g}^S$, and an i.i.d. transitory shock ε_a^S, normally distributed with gender-specific variance $(\sigma^S)_g^2$. Specifically,

$$U_{a,l}^S = \delta_{0,l}^S - \delta_{1,g}^S \mathbb{1}\{d_{a-1} \neq S\} - \tau_1 \mathbb{1}\{E_a \geq 12\} - \tau_2 \mathbb{1}\{E_a \geq 16\} + \varepsilon_a^S. \quad (4)$$

As a counterpart, they increase their education, $E_{a+1} = E_a + \mathbb{1}\{d_a = S\}$, which provides a return in the future.

Finally, individuals deciding to remain at home perceive the following non-

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[9] The different return to schooling for immigrants and natives may be the result of immigrants undertaking (part of) their education abroad (e.g. learning Chinese calligraphy may not be as useful as learning English to work in the U.S.). Ideally, I would allow the return to the education *obtained* the U.S. and abroad to differ; however, such information is not observable in the data. Therefore, it is the return to *all* education what is different for natives and immigrants.

[10] Eckstein and Weiss (2004), using data for Israel, find that foreign experience is almost unvalued upon arrival, and that conditional convergence takes place as the immigrant keeps accumulating local experience.

pecuniary utility:

$$U_{a,t,l}^{H} = \delta_{0,l}^{H} + \delta_{1,g}^{H} n_a + \delta_{2,g}^{H} t + \varepsilon_a^{H}. \tag{5}$$

In this case, on top of its permanent and transitory components $\delta_{0,l}^{H}$ and ε_a^{H}, utility is increased by a gender-specific amount $\delta_{1,g}^{H}$ for each preschool children living at home, n_a.[11] Additionally, I add a gender-specific trend $\delta_{2,g}^{H} t$ to correct for the linear utility assumption. A linear utility function implies no income effect in the labor force participation decision, and, hence, everything is driven by the substitution effect; in a framework with growing wages, everyone would eventually end up working at some point. Including a linear trend in the utility is a reduced form way to circumvent this problem.

B. Aggregate production function and the demand for labor

The economy is represented by an aggregate firm that produces a single output, Y_t, combining labor (blue collar and white collar labor skill units, S_{Bt} and S_{Wt}) and capital (structures and equipment capital, K_{St} and K_{Et}) with a technology that is described by the following nested Constant Elasticity of Substitution (CES) production function:

$$Y_t = z_t K_{St}^{\lambda} \{\alpha S_{Bt}^{\rho} + (1-\alpha)[\theta S_{Wt}^{\gamma} + (1-\theta)K_{Et}^{\gamma}]^{\rho/\gamma}\}^{(1-\lambda)/\rho}. \tag{6}$$

Equation (6) is a Cobb-Douglas production function that combines structures with a composite of labor and equipment capital. This composite is a CES aggregate that combines blue collar labor with another CES aggregate of equipment capital and white collar labor. Neutral technological progress is provided by the aggregate productivity shock z_t. Parameters α, θ, and λ are connected with the factor shares, and ρ and γ are related to the elasticities of substitution between the different inputs. The elasticity of substitution between equipment capital and white collar labor is given by $1/(1-\gamma)$, and the elasticity of substitution between equipment capital or white collar labor and blue collar labor is $1/(1-\rho)$.

Skill units are supplied by workers according to equation (3). As individuals are not allowed to save, capital and output are taken from the data. Given that capital stocks are equilibrium quantities, the implicit assumption is that labor supply only affects capital through changes in the aggregate labor supply, but not through the distribution of skills; likewise, only the aggregate capital stock, but not the distribution of assets, have an effect on labor supply.[12]

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[11] The variable n_a is assumed to take one of the following values: 0, 1 or 2 (the latter for 2 or more children). Fertility is exogenous (transition probability matrix is taken from the data) and depends on gender, education, age and cohort (see Appendix C).

[12] This assumption is relevant for the counterfactual exercises in Section V. Counterfactual capital in the absence of immigration is required to correctly asses the effect of immigration on wages. To account for this, I simulate different scenarios for counterfactual capital.

The aggregate productivity shock z_t is obtained as the residual in equation (6).[13] Its evolution is assumed to be described by the following autoregressive model:

$$\ln z_{t+1} - \ln z_t = \phi_0 + \phi_1(\ln z_t - \ln z_{t-1}) + \varepsilon_{t+1}^z, \quad \varepsilon_{t+1}^z \sim \mathcal{N}(0, \sigma_z^2). \qquad (7)$$

This process allows for a constant exogenous productivity growth rate, and business cycle fluctuations around it.

I abstract from modeling the effect of immigration on the demand of the produced good and its equilibrium feedback on wages. Two assumptions are consistent with this: perfectly inelastic product demand (i.e. a tradable good whose price is fixed at international goods market) or that immigration increases the size of the market for the produced good proportionally to how it increases the labor force. The latter seems plausible at the aggregate level —at a more disaggregate level, there is some evidence suggesting that immigration affected the price of some goods more than others (e.g. Cortés, 2008). The implications of this assumption are discussed in Borjas (2009).

Economic theory suggests that immigration affects wages by lowering the wage of competing workers (Borjas, 1999). As argued by Dustmann et al. (2013), however, the definition of competing workers should take into account that immigrants often downgrade at entry. The analysis at the occupational level is convenient in this context. A foreign engineer working in a farm is not competing with a native professional engineer, but with a native farmer. As discussed in Section I, natives and immigrants concentrate in different occupations given observable skills, and foreign workers are increasingly more clustered in blue collar jobs. Additionally, it is easier for workers to switch occupations than skills as a mechanism to overcome immigrant competition. Peri and Sparber (2009) argue that immigration caused natives to reallocate their task supply, thereby reducing downward wage pressures. Kambourov and Manovskii (2009) model the importance of switching occupations in explaining the increase in wage inequality.

Blue collar and white collar workers are broad groups. As mentioned in Section I, however, these two categories seem to be narrow enough to describe the differential supply shock across occupations in this context. The larger the number of skill prices, the more heterogeneous effects of immigration on wages will be allowed for in the model. However, the computational burden increases with the number of skill prices to be solved in equilibrium.[14]

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[13] As z_t affects labor supply decisions though its effect on wages, this aggregate shock needs to be jointly determined with aggregate skill units. This joint determination is solved as a fixed point problem, as described in Section III.

[14] The state space of the individual maximization problem increases exponentially with the number of aggregate variables and prices. Additionally, the cost of solving for equilibrium skill prices also increases with the number of prices to be solved for. And, finally, the complexity of

Equation (6) is different from the three-level nested CES proposed by Card and Lemieux (2001) that has become popular in the immigration literature since its introduction by Borjas (2003). This production function proposes a technology that is a Cobb-Douglas combination of capital and a labor aggregate. Labor is a CES aggregation of four educational cells, each being itself a CES aggregate over five experience cells. Labor supply in each education-experience cell is computed as worker counts. Equation (6) differs from the three-level nested CES in the following aspects: (i) it adds the occupational layer; (ii) it allows for capital-skill complementarity as a source of skill-biased technical change; (iii) the marginal rate of substitution between two workers is increasing in the productivity gap between them, even within occupations;[15] and (iv) it implies solving for two equilibrium prices instead of thirty-two (see footnote 14).[16]

Capital-skill complementarity is important to account for skill-biased technical change. Krusell et al. (2000) use a production function similar to equation (6) to link the decline in the relative price of equipment capital beginning in the early 70s (technical change), to the increase in the college-high school wage gap (skill-biased). This link is provided by $\rho > \gamma$, meaning that equipment capital is more complementary to skilled labor (in their paper college workers, in this paper white collar workers) than to unskilled labor (high school or blue collar workers). As a result, the increasing speed of accumulation of equipment capital —exogenous in this model, but generated by the decline in its price as shown in Krusell et al. (2000)— would increase the relative demand of white collar workers.

C. The equilibrium

The aggregate supply of skill units in occupation $j = B, W$ is given by

$$S_t^j = \sum_{a=16}^{65} \sum_{i=1}^{N_{a,t}} s_{a,i}^j \mathbb{1}\{d_{a,i} = j\}. \tag{8}$$

where $N_{a,t}$ is the cohort size. The aggregate demand comes from the aggregate firm's profit maximization, which equalizes marginal returns to skill rental prices:

$$r_{S_B t} = (1-\lambda)\alpha \left(z_t K_{St}^\lambda\right)^{\frac{\rho}{1-\lambda}} S_{Bt}^{\rho-1} Y_t^{1-\frac{\rho}{1-\lambda}}, \tag{9}$$

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the expectation rules for individuals to forecast future skill prices is also affected by the number of skill prices to be forecasted.

[15] The three-level nested CES assumes that the elasticity of substitution between a high school dropout worker and a college graduate is the same as the one between a high school dropout and a high school graduate. In this model, although individual skill units are perfect substitutes within an occupation, workers are not (e.g. a one percent reduction in the number high school dropouts needs to be replaced by a larger number of high school graduate workers than of college graduates to keep output constant).

[16] The thirty-two skill prices come from four education groups times eight experience groups.

$$r_{S_W t} = (1 - \lambda)(1 - \alpha)\theta \left(z_t K_{St}^{\lambda}\right)^{\frac{\rho}{1-\lambda}} S_{Wt}^{\gamma-1} KW_t^{\rho-\gamma} Y_t^{1-\frac{\rho}{1-\lambda}}, \qquad (10)$$

where $KW_t \equiv [\theta S_{Wt}^{\gamma} + (1 - \theta)K_{Et}^{\gamma}]^{1/\gamma}$. The labor market equilibrium is given by the skill prices —r_{jt} for $j = S_B, S_W$— that clear the market of skill units.[17]

Given equations (9) and (10) we can write the (log of the) relative white collar to blue collar skill price as:

$$\ln \frac{r_{Wt}}{r_{Bt}} = \ln \frac{(1-\alpha)\theta}{\alpha} + (\rho - 1) \ln \frac{S_{Wt}}{S_{Bt}} + \frac{\rho - \gamma}{\gamma} \ln \left(\theta + (1 - \theta)\left(\frac{K_{Et}}{S_{Wt}}\right)^{\gamma}\right). \quad (11)$$

Equation (11) can be interpreted as a reformulation of Tinbergen's race between technology and the supply of skills (Tinbergen, 1975).[18] The second term of this equation is the negative contribution of the relative supply of skills (provided by $\rho < 1$) and the last term captures the biased technical change through the speeding up in the accumulation of equipment capital (whenever $\rho > \gamma$).

Every year t, workers make a forecast of the future path of the information set in the state points they expect to reach. The information set at year t, $\Omega_{a,t}$, is given by the following state variables: age, education, blue collar and white collar effective work experience, foreign potential experience, previous year decision, calendar year, number of children, idiosyncratic shocks, and skill prices. Among them, they face uncertainty about future skill prices, number of children, and idiosyncratic shocks. The fertility process is exogenous and (given education and age) known by all agents, i.e. all individuals know the probability of having 0, 1 or 2+ children in the next period conditional on the number of children today, their education, and their age. Idiosyncratic shocks have no persistence. Therefore, the best forecast is their conditional mean. The path of future skill prices is determined by the sequence of aggregate variables and the aggregate shock. In order to forecast the aggregate shock, individuals use the process given by equation (7). Forecasting the sequence of aggregate variables is more complicated. The future supply of aggregate skill units depends on the future distribution of state variables over the population, whose sufficient statistic is its current distribution. Therefore, rationality implies that individuals use this current distribution of state variables to forecast future skill prices. Handling such a distribution as a state variable is not feasible in practice. To make the problem tractable, I follow an approach inspired

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[17] There are two additional first order conditions that deliver the demands for structures and equipment capital. Given equilibrium capital stocks (taken from the data), these two conditions are irrelevant to solve the labor market equilibrium. However, they are used in counterfactual exercises in Section V to recover interest rates in the counterfactual scenario in which I assume perfect capital adjustment.

[18] Tinbergen (1975) suggests that the overall change in the gap between skilled and unskilled wages is driven by two contrasting forces: the relative increase in the supply of skills, which tends to close the gap, and a skill-biased technical change, which opens it. Acemoglu (2002), and Acemoglu and Autor (2011) survey the literature that have tested this hypothesis.

by Krusell and Smith (1998) and Altuğ and Miller (1998), and similar to the one in Lee and Wolpin (2006, 2010). More concretely, I approximate the expectation rule for future skill prices using a subset of the information included in the current distribution of state variables that contains most of the relevant information that is needed to predict future skill prices: current skill prices. The following VAR replicates fairly well the path of skill prices:

$$\Delta \ln r_{t+1}^j = \eta_0^j + \eta_B^j \Delta \ln r_t^B + \eta_W^j \Delta \ln r_t^W + \eta_z^j \Delta \ln z_{t+1}. \tag{12}$$

This rule is an approximation to rational expectations as long as the estimated process provides the best fit to the data that is generated using the rule itself to solve the individual maximization problem. In other words, it is a good approximation to rational expectations if the estimated parameter vector $\hat{\eta}$ is a fixed point of an algorithm that uses equation (12) to solve individuals' problem and to generate a sequence of equilibrium skill prices, and then updates its parameter values estimating the equation with the generated data.

An additional aspect that is important for this paper is the forecasting of future immigration. This forecasting is implicit in the estimated parameters $\hat{\eta}$. Therefore, I assume that individuals also form rational expectations on future immigration, and that current skill prices are also a sufficient statistic for it.

III. Model solution and estimation

The equilibrium model presented in Section II does not have a closed form solution and needs to be solved numerically. The solution and estimation algorithm is explained in detail in Appendix B. Data sources and definitions are described in Appendix C. In this section I briefly describe the intuition of the proposed algorithm, and I highlight the main features of the data used in the estimation.

In order to give the intuition of the solution and estimation algorithm it is convenient to differentiate two types of parameters: *expectation parameters*, Θ_2, which are given by the forecasting rules described in equation (12), and the process for the aggregate shock (7), and *fundamental parameters* of the model, Θ_1, which are the remaining parameters described in Sections II.A and II.B. Forecasting rules are part of the solution of the model, in the sense that their parameters η are implicit functions of the fundamental parameters. Parameters from the aggregate shock process are fundamental by nature, but since the aggregate shock is estimated as a residual (i.e. an implicit function of the data and fundamental parameters), and it is used to forecast future skill prices in the same way forecasting rules given by equation (12) are used, I treat (and estimate) them as expectation parameters. We can express Θ_2 as $\Theta_2(\Theta_1)$.

Parameters in Θ_1 are estimated by Simulated Minimum Distance. The Simulated Minimum Distance estimator minimizes the distance between a large number of statistics from the data (or data points) and their simulated counterparts. $\Theta_2(\Theta_1)$ is obtained as the fixed point of an algorithm that simulate the behavior of individuals using a guess of Θ_2, and then estimates equations (7) and (12) from the simulated data to update the guess. Therefore, the estimator requires a nested algorithm with a procedure that estimates Θ_1, and another solving Θ_2 given Θ_1.

Lee and Wolpin (2006, 2010) describe a natural nested algorithm in which an inner procedure finds the fixed point in Θ_2 for every guess of Θ_1, and an outer loop solves the Θ_1 estimation problem with a polytope algorithm. The main drawback of this procedure is that it requires solving the fixed point problem in every evaluation of Θ_1, and this increases the computational burden significantly.[19] I propose an alternative algorithm that avoids having to solve the fixed point in every iteration of Θ_1. In particular, I propose a swapping of the two procedures which is in the same spirit of the swapping of conditional choice probabilities and parameter estimation proposed by Aguirregabiria and Mira (2002). Θ_1 is estimated for every guess of Θ_2, which is updated at a lower frequency. In other words, I estimate $\Theta_1(\Theta_2)$ for every guess of Θ_2 instead of the opposite.

The model is fitted to a large number of statistics computed with micro-data from 1967 to 2007. These statistics are listed in Table B1 in Appendix B. Their simulated counterparts are obtained by simulating the behavior of cohorts of 5,000 natives and 5,000 immigrants (some of them starting their life abroad and not making decisions until they arrive in the U.S.). Cross-sectional simulated data are, hence, calculated with a sample of up to 500,000 observations, which are weighted using data on cohort sizes.

Additional data for exogenous variables is used in the solution of the model. These variables include output, structures and equipment capital stocks, cohort sizes (by gender and immigrant status), the distribution of entry age for immigrants, the distribution of initial schooling (at age 16 for natives and upon entry in the U.S. for immigrants), the distribution of immigrants by region of birth, and the fertility (preschool children) process. Their sources, definitions, and construction are detailed in Appendix C.

Appendix B also discusses parameter identification. No formal proof is available, but some intuition is provided. As an heuristic check Figure D1 in Appendix D plots different *sections* of the objective function in which I move one parameter

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[19] This problem is relatively exacerbated if one uses the parallel version of the Simplex Method developed by Lee and Wiswall (2007) in the minimization problem. The basic idea in Lee and Wiswall (2007) is to move the p worst parameters in each Simplex iteration. The problem is that if one of the processors takes more iterations to find the fixed point in $\Theta_2(\Theta_1)$ than all others, the latter will remain idle while the former performs further iterations.

and keep the others constant to the estimated values. Although this exercise is uninformative about the curvature in the multidimensional space, it shows plenty of unilateral curvature for all parameters. Pointing in the same line, standard errors of the estimates reported below are very small, which is significant because they depend on the curvature of the objective function around parameter estimates —see Appendix E. Regarding uniqueness, I started the estimation from different initial conditions and kept the local minimum that gave a smaller value for the objective function.

IV.   Estimation results

A.   Parameter estimates

In this Section, I discuss parameter estimates, presented in Table 2 and Table 3. Standard errors, in parentheses, take into account both sampling error and a simulation error (see details on their calculation in Appendix E).[20]

Fundamental parameters of the model.   Panel A in Table 2 presents gender × origin constants for each alternative. Women are less productive than men in both occupations (to a larger extent in blue collar), obtain a larger utility from attending school, and a smaller utility from staying at home; all this is consistent with the observed wage gap, enrollment rates, and female concentration in white collar occupations. Similarly, native-immigrant differentials in wages and home utility mimic the corresponding wage gaps (none for Western immigrants, very large for Latin Americans, and somewhere in between for Asian/African). Except for Latin Americans, immigrants get a larger utility from schooling than natives, which, although at the first glance may seem at odds with their lower enrollment, is necessary to replicate their decisions given the large school reentry cost.

Estimates for wage equations are presented in Panel B. The return to an additional year of schooling for natives is estimated to be 7.3% in blue collar occupations and 11.0% in white collar. For immigrants, returns are smaller in blue collar occupations (5.7%), and similar in white collar (11%). These estimates fit within the variety of results surveyed by Card (1999), which range from 5 to 15% with most of the estimated causal effects clustering between 9% and 11%; results are also qualitatively in line with (although somewhat larger than) Keane and Wolpin (1997), Lee (2005), and Lee and Wolpin (2006). Both blue collar and white collar own experience are estimated to have a quadratic return. Returns to cross experience are much lower, much flatter, and turn negative after few years of experience. Standard deviations for male and for white collar wages are esti-

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[20] Standard errors from expectation rules and the aggregate shock process are regression standard errors instead of minimum distance standard errors.

TABLE 2—PARAMETERS ESTIMATES

A. Origin×gender constants:	Nat. male	Nat. female	Western countries	Latin America	Asia/ Africa
Blue collar	0	-0.338 (0.0010)	0.086 (0.0292)	0.046 (0.0169)	-0.005 (0.0060)
White collar	0	-0.292 (0.0015)	0.157 (0.0355)	-0.170 (0.0169)	0.059 (0.0140)
School	2,424 (68)	5,606 (84)	7,545 (249)	2,646 (249)	10,184 (382)
Home	16,678 (53)	11,341 (29)	16,379 (764)	12,298 (240)	14,962 (143)

B. Wage equations:	Blue collar		White collar	
Education—Natives ($\omega_{1,nat}$)	0.073	(0.0001)	0.110	(0.0001)
Education—Immigr. ($\omega_{1,imm}$)	0.058	(0.0005)	0.110	(0.0005)
BC Experience (ω_2)	0.094	(0.0001)	0.001	(0.0003)
BC Experience squared (ω_3)	-0.0023	(0.00018)	-0.0005	(0.00016)
WC Experience (ω_4)	0.029	(0.0000)	0.105	(0.0000)
WC Experience squared (ω_5)	-0.0013	(0.00001)	-0.0029	(0.00001)
Foreign Experience (ω_6)	0.018	(0.0005)	-0.046	(0.0012)
Variance-covariance matrix of i.i.d. shocks:				
Std. dev. male (σ_{male})	0.443	(0.0058)	0.547	(0.0039)
Std. dev. female (σ_{female})	0.392	(0.0024)	0.492	(0.0035)
Correlation coefficient (ρ_{BW})	0.062	(0.0052)		

C. Utility parameters:	Male		Female	
Labor market reentry cost (δ_1^{BW})	8,851	(76)	12,442	(180)
School utility parameters:				
Undergraduate Tuition (τ_1)	12,584	(85)		
Graduate Tuition ($\tau_1 + \tau_2$)	33,541	(869)		
Disutility of school reentry (δ_1^S)	30,829	(207)	33,465	(597)
Home utility parameters:				
Children (δ_1^H)	-1,775	(47)	3,663	(75)
Trend (δ_2^H)	55.59	(0.73)	52.68	(0.54)
Standard dev. of i.i.d. shocks:				
School (σ^S)	1,280	(9)	1,339	(9)
Home (σ^H)	10,437	(651)	5,011	(229)

D. Production function:	Elast. of substit. param.		Factor share parameters		
	BC vs Eq. (ρ)	WC vs Eq. (γ)	Struct. (λ)	BC (α)	WC (θ)
	0.289 (0.006)	-0.067 (0.005)	0.091 (0.013)	0.547 (0.007)	0.444 (0.010)

E. Aggregate shock process:	Constant (ϕ_0)	Autoregressive term (ϕ_1)	St. dev. of innovations (σ_z)
	0.002 (0.003)	0.323 (0.115)	0.025 (0.021)

Note: The table presents parameter estimates for equations (2) to (7). Native male constant for wage equations is normalized to zero. Immigrant male and native female constants are estimated. The constant for a female immigrant from region i is obtained as the sum of the constant for a male immigrant from region i and the difference between the constant for native females and native males. The individual subjective discount factor, β, is set to 0.95. A more detailed description of each parameter can be found in the main text. Standard errors (calculated as described in Appendix E) are in parentheses.

mated to be larger than for female and blue collar wages, mimicking the observed pattern for variances in log wages. The correlation between the two shocks is around 0.07, which pins down, together with returns to crossed-experience, the observed transitions across occupations. Potential experience abroad is less productive than own effective experience in the U.S. in both occupations. This lower return generates conditional wage convergence for immigrants as they spend time in the United States, which can be interpreted as immigrant assimilation in the sense of LaLonde and Topel (1992). These results are in line with the findings in Eckstein and Weiss (2004) for Israel.

Utility parameters are presented in Panel C. The labor market reentry cost is estimated to be close to nine thousand US$ for males, and above twelve thousand for females, which represent around one quarter and almost one half of the average full-time equivalent annual wage for males and females respectively. Tuition fees (as a difference from high school cost) are estimated to be slightly above twelve thousand dollars for a bachelors degree, and around thirty-three for post-college, in line with other estimates in the literature (e.g. Lee (2005), Lee and Wolpin (2006, 2010)). School reentry cost is quite large (close to the male average annual wage, larger for females than for males), consistent with the rather unfrequent transitions back to school observed in the data. Female obtain a larger additional utility than male from staying at home when preschool children are present, replicating the observed pattern of maternity/paternity leaves.[21] The trend component of the utility is estimated to be 52-55 U.S.$ per year, which despite being a modest increase in relative terms (an overall utility increase of around $2,100 - 2,300$ U.S.$ over the sample years) is in line with the modest growth of the aggregate shock that is generated by the model over this period. Variances of school i.i.d. idiosyncratic shocks are somewhat small, whereas for the home alternative, they are larger, but substantially smaller for female than for male.

Estimates for the production function parameters and the aggregate shock process are presented in Panels D and E. Elasticities of substitution implied by ρ and γ are respectively 1.41 and 0.94. These estimates imply that equipment capital and white collar labor are relative complements. This result —capital-skill complementarity— is necessary to link the fast accumulation of equipment capital and the increase in the white collar/blue collar (and college/high school) wage gap (see equation (11)). Several papers have tested capital-skill complementarity with different data since the seminal work by Griliches (1969). As noted by Hamermesh (1986), although most of these studies agree in the existence of some degree of

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[21] Indeed, preschool children at home reduce male's home utility. Given that individuals instead of households are modeled, this negative parameter could be interpreted as male working further to compensate for spouse's maternity leave.

Table 3—Expectation Rules for Skill Prices

	Blue-collar skill price		White-collar skill price	
Coefficient estimates:				
Constant (η_0)	0.001	(0.001)	0.002	(0.002)
Δ Blue-collar skill prices (η_B)	0.055	(0.313)	0.523	(0.488)
Δ White-collar skill prices (η_W)	0.192	(0.218)	-0.026	(0.341)
Δ Aggregate shock (η_z)	0.788	(0.044)	1.100	(0.068)
R-squared goodness of fit measures:				
Differences	0.855		0.858	
Levels	0.999		0.999	
Using predicted shock	0.193		0.215	

Note: The table includes estimates for the coefficients of expectation rules for aggregate skill prices — equation (12). Goodness of fit measures are reported in the bottom panel. These measures are computed for the prediction of $\Delta \ln \hat{r}_t^j$, $\ln \hat{r}_t^j$ and $\ln \tilde{r}_t^j$ for $j = B, W$, where the last one uses the predicted increase in the aggregate shock obtained from equation (7). A more detailed description can be found in the main text. Standard errors (in parenthesis) computed from the regression in the standard way, i.e. they do not account for estimation error of the fundamental parameters.

complementarity between capital and skilled labor, there is a large variety of estimates for elasticities of substitution between capital and skilled/unskilled labor. Estimates in this paper are very much in line with Krusell et al. (2000).
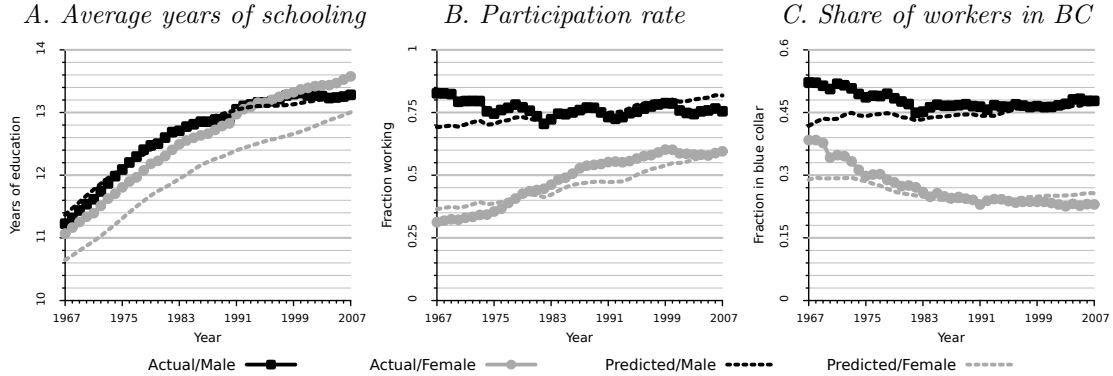
Parameters α and θ are relative to the normalization of the native male wage constants. Estimated parameters imply a 9% share of structures —Krusell et al. (2000) estimate is 11.7%, and Greenwood, Hercowitz and Krusell (1997) calibrate it to a 13%—, a roughly constant overall capital share[22] —in line with Kaldor's stylized facts (Kaldor, 1957)—, and an increasing importance of white collar within the labor share —consistent with the observed blue collar and white collar aggregate wage bills. Parameters from the aggregate shock process display a small deterministic growth rate, and an important cyclical component; the standard deviation of the innovation indicates an almost three percentage points average deviation from the predictable part of the growth rate of the aggregate shock, which is quite large.

Expectation rules. Table 3 presents parameter estimates for the expectation rules given by equation (12). According to the table, the growth rate of the aggregate shock almost maps one to one into growth rate of skill prices, especially for white collar. Additionally, estimates also show some state-dependence, and an additional small positive trend for both skill prices (which adds to the trend in the aggregate shock, that is also passed to skill prices through η_z).

The selection of these particular rules as an approximation to rational expectations balanced a trade-off between simplicity and goodness of the approximation. The bottom panel of the table summarizes the explanatory power of these rules

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[22] Blue collar labor, white collar labor, and equipment capital shares are time-varying.

FIGURE 2. ACTUAL AND PREDICTED EDUCATION AND LABOR SUPPLY

A. *Average years of schooling* B. *Participation rate* C. *Share of workers in BC*

Actual/Male ■——■   Actual/Female ●——●   Predicted/Male ••••••   Predicted/Female ------

Note: The figure plots observed and predicted average years of education (left), labor force participation rate (center), and fraction of employees working in blue collar occupations (right). The sample is restricted to individuals aged 25-55. Actual data is obtained from March Supplements of the CPS (survey years from 1968 to 2008).

into three different R^2 measures. The rules are able to predict around 86% of the variation in growth rates of skill prices (top row), and display almost perfect fit for the skill prices in levels (central row). This large explanatory power, however, does not imply that individuals have perfect foresight of future skill prices, as they do not observe z_{t+1} in period t. The third pseudo-R^2 (bottom row) predicts z_{t+1} using equation (7), as individuals do; this measure indicates that, in period t, they are able to forecast around one fourth of the variation in (the growth rate of) skill prices one period ahead, which, indeed, is far from perfect foresight.

B.   *Model fit*

In this section, I compare predicted and actual values of the most relevant aggregates for individuals aged 25 to 54 in order to evaluate the goodness of fit of the estimated model. I focus on this age range because it is the one for which I compare baseline and counterfactual outcomes in Section V.

Figure 2 plots actual and predicted statistics on education, labor force participation and occupation. Panel A plots actual and simulated average years of schooling for male and female.[23] The model accuracy in predicting education for males is remarkable: it predicts very well both the level and the increase in years of schooling over the sample period. For females, the model accurately fits the increase observed in the data (around 2.5 years), but slightly under-predicts the level throughout (by around a third of a year). Panel B evaluates the goodness of fit of the model in terms of labor force participation. The model does a good prediction of the participation level, the increase in female labor force participa-

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[23] Average years of education are computed as follows: 0 if no education, preschool or kindergarten, 2.5 if 1st to 4rth grade, 6.5 if 5th to 8th grade, 9, 10, 11, and 12 for the corresponding grades, 14 for some college, and 16 for bachelors degree or more.

FIGURE 3. ACTUAL AND PREDICTED EXPERIENCE DISTRIBUTIONS

FIGURE 3. ACTUAL AND PREDICTED EXPERIENCE DISTRIBUTIONS
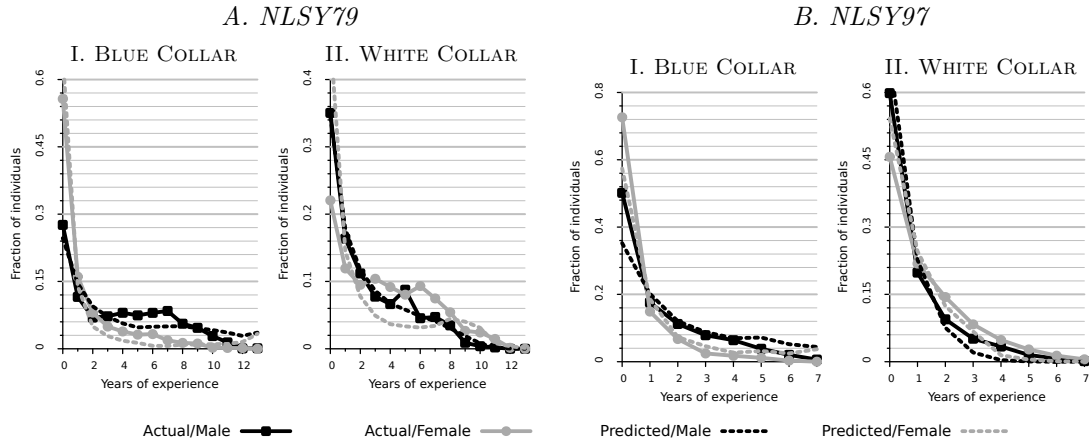
Note: The figure plots observed and predicted distribution of years of experience in blue collar and white collar accumulated by individuals from the NLSY samples. Experience is counted at the closest available year to 1993 (NLSY79) or 2006 (NLSY97).

tion, and the gender gap. It accurately predicts as well the level of male labor force participation, although there is a minor discrepancy in replicating the trend for this group as the model predicts a slightly increasing pattern, compared to the roughly constant —rather slightly decreasing in early years— shape observed in the data. Panel C compares actual and simulated fraction of employees working in blue collar occupations. The levels, the gender gap, and the decreasing importance of blue collar occupations in both male and female employment are replicated by the model. There is a slight under-prediction of the importance of white collar in early years.

Figure 3 plots the actual and predicted distributions of blue collar and white collar experience for individuals in the NLSY samples. For individuals in the NLSY79 (Panel A), experience is measured around 1993, when individuals are aged around 30. For the NLSY97 sample (Panel B), it is measured around 2006, with individuals aged around 25. In general, the model generates experience distributions with a very similar shape to their data counterparts.

TABLE 4—ACTUAL VS PREDICTED TRANSITION PROBABILITY MATRIX

| | Choice in t | | | | | | | |
| | Blue collar | | White collar | | School | | Home | |
Choice in $t-1$	Act.	Pred.	Act.	Pred.	Act.	Pred.	Act.	Pred.
Blue collar	0.75	0.74	0.11	0.12	0.00	0.00	0.14	0.14
White collar	0.06	0.07	0.83	0.83	0.00	0.00	0.10	0.10
Home	0.11	0.08	0.13	0.12	0.01	0.01	0.76	0.79

Note: The table includes actual and predicted one-year transition probability matrix from blue collar, white collar, and home (rows) into blue collar, white collar, school, and home (columns) for individuals aged 25-55. Actual and predicted probabilities in each row add up to one. Actual data is obtained from one-year matched March Supplements of the CPS (survey years from 1968 to 2008).

FIGURE 4. ACTUAL AND PREDICTED WAGES

A. *Average log hourly wages*   B. *College-high school wage gap*   C. *WC-BC wage gap*

Actual/Male ■—■—■   Actual/Female ●—●—●   Predicted/Male ••••••   Predicted/Female ••••••
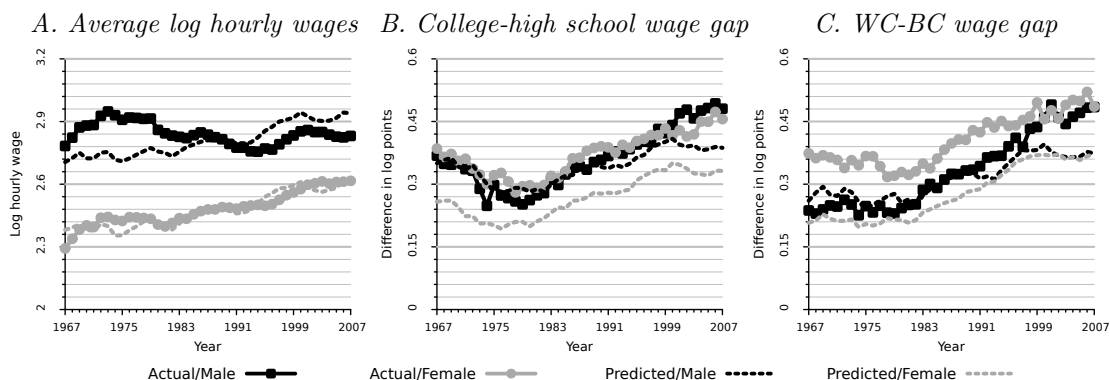
Note: The figure plots observed and predicted average log hourly wages (left), college-high school wage gap (center) and white collar-blue collar wage gap (right). High school workers are those with 12 or less years of education, and college are those with more than 12 years. The sample is restricted to individuals aged 25-55. Actual data is obtained from March Supplements of the CPS (survey years from 1968 to 2008).

The predictive power of the model in terms of transition probabilities is evaluated in Table 4. The table presents actual and predicted transition probability matrix from blue collar, white collar, and home alternatives into blue collar, white collar, school, and home.[24] Transitions from the three alternatives are extremely well replicated by the model. In particular, the model captures very well the persistence in each of the alternatives, occupational switches, the fact that individuals rarely go back to school after leaving it, and transitions back and forth from working to home.

Figure 4 evaluates the fit of the model in terms of wages. Panel A compares fitted and actual average log hourly wages for male and female over the sample period. The model predicts female wages very well; it also picks the level of male wages and, hence, the gender wage gap. However, it is not able to replicate the hump shape in the evolution of male wages observed between 1970 and 1990. This could be the result of the rather simple parametrization of the aggregate production function, or of not allowing returns to skills to vary over such a long period. Both assumptions may have an effect on the identification of the aggregate shock, which ultimately drives the evolution of wages. Panel B in Figure 4 compares actual and predicted college-high school wage gap. The model clearly predicts the evolution of the gap, with a slight decrease in early years and a sharp increase after mid 1970s. For females, although the evolution of the gap is well generated by the model, the level is somewhat under-predicted. A fairly similar pattern can be appreciated for the white collar-blue collar wage gap in Panel C.

So far, I have shown that model's power in predicting the main aggregates is

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[24] Transitions from school into each of the four categories is omitted from the table because very few people is in school in the relevant age group (25-54).

TABLE 5—OUT OF SAMPLE FIT: ACT. VS PRED. STATISTICS FOR IMMIGRANTS

| | Out-of-sample | | | | | | In-sample | |
| | 1970 | | 1980 | | 1990 | | 1993-2007 | |
	Act.	Pred.	Act.	Pred.	Act.	Pred.	Act.	Pred.
A. Male								
Share with high school or less	0.67	0.61	0.57	0.56	0.52	0.54	0.55	0.56
Average years of education	10.8	11.6	11.4	12.0	11.7	12.1	11.9	12.0
Participation rate	0.77	0.64	0.68	0.67	0.63	0.71	0.75	0.75
Share of workers in blue collar	0.57	0.55	0.55	0.53	0.53	0.52	0.58	0.52
B. Female								
Share with high school or less	0.78	0.79	0.68	0.71	0.56	0.62	0.54	0.57
Average years of education	10.3	10.7	10.9	11.4	11.5	11.9	12.0	12.2
Participation rate	0.32	0.27	0.36	0.31	0.41	0.39	0.49	0.49
Share of workers in blue collar	0.46	0.49	0.45	0.48	0.39	0.46	0.41	0.45

Note: The table presents actual and predicted values of four aggregate variables for immigrants. Statistics for 1993-2007 are obtained from March Supplements of the CPS, and are used in the estimation. Data for 1970, 1980, and 1990 are obtained from U.S. Census microdata samples and not used in the estimation.

substantial. This conclusion is reached by comparing actual and simulated data for several aggregate statistics. However, all these simulations are in-sample, in the sense that they are the combination of different statistics used in the estimation. Table 5 provides additional validation evidence to check the out-of-sample predictive power of the model. In particular, I use the fact that, as it emerges from Table B1 in Appendix B, statistics that are conditional on region of origin or immigrant status of the individual are only available in the CPS starting in 1993. Therefore, for the period before 1993, no separate information for natives and immigrants have been used in the estimation. Given that the fraction of immigrants in the population working-age was below 10%, we can consider that the immigrant group is small enough not to be driving the main aggregate trends. Moreover, as discussed in Section I, the composition of immigrants in terms of education and occupation diverged from that of natives over the years. And additionally, the fact that the model replicates well immigrant behavior is crucial to correctly quantify the size of the immigrant shock. The Table compares actual and predicted values of four aggregate variables for immigrants —the share with high school diploma or less, average years of education, participation rate, and the share of workers employed in blue collar occupations— in 1969, 1979, and 1989. These data are obtained from U.S. Census microdata samples for survey years 1970, 1980, and 1990 and not used in the estimation.[25] The different statistics are compared separately for male and female. As it emerges from the table, the model does a good job in predicting levels, trends, and gender gaps for the four aggregates.

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[25] Wages are not included in the table for comparability issues across databases.

V. Understanding the consequences of immigration: counterfactual exercises

In order to disentangle the labor market consequences of immigration, I simulate a set of counterfactual scenarios that characterize "a world without large scale immigration" under different assumptions. Specifically, I use the estimated model to simulate a world where, everything else equal, the share of immigrants amongst individuals working-age is kept to pre-immigration levels. I consider 1967 as the baseline/pre-immigration year, and 2007 as a final year.[26] The choice of this particular period is based on three main reasons. First, during mid 1960s, the fraction of foreign born individuals in the U.S. population reached its minimum level of the century. Second, one of the largest changes in U.S. immigration policy, the Amendments to the Immigration and Nationality Act, was passed in 1965. And third, it coincides with the estimation period.[27]

Keeping the fraction of immigrants in the workforce constant as in 1967 is not equivalent to completely closing the borders from then on. Some immigration is allowed for, in order to compensate for native population growth and retirement/death of previous immigrant cohorts so that the share of immigrants in the population working-age (by age and gender) is constant. The counterfactual only changes aggregate quantities, but the composition of the immigrant population (national origin, age at entry, initial education) evolves as in the baseline.[28]

How much should capital be allowed to adjust to immigration has been debated widely in the literature. Borjas (2003) assumes that the capital is the same in baseline and counterfactual scenarios (short run effects); Ottaviano and Peri (2012) argue in favor of keeping the return to capital fixed (long run effects for a small open economy). Most likely, the *correct* counterfactual would imply a partial adjustment of capital, as the U.S. is a large economy that is likely to affect world interest rates (Borjas, 2009). Given that capital supply is not modeled in this paper, and capital supply elasticities have not been estimated in the literature (to the best of my knowledge), I simulate the two extreme cases —no adjustment vs full adjustment— so that estimated effects are consistent bounds for the *true* effect of immigration on wages.[29]

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[26] The share of immigrants in the workforce in 1967 was 5.1%.

[27] Similar counterfactual exercises have been simulated as well for 1980-2000 and for 1990-2007, for comparability with other papers in the literature. Results, not reported but available upon request, are in line with the ones presented in this section.

[28] Individuals are exposed to the same sequence of aggregate and idiosyncratic shocks in the baseline and counterfactual scenarios. The difference between scenarios, hence, is in the population elevation weights used to compute the aggregate supplies that determine the equilibrium. As a result, individuals are exposed to a different sequence of equilibrium skill prices under the different scenarios.

[29] In the full capital adjustment scenario, the counterfactual returns to structures and equip-

The results presented in this section are for native male aged 25-54. This particular subset of the population is targeted for two reasons: first, to make results comparable to the existing literature; and second, to clean the estimated results from confounding effects —e.g. some workers still in school at early ages, early retirement for the oldest, and the change in female labor force participation over the sample period. Results for other sub-populations are available upon request.

A. The effect of immigration on average wages

A crude approach to quantify the labor market effect of immigration is to look at average wages. Table 6 presents the difference between baseline and counterfactual average log wages and skill prices. In the top panel, counterfactual capital is assumed to evolve as in the data (no adjustment); in the bottom panel, it is the counterfactual return to capital what evolves as in the baseline (full adjustment, if the United States were a small open economy). The left panel gives the raw difference between counterfactual and baseline wages, and the right panel provides the corresponding change in skill prices.

The first row from each panel presents the results of a counterfactual exercise in which individuals are not allowed to adjust to immigration.[30] This counterfactual is equivalent to existing exercises in the literature (e.g. Borjas, 2003; Ottaviano and Peri, 2012). The estimated effects under this approach suggest that the observed increase in immigration between 1967 and 2007 reduced native male average wages. In particular, results point to a fall in average wages induced by immigration of 4.7% and 0.6% respectively in the two different capital scenarios. The implied elasticities are -0.34 without capital adjustment (very much in line with the estimates in Borjas (2003)) and -0.04 with full capital reaction (similar to Ottaviano and Peri (2012)).[31]

Labor market adjustments are allowed for in the last row from each panel. Results suggest that immigration reduced native male wages by 3% on average if capital is not allowed to adjust. With full capital adjustment, immigration increased average wages by 0.6%. The wage elasticities to immigration implied

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ment capital are assumed to be the same as in the baseline so that the elasticity of the capital supply is infinity. The fact that the model delivers different returns to each of the two types of capital is not necessarily inconsistent with the presence of a single world interest rate, as depreciation rates of structures and equipment capital may differ.

[30] In practice, this implies simulating baseline individual decisions, and then use counterfactual instead of baseline cohort sizes as population elevation weights to compute labor aggregates in the terminal year. Then, using the resulting counterfactual labor supplies, skill prices are obtained from the first order conditions of the production function.

[31] These elasticities are computed as the ratio between the percentage increase in wages (reported in the table) and the percentage increase in the workforce induced by immigration —i.e. $(P_{2007} - P_{2007}^c)/P_{2007}^c$, where P_{2007} is the observed population working-age in 2007, and P_{2007}^c is its counterfactual counterpart—, which is 13.7%.

TABLE 6—AGGREGATE EFFECTS AND THE ROLE OF EQUILIBRIUM

	Wages:			Skill prices:	
	Average	BC	WC	BC	WC
No capital adjustment ($\partial K/\partial m = 0$):					
No labor market adjustment	-4.71	-6.12	-3.51	-6.12	-3.51
Equilibrium effect	1.75	3.86	-1.77	3.49	0.20
Total effect	-2.96	-2.26	-5.28	-2.63	-3.30
Full capital adjustment ($\partial r_K/\partial m = 0$):					
No labor market adjustment	-0.62	-2.90	1.32	-2.90	1.32
Equilibrium effect	1.22	2.70	-1.41	2.76	-1.33
Total effect	0.60	-0.20	-0.09	-0.14	0.00

Note: The table compares baseline and counterfactual average log wages and skill prices for native male aged 25-55. Different panels correspond to different assumptions on counterfactual capital as indicated. "No labor market adjustment" indicates a scenario in which individuals are not allowed to adjust their human capital, occupational choice, and labor supply. "Equilibrium effect" is the difference between the total effect and the effect without labor market adjustment.

by these numbers are around -0.22 and 0.04 respectively. Therefore, labor market equilibrium adjustments compensated the initial effect by 1.8 and 1.2 percentage points respectively in the two capital scenarios —the difference between third and first rows from each panel in Table 6, presented in the second row. These differences indicate that labor supply adjustments mitigated the initial effect by more than one third in the first case, and turned it into positive in the second.

The analysis at the occupational level, presented in the second and third columns of Table 6, provides interesting insights. In the first row from each panel, we can observe that, initially, blue collar wages are way more affected by immigration than white collar wages. This is not surprising, given that immigrants tend to cluster in blue collar jobs. What can be more surprising, though, is that after labor market is allowed to adjust (third row), white collar wages are more affected than blue collar ones. In particular, the magnitude of the effect on blue collar wages decreases from 6.1% to 2.3% when capital is not allowed to adjust, whereas the effect on white collar wages increases, from 3.5% to 5.3%. When capital is allowed to adjust completely, these effects go from a 2.9% to a 0.2% decrease, and from a 1.3% increase to a 0.1% decrease respectively. This result suggests that some individuals adjust their decisions switching occupations and leaving the labor market.

The mitigation of the initial effect of immigration can be explained by the combination of three equilibrium mechanisms: changes in skills, composition effects, and skill price adjustments after individuals' re-optimization. Skill prices are the primary channel through which immigration affects natives. The effect of immigration on skill prices is analyzed in the right panel of Table 6. By construction, with no labor market adjustment immigration affects skill prices and average

wages equivalently (Table 6, first row from each panel). After labor market adjusts, however, conclusions change. When capital does not adjust, the magnitude of the effect on the blue collar skill price is reduced by almost four percentage points, as so is the effect on average blue collar wage. However, the effect on the white collar skill price is slightly mitigated, which is in contrast with the exacerbation observed for the effect on average white collar wages. This different behavior is the consequence of a change in the average skills of white collar and blue collar workers after equilibrium adjustments, as discussed below.

B. Human capital and labor supply adjustments

The change in the average skill units of blue collar and white collar workers can be the result of individual changes in skills and/or of composition effects. Composition effects can be of different natures. Occupational switches are likely to introduce less productive white collar workers into the pool, which reduces average skills, whereas individuals dropping out from the labor force will typically be the least productive ones, thus increasing the average. Changes in skills can be the result of adjustments in education and/or in the experience accumulation path. Two confronting forces are expected to work in this case: on the one hand, if skill prices are initially reduced, the return to human capital investments is also reduced, and, anticipating this, individuals may decide to invest less;[32] on the other hand, if a worker, as a result of the change in relative skill prices, is now more likely to work in a white collar job, then she might decide to further invest in education, as it is more rewarded in these occupations.

Table 7 compares individual baseline and counterfactual choices in the terminal year, 2007. Even though the figures refer to a single year, they are the result of a different exposure to immigration over several decades. The first column presents the fraction of individuals that make different decisions in baseline and counterfactual scenarios. The right panel presents the fraction of these individuals switching to each of the three remaining alternatives.

When capital is not allowed to adjust, 13.8% of the individuals that would have worked in a blue collar job in the absence of immigration do something else at the observed immigration levels. Of them, almost one third decided to switch to a white collar job, two thirds resigned to work, and a small fraction returned to (or stayed longer at) school. Similarly, a 6.6% of otherwise white collar workers are not such as a consequence of immigration; most of them decided to stay at home instead. This sizeable detachment from the labor market in both occupations is the consequence of both skill prices being reduced by immigration in this scenario.

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[32] Additionally, if the worker becomes more likely to spend some periods at home, the expected return to human capital becomes even lower.

TABLE 7—LABOR SUPPLY ADJUSTMENTS

Choice w/o immigration	Fraction adjusting	Of which adjust to:			
		Blue collar	White collar	Home	School
No capital adjustment ($\partial K/\partial m = 0$):					
Blue collar	13.80	—	30.72	65.99	3.28
White collar	6.60	5.20	—	90.93	3.87
Home	0.94	13.08	67.39	—	19.54
Full capital adjustment ($\partial r_K/\partial m = 0$):					
Blue collar	8.24	—	56.31	41.84	1.85
White collar	0.56	11.52	—	82.26	6.22
Home	1.23	5.69	88.83	—	5.48

Note: The left column presents the percentage of native male aged 25-55 that make different choices in baseline and in counterfactual simulations in the terminal year 2007. The right panel then presents the fraction of these individuals that switch to each of the three alternative choices. Top and bottom panels make different assumptions on counterfactual capital as indicated.

The fact that some individuals (around 4% — i.e., 30.7%×13.8%— of all otherwise blue collar workers) switch from blue collar to white collar jobs is the result of the initial effect on the relative skill prices.

If capital completely reacts, labor market adjustments are somewhat different. A large fraction of the otherwise blue collar workers still adjust (8.2%), but very few of the otherwise white collar workers (0.6%) do it. Indeed, even a 1.2% of individuals who would not work otherwise, are now employed, mostly in white collar jobs. These changes are the result of the smaller reduction of the blue collar skill price, and the increase in the white collar one. Therefore, most of the difference between the two capital scenarios comes from a smaller effect on labor force participation. Now, more than a half of the otherwise blue collar workers that changed their decision (still around a 4% of the total) switch to white collar, whereas only forty percent of them (around 3.4% of the total, much lower than the 9.1% in the no capital adjustment scenario) leave the labor market.

Table 7 suggests that immigration induces individuals to switch careers and/or to detach from the labor market. The presented transition probabilities at the terminal year provide an estimate of the probability of adjusting decisions as a consequence of immigration. However, their main limitation is that they only refer to a single period. As an alternative, Table 8 looks at career adjustments through the lens of accumulated work experience. The table presents the fraction of native male aged 25-54 that maintained, decreased, and increased their accumulated experience after age twenty five. Additionally, it provides the fraction in each group that increased white collar experience.

Results presented in the table confirm the findings in Table 7. Around 10-15% of native males in the selected age range adjust their experience when capital is not

Table 8—Career Adjustments

	No capital adjustment $(\partial K/\partial m = 0)$			Full capital adjustment $(\partial r_K/\partial m = 0)$		
	Age group:			Age group:		
	25-34	35-44	45-54	25-34	35-44	45-54
Total experience unchanged	89.90	85.20	87.41	97.77	94.60	95.84
of which increase white collar	0.54	0.33	0.31	0.27	0.44	0.40
Decrease total experience	8.68	12.33	11.83	1.48	3.16	1.85
of which increase white collar	8.52	10.30	4.85	24.53	40.79	33.31
Increase total experience	1.43	2.47	0.76	0.74	2.24	2.30
of which increase white collar	86.24	95.09	96.85	96.78	97.69	96.68

Note: The table presents the fraction of native male aged 25-54 (by age categories) that maintained, decreased and increased their experience accumulated after age twenty five. Additionally, it provides the fraction of individuals in each group that increased white collar experience. Different panels correspond to different assumptions on counterfactual capital as indicated.

allowed to adjust, and 3-6% of them do it when capital adjusts completely. The main difference between the two scenarios is an 8-10 percentage point difference in the fraction of individuals decreasing their experience; this larger detachment from the labor market is the result of the larger decrease in skill prices experienced in the first scenario. These results confirm the findings described above on the existence of an important deterrence effect, whose consequences for measuring the effect of immigration along the distribution of wages are discussed below.

The percentage of individuals increasing white collar experience is around 2-4% depending on the age range and the counterfactual scenario.[33] This fraction is larger for individuals who increase their total experience, but it is also very substantial among those reducing it, especially when capital fully adjusts. Hence, results suggest that occupational mobility is an important mechanism used by natives to overcome the extra competition induced by immigrants.

In light of these adjustments, it is not obvious *a priori* whether individuals increase or decrease their education. On the one hand, as wages fall, especially in the no capital adjustment case, the expected return to education is decreased, and incentives to invest fall. This effect is amplified by the lower labor market attachment of individuals, as their human capital will be rewarded on average fewer periods. On the other hand, however, the larger probability of working in a white collar job increases the expected return to education, as it is more valuable in white collar than in blue collar occupations.

Which of the two effects prevails is an empirical question, and it is assessed in Table 9. The table analyzes the probability of adjusting education, the probability of increasing it, and the average years of adjustment for different groups. The left

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[33] In this case, there is no much difference across counterfactual capital scenarios because the original effect on relative wages is rather similar across them.

TABLE 9—CHANGES IN EDUCATION CONDITIONAL ON CAREER ADJUSTMENTS

	Time at home is:			Incr. WC experience:		
	Incr.	Unch.	Decr.	T@H↑	T@H∼	T@H↓
No capital adjustment ($\partial K/\partial m = 0$):						
% adjusting education	35.73	1.67	38.38	41.42	59.82	22.77
of which increasing it	4.56	6.37	46.35	12.33	3.44	46.08
Average incr. education (years)	-1.19	-0.03	0.25	-1.07	-1.04	0.30
conditional on adjusting it	-3.33	-1.62	0.65	-2.58	-1.74	1.33
Full capital adjustment ($\partial r_K/\partial m = 0$):						
% adjusting education	35.01	0.42	25.76	27.40	30.59	22.43
of which increasing it	26.30	49.14	86.54	72.34	72.78	88.35
Average incr. education (years)	-0.43	0.00	0.60	0.45	0.59	0.56
conditional on adjusting it	-1.23	0.43	2.31	1.65	1.92	2.48

Note: The first row from each panel presents the percentage of individuals in each subpopulation that have different education in baseline and counterfactual scenarios; the second row is the percentage of these individuals that increased it as a consequence of immigration; the third row is the average increase in the number of years in the specific subpopulation; and the fourth is the average increase for individuals adjusting it. Different columns refer to different subpopulations; columns in the left panel include individuals that increased, maintained, or decreased the time spent at home after age twenty five respectively; columns in the right panel include the same groups for to individuals that increased white collar experience. In all cases, the population of interest is native male aged 25-54. Top and bottom panels include different assumptions on counterfactual capital as indicated.

panel analyzes these outcomes depending on whether the individual increased, decreased, or maintained the number of years spent at home after age twenty five (indicated as T@H).[34] Results suggest different patterns, depending on the specific career adjustment. For individuals reducing their attachment to the labor market (i.e., increasing the time spent at home), the first effect clearly prevails, as they substantially reduce their education. In both scenarios, above one third of the individuals adjust their education, most of them reducing it, with an average reduction of 3.3 years with no capital adjustment, and 1.2 years with full capital adjustment. This reduction is sizeable, as the total increase in average years of education between 1967 and 2007 was around 2.5 years.

Conversely, not many of the individuals that do not adjust their career path change their education as a consequence of immigration. Only 1.7% do so in the no capital adjustment scenario, and 0.4% in the full capital adjustment. When they do it, the first effect seems to dominate in the no capital adjustment scenario, with an average reduction of 1.6 years, whereas the second slightly prevails in the full capital adjustment scenario, consistent with the changes in skill prices in

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[34] Years spent at home after age twenty five and years of experience accumulated after that age are mirror images, except for individuals that are still in school. Even though the focus on the 25-54 age range limits substantially the presence of individuals in school, I opted for years at home to avoid creating a systematic relationship between increase in education and reduction of work experience in that situation. Results, available upon request, are roughly similar if experience instead of time at home is used.

each case. Nonetheless, the overall effect on the average education of the group is negligible (-0.03 and less than 0.01 years respectively), given that only small fraction of individuals adjusted.

Finally, for individuals increasing their attachment to the labor market the second effect prevails, especially when capital fully reacts. In the no capital adjustment scenario, above one third of these individuals adjust their education, although only about one half of them increase it. Yet, their average adjustment is positive, of around 0.6 years. With full capital adjustment, among the almost one quarter of individuals that adjust their education, most of them increase it. On average, they increase their education by 2.3 years, which is again substantial.

The right panel replicates the same exercise restricting the sample to individuals that increased their white collar experience as a consequence of immigration. In this case, differences between capital scenarios are exacerbated. In the no capital adjustment case, individuals that reduced their attachment to the labor market (despite increasing their white collar experience), still reduce their education substantially. Similarly, those who increased their white collar experience without altering the time spent at home also reduce their education.[35] However, for individuals reducing time spent at home, their average increase in years of education more than doubles the corresponding increase in the left panel. When capital fully adjusts, between one quarter and one third of the individuals that increase their white collar experience adjust their education, most of them increasing it. The average increase in years of education for those adjusting is 1.7, 1.9. and 2.5 years respectively depending on whether they increased, maintained, or decreased time at home. This implies that, among individuals increasing their white collar experience, education increased on average by 0.5-0.6 years, one fifth of the observed increase in the last four decades.

C. Self-selection and the effect of immigration along the wage distribution

Immigration does not affect all individuals in the same way. In Section I we have seen that immigrants are less skilled than natives, and increasingly more concentrated in blue collar occupations. Therefore, *similar* natives are likely to be more affected by immigration. Dustmann et al. (2013) define similar individuals depending on their position along the native wage distribution. This approach has important advantages compared to assigning individuals to skill cells based on observable characteristics, as the authors emphasize. It is also a natural approach to analyze heterogeneous effects of immigration on wages of different individuals.

In a similar spirit, Figure 5 plots the effect of immigration along the distribu-

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[35] Results for this group should be interpreted with caution, as they could have increased white collar experience at the expense of schooling.

FIGURE 5. WAGE EFFECTS OVER THE WAGE DISTRIBUTION

A. No capital adjustment   B. Full capital adjustment
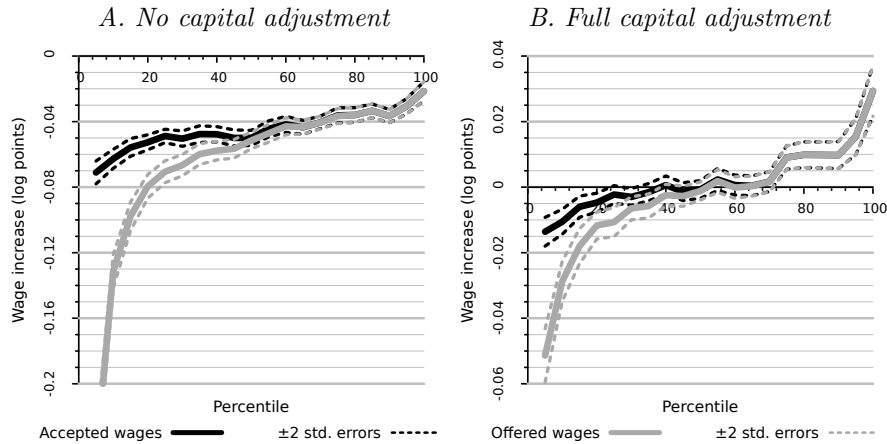
Note: The figure plots the average differences between log hourly wages in baseline and counterfactual scenarios for native male workers aged 25-54 along the baseline wage distribution. Each figure corresponds to a different assumption of the counterfactual evolution of capital as indicated. Black lines indicate the difference between baseline and counterfactual accepted wages. Gray lines indicates the difference in accepted wages for all the individuals working in the no immigration case (counterfactual).

tion of wages of native male aged 25-54. Black solid lines represent the increase in accepted wages induced by immigration in each percentile. Results differ depending on the assumed counterfactual evolution of capital. If capital does not adjust, immigration decreases wages by 2% at the top of the distribution, going down to 7% at the bottom. With full capital adjustment, immigration increases wages above the median, up to a 3% at the top of the distribution, whereas they decrease wages below the median, up to a 1% at the bottom of the distribution. One feature shared by the two scenarios is, hence, that individuals at the bottom tail of the distribution are more negatively affected than individuals at the top. This result is in line with the findings in Dustmann et al. (2013).

As the existing estimates in the literature, black lines in Figure 5 represent the effect of immigration on accepted wages. Hence, baseline and counterfactual wages are computed in each case with individuals that are working. Similarly, Dustmann et al. (2013), compare observed wages at different points of the wage distribution across regions that received different levels of immigration. However, as Table 7 above suggests, some individuals abandoned the labor market as a consequence of immigration. This labor market detachment is unlikely to be random; instead, we would expect that individuals at the bottom tail of the distribution are overrepresented among deterred individuals. Then, these results may suffer from a self-selection bias.

One of the main advantages of the structural model estimated in this paper is that it allows to naturally correct this bias. This is so because in the simulation of the model, we observe wage offers in baseline and counterfactual scenarios. Additionally, as discussed in Section V.B, we observe the decisions made by individuals

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under the different scenarios. Therefore, we can compute the effect of immigration on offered (instead of accepted) wages for all individuals that work in absence of immigration. This comparison is depicted by gray lines in Figure 5. Results show that self-selection bias severely affects estimates of wage effects below the median. At the 5th percentile, the wage drop induced by immigration is substantially larger once self-selection bias is corrected: from 7% to 20% in the no capital adjustment scenario, and from 1% to 5% in the full capital adjustment case.

To the best of my knowledge, this is the first paper pointing to a self-selection (participation) bias in the estimates of immigration on wages of less skilled workers. And the bias appears to be very large. Therefore, these findings reinforce the importance of taking into account labor market equilibrium adjustments when analyzing the effect of immigration on wages.

VI.   Concluding remarks

This paper estimates a labor market equilibrium model that takes into account human capital and labor supply adjustments to immigration. These adjustments are important to quantify the effect of immigration on wages. The model is estimated by minimum distance using CPS and NLSY data for 1967-2007. The estimated model is then used to measure the effect of immigration on wages simulating a counterfactual world without the last four decades of large scale immigration.

Results suggest that the wage effects of immigration are very important initially, but that they are then mitigated by equilibrium forces, as natives tend to adjust their human capital and labor supply. When capital is not allowed to adjust in the counterfactuals, native workers detach substantially from the labor market; this effect is less severe when capital adjusts completely. Regarding human capital (mainly education, but also work-experience) two opposite forces are at place: on the one hand, downward wage pressures reduce the expected returns to human capital; on the other hand, changes in relative wages make a white collar career more attractive, which increases the expected return to education. On aggregate, the first channel seems to dominate, especially for individuals that reduce their attachment to the labor market, but the second prevails for individuals increasing their labor market participation and for individuals switching to a white collar career. Finally, immigration has heterogeneous effects on wages along the native wage distribution. Self-selection out of the labor force produces important biases in these estimates, especially at the lower tail. Results suggest negative effects of immigration at the lowest percentiles, especially when the self-selection bias is corrected for; at the top of the distribution, individuals are less affected or their wages are even increased, depending on the assumption on counterfactual capital.

These results highlight the importance of taking human capital and labor sup-

ply adjustments into account when analyzing wage effects of immigration. This opens interesting avenues for future research. The self-selection bias pointed in Section V.C should be analyzed from different lenses, to gain more insight on its implications for existing papers in the literature. Studying in more detail direct and indirect effects of immigration on human capital, occupation specialization, and employment decisions (along the lines of recent papers like Hunt (2012), Peri and Sparber (2009), and Smith (2012)) would be interesting as well. Extending the model to account for the role of endogenous migration decisions would be another interesting line of future research. And, additionally, the framework of this paper could be used to evaluate immigration policies for the United States.

The results from this paper improve our understanding of labor market consequences of immigration in several dimensions, and have important implications for policy design. However, policy makers should bear in mind that immigration may affect the receiving society in other dimensions that are not included in the current analysis. For instance, immigration may affect prices of goods and services, taxes, welfare state, pension systems, or the use of public goods among others. Our understanding of the consequences of immigration on some of these outcomes is still limited.

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Table 1 in Section I shows that the share of immigrants among the less educated increased faster than among any other group during the last four decades. The increase in the share of immigrants among high school dropouts was twice as large as the average increase. In absolute terms, however, this does not mean that immigrants are less educated than four decades ago; instead, it is the result of a slower increase in their education compared to natives. Table A1 shows that the share of immigrants with less than a high school diploma decreased from 49.8 to 27.4 percent, whereas it decreased from 41 to 10.7 percent for natives. An interesting insight from Table A1 is that most of this slower increase in education is driven by the substitution of Western immigrants by Latin Americans and, to a lesser extent, Asians and Africans (see the trends in Figure A1 below). Indeed, if we constructed the counterfactual evolution of the distribution of education for immigrants aggregating the distributions of education by region of origin in each period from Table A1 keeping the distribution of immigrants by region of origin constant to the one in 1970, we would have obtained a distribution of education that would have evolved very similarly to the one for natives.

Another important conclusion from Table 1 in Section I is that immigrants are (increasingly) more clustered in blue collar jobs, even conditional on educational levels. This is also true for more disaggregated occupational levels. Table A2 shows that in all categories included in the blue collar aggregate, the share of immigrants increased faster than the overall share, whereas the opposite is true for all white collar categories. The case of farming-related occupations is very illustrative: farm laborer (blue collar) is the occupation with the largest share of immigrants, whereas farm manager (white collar) is the occupation with fewer immigrants. This finding is in line with the argument of occupation/task specialization of Peri and Sparber (2009). The most important conclusion from Table A2 is that, although sometimes the blue/white collar classification is seen as too broad and heterogeneous (especially for a long period of time), in this case it seems enough to describe the differential supply shock across occupations.

As it emerges from Table A1, the national origin of immigrants plays an important role in explaining their skill composition. Figure A1 summarizes the main trends of the distribution of immigrants by national origin. As it emerges from the picture, after several decades with more than a 90% of the immigrants born in Western Countries, this pattern started to change by the end of the 1960s. Starting then, a surge of immigration from Latin American countries (mainly but not exclusively from Mexico) led to the current picture, where more than 50% of

	1970	1980	1990	2000	2008
A. Natives					
High school dropouts	41.0	28.2	16.7	12.8	10.7
High school graduates	35.5	38.7	34.8	32.4	37.5
Some college	13.5	18.2	29.0	31.7	26.2
College graduates	10.1	14.8	19.4	23.0	25.6
B. Immigrants					
High school dropouts	49.8	39.0	31.8	30.6	27.4
High school graduates	26.5	27.3	26.2	25.9	28.9
Some college	12.1	16.9	21.8	20.5	17.4
College graduates	11.6	16.8	20.1	23.0	26.3
a. Western Countries					
High school dropouts	49.1	32.2	18.7	11.6	7.7
High school graduates	28.8	33.7	31.2	27.6	29.8
Some college	11.9	17.9	27.1	28.1	24.1
College graduates	10.2	16.3	23.1	32.7	38.4
b. Latin America					
High school dropouts	61.4	56.4	49.4	47.6	42.7
High school graduates	21.8	22.4	25.8	28.1	32.2
Some college	10.0	13.1	16.7	15.7	14.2
College graduates	6.9	8.1	8.2	8.6	10.9
c. Asia and Africa					
High school dropouts	31.5	22.6	16.4	13.2	10.9
High school graduates	22.4	22.8	22.3	21.2	22.6
Some college	16.9	21.5	25.0	23.9	19.6
College graduates	29.2	33.1	36.3	41.7	46.9

Note: Figures indicate the percentage of the population working-age from each region of origin who has the corresponding educational level (columns for each region of origin add to 100%). Immigrants from Western countries include individuals from Canada, Europe and Oceania. *Sources*: Census data (1970-2000) and ACS (2008).

the immigrant population is of Latin American origin. A similar (though softer) pattern is observed for Asian and African immigrants, mainly for Filipino and Vietnamese (the latter mostly refugees after the Vietnam War) in the 70s and 80s, and, more recently, Indian and Chinese immigrants.

Immigration policy plays an important role in this sudden change. In 1965, the Amendments to the Immigration and Nationality Act drastically changed the U.S. immigration policy. The National Origins Formula (a system that assigned immigration quotas to each origin country according to stock of immigrants from that country living in the U.S. in 1920) was abolished. Numerical limitations were set at the Hemisphere level (Eastern Hemisphere countries were served a fixed amount of visas per year with a fixed maximum per country, and Western countries had also a limited amount of visas, but they were issued in a first-come first-served basis) until 1976, when a world quota was set with a per country limit. Additionally, this reform introduced the Family Reunification visas, that

	1970	1980	1990	2000	2008
A. Blue-collar	**6.03**	**7.83**	**11.21**	**17.53**	**24.08**
Farm laborers	8.32	14.06	26.08	40.08	51.11
Laborers	5.47	7.40	11.87	21.48	31.27
Service workers	7.58	9.62	13.65	19.58	25.59
Operatives	5.84	8.38	11.74	18.55	23.98
Craftsmen	5.38	6.06	8.16	12.69	18.24
B. White-collar	**4.96**	**5.76**	**7.70**	**10.78**	**13.34**
Professionals	6.29	6.90	8.64	11.95	14.50
Managers	5.02	5.93	7.76	10.75	13.37
Clerical and kindred	4.27	5.17	7.14	9.97	12.47
Sales workers	4.78	5.03	6.78	9.29	11.52
Farm managers	1.52	1.56	2.87	4.87	6.38

Note: Figures indicate the percentage of the workers employed in each occupation who are immigrants. *Sources*: Census data for 1970-2000 and ACS for 2008.

were granted in an unlimited number to immediate relatives (parents, spouses and children) of U.S. citizens and legal immigrants. This policy change, as suggested by Figure A1, switched radically the main sources of immigrants, motivating, additionally, an important change in their skill composition.

FIGURE A1. IMMIGRANTS BY NATIONAL ORIGIN (1875-2007)
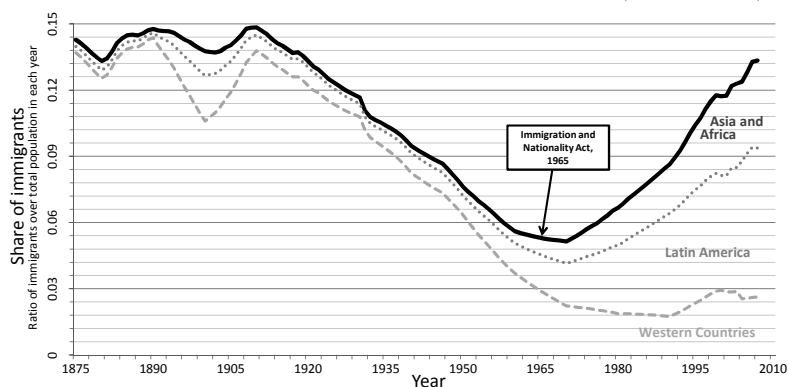
Note: The black solid line represents the share of the population working-age which is foreign born. The area below the dashed line corresponds to part of it that was born in Western Countries (Canada, Europe, and Oceania). The area between the dashed and the dotted lines corresponds to Latin American immigrants. And the area between the dotted and the solid lines represents the share of Asian and African immigrants. *Sources:* Census data (1870-2000) and ACS (2001-2008). Inter-Census interpolations based on the intensity of legal entry (Yearbook of Immigration Statistics 2009, U.S. Department of Homeland Security) excluding the legalization of illegal immigrants granted with an amnesty by IRCA 1986.

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B1. A nested estimation algorithm

The equilibrium model presented in Section II does not have a closed form solution and needs to be solved numerically. To explain the solution and estimation algorithm, it is convenient to differentiate two types of parameters: *expectation parameters*, Θ_2, which are given by the forecasting rules described in equation (12), and the process for the aggregate shock (7), and *fundamental parameters* of the model, Θ_1, which are the remaining parameters described in Sections II.A and II.B. Forecasting rules are part of the solution of the model, in the sense that their parameters η^js are implicit functions of the fundamental parameters. Parameters from the aggregate shock process are fundamental by nature, but since the aggregate shock is estimated as a residual (i.e. an implicit function of the data and fundamental parameters), and it is used to forecast future skill prices in the same way forecasting rules given by equation (12) are used, I treat (and estimate) them as expectation parameters. Hence, we can express Θ_2 as $\Theta_2(\Theta_1)$.

Parameters in Θ_1 are estimated by Simulated Minimum Distance. The Simulated Minimum Distance estimator minimizes the distance between a large number of statistics from the data (or data points) and their simulated counterparts. $\Theta_2(\Theta_1)$ is obtained as the fixed point of an algorithm that simulate the behavior of individuals using a guess of Θ_2, and then estimates equations (7) and (12) from the simulated data to update the guess. Therefore, the estimator requires a nested algorithm with a procedure that estimates Θ_1, and another solving Θ_2 given Θ_1.

Lee and Wolpin (2006, 2010) describe a natural nested algorithm in which an inner procedure finds the fixed point in Θ_2 for every guess of Θ_1, and an outer loop solves the Θ_1 estimation problem with a polytope algorithm. The main drawback of this procedure is that it requires solving the fixed point problem in every evaluation of Θ_1, and this increases the computational burden significantly.[36]

I propose an alternative algorithm that avoids having to solve the fixed point in every iteration of Θ_1. In particular, I propose a swapping of the two procedures which is in the same spirit of the swapping of conditional choice probabilities and parameter estimation proposed by Aguirregabiria and Mira (2002). Θ_1 is

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[36] This problem is relatively exacerbated if one uses the parallel version of the Simplex Method developed by Lee and Wiswall (2007) in the minimization problem. The basic idea in Lee and Wiswall (2007) is to move the p worst parameters in each Simplex iteration. The problem is that if one of the processors takes more iterations to find the fixed point in $\Theta_2(\Theta_1)$ than all others, the latter will remain idle while the former performs further iterations.

estimated for every guess of Θ_2, which is updated at a lower frequency, i.e., I estimate $\Theta_1(\Theta_2)$ for every guess of Θ_2. The algorithm consists of the following steps:

1) Choose a set of parameters $[\Theta_1]^0$ and $[\Theta_2]^0$.[37]

2) Solve the optimization problem for each cohort that exists from $t = 1$ to $t = T$.[38] This dynamic programming problem (given by equation (1)) is solved recursively by backwards induction from age 65 to age 16. This solution is not analytic. Moreover, the size of the state space is infinite, and even discretizing the continuous variables with a relatively small number of grid points, it still remains impossible to handle. As introduced by Keane and Wolpin (1994, 1997), in each period I solve the problem for a subset of the state space and then I estimate an interpolation rule as a function of the state variables.[39] Unlike in these papers and in Lee and Wolpin (2006, 2010), I use a gaussian quadrature instead of Monte Carlo integration to numerically compute the multiple-dimensional integrals from the expectation of the value function in $t + 1$.[40]

3) Find the skill rental prices that clear the market and the aggregate shock that closes the production function simulating the economy from $t = 1$ to $t = T$. More specifically,

   a) Guess skill rental prices of period $t = 1$.

   b) Find the supply of skills at this price using the solution of the individual optimization problem obtained in step 2.

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[37] A very natural initial guess for Θ_2 is given by the solution of the fixed point algorithm described in step 5 given $[\Theta_1]^0$.

[38] I assume that the economy begins in 1860. This very early initial date is so to overcome the arbitrary initial conditions that I assign to all cohorts existing in $t = 1$. In 1967, the first estimation year, slightly more than two entire generations have gone by. Hence, the oldest individuals (the ones turning 65 that year) have never coexisted in the model with any of the initial cohorts. T is the last estimation year, which is 2007; the youngest individuals that are in the model that year will die in 2057.

[39] The model is solved at 1,280,000 different points of the state space. For each of this points, the expected value function at the selected alternative —known in the literature as the Emax function— is obtained. Then, the interpolation rule is estimated as a set of regressions of the log Emax on education, a quadratic in blue collar and white collar experienced the interaction of education, blue collar experience, and white collar experience, predicted skill prices using equation (12), interactions of these predicted skill prices with education, blue collar experience, and white collar experience, a time trend, number of children, and foreign potential experience. These eighteen regression coefficients are estimated for every age, individual type, and for each of the four alternatives chosen potentially chosen in the preceding period. Hence, the interpolation rule that delivers the Emax at every potential point of the state space consists of 28,224 regression coefficients.

[40] Although being more time consuming, gaussian quadrature is known to be widely more accurate than Monte Carlo integration.

c) Plug the supply of skills into the production function and, together with data on capital and output, recover the aggregate shock as a residual.

d) Update skill rental prices with the demand equations (9) and (10), using the supply of labor obtained in step 3b and the aggregate shock from step 3c.

e) Repeat steps 3b to 3d using the prices obtained in 3d as the updated guess. Keep iterating to find a fixed point in skill prices. These are the skill prices that clear the market, since they equalize supply and demand.

f) Repeat steps 3b to 3e for $t = 2, ..., T$.

4) Compare the statistics computed with simulated data and their observed counterparts. Update Θ_1 with a simplex iteration and repeat steps 2 and 3 with $[\Theta_1]^1$. Keep updating Θ_1 till finding the set of parameters that minimize the distance between simulated and observed data, $\widehat{\Theta}_1([\Theta_2]^0)$.

5) Given $\widehat{\Theta}_1([\Theta_2]^0)$, update $[\Theta_2]^1 = \widehat{\Theta}_2(\widehat{\Theta}_1([\Theta_2]^0))$. In particular, fit OLS regressions of equations (7) and (12) with the simulated aggregate data obtained at the end of step 3. Iterate solving steps 2 and 3 using these OLS estimates to compute expectations until reaching the fixed point.[41]

6) If $[\Theta_2]^1 = [\Theta_2]^0$, the algorithm finishes. Otherwise, repeat steps 2 to 5 with the updated guesses $[\Theta_2]^1$ and $\widehat{\Theta}_1([\Theta_2]^0)$ until convergence is reached.

B2. Data and estimation

The Simulated Minimum Distance estimator minimizes a weighted average squared distance between a large set of statistics from the data or data points, and their simulated counterparts.[42] Table B1 lists the set of statistics I use in the estimation. Each statistic is weighted by the inverse of the sample size used in its calculation (see further details in Appendix E).

The model is fitted to annual data from 1967 to 2007. The annual frequency introduces the problem that individuals may not spend the full year doing the same activity. Therefore, in order to assign individuals to one of the four mutually exclusive alternatives, I apply the following rules:

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[41] This step does not necessarily need to be done after reaching a convergence in Θ_1 given $[\Theta_2]^0$. Periodic updates of expectation parameters can also be programmed after K iterations. Indeed, if $K = 1$, this algorithm coincides with the one described in Lee and Wolpin (2006, 2010).

[42] They are data points in the same sense that a cohort observed at a point in time is an individual observation in a cohort analysis, or the labor supply in an education-experience cell is an observation in Borjas (2003) regressions.

Group of statistics	Source		Number of statistics
TOTAL			**27,636**
Proportion of individuals choosing each alternative..			**5,074**
By year, sex, and 5-year age group	CPS	$41 \times 2 \times 10 \times (4-1)$	2,460
By year, sex, and educational level	CPS	$41 \times 2 \times 4 \times (4-1)$	984
By year, sex, and preschool children	CPS	$41 \times 2 \times 3 \times (4-1)$	738
By year, sex, and region of origin	CPS	$15 \times 2 \times 4 \times (4-1)$	360
Immigr., by year, sex, and foreign potential exp.	CPS	$15 \times 2 \times 5 \times (4-1)$	450
By sex and experience in each occupation	NLSY	$2 \times (5 \times 5 + 4 \times 4) \times (2-1)$	82
Wages:			**6,044**
Mean log hourly real wage...			*3,000*
By year, sex, 5-year age group, and occupation	CPS	$41 \times 2 \times 10 \times 2$	1,640
By year, sex, educational level, and occupation	CPS	$41 \times 2 \times 4 \times 2$	656
By year, sex, region of origin, and occupation	CPS	$15 \times 2 \times 4 \times 2$	240
Immigrants, by year, sex, fpx, and occupation	CPS	$15 \times 2 \times 5 \times 2$	300
By sex, experience in each occupation, and occ.	NLSY	$2 \times (5 \times 5 + 4 \times 4) \times 2$	164
Mean 1-year growth rates in log hourly real wage...			*2,148*
By year, sex, previous, and current occupation	CPS§	$35 \times 2 \times 2 \times 2$	280
By year, sex, 5-year age group, and current occ.	CPS§	$35 \times 2 \times 10 \times 2$	1,400
By year, sex, region of origin, and current occ.	CPS§	$13 \times 2 \times 4 \times 2$	208
Immigr., by year, sex, years in the U.S., and occ.	CPS§	$13 \times 2 \times 5 \times 2$	260
Variance in the log hourly real wages...			*896*
By year, sex, educational level, and occupation	CPS	$41 \times 2 \times 4 \times 2$	656
By year, sex, region of origin, and occupation	CPS	$15 \times 2 \times 4 \times 2$	240
Career transitions...			**12,138**
By year and sex	CPS§	$35 \times 2 \times 4 \times (4-1)$	840
By year, sex, and age	CPS§	$35 \times 2 \times 10 \times 4 \times (4-1)$	8,400
By year, sex, and region of origin	CPS§	$13 \times 2 \times 4 \times 4 \times (4-1)$	1,248
New entrants taking each choice by year and sex	CPS	$15 \times 2 \times (4-1)$	90
Immigrants, by year, sex, and years in the U.S.	CPS§	$13 \times 2 \times 5 \times 4 \times (4-1)$	1,560
Distribution of highest grade completed...			**4,260**
By year, sex, and 5-year age group	CPS	$41 \times 2 \times 10 \times (4-1)$	2,460
By year, sex, 5-year age group, and immigr./native	CPS	$15 \times 2 \times 10 \times 2 \times (4-1)$	1,800
Distribution of experience...			**120**
Blue collar, by sex	NLSY	$2 \times (13+7)$	40
White collar, by sex	NLSY	$2 \times (13+7)$	40
Home, by sex	NLSY	$2 \times (13+7)$	40

Note: Data are drawn from March Supplements of the Current Population Surveys for survey years from 1968 and 2008 (CPS); the National Longitudinal Survey of Youth both for 1979 and 1997 cohorts (NLSY); and the CPS matched over two consecutive years —survey years 1971-72, 1972-73, 1976-77, 1985-86 and 1995-96 can not be matched— (CPS§). Statistics from the CPS that distinguish between natives and immigrants can only be computed for surveys from 1994 on. There are 10 five-year age groups (ages 16-65), two genders (male and female), two immigrant status (native and immigrant), four regions of origin (U.S. (natives), Western countries, Latin America, and Asia/Africa), four educational levels (¡12,12,13-15 and 16+ years of education), three categories of preschool children living at home (0, 1 and 2+), and five foreign potential experience (fpx)/years in the country groups (0-2,3-5,6-8,9-11 and 12+ years). Redundant statistics that are linear combinations of others (e.g. probabilities add up to one) are not included (neither in the table, nor in the estimation). A more detailed description of data construction and sources is available in Appendix C.

i. An individual is assigned to school if she reported that school was her main activity during the survey week (CPS) or if she was attending school at survey date (NLSY).

ii. She is assigned to work in one of the two occupations if she is not assigned to school, and she worked at least 40 weeks during the previous year and at least 20 hours per week. When an individual is assigned to work, her occupation is the one held during the last year (CPS) or the most recent one (NLSY). Craftsmen, operatives, service workers, laborers, and farmers are classified as blue collar workers, whereas professionals, clerks, sales workers, managers and farm managers are white collar workers.

iii. Individuals that are neither assigned to attend school nor to work are considered to stay at home.

The simulated counterparts of the statistics described in Table B1 are obtained by simulating the behavior of cohorts of 2,000 natives and 3,000 immigrants (some of them starting their life abroad and not making decisions until they enter the U.S.). Therefore, cross-sectional simulated data are calculated with a sample of up to 250,000 observations, which are weighted using data on cohort sizes.

The solution of the model requires additional data for exogenous aggregate variables: output, stock of equipment capital and structures, cohort sizes (by gender and immigrant status), the distribution of entry age for immigrants, the distribution of initial schooling (at age 16 for natives and upon entry in the U.S. for immigrants), the distribution of immigrants by region of origin, and the fertility (preschool children) process. The sources, definitions, and construction of all these variables are detailed in Appendix C.

Identification of the parameters of the model requires that there is no parameter vector that is "observationally equivalent" to the true parameter vector. Under correct specification of the model, the true parameter vector makes the difference between the population statistics and the counterparts generated by the model (when the number of simulated individuals tends to infinity) equal to zero. The identification condition requires that there is no other parameter vector that achieves this value. Unfortunately, there is no formal proof of whether this condition is satisfied for the set of statistics listed in Table B1. It is a matter of uniqueness of the global minimum and curvature around it. Heuristically, I present an informal check of the latter in Figure D1 in Appendix D. This figure plots different *sections* of the objective function in which I move one parameter and keep the others constant to the estimated values. Although this exercise is uninformative about the curvature in the multidimensional space, it shows plenty of unilateral curvature for all parameters. Pointing in the same line, standard errors of the

estimates reported below are very small, which is significant because they depend on the curvature of the objective function around parameter estimates —see Appendix E. Regarding uniqueness, the only robustness that can be performed is to start the estimation from different initial conditions and keep the local minimum that gives a smaller value for the objective function.

Despite not being able to formally prove identification, we can have an intuition on what is the variation that identifies the parameters with the used data. Identification would be achieved by a combination of functional forms and distributional assumptions, along with exclusion restrictions. The present analysis is not very different in spirit from the synthetic cohort panel data analysis used, for example, in Browning, Deaton and Irish (1985) (indeed, a large fraction of the data listed in Table B1 are cohort specific). Exclusion restrictions to identify wage equations are provided by variables that affect utilities and not wages (e.g. preschool children), and, for utility functions, they are given by variables that are in wage equations and not in utility functions (e.g. experience). Production function parameters are identified by functional form assumptions from the aggregate supply of skill units plus aggregate data on capital and output; current and past cohort sizes act as instruments for skill units.

APPENDIX C: VARIABLE DEFINITIONS AND SOURCES

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Both the solution and the estimation of the model combine a variety of aggregate and micro-level data. In this Appendix, I describe the construction of the variables and the data sources.

C1. Aggregate data

Aggregate macro data are used in the solution of the model, as described in the main text. The estimation period is 1967-2007. However, in order to vanish initial conditions, I simulate the model starting in 1860. The model is initialized by simulating the first 40 years (1860-1900) using aggregate data for 1900. Then I simulate the remaining years (1900-2007) with actual macro data. As a result, two entire generations go by before the first year of estimation.

Output. Output is measured as Gross Domestic Product at chain 2000 U.S. dollars, provided by the Bureau of Economic Analysis (BEA), NIPA Table 1.1.6. Given that the original series starts in 1929, I use the average annual growth rate (1929-2007) to extrapolate backwards to year 1900.

Capital stock. There are two types of capital in the model: structures and equipment capital. Both series are extracted from BEA, combining flow data from Fixed Assets Tables 1.2 ("Chain-Type Quantity Indexes for Net Stock of Fixed Assets") with year 2000 stock data from Fixed Assets Table 1.1 ("Current Cost Net Stock of Fixed Assets"). Resulting series are expressed in chain 2000 U.S. dollars. Series start in 1925, so I extrapolate them backwards to 1900 using average annual growth rates.

Cohort sizes. Cohort sizes are extracted from Integrated Public Use Microdata Series (IPUMS) of the U.S. Census.[43] In particular, I use information from the decennial Censuses from 1900 to 2000, and from the American Community Survey (ACS) 2001-2007. A person is classified as an immigrant if born abroad; individuals born in Puerto Rico and other outlying areas are categorized as natives. Native and immigrant inter-census cohort sizes are estimated following different procedures. For natives, I distributing the cumulative decade cohort size decrease to each year using annual data on mortality rates by age from Vital Statistics of the U.S. (National Center for Health Statistics). For immigrants, I use a similar procedure, using the estimates of the entry age distribution described below instead of mortality rates.

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[43] Ruggles, Sobek, Alexander, Fitch, Goeken, Hall, King and Ronnander (2008).

Age at entry. The distribution of entry age of immigrants is estimated using U.S. Census IPUMS. In order to reduce small sample noise, I average out the distributions for immigrants who arrived at $t-1$, $t-2$,..., $t-5$. Since the exact year of immigration is only available in 1900-1930 and 2000 Censuses, and in the ACS (2001-2007), intermediate years are linearly interpolated. Given that the distribution is stable over the years, I estimate a single distribution for each of the following intervals: 1900-1930, 1931-1940, 1941-1950, 1951-1960, 1961-1970, 1971-1980, 1981-1990 and 1991-2007. Finally, in order to obtain the joint distribution of age at entry and initial education, I estimate the entry age distribution conditional on education. Because of data limitations, I approximate it using the "relative" distribution by educational level, i.e. I compute the ratio of conditional and unconditional distributions from the Census 2000, and then I multiply this relative distribution with the time varying unconditional age at entry distribution.[44]

Regions of origin. I consider three regions of origin for immigrants: Western Countries, Latin America, and Asia-Africa. Western Countries include Europe, Canada and Atlantic Islands, and Oceania; Latin America include Caribbean Countries, Mexico, and Central and South America; Asia-Africa includes all immigrants from these two continents. The stock of immigrants from each of these regions are drawn from U.S. Census IPUMS 1900-2000 and ACS 2001-2007. Inter-census estimates of the stock of immigrants from each region of origin are obtained by combining a linear interpolation of the share of immigrants from each region and the estimated of cohort sizes described above. The share of the total inflow of immigrants in year t that comes from region i, $s_{i,t}^{flow}$, is then estimated as:

$$s_{i,t}^{flow} = \frac{M_t s_{i,t} - M_{t-1} s_{i,t-1} + s_{65,i,t-1} M_{65,t-1}}{M_t - M_{t-1} + M_{65,t-1}}, \tag{C1}$$

where M_t is the stock of immigrants in year t, $s_{i,t}$ is the share of immigrants that are natural from region i in period t, and $M_{65,t}$ is the stock of 65 years old immigrants in year t. The share $s_{65,i,t-1}$ is approximated with $s_{i,t-35}$ because the average age at entry is around 30 years. The numerator of equation (C1) is the flow of immigrants from region i in period t, i.e. the observed increase in the stock plus the recovery of those who died (reached age 65); the denominator is the total inflow in period t.

Initial education. Immigrants and natives are assigned initial years or education differently. Initial education of natives is allocated at age 16. The distribution of years of education at this age (by gender) is estimated using U.S. Census IPUMS

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for 1940-2000 and ACS 2001-2007. Inter-census estimates are linearly interpolated. In censuses before 1940 there is no information on education. Therefore, I use the 1940 Census to infer the initial education of cohorts aged 16 in each of the previous census years, assuming that they concentrate education at the beginning of their lives, and that mortality at these ages is small enough so that it does not induce any bias. Immigrants are assigned education when they enter the United States. To this end, I use U.S. Census IPUMS for years 1970-2000. I assume that immigrants also concentrate their education spells at the beginning of their life; therefore, an individual with a college degree that enters at age 40 is assumed to enter with the college degree, whereas another that entered at age 18 is assumed to enter with a high school diploma.[45] To impute education to earlier cohorts of immigrants, I estimate the distribution of years of education by cohort of entry using U.S. Census of 1970.

Fertility process. The fertility process is given by the transition probability matrix from 0, 1, or 2+ preschool children at home in period t into 0, 1 or 2+ in $t + 1$, conditional on age, education, and gender. Data are drawn from CPS 1964-2007 and U.S. Census 1900-1960. Before 1960, the transition probability matrix is not conditional on education.

Wage adjustments. To avoid biases in parameter estimates, I make three adjustments to wages and/or aggregate skill units. On the one hand, both CPS wages and output data include taxes, but individuals make decisions on a net income basis; to correct for this, I simulate individuals' decisions using net wages, deflating gross simulated wages (fitted to the data) by the ratio of Disposable Personal Income over Personal Income (Bureau of Economic Analysis, NIPA Table 2.1). On the other hand, there are two reasons why total labor compensation produced by the model could be underestimated without further adjustments (and factor shares, biased as a result): first, the focus on intensive margin, and the use of the year as the time unit, generates some discrepancies between aggregated earnings simulated from the model and actual aggregate earnings (some individuals that work a small fraction of the year are considered as not working, whereas others that work a large fraction of the year, but not the entire period, are assumed to work full time for the whole year); and, second, there are some forms of labor compensation that are not wages (e.g. some types of bonuses and in-kind payments). These two discrepancies are corrected by adjusting total wage compensation appropriately. To correct for the first, I adjust the aggregate simulated wage compensation by the ratio of BEA Total Wage and Salary Dis-

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[45] This assumption is supported by the human capital investment literature (e.g. Becker, 1964).

bursements (NIPA Table 2.1) over the aggregation of wages obtained from the CPS. The second concern is addressed using the ratio of BEA Total Wage and Salary Disbursements over the Total Compensation of Employees (NIPA Table 2.1).

C2. Microdata

All micro-data statistics used in the estimation (and listed in Table B1) are constructed with data from two different sources: March Supplement of Current Population Survey (CPS), and the two cohorts (1979 and 1997) from the National Longitudinal Survey of Youth (NLSY).[46]

Age groups. Individuals are grouped in ten 5-year age groups from 16-20 years old to 61-65. Individuals above 65 and below 16 are not in the model and they are dropped from the samples.

Educational level. I categorize individuals in four education groups: high school dropouts (¡12 years of education), high school graduates (12), persons with some college (13-15), and college graduates (16+). In 1992, a methodological change was introduced to CPS regarding education. Before that year, the education variable gives the respondent's highest grade of school or year of college completed; beginning in 1992, the variable classifies high school graduates according to their highest degree or diploma attained. I use the IPUMS recoded educational attainment variable to make it comparable over the years.

Experience. Years of effective experience in blue collar and white collar occupations are calculated from NLSY. The samples are restricted to individuals born from 1962 to 1964 for NLSY79 and from 1980 to 1984 for the NLSY97. I consider only individuals for which their entire path of choices from age 18 to either 1993, 1992, 1991 or 1990 for NLSY79 or to 2006, 2005 or 2004 for NLSY97 is observable. Individual choices are assigned as described below. Experience is counted as the number of years that the individual's choice was to work in the corresponding occupation.

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[46] CPS data are extracted from IPUMS (Ruggles et al., 2008). The CPS interviews households for 8 eight months; more concretely, when a household enters the sample for the first time is interviewed four consecutive months, then not interviewed during eight months, and finally interviewed four additional consecutive months (which are the same four calendar months from the first spell, but in the subsequent year). Therefore, a household that is in the March sample is interviewed in March for two consecutive years. As a result, in most of the survey years, it is possible to match a subset of households for two consecutive years obtaining a small panel. IPUMS data has a recoded individual and household identifier that does not allow to match consecutive surveys, and for this reason, I use samples extracted from the NBER to do the matching. Survey years 1971-72, 1972-73, 1976-77, 1985-86 and 1995-96 can not be matched due to survey changes.

Choices. Individuals are assigned to one of the four mutually exclusive year round alternatives: blue collar or white collar work, attend school, or stay at home. The procedure to assign individuals follows a hierarchical rule. An individual is assigned to school if she reported that school was her main activity during de survey week (CPS) or if she was attending school at survey date (NLSY). She is assigned to work in either of the two occupations if she is not assigned to school and she worked at least 40 weeks during the year before the survey date, and at least 20 hours per week.[47] When an individual is assigned to work, she is assigned to the occupation held during the last year (CPS) or the most recent (NLSY). Blue collar occupations include craftsmen, operatives, service workers, laborers, and farmers, and white collar include professionals, clerks, sales workers, managers, and farm managerial occupations. Finally, those individuals that are not assigned neither to work nor to attend school are assigned to stay at home.

Wages. Hourly wage is computed for individuals that are assigned to either of the work alternatives according to the previous definition. Workers are assumed to earn their wage entirely in the occupation they are assigned to. Earnings include wage and salary income, and self-employment earnings, deflated to year 2000 U.S.\$ using the Consumer Price Index. Top-coded annual earnings are multiplied by 1.4; extreme observations are dropped (hourly real wage lower than \$2 or larger than \$200).[48] Hours worked are calculated combining information on weeks worked last year and hours worked last week.[49] [50]

Preschool children. Individuals are allowed to have 0,1, or 2+ preschool children (less than five years old). In the data, households are defined as family units; preschool children living in a two family home are only assigned to their parents. In order to link children with their parents, I use IPUMS-created variables *momloc* and *poploc*, which identify the position of the mother and father in the household respectively. Parent definition includes biological, step- and adoptive parents. Although they fully comparable over years, there are some minor changes that are listed in the database documentation.

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[47] Hours per week are approximated by the number of hours worked in the previous week.

[48] This approach is followed, for instance, by Lemieux (2006).

[49] Before 1976, weeks worked last year are only available by intervals; in particular, the relevant intervals are 40-47, 48-49 and 50-52 weeks. Each interval is imputed, respectively 43.1, 48.3 and 51.9 weeks. These figures are obtained from sample means for each interval using data for the five years after 1975.

[50] In the model, individuals are assumed to work 2080 hours per year (40 hours, 52 weeks). Although hours worked by individuals assigned to working categories average a little above this quantity, there is an important concentration of workers in the amount of 40 hours per week (Keane and Moffitt, 1998).

Region of origin. The region of birth is assigned as described above for the aggregate data. A small number of individuals for which the country of birth is unknown are dropped from the corresponding samples. CPS started to ask questions related to immigrant status in survey year 1994. Therefore, statistics that include this information are only used from that survey date onwards.

Potential experience abroad. The initial experience endowment for immigrants (experience obtained abroad) is measured as "potential experience" given data availability. In particular, this variable is defined as age at entry minus years of education, minus 6. In the CPS, year of immigration is only available by intervals; additionally, education is also grouped in 0-4, 5-8, 9, 10, 11, 12, 13-15 and 16+ years of education intervals. To construct experience abroad, I use the central point of the corresponding interval both for age at entry and for years of education. Since I do not observe where did the education take place, I assume that individuals concentrate their education spells in the beginning of their lives, regardless of the country in which they were living. Therefore, if an individual's age at entry minus completed education (and minus 6) is zero or negative, I assume that the individual entered in the U.S. with zero experience. The resulting variable is then grouped into the following categories: 0-2, 3-5, 6-8, 9-11 and 12+ years.

Years in the U.S. This variable is constructed in an analogous way to potential experience abroad. It is also grouped in the same categories.

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FIGURE D1. SECTIONS OF THE OBJECTIVE FUNCTION

NOTE.— Solid lines plot the evolution of the objective function when changing the corresponding parameter and leaving others constant at the estimated values. Red dots indicate parameter point estimates.

APPENDIX E: STANDARD ERRORS

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Parameter estimates are the result of the following minimum distance estimation problem:

$$\hat{\theta} = \arg\min_{\theta} ||\hat{\pi}(x) - \tilde{\pi}(x_S(\theta))|| =$$
$$= \arg\min_{\theta}[\hat{\pi}(x) - \tilde{\pi}(x_S(\theta))]'W[\hat{\pi}(x) - \tilde{\pi}(x_S(\theta))]. \tag{E1}$$

Weights are proportional to the sample size used to calculate each statistic. In particular, I consider a diagonal matrix with the (weighted) sample size of each element.[51]

The asymptotic distribution of parameters is obtained by applying the delta method to the sample statistics. In particular,

$$Var(\hat{\theta}) = (G'WG)^{-1}G'WV_0WG(G'WG)^{-1}, \tag{E2}$$

where G is the $P \times R$ matrix of partial derivatives of the R statistics included in π with respect to the P parameters included in θ.

In the estimation problem defined by equation (E1) there are two sources of error. First, data statistics $\hat{\pi}(x)$ are estimated with sampling error. And second, the function that maps parameters into statistics, $\tilde{\pi}(x_S(\theta))$, does not have a closed form solution, and I need to simulate it, introducing a simulation error.

The remainder of this Appendix is devoted to provide an estimator of V_0. It is important to notice that, given the two sources of error, asymptotic theory should be applied two-way: taking the sample size and the number of simulations to infinity. To handle it, the problem can be split in the difference between the following two elements: $\sqrt{N}\left(\hat{\pi}(x) - \pi(\theta_0)\right)$ and $\sqrt{M}\left(\tilde{\pi}(x_S(\theta_0)) - \pi(\theta_0)\right)$, where N is the sample size and M is the number of simulations.

E1.   Minimum distance asymptotic results

Consider R statistics from the data such that:

$$\mathbb{E}[Y_K] = \pi_k(\theta_0), \quad k = 1, ..., R. \tag{E3}$$

We are assuming that those statistics are means, but this can be done without a loss of generality. Those means are estimated with k different samples S_k, each of

---

[51] Weighted sample size is defined in this context as $\left(\sum_i p_i^2 / \left(\sum_i p_i\right)^2\right)^{-1}$, where p_i is the individual weight in the sample. If $p_i = p \; \forall i$, this sum is equal to the sample size. The weighted sample size is inverse of the precision of the variance of the weighted sample mean: $Var(\bar{x}) = \sigma_x^2 \sum_i p_i^2 / \left(\sum_i p_i\right)^2$.

them of size N_k. Notice that some of these samples may overlap (e.g., the sample used to estimate the share of 16-20 years old males choosing to work in blue collar in year 1967 may include some individuals that are also used to estimate the share of high school dropout males choosing blue collar in that year). Sample counterparts of these statistics are given by

$$\hat{\pi}_k = \frac{1}{N_k} \sum_{i \in S_k} Y_{ki}. \tag{E4}$$

Therefore, if the functional form of $\pi(\theta)$ was known, we could write

$$\hat{\theta} = \arg \min_{\theta \in \Theta} ||\hat{\pi} - \pi(\theta)||. \tag{E5}$$

Let us introduce some additional notation:

$$d_{ki} \equiv \mathbb{1}\{i \in S_k\}, \tag{E6}$$

$$S_{ij} \equiv S_i \cap S_j, \tag{E7}$$

$$S \equiv S_1 \cup ... \cup S_R, \tag{E8}$$

$$N \equiv \sum_{i \in S} \left(\sum_k d_{ki} - \sum_k \sum_j d_{ki} d_{ji} \right), \tag{E9}$$

$$\lambda_{kN} \equiv \frac{N_k}{N} \xrightarrow{N \to \infty} \lambda_k, \tag{E10}$$

$$\psi_{ki} \equiv Y_{ki} - \pi_k(\theta_0). \tag{E11}$$

Now we can write

$$\begin{pmatrix} \sqrt{N_1}(\hat{\pi}_1 - \pi_1) \\ \sqrt{N_2}(\hat{\pi}_2 - \pi_2) \\ ... \\ \sqrt{N_R}(\hat{\pi}_R - \pi_R) \end{pmatrix} = \begin{pmatrix} \frac{1}{\sqrt{N_1}} \sum_{i \in S_1} \psi_{1i} \\ \frac{1}{\sqrt{N_2}} \sum_{i \in S_2} \psi_{2i} \\ ... \\ \frac{1}{\sqrt{N_R}} \sum_{i \in S_R} \psi_{Ri} \end{pmatrix} = \begin{pmatrix} \sqrt{\lambda_{1N}} & 0 & ... & 0 \\ 0 & \sqrt{\lambda_{2N}} & ... & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & ... & \sqrt{\lambda_{RN}} \end{pmatrix}^{-1} \times$$

$$\times \frac{1}{\sqrt{N}} \sum_{i \in S} \begin{pmatrix} d_{1i} \psi_{1i} \\ d_{2i} \psi_{2i} \\ ... \\ d_{Ri} \psi_{Ri} \end{pmatrix} \equiv \Lambda \frac{1}{\sqrt{N}} \sum_{i \in S} d_i \circ \psi_i, \tag{E12}$$

where $\circ$ denotes the Hadamard or element-by-element product. Due to the central limit theorem (CLT), and Cramer's theorem, as $N \to \infty$:

$$\Lambda \frac{1}{\sqrt{N}} \sum_{i \in S} d_i \circ \psi_i \xrightarrow{d} \mathcal{N}\left(0, \Lambda \mathbb{E}[(d_i \circ \psi_i)(\psi_i \circ d_i)'] \Lambda\right). \tag{E13}$$

Therefore, by the analogy principle we can define an estimator of the variance-covariance matrix of the R sample statistics as

$$\hat{\Omega} = \begin{pmatrix} \frac{1}{N_1}\hat{\sigma}_1^2 & \frac{N_{12}}{N_1 N_2}\hat{\sigma}_{12} & \cdots & \frac{N_{1R}}{N_1 N_R}\hat{\sigma}_{1R} \\ \frac{N_{12}}{N_1 N_2}\hat{\sigma}_{12} & \frac{1}{N_2}\hat{\sigma}_2^2 & \cdots & \frac{N_{2R}}{N_2 N_R}\hat{\sigma}_{12} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{N_{1R}}{N_1 N_R}\hat{\sigma}_{1R} & \frac{N_{2R}}{N_2 N_R}\hat{\sigma}_{2R} & \cdots & \frac{1}{N_R}\hat{\sigma}_R^2 \end{pmatrix} \tag{E14}$$

where $\hat{\sigma_{ij}} = \frac{1}{N_{ij}}\sum_{k \in S_{ij}} \psi_{ki}\psi'_{kj}$, and $\hat{\sigma_i^2} = \frac{1}{N_i}\sum_{k \in S_i} \psi_{ki}\psi'_{ki}$.

E2.   Simulated minimum distance asymptotic results

Suppose that $\hat{\pi}$ is an estimator of some characteristic π of the distribution of Y based on the sample $\{Y_i\}_{i=1}^N$ such that

$$\sqrt{N}[\hat{\pi} - \pi(\theta_0)] \xrightarrow{d} \mathcal{N}(0, \Omega). \tag{E15}$$

Let us assume that for known functions $g(.,.)$ and $F(.)$,

$$Y = g(U, \theta_0) \qquad U \sim F. \tag{E16}$$

Let $\tilde{\pi}(\theta_0, U^M)$ represent the same estimating formula as $\hat{\pi}$ but based on the artificial sample $\{g(U_j, \theta_0)\}_{j=1}^M$ constructed from a simulated sample U^M. As $M \to \infty$ we have

$$\sqrt{M}[\tilde{\pi}(\theta_0, U^M) - \pi(\theta_0)] \xrightarrow{d} \mathcal{N}(0, \Omega) \tag{E17}$$

independently of $\hat{\pi}$. Therefore, as long as $0 < \lim_{N,M \to \infty}(N/M) \equiv \kappa < \infty$

$$\sqrt{N}[\hat{\pi} - \tilde{\pi}(\theta_0, U^M)] =$$

$$= \sqrt{N}[\hat{\pi} - \pi(\theta_0)] - \sqrt{\frac{N}{M}}\sqrt{M}[\tilde{\pi}(\theta_0, U^M) - \pi(\theta_0)] \xrightarrow{d} \mathcal{N}\left(0, (1+\kappa)\,\Omega\right) \tag{E18}$$

Note that this result includes the case in which we can simulate a sample of size m for every observation $i = 1, ..., N$, so that $M = mN$, and $\kappa = 1/M$, which is the case analyzed in McFadden (1989).

Finally, to generalize the result to multiple statistics with overlapping samples as in Section E1, let $(l_{1i}, ..., l_{Ri})$ and $(\delta_1, ..., \delta_R)$ play the role of $(d_{1i}, ..., d_{Ri})$ and $(\lambda_1, ..., \lambda_R)$ in the simulated samples, we similarly have that

$$\begin{pmatrix} \sqrt{M_1}(\tilde{\pi}_1(\theta_0, U^{M_1}) - \pi_1) \\ \sqrt{M_2}(\tilde{\pi}_2(\theta_0, U^{M_2}) - \pi_2) \\ ... \\ \sqrt{M_R}(\tilde{\pi}_R(\theta_0, U^{M_R}) - \pi_R) \end{pmatrix} \equiv \Delta \frac{1}{\sqrt{M}}\sum_{i \in U^M} l_i \circ \psi_i \xrightarrow{d} \mathcal{N}\left(0, \Delta\,\mathbb{E}[(l_i \circ \psi_i)(\psi_i \circ l_i)']\Delta\right). \tag{E19}$$

Therefore,

$$
\begin{pmatrix}
\sqrt{N_1}(\hat{\pi}_1 - \tilde{\pi}_1(\theta_0, U^{M_1})) \\
\sqrt{N_2}(\hat{\pi}_2 - \tilde{\pi}_2(\theta_0, U^{M_2})) \\
... \\
\sqrt{N_R}(\hat{\pi}_R - \tilde{\pi}_R(\theta_0, U^{M_R}))
\end{pmatrix}
\xrightarrow{d} \mathcal{N}(0, V_0),
\tag{E20}
$$

and

$$
\hat{V} =
\begin{pmatrix}
\left(\frac{1}{N_1} + \frac{1}{M_1}\right)\hat{\sigma}_1^2 & \left(\frac{N_{12}}{N_1 N_2} + \frac{M_{12}}{M_1 M_2}\right)\hat{\sigma}_{12} & \cdots & \left(\frac{N_{1R}}{N_1 N_R} + \frac{M_{1R}}{M_1 M_R}\right)\hat{\sigma}_{1R} \\
\left(\frac{N_{12}}{N_1 N_2} + \frac{M_{12}}{M_1 M_2}\right)\hat{\sigma}_{12} & \left(\frac{1}{N_2} + \frac{1}{M_1}\right)\hat{\sigma}_2^2 & \cdots & \left(\frac{N_{2R}}{N_2 N_R} + \frac{M_{2R}}{M_2 M_R}\right)\hat{\sigma}_{12} \\
\vdots & \vdots & \ddots & \vdots \\
\left(\frac{N_{1R}}{N_1 N_R} + \frac{M_{1R}}{M_1 M_R}\right)\hat{\sigma}_{1R} & \left(\frac{N_{2R}}{N_2 N_R} + \frac{M_{2R}}{M_2 M_R}\right)\hat{\sigma}_{2R} & \cdots & \left(\frac{1}{N_R} + \frac{1}{M_R}\right)\hat{\sigma}_R^2
\end{pmatrix}.
\tag{E21}
$$