

IMMIGRATION, WAGES, AND EDUCATION: A LABOR MARKET EQUILIBRIUM STRUCTURAL MODEL

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ABSTRACT.— This paper analyzes the effect of immigration on wages taking into account human capital adjustments by natives and previous immigrants. To this end, I propose and estimate a labor market equilibrium structural model. On the labor supply side, individuals make endogenous decisions on education, participation, and occupation. On the demand side, an aggregate firm uses a technology that combines labor skill units with capital to produce a single output, and accounts for skill-biased technical change. I estimate the model using U.S. micro-data for 1967-2007. Results suggest that immigration reduced wages considerably even though natives adjusted their human capital and labor supply behavior to compensate for the change in skill prices.

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1. INTRODUCTION

How do human capital investments react to immigration? Would U.S. natives have spent less years in school without the mass inflow of foreign workers? These questions are crucial to understand the wage consequences of immigration. However, most of the literature does not take them into account.

During the last forty years, 26 million immigrants of working-age entered the United States. These immigrants are different from natives both in terms of skills and in their concentration into different occupations. Presumably, such a huge inflow of workers not only affected overall wages, but also changed relative prices of skills. If this is true, then incentives to invest in human capital may have changed as well.

To what extent this important change in the U.S. labor supply harmed labor market opportunities of native workers has concerned economists and policy makers for years. In particular, economists have not reached a consensus on what is the effect of immigration on wages. Traditionally, this issue has been addressed by looking at the cross-city variation of immigration —seminal work includes Grossman (1982) and Borjas (1983). Results show that negative effects of immigration on economic opportunities of natives are modest. More recent studies find sizeable effects of immigration on wages at the national level (e.g. Borjas, 2003). However, this body of research does not take into account how the change in relative wages make natives adjust their human capital investment and labor supply behavior. Failing to take these adjustments into account may lead to an underestimation of negative effects of immigration.

In this paper, I propose and estimate an equilibrium structural model of a labor market with immigration. Importantly, I explicitly model the labor supply and human capital investment behavior of workers. Additionally, the model takes into account skill-biased technical change. Results suggest that immigration reduced importantly wages of competing natives. I also find that human capital and labor supply adjustments contribute importantly to mitigate negative effects of immigration.

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), extended to accommodate immigrant and native workers. 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 of learning-by-doing on the job leads to accumulation of (occupation-specific) work experience.

On the demand side, blue- and white-collar labor is combined with capital to

produce a single output. Labor is defined in skill units, i.e. workers have heterogeneous productivity depending on their education, occupation-specific experience, nationality, 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).

The equilibrium structure of the model, and the distinction between the skills and their market price allow me to disentangle price from composition effects of immigration on average wages. This distinction is important, as immigrants only affect natives through skill prices.¹

I estimate the model combining data from CPS and NLSY for the period 1967-2007.² I use the model to quantify the effect of immigration on wages and education. 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 and human capital with baseline simulations using the estimated parameters.

Results suggest that immigration reduced average wages. In particular, skill prices fell considerably as a consequence of the larger competition introduced by immigrants. Blue-collar skill prices were more affected than white-collar skill prices. However, natives (partially) compensated these pressures by increasing their human capital. Finally, an important fraction of the decline in the average wage is due to a composition effect, i.e. there is a higher proportion of low wage earners among immigrants.

There is a huge 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. It was pioneered by Grossman (1982) and Borjas (1983), and notably followed by Borjas (1985, 1995), Card (1990, 2001), Altonji and Card (1991), and Lewis (2010). This methodology exploits the fact that immigrants cluster in a small number of geographic areas, generating a large cross-city variation in immigrant 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 being exogenously penetrated by immigrants. This assumption, however, may be too restrictive as observed by Borjas, Freeman, and Katz (1997). On the one hand, Borjas and coauthors argued that prosperous cities receive more immigrants, inducing a spurious correlation that can be wrongly interpreted as immigration improving native economic opportunities.³

¹ Throughout the paper, I refer continuously to the effect of immigration on natives. However, except when otherwise noted, I am implicitly including the effect on previous immigrants as well.

² Further aggregate data from Census and BEA is used in the solution of the model (see below).

³ This reluctance was not new. Altonji and Card (1991), and LaLonde and Topel (1991) had

On the other hand, they claim that natives may respond to the inflow of immigrants by moving their labor to other cities until wages are equalized across areas.⁴ As a result of both drawbacks, Borjas (2003) find that negative effects are far smaller at the state than at the national level, and Cortes (2008) find state-level effects to be more sizable than those at the city level. They conclude that negative effects are attenuated at the local level by native migration responses.⁵

Closer to 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. It uses information on elasticities of substitution among skill groups to compute the relative wage consequences of the supply shock. Initial studies borrowed elasticities from the literature whereas in more recent studies, beginning with Card (2001) and Borjas (2003, Sec. VII), those elasticities are estimated.⁶

Although the latter strand of the literature does not have the problem of native responses in terms of migration (out-migration in the U.S. at the national level is by far less severe than internal migration), natives can react to the inflow of immigrants in many other dimensions, mainly, adjusting their labor supply and human capital investment behavior. If so, counterfactuals of the factor proportions approach do not correctly measure the effect of immigration on wages. Therefore, the main contribution of this paper is to endogenize both.

Human capital may be adjusted because of two conflicting factors. On the one hand, if immigrants alter relative prices of skills (increasing education and white-collar experience premia), natives’ incentives change. As a result, they may increase their human capital mitigating downward pressures on low-skilled workers. On the other hand, if immigration reduces wages, individuals may obtain a lower reward to their investments in human capital —both because investment costs are not altered

already used instrumental variables before. However Borjas (1999) noted that the instruments used in the literature do not help to identify any parameter of interest, and that valid instruments are hard to find.

⁴ Borjas, Freeman, and Katz (1997), Card (2001), and Borjas (2006) analyze how immigration affects the joint determination of wages and internal migration behavior.

⁵ An alternative argument by Lewis (2010) suggests that plants in areas with high immigration adopted significantly less machinery per unit of output, compensating, as a result, negative effects of immigration on low skilled workers in those cities.

⁶ More recent papers on this literature include Borjas and Katz (2007), Borjas, Grogger, and Hanson (2008, 2010), and Ottaviano and Peri (2010). A special mention should be made of Borjas (2003, Secs. II-VI) that identifies the impact of immigration on the labor market by exploiting the variation across schooling groups, experience cells and over time in a reduced form fashion.

by immigration, and because they participate less in the labor market. In this case, natives would reduce their human capital. As mentioned above, results suggest that the first effect is dominating, as individuals increased their human capital to compensate negative effects of immigration.

Labor supply may also adjust to immigration. First, the fall in wages will motivate some individuals to leave the labor market. This participation effect will tend to increase average wages because lower earners are more likely to leave the market. Additionally, a change in relative prices will induce some individuals to switch occupations. In this case, the effect is ambiguous. The counterfactual exercises show that the overall supply adjustment effect is negative but very small.

The rest of the paper is organized as follows. The next section briefly reviews some descriptive evidence. Section 3 presents the labor market equilibrium structural model with immigration. Section 4 discusses the nested algorithm used for the solution and estimation of the model, and it briefly describes the data used in the estimation and their simulated counterparts. In Section 5, I present parameter estimates and the validation of the model. Section 6 shows counterfactual exercises. Concluding remarks are in Section 7.

2. SOME FACTS ABOUT U.S. MASS IMMIGRATION

2.1. Immigration, wages, and education

During the last four decades, the U.S. labor force was enlarged by about 26 millions of working-age immigrants, almost 0.7 millions of workers per year. Such a huge immigrant-induced labor supply increase has motivated a lot of debate. Researchers are concerned about the economic consequences for native workers, and immigration policy is constantly in the political arena.

Many studies analyze the effect of immigration on wages. As immigrants cluster in a small group of geographic areas, most of the literature, beginning with Grossman (1982) and Borjas (1983), exploit cross-city variation to identify wage effects of immigration. The “spatial correlations” emerging from this comparison tend to find negative but small effects. However, the endogeneity of immigrant locations and the reallocation of natives motivated some authors to switch the analysis to the national level. In fact, Borjas (2003) finds that negative effects are smaller at the state than at the national level, and Cortes (2008) finds that state-level effects are more sizable than those at the city level. Both conclude that negative effects are attenuated at the local level by native migration responses.

Borjas, Freeman, and Katz (1992, 1997) established the “factor proportions ap-

TABLE I
WAGE EFFECTS OF IMMIGRATION

Authors	Period	Main findings
Borjas, Freeman, and Katz (1997)	1980-1995	3-6 percent decline in relative wages of high school vs dropouts, 0.7-1.3 percent decline in relative college vs high school wages, 0.35 to -2.49 percent increase in earnings of skilled workers and 4.5-4.6 percent decline for unskilled (depending on the assumptions about the stock of capital).
Borjas (2003)	1980-2000	3.2 percent decline on average, 8.9 percent for dropouts, 2.6 for high school, 0.3 for some college and 4.9 percent for college graduates.
Borjas and Katz (2007)	1980-2000	Very similar to Borjas (2003) but additionally they find that Mexican immigrants account for most of the effect on dropouts and half of the effect on high school.
Ottaviano and Peri (2010)	1990-2006	0.6 to -0.1 percent increase in wages of native dropouts, 0.6 percent on the average native wage, and 6 percent decline in wages of previous immigrants.
Borjas, Grogger, and Hanson (2010)	1980-2000	5.3 and 6.8 percent decline for black and white dropouts respectively, 2.0 and 2.5 for high school, 2.2 and 2.8 for some college, and 2.9 and 3.7 percent for college graduates.

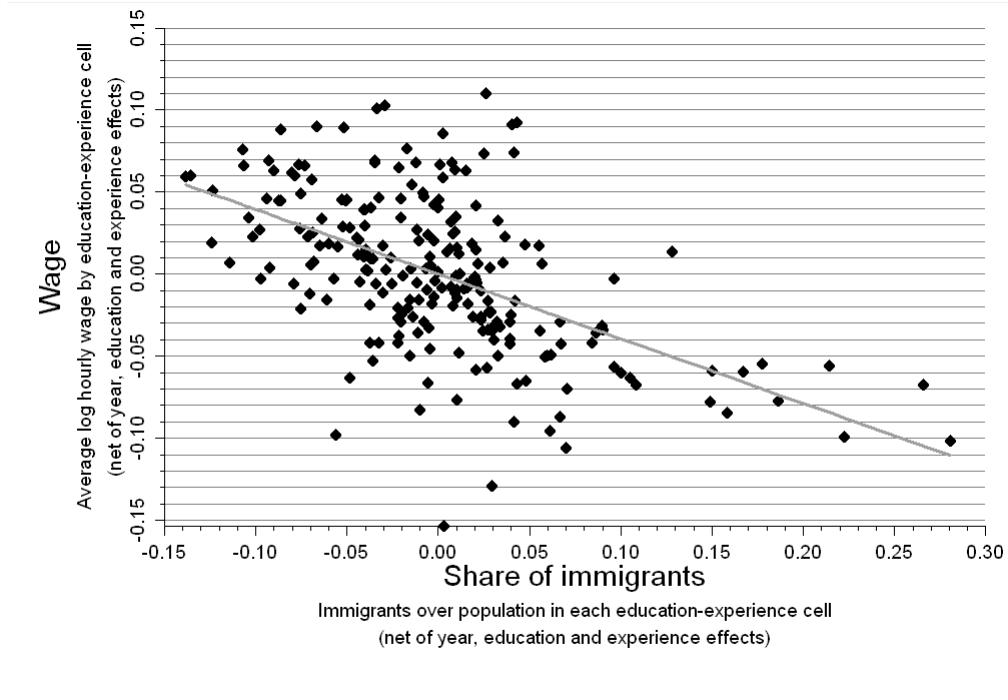
NOTE: This table summarizes the main findings in the “factor proportions approach” literature (it does not include any of the large amount of papers in the “spatial correlations approach” literature). The central column refers to the period of analysis. All numbers presented here represent the cumulative increase or decrease of average wages over the entire period.

proach”, that simulates wage effects of immigration by comparing actual supplies of workers in particular skill groups with those that would have been observed in the absence of immigration. Many papers have built on this approach with different findings. Most of them find sizeable negative effects. Table I summarizes the most influential ones.

Results in Table I suggest that there exists at least some negative correlation among wages and immigration. The problem with the analysis at the national level is that there is only one observation at each point in time. Borjas (2003) circumvents this problem by comparing immigration and wages in different education-experience cells. I follow his idea to fit a fixed effects regression including education, experience and year dummies. Figure I shows that the correlation is indeed negative. In particular, a one percentage point increase in the share of immigrants is associated to a 0.39 percent decrease in hourly wages.

The question I am addressing in this paper is about how human capital investments

FIGURE I
IMMIGRATION AND WAGES (1960-2008)



NOTE: Both wages and immigrant shares have been subtracted year, education, and experience fixed effects. Each observation is defined by an education-experience cell for a particular Census year (1960-2008). The horizontal axis represents the share of immigrants in each cell. The vertical axis plots average hourly wages. Education is grouped in four categories: dropouts, high school, some college, and college. Experience is potential (age minus education), and it is categorized in 10 five-year experience groups. The sample includes full time workers (more than 20 hours per week, more than 40 weeks per year) aged 16-65 years old. The line represents the following fixed effects regression of log average hourly wages of individuals with education i , experience j , at census year t ($\ln w_{ijt}$) on the share of immigrants in that cell (m_{ijt}):

$$\ln w_{ijt} = -0.394m_{ijt} + \nu_i + \nu_j + \delta_t + \epsilon_{ijt}.$$

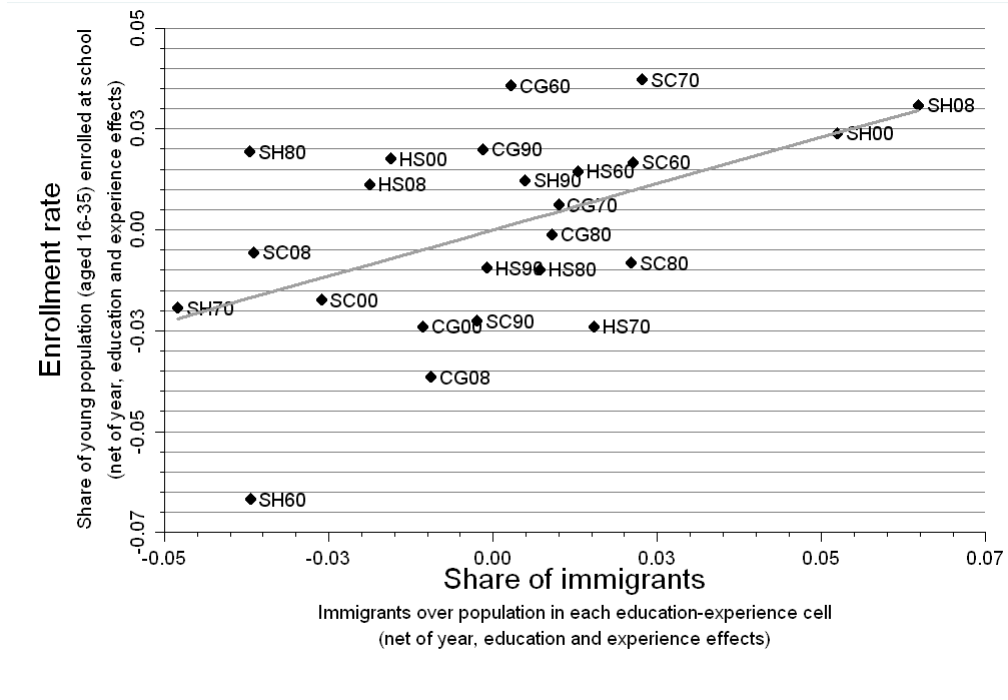
(0.031)

Regression fitted to 240 observations. Robust standard error in parenthesis.

Sources: Census data for 1960 to 2000 and ACS for 2008.

and labor supply respond to immigration. Figure II looks at the association between school enrollment rates (share of population aged 16-35 that is enrolled in school) and immigration. By construction, in this case it does not make sense to group individuals by experience, so I only create education cells. The idea is as follows: if an individual has just completed, say, high school and she has to decide whether to go to the job market or to keep studying for an additional year, she will look at how tough is the competition in the market for high school graduates, and she will decide accordingly. Therefore, I fit a fixed effects regression with education and year dummies. Figure II presents a positive correlation between immigration and school enrollment. In this case, a one percentage point increase in the share of immigrants is associated with a

FIGURE II
IMMIGRATION AND SCHOOL ENROLLMENT (1960-2008)



NOTE: Both wages and immigrant shares have been subtracted year, education, and experience fixed effects. Each observation is defined by an education group for a particular Census year (1960-2008). The horizontal axis represents the share of immigrants over working age population (16-65) in each education group at each point in time. The vertical axis plots the share of young individuals (16-35) that is enrolled at school in each group. Labels of different data points are as follows: the two letters indicate current educational level (SH–Some high school, HS–High School, SC–Some College, CG–College Graduates); the two numbers indicate Census year. The line represents the following regression for the enrollment rate of individuals in educational category i at census year t (s_{it}) on the share of immigrants in that cell (m_{it}):

$$s_{it} = 0.456m_{it} + \nu_i + \delta_t + \epsilon_{it}. \quad (0.199)$$

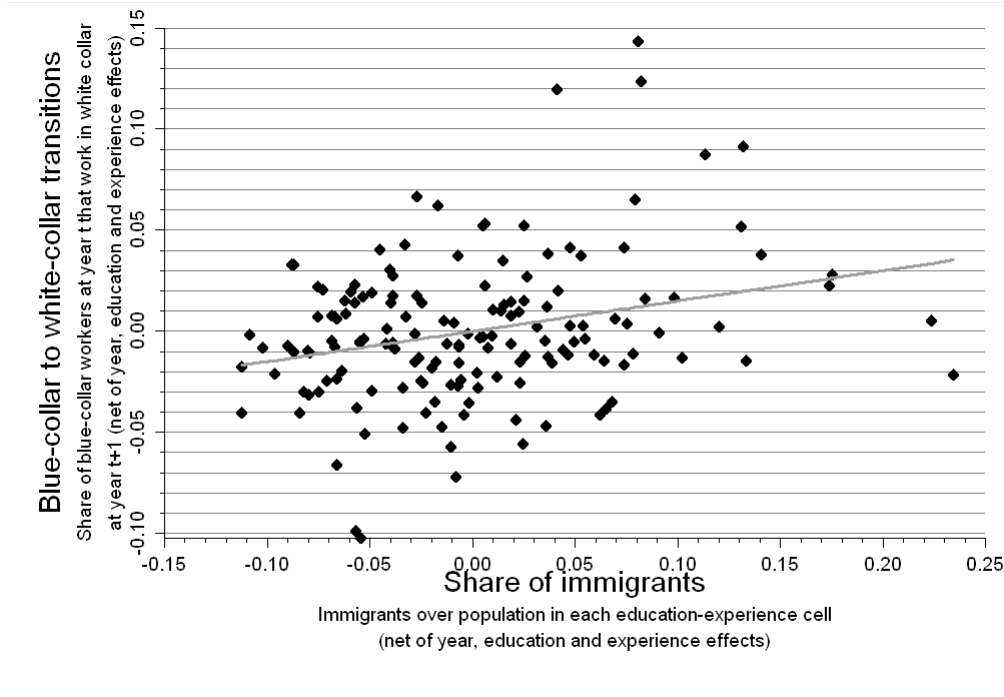
Regression fitted to 24 observations. Robust standard error in parenthesis.

Sources: Census data for 1960 to 2000 and ACS for 2008.

0.46 points increase in enrollment rates.

Finally, I also look at the correlation of immigration and blue- to white-collar transitions. Individuals switch occupations not only to benefit from a different wage, but also to change their experience accumulation profile. This particular transition probability is interesting because immigrants are more clustered in blue-collar jobs (see Section 2.2). The increasing competition in blue-collar jobs due to the increase in immigration pushes down blue-collar wages, and it makes more attractive to accumulate experience in white-collar jobs. Figure III presents an estimate of a fixed effects regression between this transition probability and immigration across education-experience-year cells. A one percentage point increase in the immigrant share is associated with

FIGURE III
IMMIGRATION AND OCCUPATION TRANSITIONS (1970-2008)



NOTE: Both transitions and immigrant shares have been subtracted year, education, and experience fixed effects. Each observation is defined by an education-experience cell for a particular Census year (1960-2008). The horizontal axis represents the share of immigrants in each cell. The vertical axis plots the share of individuals that work in blue-collar in year t and in white-collar in year $t + 1$ over all individuals that work in blue-collar in year t in each cell. Education is grouped in four categories: dropouts, high school, some college, and college. Experience is potential (age minus education), and it is categorized in 10 five-year experience groups. See the text for details on how individuals are assigned to each occupation. The line represents the following fixed effects regression of blue- to white-collar transition probability of individuals with education i , experience j , from census year t to year $t + 1$ (p_{ijt}) on the share of immigrants in that cell (m_{ijt}):

$$p_{ijt} = 0.150m_{ijt} + \nu_i + \iota_j + \delta_t + \epsilon_{ijt}. \\ (0.048)$$

Regression fitted to 155 observations (cells with less than 20 observations in the CPS have been eliminated). Robust standard error in parenthesis.

Sources: Census data for 1970 to 2000 and ACS for 2008 for immigrant shares. Matched March Supplements of CPS for occupation transitions (1970-71 to 2007-2008 Supplements).

a 0.15 percentage points increase in the blue-white collar transition probability.⁷ This correlation is in line with the result by Peri and Sparber (2009) that natives reallocate their task supply as a reaction to immigration to compensate downward pressures in wages.

⁷ The average transition probability is around 13 percent.

2.2. Mass immigration

The large scale immigration of the last four decades increased the share of immigrants in the labor force from 5.7 to more than 16.6 percent (see Table II). The composition of the inflow of new workers is very important as it will determine how immigration affects relative skill prices. The following lines describe to what extent immigrants are different from natives and how has the skill composition of the former changed over time.

TABLE II
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:					
Dropouts	6.84	9.60	17.93	29.02	33.73
High school	4.32	5.14	7.94	12.04	13.27
Some college	5.14	6.63	7.92	9.96	11.65
College	6.48	8.02	10.60	14.59	16.92
C. In blue collar jobs:					
<i>All education levels</i>	<i>6.03</i>	<i>7.83</i>	<i>11.21</i>	<i>17.53</i>	<i>24.07</i>
Dropouts	7.18	12.18	23.75	41.03	55.45
High school	4.19	4.94	7.57	12.47	17.30
Some college	5.95	6.14	7.26	9.82	14.07
College	9.53	9.52	12.14	17.89	23.82

NOTE: Figures in each panel indicate the percentage of immigrants among the overall working-age population, among workers in each education group, and among blue-collar workers respectively. *Sources:* Census data for 1970-2000 and ACS for 2008.

Table II shows that the presence of immigrants has increased quickly among less educated than among other groups. In particular, the share of immigrants among dropouts increased twice as fast as in the other education groups. In absolute terms, this does not mean that immigrants are less educated than four decades ago, but that their education has increased slowly compared to native education. Table III shows that the share of dropouts among immigrants decreased from 49.8 to 27.4 percent whereas it decreased from 41 to 10.7 percent among natives. An interesting insight from Table III 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 IV). If the composition of the inflow of immigrants in terms of regions of origin had remained as in 1960s, immigrant education would probably have increased at the same speed as native education.⁸

⁸ In fact, if we aggregate regional distributions of education from Table III using the distribution

TABLE III
EDUCATION OF NATIVES AND IMMIGRANTS (%)

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

NOTE: Figures indicate the percentage of individuals from each origin in each education group. Columns for each panel add to 100%. Western countries include immigrants from Canada, Europe and Oceania. *Sources:* Census data for 1970-2000 and ACS for 2008.

Another important conclusion from Table II is that immigrants are (increasingly) more clustered in blue-collar jobs. This is also true by 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 among all dropouts.

Table IV shows that immigrants are more prevalent in blue-collar occupations. In all categories included in blue-collar, the share of immigrants increased faster than the overall share, whereas the opposite is true for all white-collar categories. Farming-related occupations deserve a special mention because farm laborer (blue-collar) is the occupation with the highest share of immigrants, whereas farm manager (white-collar) is the occupation with less immigrants.

An important conclusion from Table IV is that, although some times the blue/white

of regions of origin of 1970, we observe that education would have increased roughly at the same speed.

collar classification may be too broad and heterogeneous (especially for a long time period), in this case it seems enough to describe the differential supply shock across occupations.

TABLE IV
SHARE OF IMMIGRANTS AMONG WORKERS IN EACH OCCUPATION (%)

	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 share of immigrants among workers employed in each occupation. *Sources*: Census data for 1970-2000 and ACS for 2008.

2.3. Policy background

Although the focus of this paper is on the recent boom in immigration, it is important to remark that immigration is not a new phenomenon in the United States. Throughout its history, the United States has been a nation of immigrants. From colonial times to mid-nineteenth century Western Europeans (especially British and Irish, but also German and Scandinavian) kept entering the U.S. without any federal legislation (and without a major concern from locals). Beginning in 1850s, the so-called “new immigration” brought in immigrants from Eastern and Southern Europe as well as from Asia and Russia. Americans’ preference for “old” rather than “new” immigration reflected a sudden rise in conservatism and the appearance of the first nativist movements. In 1875 the first federal immigration law was passed; this law prohibited the entrance of criminals and convicts, as well as Asian women who would engage in prostitution.

This law paved the road for the 1882 Chinese Exclusion Act, which almost prohibited Chinese workers to enter the United States.⁹ It was the first law that targeted a specific ethnic group, starting a bias against Asian that lasted until 1952.¹⁰ The

⁹ Over further decades, Chinese were issued Japanese passports to enter the United States. In 1907, a “Gentleman’s Agreement” with Japan effectively ended with Chinese immigration.

¹⁰The Immigration and Naturalization Act of 1952 removed racial distinctions in the legislation for the first time in U.S. immigration policies.

Immigration Act of 1917 defined a “barred zone” of nations in the Asia-Pacific triangle from which immigration was prohibited

In 1921 the U.S. Congress passed the Emergency Quota Act, which limited the annual number of immigrants to be admitted from any country to a maximum of the 3% of the number of persons from that country living in the U.S. in 1910. In 1924, the share was reduced to 2% and the reference year was switched to 1890. It was the birth of the National Origins Formula. This restriction, aimed to preserve the ethnic composition of U.S. population, especially affected Southern and Eastern European immigrants.

The 1965 Amendments to the Immigration and Nationality Act drastically changed the U.S. immigration policy. The National Origins Formula was abolished. Numerical limitations were set at the Hemisphere level; Eastern Hemisphere was served a fixed amount of visas per year with a fixed maximum per country; 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 country limit. Nevertheless, the new policy allowed to issue an unlimited amount of visas to immediate relatives (parents, spouses and children) of U.S. citizens and legal immigrants.

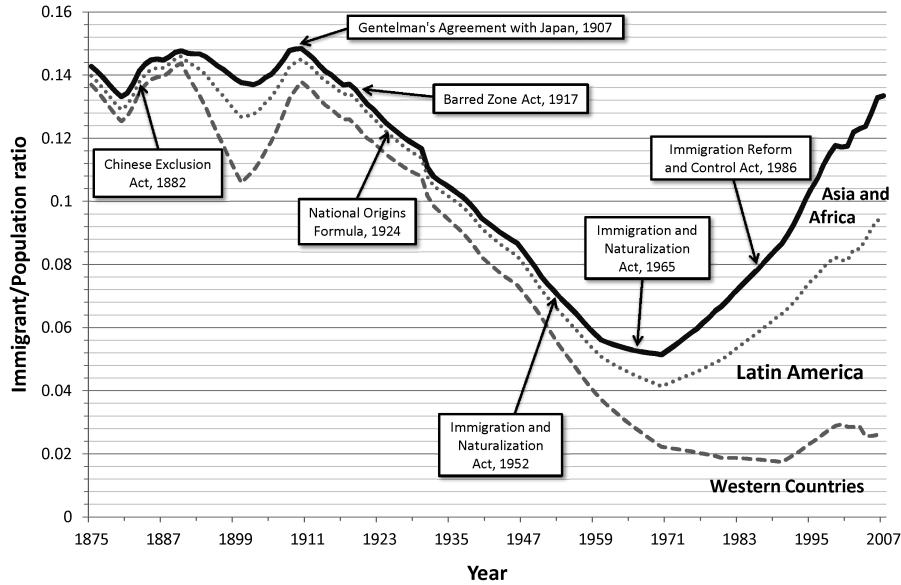
Subsequent policies concentrated in preventing illegal immigration (e.g., 1986 Immigration Reform and Control Act (IRCA) and the subsequent amnesty, and 1996 Illegal Immigration Reform and Immigrant Responsibility Act). The most important policy change after 1965 came with the 1990 Immigration Act (effective in 1992) which restricted the number of visas to be issued to immediate relatives of previous immigrants and U.S. citizens.

Figure IV shows how different policy changes correlate with long run trends in immigration. In particular, it graphs the share of foreign born in the population from 1875 to 2007, with a disaggregation by regions of origin. During the nineteenth century and the first decades of the twentieth century, around 14% of the population was foreign born. Most of them were Europeans, especially after the introduction of policies biased against Asians.

The two World Wars, the Great Depression, and the National Origins Formula shrank the inflow of workers, trimming down the share of immigrants to around 6%, but with the same composition in terms of origins (an obvious result of the National Origins Formula). After 1952, the share of Asians increased as a consequence of the abolition of racial distinctions in admission.

The main change, however, was introduced by the 1965 Amendments to the Immigration and Naturalization Act. President Lyndon B. Johnson signed the legislation into law, saying “*This —the previous— system violates the basic principle of American*

FIGURE IV
IMMIGRATION POLICIES (1875-2007)



NOTE: The black solid line represents the share of the population born abroad. The area below the dashed gray line represents the share of immigrants from Western Countries. The area between the dashed and the dotted lines represents the share of Latin Americans. And the area between the dotted and the solid lines represents the share of Asian and African. *Sources:* Census data for 1870-2000 and ACS for 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.

democracy, the principle that values and rewards each man on the basis of his merit as a man. It has been un-American in the highest sense, because it has been untrue to the faith that brought thousands to these shores even before we were a country.”. Senator Ted Kennedy, on the other hand, stated that “*our cities will not be flooded with a million immigrants annually*”. Therefore, the aim of the law was clearly to remove “*an archaic form of chauvinism*”.

In light of the previous quote, Figure IV shows that the subsequent resurgence of large scale immigration was unpredicted by policy makers at that time. From the end of 1960s to the present day, the share of immigrants in the population increased steadily. Moreover, the sources of immigrants changed drastically: while the presence of Western immigrants kept falling during the following decades, crowds of Latin Americans, and to a lesser extent Asians, continuously flooded the U.S. since then.

As I mentioned before, numerical limits did not end with the 1965 Amendments. Initially, a quota was set by hemispheres (170,000 with a 20,000 limit by country for the

Eastern Hemisphere, and 120,000 for the Western Hemisphere without the per-country limit until 1976), and in 1978 they merged into a world quota of 290,000.¹¹ According to Department of Homeland Security (Yearbook of Immigration Statistics), quotas were, in general, filled every year since 1986 (the first year with available data on legal entrants by class of admission). Therefore, these quotas were a binding constraint to the inflow of immigrants.

3. A LABOR MARKET EQUILIBRIUM MODEL WITH IMMIGRATION

In this section, I present a labor market equilibrium model with immigration. This model is used to quantify the effect of four decades of large scale immigration into the U.S. on wages and human capital investments of natives. The main contribution of the current approach is to explicitly model the labor supply and human capital investment decisions. I also account for skill-biased technical change as an alternative source of the increasing wage inequality.

On the supply side, forward-looking individuals decide on education, labor market participation, and occupation. Education and occupation-specific work experience are rewarded in the future with higher wages, and leisure produces utility. The previous literature typically assumes perfectly inelastic labor supply and exogenous education-experience profiles (e.g., Borjas (2003), Borjas and Katz (2007), Ottaviano and Peri (2010), Borjas, Grogger, and Hanson (2010)). This assumption may produce biases as immigration affects education, participation and occupation decisions. For example, if the inflow of foreign workers reduces native participation in the labor market (i.e., if the labor supply curve has a finite positive slope), negative effects of immigration on wages may be underestimated. Or, if natives increase (reduce) their education as a consequence of immigration, this may lead to underestimate (overestimate) negative wage effects.

On the demand side, the production function of the aggregate firm includes heterogeneous labor and skill-biased technical change. As in the “canonical model” of wage inequality,¹² I consider two types of labor: skilled labor, given by white-collar aggregate skill units, and unskilled labor, provided by blue-collar skill units.¹³ Moreover, simi-

¹¹ Immediate relatives (spouses, children, and parents) were allowed to enter without any limitation until 1992. After 1992, the overall quota (including relatives) was set to around 700,000.

¹² See a detailed description of this model in the surveys by Acemoglu (2002) and Acemoglu and Autor (2010).

¹³ Labor supply is measured in skill (or efficiency) units, i.e., for a given occupation, it is adjusted by education, experience, and unobserved heterogeneity in productivity. Individual wages are given by individual skill units and their equilibrium prices. As a result, the model is able to produce heterogeneity in wages (inequality) within occupations. The structure of the model provide an explicit form for the individual production function of skill units.

larly to Krusell, Ohanian, Rios-Rull, and Violante (2000), skill-biased technical change is induced by capital-skill complementarity and the dynamics of capital equipment.

3.1. Career decisions and the labor supply

Individuals enter the model at age $a = 16$ (or at entry into the U.S. in the case of immigrants) and make decisions each year until the age of 65 when they die with certainty. They choose among four mutually exclusive alternatives to maximize their lifetime expected utility: to work in a blue-collar job, $d_a = B$; to work in a white-collar job, $d_a = W$; to attend school, $d_a = S$, or to stay at home, $d_a = H$. The population consists of L types of individuals that differ in skill endowments and preferences, as described below. I define the types of individuals based on observable characteristics. Natives differ by gender (males and females). Immigrants additionally differ in their region of origin (Western countries, Latin America, and Asia and Africa). As a result, there are eight types of individuals, six types of immigrants and two of natives.

Immigrants enter the U.S. exogenously and with a given skill endowment. This assumption is standard in the literature. Attempting to endogenize migration decisions would be very difficult, as it requires to observe immigrants in their country before immigration, and those data are not available. However, immigrants might be more attracted when wages are relatively high. Should that happen, it would generate a spurious positive correlation of wages and immigration, and an upward bias as a result.¹⁴

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

$$V_a(\Omega_{at}) = \max_{d_a} U_a(\Omega_{at}, d_a) + \beta E[V_{a+1}(\Omega_{a+1,t+1}) \mid \Omega_{at}, d_a], \quad (1)$$

with a terminal value $V_{65+1} = 0$. β is a subjective discount factor, and Ω_{at} is the information set at age a and time t . The instantaneous utility function is choice-specific, $U_a(\Omega_{at}, d_a = j) \equiv U_a^j$ for $j = B, W, S, H$. Workers are not allowed to save and, therefore, they are not allowed to smooth consumption. As a consequence, utility is assumed to be linear.¹⁵ This assumption is consistent with individuals maximizing life-time discounted earnings (plus additional non-pecuniary utility).

¹⁴ Nevertheless, long run trends in U.S. immigration seem to be driven additionally by something else. First of all, Section 2.3 shows that immigration policy reform in 1965 —apparently driven by ethical/diplomatic concerns more than by labor market pressures— clearly marked a change in long run trends and composition of the immigrant stock. Additionally, moving costs changed considerably during this time. And, finally, country-specific shocks in different source countries may also have played a role.

¹⁵ Introducing a continuous decision variable is very expensive computationally. See further details on the solution algorithm below.

Working utilities are given by occupation-specific wages, $U_{a,l}^j \equiv w_{t,a,l}^j$ for $j = B, W$. Wages are defined as the product of individual skill units (productivity) times their market price (productivity adjusted wage rate): $w_{t,a,l}^j \equiv r_t^j \times s_{a,l}^j$. Prices of skill units, r_t^j , are obtained in equilibrium, and individual skill units are defined by a fairly standard Mincer equation (Mincer, 1974):

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

The exponential part of equation (2) is the production function of skill units. All ω^j s, interpreted as technology parameters, represent the return of 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. Returns to education, $\omega_{1,is}^j$, are different for immigrants and natives ($is = nat, immig$).¹⁶ Aside from the returns to investments in human capital, equation (2) also includes permanent and transitory heterogeneity in productivity, $\omega_{0,l}^j$, and ε_a^j . The transitory shock is iid normally distributed with gender-specific variance σ_g^j .

Skill prices r_t^j are only identified up to scale in equation (2). Therefore, I impose the normalization $\omega_{0,male,nat}^j = 0$. Given this normalization, skill prices are interpreted as average wages in occupation j of native males without any education and experience.

Equation (2) accounts 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 in the sense that they accumulate skills in the U.S. that they would not have accumulated in their home country (Borjas, 1999). In terms of the present model, assimilation is provided by (the possibility of) a higher return to one year of U.S. experience than to one year of experience abroad.

Individuals who decide to attend school face a monetary cost, which varies for undergraduate, τ_1 , and graduate studies, $\tau_1 + \tau_2$. Additionally, they have a non-pecuniary utility which is defined by 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 iid transitory shock, ε_a^S , normally distributed with gender-specific variance σ_g^S . Specifically,

$$U_{a,l}^S = \delta_{0,l}^S - \delta_{1,g}^S \mathbb{1}\{d_{a-1} \neq E\} - \tau_1 \mathbb{1}\{E_a \geq 12\} - \tau_2 \mathbb{1}\{E_a \geq 16\} + \varepsilon_a^S. \quad (3)$$

¹⁶ Different returns to years of schooling for immigrants and natives may be the consequence of immigrants undertaking (part of) their education abroad. For example, one may tend to think that a share of the skills that are transmitted in school have a country-specific component, and less useful in a different country (e.g. non-English language skills). Alternatively, I could consider a different return to education in the U.S. and abroad; however, I do not observe where the immigrants attended school.

As a counterpart, their stock of years of education increases accordingly $E_{a+1} = E_a + \mathbb{1}\{d_a = E\}$, providing a return in the future.

Finally, those individuals who decide to remain at home do not receive any pecuniary payoff, and they experience the following utility:

$$U_{a,l}^H = \delta_{0,l}^H + \delta_{1,g}^H n_a + \varepsilon_a^H. \quad (4)$$

In this case, their permanent and transitory utility is increased by $\delta_{1,g}^H$ units for each preschool children living with them at home, n_a .¹⁷

3.2. Aggregate production function and the demand of labor

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

$$Y_t = z_t K_{St}^\lambda \{ \alpha S_{Bt}^\rho + (1 - \alpha) [\theta S_{Wt}^\gamma + (1 - \theta) K_{Et}^\gamma]^{\rho/\gamma} \}^{(1-\lambda)/\rho}. \quad (5)$$

Equation (5) is a Cobb-Douglas production function that combines capital structures and a composite of equipment and labor. This composite is itself a CES combination of blue-collar labor and another CES aggregation of equipment and white-collar. Neutral technological change 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. In particular, the elasticity of substitution between equipment and white-collar labor is given by $1/(1 - \gamma)$, and the elasticity of substitution between equipment/white-collar and blue-collar labor is $1/(1 - \rho)$.

Skill units are supplied by workers according to equation (2). As individuals are not allowed to save, capital and output are taken from the data. The aggregate productivity shock is obtained as the residual in equation (5). The assumption of capital exogeneity is consistent, for example, with capital flowing from international markets. I evaluate different scenarios of counterfactual capital in Section 6.

Economic theory suggests that immigration affects wages by lowering the wage of competing workers (Borjas, 1999). The analysis at the occupational level is convenient in this context. From a theoretical point of view, a foreign engineer working in a farm is not competing with a native professional engineer, but with a native farmer. Section 2 points out that natives and immigrants concentrate in different occupations

¹⁷ 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 (taken from the data) and depends on gender, education, age and cohort (further details in Appendix A).

given observable skills, and foreign workers are increasingly more clustered in blue-collar jobs.¹⁸ Moreover, it is easier for workers to switch occupations than skills as a mechanism to compensate negative effects of immigration. 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. Table IV in Section 2 shows, however, that, in this case, this classification is enough to describe the differential supply shock across occupations. This is also true by educational levels. Ideally, one would like to define as many types of labor as possible, because the larger the amount of prices, the more heterogeneous effects will be generated by the model. However, the computational burden increases with the amount of prices to be solved in equilibrium.¹⁹

Equation (5) is different from the three-level nested CES that has become popular in the immigration literature since its introduction by Borjas (2003). Borjas considers a technology that is a Cobb-Douglas combination of capital and a labor aggregate. Labor, measured in worker counts, is a CES aggregation of four educational cells, each being itself a CES aggregate of five experience cells. Equation (5) differs from Borjas' production function in the following aspects: (i) it adds the occupational layer (blue-collar and white-collar workers); (ii) it includes capital-skill complementarity as a source of skill-biased technical change; (iii) the marginal rate of substitution between workers is increasing in workers' productivity;²⁰ and (iv) it implies solving for two equilibrium prices instead of twenty (see footnote 19).

I include capital-skill complementarity to account for skill-biased technical change. Krusell, Ohanian, Rios-Rull, and Violante (2000) use a production function similar to equation (5) to link the faster decline in the relative price of capital equipment beginning in the early 70s, to the increase in college-high school wage gap. This link is provided by $\rho > \gamma$, meaning that equipment capital is more complementary to

¹⁸ The increasing concentration of immigrants in blue-collar jobs given observed skills may generate biases if it is not taken into account. The average wage in a given skill (education) cell would artificially decrease with the inflow of immigrants because the share of blue-collar (lower-paid) workers in the given group would be increased by immigration. Allowing imperfect substitution among immigrants and natives in each group (as in Ottaviano and Peri, 2010) may not be enough to correct this problem.

¹⁹ On the one hand, solving each price in equilibrium is time consuming. On the other hand, and more importantly, the state space of the individual maximization problem increases with the amount of aggregate variables and prices.

²⁰ Borjas (2003) assumes that the elasticity of substitution between a dropout worker and a college graduate is the same as between a dropout and a high school graduate. In this paper, within an occupation, skill units are perfect substitutes; however, a one percent increase in the number of dropouts requires a larger percentage reduction of high school graduate workers than of college graduates to produce the same output. As a corollary, equation (5) also implies that the effect of a new immigrant is increasing in her productivity.

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 capital equipment —due to the decline in its price— increases the relative demand of skilled workers.

3.3. The equilibrium

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

$$S_t^j = \sum_{a=16}^{65} \sum_{n=1}^{N_{a,t}} s_{a,n}^j \mathbb{1}\{d_{a,n} = j\}. \quad (6)$$

where $N_{a,t}$ is the cohort size. On the other hand, in each period, the aggregate firm maximizes profits by equalizing marginal returns to rental prices:

$$r_{S_B t} = (1 - \lambda) \alpha (z_t K_{S_t}^\lambda)^{\frac{\rho}{1-\lambda}} S_{B_t}^{\rho-1} Y_t^{1-\frac{\rho}{1-\lambda}}, \quad (7)$$

$$r_{S_W t} = (1 - \lambda)(1 - \alpha) \theta (z_t K_{S_t}^\lambda)^{\frac{\rho}{1-\lambda}} S_{W_t}^{\gamma-1} K W_t^{\rho-\gamma} Y_t^{1-\frac{\rho}{1-\lambda}}, \quad (8)$$

$$r_{K_E t} = (1 - \lambda)(1 - \alpha)(1 - \theta) (z_t K_{S_t}^\lambda)^{\frac{\rho}{1-\lambda}} K_{E_t}^{\gamma-1} K W_t^{\rho-\gamma} Y_t^{1-\frac{\rho}{1-\lambda}}, \quad (9)$$

$$r_{K_S t} = \lambda \frac{Y_t}{K_{S_t}} \quad (10)$$

where $K W_t \equiv [\theta S_{W_t}^\gamma + (1 - \theta) K_{E_t}^\gamma]^{1/\gamma}$. The labor market equilibrium is given by the skill rental prices that clear the market of skill units.

Every year t , workers make a forecast about the future path of information sets in the states they expect to reach. They face uncertainty about future skill prices, fertility, and idiosyncratic shocks. The fertility process is known by all agents. Idiosyncratic shocks have no persistence, so the best forecast is their conditional mean. Finally, the path of future skill prices is provided by the sequence of aggregate variables. I assume that individuals have perfect foresight of capital stocks and the stock of immigrants. However, in order to forecast future stocks of aggregate skill units, individuals need to forecast the evolution of the aggregate shock z_t . They also need the distribution of individual skill units in the current population. To forecast the aggregate shock, I assume that it is well described by the following AR(1) process:

$$\ln z_{t+1} - \ln z_t = \phi_0 + \phi_1 (\ln z_t - \ln z_{t-1}) + \varepsilon_{t+1}^z, \quad \varepsilon_{t+1}^z \sim \mathcal{N}(0, \sigma_z). \quad (11)$$

For computational reasons, the current distribution of individual skills can not be included in the state space. To make the problem tractable, I assume that the individual information set is bounded in the sense that it includes skill aggregates, but not the

entire individual distribution of skills. Therefore, workers are assumed to be boundedly rational, meaning that they make the best choices with their limited information set. Additionally, I assume that the evolution of aggregate skill units in occupation j is well approximated by the following VAR:

$$\begin{aligned}\Delta \ln S_{jt+1} = & \eta_0^j + \eta_1^j \Delta \ln S_{B,t} + \eta_2^j \Delta \ln S_{W,t} + \eta_3^j \Delta \ln K_{E,t+1} + \\ & + \eta_4^j \Delta \ln K_{S,t+1} + \eta_5^j \Delta \ln z_{t+1} + \eta_6^j \Delta \ln M_{t+1},\end{aligned}\tag{12}$$

where M_t is the stock of immigrants in year t .

4. MODEL SOLUTION AND ESTIMATION

4.1. A nested estimation algorithm

The equilibrium model presented in Section 3 does not have a closed form solution and needs to be solved numerically. There are two types of parameters to be estimated: *expectations parameters*, Θ_2 , given by forecasting rules (11) and (12) described in Section 3.3, and *fundamental parameters* of the structural model, Θ_1 , which are the remaining parameters of the model described in sections 3.1 and 3.2. Expectation parameters are not proper parameters in the sense that they are part of the solution of the model; in fact, they are implicit functions of the fundamental parameters, so we can write $\Theta_2(\Theta_1)$.

Parameters in Θ_1 are estimated by Simulated Minimum Distance. The Simulated Minimum Distance estimator minimizes the distance between a large number of data points or statistics and their simulated counterparts. $\Theta_2(\Theta_1)$ is solved by finding a fixed point in the comparison of the forecasting rules used to solve the individual maximization problem, and regression estimates of equations (11) and (12) with data simulated by the model using those forecasting rules. Therefore, the estimation requires a nested algorithm with a procedure that estimates Θ_1 , and another solving for Θ_2 given Θ_1 .

Lee and Wolpin (2006, 2010) describe a natural nested algorithm in which an inner procedure solves for 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 for the fixed point of Θ_2 in every evaluation of Θ_1 , and every try of Θ_2 imply an important computational burden.²¹ Alternatively, I use an algorithm that,

²¹ 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.

at least in the current exercise, outperforms the one by Lee and Wolpin (2006, 2010). Basically, what I propose is to swap the order of the nesting so that Θ_1 is estimated for every guess of Θ_2 , which is updated at a lower frequency. In particular, the algorithm consists of the following steps:

1. Choose a set of parameters $[\Theta_1]^0$ and $[\Theta_2]^0$.²²
2. Solve the optimization problem for each cohort that exists from $t = 1$ to $t = T$.²³
To do so, the dynamic programming problem described by equation (1) is solved recursively by backward induction from age 65 to age 1. 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. Therefore, to solve the problem I use an interpolation method based on the one described in Keane and Wolpin (1994, 1997). However, instead of Monte Carlo integration, I use quadrature to solve numerically the integrals from the expectation of the value function in $t + 1$.
3. Find the equilibrium skill rental prices and the aggregate shock simulating the economy from $t = 1$ to $t = T$. In particular,
 - (a) Guess skill rental prices of period $t = 1$.
 - (b) Find the supply of skills at this price using the solution obtained in item 2.
 - (c) Plug the supply of skills into the production function and, together with data on capital and output, recover the aggregate shock.
 - (d) Update skill rental prices with the demand equations (7) and (8), using the supply of labor obtained in step 3b and the aggregate shock from step 3c.
 - (e) Repeat steps 3b to 3d with the prices obtained in 3d. Keep iterating to find a fixed point in skill prices.
 - (f) Repeat steps 3b to 3e for $t = 2, \dots, T$.
4. Compare simulated data with their observed counterparts. Update Θ_1 with a simplex iteration and repeat steps 2 and 3 with $[\Theta_1]^1$. Keep updating Θ_1 to find the set of parameters that minimize the distance between simulated and observed data, $\hat{\Theta}_1([\Theta_2]^0)$.

²² A very natural initial guess of Θ_2 is provided by solving the fixed point described in step 5 for the given $[\Theta_1]^0$.

²³ In particular, I assume that the economy begins in 1860 and ends in 2007. This very early initial date is so to overcome the arbitrary initial conditions that I assign to all cohorts existing in $t = 1$. As a result, in 1967, the first estimation year, the oldest individuals have never been in the model with any of the initial cohorts, since a bit more than two entire generations have gone by.

5. Given $\hat{\Theta}_1([\Theta_2]^0)$, update Θ_2 solving for the fixed point in expectation rules. In order to do so, repeat steps 2 and 3 with $\hat{\Theta}_1$ and $[\Theta_2]^0$. Then fit OLS regressions of equations (11) and (12) with simulated data to update Θ_2 . Iterate to find a fixed point $\hat{\Theta}_2(\hat{\Theta}_1)$. If $\hat{\Theta}_2(\hat{\Theta}_1) = [\Theta_2]^0$, the algorithm finishes. Otherwise, repeat the entire process with updated $[\Theta_2]^1 = \hat{\Theta}_2(\hat{\Theta}_1)$ and $\hat{\Theta}_1([\Theta_2]^0)$ until convergence.²⁴

4.2. Simulated minimum distance

The Simulated Minimum Distance Estimator minimizes a weighted average distance between a large set of data points or statistics, and their simulated counterparts.²⁵ Table V lists those data. Each observation is weighted by the inverse of the —weighted— sample size used in its calculation (see further details in Appendix B).

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

- 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. Finally, those individuals that are neither assigned to attend school nor to work are considered to stay at home.

The simulated counterparts of the data described in Table V 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.).

²⁴ 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.

²⁵ 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.

TABLE V
DATA

Description	Source		Number of observations
TOTAL			30,012
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
Immigrants, by year, sex, and foreign potential experience	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:			6,404
<i>Mean log hourly real wage...</i>			<i>3,000</i>
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 occupation	NLSY	$2 \times (5 \times 5 + 4 \times 4) \times 2$	164
<i>Mean 1-year growth rates in log hourly real wage...</i>			<i>2,508</i>
By year, sex, previous, and current occupation	Matched CPS	$41 \times 2 \times 2 \times 2$	328
By year, sex, 5-year age group, and current occupation	Matched CPS	$41 \times 2 \times 10 \times 2$	1,640
By year, sex, region of origin, and current occupation	Matched CPS	$15 \times 2 \times 4 \times 2$	240
Immigrants, by year, sex, years in the U.S., and occupation	Matched CPS	$15 \times 2 \times 5 \times 2$	300
<i>Variance in the log hourly real wages...</i>			<i>896</i>
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...			14,154
By year and sex	Matched CPS	$41 \times 2 \times 4 \times (4 - 1)$	984
By year, sex, and age	Matched CPS	$41 \times 2 \times 10 \times 4 \times (4 - 1)$	9,840
By year, sex, and region of origin	Matched CPS	$15 \times 2 \times 4 \times 4 \times (4 - 1)$	1,440
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.	Matched CPS	$15 \times 2 \times 5 \times 4 \times (4 - 1)$	1,800
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 immigrant/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: All statistics are calculated for 41 years (1967-2007) except for those that use immigration-specific information, which are calculated for 15 (1993-2007). The number of 5-year age groups is $50/5=10$ (16-65). There are two genders (male and female). Immigrant status are also two (native and immigrant). Regions of origin are four (U.S. (natives), Western countries, Latin America, and Asia/Africa). There are four educational levels ($<12, 12, 13-15$ and $16+$ years of education). The categories of preschool children living at home are three (0, 1 and $2+$). And foreign potential experience (fpx) is classified in five groups, which are the same as for years in the country (0-2, 3-5, 6-8, 9-11 and $12+$ years). Calculations do not include those statistics that are linear combinations of others, neither they are included in estimation (for example, the share of individuals staying at home is redundant given the shares in blue- and white-collar jobs, and attending school). CPS stands for the March Supplement of the Current Population Surveys for survey years from 1968 and 2008; NLSY indicate the National Longitudinal Survey of Youth in their two editions (1979 and 1997 cohorts); finally, matched CPS denote 2-years matched March Supplements of CPS. See Appendix A for further details.

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 vari-

ables: output, stock of capital equipment 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 at entry for foreigners), the distribution of regions of origin of immigrants, and the fertility (preschool children) process. Further details on the definitions and construction of all the variables are in Appendix A.

Identification of the model parameters requires that there is a unique solution to the mapping between data and their model-based simulated counterparts. In practice, it is a matter of uniqueness of the global minimum and curvature around it. Figure C.I in Appendix C draws how the objective function changes when moving each of the parameters holding the others fixed to parameter estimates. Although this Figure does not prove the existence of enough curvature in the multidimensional space, it shows plenty of unilateral curvature for all parameters. The invertibility of the product of partial derivatives used to calculate the variance-covariance matrix for the parameter estimates —see Appendix B— points in the same direction.

From an heuristic point of view, identification is achieved by a combination of functional forms and distributional assumptions, along with exclusion restrictions. A large fraction of the data listed in Table V are cohort specific; the present analysis is, indeed, not very different from synthetic cohort panel data analysis used, for example, in Browning, Deaton, and Irish (1985). 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 for the aggregate supply of skill units plus aggregate data on capital and output; current and past cohort sizes act as if they were instruments for skill units.

5. ESTIMATION RESULTS

5.1. *Parameter estimates*

In this Section, I discuss parameter estimates. All tables include standard errors in parentheses. These take into account errors in measuring the statistics described in Section 4.2 with the data, and simulation error. Further details are in Appendix B.

Production function. Table VI presents parameter estimates for the production function. Elasticities of substitution implied by ρ and γ are respectively 1.37 and 0.74. These elasticities imply that capital equipment and blue-collar labor are closer substitutes than equipment and white-collar labor. This result —capital-skill

complementarity— is crucial for equation (5) to produce skill-biased technical change and explain the widening of the blue-white collar (and college-high school) wage gap. To see this, from equations (7) and (8) we can write:

$$\ln \left(\frac{r_{Wt}}{r_{Bt}} \right) = \ln \frac{(1 - \alpha)\theta}{\alpha} + (\rho - 1) \ln \left(\frac{S_{Wt}}{S_{Bt}} \right) + \frac{\rho - \gamma}{\gamma} \ln \left(\theta + (1 - \theta) \left(\frac{K_{Et}}{S_{Wt}} \right)^\gamma \right). \quad (13)$$

Equation (13) can be interpreted as a reformulation of Tinbergen’s famous race between technology and the supply of skills (Tinbergen, 1975).²⁶ The second term of equation (13) is the negative contribution of the supply of skills (provided by $\rho < 1$) and the last term captures biased technical change. As I mentioned above, Krusell, Ohanian, Rios-Rull, and Violante (2000) propose a production function, which is similar to equation (5), to link the rapid fall in the price of equipment and the widening of the wage gap. The last term in equation (13) captures precisely this effect by building a positive correlation of the stock of equipment and the wage gap as long as $\rho > \gamma$. Therefore, point estimates of Table VI, indicating capital-skill complementarity, are in line with this prediction.

Seminal work on the capital-skill complementarity hypothesis is provided by Griliches (1969). As noted by Hamermesh (1986), although most of the studies on this issue agree in the existence of some degree of complementarity among capital and skilled labor, there is a huge variety in the estimates of the absolute size of the demand elasticities for blue-collar and white-collar labor. Although they are not directly comparable, Krusell, Ohanian, Rios-Rull, and Violante (2000) estimate elasticities of 1.67 for high-school and 0.67 for college respectively.

As I mentioned in Section 3.1, I normalize the “ability” of native males to zero for both in blue-collar and white-collar wage equations. Aggregate skill units are relative to this normalization, and so are parameters α and θ , connected to factor shares. Given the CES production function in equation (5), only λ is directly interpretable as a factor share. Conversely, blue-collar, white-collar and equipment time-varying factor shares are given by the following equation:

$$\frac{r_{it}Q_{it}}{Y_t} = (1 - \lambda)A_i \frac{(Q_{it}/KW_t)^{B_i}}{\alpha(S_{Bt}/KW_t)^\rho + (1 - \alpha)}, \quad (14)$$

where Q_i is the stock of factor i (S_B , S_W , and K_E respectively), KW_t is the CES aggregation of white-collar and equipment, A_i is α , $(1 - \alpha)\theta$, and $(1 - \alpha)(1 - \theta)$ for

²⁶ 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 (2010) provide an interesting review of how researchers have tested this hypothesis with data. This equation is usually presented in a framework in which skilled labor is identified by college and unskilled by high school. However, because returns to education in white-collar are higher than in blue-collar, the same arguments apply to equation (13).

TABLE VI
PRODUCTION FUNCTION

A. Elasticities of substitution:		
Blue vs Equipment (White) (ρ)	0.270	(0.001)
White vs Equipment (γ)	-0.353	(0.001)
B. Factor share parameter:		
Structures (λ)	0.206	(0.002)
Blue-collar (α)	0.720	(0.001)
White-collar (θ)	0.076	(0.001)

NOTE: The parameters from this table are included in the production function of the aggregate firm (equation (5)):

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

Elasticities of substitution of blue-collar vs equipment (or vs white-collar), and white-collar vs equipment are given by $1/(1 - \rho)$ and $1/(1 - \gamma)$ respectively. Parameter λ is the capital structures share of output. Blue-collar, white-collar, and capital equipment shares are given by equation (14). Standard errors in parentheses (see Appendix B).

blue-collar, white-collar and capital equipment respectively, and B_i is ρ for blue-collar and γ for the other two.²⁷

Estimates listed in Table VI imply a capital share, including structures and equipment, that fluctuates around forty percent, which is slightly above the standard one third of the literature, but seems reasonable.²⁸ Blue-collar and white-collar labor shares are also within reasonable values (around 0.23 and 0.36 respectively, with the latter increasing with respect to the former). Own estimates using CPS data suggest that blue-collar wages account for around a forty percent of total labor earnings, and that this share is decreasing over time.

Wages. Wage equations estimates are presented in Table VII. For each occupation, I allow for different returns to education for natives and immigrants (see Section 3.1). Results suggest that an additional year of education increase blue-collar wages by a 5.6% for natives and a 5.3% for immigrants. In the case of white-collar jobs, the return to one year of education is 10.2% and 11.0% respectively.

Card (1999) surveys the enormous literature on returns to schooling, listing wide variety of estimates that range from 5 to 15%. At the occupational level, Keane and

²⁷ Notice that in the Cobb-Douglas case ($\rho = \gamma = 0$), the shares are respectively $(1 - \lambda)\alpha$, $(1 - \lambda)(1 - \alpha)\theta$, and $(1 - \lambda)(1 - \alpha)(1 - \theta)$.

²⁸ This slightly large estimate is mainly provided by the point estimate of λ , 0.206, which is somewhat larger than previous estimates in the literature. Krusell, Ohanian, Rios-Rull, and Violante (2000) estimate a production function similar to the one estimated here, although they define the two types of labor as college and high school. They report an estimate of 0.117, and Greenwood, Hercowitz, and Krusell (1997) calibrate this share to a 13%.

TABLE VII
WAGES

	Blue-collar		White-collar	
A. Returns:				
Education ($\omega_{1,i}$):				
Natives	0.056	(0.000)	0.102	(0.000)
Immigrants	0.053	(0.001)	0.110	(0.000)
BC experience (ω_2)	0.071	(0.000)	0.008	(0.001)
BC experience ² (ω_3)	-0.0010	(0.0009)	-0.0024	(0.0003)
WC experience (ω_4)	0.010	(0.000)	0.068	(0.000)
WC experience ² (ω_5)	-0.0015	(0.0001)	-0.0007	(0.0000)
Foreign experience (ω_6)	-0.007	(0.000)	0.017	(0.001)
B. Heterogeneity parameters ($\omega_{0,l}$):				
Western countries	0.055	(0.005)	-0.027	(0.005)
Latin America	0.057	(0.007)	-0.233	(0.008)
Asia and Africa	0.032	(0.009)	-0.052	(0.010)
Female	-0.176	(0.002)	-0.186	(0.002)
C. Variances:				
Male	0.610	(0.003)	0.584	(0.002)
Female	0.341	(0.005)	0.369	(0.002)

NOTE: All parameters from this table are included in the individual wage equations for each occupation (equation (2)):

$$w_{t,a,l} = r_t \exp\{\omega_{0,l} + \omega_{1,i}E_a + \omega_2X_{Ba} + \omega_3X_{Ba}^2 + \omega_4X_{Wa} + \omega_5X_{Wa}^2 + \omega_6X_{Fa} + \varepsilon_a\}.$$

Heterogeneity parameter for native males is normalized to zero. For a female immigrant from country i , the parameter is the sum of the corresponding male counterpart and the native female's. Standard errors in parentheses (see Appendix B).

Wolpin (1997) find a return of 7% for white-collar workers and 2.4% for blue-collar workers (9.3 and 1.9 respectively in their basic model). Similarly, Lee (2005) estimate an additional year of schooling to produce a 8.1% increase of white-collar wages and a 5.4% of blue-collar wages. Finally, in Lee and Wolpin (2006) white-collar returns to education range from 5.4 to 7.6% (for goods and services sectors respectively) whereas blue-collar returns range from 2.7 to 4.4%. My estimates are in the range of estimates surveyed by Card, and qualitatively in line with Keane and Wolpin (1997), Lee (2005), and Lee and Wolpin (2006).

Both blue-collar and white-collar own experience have a similar return. In both cases, an additional year of own experience have a decreasing return with a peak that is reached after between thirty and forty years of experience. Potential experience abroad, is less productive than own effective experience in the U.S. in both occupations. This lower return to foreign experience generates wage convergence for immigrants as they spend time in the United States.²⁹

²⁹ LaLonde and Topel (1992) define assimilation as the process whereby the wage of an immigrant

TABLE VIII
UTILITY PARAMETERS

	Male		Female	
A. School:				
Heterogeneity parameters ($\delta_{0,l}^S$):				
Natives	6,754	(79)	5,263	(72)
Western countries	-340	(149)	-1,831	(172)
Latin America	5,256	(518)	3,765	(517)
Asia and Africa	6,773	(244)	5,282	(246)
Tuition fees:				
Undergraduate (τ_1)		8,659	(44)	
Graduate ($\tau_1 + \tau_2$)		10,925	(73)	
Reentering disutility (δ_1^S)	10,208	(72)	8,606	(68)
Variance (σ^S)	430	(1)	1,881	(8)
B. Home:				
Heterogeneity parameters ($\delta_{0,l}^H$):				
Natives	18,782	(54)	18,284	(41)
Western countries	12,295	(598)	11,797	(599)
Latin America	15,246	(137)	14,749	(131)
Asia and Africa	15,161	(638)	14,664	(636)
Children (δ_1^H)	6,835	(64)	7,038	(127)
Variance (σ^H)	1,200	(38)	1,088	(32)

NOTE: The parameters from the top panel of this table are included in the school utility (equation (3)):

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

and the ones from the bottom panel are from the home utility (equation (4)):

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

For a female immigrant from country i , the unobserved heterogeneity parameter for alternative j ($j = S, H$) is calculated as follows: $\delta_{i,fem}^j = \delta_{i,male}^j + (\delta_{nat,fem}^j - \delta_{nat,male}^j)$. The subjective discount factor of individuals, β , is set to 0.95. Standard errors in parentheses (see Appendix B).

Consistent with wage differences in the data, women are less productive than men in both occupations. Immigrants, on the other hand, show heterogeneous results depending on the region of origin. They are more productive in blue-collar, which is consistent with their clustering in this occupation. Latin Americans are extremely less productive in white-collar occupations, which is also consistent with observed wage differentials.

Utility parameters. Table VIII shows estimates of utility parameters for the school and home options. School utility for women is lower than that of men, although their reentry cost is also lower. Tuition fees are around 8,700US\$ for undergraduate studies and almost 11,000US\$ for graduate. Home alternative has also a similar utility for

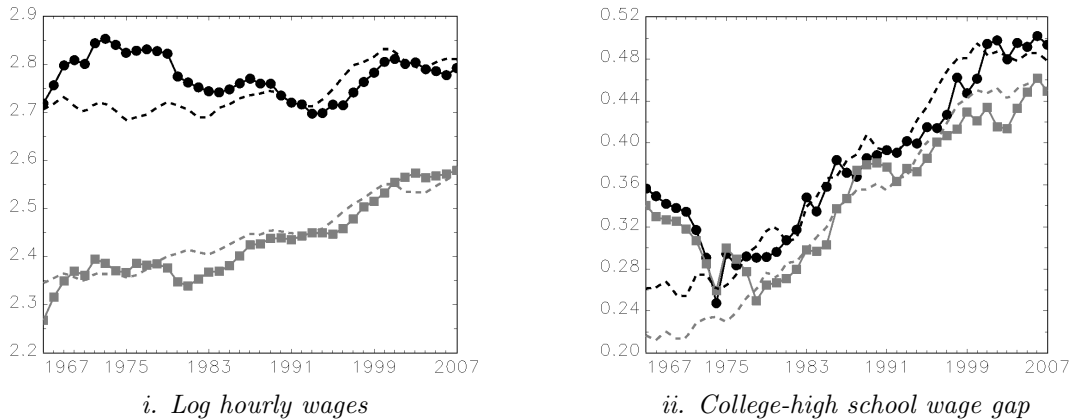
converge to that of an observationally equivalent immigrant that entered the U.S. before. As a result, relative wages increase as the weight of foreign experience in the experience bundle falls.

males and females, although it should be noted that women will be more likely to stay at home as they earn lower wages. Immigrants, on the other hand, have lower utilities both for attending school and for staying at home.

5.2. Model fit

In order to assess the credibility of counterfactual exercises described below, it is important to check how well the model fits the data. Figure V evaluates the goodness of the model in fitting wages. Panel (i) plots log hourly wages. The model captures the level of wages, the male-female wage gap, and the faster growth of female wages; on the other hand, it is not able to capture the initial increase in early 1970s and subsequent decrease of the male average wage, though the cumulative change over the period is well replicated. Panel (ii) checks the capacity of the model in replicating the increase in college-high school wage gap. It is interesting to note that the model does a good job explaining this increase despite the assumptions of a constant return to education in the skill production functions of individuals, and the capital-skill complementarity at the occupational level instead of the educational level.

FIGURE V
ACTUAL AND PREDICTED WAGES



NOTE: Solid lines are data; dashed are simulations. Black lines are for males; gray for females. Wages: average real log hourly wage. College-high school wage gap: difference in average real log hourly wage of college workers (more than 12 years of education) and high school workers (12 or less years of education). *Data sources:* March Supplements of CPS for survey dates from 1968 to 2008.

Additionally, I check how the model replicates human capital and labor supply variables. Table IX compares actual and predicted averages over the estimation period. In particular, it checks the goodness of the model in fitting the increase in average years of education, the share of dropouts, the share of workers in blue-collar and the participation rate. Actual and predicted averages are quite close. Female education

however, is slightly underestimated.

TABLE IX
ACTUAL AND PREDICTED HUMAN CAPITAL AND
LABOR SUPPLY VARIABLES (1967-2007)

	Male		Female	
	Actual	Predicted	Actual	Predicted
Participation rate	63.50	62.45	40.93	36.94
Share of workers in blue-collar	49.83	54.10	27.38	30.93
Share of dropouts	23.67	31.17	22.38	32.67
Increase in average years of education	2.12	1.85	2.39	1.56

NOTE: Predicted data are computed with the estimated parameters reported in Section 5.1. All figures but the increase in average years of education are in percentages. *Data sources:* March Supplements of CPS for survey dates from 1968 to 2008.

6. UNDERSTANDING THE CONSEQUENCES OF IMMIGRATION: COUNTERFACTUAL EXERCISES

The fundamental question of this paper is about the effect of immigration on wages. I use the estimated model to predict the counterfactual evolution of wages in the absence of the large scale immigration of the last four decades.

My definition of a “world without mass immigration” consists of a scenario in which foreign workers enter the country only to maintain the share of immigrants in the workforce constant to 1967 levels (5.7%). More precisely, I calculate the net inflow of immigrants necessary to keep this share constant, refreshing the cohorts to hold the age and gender composition of 1967. All other variables are left constant to baseline levels including, among others, aggregate and idiosyncratic shocks, and exogenous variables for immigrants —distributions of entry age, region of origin and initial education.

Table X compares baseline and counterfactual wages. The main conclusion is that wages were adversely affected by mass immigration. The average wage fell by 5.95 percent. However, this effect is heterogeneous among different groups of individuals. High school workers were more affected than college workers. Moreover, the average wage of immigrants fell more than that of natives. Finally, male wages were also more reduced than female wages. Overall, Table X indicates that immigration reduced average wages in general, but it particularly affected those individuals that are closer substitutes to immigrants: high school workers more than college workers, as immigrants are less educated than natives; other immigrants more than natives, as they

TABLE X
THE EFFECT OF IMMIGRATION ON WAGES

	Total	Male	Female	Natives	Immigrants
Average wage	-5.95	-7.82	-4.32	-2.37	-12.07
High school	-5.92	-8.29	-4.82	-0.95	-10.38
College	-3.50	-4.31	-2.56	-2.49	-15.43

NOTE: Figures represent the difference between baseline and counterfactual simulations. They should be interpreted as the percentage decrease of the average wage of each group induced by immigration. Simulations are computed with the estimated parameters reported in Section 5.1. See further details on the counterfactual design in the text. All figures are in percentages.

have similar characteristics; and males more than females, as a higher fraction of males work in blue-collar than females.

An important feature of the current model is that it allows me to separate price and composition effects of immigration. Panel A in Table XI present the effect of immigration of skill prices. Both prices were considerably reduced, although less than average wages. Blue-collar skill prices were more affected than white-collar.

A raw comparison of Panel A in Table XI and Table X suggest that the total fall in average wages is a mixture of price effects and different changes in the composition of the workforce. First of all, having a larger share of immigrants in the labor force reduces wages simply because immigrants typically earn lower wages. Moreover, average skills of natives —and incumbent immigrants— may change because of human capital adjustments to immigration. And, finally, some workers may exit the labor force because of the fall in wages, and others may change their occupation as a result of the change in relative prices. In order to quantify these three magnitudes, I decompose the change in average wage in the following components:

$$w_1 - w_0 = (w_1 - w_1^{ST}) + (w_1^{ST} - w_1^H) + (s_1^H - s_0) + (r_1^H - r_0), \quad (15)$$

where each element represents new entrants, supply adjustment, human capital adjustment and price effects respectively. Subscript 1 indicates the scenario with immigration (baseline), and 0 indicates the one without mass immigration (counterfactual). All wages are averages; L indicates workers (as opposed to N below that indicates individuals).

Price effects, defined as

$$r_1^H - r_0 = (r_{1B} - r_{0B}) \frac{L_{0B}}{L_0} + (r_{1W} - r_{0W}) \frac{L_{0W}}{L_0}, \quad (16)$$

compare changes in skill prices, weighting them according to the share of workers in each occupation in the scenario without immigration. Results from this comparison

TABLE XI
SKILL PRICES, PRICE VS COMPOSITION EFFECTS,
COLLEGE-HIGH SCHOOL WAGE GAP, AND CAPITAL ADJUSTMENT

	1967-2007	1980-2000
A. Skill prices		
Blue collar	-3.76	-2.66
White collar	-3.37	-2.86
B. Price vs composition effects		
Price effect	-3.54	-2.77
Human capital adjustment	0.73	1.26
Supply effect	-0.19	-0.06
New entrants effect	-2.95	-2.17
<i>Total effect</i>	<i>-5.95</i>	<i>-3.74</i>
C. Increase in college-high school wage gap		
Immigration induced	10.30	12.46
Total increase	25.51	26.89
D. Full capital adjustment (fixed r_K)		
Average wage	-5.54	-2.91
High school	-5.19	-2.61
College	-1.83	-1.08

NOTE: The table compares the baseline solution of the model to counterfactual simulations of a world without mass immigration. Simulations are computed with the estimated parameters reported in Section 5.1. See further details on the counterfactual design in the text. All figures are in percentages.

are in the first line of the Panel B in Table XI. As already noted by Panel A, price effects are negative. The average price of skill units fell by 3.6 percent. This result implies that the average wage would have been reduced by such amount in the absence of human capital and labor supply adjustments.

The human capital adjustment can be summarized by the third component of equation (15):

$$s_1^H - s_0 = (s_{1B}^H - s_{0B}) \frac{L_{0B}}{L_0} + (s_{1W}^H - s_{0W}) \frac{L_{0W}}{L_0}, \quad (17)$$

where

$$s_{1j}^H = \frac{s_{1B}^{nat} L_{0j}^{nat} + s_{1j}^{im} L_{0j}^{im}}{L_{0j}}. \quad (18)$$

Equation (17) compares average skill units with and without immigration leaving labor supply decisions constant to the non-immigration scenario. A positive human capital adjustment effect implies that natives increase their human capital as a consequence of the immigration-induced increasing competition for low-skilled jobs. Panel B shows that individuals indeed adjusted their human capital to compensate negative effects of immigration. On average, additional investments in human capital would have increased wages by slightly less than one percent if skill prices had not changed.

The second element of equation (15) is the labor supply adjustment effect:

$$w_1^{ST} - w_1^H = \left(w_{1B}^{ST} \frac{L_{1B}^{ST}}{L_1^{ST}} + w_{1W}^{ST} \frac{L_{1W}^{ST}}{L_1^{ST}} \right) - \left(w_{1B}^H \frac{L_{0B}}{L_0} + w_{1W}^H \frac{L_{0W}}{L_0} \right), \quad (19)$$

where

$$w_{1j}^{ST} = (r_{1j} + s_{1j}^{nat}) \frac{L_{0j}^{ST,nat}}{L_{0j}^{ST}} + (r_{1j} + s_{1j}^{im}) \frac{L_{0j}^{ST,im}}{L_{0j}^{ST}}; \\ L_{0j}^{ST,k} = L_0^k \frac{L_{1j}^k}{N_1^k}; \quad \text{and} \quad w_{1j}^H = r_{1j} + s_{1j}^H. \quad (20)$$

This component includes both changes in participation and in occupation. It emerges from Table XI that immigration induced individuals both to switch occupations and to leave the labor market. This labor supply adjustment had a negative net effect on average wages of 0.2 percent. This negative effect is the combination of a positive effect induced by individuals leaving the labor market, and a negative effect—which in the end dominates—by individuals switching from white- to blue-collar.

Lastly, the first element is the new entrants effect. This component compiles the fall in average wages that is induced by the fact that immigrants earn less than natives. Obviously, Table XI shows a negative effect. This result implies that average wages fell by three additional percentage points simply because of the inclusion of more immigrants, which earn lower wages, in the average.

As mentioned throughout the paper, immigration and skill-biased technical change are rival explanations for the widening of the college-high school wage gap since mid 1970s. Panel C shows that immigration accounted for roughly a forty percent of the total increase, which is a substantial share.

All results described above assume that the stock of capital did not react to the inflow of workers. As a consequence, these results can be seen as upper bounds of the fall in wages—the capital-labor ratio falls the most as a consequence of immigration. A lower bound is provided by the scenario in which capital reacted to immigration such that the counterfactual and the baseline return to capital is the same. It is a lower bound because if the United States were a small open economy, the observed return to capital should determine the capital-labor ratio both in the baseline and in the counterfactual scenarios. Of course, it is hard to assume that the U.S. is a small economy that does not affect the interest rate of international markets, so the final (long run) effect of immigration should be somewhere in between. Panel D of Table XI shows the results from this alternative scenario. Although negative effects are obviously smaller than the ones presented in Table X, they are still substantially negative. Therefore, the four decades of mass immigration reduced average wages by at least 5.5 percent.

The second column of Table XI shows qualitatively similar results for the period 1980-2000. Importantly, this column is comparable to most of the studies listed in Table I in Section 2. For example, Borjas (2003) finds a decrease of the average wage of 3.2 percent. Panel B in Table XI suggest that the average wage fell by 3.7 percent over that period. However, natives were much less affected; 2.2 percentage points of the drop were due to the fact that the average wage includes a larger fraction of immigrants, which are lower wage earners. The native average wage fell by 2.8 percent initially (the price effect). This decline was slightly exacerbated by labor supply adjustments. However, human capital adjustments increased the average wage in 1.3 percentage points in order to compensate the negative effect. In the end, their average net wage loss was as large as 1.6 percent.

7. CONCLUDING REMARKS

This paper estimates a labor market equilibrium model that takes into account native 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 parameterized model is then used to measure the effect of immigration on wages simulating a counterfactual world without large scale immigration.

Results suggest that, during the last four decades, immigration reduced the average wage by 5.95 percent. Moreover, it was particularly harmful for high school workers, for male workers, and for immigrants themselves, all of them closer substitutes to immigrants. However, this result does not imply that wages of natives were reduced by such amount. Half of the decline in the average wage is due to a composition effect, i.e. there is a higher fraction of low wage earners among immigrants. Wages of natives—and incumbent immigrants—that did not change their human capital investment and labor supply behavior were reduced 3.5 percent. However, some of them adjusted their human capital and labor supply behavior to mitigate the negative effects.

The results described above highlight the importance of taking human capital and labor supply adjustments into account when analyzing wage effects of immigration. However, there is still space for some forthcoming additional results. First, it is interesting to analyze in more detail how those adjustments took place—education, experience, labor force participation, occupation switches, and so on. Additionally, it would also be valuable to compare my results with the factor proportions approach using the elasticities and production functions from the literature, and counterfactual labor supplies in each skill group from my model. Furthermore, this model is attractive

to analyze labor market consequences of different immigration policies.

Although understanding human capital investment and labor supply adjustments is a crucial step to disentangle the labor market consequences of immigration, the literature still lacks additional improvements to fully understand how immigration affects wages. For example, migration decisions are typically left out of the analysis. It would be important to understand how self-selection of immigrants and, particularly, changes in immigrant self-selection altered economic opportunities of workers in the United States. In order to extract policy recommendations, we additionally should put together labor market effects of immigration with the effect of immigration on other aspects of the economy such as prices, crime, taxes, use of public goods.

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APPENDIX A: VARIABLE DEFINITIONS AND SOURCES

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 their sources.

A.1. Aggregate data

Aggregate macro data are used in the solution of the model, as described in the main text. The model is fit to micro-data for years 1967-2007. However, to vanish initial conditions, the model is simulated starting in 1860. To initialize the model, I simulate the first 40 years (1860-1900) with aggregate data of 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. This subsection describes the construction of macro series for the twentieth and the ongoing twenty-first centuries.

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

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

Cohort sizes. Cohort sizes are extracted from Integrated Public Use Microdata Series (IPUMS) of the U.S. Census.³⁰ 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 intercensal cohort sizes are estimated following different procedures. The former is obtained by distributing the decade cohort reduction to each year using annual data on mortality rates by age from Vital Statistics of the U.S. (National Center for Health

³⁰ Steven Ruggles, Matthew Sobek, Trent Alexander, Catherine A. Fitch, Ronald Goeken, Patricia Kelly Hall, Miriam King, and Chad Ronnander. *Integrated Public Use Microdata Series: Version 4.0*. Minneapolis, MN: Minnesota Population Center, 2008. <http://usa.ipums.org/usa/>

Statistics). The latter are imputed with a similar procedure, using the estimates of the entry age distribution described below.

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 $t-1, t-2, \dots, t-5$. Since the exact year of immigration is only available for 1900-1930 and 2000 Censuses, and for 2001-2007 ACS, intermediate years are linearly interpolated. Because the distribution is stable over the years, I estimate a 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, obtaining the joint distribution of age at entry and initial education requires an estimate of the entry age distribution conditional on education. Because of data limitation, I compute the “relative” distribution by educational level, i.e. the ratio of conditional and unconditional distributions, with the Census 2000, and then I multiply this relative distribution and the time varying unconditional age at entry distribution.³¹

Region of origin. As described above, 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, 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. Intercensus stocks are obtained by combining a linear interpolation of the share of immigrants from each region and intercensus estimates of cohort sizes described above. Finally, the share of the total inflow of immigrants in year t from region i , $s_{i,t}^{flow}$, is given by:

$$s_{i,t}^{flow} = \frac{M_t s_{i,t} - M_{t-1} s_{i,t-1} + s_{65,i,t-1} M_{65,t-1}}{M_t - M_{t-1} + M_{65,t-1}}, \quad (\text{A.1})$$

where M_t is the stock of immigrants in year t , $s_{i,t}$ is the share of immigrants from region i , 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 old. The numerator of equation (A.1) is the flow of immigrants from region i , i.e. the actual increase in the stock plus the recovery of those who died (reached age 65); the denominator is the total inflow.

Initial education. Immigrants and natives are assigned initial years or education differently. Initial education of natives is allocated at age 16. The distribution of

³¹ This calculation assumes that the relative distribution is constant over time. Estimates using 1970-1990 Censuses (for which the year of entry is only available by five-year intervals) support this assumption.

years of education at this age (by gender) is estimated with U.S. Census IPUMS for 1940-2000 and ACS 2001-2007. Intercensus estimates are linearly interpolated. 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. 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.³² 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 of having 0, 1 or 2+ preschool children at home to having 0, 1 or 2+, 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 important 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 this, I simulate net wages deflating gross simulated wages 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 compensation of employees produced by the model would be underestimated (and factor shares biased as a result) without further adjustments: first, discretization of individual decisions to one choice per year eliminates earnings of some part time workers and of individuals that work a small fraction of the year from the aggregation of total labor income; and, second, wages do not reflect the total labor compensation. These two issues are corrected by adjusting total wage compensation appropriately. To correct for the first, I adjust by the ratio of BEA Total Wage and Salary Disbursements (NIPA Table 2.1) and the equivalent measure aggregating my wage micro-data from CPS. The second is corrected with the ratio of BEA Total Wage and Salary Disbursements over the Total Compensation of Employees (NIPA Table 2.1).

³² This assumption is supported by the human capital investment literature (Becker, 1964).

A.2. Microdata

All micro-data statistics used in the estimation (and listed in Table V) are constructed with data from three different sources: March Supplement of CPS,³³ NLSY79 and NLSY97.

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, classifying high school graduates according their highest degree or diploma attained, but IPUMS recoded the variable to make it comparable over the years.

Preschool children. This variable measures whether there individual is living with 0,1, or 2+ preschool (less than five years old) children in the same household. My definition of household only includes family units, so if there are preschool children in a two family home, only their parents are considered to have them. In order to link children with their parents, I use the IPUMS variables *momloc* and *poploc* that identify the position of the mother and father in the household respectively. Those variables include biological, step- and adoptive parents. Although both of them are fully comparable over years, there are some minor changes that are listed in the database documentation.

Region of origin. I consider three regions of origin: Western Countries, Latin America, and Asia-Africa. Western Countries include Europe, Canada and Atlantic Islands, and Oceania; Latin America include Caribbean Countries, Mexico, Central, and South America; Asia-Africa includes all immigrants from these two continents. A small number of individuals for which the country of birth is unknown are dropped from

³³ Data are extracted from IPUMS, except for Matched CPS which are drawn from NBER. CPS interviews all households 8 times. In particular, a household that enters the survey at month t is interviewed four consecutive months until $t + 3$, then not interviewed during eight months, and finally interviewed four additional consecutive months from $t + 12$ to $t + 15$. 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. However, IPUMS data has a recoded individual and household identifier that does not allow to match consecutive surveys. Survey years 1971-72, 1972-73, 1976-77, 1985-86 and 1995-96 can not be matched.

the corresponding samples. Both this variable and any other that needs to separate immigrants from natives are only available starting in (survey year) 1994.

Potential experience abroad. As immigrant decisions before they enter the U.S. are not observable, I use potential experience abroad to measure their initial endowment of work experience. This variable is defined as age at entry minus years of education minus 6. The main difficulty to construct it is that year of immigration is only available by intervals. Moreover, education is also grouped in 0-4, 5-8, 9, 10, 11, 12, 13-15 and 16+ years of education. To construct the variable 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 again that individuals concentrate their education spells in the beginning of their lives regardless of the country in which she was living. In order to reduce errors induced by these assumptions, I group potential experience in the following categories: 0-2, 3-5, 6-8, 9-11 and 12+ years.

Years in the U.S. This variable is constructed exactly as the previous one with the obvious exception that it does not use information on education. It is also intervalled in the same categories.

Experience. Years of experience are calculated with NLSY for those individuals for which their entire path of choices from age 18 to either 1990, 1991, 1992 or 1993 for NLSY79, and to either 2004, 2005 or 2006 for NLSY97 is observable. The samples include all individuals born from 1962 to 1964 for NLSY79 and 1980 to 1984 (all individuals) for the NLSY97.

Choices. Individuals are assigned to one of the four mutually exclusive year round alternatives: blue- 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 the 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 did work at least 40 weeks during the year before the survey date and at least 20 hours per week.³⁴ 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

³⁴ Hours per week are approximated by the number of hours worked in the previous week.

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 work according to the previous definition. They are assumed to earn all their wage in the occupation in which they are assigned. Earnings include wage and salary income plus self-employment earnings (farm and non-farm), deflated to year 2000 U.S.\$ using the Consumer Price Index. Top-coded anual earnings are multiplied by 1.4. Extreme observations are dropped (those with an hourly real wage lower than \$2 or higher than \$200; see Lemieux (2006) as an example). Hours worked last year are calculated combining information on weeks worked last year³⁵ and hours worked last week.³⁶

APPENDIX B: STANDARD ERRORS.

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

$$\begin{aligned}\hat{\theta} &= \arg \min_{\theta} ||\hat{\pi}(x) - \tilde{\pi}(x_S(\theta))|| = \\ &= \arg \min_{\theta} [\hat{\pi}(x) - \tilde{\pi}(x_S(\theta))]' W [\hat{\pi}(x) - \tilde{\pi}(x_S(\theta))].\end{aligned}\tag{B.1}$$

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.³⁷

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

$$Var(\hat{\theta}) = (G'WG)^{-1}G'WV_0WG(G'WG)^{-1},\tag{B.2}$$

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 (B.1) there are two sources of error. On the one hand, sample statistics $\hat{\pi}(x)$ are estimated with error. On the other hand,

³⁵ Before 1976, this variable is only available by intervals; in particular, the relevant intervals are 40-47, 48-49 and 50-52 weeks. To use a correct approximation of how many weeks to impute to each interval, I calculated sample means for each interval using data for a five years after 1975. Estimates are 43.1, 48.3 and 51.9 respectively.

³⁶ 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).

³⁷ Weighted sample size is defined in this context as $\left(\sum_i p_i^2 / (\sum_i p_i)^2\right)^{-1}$, where p_i is the individual weight in the sample. Obviously, when $p_i = p \forall i$ it is equal to the sample size. This expression is inverse of the precision of the variance of the weighted sample mean: $Var(\bar{x}) = \sum_i p_i^2 \sigma_x^2 / (\sum_i p_i)^2$.

because the function mapping parameters into statistics $\tilde{\pi}(x_S(\theta))$ does not have a closed form solution I simulate it, introducing a simulation error.

The remainder of this Appendix is devoted to find an estimate of V_0 . It is important to notice that because the two sources of error require to do asymptotics in two dimensions: the sample size and the number of simulations. In particular, the problem can be split in the difference between the following two elements: $\sqrt{N}(\hat{\pi}(x) - \pi(\theta_0))$ and $\sqrt{M}(\tilde{\pi}(x_S(\theta_0)) - \pi(\theta_0))$, where N is the sample size and M is the number of simulations.

B.1. Minimum distance asymptotics

Consider R statistics from the data such that:

$$E[Y_K] = \pi_k(\theta_0), \quad k = 1, \dots, R. \quad (\text{B.3})$$

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

$$\hat{\pi}_k = \frac{1}{N_k} \sum_{i \in S_k} Y_{ki}. \quad (\text{B.4})$$

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

$$\hat{\theta} = \arg \min_{\theta \in \Theta} \|\hat{\pi} - \pi(\theta)\|. \quad (\text{B.5})$$

Let us introduce some additional notation:

$$d_{ki} \equiv \mathbb{1}\{i \in S_k\}, \quad (\text{B.6})$$

$$S_{ij} \equiv S_i \cap S_j, \quad (\text{B.7})$$

$$S \equiv S_1 \cup \dots \cup S_R, \quad (\text{B.8})$$

$$N \equiv \sum_{i \in S} \left(\sum_k d_{ki} - \sum_k \sum_j d_{ki} d_{ji} \right), \quad (\text{B.9})$$

$$\lambda_{kN} \equiv \frac{N_k}{N} \xrightarrow{N \rightarrow \infty} \lambda_k, \quad (\text{B.10})$$

$$\psi_{ki} \equiv Y_{ki} - \pi_k(\theta_0). \quad (\text{B.11})$$

Now we can write

$$\begin{aligned} \begin{pmatrix} \sqrt{N_1}(\hat{\pi}_1 - \pi_1) \\ \sqrt{N_2}(\hat{\pi}_2 - \pi_2) \\ \vdots \\ \sqrt{N_R}(\hat{\pi}_R - \pi_R) \end{pmatrix} &= \begin{pmatrix} \frac{1}{\sqrt{N_1}} \sum_{i \in S_1} \psi_{1i} \\ \frac{1}{\sqrt{N_2}} \sum_{i \in S_2} \psi_{2i} \\ \vdots \\ \frac{1}{\sqrt{N_R}} \sum_{i \in S_R} \psi_{Ri} \end{pmatrix} = \begin{pmatrix} \sqrt{\lambda_{1N}} & 0 & \cdots & 0 \\ 0 & \sqrt{\lambda_{2N}} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sqrt{\lambda_{RN}} \end{pmatrix}^{-1} \times \\ &\times \frac{1}{\sqrt{N}} \sum_{i \in S} \begin{pmatrix} d_{1i} \psi_{1i} \\ d_{2i} \psi_{2i} \\ \vdots \\ d_{Ri} \psi_{Ri} \end{pmatrix} \equiv \Lambda \frac{1}{\sqrt{N}} \sum_{i \in S} d_i \circ \psi_i, \end{aligned} \quad (\text{B.12})$$

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

$$\Lambda \frac{1}{\sqrt{N}} \sum_{i \in S} d_i \circ \psi_i \xrightarrow{d} \mathcal{N}(0, \Lambda E[(d_i \circ \psi_i)(\psi_i \circ d_i)'] \Lambda). \quad (\text{B.13})$$

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

$$\hat{\Omega} = \begin{pmatrix} \frac{\hat{\sigma}_1^2}{N_1} & \frac{N_{12}}{N_1 N_2} \hat{\sigma}_{12} & \cdots & \frac{N_{1R}}{N_1 N_R} \hat{\sigma}_{1R} \\ \frac{N_{12}}{N_1 N_2} \hat{\sigma}_{12} & \frac{\hat{\sigma}_2^2}{N_2} & \cdots & \frac{N_{2R}}{N_2 N_R} \hat{\sigma}_{12} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{N_{1R}}{N_1 N_R} \hat{\sigma}_{1R} & \frac{N_{2R}}{N_2 N_R} \hat{\sigma}_{2R} & \cdots & \frac{\hat{\sigma}_R^2}{N_R} \end{pmatrix} \quad (\text{B.14})$$

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

B.2. Simulated minimum distance asymptotics

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

$$\sqrt{N}[\hat{\pi} - \pi(\theta_0)] \xrightarrow{d} \mathcal{N}(0, \Omega). \quad (\text{B.15})$$

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

$$Y = g(U, \theta_0) \quad U \sim F. \quad (\text{B.16})$$

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 $M \rightarrow \infty$ we have

$$\sqrt{M}[\tilde{\pi}(\theta_0, U^M) - \pi(\theta_0)] \xrightarrow{d} \mathcal{N}(0, \Omega) \quad (\text{B.17})$$

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

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

$$= \sqrt{N}[\hat{\pi} - \pi(\theta_0)] - \sqrt{\frac{N}{M}}\sqrt{M}[\tilde{\pi}(\theta_0, U^M) - \pi(\theta_0)] \xrightarrow{d} \mathcal{N}(0, (1 + \kappa)\Omega) \quad (\text{B.18})$$

Note that this result includes the case in which we can simulate a sample of size m for every observation $i = 1, \dots, N$, 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 B.1, let $(l_{1i}, \dots, l_{Ri})$ and $(\delta_1, \dots, \delta_R)$ play the role of $(d_{1i}, \dots, d_{Ri})$ and $(\lambda_1, \dots, \lambda_R)$ in the simulated samples, we similarly have that

$$\begin{pmatrix} \sqrt{M_1}(\tilde{\pi}_1(\theta_0, U^{M_1}) - \pi_1) \\ \sqrt{M_2}(\tilde{\pi}_2(\theta_0, U^{M_2}) - \pi_2) \\ \dots \\ \sqrt{M_R}(\tilde{\pi}_R(\theta_0, U^{M_R}) - \pi_R) \end{pmatrix} \equiv \Delta \frac{1}{\sqrt{M}} \sum_{i \in U^M} l_i \circ \psi_i \xrightarrow{d} \mathcal{N}(0, \Delta E[(l_i \circ \psi_i)(\psi_i \circ l_i)'] \Delta). \quad (\text{B.19})$$

Therefore,

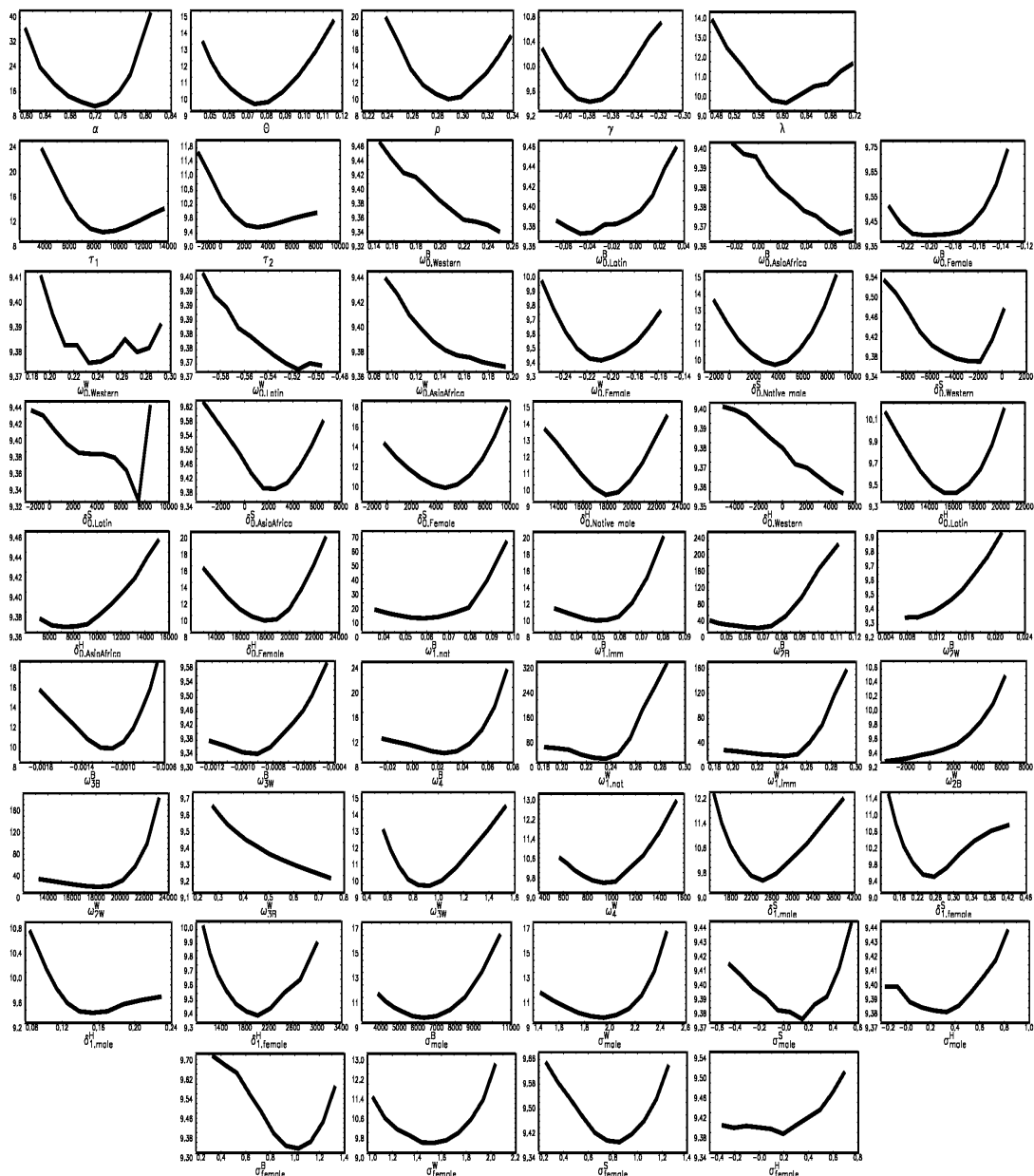
$$\begin{pmatrix} \sqrt{N_1}(\hat{\pi}_1 - \tilde{\pi}_1(\theta_0, U^{M_1})) \\ \sqrt{N_2}(\hat{\pi}_2 - \tilde{\pi}_2(\theta_0, U^{M_2})) \\ \dots \\ \sqrt{N_R}(\hat{\pi}_R - \tilde{\pi}_R(\theta_0, U^{M_R})) \end{pmatrix} \xrightarrow{d} \mathcal{N}(0, V_0), \quad (\text{B.20})$$

and

$$\hat{V} = \begin{pmatrix} \left(1 + \frac{N_1}{M_1}\right) \frac{\hat{\sigma}_1^2}{N_1} & \left(\frac{N_{12}}{N_1 N_2} + \frac{M_{12}}{M_1 M_2}\right) \hat{\sigma}_{12} & \dots & \left(\frac{N_{1R}}{N_1 N_R} + \frac{M_{1R}}{M_1 M_R}\right) \hat{\sigma}_{1R} \\ \left(\frac{N_{12}}{N_1 N_2} + \frac{M_{12}}{M_1 M_2}\right) \hat{\sigma}_{12} & \left(1 + \frac{N_2}{M_2}\right) \frac{\hat{\sigma}_2^2}{N_2} & \dots & \left(\frac{N_{2R}}{N_2 N_R} + \frac{M_{2R}}{M_2 M_R}\right) \hat{\sigma}_{12} \\ \vdots & \vdots & \ddots & \vdots \\ \left(\frac{N_{1R}}{N_1 N_R} + \frac{M_{1R}}{M_1 M_R}\right) \hat{\sigma}_{1R} & \left(\frac{N_{2R}}{N_2 N_R} + \frac{M_{2R}}{M_2 M_R}\right) \hat{\sigma}_{2R} & \dots & \left(1 + \frac{N_R}{M_R}\right) \frac{\hat{\sigma}_R^2}{N_R} \end{pmatrix}. \quad (\text{B.21})$$

APPENDIX C: CURVATURE OF THE OBJECTIVE FUNCTION

FIGURE C.I
SECTIONS OF THE OBJECTIVE FUNCTION



NOTE: Solid lines represent changes in the objective function when moving each of the parameters leaving others constant at the estimated minimum. All parameters are moved two standard deviations up and down.