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

Joan Llull[*§]

CEMFI

PRELIMINARY AND INCOMPLETE VERSION.

PLEASE ASK FOR A MORE RECENT VERSION BEFORE QUOTING.

June 2010

Abstract

This paper analyzes the consequences of immigration on wages and education with a labor market equilibrium structural model. Heterogeneous workers make yearly decisions on education, participation, and occupation. The labor demand takes into account skill-biased technical change. The equilibrium approach allows to disentangle price from composition effects of immigration on wages. Preliminary results suggest that the 40 years of mass immigration experimented by the US reduced wages a 5% on average, with a more severe fall of blue-collar wages. Natives, on the other hand, adjusted their human capital investment behavior to partially compensate the fall. Further counterfactuals (still work in progress) (will) analyze the existing literature using data simulated by the model, and I (will) evaluate two immigration policies: a quota system and a selective admission policy.

1 Introduction

Does immigration worsen or improve the labor market outcomes of native workers? During the last four decades, more than 26 millions of foreign workers entered the US.

[*] Centro de Estudios Monetarios y Financieros (CEMFI). C/ Casado del Alisal, 5, 28014, Madrid, Spain. E-mail: joan.llull@cemfi.es. URL: http://www.cemfi.es/~joanllull.

[§]I am indebted to Manuel Arellano for his constant encouragement and advice. I am also very grateful to Jim Walker for his outstanding sponsorship and invaluable comments to the paper at the University of Wisconsin-Madison. I wish to thank Stephane Bonhomme, Enzo Cerletti, David Dorn, Carlos González-Aguado, Marcel Jansen, John Kennan, Sang Yoon "Tim" Lee, Pedro Mira, Claudio Michelacci, Ignacio Monzón, Enrique Moral-Benito, Salvador Navarro, Josep Pijoan-Mas, Ricardo Serrano-Padial, Ananth Seshadri, Chris Taber, Ernesto Villanueva, participants at the 3rd EALE/SOLE International Conference (UCL, June 2010), and seminar participants at CEMFI, the Bank of Spain, and the University of Wisconsin-Madison for helpful comments and discussions. Financial support from the Bank of Spain is gratefully acknowledged. This paper was partially written when I was visiting the Bank of Spain and the University of Wisconsin-Madison; I appreciate the hospitality of both institutions. Previous versions of the paper circulated under the title *"Immigration, Wages, and Education: A General Equilibrium Dynamic Discrete Choice Structural Model"*.

Such a huge inflow has motivated a lot of research. The education gap between immigrants and natives has increased steadily; moreover, immigrants are gradually more clustered in blue collar jobs. The simplest textbook model of a competitive labor market suggests that immigration reduces the wage and labor supply of competing natives. Additionally, a more sophisticated model would suggest an adjustment in human capital investment by natives to differentiate themselves from new immigrants. However, the empirical findings of the literature are not so straightforward. Although some papers find the negative expected effect of immigration on wages, others estimate a small, zero or even positive outcomes.

This paper analyzes the effect of immigration on wages and education. In particular, I quantify the effect of immigration on wages. Moreover, I analyze whether incumbents adjust their human capital investment behavior as a consequence of the inflow of immigrants.[1] Finally, I evaluate the consequences of two alternative policies: the National Origins Formula (a country-based quota system in force in the US until 1965) and selective immigrant policies (in application to many developed countries).

I present and estimate a labor market equilibrium model to tackle the previous issues in a unified framework. Heterogeneous workers decide endogenously on education, participation and occupation. An aggregate firm combine labor and capital to produce a single output. The key contribution of the paper is in modeling labor supply and the equilibrium. The 40 year period spanned by the data is too long to consider education as exogenous. Additionally, immigration may affect participation and the occupational choice by changing relative wages. Finally, the equilibrium framework disentangles price and composition effects of immigration.

I estimate the model combining data from CPS and NLSY for the period 1967-2007.[2] Then, I use estimated parameters to simulate the counterfactual experiments that provide the answers to previous questions. In particular, I define a counterfactual "world without mass immigration" in which immigrant/native ratio is kept constant to 1967 levels. Additionally, I use simulated data by the model to evaluate the results from the literature. Finally, I evaluate the policies described above.

The model builds on the general equilibrium models described in Heckman, Lochner, and Taber (1998), Lee (2005), and Lee and Wolpin (2006). The supply side of the model extends the framework of Keane and Wolpin (1997) to accommodate immigrant and native workers. Individuals live from age 16 to 65 and make yearly forward looking decisions on occupation, education and participation.

Immigrants enter the US endogenously with a given amount of skills and start taking

[1] Throughout the paper, I refer to incumbent workers in the US (natives and previous immigrants) as simply incumbents.

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

decisions in the first year they are in the country. They differ from natives in abilities, and in that while incumbents were in the US accumulating domestic experience, they were abroad accumulating (presumably less productive) foreign experience.

On the demand side, blue and white collar labor is combined with capital to produce a single output. The production function is modeled to allow for heterogeneous labor; in particular, workers productivity depending on their education, occupation-specific experience, nationality, gender, foreign experience and unobserved heterogeneity.

I assume a nested Constant Elasticity of Substitution (CES) production that allow for skill biased technical change through capital-skill complementarity and the fast accumulation of capital equipment in recent decades (see Krusell, Ohanian, Rios-Rull, and Violante, 2000).[3] There are two occupations: blue- and white-collar. Labor is measured in skill units rather than worker counts. Therefore, the marginal rate of substitution among two different workers will depend on their productivity (heterogeneous in the dimensions I mentioned in above).

The equilibrium object of this model is the price of the skill unit. This specific modeling choice is convenient because it allows me to disentangle price from composition effects of immigration on average wages. This distinction is important, as immigrants only affect incumbents through prices. For example, imagine that native wages do not change with immigration; however, if new entrants earn less than incumbents, the average wage will obviously fall even though nobody is affected by immigration.

Preliminary results are in line with textbook predictions. Counterfactual experiments suggest that, on average, immigration reduced wages by around a 5% over the last four decades. Moreover, wages fell especially for blue-collar workers, which are competing harder with immigrants to find a job. These results are, however, lower than others found in the literature (see, for instance, **?**). This lower effect is the consequence of the adjustment of human capital by natives.

There is a huge amount of papers 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), and Altonji and Card (1991) among many others. This methodology exploits the fact that immigrants cluster in a small number of geographic areas. As a result of this concentration, there is an enormous cross-city variation in the incidence of immigration that 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

[3] Introducing skill biased technical change is crucial in the model as it is competing with immigration as sources of the recent increase in wage inequality.

and coauthors argued that prosperous cities receive more immigrants, inducing a spurious correlation that can be wrongly interpreted as the immigration improving native economic opportunities.[4] 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.[5] As a result of both drawbacks, the comparison of the economic opportunities that natives face in different cities will hardly identify the actual effect of immigration on labor market outcomes.

A more recent strand of the literature changes the unit of analysis to the national level. Borjas, Freeman, and Katz (1992) established 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 that it would have had 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 while more recently, beginning with Card (2001) and Borjas (2003, Sec. VII), those elasticities have been estimated.[6]

Although this strand of the literature is evolving rapidly, it still has some drawbacks. First of all, it assumes that labor is inelastically supplied; this assumption is very restrictive both because immigration may affect the decision to supply labor and because participation of immigrants appear to be different to that of natives. Second, as noted by Borjas (2003, p.1362), least squares regressions used to estimate the corresponding elasticities may lead to biased estimates of the different elasticities because the supply of workers to each educational group is endogenous over the 40-year period spanned by the data often used.[7] Third, this approach does not distinguish between blue- and white-collar occupations and it might generate even stronger biases: increasing clustering of immigrants in blue-collar jobs will reduce average wages for a particular skill group because of composition effects (i.e. because the entrants themselves earn a lower wage). And the final remark (that is also applicable to the spatial correlations approach) is that, in general, they do not identify the true effect on incumbents which is the price effect (as opposed to composition effects).

[4] This reluctance was not new. Altonji and Card (1991), LaLonde and Topel (1991), and Schoeni (1997) had 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 a valid instrument will be hard to find.

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

[6] More recent papers on this literature include Ottaviano and Peri (2007, 2008), Borjas and Katz (2007) Borjas, Grogger, and Hanson (2008), and Wagner (2009) among many others. A special mention should be made of Borjas (2003, Secs. II-VI) that tries to identify 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.

[7] Although he uses the number of immigrants in each skill group as an instrument, he acknowledges that the supply of immigrants in a skill group responds to shifts in the relative wage structure.

The present paper has a factor proportions flavor: it compares national level supplies of skills and it uses counterfactuals to quantify the effect of immigration on wages. However it tries to correct some of the drawbacks described above. The present structural model helps to identify the effect of immigration on wages by modeling the labor supply decision and taking into account equilibrium feedback effects, mitigating endogeneity problems. Moreover, it includes further important features such as skill-biased technical change, may its omission bias the results. Finally, the labor market equilibrium delivers the prices of skill units, which allows me to separate price from composition effects of immigration on average wages.

The paper is organized as follows. The next section briefly reviews some descriptive evidence. Section 3 presents the structural model that is being estimated. Section 4 describes the solution and estimation algorithm together with the data that is being used. Parameter estimates and the fit of the model are shown and commented in Section 5. Finally, Section 6 discuss the counterfactuals before concluding in Section 7.

2 Descriptive evidence: some facts about US mass immigration

During the last four decades, the US workforce was enlarged by about 26 millions of working-age immigrants. Such a huge immigrant-induced supply increase of about 0.7 millions of workers per year has motivated a lot of debate about how has it altered economic opportunities for incumbent workers and over what types of policies should be pursued. This section describes some important facts about US immigration that motivate this paper.

Policy background. Although the focus of this paper is on this recent boom in immigration, it is important to notice that immigration is not a new phenomenon. 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 US without any federal legislation (and without a major concern from locals). Beginning in 1850s, what was so-called "new immigration" brought in immigrants from Eastern and Southern Europe as well as from Asia and Russia. Americans' preference of old immigration rather than new immigration reflected a sudden rise in conservatism and the first nativist movements appeared. In 1875 the first federal immigration law was passed; this law prohibited the entrance of criminals and convicts, as well as Asian woman who would engage in prostitution. This law paved the road through the 1882 Chinese Exclusion Act that almost prohibited Chinese workers to enter the US. It was the first law that targeted a specific ethnic group.

In 1921 the US Congress passed the Emergency Quota Act that 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 US in 1910.[8] This policy was the result of the isolatist tendencies that emerged in the US between the two World Wars. This restriction affected especially to Southern and Eastern European immigrants. In 1943, the Chinese exclusion laws were repealed; in 1952, racial distinctions in the legislation were removed for the first time in the US immigration law history.

The 1965 Amendments to the Immigration and Nationality Act drastically changed the US immigration policy. The National Origins Formula was abolished and a fixed quota per Hemisphere were set. Eastern Hemisphere 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 served in a first-come first-served basis. However, the new policy allowed to issue an unlimited amount of visas to immigrants that already had relatives residing in the US. As a consequence of both this policy change and of major economic and political changes in the source countries the national mix of the immigrant flow changed substantially in subsequent decades: while Europe and Canada were the main issuers of US immigrants until 1950s, large scale immigration from Latin America (especially Mexico) and Asia took place afterwards. Most of this act is still in effect today, and it drove the immigration policy for the period of study in this paper.

Subsequent policies concentrated in preventing illegal immigration (1986 Immigration Reform and Control Act, and 1986 amnesty, reports from the US Commission on Immigration Report, 1996 Illegal Immigration Reform and Immigrant Responsibility Act...). The 1990 Immigration Act increased the maximum amount of visas to be issued but maintained the family reunification as the main criteria of admission.

Some numbers. 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% (see Table I). The composition of the inflow of new workers is very important. If the skill distribution of immigrants is very different to that of natives, the supply shock may shift the relative skill prices and have, therefore, an impact on the distribution of wages.

In fact, although they are increasingly more educated, the education gap between immigrants and natives has increased over the years. Panel B of Table I and Table II illustrate this fact. The top panel of Table Table II shows that immigrants have, in effect, increased their education. For example, the share of high school dropouts fell from roughly 50% of foreigners in 1970 to 27% in 2005-2007 while the share of college graduates increased from 11.57% to 25.69%. However, a comparison with the second panel evidences

[8] In 1924, the share was reduced to 2% and the reference year was switched to 1890.

TABLE I

Share of immigrants in the population (%)

	1970	1980	1990	2000	2005-2007
A. Working-age population	5.70	7.14	10.27	14.63	16.58
B. By education:					
High school dropouts	6.85	9.59	17.89	29.04	32.96
High school graduates	4.33	5.14	7.94	12.04	14.57
Some college	5.14	6.64	7.92	9.98	11.08
College graduates	6.48	8.04	10.59	14.58	16.73
C. In blue collar jobs:					
All education levels	*6.03*	*7.83*	*11.22*	*17.51*	*23.71*
High school dropouts	7.18	12.18	23.75	41.03	52.95
High school graduates	4.19	4.94	7.58	12.44	18.48
Some college	5.95	6.14	7.26	9.82	12.89
College graduates	9.53	9.52	12.14	17.89	24.06

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 microdata (IPUMS) for 1970-2000 and American Community Survey (ACS) microdata (IPUMS) for the 2005-2007 period. Data for the period 2005-2007 are pooled to increase the sample size.

TABLE II

Education of natives and immigrants

	1970	1980	1990	2000	2005-2007
A. Immigrants:					
High school dropouts	49.82	39.02	31.84	30.60	26.99
High school graduates	26.51	27.32	26.24	25.93	27.56
Some college	12.10	16.86	21.80	20.50	19.76
College graduates	11.57	16.80	20.11	22.96	25.69
B. Natives:					
High school dropouts	40.96	28.26	16.72	12.81	10.91
High school graduates	35.44	38.74	34.83	32.45	32.14
Some college	13.50	18.22	29.03	31.68	31.54
College graduates	10.11	14.78	19.42	23.05	25.41
C. New immigrants:					
High school dropouts	49.17	42.41	35.71	33.74	30.28
High school graduates	22.24	22.42	25.32	25.71	27.63
Some college	11.94	17.12	18.56	16.34	15.74
College graduates	16.65	18.05	20.41	24.21	26.35

Note: Figures indicate the percentage of individuals in each education group. Each panel column add to 100%. New immigrants are those which entered into the US in the previous 5 years. *Sources*: Census microdata (IPUMS) for 1970-2000. American Community Survey (ACS) microdata (IPUMS) for the 2005-2007 period. Data for the period 2005-2006 are pooled to increase the sample size.

TABLE III

Share of workers choosing blue-collar jobs

	1970	1980	1990	2000	2005-2007
A. Immigrants					
High school dropouts	78.80	82.80	84.77	84.87	87.32
High school graduates	53.23	55.75	61.02	65.05	68.89
Some college	30.01	35.72	36.90	38.78	42.58
College graduates	8.22	13.17	12.17	12.24	14.28
Overall	*55.68*	*52.70*	*49.52*	*50.61*	*52.83*
B. Natives					
High school dropouts	75.63	74.63	76.34	74.53	72.99
High school graduates	49.42	51.12	54.08	55.41	54.05
Some college	25.63	32.77	34.37	34.48	34.51
College graduates	5.48	10.14	9.23	8.47	8.65
Overall	*50.57*	*44.50*	*39.30*	*36.83*	*34.90*

Note: Figures indicate the percentage of workers employed in blue-collar jobs in each education group. New immigrants are those which entered into the US in the previous 5 years. *Sources*: Census microdata (IPUMS) for 1970-2000. American Community Survey (ACS) microdata (IPUMS) for the 2005-2007 period. Data for the period 2005-2006 are pooled to increase the sample size. Only working individuals are considered

that this increase has not compensated the natives' trend. For example, in 1970, the share of dropouts among immigrants was slightly larger than natives'; however, in 2005-2007, the share of immigrant dropouts was 2.5 times larger than that of natives. This increase took place at the expense of college educated workers.[9] Not surprisingly, Table I shows that one third of dropouts are immigrants while only a 16.54% of the overall workforce is foreign born.

Not only immigrants are increasingly less educated than natives, but they are also increasingly more clustered in blue collar jobs. Table III confirms this statement, especially for high school workers; for example, the share of immigrant dropout workers that are employed in blue-collar jobs increased from 78% to 87%, while natives' fell from 75% to 73%. Table I reinforces this conclusion; except for workers with some college, the share of immigrants increased much faster among blue-collar workers than among the overall workforce in each education cell. For example, the share of immigrants among dropouts increased from 7 to 36%, while the share of foreign born among blue-collar dropout workers increased from 7 to 53%. Overall, the share of immigrants among blue-collar workers increased from 6 to 24%.

[9] Panel C reinforces this conclusion. In fact, it shows that starting in 1980s, new entrants are less educated that incumbent immigrants.

3 The model

The goal of this paper is to quantify the effect of 40 years of mass immigration on wages and education of incumbent workers in the US. I present and estimate a labor market equilibrium model to make this assessment. This section describes the model. In particular, there is a subsection describing the labor supply, another with the demand, and a third explaining the equilibrium. Before that, in the following paragraphs I discuss some of the critical features of the model.

The main contribution of the current approach with respect to the existing literature is to explicitly model the labor supply decision. Assuming perfectly inelastic labor -as the literature has done so far- may produce biases provided that immigration affects education, participation and occupation decisions. The present paper models forward-looking working-age individuals taking participation, education and occupation decisions endogenously. Education and occupation-specific experience are rewarded in the future with higher wages, while leisure produce some utility.

Immigrants enter the US exogenously and with a given skill endowment, and start taking decisions upon entry. Ideally, one would like to model the immigration decision endogenously. Nevertheless, this would require observing individuals before and after migration, which is extremely difficult. At a first glance, one tends to think that immigrant inflows are somehow correlated with fluctuations of labor market conditions. In the long run, however, the picture is somehow different. As the historical review in the previous section illustrates, the main turning points in long run trends of US immigration throughout the history are given by policy changes. These policies, although of course they could be partly motivated by labor market outcomes, they were mainly driven by diplomacy and ethnic preservation issues.[10] Therefore, the implicit assumption is that there is a pull of immigrants willing to enter though not all of them are allowed, and these "exogenous" policy changes are the determinants of long run trends in the stock of immigrants.

A similar story for the skill endowments could be told. The superb work by Borjas (1987) rose the hypothesis of self-selection of immigrants. According to it, low skilled immigrants have the greater incentives to migrate from a country with relatively high returns to skills (negative selection), while high skilled will fly from countries with relatively low returns to skills (positive selection). Traditionally, for example, Western Europe have

[10] For example, the first federal regulation of immigration came after the "old immigration" from Western Europe turned into the "new" one by Catholics from Southern and Eastern Europe; immigration from China was forbidden for almost half of a century; the largest policy change in the beginning of 1920s was to introduce a National Origins Formula that basically restricted the amount of people that could enter from each country based on late 19th Century censuses (in order to favor the entry of Western Europeans as opposed to other immigrants); and the last major change, in 1965, was to remove this formula (for diplomacy reasons) and allow an unlimited amount of visas for family reunification purposes (ethnic preservation).

been a source of positively selected immigrants while Latin America one of negatively selected. Therefore, the main changes in skill composition of immigrants are associated with changes in sources, and these changes were induced by our "exogenous" policy changes. In fact, it would be otherwise hard to explain that while the skill premia increased (e.g. due to skill-biased technical change) immigrants were relatively (and progressively) less educated. Moreover, I also take into account the country of origin to estimate the unobserved skills of immigrants.[11]

On the demand side, the focus is on how heterogeneous are the effects of immigration on incumbents and on what possibilities of substitution among workers are allowed for. An aggregate firm combines capital and labor to produce a single output. Labor is expressed in skill units, which imply that the marginal rate of substitution among different workers is increasing with productivity differentials.[12] There are two types of labor: blue-collar and white-collar which implies that there are two equilibrium prices of skill units. The equilibrium price of the skill unit is the central element of this model, as it is the channel through which immigrants affect incumbents. Immigration is expected to affect especially similar workers (Borjas, 1999). In this sense, the analysis at the occupational level is convenient. From the theoretical point of view, assuming that immigrants affect more those incumbents competing for the same jobs is appealing. Moreover, from an empirical point of view, each occupation will attract (in equilibrium) a particular profile of workers in terms of skills: for example, less educated, more (blue-collar) experienced, and immigrants (see Section 2) will be more likely to end up working in blue-collar jobs; therefore, the more affected workers will end up to be similar also in terms of skills. Moreover, workers are able to switch occupations easier than skills, so it is a likely mechanism to compensate negative effects (see the argument by Peri and Sparber (2009) about task specialization). Ideally, one would like to define as many types of labor as possible, as 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.

Finally, the model takes into account skill-biased technological change. The production function is specified to allow for capital-skill complementarity; Krusell, Ohanian, Rios-Rull, and Violante (2000) argue that this complementarity and the fast accumulation of capital equipment can account for most of the skill-biased technical change. This partic-

[11] It is worth noting at this point that if any of the previous assumptions were not valid, the induced bias would tend to underestimate negative effects of immigration. The intuition of this result is that we would observe higher immigration in periods of good wage realizations and lower immigration in bad periods, introducing as a result, a positive spurious correlation among immigration (maybe of some particular skills) and wages.

[12] In this model, I define wages as the product of the price of a skill unit times the amount of skill units an individual is able to produce. I define the price of the skill unit as the average wage earned by native male without any observable skills (education and experience). This individual will be able to produce one skill unit. Returns to observed and unobserved skills will generate a continuum of wages.

ular form of technical progress is competing with immigration to explain the widening of the high school-college wage gap.

3.1 Career decisions and the labor supply

Individuals enter the model at age $a = 16$ (or at entry in the case of immigrants) and make decisions each year until the age of 65 when they die with certainty. They choose among 4 alternatives to maximize their lifetime expected utility: to work in a blue-collar job, $d_a = B$ or in a white-collar job, $d_a = W$, to attend school, $d_a = S$, or to stay at home, $d_a = H$. 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: in the case of natives, there are males and females; in the case of immigrants, they additionally differ in their country of origin (Western countries, Latin America, and Asia and Africa).

At every point in time t, and individual of type l and age a solves the following dynamic programming problem:[13]

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

with a terminal value $V_{65+1} = 0$. The instantaneous utility function is choice-specific, $U_a(\Omega_{at}, d_a = j) \equiv U_a^j$ for each alternative j, and it is described in the following lines.

Workers are not allowed to save. Therefore, utility is assumed to be linear in consumption, as individuals are not able to smooth. This assumption is consistent with individuals maximizing life-time discounted earnings (plus non-pecuniary additive utility). Finally, β is a subjective discount factor and Ω_{at} is the information set at age a and time t.

Working utilities are given by occupation-specific wages. As I mentioned above, wages are defined as the product of the amount of skill units supplied by the individual (productivity) and the skill rental market price (productivity adjusted wage rate): $w_{t,a,l}^j \equiv r_t^j \times s_{a,l}^j$. In particular, skill units are defined by a pretty standard Mincer equation:

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

This expression includes returns to education E_a, to blue- and white-collar effective experience in the US X_B and X_W, and to foreign (potential) experience X_F.[14] Returns to

[13] The dynamic programming problem of this paper is similar to those in Keane and Wolpin (1997), Lee (2005), and Lee and Wolpin (2006). I omit individual subscripts to simplify notation, but all variables indexed by age (a) are individual-specific.

[14] Since data does not specify in which country did education take place, the identifying assumption is that individuals concentrate education spells at the beginning of their life, which is in line with the standard theories of human capital (Becker, 1964). For example, a college graduate enters the US at age 18, then she will enter with a high school diploma, while if she enters at age 40, then she will have obtained her college degree abroad.

education, $\omega^j_{1,i}$, are different for immigrants and natives.[15] Moreover, it also introduces unobserved heterogeneity that has a permanent (ω_0) and a transitory (ε^j_a, normally distributed with gender-specific variance σ^j_g) components. Notice that equation (2) together with the normalization of some $\omega^j_0 = 0$ (in particular, I normalize native male's) provides us with a clear interpretation of the skill prices: the average wage perceived for a native male with no observed skills (education and experience). Any deviation from this wage will be proportional to a change in skills that is mapped by (2) into a change in productivity.

There are two important connections of equation (2) with the immigration literature. On the one hand, country of origin-specific unobserved skills is the result of the *self-selection* hypothesis introduced by Borjas (1987): immigrants from some countries are positively selected and others, negatively. On the other hand, equation (2) also 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 US earns more. According to this definition, immigrants assimilate in the sense that they are accumulating skills in the US 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 lower return to one year of experience abroad than to one year in the US.

Individuals who decide to attend school face a monetary cost, which is different for undergraduate and graduate studies. Additionally, they have a non-pecuniary utility (again with a permanent and a transitory elements, the latter normally distributed with gender-specific variance σ^S_g). Specifically,

$$U^S_{a,l} = \delta^S_{0,l} - \tau_1 \mathbb{1}\{E_a \geq 12\} - \tau_2 \mathbb{1}\{E_a \geq 16\} + \varepsilon^S_a. \tag{2}$$

As a counterpart, their education increases by one year ($E_{a+1} = E_a + \mathbb{1}\{d_a = E\}$) which provides a return in the future.

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

$$U^H_{a,l} = \delta^H_{0,l}(1 + \delta^H_{1,g} t) + \delta^H_{2,g} n_a + \varepsilon^H_a. \tag{3}$$

In this case, individuals experience gender-specific utility if they have preschool children living with them at home.[16] Additionally, as individuals cannot smooth consumption, they do not experience income effects (only substitution effects). As a result, if wages kept

[15] The subindex *is* stands for immigrant status. On the other hand, subindex g denotes gender; l denotes the type, and it is a combination of the previous as I described above.

[16] 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) but correlated with education. In particular, it depends on age, cohort and education.

increasing due to technical progress, choices would degenerate into everyone participating in the labor market. To avoid that, I include a gender specific time trend.[17] Finally, the utility includes again a fixed and an idiosyncratic transitory shocks, the latter with gender-specific variance σ_g^H.

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 (S_{Bt}) and white-collar (S_{Wt}) skill units with capital structures (K_{St}) and equipment (K_{Et}). Each period, the economy faces an aggregate productivity shock (z_t) that embeds neutral technological change. In particular, production at time t is given by the following nested Constant Elasticity of Substitution (CES) production function:

$$Y_t = z_t K_{St}^{\lambda}\{\alpha S_{Bt}^{\rho} + (1-\alpha)[\theta S_{Wt}^{\gamma} + (1-\theta)K_{Et}^{\gamma}]^{\rho/\gamma}\}^{(1-\lambda)/\rho}. \tag{4}$$

The parameters α, θ, and λ are connected with the factor shares while 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 that between equipment/white-collar and blue-collar labor is $1/(1-\rho)$.

Notice that (4) 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 another CES (white-collar labor and equipment) with blue-collar labor. Therefore, the elasticity of substitution between white-collar labor and equipment is different (typically lower) to that of equipment and blue-collar labor.

Equation (4) is different from the three-level nested CES that has become popular in the immigration literature since its introduction in Borjas (2003). That production is a Cobb-Douglas combination of capital and a labor aggregate; the labor (measured in worker counts) is a CES aggregate of four educational cells, each being itself a CES aggregate of labor supply in five experience cells. Equation (4) differs from Borjas' production function in the following aspects: (i) it adds a distinction between blue- and white-collar workers; (ii) labor is measured in skill units (which generates a different formulation for the elasticity of substitution and helps to disentangle price from composition effects); (iii) it takes into account capital-skill complementarities.

Apart from the theoretical motivation provided above, working at the occupational level seems realistic in light of the facts described in Section 2. We have seen that natives and immigrants concentrate in different occupations given observable skills, and, more importantly, the latter are increasingly more clustered in blue-collar jobs.[18] In an equilib-

[17] I considered other alternatives such as a function of the aggregate shock (which is the driving force of aggregate variables). However, including it add further complexity to the problem.

[18] The increasing concentration of immigrants in blue-collar jobs given observed skills may generate

rium model, moreover, natives may react to the inflow of workers and change occupations (Peri and Sparber, 2009), and partially offset negative effects.

Setting the analysis at the level of skill units (productivity) allows for a wide variety of possibilities of imperfect substitution among workers. In particular, the marginal rate of substitution between two workers with different skills working in the same occupation will increase with their productivity. Workers can differ in education, blue- and white-collar experience, experience abroad, age, and unobserved heterogeneity (see Subsection 3.1 for further details). As a result, the model will produce a continuum of wages and it will allow to separate price from composition effects: in an education-experience cell, the inflow of lower-paid immigrants can artificially reduce average wages; in this model, the effect of immigration is channeled through the price of the skill unit. Furthermore, using a production function like the one in Borjas (2003) in an equilibrium context would imply solving for 20 equilibrium prices which is unfeasible computationally.

Finally, in this paper I take into account skill-biased technical change. The constant returns to scale production function (4) is inspired on that estimated in Krusell, Ohanian, Rios-Rull, and Violante (2000). With their production function, these authors argue that last forty years of skill-biased technical change in the US can be explained by the evolution of capital equipment and its complementarity with skilled labor. Therefore, the fast accumulation of capital equipment will widen the blue-white collar wage gap, as immigration of blue-collar workers will do, allowing to disentangle both simultaneous effects.

For tractability reasons, I follow Lee (2005) and Lee and Wolpin (2006) not modeling savings. Solving for the life cycle savings decision imply a very costly complication of the model which might not be worthy. Capital and output are taken from the data in the solution of the model. As long as we observe equilibrium quantities in the data, this assumption is consistent with an open economy in which capital flows from international markets. Therefore, the implicit assumption that I am making is that savings and labor supply decisions are independent.[19]

Aggregate uncertainty (the aggregate shock z_t) is introduced to close the production function, as capital and output from the data. It is obtained as a residual in the pro-

biases if it is not taken into account. 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 have increased. Allowing imperfect substitution among immigrants and natives in each group (see, for instance, Ottaviano and Peri, 2007, 2008) would probably isolate the bias only for immigrant wages but it would not eliminate the problem as long as the elasticity of substitution between natives and immigrants would have been assumed to be constant.

[19] There are two complications of this assumption. On the one hand, a consequence of this assumption is that while workers' expectations about future labor supply depend on the current distribution of skills across workers, it only depends on aggregate capital figures -instead of on a distribution of assets (see Section 3.3). On the other hand, I check the robustness to different assumptions about the counterfactual evolution of capital in the counterfactuals described in Section 6.

duction function. Hicks-neutral technological change is provided by the persistence of z_t. Specifically, the shock is assumed to follow an AR(1) process in growth rates:

$$\log z_{t+1} - \log z_t = \phi_0 + \phi_1(\log z_t - \log z_{t-1}) + \varepsilon^z_{t+1}, \tag{5}$$

where innovations are drawn from a normal distribution with zero mean and variance σ^z. Notice that $\phi_0 \neq 0$ makes z_t to grow over time.

3.3 The equilibrium

The aggregate supply of skill units is given by

$$S^j_t = \sum_{a=16}^{65} \sum_{n=1}^{N} s^j_{a,n} \mathbb{1}\{d_{a,n} = j\} \tag{6}$$

On the other hand, in each period, the aggregate firm maximizes profits. The demands of production factors equalize marginal productivities to rental prices:

$$r_{S_B t} = (1-\lambda)\alpha \left(z_t K^\lambda_{St}\right)^{\frac{\rho}{1-\lambda}} S^{\rho-1}_{Bt} Y_t^{1-\frac{\rho}{1-\lambda}} \tag{7}$$

$$r_{S_W t} = (1-\lambda)(1-\alpha)\theta \left(z_t K^\lambda_{St}\right)^{\frac{\rho}{1-\lambda}} S^{\gamma-1}_{Wt} KW_t^{\rho-\gamma} Y_t^{1-\frac{\rho}{1-\lambda}} \tag{8}$$

$$r_{K_E t} = (1-\lambda)(1-\alpha)(1-\theta) \left(z_t K^\lambda_{St}\right)^{\frac{\rho}{1-\lambda}} K^{\gamma-1}_{Et} KW_t^{\rho-\gamma} Y_t^{1-\frac{\rho}{1-\lambda}} \tag{9}$$

$$r_{K_S t} = \lambda \tfrac{Y_t}{K_{St}} \tag{10}$$

where $KW_t \equiv [\theta_t S^\gamma_{Wt} + (1-\theta_t)K^\gamma_t]^{1/\gamma}$. The equilibrium of the economy is given by market clearing conditions.

Every year t, workers make a forecasts of the future path of the 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 the mean (which is zero). Therefore, the difficulty is in forecasting the path of future skill prices.

Rational expectations imply that individuals make the best possible forecast with the information available. In this case, they would need the whole distribution of current individual state spaces in order to forecast the future aggregate supply of skill units. However, this object imply an infinite state space. To make the problem tractable, I need to propose an expectation rule for future aggregate variables so that individuals are able to forecast future prices. The macroeconomics literature suggest some ways of doing it. Although this aspect of the model is still work in progress, I will search the best prediction rule of the following family:

$$\Delta \log S_{j,t+1} = \eta(\Delta \log z_{t+1}; S_{B,t}, S_{W,t}, K_{E,t}, K_{S,t}) \qquad j = B, W \tag{11}$$

$$\Delta \log K_{j,t+1} = \eta(\Delta \log z_{t+1}; S_{B,t}, S_{W,t}, K_{E,t}, K_{S,t}) \qquad j = S, E \tag{12}$$

These expressions basically assume that the one-period lag in the growth rate of the four aggregate variables plus the growth rate of the aggregate shock contain all the relevant information for predicting prices. The current simplified version of the model, however, considers that only the aggregate shock is moving prices (in particular, I assume that all aggregate variables grow at the same rate as the aggregate shock).

4 Solution and estimation

4.1 Solution

The solution of the model requires a numerical algorithm. As in Lee and Wolpin (2006), I use a nested algorithm in which one procedure solves the equilibrium and the other chooses the parameters that minimize the distance between a large amount of data points and their simulated counterparts.

Therefore, there are two types of parameters to be estimated: *expectations parameters* (Θ_2), given by the shock process (5) and the prediction rules for aggregate variables (11) and (12), and *fundamental parameters* of the structural model (Θ_1), which are the remaining parameters of the model. The solution of the rational expectations equilibrium (for a given Θ_1) is provided by the rational expectations parameters Θ_2 that make the fit of equations (5), (11), and (12) consistent with the individual choices they generate.

The fundamental parameters of the model are estimated by Minimum Distance. The Minimum Distance Estimator minimizes the distance between a large number of data points and their simulated counterparts (see below). Lee and Wolpin (2006) propose an nested algorithm for the estimation of this class of models that requires the full solution of rational expectations equilibrium to obtain Θ_2 for every Θ_1 iteration. Alternatively, I propose a solution and estimation algorithm that does not require the full solution of the model in each iteration. In particular, I switch 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 $[\Theta_2]^0$.

2. Solve the optimization problem for each cohort that exists from $t = 1$ to $t =$

T.[20] The solution of the dynamic programming problem in (1) is in general 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 huge. Therefore, I solve the maximization problem by backward recursion, using interpolation functions in a similar way to that proposed by Keane and Wolpin (1994, 1997) (although I evaluate the multiple integrals using a quadrature instead of Monte Carlo integration).

3. Find the equilibrium skill rental prices and the shock simulating the economy from 1860 to 2007. In particular,

   (a) Guess skill rental prices of period $t = 1860$.

   (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 functions using the supply of labor and the aggregate shock.

   (e) Iterate until finding the fixed point in which the skill rental prices equate supply and demand, emptying the labor market.

   (f) Repeat the previous steps to obtain equilibrium skill rental prices from $t = 1861$ to $t = 2007$.

4. Update Θ_2 fitting the regressions in (5), (11), and (12) to the resulting series of aggregate variables and aggregate shock. Lee and Wolpin (2006) iterate this item until finding the rational expectations equilibrium given Θ_1. Conversely, I only perform a single (costless) update for each Θ_1.

5. Compare simulated data with their observed counterparts. Keep updating $[\Theta_1]^1$ with Simplex iterations[21] to find the set of parameters that minimize the distance

[20] 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 older individuals have never been in the model with any of the initial cohorts, as a bit more than two entire generations have gone by.

[21] The Simplex method is a polytope algorithm to minimize (or to find roots of) functions (see Nelder and Mead (1965)). The version of the method that is used in this paper is the "parallelized version" described in Lee and Wiswall (2007). These authors adapt the Simplex to be run simultaneously in multiple processors of a computing cluster. This version of the method updates P vertices of the polytope instead of one each iteration (each one in one processor). The master process gathers the information of all P evaluations and update the polytope. Part of the computational gains of the algorithm that I present here comes from avoiding idle processors waiting for the others to reach converge in expectation processes.

between simulated and observed data $\widehat{\Theta}_1([\Theta_2]^n)$, where n denotes the number of updates of Θ_2 performed so far.

6. Iterate steps 2 to 4 until Θ_2 converges to $[\Theta_2]^{n*}$. If $[\Theta_2]^{n*}$ is close enough to $[\Theta_2]^n$, $\widehat{\Theta}_1 = \widehat{\Theta}_1([\Theta_2]^n)$; otherwise, repeat item 5 until Θ_2 converges to $[\Theta_2]^*$. Therefore, $\widehat{\Theta}_1 = \widehat{\Theta}_1([\Theta_2]^*)$

4.2 Estimation

The Minimum Distance Estimator minimizes a weighted average distance between a large set of data points and their simulated counterparts. Table IV describes which observations are considered. 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. Each observation is weighted by the inverse of the relative (weighted) sample size with respect to the other observations in the same group. Therefore, more precisely estimated statistics have a higher weight in the sum, although all groups of data have the same weight.

As it is described in the Table note, 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 in the same activity. Therefore, in order to assign individuals to one of the 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 de 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 has worked at least 40 weeks during last 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). Considered as blue-collar are craftsmen, operatives, service workers, laborers and farmers while those working as professionals, clerks, sales workers, managers and farm managerial occupations are assigned to work in white-collar.

iii. Finally, assigned to stay at home are those individuals that are not assigned neither to attend school nor to work.

The simulated counterparts of the data described in Table IV are obtained by simulating the behavior of cohorts of 2000 natives and 3000 immigrants (some of them starting abroad and not taking any choice until they show up into the US). Therefore, cross-sectional simulated observations are calculated with a sample of up to 250,000 observations, which I weight using data on cohort sizes.

TABLE IV
Data

Description	Source		Number of observations
TOTAL			**30,558**
Proportion of indiv. choosing each alternative...			**5,092**
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 country of origin	CPS	$15 \times 2 \times 4 \times (4-1)$	360
Immigr, by year, sex & foreign potential experience	CPS	$15 \times 2 \times 5 \times (4-1)$	450
By sex and experience in each occupation	NLSY	$(2+2) \times 5 \times 5 \times (2-1)$	100
Wages:			**6,080**
Mean log hourly real wage...			*3,036*
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, country of origin and occupation	CPS	$15 \times 2 \times 4 \times 2$	240
Immigr., by year, sex, fpx and occ.	CPS	$15 \times 2 \times 5 \times 2$	300
By sex, experience in each occ. and occ.	NLSY	$(2+2) \times 5 \times 5 \times 2$	200
Mean 1-year difference in log hourly real wage...			*2,508*
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 occ.	Matched CPS	$41 \times 2 \times 10 \times 2$	1,640
By year, sex, country of origin and current occ.	Matched CPS	$15 \times 2 \times 4 \times 2$	240
Immigr., by year, sex, yrs in the country and occ.	Matched CPS	$15 \times 2 \times 5 \times 2$	300
Variance in the log hourly real wages...			*896*
By year, sex, educational level and occupation	CPS	$41 \times 2 \times 4 \times 2$	656
By year, sex, country of origin and occupation	CPS	$15 \times 2 \times 4 \times 2$	240
Career transitions...			**14,646**
By year and sex	Matched CPS	$41 \times 2 \times 4 \times (4-1)$	984
By year and sex (work, shcool or home)	Matched CPS	$41 \times 2 \times 3 \times (3-1)$	492
By year, sex and age	Matched CPS	$41 \times 2 \times 10 \times 4 \times (4-1)$	9,840
By year, sex and country 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 country	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	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 ages is 50 (16-65); there are two sexes (male and female); immigrant status are also two (native and immigrant); countries of origin are four (Natives, Western countries, Latin America, and Asia and Africa); educational levels are also four (<12,12,13-15 and 16+ years of education); the categories of preschool children living at home are 3 (0, 1 and 2+); and potential experience abroad is classified in 5 groups, which are the same for years in the country (0-2,3-5,6-8,9-11 and 12+ years). Notice that the calculations does 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 waves: the one for the 1979 cohort and the one for that of 1997; finally, matched CPS denote 2-years matched March Supplements of CPS. See Data Appendix for further details.

Additionally, in the solution of the model I use aggregate data on output, stock of capital equipment, stock of capital structures, cohort sizes (by gender and immigrant status), the distribution of age at entry for immigrants, the distribution of initial schooling (at age 16 for natives and by the eve of immigration for foreigners), the distribution of countries of origin of immigrants, and the fertility (preschool children) process. See the Data Appendix below for further details on the construction of all variables.

It is difficult to derive a formal proof of identification in this context. However, from an econometric point of view, we can build an intuition. A large fraction of the observations listed in Table IV 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). Wage equations are identified through the combination of these cohort panel data on average wages and choices, the distributions of education and experience. Selection corrections are provided by functional form assumptions and exclusion restrictions (variables that affect utility and not wages -preschool children- and variables that affect wages and not utility -experience) similarly to the standard procedures. Aggregate data on output, capital and cohort sizes identify aggregate skills and production function parameters.

5 Estimation results (VERY PRELIMINARY)

This section presents preliminary estimation results of the parameters and some analysis about the goodness of the fit of the model. By the time I am writing this lines, an estimation is still running and it have not converged yet. Therefore, estimates presented below are my best parameter values at this moment but they are not final estimates. Moreover, I am estimating a restricted version of the model. Parameter values are presented in tables that group related parameters. I discuss on the text those parameters that are of particular interest. Standard errors are also forthcoming.

5.1 Parameter values

5.1.1. Production function

Table V presents parameter estimates for the production function. As I mentioned above, I normalize the "ability" of native males to zero for both blue- and white-collar. Therefore, the prices of the skill unit are interpreted as the average wage earned by a native male without observable skills. It is important to notice, however, that factor shares (especially α and θ) are also relative to this normalization, as so are aggregate stocks of skill units.

The elasticities of substitution implied by ρ and γ are respectively 1.36 and 0.73. These elasticities of substitution imply that capital equipment and blue-collar labor are closer substitutes than equipment and white-collar labor. Therefore, the results support the hypothesis of capital-skill complementarity. Seminal work on this hypothesis was done 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 are a huge variety in the estimates of the absolute size of the demand elasticities for blue- and white-collar. As I mentioned before, 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. Nevertheless, they obtain very similar estimates for the elasticities of substitution: 1.67 and 0.67 respectively.

Finally, the capital-structures share in the production function is estimated to be 0.512. The estimate is somehow larger than other estimates from the literature. For example, point estimate in Krusell, Ohanian, Rios-Rull, and Violante (2000) is as large as 0.117. However, the comparability in this case is harder because of the normalization as I mentioned above

TABLE V

PRODUCTION FUNCTION

Factor shares:	
Structures (λ)	0.512
Blue-collar (α)	0.434
White-collar (θ)	0.382
Inv.elast.of subs.:	
Blue vs Equipment (White) (ρ)	0.267
White vs Equipent (γ)	-0.374

NOTE: The parameters from this table are included in equation (4):

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

Elasticities of substitution of blue-collar vs equipment (or vs white-collar), and white-collar vs equipment are $1/(1-\rho)$ and $1/(1-\gamma)$ respectively.

5.2 Wages

Estimates for the main parameters of wage equations are presented in Table VI. Returns to education in this paper are assumed to be different for natives and for immigrants. Results suggests that an additional year of education increase blue-collar wages a 2.5% for natives and a 1.9% for immigrants. In the case of white-collar jobs, this additional year

TABLE VI

WAGES

	Blue-collar	White-collar
Unobserved heterogeneity ($\omega_{0,l}$):		
Western countries	1.978	0.266
Latin America	-1.600	3.462
Asia and Africa	1.318	5.010
Female	-7.980	-2.519
Returns:		
Education ($\omega_{1,i}$):		
Natives	2.593	4.644
Immigrants	1.946	3.844
BC experience (ω_2)	3.912	2.619
BC experience^2 (ω_3)	-0.012	-0.021
WC experience (ω_4)	0.110	2.919
WC experience^2 (ω_5)	-0.018	0.000
Foreign experience (ω_6)	2.196	1.297
Variances:		
Male	4.967	12.783
Female	4.965	4.039

NOTE: All parameters from this table are included in equation (2):

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

Unobserved heterogeneity (ability) for native males is normalized to zero. Immigrant female abilities are the sum of the correspondent immigrant male parameter and native female's. All coefficients are multiplied by 100.

increase wages of natives and immigrants respectively a 4.6 and a 3.8%. Card (1999) surveys a wide variety of estimates of the returns to an additional year of education ranging from 5 to 15%. At the occupational level, Keane and Wolpin (1997) find a return of 7% for white-collars and 2.4% for blue-collars (9.3 and 1.9 respectively in their basic model). Similarly, Lee (2005) estimate the 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) while blue-collar returns range from 2.7 to 4.4%. My estimates seem to be lower than those estimates, but they are closer to Lee and Wolpin (2006). Lower returns to education for immigrants may be the consequence of partially educating in their home country; ideally one would like to introduce different returns for education obtained in the US and abroad, but I do not observe were education took place.

Results for experience are in line with previous work. As in Lee (2005) and Keane and Wolpin (1997), an additional year of within occupation experience is more productive than cross-experience. Point estimates are, however, lower than the more comparable results in Lee (2005). Foreign potential experience, on the other hand, is more productive in blue-collar jobs, and in both cases is less productive than effective experience in the US. This latter result is important, as long as this lower return to foreign experience generates wage convergence for immigrants as they spend time in the US.[22]

Female are less productive than male in both occupations. Immigrants, on the other hand, show heterogeneous results depending on the country of birth. All of them are more productive in white-collar jobs (which turns out to be puzzling as they cluster in blue-collar jobs). In blue-collar jobs, only Latin Americans are less productive than natives (which is even more puzzling). Nevertheless, these coefficients are hard to compare, as the wage equation is not the same for natives and immigrants (return to foreign experience, different returns to education).

5.2.1. Utility parameters

Table VII shows estimates of the remainder utility parameters. Results show that natives experience more utility both to attend school and to stay at home than immigrants. Males are more willing to educate while females have more preference for home. Moreover, the latter is especially true when they have preschool children living with them at home.

Tuition fees are estimated to be around 13,000 US$ of year 2000 for attending college and about $25,000 for attending a graduate school. Those results are reasonable and inside the variety of results found in the literature. Lee and Wolpin (2006) estimate the cost of attending college to be approximately $27,000 and additional $18,000 for attending a graduate school; Keane and Wolpin (1997) find a cost of $6,000 for college and additional $10,000 for a graduate school; and Lee (2005) results are in between: $8,500 for college and additional $20,500 for attending a graduate school.[23]

5.2.2. Expectation processes

The current version of the model is estimated imposing some specific values for the expectation parameters. This restriction allows me to identify the parameters without having to solve the expectations equilibrium. Results are still equilibrium results, as the market clearing conditions hold, but they do not approximate to "bounded rational expectations" equilibrium. In particular, I assume an expected exogenous growth rate of the aggregate shock and all aggregate variables of 3%.

[22] As I mentioned above, LaLonde and Topel (1992) define assimilation as the process through which the wage of an immigrant converge to that of an observationally equivalent immigrant that entered the US before. As a result, relative wages increase as the weight of foreign experience in the experience bundle falls.

[23] All these figures are in year 2000 US$.

TABLE VII

Utility parameters

	Male	Female
School:		
Unobserved heterogeneity ($\delta^S_{0,l}$):		
Natives	9,266.95	5,994.05
Western countries	-7,585.21	-4,906.26
Latin America	6,667.79	4,312.86
Asia and Africa	-7,436.97	-4,810.38
Tuition fees:		
Undergraduate (τ_1)	13,039.77	
Graduate ($\tau_1 + \tau_2$)	25,724.72	
Variance (σ^S)	2,120.68	1,668.92
Home:		
Unobserved heterogeneity ($\delta^H_{0,l}$):		
Natives	23,779.24	24,837.38
Western countries	21,675.05	22,639.55
Latin America	22,859.36	23,876.56
Asia and Africa	20,407.50	21,315.59
Trend (δ^H_1)	0.0035	0.0042
Children (δ^H_2)	11,052.88	14,606.16
Variance (σ^H)	3,007.84	5,737.91

Note: The parameters from this table are included in equations (2) and (3):

$$U^S_{a,l} = \delta^S_{0,l} - \tau_1 \mathbb{1}\{E_a \geq 12\} - \tau_2 \mathbb{1}\{E_a \geq 16\} + \varepsilon^S_a$$

$$U^H_{a,l} = \delta^H_{0,l}(1 + \delta^H_{1,g} t) + \delta^H_{2,g} n_a + \varepsilon^H_a .$$

Discount factor, β, is set to 0.95. Immigrant female permanent utilities are calculated as in the following example: $\delta^S_{west,fem} = \delta^S_{nat,fem} \times \delta^S_{west,male} / \delta^S_{nat,male}$.

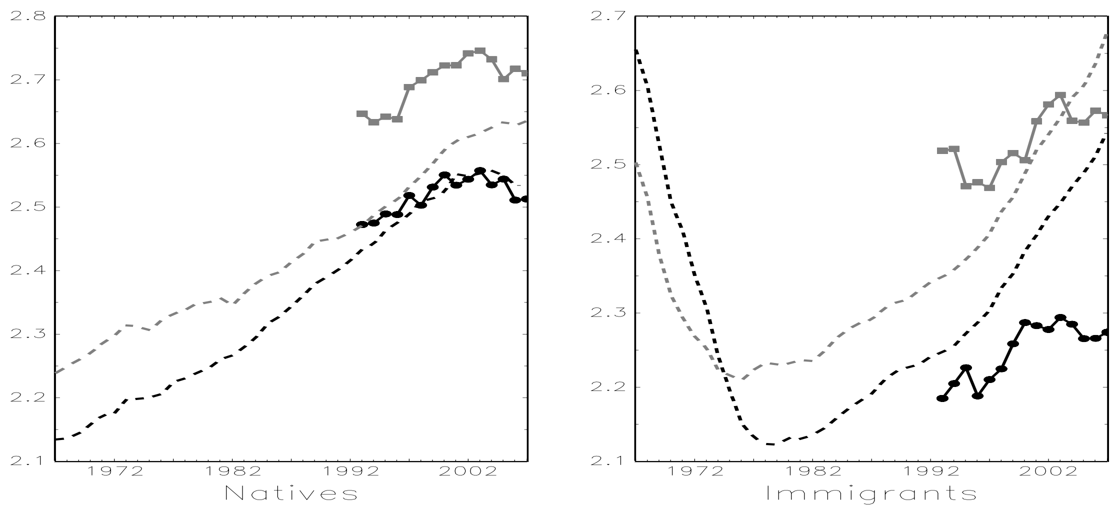
5.3 Validation (Work in progress)

Part of the validation exercise includes a good fit of the data. Goodness of fit in this model is measured in terms of distance between data and simulations. Figures I and II summarize this comparison in terms of wages. At the point when this draft is written, estimation is not finished yet, though this are the results for the best vector of parameters I have found so far. Solid lines represent the data and dashed ones are the simulations. Black lines are for high school and grey ones are for college workers.

Figure I plots male mean log hourly wages in blue-collar jobs. Data starts in 1993 which is the first year when the CPS started to ask about the country of birth in its March supplement. Current estimates allow the model to replicate the main trends shown in the

FIGURE I

Average blue-collar log hourly male wages (data vs simulations)



Note: Solid lines: data. Dashed lines: simulations. Black: high school. Grey: college. High school include individuals with 12 or less years of schooling, and College include individuals with 13+ years of education. *Source*: CPS and author's simulations.

data. However, it is still underestimating the college-high school wage gap. In the case of natives, it shows particularly good fit of high school wages and underestimates college wages. Conversely, the result for immigrants is exactly the opposite.

Figure II show the fit of male mean log hourly wage in white-collar jobs. The same conclusions as before apply, although in this case, both for immigrants and for natives, I replicate correctly the high school wage and underestimate the average white-collar wage of college workers.

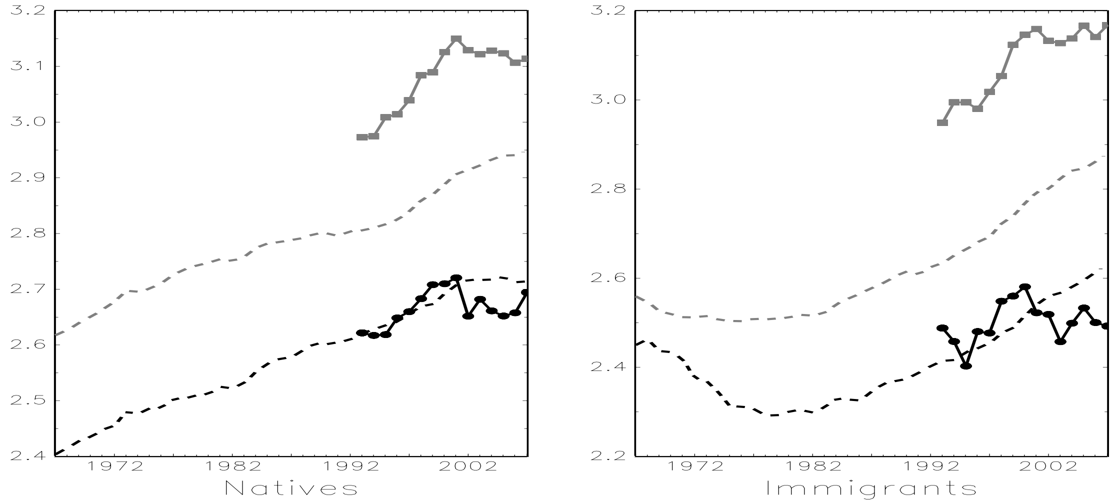
Figure III shows the goodness of the model in fitting education. In particular, it draws the share of individuals with 12 or less years of schooling (high school) among immigrants and among natives. The model replicates the fact that immigrants are less educated than natives, and it also replicate the trends. However, it tends to understate education (overstate the share of high school) especially for immigrants.

Figure IV shows a similar patern to the previous figures when comparing data and simulations of the share of workers in blue-collar jobs. Both for immigrants and natives, it underestimates the gap between high-school and college, but in the case of natives, it fits very well the share for college (understating the share for high-school), while for immigrants it does well in fitting the share for high-school (overestimating the share for college). It also replicates the fact that immigrants tend to be increasingly more clustered in blue-collar jobs.

A final note to the Figures III and IV is to emphasize the fact that they plot three

FIGURE II

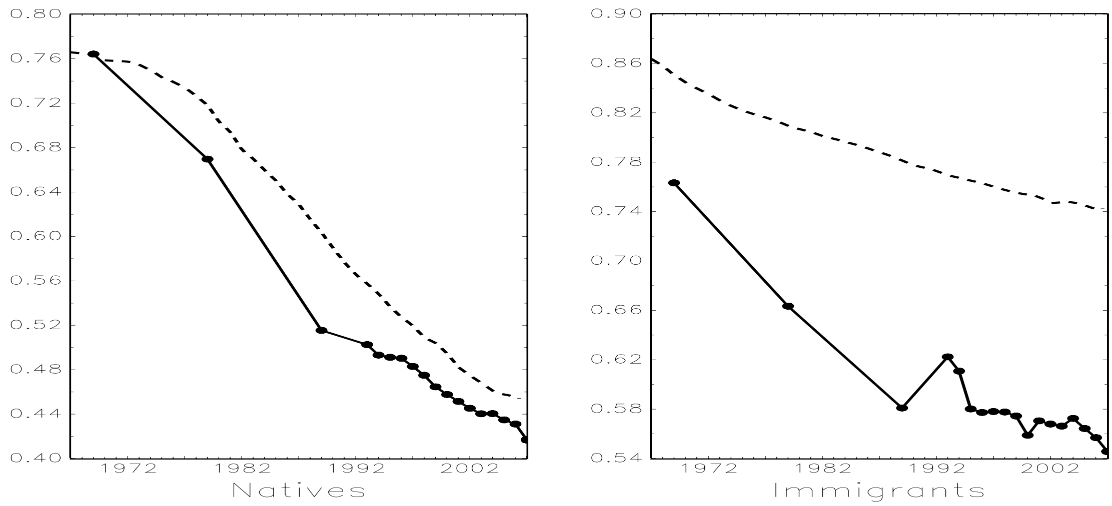
AVERAGE WHITE-COLLAR LOG HOURLY MALE WAGES (DATA VS SIMULATIONS)



NOTE: Solid lines: data. Doted lines: simulations. Black: natives. Grey: Immigrants. High school include individuals with 12 or less years of schooling, and College include individuals with 13+ years of education. *Sources*: CPS and author's simulations.

FIGURE III

SHARE OF INDIVIDUALS IN HIGH SCHOOL (DATA VS SIMULATIONS)

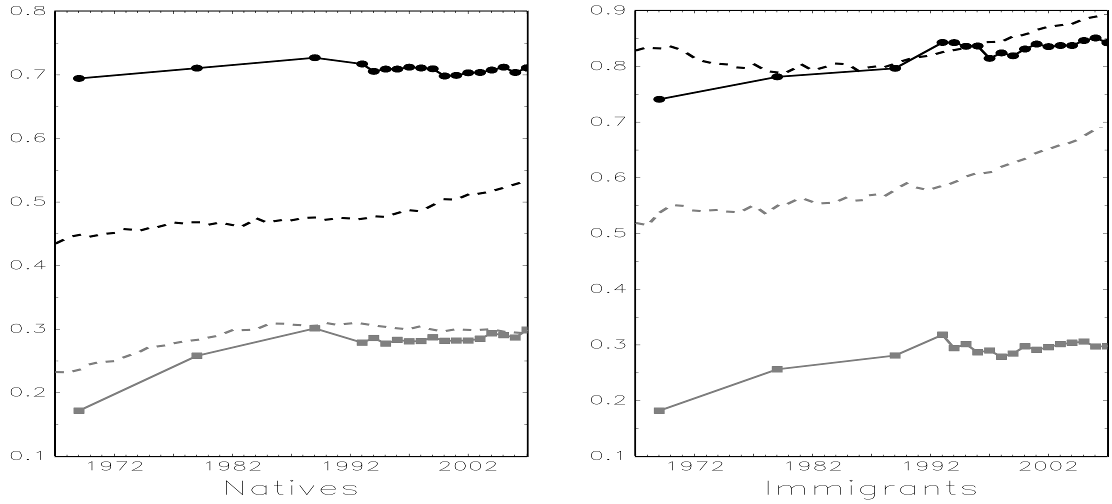


NOTE: Solid lines: data. Dashed lines: simulations. Figures represent the share of high school among immigrants and natives. High school include individuals with 12 or less years of education. *Sources*: US Census for 1969, 1979 and 1989 data points, CPS from 1993 on, and author's simulations.

additional observations (corresponding to 1970, 1980 and 1990 Censuses). It is important to note that before 1993, no information about the separate behavior of natives and immi-

FIGURE IV

Share of workers in blue-collar jobs (data vs simulations)



Note: Solid lines: data. Dashed lines: simulations. Black: high school. Grey: college. High school include individuals with 12 or less years of schooling, and College include individuals with 13+ years of education. *Sources*: US Census for 1969, 1979 and 1989 data points, CPS from 1993 on, and author's simulations.

grants is used in estimation. Therefore, this "off-sample" fit provides an extra validation of the model. Good news are that (apart from the error in fitting the levels mentioned above), the model predicts extremely good off-sample trends. Therefore, pending still the final convergence of the parameters in the current estimation preliminary results are encouraging. I am still working in obtaining comparable "off-sample" data for wages.

Again, however, all these results are very preliminary, and, in fact, the estimation procedure was still minimizing by the time I was writing these lines. Further validation exercises are also work in progress.

6 Counterfactuals and policy analysis (Very preliminary and incomplete)

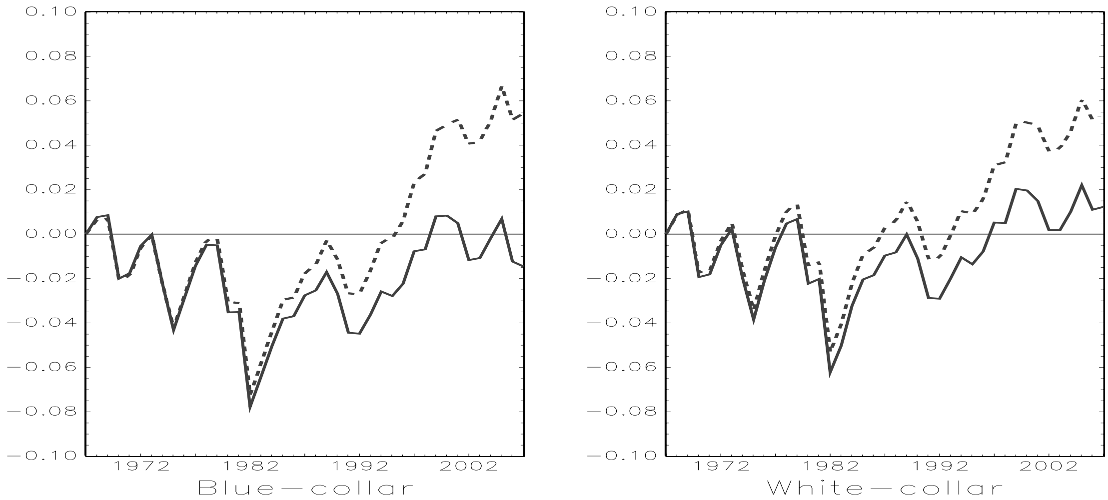
This section analyzes the counterfactual experiments evaluated with the estimated model. In particular, there are three groups of counterfactuals. The purpose of the first one (Section 6.1) is to quantify the effect of immigration on wages and education. The other two are still work in progress and are described in Section 6.2.

6.1 The effect of immigration on wages and education.

The main research question of this paper is to quantify the effect of immigration on wages and education of incumbent workers in the US. The counterfactual experiment of this subsection is aimed to answer to that question. The thought exercise I carry out consists in comparing the factual evolution of wages to its evolution in a world without mass immigration.

FIGURE V

Counterfactual evolution of (log) skill prices



Note: Solid lines: baseline. Dashed lines: counterfactual. (Log) skill prices normalized to 1967 levels. Counterfactual exercise: keep immigrant-native ratio constant to 1967 levels. See definitions and further details in the text.

My definition of a "world without mass immigration" consists of a world in which immigration is only allowed to keep constant the immigrant-natives ratio to 1967 levels. Moreover, I keep constant the age and gender distribution of immigrants to 1967 levels. Therefore, immigrants only enter into the US to compensate for those who retire every year and for native population growth.

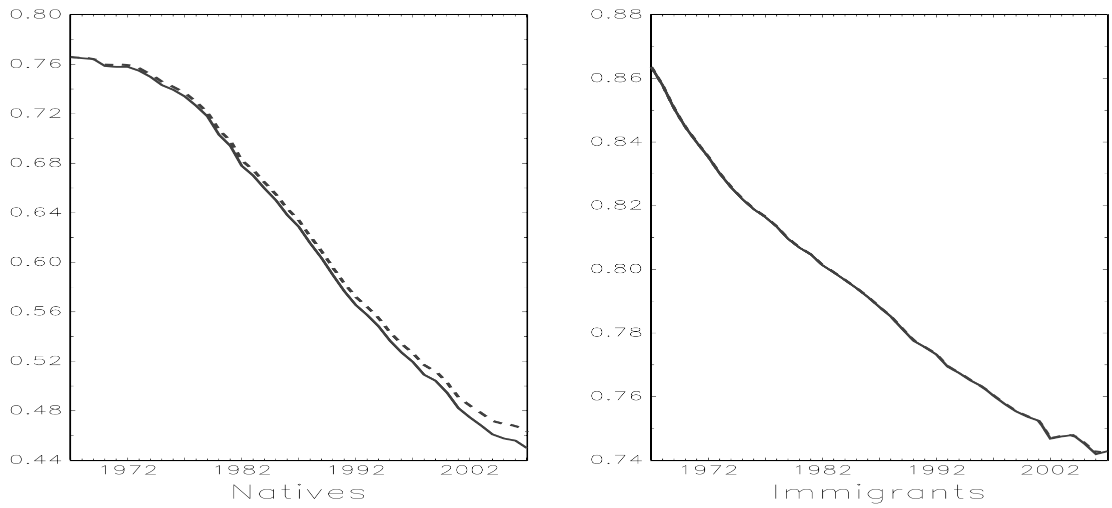
Regarding the counterfactual evolution of the capital, current simulations keep both types of capital to actual levels in *per capita* terms. However, further counterfactuals will build upper and lower bounds to the effect of immigration on wages by making different assumptions about the counterfactual evolution of capital.

Figure V show the baseline and counterfactual evolution of (the log of) the price of skill units in each occupation. As I mentioned in previous sections, the price of the skill unit can be defined (given the parameter normalization explained above) as the average wage of a native male with no observable skills (education and experience). In Figure V, I normalized the (log) price of the skill unit to 1967 levels. Therefore, we can interprete those figures as the cumulative increase/decrease in wages throughout the period.

Results suggest that without mass immigration, the wages of incumbent workers in 2007 would have been a 6.9 and a 4.1 percent larger for blue-collar and white-collar jobs respectively. These results suggests large negative effects of immigration on wages, though they are slightly lower than the results in Borjas (2003). In his simulations in section VII of the paper, Borjas find that immigration between 1980 and 2000 reduced wages by 8.9 percent for high school dropouts and by 4.9 percent for college graduates; results were more moderate for high school graduates (2.6 percent) and workers with some college (barely affected). Overall, he finds a negative effect of 3.2 percent over the 20 years he studies. The results of the present paper suggest an overall effect around 5 percent over 41 years.

FIGURE VI

COUNTERFACTUAL EVOLUTION OF EDUCATION



NOTE: Solid lines: baseline. Dashed lines: counterfactual. Figures represent the share of high school among immigrants and natives. High school include individuals with 12 or less years of education.

Figure VI summarizes the adjustment in education decisions motivated by immigration. Counterfactual simulations show that in a "world without mass immigration" the share of high schools among natives would have been 1.3 percentage points larger. In other words, natives adjusted their investments in education as a result of the changes in relative prices induced by immigration. Incumbent immigrants, on the other hand, did not adjust their investment behavior. This result could be in line with the adjustment argument that Peri and Sparber (2009) make in terms of tasks.

Both results together are appealing. They suggest that negative effects of immigration on wages are overestimated if we do not take into account long run adjustments of education. This result is provided by the equilibrium approach. Other explanations for the lower effect on wages may include occupational adjustment and changes in participation. Further counterfactuals that are still work in progress will shed some light to this comparison of results.

6.2 Further counterfactuals

Two additional counterfactual exercises are still work in progress. The first one aims to connect the results from the previous subsection with the literature. I will replicate the results by Borjas (2003) using data simulated by the model. In particular, I will estimate the production function of Section VII to see if his approach produce larger negative effects with those simulated data. This exercise will provide more intuition about the importance of equilibrium effects in this type of exercises.

On the other hand, as I mentioned in the introduction, I am interested in using the model for policy analysis. As I mentioned in Section 2, the 1965 Amendments to the Immigration and Nationality Act removed the National Origins Formula. The first policy experiment that I will do is to reset the Formula and simulate the counterfactual evolution of wages if this policy change had not occurred. *A priori*, one would expect that this change will affect especially immigration from Latin America, although in recent years it will also cut immigration from Asia.

The second experiment will evaluate a policy that is becoming common in developed countries: selective visas. I will establish some admission criterion in terms of observed skills to allow the entry into the US and simulate the counterfactual evolution of wages in this context. In this case, results are difficult to predict. On the one hand, it is not clear that increasing investments in education will still be an optimal reaction for natives. Moreover, they will be closer substitutes to natives than the average immigrant so presumably they will have more negative effects. On the other hand, however, skilled immigration has traditionally been perceived as positive for the host country. This counterfactual policy experiment will shed light on this controversy.

7 Conclusions

In this paper, I present and estimate a labor market equilibrium model that addresses three empirical issues in a unified framework: how immigration affects wages (disentangling price and composition effects); whether immigration has an effect on school enrollment; and what are the consequences of a selective immigration policy and a National Origins Formula. The model tries to correct some of the drawbacks of the literature described in the Introduction.

The demand of labor is described by a Constant Elasticity of Substitution (CES) production function with three factors (blue- and white-collar labor, and capital) and constant returns to scale. It allows for neutral and skill-biased technical change, and aggregate productivity shocks. The amount of labor in each occupation that is used for production is defined by skill units rather than workers. This is a very flexible way to take into account imperfect substitution between workers within the same occupation, as long as they are all able to produce a different amount of skill units. Moreover, it allows me to focus the analysis on the prices of skill units as opposed to wages (that include also composition effects).

On the supply side, individuals live from age 16 to 65 and decide whether to work in a blue- or white-collar job, attend school or stay at home. Immigrants enter the country with a given amount of skills and start making decisions from the first period they are in the US. They differ from natives in that they have a different ability in each of the alternatives, and in that they have some experience obtained abroad that has a different return from the one obtained in the US.

Immigration affect wages by pushing up the supply of labor. However, equilibrium forces may change the type and amount of skill units that are being supplied. Preliminary results seem to be in line with this prediction. Counterfactual experiments performed with the current estimates of the parameters suggest an average 5% fall in wages over 40 years, especially in blue-collar jobs. On the other hand, the share of high school natives (as opposed to college) decreased considerably as a result of immigration.

References

Altonji, J. G., and D. E. Card (1991): "The Effects of Immigration on the Labor Market Outcomes of Less-skilled Natives," in *Immigration, Trade and the Labor Market*, ed. by J. M. Abowd, and R. B. Freeman, pp. 201–234. Chicago: University of Chicago Press.

Becker, G. S. (1964): *Human Capital. A Theoretical and Empirical Analysis, with Special Reference to Education.* New York: National Bureau of Economic Research.

Borjas, G. J. (1983): "The Substitutability of Black, Hispanic, and White Labor," *Economic Inquiry*, 21(1), 93–106.

——— (1985): "Assimilation, Changes in Cohort Quality, and the Earnings of Immigrants," *Journal of Labor Economics*, 3(4), 463–489.

——— (1987): "Self-Selection and the Earnings of Immigrants," *American Economic Review*, 77(4), 531–553.

——— (1995): "Assimilation and Changes in Cohort Quality Revisited: What Happened to Immigrant Earnings in the 1980s?," *Journal of Labor Economics*, 13(2), 201–245.

——— (1999): "The Economic Analysis of Immigration," in *Handbook of Labor Economics*, ed. by O. C. Ashenfelter, and D. E. Card, vol. 3A, chap. 28, pp. 1697–1760. Amsterdam: North-Holland.

——— (2003): "The Labor Demand Curve Is Downward Sloping: Reexamining the Impact of Immigration on the Labor Market," *Quarterly Journal of Economics*, 118(4), 1335–1374.

——— (2006): "Native Internal Migration and the Labor Market Impact of Immigration," *Journal of Human Resources*, 41(2), 221–258.

Borjas, G. J., R. B. Freeman, and L. F. Katz (1992): "On the Labor Market Impacts of Immigration and Trade," in *Immigration and the Work Force: Economic Consequences for the United States and Source Areas*, ed. by G. J. Borjas, and R. B. Freeman, pp. 213–244. Chicago: University of Chicago Press.

——— (1997): "How Much Do Immigration and Trade Affect Labor Market Outcomes?," *Brookings Papers on Economic Activity*, 1, 1–67.

Borjas, G. J., J. Grogger, and G. H. Hanson (2008): "Imperfect Substitution between Immigrants and Natives: A Reappraisal," NBER Working Paper n.13887.

Borjas, G. J., and L. F. Katz (2007): "The Evolution of the Mexican-Born Workforce in the United States," in *Mexican Immigration to the United States*, ed. by G. J. Borjas. Cambridge: National Bureau of Economic Research Conference Report.

Browning, M., A. Deaton, and M. Irish (1985): "A Profitable Approach to Labor Supply and Commodity Demands Over the Life-Cycle," *Econometrica*, 53(3), 503–543.

Card, D. E. (1990): "The Impact of the Mariel Boatlift on the Miami Labor Market," *Industrial and Labor Relations Review*, 43(2), 245–257.

——— (1999): "The Causal Effect of Education on Earnings," in *Handbook of Labor Economics*, ed. by O. C. Ashenfelter, and D. E. Card, vol. 3A, chap. 30, pp. 1801–1863. Amsterdam: North-Holland.

——— (2001): "Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration," *Journal of Labor Economics*, 19(1), 22–64.

Griliches, Z. (1969): "Capital-Skill Complementarity," *Review of Economics and Statistics*, 51(4), 465–468.

Grossman, J. B. (1982): "The Substitutability of Natives and Immigrants in Production," *Review of Economics and Statistics*, 64(4), 596–603.

Hamermesh, D. S. (1986): "The Demand for Labor in the Long Run," in *Handbook of Labor Economics*, ed. by O. C. Ashenfelter, and D. E. Card, vol. 1, chap. 8, pp. 429–471. Amsterdam: North-Holland.

Heckman, J. J., L. Lochner, and C. Taber (1998): "Explaining Rising Wage Inequality: Explorations with a Dynamic General Equilibrium Model of Labor Earnings with Heterogeneous Agents," *Review of Economic Dynamics*, 1, 1–58.

Keane, M. P., and K. I. Wolpin (1994): "The Solution and Estimation of Discrete Choice Dynamic Programming Models by Simulation and Interpolation: Monte Carlo Evidence," *Review of Economics and Statistics*, 76(4), 648–672.

——— (1997): "The Carreer Decisions of Young Men," *Journal of Political Economy*, 105(3), 473–522.

Krusell, P., L. E. Ohanian, J.-V. Rios-Rull, and G. L. Violante (2000): "Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis," *Econometrica*, 68(5), 1029–1054.

LaLonde, R. J., and R. H. Topel (1991): "Labor Market Adjustments to Increased Immigration," in *Immigration, Trade and the Labor Market*, ed. by J. M. Abowd, and R. B. Freeman, pp. 167–200. Chicago: University of Chicago Press.

——— (1992): "The Assimilation of Immigrants in the U.S. Labor Market," in *Immigration and the Work Force: Economic Consequences for the United States and Source Areas*, ed. by G. J. Borjas, and R. B. Freeman, pp. 67–92. Chicago: The University of Chicago Press.

Lee, D. (2005): "An Estimable Dynamic General Equilibrium Model of Work, Schooling, and Occupational Choice," *International Economic Review*, 46(1), 1–34.

Lee, D., and M. Wiswall (2007): "A Parallel Implementation of the Simplex Function Minimization Routine," *Computational Economics*, 30(2), 171–187.

Lee, D., and K. I. Wolpin (2006): "Intersectoral Labor Mobility and the Growth of the Service Sector," *Econometrica*, 74(1), 1–46.

LEMIEUX, T. (2006): "Increasing Residual Wage Inequality: Composition Effects, Noisy Data, or Rising Demand for Skill?," *American Economic Review*, 96(3), 461–498.

NELDER, J. A., AND R. MEAD (1965): "A Simplex Method for Function Minimization," *Computer Journal*, 7, 308–313.

OTTAVIANO, G. I. P., AND G. PERI (2007): "Rethinking the Effects of Immigration on Wages," NBER Working Paper n.2497.

——— (2008): "Immigration and National Wages: Clarifying the Theory and the Empiraçs," Mimeo, UC Davis.

PERI, G., AND C. SPARBER (2009): "Task Specialization, Immigration, and Wages," *American Economic Journal: Applied Economics*, 1(3), 135–169.

SCHOENI, R. F. (1997): "The Effect of Immigrants on the Employment and Wages of Native Workers: Evidence from the 1970s and 1980s," The RAND Corporation.

WAGNER, M. (2009): "Understanding the Labor Market Impact of Immigration," Mimeo, University of Chicago.

A Data appendix

A.1 Aggregate data

GDP. The variable GDP includes data on GDP at chain 2000 US$ from 1901 to 2007. Data from 1929 on were obtained from the Bureau of Economic Analysis (BEA). Since data before that date were not available, I used Lee and Wolpin (2006) series to extrapolate the original series back to 1901. In particular, I applied the annual growth rate of their series to extrapolate backwards the observation of 1929.

Capital stock. I use capital stock series provided by the BEA. More specifically, data on private and government fixed assets were taken from "NIPA Table 1.2 Chain-Type Quantity Indexes for Net Stock of Fixed Assets and Durable Goods"[24]. Again, since the first observation is for year 1925, I extrapolated the series backwards using the data provided by Lee and Wolpin (2006).

Cohort sizes. Cohort sizes for each year from 1900 to 2007 were provided by the US National Census microdata, made available by the Integrated Public Use Microdata

[24] In fact, NIPA Table 1.2 provides indexes for net stock of fixed assets with year 2000=100. I multiply these indexes by the current value of fixed assets in year 2000 taken from Table 1.1

Series (IPUMS)[25]. In particular, I used information from the decennial censuses from 1900 to 2000 and from the American Community Survey (ACS) 2001-2007. Intercensus estimates were obtained following different procedures for natives and immigrants. The former were estimated using mortality data from Vital Statistics of the US. The latter were obtained distributing the net flow of the decade among different cohorts according the age of entry distribution described below.

Age of entry. The distribution of age at which immigrants entered the US was estimated using IPUMS microdata samples of the Census. Since the exact year of immigration is only available for 1900-1930 and 2000 Censuses and for 2001-2007 ACS, intermediate data was obtained by interpolation of the average distributions of 1900-1930 and 2000-2007. To calculate the distribution at one particular census date t, I averaged out the distributions of age at entry of those immigrants who arrived at $t-1$, $t-2$,..., $t-5$. This was done to reduce small sample noise. An alternative measure that I calculated is the distribution of age at entry of all those immigrants that stay in the country at census date. However, this measure biases downwards the average age at entry (see discussion below).

Since the distribution of age at entry seems to be very stable over years, and due to data limitation, I used the same distribution in all years within an interval. The intervals I used are the follwing: 1900-1930, 1931-1940, 1941-1950, 1951-1960, 1961-1970, 1971-1980, 1981-1990 and 1991-2007. The distribution was interpolated linearly among all these intervals.

Fertility process. The fertility process was mainly taken from Lee and Wolpin (2006) and updated with March CPS (provided by IPUMS) according to the description they make about the data. In particular, the variable that is calculated here is the transition matrix between having 0, 1 or more preschool children given age, gender and, after 1960, education. They obtained the data from US Censuses from 1900 to 1960 and from CPS afterwards.

Initial schooling. The distribution of schooling at age 16 (by sex) was also taken from Lee and Wolpin (2006). They calculated this distribution using US Censuses from 1910 to 1960 and CPS afterwards. They applied the same distribution for the entire decade, and used the same for 1980s and 1990s. In a similar spirit, I calculated the distribution for immigrants by cohort of entrance by using censuses from 1970, 1980, 1990 and 2000. In this case, I applied the calculated distributions to the following periods: before 1944, 1945-1954, 1955-1964, 1965-1970, 1971-1980,1981-1990, 1991-2000 and 2001-2007. Since I didn't observe the educational level they had at the event of entrance, the

[25] 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/

implicit assumption I made was that they concentrate their education at the beginning of their careers (this is in line with the human capital literature (Becker, 1964); see the main text). As a result, if a college graduate (simulated) immigrant enters the country at age 16, I assume that she entered with 10 years of education, but if she enters at age 30 I assume that she graduated abroad.

A.2 Microdata moments

In order to construct the moments that I use in the estimation, I combine data from 3 sources: March Supplement of CPS, NLSY79 and NLSY97. In general, I use CPS as provided by IPUMS. However, since I calculated some moments that require to match individuals from one survey year to the next, and identifiers that allow me to match households are not available from IPUMS, I also used raw CPS data provided by NBER[26]; in this case, I tried to replicate IPUMS harmonization of the variables to make them fully comparable over years.

In the following lines I describe the definitions of the variables that were used in the construction of data moments. This information helps in understanding how were the moments constructed.

Age. As obvious from the name, this variable represents the age of the individual. Individuals with ages above 65 and below 16 are not considered in any of the moments since they are out of the model. Both in the case of CPS and NLSY individuals are asked about their age at the interview date. However, since questions related to choices and wages are referred to the past calendar year, I subtracted one year to the reported age.

Year. As I mentioned before, both in the case of CPS and NLSY, questions related to choices and wages refer to the calendar year before the interview date. The latter is the year that I take into account when calculating the moments. I use 1968-2008 March Supplements of CPS covering, therefore, the 1967-2007 period. For the case of NLSY, see the specific references to years below.

Immigrant. I define immigrants to their place of birth. Considered as immigrants are all those individuals that were born outside the US. Individuals born in Puerto Rico and other outlying areas are considered as natives. This information and all other related to immigrant issues in only available starting in (survey year) 1994. Therefore, all moments that use these variables only cover the 1993-2007 period.

Preschool children. This variable takes the value of 0 if there is not any child aged 0-5 in the household, 1 if there is one and 2 if there are two or more. My definition of

[26] The 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 again another four 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 households for these two years obtaining a small panel.

households include only family units living in the same house. Therefore, if, for example, there is a preschool child in a two family home, only their parents are considered to have preschool children.
In order to link children with their parents, I used the IPUMS created variables *momloc* and *poploc*, that identify the position of the mother and father in the household respectively. This variable includes biological, step- and adoptive parents. Although both variables are mainly comparable over years, there are some minor changes that are listed in the documentation.

Educational level. I defined four educational levels that correspond to high school dropouts, high school graduates, some college and college graduates. In the simulated data, they correspond to <12, 12, 13-15 and 16+ years of education. This variable is used only for moments using the CPS. The CPS, however, changed the definition of the variable in 1992. Before that year, respondents were asked about their highest grade of school or year of college completed; starting in 1992, it classify high school graduates according to their highest degree or diploma attained. However, according to IPUMS, this variable is fully comparable over all years; moreover, grouping the data into four categories minimizes the impact of this methodological change.

Initial schooling. This variable is defined as years of education at age 16. The variable comes from NLSY. In particular, I considered the highest grade that the individual attended. The sample with which the moments were calculated includes all individuals from 1962 to 1964 for NLSY79 and 1980 to 1984 (the entire sample) for the NLSY97. Therefore, I observe the educational level of all individuals at age 16. Since in NLSY the educational attainment is reported as year of education, I'm, in fact, using the exact number of years of education at age 16 to make the two groups of individuals (<10 and 10 years of education at age 16).

Experience. This variable computes how many years the individual spent working on a blue-collar job, how many in a white-collar and how many was at home (see the definition of CHOICE below). I considered the same cohorts described for the INITIAL SCHOOLING variable. However, I only include individuals for which I observe the entire path of choices[27].

Potential experience abroad. The main difficulty to construct this variable is that information about year of arrival is only available by groups of years. Moreover, education is also grouped in 0-4, 5-8, 9, 10, 11, 12, 13-15 and 16+ years of education. I constructed the variable by assuming the central point of the correspondent interval both for age of entry and for years of education. Recall that, since I do not observe where the education took place, I'm assuming that it was concentrated in the earliest ages of the

[27] In particular, I include individuals for which I observe the entire path until either 1990, 1991, 1992 or 1993 for NLSY79 and until either 2004, 2005 or 2006 for NLSY97.

individual wherever she was. In order to minimize the error that this assumption may induce, I grouped potential experience in the following categories: 0-2, 3-5, 6-8, 9-11 and 12+ years.

Years in the country. This variable was constructed in a way simular to POTENTIAL EXPERIENCE ABROAD. The only difference is that this variable does not use information about education. It is also grouped in the same listed intervals.

Choices. This variable measures whether the individual worked in a blue-collar job, in a white-collar one, attended school or remained at home. The definition of each choice is as follows. An individual is assigned to school if she reported that school was her main activity during de survey week (CPS) or if she was attending school at survey date (NLSY). She is assigned to work in one of the two occupations if she is not assigned to school and has worked at least 40 weeks during last year and at least 20 hours per week[28]. When an individual is assigned to work, her occupation is the one held during the last year (CPS) or the most recent (NLSY).Considered as blue-collar are craftsmen, operatives, service workers, laborers and farmers while those working as professionals, clerks, sales workers, managers and farm managerial occupations are assigned to work in white-collar. Finally, assigned to be at home are those individuals that are not assigned neither to be at school nor to work.

Wage. This variable represents log hourly wage[29]. Individuals are assumed to earn all their wage in the occupation in which they are assigned. Annual earnings are measured as wage and salary income plus self-employment earnings (farm and non-farm). They are corrected for inflation and converted into 2000 US$. I follow the literature multiplying topcoded values by the standard factor of 1.4 and dropping extreme observations (with an hourly wage of less than $2 or more than $200 in 2000 dollars ; see Lemieux (2006) as an example). In order to calculate hours worked last year, I use information on weeks worked last year[30] and on hours worked per week (see footnote 28 for details on the measurement of the latter). Finally, hourly wage comes up by dividing annual earnings by hours worked.

[28] There are two variables that measure hours worked per week: one refers to the last week and the other to the hours usually worked per week last year. This second variable would probably be a more accurate variable to measure hours worked; however, since this variable is only available after 1976, and to avoid a change in methodology, I used hours worked last year.

[29] In the model, individuals are assumed to work 2080 hours per year (40 hours, 52 weeks)

[30] Before 1976, this variable is only available intervalled; in particular, the relevant intervals are 40-47, 48-49 and 50-52 weeks. To use a correct approximation of how many weeks impute to each interval, I gropued the data for a few years after 1975 in the same intervals and calculated means. The resulting values are the following: 43.1, 48.3 and 51.9 respectively.