Immigration, Human Capital and the Welfare of Natives

Juan Eberhard [*]

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Abstract

I analyze the effect of an unexpected influx of immigrants on the price of skill and hence on the earnings, human capital accumulation, and educational attainment of native workers. In order to study these effects, I develop a general equilibrium model with heterogeneous workers who differ in their level of skill and in their ability to learn new skills. These workers accumulate human capital optimally using information about the current and future market price of skill to guide their decisions. To assess the impact of immigration, I compare simulated earnings in the presence of immigration with a series of counterfactual experiments. My findings suggest that immigration has a small negative direct effect on earnings, but a positive and relatively large impact indirectly through human capital accumulation and educational attainment. This latter mechanism explains 60% of the variations in earnings caused by immigration.

1 Introduction

Immigration is a major source of growth in the U.S. labor market. Over the past two decades, Census data show that decennial immigration to the U.S. grew to a peak of three percent. In 2000, more than ten percent of the U.S. population was foreign born. Consequently, the main goal of the literature studying immigration has been to analyze this influx of immigrants and its effect on native wages.

In this paper I analyze the impact of immigration on both native wages and the human capital accumulation decision, using a general equilibrium model. Workers differ in their ability to accumulate

human capital. They maximize their stream of earnings deciding optimally the amount of time to devote to human capital accumulation taking as given current and future market prices. Educational attainment is endogenous.

I analyze the effect of immigration at the national level, this aggregate approach extends the literature in a number of dimensions. First, using a general equilibrium model allows me to capture changes in the behavior of natives after immigration alters the economic environment, and therefore it takes into account the subsequent feedback effects on prices. The model allows to examine not only the impact of immigration on earnings, but also its impact on human capital accumulation decisions and educational attainment. This is of particular importance, because low skilled workers use their human capital accumulation decisions to minimize the impact of immigration on their earnings. On the other hand, high skilled workers can choose to accumulate additional human capital to increase the benefits from a higher skill premium.

Second, the individuals in the model are heterogeneous in their ability to learn, have a raw labor endowment and accumulate human capital endogenously. This raw labor and their accumulated human capital are the productive factors in a non-linear production function. The non-linearity in the production function is key to the analysis of the effects of immigration. The characteristics of immigrants differ from natives along several dimensions. The average age and the shares of ability types in the immigrants and native population differ. My approach allows me to study the impact on the economy after immigration shocks to different ability and age groups. I use the overlapping generations (OLG) structure of the model to distinguish between the effects of the immigration shocks on each skill and age group.

Third, I study the impact of immigration at the individual level. By shifting the focus away from groups defined by their education and experience, I develop a better understanding of the dynamics both within and between groups. Moreover, a well known fact from the wage inequality literature[1] is that within-group inequality plays an important role in the overall dynamics of the wage distribution.

Fourth, I add skill biased technical change (SBTC) to the analysis. This accounts for changes in labor demand that affect the wage structure. In a general equilibrium context, Heckman et al. (1998) show the infeasibility of using immigration alone as an explanation for the changes in U.S. wage inequality. However, the mechanisms through which immigration and SBTC affect the economy are similar, and

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[1]See for instance Autor et al. (2008).

therefore disentangling these two effects is part of the challenge of this paper.

Finally, I undertake a more complete welfare analysis to study how immigration affects natives in their life cycle. In order to do that, I calculate the variation on welfare, measured as the present discounted value of lifetime earnings, for different types of individuals, classified by ability and age.

Using data from the March Current Population Surveys, the model is calibrated to match key features of the U.S. age-earnings profile. The parameters associated with the ability to learn, the CES production function, and the SBTC shocks are chosen to fit moments associated with the dispersion and evolution of the earnings distribution.

Further, Census data is used to obtain the age and ability distribution of migrants. This information allows counterfactual experiments to assess the impact of immigration. Comparing earnings in the presence of immigration with the counterfactual without immigration, I calculate the impact of immigration on earnings and human capital accumulation.

I find that immigration has similar effects to those in previous nation-wide studies when I restrict the analysis to the impact of immigration on the average log-earnings of education-experience groups[2]. Endogenous human capital accumulation provides an alternative mechanism to mitigate and in some cases amplify the direct effects of immigration on earnings. Workers re-optimize their human capital decisions after immigration changes the relative price of human capital. Their actions mitigate the observed effect at the education-experience group level. Thus, I conclude that immigration has a small direct effect on earnings, but a relatively large impact on human capital accumulation and educational attainment.

Previous research finds conflicting evidence regarding the impact of immigration on the native labor market. One set of studies focuses on clusters of immigrants in specific labor markets and finds small effects of immigration on earnings. These studies quantify the impact of migration using variation provided by differing levels of migrant inflow by local labor market.

Comparing local labor markets to study immigration was first introduced by Grossman (1982). Following Grossman's work, Altonji and Card (1991), and LaLonde and Topel (1991) treat immigrants and natives as two different inputs in the production function. However, there is a high degree of heterogeneity in the distribution of immigrants' skills across cities. Therefore, aggregating immigrants in one productive factor can potentially bias the estimation of the impact of immigration on natives' wages. To

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[2]Borjas (2003) analyzes immigration using similarly defined education-experience groups.

circumvent this problem, Jaeger (1996) and Card (2001) assume perfect substitutability between natives and immigrants within skill groups. Card (1990) uses the Mariel Boatlift as a natural experiment in the Miami labor market to assess the impact of an unexpected inflow of foreign workers. The consensus of these studies is that immigration has a very small impact on the wage structure.

However, workers are mobile across regions, and hence can migrate if labor conditions worsen through immigration. Hence, as Borjas et al. (1992, 1996) and Borjas (1994) note, comparisons across local labor markets can underestimate the effect of immigration. An economy-wide approach can circumvent the bias associated with internal migration, and therefore capture the impact of immigration on education-experience groups. Using this approach, Borjas finds bigger and significant negative effects of the immigration on native earnings.

There are few studies looking at immigration using a general equilibrium framework. Heckman et al. (1998) focus on explaining the wage inequality increase in the 1980s. They find that immigration cannot be the main explanation for the increase in wage dispersion. Storesletten (2003) examines the positive impact of immigration on tax revenues and concludes that immigration can have a positive effect on the fiscal budget. However, the present work differs from previous studies because my emphasis is on the interaction between immigration, human capital accumulation, and the dynamics of the earning distribution.

This paper is also related to the literature studying the dynamics of wage inequality in the U.S. using general equilibrium models. Heckman et al. (1998) extend the Ben-Porath framework adding heterogeneous agents and endogenous human capital accumulation. Nonetheless, the amount of heterogeneity is limited to only four skill groups. I allow for 20 skill groups. Heathcote et al. (2008) study the macroeconomics effect of inequality. They introduce incomplete markets, and their model explains the main features of the dynamics of the wage structure. Moreover, they use two types of skill and gender as inputs in the production function, thus they analyze the intra-household decision of consumption and education. They conclude that labor supply and human capital accumulation are used to insure against shocks. Guvenen and Kuruscu (2009) present a model with a high degree of heterogeneity which matches the main features of the U.S. wage distribution. Here I extend the latter model using a CES production function rather than a linear one. This extension allows assessment of the impact on the economy after shocks to different skill groups, which is key to the analysis of the impact of immigration in light of the high degree of skill heterogeneity across immigrants.

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2 Model

I develop a general equilibrium model with overlapping generations and heterogeneous workers to capture some key features of the dynamics of the U.S. earning distribution. These include the acceleration of earnings inequality since 1980 and the dynamics of the college/high school premium. This model has important advantages. It allows for endogenous human capital accumulation, a rich earnings distribution and a production function that incorporates SBTC.

In the following subsections, I present the details of the model. However, because the main focus of this work is to study how immigration affects human capital accumulation decisions and the earnings profiles of individuals, the discussion about how this model can explain the evolution of inequality in the U.S. is kept to a minimum.

Guvenen and Kuruscu (2009) show that the dynamics of U.S. wage inequality are mostly driven by SBTC using a model with a linear production function. Here, I extend their model, assuming a non-linear production function. The model is ideal to analyze immigration for two main reasons. First, it has a well defined notion of the skill premium. This is crucial because immigration will necessarily change the skill premium. Previous models emphasize either the skill price[3] or the educational skill premium. However, to capture the dynamics of wage inequality, both between- and within-educational groups, it is necessary to identify the tradeoff between acquiring more human capital and the cost of doing so, when prices are changing. In the case of a standard Ben-Porath model, a higher skill price produces benefits that are offset by the cost of higher investment in human capital[4]. Studies using only educational skill premiums cannot predict behavior within an educational group.

Second, this approach also allows for a high degree of heterogeneity across workers. This is crucial to analyzing the impact of immigration on the earnings distribution given the heterogenous distribution of age and human capital across immigrants. Moreover, I can calculate the effect of immigration both at the individual level, and at specific age-ability groups. The high degree of heterogeneity across individuals is consistent with microeconomic evidence showing a substantial increase in the dispersion of earnings over the life cycle within a given cohort[5].

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[3]These studies are based on Ben-Porath (1967).

[4]The cost of accumulating human capital is forgone earnings.

[5]See for instance Baker (1997), Guvenen (2007) and Huggett et al. (2006).

2.1 Consumers

In this economy, individuals are born into cohorts of the same size, each normalized to one. These cohorts make up the overlapping generations that populate the economy.

Each individual enters the economy at the age of 18, with an initial level of human capital h_0, and a raw labor endowment ℓ which I normalize to one. Each period, individuals decide to use their one unit of time to either rent their labor and human capital to the representative firm or to accumulate human capital. The fraction of time dedicated to the latter activity is denoted by i.

Workers participate in the labor force until they reach 62 years of age[6]. This implies a maximum of 45 years in the labor force. After that, the worker does not receive earnings, and therefore retired workers are not considered in the model economy.

The dynamics of human capital accumulation are

$$h_{a+1,t+1}^{j} = h_{a,t}^{j} + A^{j}(h_{a,t}^{j} \cdot i_{a,t}^{j})^{\alpha} \tag{1}$$

where t corresponds to the time period, a is age of the individual, and j represents the type. Notice that the source of heterogeneity in this economy is the parameter A, drawn from the distribution $\mathcal{A}$. According to the framework presented in Ben-Porath (1967) this parameter can be interpreted as the ability to learn. The choice of this particular mechanism of human capital accumulation is standard for these types of models[7]. Finally, α is the curvature of the Ben-Porath accumulation function.

I assume that the type j, or ability, is drawn from a uniform distribution. The details of how the parameters associated with the ability distribution are calibrated is presented in Section 4. The uniform distribution has two main advantages over other distributions. First, the distribution is characterized by only two parameters, the mean and the variance. Second, the support of the distribution is finite and bounded. Thus it is possible to exclude negative abilities to learn[8].

At any point in time, a worker rents both his human capital $h_{a,t}^{j}$ and his raw labor endowment, net of investment time, to the representative firm at prices P_t^H and P_t^L respectively. The decision to accumulate human capital depends on the current and future prices of human capital and raw labor, as well as the

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[6]62 years of age is the earliest retirement age in the U.S.

[7]See for instance Guvenen and Kuruscu (2009) and Heckman et al. (1998).

[8]I am exploring the sensibility of the results to this assumption. I intend to present alternatives in the future.

individual's ability to learn. Therefore $h_{a,t}^j$ differs by age and cohort, as well as by type. Workers' earnings are

$$y_{a,t}^j = [P_t^H h_{a,t}^j + P_t^L \ell_{a,t}^j](1 - i_{a,t}^j). \tag{2}$$

If the fraction of time invested in human capital accumulation $i_{a,t}^j$ is equal to 1, I consider the individual to be enrolled in tertiary education. If the fraction is in the interval $[0, \kappa]$, $\kappa < 1$, the worker dedicates only a fraction of his time to accumulating human capital and is considered to be engaged in on-the-job learning[9]. There are two reasons for the discontinuity in the choice set of investment time. First, it prevents workers from spending a very small, and unrealistic, amount of time at work. Second, it allows me to express the lowest possible wage in terms of the parameters of the model[10] [11].

For simplicity, the model ignores tuition costs, and therefore the only costs associated with tertiary education are forgone earnings.

It is important to notice that in this model there is a difference between observed and potential earnings. The difference is associated with adjustments at the intensive margin, represented by the fraction $i_{a,t}^j$. These adjustments are a function of aggregate prices, technological change, and the individual's human capital stock. One of the most important implications of this difference is that the skill price and observed earnings can move in opposite directions in a given period. This is because workers forecast future prices and take advantage of the higher skill premium by increasing their investment time, and consequently their observed earnings decrease temporarily while making the investment.

There is a macroeconomics literature examining capital-skill complementarities. Krusell et al. (2000) show that the elasticity of substitution between capital and high skilled workers is lower than between capital and low skilled workers. This implies that a fraction of SBTC is attributable to changes in the aggregate quantities of capital in the economy. Violante (2002) focus on the improvement of the quality of equipment, and how vintage-human capital can hinder the ability of workers to transfer skills across jobs, which increases the wage inequality. Greenwood and Yorukoglu (1997) examines how the introduction of

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[9]This way to model human capital accumulation is standard in the literature. It is used by Heckman et al. (1998), and Guvenen and Kuruscu (2009).

[10]In this case the lowest wage in a given period corresponds to the wage of a 18 year old worker of the lowest ability type, investing κ of his time in accumulating human capital.

[11]Card and DiNardo (2002) argue that changes in the minimum wage and other economic conditions play an important role in the dynamics of wage inequality. It is possible to extend this model to account for changes in the minimum wage by calibrating the parameter κ. This extension is not presented in this version.

new technologies can appear in the data as low productivity due to the delay related to the acquisition of the abilities to operate the new technology. Therefore, this apparent drop in productivity can alter the wage distribution. However, the model presented here abstracts from these implications assuming that workers acquire general skills, and that skill biased technological change, captures changes in the demand associated with the processes described above.

In addition, I assume that workers are risk neutral and they can borrow and lend freely at a fixed interest rate r, which implies that the discount factor β is equal to $1/(1+r)$. Assuming no borrowing constraints is consistent with the literature studying endogenous educational attainment. Cameron and Taber (2004), Carneiro and Heckman (2002) and Keane and Wolpin (2001) show that borrowing constraints are not empirically relevant for the educational attainment decision, mostly because income affects this decision through channels related to the family[12].

To summarize, a typical worker of ability type j, born into cohort $t - a$, solves the following maximization problem:

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\max_{\{i_{a,t}^j\}} \quad \sum_{a=1}^{45} \beta^a [P_t^H h_{a,t}^j + P_t^L](1 - i_{a,t}^j)
$$
$$
\text{s.t.}
$$
$$
i_{a,t}^j \in [0, \kappa] \cup \{1\}
$$
$$
h_{a+1,t+1}^j = h_{a,t}^j + A^j [h_{a,t}^j \cdot i_{a,t}^j]^\alpha
$$

2.2 Firms

One of the main differences between this model and previous models describing the U.S. wage structure is the use of aggregate human capital H_t and aggregate raw labor L_t as productive factors. These production factors were first introduced in Guvenen and Kuruscu (2009). They have the advantage of allowing for a high degree of heterogeneity across workers in an economy with an aggregate production function with only two factors. Notice that the aggregate amounts used as productive factors are net of investment

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[12]Family income is correlated with other aspects of the family that directly affect the ability to learn and the initial condition of human capital. Borrowing constraint corresponds to a second order effect on the educational attainment decision.

time, as is clear in the following expressions

$$L_t = \sum_a \sum_j 1 \cdot (1 - i_{a,t}^j)$$

$$H_t = \sum_a \sum_j h_{a,t}^j \cdot (1 - i_{a,t}^j)$$

The representative firm produces according to a CES production function, with a skill-neutral technological change parameter Z_t and SBTC expressed using the parameters θ_t^H and θ_t^L. I normalize these two parameters imposing that $\theta_t^H + \theta_t^L = 1$ for all t. The firm solves the following maximization problem

$$\max_{H_t, L_t} \quad Z_t(\theta_t^L (L_t)^\rho + \theta_t^H (H_t)^\rho)^{1/\rho} - P_t^H H_t - P_t^L L_t. \tag{3}$$

Notice that if $\rho = 1$, the CES production function collapses into a linear form, which is the case studied in Guvenen and Kuruscu (2009). In that particular case, the relative price of human capital with respect to raw labor becomes independent of the aggregate quantities. Interestingly, Guvenen and Kuruscu (2009) show that a model with a linear production function fits most of the features of the dynamics of the U.S. wage structure. However, studying the impact of waves of immigrants with heterogenous skills requires that human capital and raw labor are not perfect substitutes. As a result, the immigrants' composition of skill is relevant when I evaluate the effect of immigration on natives' earnings.

The firm's first order condition is

$$\frac{P_t^H}{P_t^L} = \left(\frac{\theta_t^H}{\theta_t^L}\right)\left(\frac{H_t}{L_t}\right)^{\rho-1}. \tag{4}$$

Equation (4) highlights the main differences between previous models looking at the U.S. wage structure and the approach presented here. Previous studies use college and non-college workers as productive factors[13]. That is, they use wage data to calculate the college premium for the left hand side, and data on the fraction of college educated workers in the labor force for the second term on the right hand side of equation (4). Using this information they either estimate the sequence of SBTC, or, under some regularity assumption about SBTC, they estimate the elasticity of substitution between college and non-

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[13]See for instance Heckman et al. (1998) and Acemoglu (2002).

college workers[14]. In contrast, here, the elasticity of substitution is between human capital and raw labor. This elasticity is related to the returns from investing time in human capital accumulation, even within-educational groups. Moreover, Guvenen and Kuruscu (2009) show that even when using a linear production function of human capital and raw labor, which implies perfect substitutability, there is an implied imperfect elasticity of substitution between college and non-college workers that is finite and similar to the elasticity estimated in previous papers. I confirm this finding[15] in section 5.

As was discussed above, using human capital and raw labor as productive factors has several advantages. However, these quantities are not observed directly in the data, complicating the calibration of the model. In Section 4, I describe in detail the calibration procedure, but the strategy is to choose parameters to best match various moments of the U.S. earnings distribution.

3   Data

The March Current Population Surveys (CPS) is the most suitable data set available for the calibration procedure. The span of the data, from 1964 to 2005, is the longest among comparable surveys. This is critical because the influx of foreign workers increased in size during the 1970s. Using data from years prior to 1970 moderates the effect of immigration in the calibration procedure. Furthermore, the annual frequency of the CPS data increases the precision of the calibration of parameters associated with the dynamics of the earning distribution.

The sample is constructed following the work of Autor et al. (2008). I use the weekly earnings of full time active male workers constructed by dividing annual earnings by the total number of weeks worked[16]. In particular, the sample contains information on real weekly earnings for workers ages 18 to 62, who participate in the labor force at least 40 weeks in the year, working at least 35 hours per week.

The March CPS lacks detailed information about country of birth[17]. Therefore, the Census is used to obtain information about the immigration process. I use the Censuses of 1980, 1990 and 2000 to obtain information about both the distribution of age and the number of migrants. This data is used to

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[14]For a discussion of these approaches see Acemoglu (2002).

[15]The intuition is that workers differ in their ability to accumulate human capital, and diminishing returns and opportunity costs limit the incentive of a worker with a given ability to devote time to human capital accumulation.

[16]Note that the March CPS has information about annual earnings, hours worked per week and weeks worked. Thus, it is possible to construct either hourly or weekly earnings. But, Autor et al. (2005) and Lemieux (2006) show that hourly earnings are noisy, and they are not available prior the year 1976. For that reason, I construct weekly earnings.

[17]This information becomes available in 1994.

construct the age and ability distribution of immigrants. Details about how I calibrate the immigrants' ability distribution are presented in Appendix A, but the general procedure is to choose the composition of the immigrants' ability types to match the growth rate of several moments of the immigrants' distribution of earnings. In particular I calibrate the fraction of immigrants that belong to each specific ability type.

I obtain the distribution presented in the right panel of figure 1 for twenty ability types, which is the number of ability types that I use throughout this paper. Card (2001) classifies immigrants into 6 occupational categories, ordered by the mean educational attainment of the workers belonging to that category. He finds that the distribution across occupation is similar to the one presented in figure 1.

Finally, the left panel of figure 1 displays the age distribution of immigrants for the years 1980, 1990 and 2000. Note that the average age of the immigrants has been decreasing over time. Immigrants' age distribution plays an important role in the impact of immigration on the earning distribution, because how workers adjust their human capital accumulation decision is associated with age, as it is discussed in section 7.1. Finally, another consideration about the age of the immigrants is related to the fact that younger immigrants arrive with lower educational attainment, but that does not necessarily implies that they arrive with lower ability to accumulate new human capital, because they could have been migrated before completing their optimal level of education.

4   Calibration of the Model

As was discussed in the previous section, human capital and raw labor are not observed directly in the data. For that reason the calibration procedure needs to rely on matching various moments of the U.S. earning distribution. The general idea is that given a set of parameters $\mathcal{P}_0$, I solve the model and simulate a sequence of cross section distributions of earnings for the period 1964 to 2005. Using this simulated data, I calculate a series of moments which I compare to moments from the March CPS. If the moments from the simulated sample differ too much from the U.S. moments, the set of parameters is updated[18] to $\mathcal{P}_1$, and a new iteration begins.

In a similar way to that in the standard Ben-Porath framework, human capital accumulation decisions depend on the SBTC process, current and future aggregate prices, the current level of human capital and

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[18]Using the model, I can calculate how different parameters affect the earning distribution, and hence how to update the parameters.

the discount factor. Therefore, calibrating the parameters associated with the distribution of ability, the elasticity of substitution between human capital and raw labor and the growth rate of the SBTC will suffice to match the simulated age-earnings profile and human capital accumulation path to the dynamics of the earnings distribution observed in the data[19].

The low level of immigration observed in the 1960s, as is shown in Table 3, reduces the influence of migration on the calibration of the parameters. In particular, parameters associated with the distribution of ability and the elasticity of substitution are calibrated using data from 1964 to 1974. Moreover, the growth rate of SBTC during the 1960s and 1970s was lower than in the 1980s and 1990s. Therefore the change in prices is relatively small at the beginning of the sample[20], which helps to improve the accuracy of the calibration.

The literature analyzing the dynamics of the wage structure finds that the growth rate of SBTC is not constant over time[21]. The consensus is that SBTC moved faster during the 1980s and slowed down in the second half of the next decade, although the growth rate was still faster than in the 1970s. Therefore, instead of calibrating the time series of the parameter[22] θ_t^H, I calibrate the growth rate of $\frac{\theta_t^H}{\theta_t^L}$ for the periods 1964 to 1979, 1980 to 1994, and 1995 to 2005.

4.1   Adjusting the Log-Wage Process

Guvenen and Kuruscu (2009) argue that earnings in this model can be interpreted as the systematic, or life cycle, component of a more realistic earnings process. More precisely, expressing earnings as

$$\log(\hat{y}_{a,t}^j) = \log(y_{a,t}^j) + \eta_{a,t}^j + \epsilon_{a,t}^j \tag{5}$$

allows a decomposition of log-earnings $\log(\hat{y}_{a,t}^j)$ into a systematic component $\log(y_{a,t}^j)$, a transitory shock $\epsilon_{a,t}^j$ and an auto-regressive shock $\eta_{a,t}^j$ that captures the observed serial correlation of earnings. This specification is similar to others used in this literature, and it captures the effect of idiosyncratic shocks in the earnings process[23]. Assuming that the transitory component and the auto-regressive component are

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[19]Remember that the discount factor is fixed at the $1/(1+r)$.

[20]This is documented in papers studying the dynamics of the U.S. wage distribution. See for instance Katz and Murphy (1992), and Autor et al. (2008).

[21]For a discussion of this finding see Acemoglu (2002).

[22]Remember that $\theta_t^L = 1 - \theta_t^H$, therefore the time series of θ_t^H is enough to characterize SBTC.

[23]See for instance Storesletten et al. (2001).

stationary implies that the variance of earnings observed in the data differs from the variance of earnings in the model, by only a constant. Furthermore, changes in the observed growth rate of the variance correspond to changes in the systematic component, and thus are captured by the model. Summarizing, after adjusting for a constant, the model captures movements in the level of the variance and its growth rate.

In the case of the mean of the log-earnings distribution, if the expected value of the shocks is equal to zero, the expected value of the observed log-earnings and the log-earnings from the model must coincide.

4.2 Calibration Procedure

Human capital accumulation paths differ across workers due to age and heterogeneity in the ability to learn. Moreover, earnings-experience profiles depend on the evolution of wages and the dynamics of human capital. Equation (2) indicates that potential earnings are affected by both movements in aggregate prices and changes in time invested. Assuming that from 1964 to 1974, the growth rate of the ratio $\frac{\theta_t^H}{\theta_T^L}$ was constant implies that changes in aggregate prices can be decomposed into changes in the aggregate levels of human capital and raw labor, and a linear time trend. The aggregate quantities only depend on the initial conditions and workers' human capital accumulation decisions. Therefore, the distribution of ability directly affects the shape of the earnings-experience profiles.

The ability parameter A^j is drawn from a uniform distribution with mean $E(A)$ and variance $\sigma^2(A)$. Figures 2 and 3 display how the simulated earnings profiles of one typical cohort change with the mean and the variance of the distribution of ability. The figures show the earnings-experience profile for 8 types of workers[24]. Note that some of the profiles are shorter because high ability workers spend some of their time in tertiary education, and therefore enter to the labor market later[25]. The left panel in both figures shows a base case. The right panel in Figure 2 shows how an increase in the mean of the distribution of ability affects the earning profiles. The right panel in Figure 3 displays the change in the earning profiles following an increase in the variance of the distribution of ability.

Figures 2 and 3 show that changing the ability parameters affects both the dispersion and the shape of the earning profiles for a specific cohort. In particular, the ability parameters change primarily the slope of the earning profiles in the first 15 years of work experience. This is consistent with the literature

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[24]The actual calibration uses 20 different types, equally spaced over the support of the distribution.

[25]There is no unemployment in this model, therefore experience is defined as age minus 18 minus years in college.

studying earnings profiles, for instance Murphy and Welch (1990) find that wages grow by 54% in the first 10 years in the labor market, the increase is just 18% in the next 15 years, and there is slight decline of less than 5% in the subsequent 15 years. However, the dispersion in the profiles is affected throughout the life cycle.

The average variance of the log-earnings profile is the moment chosen to match the dispersion of the earnings profile. Using the March CPS, the average cross sectional variance in the period 1964-1974 is 0.349. However, Section 4.1 illustrates the need to adjust the level of the variance simulated in order to match the one observed in the data. Guvenen (2009) calculates the variances associated with the transitory and the auto-regressive components of the earnings process, and concludes that it is necessary to subtract 0.135 from the observed variance, and thus the target for the simulated data is 0.214. Note that Guvenen (2009) calculates the variance of these innovations in a model that allows heterogeneity in the accumulation of human capital, which is consistent with the model presented in this paper.

The average growth rate of the median of the log-earnings distribution during the period 1964-1974 is 0.0157, which is the target used in the calibration. Note that as was discussed in Section 4.1, no further adjustment is needed.

Equation (4) shows that the dynamics of the relative price of human capital are associated both with SBTC and with changes in the ratio of the aggregate net quantities of human capital and raw labor. If ρ is equal to one and SBTC grows at a constant rate, the skill premium moves linearly in the period 1964-1974. However, if ρ is different from one, the ratio of the aggregate levels of human capital and raw labor affect the dynamics of the relative price of human capital. Furthermore, if ρ is far from one, changes in the aggregate quantities have a stronger effect on the relative price of human capital, and therefore the growth rate of the relative prices becomes less linear.

In order to capture the effects of the change in the aggregate quantities on the relative price, I calibrate the simulated data to match the average growth of the interquartile range of earnings for the period 1964-1974. If ρ is different from one, changes in the relative price of human capital are not linear, which affects the dispersion of the distribution of earnings, and consequently the interquartile range. The target of average growth of the interquartile range for the period 1964-1974 is 0.011.

The literature studying the dynamics of the U.S. wage distribution finds that SBTC plays an important role in the dynamics of the U.S. wage inequality. The fast increase in the wage dispersion during the

Table 1: Parameters from the Literature

Parameter		Value
r	interest rate	0.05
β	time discount rate	$1/(1+r)$
α	curvature of human capital function	0.71
T	years spent in the labor market	45
$\Delta \log(Z_t)$	growth rate of skill-neutral tech. change	1.5%

1980s, the simultaneous increase in the variance of wages within demographic and skill groups and other key features of the evolution of the wage distribution are evidence of a fast increase in the demand for more skilled workers[26]. In order to capture these features of the evolution of the wage distribution, the growth rate of SBTC is calibrated to match moments of the log-earnings distribution for three different time periods: From 1964 to 1979, from 1980 to 1994, and from 1995 to 2005. These periods coincide with the empirical findings of various paper surveyed in Acemoglu (2002).

In order to capture the change in earnings dispersion, I calibrate the model to match the average growth rate of the difference between the 90th and the 10th percentiles of the log-earnings distribution, for the periods discussed above. This measure of dispersion captures the dynamics of the tails of the distribution, and therefore captures the behavior of the high and low ability types.

Table 4.2 presents the parameters of the model that are taken from the literature. Assuming a constant interest rate of 5% is standard in the literature. The value for the curvature of the human capital accumulation function is consistent with previous studies. Most of the estimates for this curvature are between 0.7 and 0.95. Notice that increasing the value of α leads to larger adjustments in human capital accumulation decisions after changes in prices. Therefore, assuming a relatively low value of α assures that the changes in human capital are not driven by the choice of this parameter.

Table 4.2 displays the calibrated parameters. Note that the pattern of the growth rate of SBTC coincides with the pattern described in previous studies[27]. SBTC accelerated during the 1980s and slowed down after 1995.

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[26]Card and DiNardo (2002), and Lemieux (2006) present an alternative explanation associated with the decline in the real minimum wage.

[27]See for instance Autor et al. (2008) and Acemoglu (2002).

Table 2: Calibrated Parameters

$E(A)$	average ability	0.0423
$\sigma^2(A)$	variance of ability	0.0005
ρ	elasticity of substitution	0.3
Growth rate of SBTC by period		
$\Delta \log \left(\frac{\theta_t^H}{\theta_t^L} \right)$	from 1964 to 1979	0.00736
$\Delta \log \left(\frac{\theta_t^H}{\theta_t^L} \right)$	from 1980 to 1994	0.00756
$\Delta \log \left(\frac{\theta_t^H}{\theta_t^L} \right)$	from 1995 to 2005	0.00692

5 Model-Data Comparison

The last section described the calibration procedure. However, in order to accurately assess the impact of immigration on the U.S. earnings distribution, the model needs to fit the dynamics of the earnings distribution.

The literature studying the dynamics of the U.S. wage inequality has used the college premium as a measure of between-group inequality. Note that educational attainment is endogenous in this model, and therefore the calibration procedure cannot directly affect this measure of overall inequality. Figure 8 displays the evolution of the college premium calculated using the March CPS and the simulated data.

As was discussed in section 2 the elasticity of substitution between human capital and raw labor differs from the implied elasticity of substitution between college[28] and non-college educated workers. In particular, I calculate the implied elasticity of substitution between college and non-college using the standard specification[29] in the literature:

$$\log \left(\frac{w_t^c}{w_t^h} \right) = a_0 + a_1 t - \frac{1}{\phi} \log \left(\frac{N_t^c}{N_t^n} \right) + \epsilon_t \tag{6}$$

where w_t^c corresponds to the average earnings of college educated workers at time t, N_t^c is the number of

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[28]Note that in the simulated data, a worker is classified as college educated if she has been enrolled in tertiary education for at least four years.

[29]See for instance Katz and Murphy (1992).

those workers and w_t^h and N_t^h correspond to the same quantities for the high school workers. Using the March CPS data I obtain a elasticity of substitution between college and non-college workers of $\phi = 1.66$. The simulated data implies $\phi = 1.88$. Note that this number differs from the calibrated elasticity of substitution between human capital and raw labor, which is equal to $\frac{1}{1-\rho} = 1.42$.

Figure 5 displays the evolution of the 90/10 log-earnings differential for the March CPS and for the simulated data. Note that the graph shows the deviation from the initial value. As expected, the simulated data trace the general movements of the observed 90/10 differential.

5.1   Fit to Within-Groups Dynamics

One of the advantages of using human capital and raw labor as inputs in the production function is that the notion of skill premium is well defined. Moreover, educational attainment is endogenous in the model, and considering the high degree of heterogeneity across workers, it is possible to study the movements of the log-earning distribution within education-experience groups.

The literature studying the evolution of the U.S. wage inequality finds that residual[30] inequality has increase in the last 30 years (Autor et al. (2008)). The standard approach used to analyze the evolution of the within-group inequality is to estimate the residuals of a specification that includes controls for educational attainment, experience (or age), and other demographic characteristics like gender or race. Here, I estimate the residual inequality from a regression of log-earnings on four educational dummies interacted with a quartic function on experience[31].

Standard models using college and non-college workers as inputs in the production function cannot generate within-group inequality[32]. Figure 6 displays the evolution of the 90/10 residual differential for the March CPS and for the simulated data. Note that the simulated data generates less within-group dispersion than the actual data. However, the model captures some of the increase in the within-group inequality in log earnings observed since 1975.

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[30]The residual is the wage inequality unexplained after controlling for educational attainments and age or experience.

[31]This is the same specification used in Autor et al. (2008), and Katz and Murphy (1992).

[32]One alternative is to assume idiosyncratic shocks to generate the inequality within groups. But, in the present work the within-group inequality is in the structure of the model and does not rely on any shock.

5.2 Fit to Overall Dynamics

A more precise analysis of the dynamics of the U.S. wage inequality would need to account for changes in the composition of the labor force, or equivalently, to separate the cohort effect from the temporal (or price) effects. But, because this paper focuses on the impact of immigration on the earnings distribution, I present evidence suggesting that the model generates enough variation across cohorts and within cohorts to map the overall movements of the earnings distribution.

Figure 7 displays four panels with the changes in the log-earnings distribution by percentile for a number of periods of time. For instance, in the top left panel, each point represents the difference between a percentile of the log-earnings distribution in the year 2005 and its 1970 counterpart. Therefore, the figure shows the change of the entire distribution of log-earnings over that period of time. The top right panel displays the same exercise for the period 1970-1980, the bottom left panel uses the period 1980-1990 and the bottom right panel displays the period 1990-2005. Note that the simulated data captures the key trends for the different periods. For instance, the increase of the upper tail of the distribution in the period 1990-2005, or the change in the average growth rate between the 1970s and the 1980s.

6   Modeling Immigration

Immigration that occurred during the 1970s, 1980s and 1990s differs both in the age distribution of the immigrants, and in the relative size of the inflows. According to Census data, the number of immigrants arriving to the U.S. in the decade leading up the Census[33] corresponds to 6% of the U.S. population in 1980, 4% in 1990, and 4.5% in the 2000 Census[34]. For that reason, I explore the effect of each individual wave, as well as the overall effect when all the waves of immigrants are introduced. Table 3 displays the inflow and the stock of immigrants with respect to the U.S. population. Note that the inflow per decade has increased since the 1950s, and since the 1970s the inflow is bigger than the outflow, causing the stock of immigrants to increase over time.

In order to identify the effect of immigration on earnings and human capital accumulation, I assume that the influx of immigrants is unexpected and immigrants only arrive in the years 1980, 1990 and 2000.

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[33]For the 1980 Census, I consider immigrants arriving at any time before 1980, and not only in the previous decade. About a half of them arrived between 1979 and 1980.

[34]These percentages are with respect to the sample of full time male workers.

The reason for this assumption is that in a general equilibrium approach with perfect foresight about prices and inflow of immigrants, immigration would have no observable effect on prices, because workers will take current and future immigration into account when making their optimal decisions, and consequently they adjust their optimal human capital accumulation decision prior the influx of immigrants. Thus, this assumption allows me to isolate the direct effects of immigration from the subsequent changes in the economy observed in the period between each wave of immigrants.

In appendix D, I present results when immigrants arrive yearly. In this case, assuming immigration as an unexpected process is not realistic. Therefore, I present the results when natives use past immigration as proxy for future immigrations, and when natives use a more sophisticated bayesian update, to forecast the trend on the influx of immigrants. Naturally, the results are quantitatively smaller due to the smaller deviation from the optimal pre-immigration human capital accumulation plan, but are qualitatively the same.

As was discussed previously, immigration changes the relative prices of skills and that affects the optimal decisions of the individuals populating the economy. In order to disentangle the direct effect on prices and the feedback effect from the re-optimization process, I present a counterfactual experiment, in which immigrants arrive and join the labor market, but natives are not allowed to change their optimal decisions[35]. Note that in this case natives decisions are not consistent with the aggregate prices. This *restricted* counterfactual captures the effect of immigration through aggregate prices, while shutting down the feedback effect from the changes in the optimal decisions of natives.

7 Results

In this section, I examine the effects of immigration on earnings distribution and human capital accumulation decisions using a number of different approaches.

First, I examine the effect at the individual level. I compare the earnings of a counterfactual economy without immigration with the earnings of an economy in the presence of immigration. Moreover, I compare changes in the human capital accumulation decision and decompose the effect of immigration into its effect on aggregate variables and on individual variables.

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[35]For this experiment I make the somewhat unrealistic assumption that younger workers, born after immigration has affected the economy, follow the human capital accumulation decision associated with an economy without immigration. This allows me to compare the different counterfactual experiments for all ages.

Second, I detail a present discounted value analysis of the effect of immigration. This analysis highlights the heterogeneity of the effect of immigration across age and ability types. I also show the present discounted value analysis for different age and educational attainment groups. Moreover, using the present discounted value of the *restricted* counterfactual economy, I calculate the benefits of allowing workers to re-optimize their human capital accumulation decisions.

Finally, I revisit the results from empirical approaches, and I present evidence suggesting that the mechanism of adjusting human capital accumulation decision is consistent with results presented in the three papers using empirical methodologies to assess the impact of immigration.

7.1   Counterfactual Experiments

As was discussed in previous sections, immigration affects the relative price of human capital and raw labor. However, the change in the skill premium, defined as $\frac{P_t^H}{P_t^L}$, is small. Table 4 presents the average percentage change in the skill premium for different periods of time and for the different experiments. Note that, individual waves can only produce less than 1% variation. When the size of the cumulative influx of immigrants reaches around 10% (adding the size of the 1980 and 1990 immigration flows), the change in the skill premium reaches 2%.

The SBTC plays an important role. The 1990 wave of immigration is only 70% of the size of that in 1980, but the effect of the 1990 wave on the skill premium, measured over the decade following 1990, was more than 80% the size of the change in skill premium associated with the wave in 1980. The main difference between these two experiments is that in 1990 SBTC was at the peak of its acceleration, while in 1980 SBTC was just starting to accelerate. The intuition for this difference is that when the technology is more skill biased, for instance after ten years of high rates of growth in SBTC, changes in the composition of the labor force induce larger changes in the skill premium. This is because, if relative human capital becomes more scarce, each unit is relatively more productive, and therefore the skill premium increases by more.

The *restricted* counterfactual produces qualitatively similar results. However, the change in the skill premium is smaller because workers cannot re-optimize their decision . At first this may seem counterintuitive. Consider, however, that when workers face higher skill prices most of them will decide to increase their investment in human capital, temporarily reducing the actual amount of aggregate human capital

available for production but thereafter further increasing the supply of human capital. Note that this effect is equivalent to the lag between SBTC and changes in observed earnings discussed in Heckman et al. (1998) and Guvenen and Kuruscu (2009).

7.2 Effects by Ability Type

Using counterfactual experiments, I investigate the effect of immigration by ability type. Moreover, I present results for different cohorts, thus it is possible to study how the effect of immigration changes across age and ability.

Workers use the fraction of time invested in accumulating human capital to mitigate, or in some cases augment, the changes in the skill premium. For instance, a worker with a low ability to learn, and consequently a relatively low level of human capital, would observe a decrease in her relative earnings after a increase in the skill premium. She faces the following tradeoff. She may increase the time invested in accumulating human capital leading to higher future earnings. However, with the new prices, each fraction of time used in the accumulation of human capital is now more costly. Considering that she has low ability to learn, her decision would be to decrease the amount of time dedicated to accumulating human capital and therefore closing the gap between observed and potential earnings, and attenuating the negative effect of the drop in her relative earnings.

Conversely, a worker with high ability to learn facing the same tradeoff would be better off investing more time in accumulating human capital, and therefore magnifying her benefit from the small change in the skill premium. Note that this effect is observable in the present discounted value because in the time periods just after immigration results in new relative prices, a high ability worker would invest more time accumulating human capital, and therefore observed earnings can potentially go down for a few periods.

Finally, very high ability workers, or workers that already have very high levels of human capital, may decide not to increase their time invested in human capital accumulation, because for them it is more costly to do so. In particular, using the immigrant arrivals of 1980 and 1990, the average change of the present discounted value across all cohorts for workers with the second highest ability type is 3.1% higher than for the highest ability type. But if I only consider the five youngest cohorts, I find the opposite, and the highest ability worker benefits more than the second highest ability type by 2.1%. The intuition is that younger cohorts can make a larger adjustment to their optimal decisions in response to changes in

the skill premium, and there is less dispersion in their levels of accumulated human capital[36].

Table 5 presents the percentage change in the present discounted value (PDV) for different ability types and different cohorts. Note that the change is defined as the difference between the PDV associated with an economy with immigration and the PDV associated with the economy without immigration. As for previous results, I present this analysis for each individual wave of immigrant arrivals and for the sum of consecutive waves.

Consistent with the intuition discussed before, low ability types suffer a decrease in their PDV. Older cohorts are less exposed to the impact of immigration, and thus the loss in welfare is reduced.

Middle ability types exhibit interesting patterns in the changes of their PDV. First, younger cohorts benefits from the change in the skill premium induced by immigration. Older cohorts suffer a loss in their PDV with a pattern similar to the one exhibit by the low ability types. However, the drop in PDV in this case is roughly 20% smaller. The intuition is that ability to adjust is crucial in this particular ability group.

Immigration produces benefits for the high ability workers. The more they can adjust their investment, the more they benefit. Therefore, age and benefits from immigration are negatively correlated for this group. Note that an increase of 1% in the average skill premium (see Table 4) produces an increase of the PDV of more than 4% for the younger cohorts presented in Table 5. This multiplicative effect comes through the re-optimization of the human capital accumulation decisions. This effect is clearly observed when we compare Table 5 with the same PDV calculated in the *restricted* counterfactual presented in Table 6.

The results using the *restricted* counterfactual are qualitatively similar. Low ability workers suffer losses in their PDV, high ability workers benefit from immigration, and middle ability workers can benefit or lose from the change in the skill premium depending on their age at the time of the wave of immigration. However, the most important difference is that the losses and the gains are smaller for this experiment. This is consistent with the intuition that workers use the investment time dedicated to accumulation of human capital to amplify (in the case of benefits) the effect of a change in the relative prices induced by immigration.

Note that the change in skill premium for the *restricted* counterfactual is smaller than the change in

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[36]Individuals with high ability to learn are the ones that enrolled in tertiary education. In particular, the highest ability type always completes college in this model.

skill premium observed in the standard experiment. Therefore, the losses for the low ability workers are expected to be smaller in the *restricted* experiment. Moreover, Table 4 shows that the change in the skill premium in the standard is more persistent than the one associated with the *restricted* counterfactual. Thus, these patterns on the skill premium imply the bigger losses observed in the PDV for the standard experiment.

Comparing these two tables allows me to disentangle the effect associated with the change in prices and the effect associated with the reaction of workers after a change in prices. The average loss in PDV across cohorts for the low ability types presented in Table 5, only the 15% corresponds to the change in PDV displayed in Table 6. Therefore, the change in aggregate prices can only explain 15% of the variation in PDV for the low ability workers. For the middle ability types, the *restricted* counterfactual can explain 30% the variation in the PDV, but for the high ability workers, this explanatory power reaches 75%. Overall, the *restricted* counterfactual explains 40% of the change in the PDV associated with immigration.

Another way to asses how important is the ability to adjust is calculating how much the PDV calculated using the *restricted* counterfactual can explain the PDV presented in Table 5 for different cohorts. For the cohort of 1943, the restricted change in PDV corresponds to 76% of the change presented in the unrestricted one. For the youngest cohort, only 5% of the variation can be explained by the *restricted* counterfactual. This is consistent with the notion that younger cohorts adjust more to changes in the relative prices.

Finally, calculating the average change in the PDV associated with the waves of immigration in 1980 and 1990 across all types and across the cohorts from 1943 to 1973, I find that immigration produces an overall increase in the PDV of 0.4%. This gain in welfare is mainly driven by the gains of the highest ability types that amplify the effect on the skill premium produced after an influx of immigrants arrives to the economy. This overall change in PDV drops to a loss of -0.17% when only the ten lowest ability types are considered.

Tables 7, and 8 present a similar decomposition, but now using educational attainment categories. The findings from the previous tables are present in this new decomposition. High school workers suffer a drop in their PDV due to immigration, college educated workers benefits from immigration, and only the younger college dropouts can increase their PDV after the waves of immigration have affected the

economy.

Note that the benefits for the college workers are higher than the benefits of the highest ability types presented in Table 5. The intuition is that workers that before immigration were at the margin of increase the time enrolled in tertiary education[37] take advantage of the higher skill price and stay longer in college, producing a significant increase in their earnings. Thus, changes at the extensive margin of educational attainment produces effects on earnings significantly larger than the ones observed in the restricted counterfactual.

7.3   Immigration and SBTC

Immigration has continually changed the U.S. labor market, as is shown in Table 3. Therefore, it is difficult to identify its influence in the observed earnings distribution. Moreover, every day immigrants arrive and join the labor market. This makes modeling immigration in the context of the model presented above a complex task.

In order to deal with these difficulties, I present a number of different experiments to highlight important aspects of the immigration process, how it affects the labor market, and the significance of the problem of measuring immigration[38].

First, I show in appendix B that without SBTC, immigration is not able to produce enough variation in the earnings distribution to match the U.S. data. This result is consistent with Heckman et al. (1998), where a 25% increase in the low-skilled workers it is not enough to replicate the movements in the wage distribution. Therefore, SBTC must also be included in the model. However, calibrating SBTC requires the use of data from 1964 to 2005, a period during which the rate of immigration was increasing and consequently affecting the moments used for the calibration procedure.

Second, I explore the differences between one experiment where I add immigrants to the labor market and another where I subtract them from the labor market. In the first, immigration affects the economy through the incorporation of workers into the labor force and through the change in the composition of human capital and raw labor. The weakness of this experiment is that the data used for the cali-

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[37]The parameter κ plays a crucial role in this decision. Remember that individuals can be enrolled in tertiary education, or on the job learning with investment time between 0 and κ.

[38]An alternative way to think about this issue is to consider that the supply of workers is measured with error. If that is the case, I show that the calibration and the mechanism presented in this paper, are robust to small amounts of measurement error.

bration already include the effects of immigration on prices. The second experiment takes this problem into account, and thus the counterfactual experiment corresponds to a study of the economy without immigrants. However, the second experiment has a different but related weakness. The drawback of the second experiment is that the calibrated SBTC used in the model economy without immigration is biased, because it has been obtained from data from a world with immigration.

Both experiments produce qualitatively similar results. Therefore I conclude that the results using the first experiment type, that is, immigration as an addition to the labor force, highlight the feed back effect of the re-optimization in human capital accumulation decisions on prices, when immigrants arrive to the economy, and change the skill premium. Appendix C presents the tables of the key results when immigration is modeled as a subtraction of workers from the labor market.

The ideal experiment consists on annually adding immigrants to the economy, and at the same time calibrate the parameter associated with SBTC. However, this experiment is unfeasible considering that only decennial data is available[39]. It would be necessary make assumptions about the annual pattern of immigration, which can contaminate the results of the calibration procedure. Equation (4) shows that changes in the labor supply and SBTC have similar effects on the aggregate prices P_t^H and P_t^L. Therefore, assumptions regarding the pattern of immigration likely will affect the calibration of the SBTC parameters. For these reasons, I only use the data available, and the experiments described previously, to calibrate the growth rate of SBTC. Note that when immigration is introduced yearly, as presented in appendix D, SBTC is the main force behind the evolution of the earning distribution, because in this case the size of the inflow of immigrants is not enough to produce the variations on skill premium that we observe in the data.

8   Concluding Remarks

In this paper I develop a general equilibrium model to analyze the impact of immigration on both native wages and the human capital accumulation decision. This model has a number of features that allows me to study the direct effect of immigration on the relative price of human capital and the indirect effect through changes in the human capital accumulation decisions of workers. Some of these features include heterogeneity in the ability to learn, overlapping generations, and a CES production function with skill

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[39]Only since the mid 1990s the March CPS contains detailed information about immigration status

biased technical change.

In this economy, workers are heterogeneous in their ability to accumulate human capital due to variation in their ability to learn. This feature is crucial when studying the impact of immigration. On one hand, immigration increases the skill premium and this effect is amplified in individuals of high ability. In contrast, low ability workers try to attenuate the adverse effects of immigration in their relative earnings by decreasing human capital investment in order to increase observed earnings.

The significant amount of heterogeneity in this model allows me to decompose the effect of immigration across age and ability types. Moreover, using a series of counterfactual experiments, I separately analyze the effect of immigration on prices, and on human capital accumulation for a number of different age and ability categories.

I find that older workers were moderately affected by immigration. The relatively large change in the present discounted value of younger workers was associated with the introduction of more significant changes in their human capital accumulation paths. For the younger workers, only 5% of the variation of the present discounted value of earnings was attributable to the change in relative prices produced by immigration.

Low skilled workers suffered losses in their present discounted value. Only 15% of these losses were associated with the change in prices, and the remaining losses corresponded to their difficulty in adjusting to the change in relative prices.

Finally, I find that more than 60% of the variation in the present discounted value of earnings came from changes in human capital accumulation decisions. Moreover, changes in educational attainment could produce benefits of more than 6% in the present discounted value. The overall effect of immigration on the present discounted value is 0.4%. However, immigration produces a 0.17% drop in the welfare of low skilled workers.

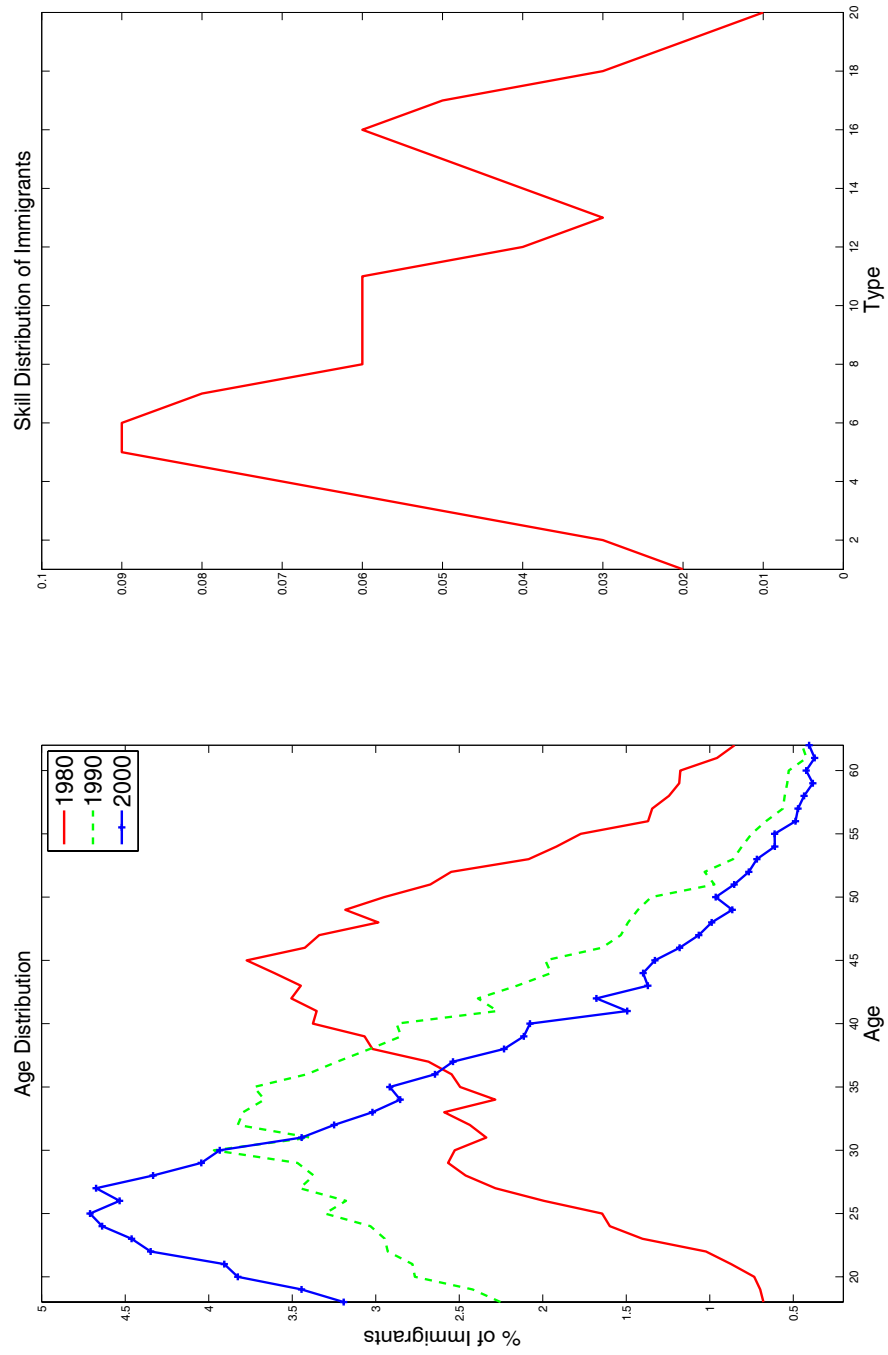Figure 1: Immigrants' Distribution of Age and Ability

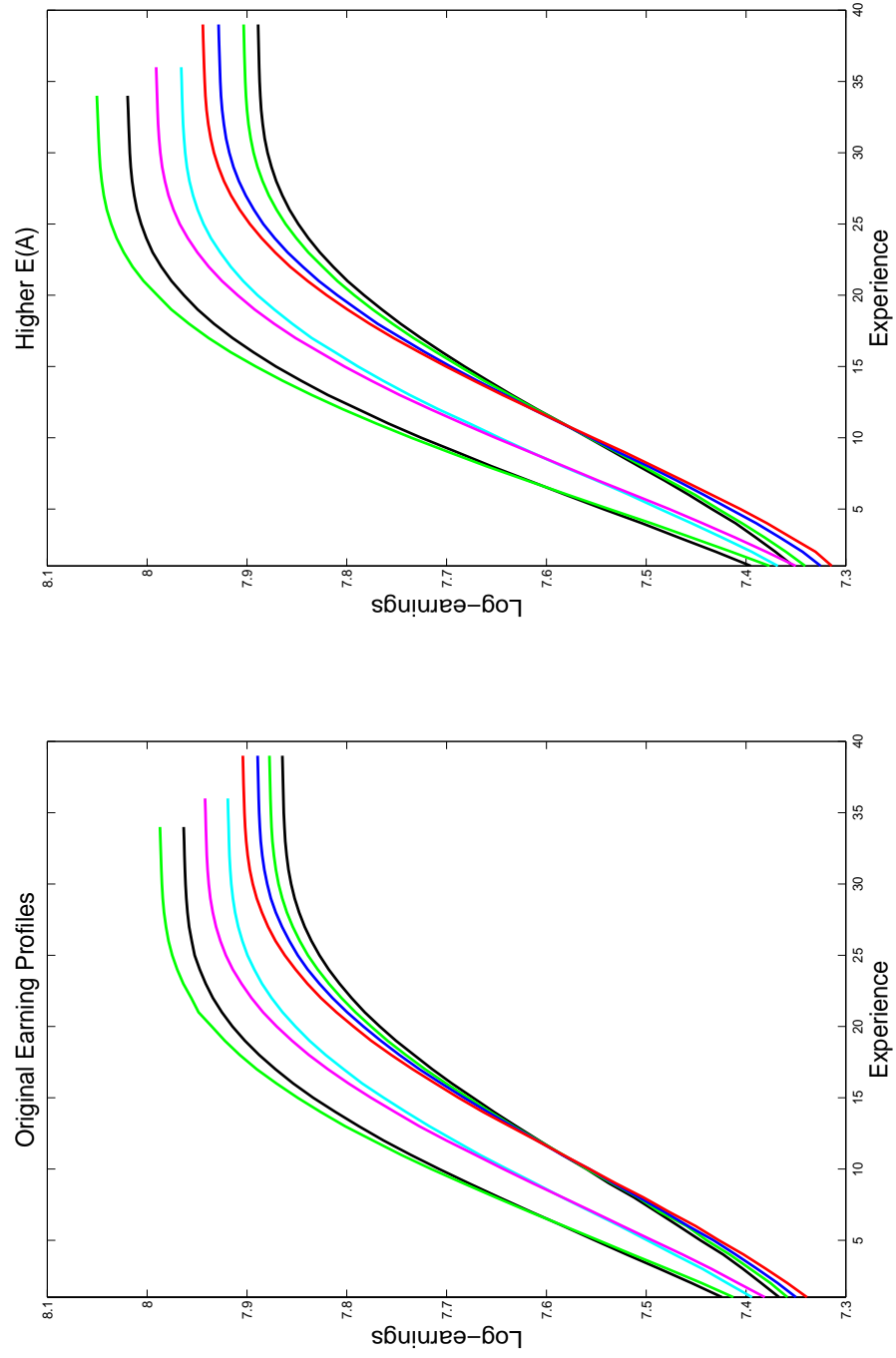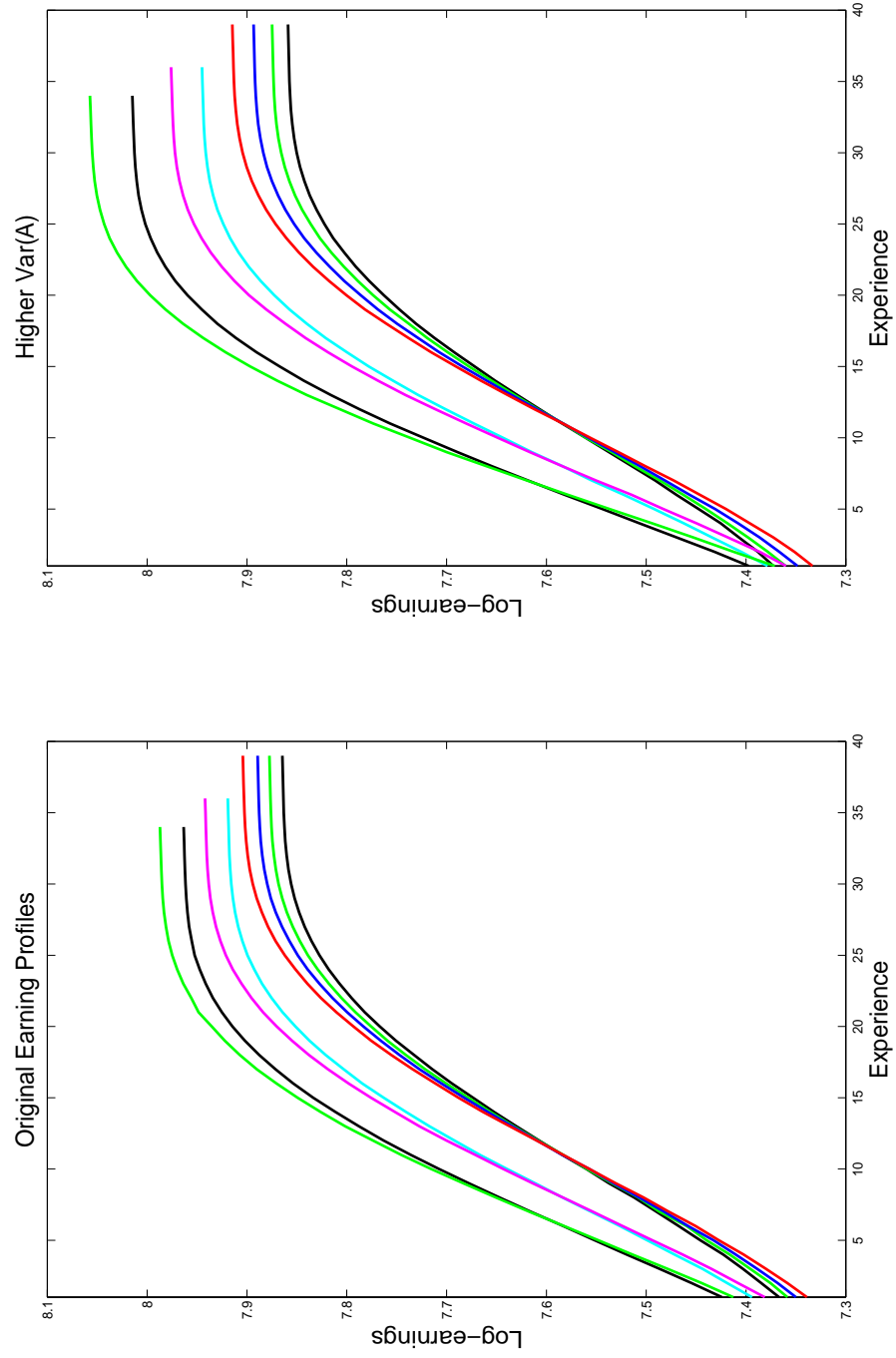Figure 2: Calibration of Ability Distribution I

Figure 3: Calibration of Ability Distribution II
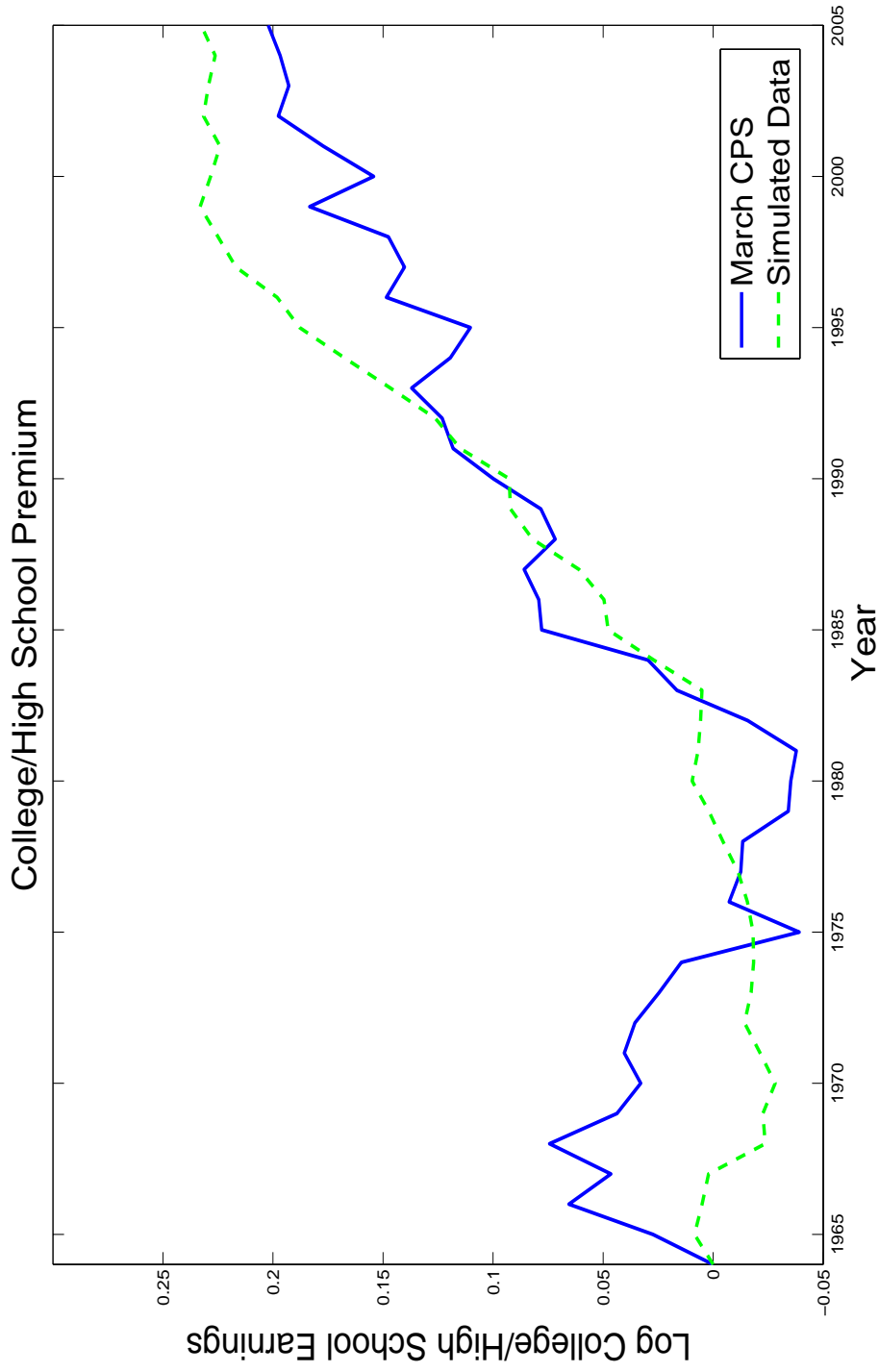
Figure 4: College/High School Premium

Figure 5: 90/10 overall inequality

Figure 6: 90/10 residual inequality

Figure 7: Fit to the Data

Table 3: Stock and flow of Immigration in the U.S.

year	Percentage of U.S. population foreign-born	Percentage of U.S. population arriving during previous decade
1950	6.9	0.7
1960	5.4	1.5
1970	4.7	1.7
1980	6.2	2.7
1990	7.9	3.0
2000	10	3.0

[a] *Source:* U.S. Census Bureau.

Table 4: Impact of Immigration on the Skill Premium

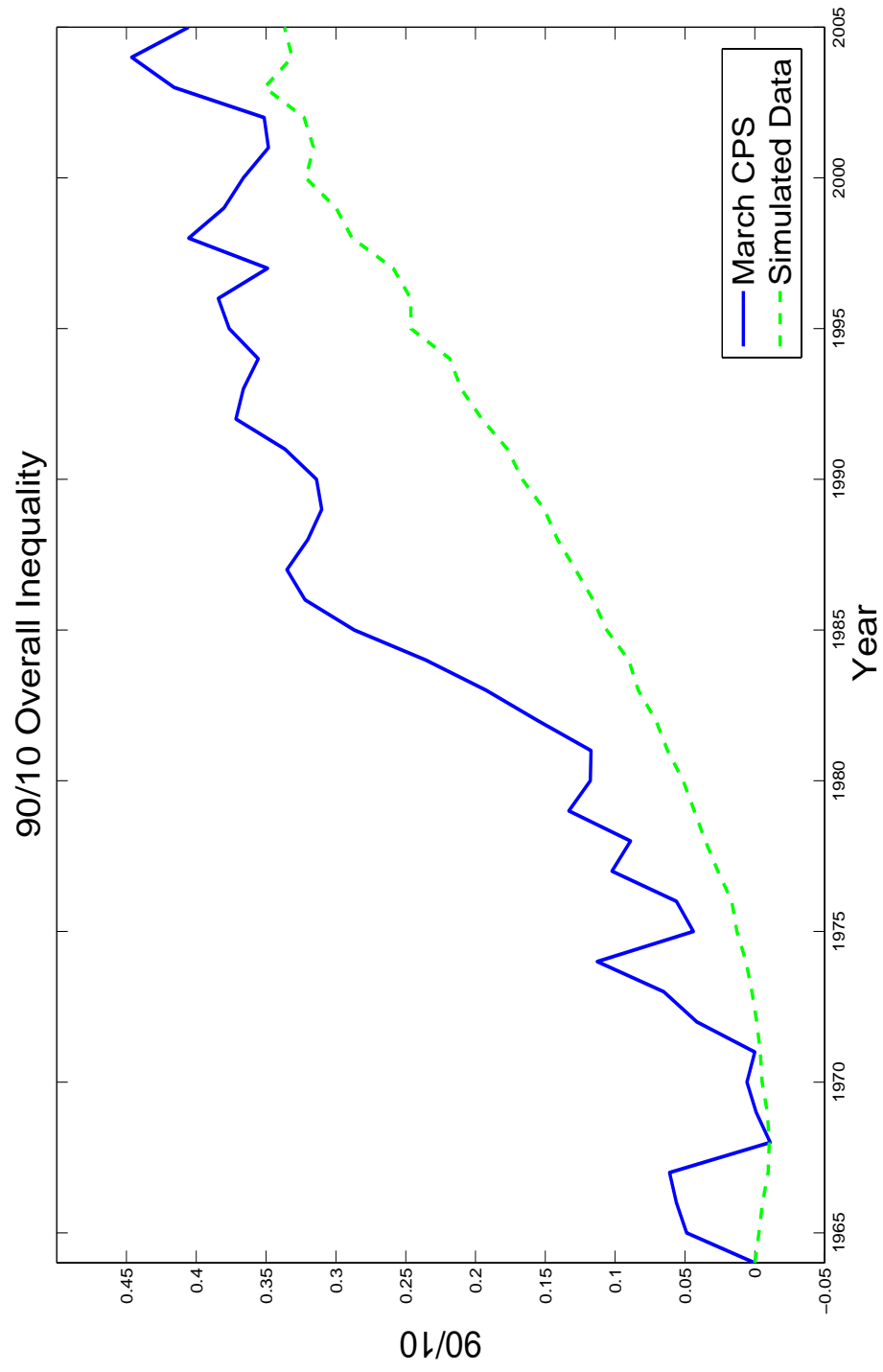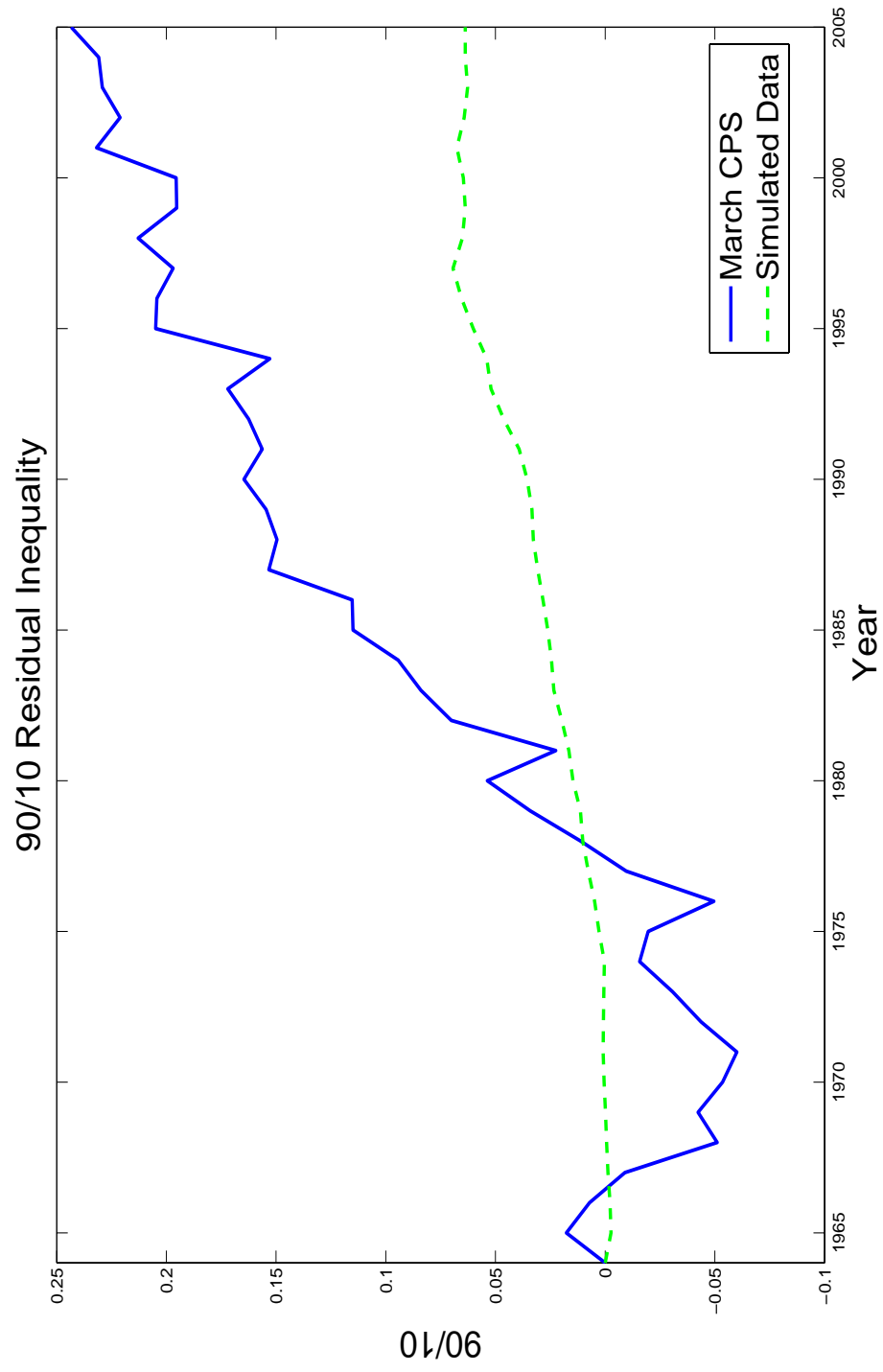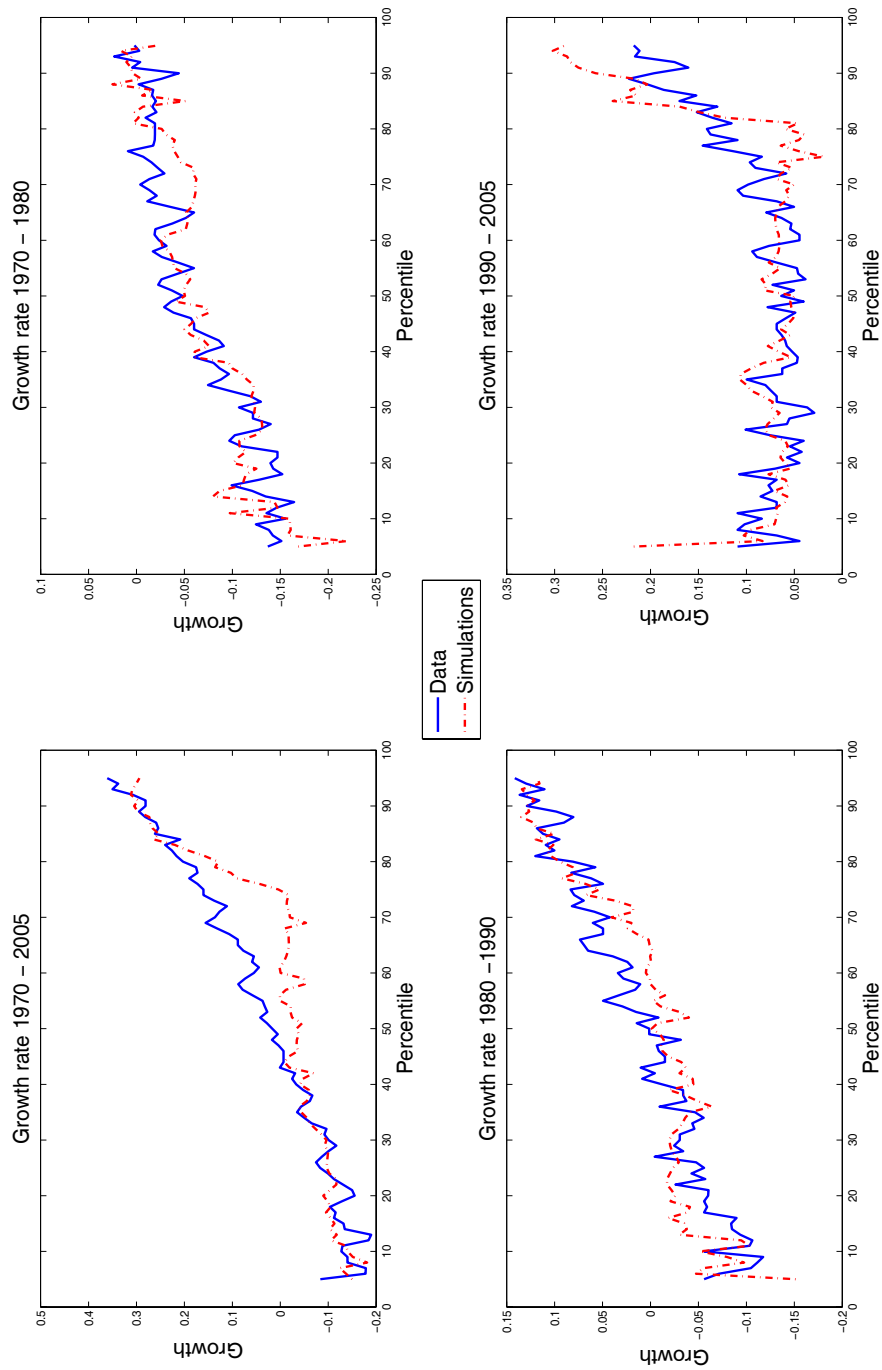|	Immigration Experiments		
	Wave 1980	Wave 1990	Waves 1980 and 1990
Average change in skill premium (%)1980-1990	0.81	–	0.81
Average change in skill premium (%)1990-2000	0.54	0.68	2.45
Average change in skill premium (%)1990-2005	0.49	0.63	2.08
Average change in skill premium (%)1980-2005	0.61	–	1.59

	Restricted Counterfactual		
	Wave 1980	Wave 1990	Waves 1980 and 1990
Average change in skill premium (%)1980-1990	0.80	–	0.80
Average change in skill premium (%)1990-2000	0.39	0.65	1.11
Average change in skill premium (%)1990-2005	0.15	0.53	0.89
Average change in skill premium (%)1980-2005	0.40	–	0.86

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Table 5: Impact of immigration in terms of % change in PDV. Ability types.

| | Immigration Experiments | | |
	Wave 1980	Wave 1990	Waves 1980 and 1990
Low Ability types (1-3)			
Cohort 1943	-0.042	-0.020	-0.082
Cohort 1953	-0.073	-0.036	-0.127
Cohort 1963	-0.124	-0.067	-0.226
Cohort 1973	-0.10	-0.126	-0.308
Medium Ability types (11-14)			
Cohort 1943	-0.028	-0.014	-0.012
Cohort 1953	-0.062	-0.028	-0.096
Cohort 1963	-0.102	-0.048	-0.201
Cohort 1973	0.007	0.008	0.012
High Ability types (17-20)			
Cohort 1943	0.070	0.033	0.111
Cohort 1953	0.093	0.059	0.274
Cohort 1963	2.415	0.577	2.743
Cohort 1973	4.718	4.905	5.039

Table 6: Impact of immigration in terms of % change in PDV. *Restricted* Counterfactual. Ability types.

	Immigration Experiments		
	Wave 1980	Wave 1990	Waves 1980 and 1990
Low Ability types (1-3)			
Cohort 1943	-0.016	-0.009	-0.030
Cohort 1953	-0.008	-0.003	-0.033
Cohort 1963	-0.002	-0.001	-0.043
Cohort 1973	-0.001	-0.001	-0.020
Medium Ability types (11-14)			
Cohort 1943	-0.005	-0.003	-0.012
Cohort 1953	-0.002	-0.001	-0.011
Cohort 1963	-0.001	-0.000	-0.022
Cohort 1973	0.115	0.076	0.034
High Ability types (17-20)			
Cohort 1943	0.097	0.052	0.149
Cohort 1953	0.131	0.101	0.218
Cohort 1963	0.132	0.217	0.286
Cohort 1973	0.284	0.401	0.440

Table 7: Impact of immigration in terms of % change in PDV. Educational attainment.

	Immigration Experiments		
	Wave 1980	Wave 1990	Waves 1980 and 1990
High School			
Cohort 1943	-0.040	-0.019	-0.090
Cohort 1953	-0.071	-0.035	-0.121
Cohort 1963	-0.121	-0.064	-0.220
Cohort 1973	-0.087	-0.106	-0.293
College Dropouts			
Cohort 1943	-0.026	-0.012	-0.015
Cohort 1953	-0.061	-0.027	-0.089
Cohort 1963	-0.094	-0.043	-0.195
Cohort 1973	0.304	0.301	0.012
College			
Cohort 1943	0.045	0.022	0.055
Cohort 1953	0.033	0.033	0.149
Cohort 1963	1.631	0.397	1.749
Cohort 1973	7.343	7.656	6.973

Table 8: Impact of immigration in terms of % change in PDV. *Restricted* Counterfactual. Educational attainment.

	Immigration Experiments		
	Wave 1980	Wave 1990	Waves 1980 and 1990
	High School		
Cohort 1943	-0.014	-0.008	-0.027
Cohort 1953	-0.006	-0.004	-0.030
Cohort 1963	-0.002	-0.002	-0.039
Cohort 1973	-0.001	-0.001	-0.023
	College Dropouts		
Cohort 1943	-0.003	-0.002	-0.008
Cohort 1953	-0.001	-0.001	-0.007
Cohort 1963	-0.001	-0.000	-0.018
Cohort 1973	0.116	0.078	0.037
	College		
Cohort 1943	0.065	0.035	0.100
Cohort 1953	0.093	0.075	0.152
Cohort 1963	0.091	0.157	0.189
Cohort 1973	0.233	0.298	0.308

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A   Calibrating Immigrants' Ability Distribution

One of the challenge of the calibration procedure is to calibrate the immigrants' distribution of ability. In order to do so, I use information from the Census data for the years 1980, 1990 and 2000 to obtain three cross sections of the immigrants' earnings distribution.

Note that the information about immigrants' educational attainment is available, but this data may not be comparable with the educational system in the U.S. Moreover, some of countries exhibit constraints in the supply of higher education, which can further contaminate this information.

Therefore, it is necessary to use a different approach to calibrate the immigrants' ability distribution. The model predicts that age-earnings profile differ according to ability level. High ability individuals present steeper profiles, once they are out of school. Thus, the growth rate of earnings, for different ages, is informative of the underlying ability parameter.

The cross sections allows me to calculate the growth rate of log-earnings for 5 different age categories[40]. Moreover, I calculate the growth rate for each decile on each age category. For example: first, I obtain

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[40]I split the age range using 10 years intervals.

the first decile of the log earnings distribution of workers with ages between 18 and 27 years old in the year 1980; second, I obtain the first decile of the log earnings distribution of workers with ages between 28 and 37 years old in the year 1990; then, I calculate the growth rate of the first decile for immigrants born between 1957 and 1966.

Calculating the growth rate of all of these moments allows me to study different pieces of the age-earnings profiles. In particular, I obtain information on the steepness and dispersion of the earnings profile for different ages and for workers with potentially different abilities. Using the simulated data, I calibrate the immigrants' ability distribution to match the moments calculated above. Note that, I only need to calibrate the fraction of each ability type.

B   Immigration Explaining the Dynamics of the U.S. Earning Distribution

Equation (4 shows that immigration and SBTC affect the aggregate prices in similar ways. Therefore, it is hard to disentangle how much of the change in the dispersion of the earnings distribution is attributable to inflows of immigrants, and how much is associated with the dynamics of the SBTC.

Heckman et al. (1998) found that immigration is unable to produce enough variation in the skill price to explain the dynamics of the earnings distribution. They noted that a 25% increase in the supply of low skilled workers is not enough to create the change observed in the data. These results are consistent with the findings presented in Table 4. Immigration only produces small changes in the skill premium.

Figure 8 presents the changes in the 90/10 log earnings differential from 1980 to 2000, for two different sets of data. The first is the March CPS, and the second is from a counterfactual economy without SBTC, but with the waves of immigration described in section 6. It is easy to observe that the amount of dispersion produced solely by immigration accounts for half of the growth in earnings inequality observed in the data. In conclusion, SBTC must be included in the model to account for some of the increase in the dispersion observed in the earnings distribution.

Figure 8: 90/10 overall inequality. Counterfactual.
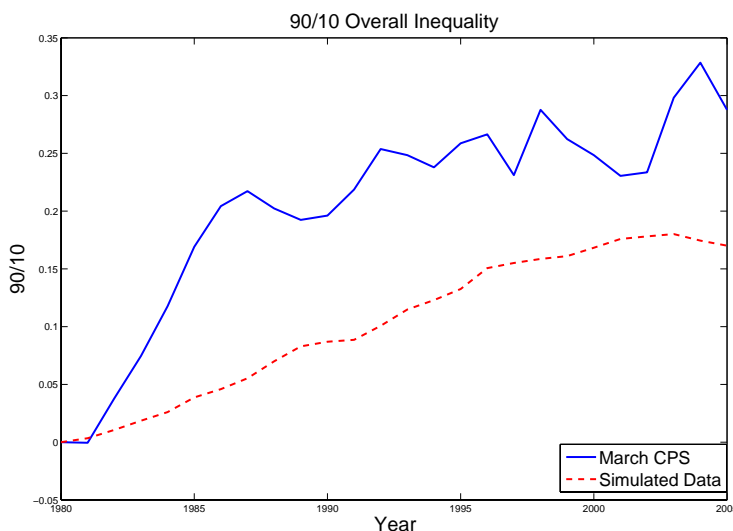
C   Subtracting Immigration from the Economy

In section 2.7.4, I discuss the difficulty of calibrating the parameters associated with SBTC. The data from the March CPS already contains information affected by immigration. According to our model, individuals change their human capital accumulation decisions after immigration changes the labor supply. Therefore, earnings information from the March CPS captures the adjusted earning profile of the individuals living in the economy.

In order to asses how important is the bias associated with this issue, I simulate an alternative counterfactual. The experiment consists in subtract immigration from the economy, instead of adding immigrants to the labor force. For brevity, I present only the results associated with the change in the PDV, and the skill premium when immigrants arrive in 1980 and 1990. Tables 9 and 10 displays the results for this alternative counterfactual.

Note that the results are smaller than the one presented in tables 4 and 5. In this alternative counterfactual, immigration and SBTC cause opposite effects. On one hand, SBTC increases the skill premium, and consequently the earnings of high ability workers. On the other hand, less immigration increases the demand for low ability workers, decreasing the skill premium and increasing the PDV of those workers. However, qualitatively the results are the same. High ability workers benefit from immigration, meanwhile

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Table 9: Impact of Immigration on the Skill Premium. Counterfactual

	Waves 1980 and 1990
Average change in skill premium (%)1980-1990	0.61
Average change in skill premium (%)1900-2000	1.95
Average change in skill premium (%)1990-2005	1.43
Average change in skill premium (%)1980-2005	1.07

low ability, and older workers are not able to adjust enough to counter the effect of immigration.

D Yearly Waves of Immigration

Throughout the paper I have assumed that immigration is unexpected and arrives only in 1980, 1990 and 2000. However, the actual process of immigration occurs on a yearly basis.

Table 11 presents the variation in the PDV of lifetime earnings when immigration is introduced every year, according to the data from the Census. I calculate the change in PDV under three possible scenarios. First, natives never expect immigration. They always assume that is one time shock, adjust their human capital accumulation decision, but they do not forecast any future immigration. They do this adjustment every year. This experiment allows me to compare with the decennial shock presented in the main body of the paper. In these cases, immigration is unexpected.

The second and third scenarios present a more realistic adjustment for the natives. The results associated with *Rational I*, correspond to the case in which natives forecast future immigration, using the current one. That is, they assume that the distribution of immigrants that they will receive the following year is the same distribution currently observed.

Finally, the column *Rational II* presents the variation on the PDV when natives use past information to produce a trend of immigration influx. They update this trend when new information arrives, using a bayesian rule.

As expected, the results are quantitatively smaller, but they preserve qualitatively the results presented in the main body of the paper. Note that this results indicate the non-linearity in the natives response to shocks of different size.

Table 10: Impact of immigration in terms of % change in PDV. Counterfactual. Ability types.

	Waves 1980 and 1990
	Low Ability types(1-3)
Cohort 1943	-0.019
Cohort 1953	-0.112
Cohort 1963	-0.189
Cohort 1973	-0.156
	Medium Ability types (11-14)
Cohort 1943	-0.018
Cohort 1953	-0.086
Cohort 1963	-0.176
Cohort 1973	0.031
	High Ability types (17-20)
Cohort 1943	0.108
Cohort 1953	0.178
Cohort 1963	2.934
Cohort 1973	5.888

Table 11: Impact of immigration in terms of % change in PDV. Yearly Waves. Ability types.

	Immigration Experiments			
	Waves 1980 and 1990	Yearly waves	Rational I	Rational II
Low Ability types (1-3)				
Cohort 1943	-0.082	-0.025	-0.025	-0.024
Cohort 1953	-0.127	-0.039	-0.039	-0.038
Cohort 1963	-0.226	-0.070	-0.070	-0.067
Cohort 1973	-0.308	-0.068	-0.067	-0.063
Medium Ability types (11-14)				
Cohort 1943	-0.012	-0.003	-0.003	-0.003
Cohort 1953	-0.096	-0.037	-0.038	-0.036
Cohort 1963	-0.201	-0.064	-0.067	-0.066
Cohort 1973	0.012	0.016	0.018	0.016
High Ability types (17-20)				
Cohort 1943	0.111	0.060	0.061	0.062
Cohort 1953	0.274	0.032	0.009	0.009
Cohort 1963	2.743	0.764	0.643	0.638
Cohort 1973	5.039	2.163	1.756	1.420