THE FADING DYNAMISM OF THE US LABOR MARKET: THE ROLE OF DEMOGRAPHICS

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ABSTRACT. We study the increasing sluggishness of the U.S. labor market over the last three decades. Population aging and rising educational attainment are found to be the two most important driving forces behind the downward trends in labor market turnover rates. Empirically, these two demographic characteristics explain between 75 and 90 percent of the total decline in the aggregate unemployment inflow rate from 1976 to 2011. We examine theoretically why and how age and education affect the dynamism of worker flows. Since older and more-educated workers possess more job-specific human capital, the compositional shifts in the labor force induce an increase in the accumulated job-specific human capital. This in turn reduces incentives to destroy jobs and drives the secular trends in labor market fluidity. We show that a relatively stylized search and matching model with endogenous separations, featuring higher amounts of on-the-job training for more-educated workers and skill obsolescence for old unemployed workers, can go a long way in quantitatively accounting for the observed empirical patterns.

Keywords: labor market turnover, worker flows, human capital, demographic trends.
JEL Classification: E24, J11, J24, J63.

1. INTRODUCTION

The U.S. labor market has been historically hallmarked as an extremely dynamic one, especially when compared to its European counterparts that have been frequently diagnosed as being sclerotic. Over time, such a view has become increasingly less warranted. Indeed, several measures of labor market turnover point to the fading dynamism of the U.S. labor market. First, worker flows, as exemplified by the behavior of the unemployment flow rates, have been trending down for the last three decades. Second, job flows, as summarized by job creation, job destruction, and job reallocation measures, share a similar declining pattern. Nevertheless, the literature still lacks an empirically grounded theoretical explanation that could encompass the aforementioned downward trends in labor market flows. Identifying such an explanation is an important task, since actions of policymakers – for example when addressing issues like

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long-term unemployment – depend to a large extent on the nature of economic mechanisms behind the observed trends.

The main focus of this paper is the analysis of secular trends in worker flows. To this end, we quantitatively investigate the role of changing demographic structure in explaining the declining unemployment flow rates. In particular, we document that population aging and rising educational attainment play a crucial role in explaining the downward trend in the aggregate unemployment inflow rate, since older and more-educated workers experience lower inflows into unemployment. The decomposition exercises performed using microdata from the Current Population Survey show that between 75 and 90 percent of the total decline in the aggregate unemployment inflow rate from 1976 to 2011 can be attributed to demographics. The empirical results also show that the effect of demographics on shaping the behavior of the aggregate unemployment outflow rate is more limited, given the small differences in outflow rates observed across demographic groups.

In order to further our understanding of these empirical developments, we need to identify a plausible economic mechanism that can explain why and how age and education lead to a lower unemployment inflow rate in the first place. We argue that older workers on average posses more job-specific human capital, which is also true for the more-educated workers due to the tight complementarity between formal schooling and on-the-job training. Following the seminal insight of Becker (1964), higher amounts of job-specific human capital reduce incentives to destroy jobs and subsequently lead to lower labor market turnover.

Our findings show that a relatively stylized search and matching model with endogenous separations, featuring higher amounts of on-the-job training for more-educated workers and skill obsolescence for old unemployed workers, can go a long way in quantitatively accounting for the observed empirical patterns. More precisely, we parametrize the model by using micro evidence on initial on-the-job training by education group and on wage losses upon displacement by age group. The simulation results reveal that the model can account for the observed cross-sectional differences in unemployment flow rates across education and age groups. Moreover, the model also demonstrates that the observed changes in the composition of the labor force towards older and more-educated workers can explain virtually all of the decline in the unemployment inflow rate that we observe in the data.

Several recent papers provide evidence on declining labor market turnover in the U.S. over the last three decades. Downward trends in worker flows have been documented for unemployment inflows as measured by the Current Population Survey (CPS) unemployment duration data (Davis et al., 2010) and by the CPS gross flows data (Davis et al., 2006, Fujita, 2012), and for employer-to-employer transitions as measured by the CPS gross flows data (Fallick and Fleischman, 2004, Rogerson and Shimer, 2011, Mukoyama, 2013) and by the Longitudinal Employer-Household Dynamics (LEHD) data (Hyatt and McEntarfer, 2012). Additionally, Mukoyama and Şahin (2009) report a substantial increase in the average duration of unemployment relative to the unemployment rate, whereas Lazear and Spletzer (2012a) find a decrease in labor market churn, when analyzing the Job Openings and Labor Turnover Survey (JOLTS) data. Falling job flows have been observed by Faberman (2008) and Davis et al.

(2010), while Davis (2008), Davis et al. (2012), and Hyatt and Spletzer (2013) present related evidence on declining labor markets flows in general.

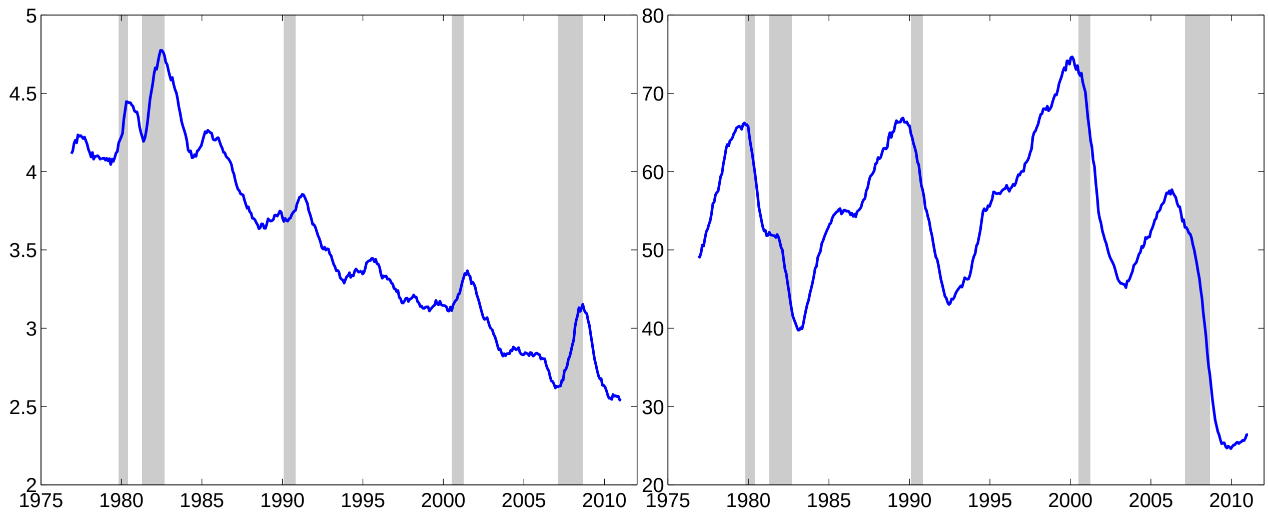
Despite the vast evidence on declining labor market mobility, very few papers attempted to provide an explanation for the observed low-frequency trend. Two notable exceptions are Davis et al. (2010) and Fujita (2012). Particularly, Davis et al. (2010) argue that declines in job destruction intensity can lead to lower unemployment inflows; according to their results, the observed decline in the quarterly job destruction rate in the U.S. private sector can account for 28 percent of the fall in unemployment inflows from 1982 to 2005. One possible interpretation, which they offer, is a secular decline in the intensity of idiosyncratic labor demand shocks, but they also do not rule out other interpretations, like greater compensation flexibility over time or increased adjustment costs. Fujita (2012) proposes an explanation according to which the economic turbulence has increased over time. In particular, if the risk of skill obsolescence during unemployment has risen, then workers should be less willing to separate and accept lower wages in exchange for keeping the job. As mentioned by Fujita (2012), this mechanism can explain the decline in the separation rate qualitatively, while, absent a direct empirical measure for turbulence, it is more difficult to assess the quantitative success of the model. Moreover, the model predicts declining wage losses due to unemployment and a higher fraction of workers switching from experienced to inexperienced (which can be related to the occupation switching of unemployed in the data) – the empirical evidence on both model's predictions seems to be mixed.

Following this introduction, Section 2 provides empirical evidence on the importance of demographics in shaping the behavior of aggregate unemployment inflow and outflow rates. Section 3 presents the model. Section 4 contains the parameterization of the model and presents the simulations results. Finally, Section 5 concludes.

2. Empirical Evidence

In order to provide evidence on the behavior of worker flows over time, we construct empirical measures of transition rates between different labor market states. We focus our analysis on the period since 1976 onwards, guided by the availability of CPS microdata. Our preferred empirical measures consist of unemployment inflow and outflow rates, which are based on the unemployment duration data. More precisely, we follow Shimer (2012) and compute unemployment inflow and outflow rates by using time-series data for employment, unemployment, and short-term unemployment (unemployment with duration of less than 5 weeks). We prefer this procedure over gross flows data – which also include movements in and out of the labor force – since the latter suffer from the misclassification error. Importantly for the purpose of our analysis, Poterba and Summers (1986) find that the misclassification error varies across demographic groups, with the error being particularly large for young people. Nevertheless, as shown in Appendix A, our main empirical findings are robust to both the two-state and the three-state decomposition of worker flows.

Figure 1 summarizes the evolution of the aggregate unemployment inflow and outflow rate since 1976 onwards. One can observe a stark secular decline in the unemployment inflow rate, which dropped by roughly two percentage points over last three decades. On the other hand, a trend in the unemployment outflow rate is less apparent, although one should allow for the possibility that a period of relative macroeconomic stability between 1984 and 2007 (the so-called "Great Moderation") had masked underlying trends, which then become apparent during the latest recession. Indeed, as shown by Mukoyama and Şahin (2009), the average duration of unemployment – roughly speaking, the inverse of the unemployment outflow rate – *relative to the unemployment rate* increased over the last three decades.



(A) Unemployment inflow rate

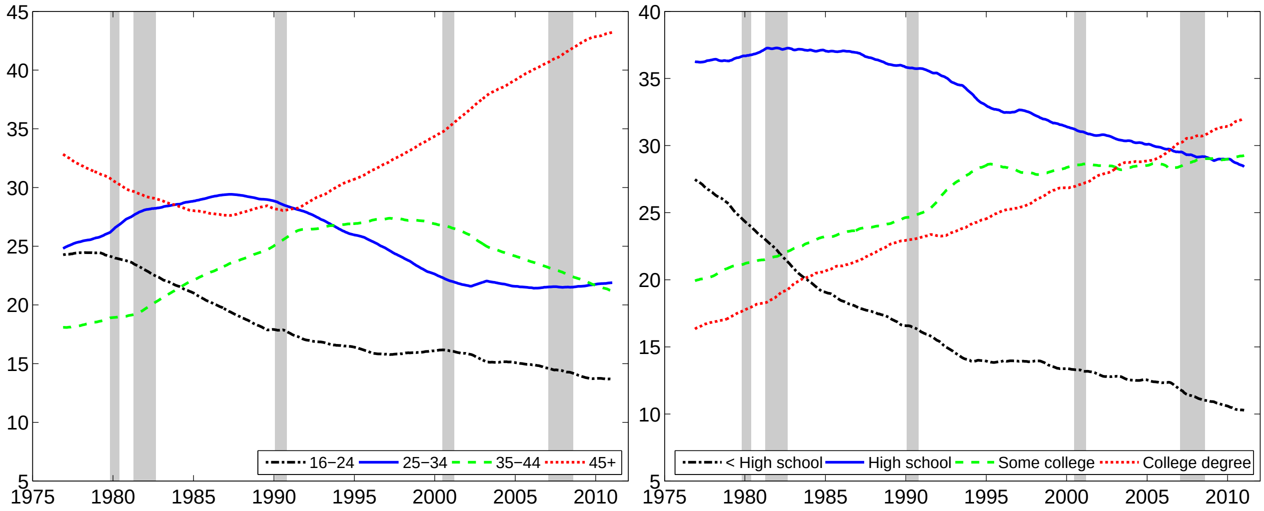
(B) Unemployment outflow rate

FIGURE 1. Unemployment transition rates

Notes: We plot twelve-month moving averages of monthly data. The sample period is 1976:01 - 2011:12. All variables are constructed from CPS microdata. Shaded areas indicate NBER recessions.

One likely explanation for the observed secular decline in unemployment (in)flow rates relates to demographics and this paper quantitatively examines how much of the decline can be accounted for in this way. As it is well known, the demographic structure of the U.S. labor force has changed dramatically over the post-war period. These changes have been mostly driven by two demographic characteristics: age and education. First, as a result of the baby boom, the labor force share of young people peaked in the mid-1970s and the labor force share of people with at least 45 years started to surge in the beginning of 1990s (see Figure 2a). Second, at the end of 1970s about two thirds of the U.S. labor force had at most a high school degree, while nowadays nearly 60 percent of the population have spent at least some years in college (see Figure 2b).

In order to quantify the importance of demographics shifts in shaping the behavior of aggregate unemployment flows, we proceed by dividing the U.S. labor force into four age groups (16-24, 25-34, 35-44, 45+) and four education groups (less than high school, high school, some college and college degree). Overall, we consider sixteen demographic groups and Ω represents the set of all of them. Figure 3 reveals substantial differences in the unemployment inflow rate by age and education. In particular, the inflow rate is decreasing in both dimensions and the differences are sizable and persistent over time. With respect to the unemployment outflow rate, we observe some differences by age – in particular a very high outflow rate for the youngest group – and virtually negligible differences by education.



(A) Age (B) Education

FIGURE 2. Structure of the U.S. labor force

Notes: We plot twelve-month moving averages of monthly data. The sample period is 1976:01 - 2011:12. All variables are constructed from CPS microdata. Shaded areas indicate NBER recessions.

2.1. *Importance of Demographic Shifts for the Aggregate Unemployment Inflow Rate*

Notice that the theoretical aggregate unemployment inflow rate, s_t, can be computed as the employment-weighted average of inflow rates for each demographic group. In particular, let S_t be the aggregate number of separations and E_t the aggregate number of employed in period t. With index i denoting group-specific variables, we get:

$$s_t \equiv \frac{S_t}{E_t} = \frac{\sum_{i\in\Omega} S_{it}}{E_t} = \frac{\sum_{i\in\Omega} E_{it} s_{it}}{E_t} = \sum_{i\in\Omega} \omega^e_{it} s_{it},$$

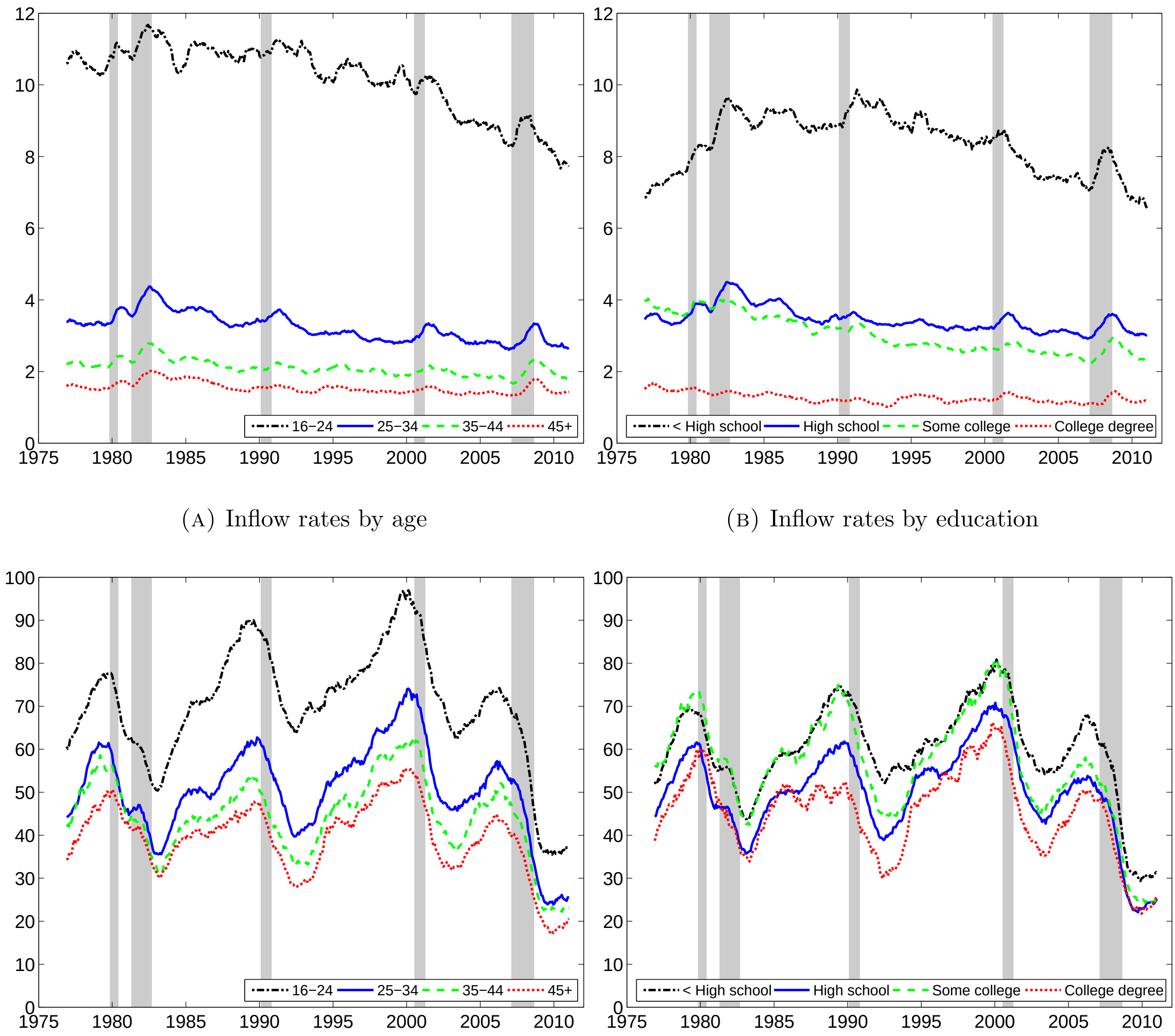
where ω^e_{it} stands for the fraction of employed workers in group i at time t. We examine the role of changing demographic structure in explaining the behavior of the aggregate inflow rate by performing three decomposition exercises.

The first decomposition consists of computing the genuine inflow rate by using *fixed employment weights* – in calculations we use the average of 1976 as our base period t_0.[1] The main advantage of this decomposition is its straightforward interpretation, as it allows us to answer the following question: "How would have the aggregate inflow rate behaved, if demographics had remained unchanged over time?". The underlying assumption is that, if the structure of the employment pool had remained unchanged at some initial shares $\left\{\omega^e_{it_0}\right\}_{i\in\Omega}$, the behavior of the group-specific inflow rates $\{s_{it}\}_{i\in\Omega}$ would have been the same as the one that we observe from t_0 to t_1. Thus, we define the genuine inflow rate at time t_1 as:

$$s^G_{t_1,t_0} \equiv \sum_{i\in\Omega} \omega^e_{it_0} s_{it_1}.$$

The second counterfactual exercise consists of *decomposing changes* in the aggregate inflow rate between periods t_0 (in calculations we again use the average of 1976 as our base period)

[1]Shimer (1999) provides a similar adjustment for the case of the unemployment rate.



(A) Inflow rates by age

(B) Inflow rates by education

(C) Outflow rates by age

(D) Outflow rates by education

FIGURE 3. Description of the U.S. labor market by demographic group

Notes: We plot twelve-month moving averages of monthly data. The sample period is 1976:01 - 2011:12. All variables are constructed from CPS microdata. Shaded areas indicate NBER recessions.

and t_1 into two terms:

$$\Delta s_{t_1,t_0} = s_{t_1} - s_{t_0} = \sum_{i\in\Omega} \Delta\omega^e_{it_1}\bar{s}_i + \sum_{i\in\Omega} \bar{\omega}^e_i \Delta s_{it_1},$$

where $\bar{s}_i = \frac{1}{2}(s_{it_0} + s_{it_1})$ and $\bar{\omega}^e_i = \frac{1}{2}\left(\omega^e_{it_0} + \omega^e_{it_1}\right)$.[2] The first term measures the change in the demographic composition of the economy between t_0 and t_1. The second term captures the change in the group-specific inflow rates between t_0 and t_1.

The third and last decomposition that we perform is based on the cross-sectional methodology proposed by *Olley and Pakes (1996)* for analyzing industry productivity. For the purpose of

[2]A similar decomposition has been recently used by Lazear and Spletzer (2012b) to analyze changes in the unemployment rate over time.

our analysis we decompose the aggregate inflow rate in period t into two components:

$$s_t = \bar{s}_t + \sum_{i\in\Omega}(\omega^e_{it} - \bar{\omega}^e_t)(s_{it} - \bar{s}_t),$$

where now $\bar{s}_t$ and $\bar{\omega}^e_t$ represent unweighted means in some period t. The second component is a covariance that informs us about whether the employment pool is disproportionately formed by individuals with higher inflow rates. It is worth noting that this last decomposition exercise is especially suited to overcome the criticism that the previous two exercises might be affected by the selection of the base period.

Figure 4 summarizes the results. In particular, Figure 4a depicts the evolution of the actual aggregate unemployment inflow rate together with the three counterfactual inflow rates, which keep the demographic structure constant over time. As it can be inferred from this figure, the behavior of the aggregate unemployment inflow rate during the recent decades has been highly influenced by the changes in the demographic structure of the economy. Once we control for the demographics shifts, the downward trend in the inflow rate nearly vanishes. More precisely, Figure 4b shows the actual changes in the aggregate unemployment inflow rate together with the contribution of demographics to those changes. The aggregate unemployment inflow rate has declined 1.6 percentage points during the whole period, from an average of 4.1 percent in 1976 to an average of 2.5 percent in 2011. Depending on the counterfactual exercise used, demographics can explain between 1.2 percentage points (Olley & Pakes decomposition) and 1.4 percentage points (decomposition of changes) of that decline. To sum up, all three decompositions suggest that demographics play a pivotal role in explaining the downward trend in the aggregate unemployment inflow rate over the last three decades, explaining between 75 to 90 percent of the total decline.

2.2. *Importance of Demographic Shifts for the Aggregate Unemployment Outflow Rate*

This section quantifies the role played by demographics in explaining the evolution of the aggregate unemployment outflow rate. To do so we follow the same structure as for the case of the aggregate unemployment inflow rate and we perform three decomposition exercises.

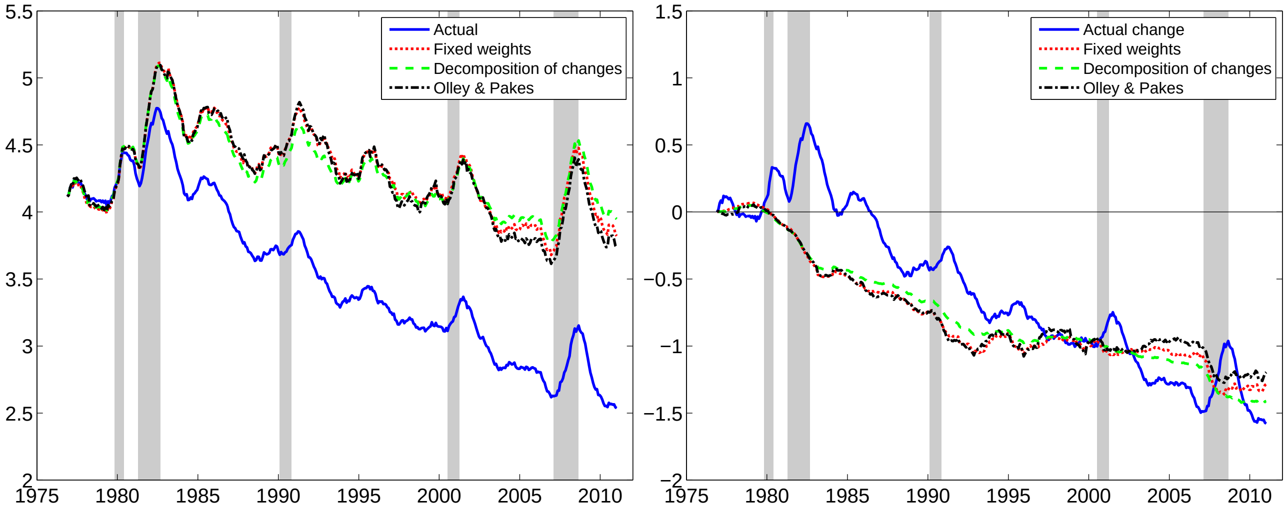
Similar as before, the theoretical aggregate unemployment outflow rate, f_t, can be computed as the unemployment-weighted average of the outflow rate for each demographic groups. In particular, let H_t be the aggregate number of hires and U_t the aggregate number of unemployed in period t. With index i denoting group-specific variables, we get:

$$f_t \equiv \frac{H_t}{U_t} = \frac{\sum_{i\in\Omega} H_{it}}{U_t} = \frac{\sum_{i\in\Omega} U_{it} f_{it}}{U_t} = \sum_{i\in\Omega}\omega^u_{it} f_{it},$$

where ω^u_{it} stands for the fraction of unemployed workers in group i at time t.

The first counterfactual exercise that we perform consists of computing the genuine outflow rate in an analogous way as we did for the genuine inflow rate, that is by keeping unemployment weights fixed over time (again we use the average of 1976 as our base period t_0):

$$f^G_{t_1,t_0} \equiv \sum_{i\in\Omega}\omega^u_{it_0} f_{it_1}.$$



(A) Actual vs. counterfactual - levels

(B) Actual change and contribution of demographics

FIGURE 4. The effect of demographics on the aggregate unemployment inflow rate

Notes: We plot twelve-month moving averages of monthly data. The sample period is 1976:01 - 2011:12. All data variables are constructed from CPS microdata. Shaded areas indicate NBER recessions. We consider 16 demographic groups in order to construct the counterfactual exercises. All counterfactuals are constructed to have the same level as the actual aggregate unemployment inflow rate in the first period.

The second counterfactual exercise consists of decomposing changes in the aggregate unemployment outflow rate between period t_0 and t_1 into two terms:

$$\Delta f_{t_1,t_0} = f_{t_1} - f_{t_0} = \sum_{i\in\Omega} \Delta\omega^u_{it_1}\bar{f}_i + \sum_{i\in\Omega} \bar{\omega}^u_i \Delta f_{it_1},$$

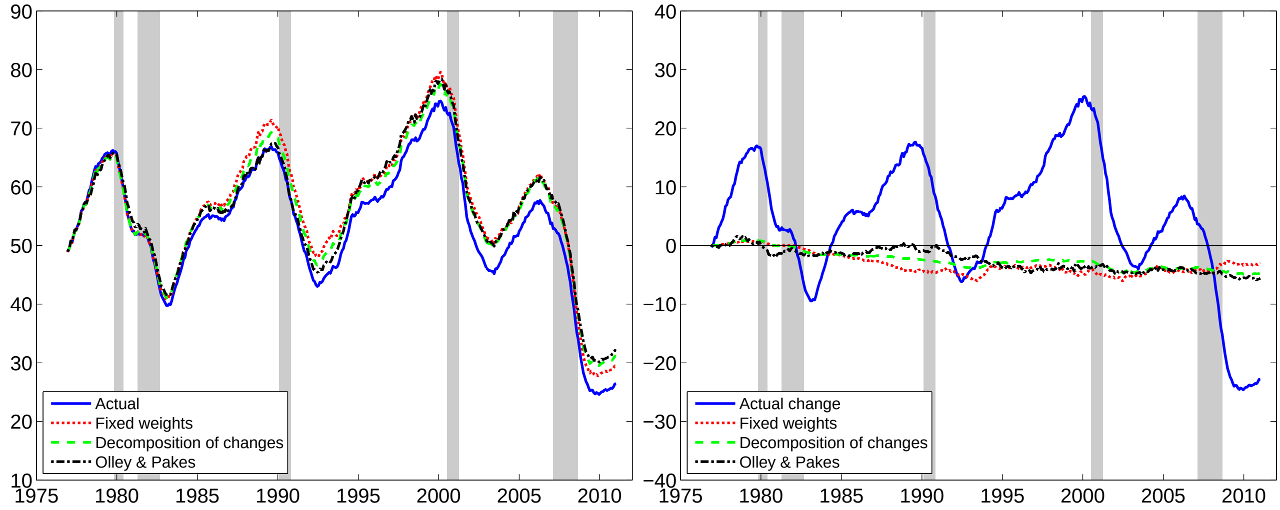
where $\bar{f}_i = \frac{1}{2}(f_{it_0} + f_{it_1})$ and $\bar{\omega}^u_i = \frac{1}{2}\left(\omega^u_{it_0} + \omega^u_{it_1}\right)$.

Finally, the last exercise consists of applying the Olley and Pakes (1996) decomposition to the aggregate unemployment outflow rate:

$$f_t = \bar{f}_t + \sum_{i\in\Omega}(\omega^u_{it} - \bar{\omega}^u_t)(f_{it} - \bar{f}_t)$$

where $\bar{f}_t$ and $\bar{\omega}^u_t$ represent unweighted means in some period t. Similar to the case of the inflow rate, the outflow rate can be decomposed into a component that captures the unweighted mean and a second component, a covariance term, that informs us whether the unemployment pool is disproportionately formed by individuals with higher outflow rates.

The results are summarized in Figure 5. Overall, the effect of demographics in shaping the behavior of the aggregate unemployment outflow rate is limited, as anticipated given the small differences in outflow rates across demographic groups. More precisely, Figure 5b shows that demographics contributed only between 3 percentage points (fixed weights decomposition) and 6 percentage points (Olley & Pakes decomposition) to a decline in aggregate unemployment outflow rate over time.



(A) Actual vs. counterfactual - levels

(B) Actual change and contribution of demographics

FIGURE 5. The effect of demographics on the aggregate unemployment outflow rate

Notes: We plot twelve-month moving averages of monthly data. The sample period is 1976:01 - 2011:12. All data variables are constructed from CPS microdata. Shaded areas indicate NBER recessions. We consider 16 demographic groups in order to construct the counterfactual exercises. All counterfactuals are constructed to have the same level as the actual aggregate unemployment outflow rate in the first period.

2.3. *Discussion of Empirical Findings*

Our empirical findings show that demographic shifts importantly influenced the changing behavior of the aggregate unemployment inflow rate over time, whereas the effect on the aggregate unemployment outflow rate was relatively muted. The latter result is not surprising given relatively small differences between group-specific outflow rates as illustrated in Figure 3. Similar results regarding small differences in unemployment outflows between demographic groups were also obtained by Elsby et al. (2010), who additionally report relatively modest heterogeneity in unemployment inflows and outflows by gender – for this reason, we decided to abstract from that demographic characteristic.[3] Our reported measures of unemployment inflows and outflows are based on the unemployment duration data, in order to avoid misclassification errors inherent in gross flows data. Nevertheless, we also calculated employment-unemployment and unemployment-employment flow hazard rates and find very similar results in terms of differences between demographic groups – see Figure 6 and Tables 5 and 6 in Appendix A. Moreover, in a recent paper Fujita (2012) shows that roughly one-half of the decline in the separation rate (obtained from gross flows data) can be accounted for by the aging of the labor force (he abstracts from adjusting for the education composition).

One important assumption underlying our counterfactual decompositions was that changes in the labor force composition have no effect on group-specific flow hazard rates. Such an assumption is common to all demographic adjustments of the unemployment rate and other labor market variables. Moreover, as Figure 3 shows, despite huge demographic shifts observed over the last three decades, group-specific flow hazard rates have remained strikingly stable

[3]For a recent analysis of the gender gap in the unemployment rate, see Albanesi and Şahin (2012).

over time. Indeed, if one worried that an increase (or decrease) in the share of certain group would substantially affect that groups's flow hazard rate, then Tables 7 and 8 in Appendix A, which provides unemployment inflow rates for 16 demographic groups and reveals remarkable stability in those rates over time, illustrate that empirically such concerns appear to be invalid.

One could also ask whether we can meaningfully distinguish between relative contribution of age and education in accounting for observed aggregate shifts in flow rates. Such an exercise would be difficult because of the mix effects.[4] For example, one of the main reasons why teenagers experience high unemployment inflow rates, is precisely because teenagers on average have lower education – and lower education leads by itself to higher unemployment inflow rates. In any case, as Table 1 indicates, it appears that both age and education are roughly equally important for demographic adjustments of the aggregate unemployment inflow rate – even after controlling for one characteristic, the other characteristic still results in substantial heterogeneity in unemployment inflows. Similarly, we calculated fixed employment weights counterfactuals separately for age and education and both decompositions give similar magnitude of the effect (but of course, they do not sum up to the total counterfactual due to mix effects).

TABLE 1. Unemployment inflow rates, 1976-2011 (means, in percent)

	Education level				
Age group	< High school	High school	Some college	College degree	Aggregate
16-24	18.85	8.57	6.95	4.32	10.15
25-34	7.47	3.81	2.86	1.49	3.23
35-44	4.77	2.39	1.88	0.98	2.11
>45	2.82	1.57	1.39	0.81	1.55
Aggregate	8.32	3.45	3.05	1.27	3.52

Finally, any demographic adjustment crucially relies on how detailed demographic groups are. Indeed, if we were to use a greater number of demographic groups, we would, at least in theory, obtain bigger effects of demographics. However, we calculated the same counterfactual decompositions for six age groups (16-19, 20-24, 25-34, 35-44, 45-54, 55+) and four education groups, and the results remain almost unaffected. Moreover, due to data limitations we sometimes run into problems, since with a finer decomposition some demographic groups simply do not have enough observations in the CPS microdata.

3. MODEL

Our goal here is to construct the simplest possible model that can illustrate the economic mechanisms behind the age and education effects on unemployment flows. Our main working hypothesis is that human capital accumulation drives differences in labor market experiences across different demographic groups. In our model economy workers differ across two main dimensions: age and education. Regarding age, we consider two age groups: young and old. Young workers need to obtain their job-specific skills through the process of initial on-the-job training, while old workers in existing jobs already possess job-specific human capital.[5] The

[4]Similar argument for the case of adjustments in the unemployment rate was put forward by Shimer (1999).

[5]In a more general model, this "job-specific human capital" could also be thought of as representing effects related to job-hopping of young people before finding a good match.

most important difference between young and old workers is that, upon displacement, old worker not only lose their job-specific skills (like young workers do) but also experience a permanent deterioration of their general human capital (this modeling choice captures cases where the worker's current industry permanently disappears and hence the worker needs to switch to another industry). Regarding education, we follow our previous work (Cairó and Cajner, 2011) and assume that the main economic mechanism for distinguishing between people with different education levels relates to required on-the-job training. More precisely, following vast empirical evidence on strong complementarities between education and training, we assume that people with higher education need more initial on-the-job training.[6]

3.1. *Environment*

We model a discrete-time economy containing a finite number of segmented labor markets indexed by education level i. The size of each segmented labor market is exogenously determined by its labor force l^i. For simplicity, we only consider two types of education levels, low and high, with sizes l^L and l^H respectively. We further normalize the total size of the labor force to one, thus $l^L + l^H = 1$.

In each segmented labor market workers can be either young or old. Young people become old with probability ρ and old people retire with probability δ, at which point they are replaced by young unemployed. Young workers are endowed with one unit of general human capital. As they get old, their general human capital capital remains unchanged as long as they remain employed. However, upon displacement, old workers suffer a permanent deterioration of their general human capital. Thus, other things equal, an old unemployed worker produces a fraction κ less than a young worker upon re-employment.[7]

In each segmented labor market, there is a continuum of measure l^i of risk-neutral and infinitely-lived workers that maximize their expected discounted lifetime utility defined over consumption, $\mathbb{E}_t \sum_{k=0}^{\infty} \beta^k c_{t+k}$, where $\beta \in (0,1)$ represents the discount factor. Workers can be either employed or unemployed. Thus, we abstract from labor force participation decisions as all unemployed workers are looking for a job. Employed workers receive a wage, while unemployed workers have access to home production with a value of b consumption units per period. The parameter b reflects the opportunity cost of working.[8]

The model also features a large measure of firms that maximize their present discounted value of profits in each segmented labor market. Firms post vacancies in order to hire workers in a labor market and a job consists of a matched firm-worker pair. Firms can freely decide in which segmented labor market they want to post vacancies. However, they can only post one vacancy and they have to pay a cost c expressed in units of output every period that the vacancy is open. After a vacancy meets an unemployed worker, they draw an idiosyncratic

[6] In order to emphasize our main working hypothesis (i.e. that human capital accumulation drives differences in labor market experiences across different demographic groups) we abstract from introducing worker heterogeneity in terms of productivity related to the level of education.

[7] For simplicity, we do not allow for a gradual depreciation of general human capital as individuals get older. We could model the aging of the individual as a gradual loss in general human capital, particularly severe after a period of unemployment. However, this would entail adding a new state variable into the model, namely the age of the individual, while keeping unaltered the key insights of this relatively stylized model.

[8] We abstract from differences in the value of home production across demographic groups.

productivity a. If this productivity is above a certain threshold defined below, then the firm and the worker form a match and start producing.

Importantly, firms in each segmented labor market have to provide on-the-job training to new hires, regardless of their age, with the amount of training depending on worker's education. In particular, we assume that on-the-job training takes place during the first period in the job and that the cost of this training is a proportion τ^i of the worker's productivity.[9] This training is specific to the worker-firm match, thus, all new hires need to receive this training in order to perform the job. Therefore, during the first period the matched firm-worker pair will produce $a(1-\tau^i)$ of output if the new hire is young and $a(1-\kappa)(1-\tau^i)$ if the new hire is old.[10]

The only source of uncertainty in the model is the idiosyncratic productivity a. In particular, it is assumed that a is stochastic and evolves over time according to a Markov chain $\{\mathbf{a}, \mathbf{\Pi^a}\}$, with finite grid $\mathbf{a} = \{a_1, a_2, ..., a_m\}$ and transition matrix $\mathbf{\Pi^a}$ being composed of elements $\pi^a_{jk} = \mathbb{P}\{a' = a_k \mid a = a_j\}$. The initial probability vector is composed of elements $\pi^a_k = \mathbb{P}\{a' = a_k\}$.

3.2. *Labor Markets*

In each segmented labor market i, a constant returns to scale matching function governs the matching process between vacancies and unemployed workers

$$m(u, v) = \mu u^{\alpha} v^{1-\alpha},$$

where u denotes the measure of unemployed and v denotes the measure of vacancies, the parameter μ stands for matching efficiency and the parameter α for the elasticity of the matching function with respect to unemployment. Labor market tightness is defined as $\theta \equiv v/u$. We can also define the endogenous probability of an unemployed worker to meet a vacancy as

$$p(\theta) = \frac{m(u, v)}{u} = \mu\theta^{1-\alpha}, \tag{1}$$

and the endogenous probability of a vacancy to meet with an unemployed worker as:

$$q(\theta) = \frac{m(u, v)}{v} = \mu\theta^{-\alpha}. \tag{2}$$

3.3. *Description of the state of the economy*

The introduction of worker heterogeneity increases the number of state variables that are relevant from the view point of the worker and the firm. As will become clear below, the age composition of the unemployment pool affects the firm's decision to post vacancies. This, in turn, affects the meeting probabilities of workers and firms. As a result, the worker and the firm need to keep track of the distribution of workers across the different labor market states, within each segmented labor market. In particular, the agents in our economy need to know the

[9]Notice that in our setup on-the-job training lasts only one period, which we assume to be one month in our calibration strategy. Empirical studies of training do find that on-the-job training entails short periods of time, even though the average is around three months. We could easily introduce longer training times, and a gradual closing of the productivity gap between trainees and incumbent workers. However, this would further complicate the model, leaving the main results unchanged.

[10]Note that we do not allow workers to search for new jobs while being employed, hence we rule out job-to-job transitions. This implies that all new hires come from the unemployment pool. This is also the reason why all new hires that are old experience a depreciation κ of their general human capital.

number of young employed and unemployed workers ($n^{i,Y}$ and $u^{i,Y}$, respectively), the number of old workers employed that did not suffer a depreciation of their general human capital ($n^{i,O}$), the number of old workers employed that did suffer a depreciation of their general human capital ($n^{i,D}$) and, finally, the number of old workers unemployed ($u^{i,D}$). Because the size of each segmented labor market is exogenously determined by its labor force l^i, workers and firms only need to keep track of four of these labor market states, as the following equality holds: $n^{i,Y}+u^{i,Y}+n^{i,O}+n^{i,D}+u^{i,D}=l^i$. We summarize in $x=\left\{a,n^{i,Y},u^{i,Y},n^{i,O},n^{i,D}\right\}$ the vector of state variables in our model. The evolution of the idiosyncratic productivity a is governed by a Markov process, and the evolution of the rest of the state variables will be described below. Notice, however, that we are analyzing an economy in steady state, thus, all labor market flows will be constant in equilibrium. This will greatly simplify the solution of the model.

3.4. *Characterization of Recursive Equilibrium*

We write the model in terms of the standard match surplus equations (see Appendix B for details on the derivation), where subscript t denotes the age of the job match:

$$\begin{aligned}
S_t^{i,Y}(x) = \max\Big\{0, a(1-\mathbb{1}_{t=1}\tau^i) - b - \beta\eta p(\theta^i(x))\mathbb{E}_x\Big\{(1-\rho)S_1^{i,Y}(x') + \rho S_1^{i,D}(x')\Big\} \\
+\beta\mathbb{E}_x\Big\{(1-\rho)S_{t+1}^{i,Y}(x') + \rho S_{t+1}^{i,O}(x')\Big\}\Big\}, \quad (3)
\end{aligned}$$

$$S_t^{i,O}(x) = \max\Big\{0, a - b - \beta(1-\delta)\eta p(\theta^i(x))\mathbb{E}_x\big\{S_1^{i,D}(x')\big\} + \beta(1-\delta)\mathbb{E}_x\big\{S_{t+1}^{i,O}(x')\big\}\Big\}, \quad (4)$$

$$\begin{aligned}
S_t^{i,D}(x) = \max\Big\{0, a(1-\kappa)(1-\mathbb{1}_{t=1}\tau^i) - b - \beta(1-\delta)\eta p(\theta^i(x))\mathbb{E}_x\big\{S_1^{i,D}(x')\big\} \\
+\beta(1-\delta)\mathbb{E}_x\big\{S_{t+1}^{i,D}(x')\big\}\Big\}. \quad (5)
\end{aligned}$$

Equation (3) presents the surplus that a job filled by a young worker produces, while equations (4) and (5) are the corresponding ones for a job filled by an old worker. The difference between the last two equations is that in equation (4) the old worker maintains the full value of his general human capital, while in equation (5) the old worker suffered a depreciation κ of his general human capital. Note that the training cost τ^i is paid only in the first period of the job match.[11] Notice as well that the worker and the firm will mutually agree to endogenously dissolve the job match when the value of the surplus is negative. That is, when the idiosyncratic productivity is at or below the reservation productivities $\tilde{a}_t^{i,Y}$, $\tilde{a}_t^{i,O}$ and $\tilde{a}_t^{i,D}$, implicitly defined as the maximum values of the idiosyncratic productivity that exhaust a positive surplus.

In order to determine the optimal job creation condition, we assume that there is free entry. Therefore, in equilibrium, the total expected costs of posting a vacancy should be equalized to the total expected benefits of filling it in each segmented labor market i. The job creation condition (or free-entry condition) in terms of the surplus can be written as:

$$\frac{c}{q(\theta^i(x))} = \beta(1-\eta)\mathbb{E}_x\Big\{\gamma^i S_1^{i,Y}(x') + (1-\gamma^i)S_1^{i,D}(x')\Big\}, \quad (6)$$

[11]Importantly, the training cost is non-sunk and thus is fully taken into account in the surplus of the match.

where η is the worker's bargaining power γ^i is the endogenous share of young among unemployed in the segmented labor market i (i.e. $\gamma^i \equiv u^{i,Y}/u^i$).

In order to close the model, we specify the evolution of the labor market flows. In particular, the laws of motion for employed and unemployed workers are given by:

$$(n^{i,Y})' = (1-\rho)(1-s^{i,Y})n^{i,Y} + p(\theta^i)(1-G(\tilde{a}_1^{i,Y}))(1-\rho)u^{i,Y}, \tag{7}$$

$$(u^{i,Y})' = \left[1-p(\theta^i)(1-G(\tilde{a}_1^{i,Y}))\right](1-\rho)u^{i,Y} + s^{i,Y}(1-\rho)n^{i,Y} + \delta(n^{i,O}+n^{i,D}+u^{i,D}), \tag{8}$$

$$(n^{i,O})' = (1-\delta)(1-s^{i,O})n^{i,O} + \rho(1-s^{i,O})n^{i,Y}, \tag{9}$$

$$(n^{i,D})' = (1-\delta)(1-s^{i,D})n^{i,D} + p(\theta^i)(1-G(\tilde{a}_1^{i,D}))(\rho u^{i,Y}+(1-\delta)u^{i,D}), \tag{10}$$

$$(u^{i,D})' = \left[1-p(\theta^i)(1-G(\tilde{a}_1^{i,D}))\right](\rho u^{i,Y}+(1-\delta)u^{i,D}) \tag{11}$$

$$+ s^{i,O}(\rho n^{i,Y}+(1-\delta)n^{i,O}) + s^{i,D}(1-\delta)n^{i,D}, \tag{12}$$

where $s^{i,Y}$, $s^{i,O}$ and $s^{i,D}$ are the endogenous separation rates.

In the steady state, all labor market flows are constant.[12] Aggregate employment and unemployment are defined, respectively, as:

$$n^i = n^{i,Y} + n^{i,O} + n^{i,D},$$
$$u^i = u^{i,Y} + u^{i,D}.$$

And the labor force in labor market i, as mentioned before, is normalized to l^i:

$$n^i + u^i = l^i.$$

Finally, the recursive equilibrium of the model can be characterized as the solution of equations (1)-(12), for each segmented labor market i. The solution of the model consists of equilibrium labor market tightness $\theta^i(x)$ and reservation productivities $\tilde{a}_t^{i,Y}$, $\tilde{a}_t^{i,O}$ and $\tilde{a}_t^{i,D}$. Appendix B describes the computational strategy used to solve the model.

4. Numerical Exercise

This section contains the simulation results of the model. With the objective of quantitatively illustrating the main mechanism at work, we consider two types of economies characterized by high and low levels of turnover rates. The high turnover economy is characterized by a high fraction of young and low educated workers and it is meant to capture the early years of our sample period (1976-1990). The low turnover economy is characterized by a high fraction of old and high educated workers, and is meant to capture the last years of our sample period (1991-2011). We first calibrate the model to be consistent with a high turnover economy at the aggregate level. Then, we analyze whether the model is able to explain the cross-sectional differences in unemployment flow rates across demographic groups. Finally, we check whether an exogenous change in the composition of the labor force towards older and more educated workers can deliver a decline in the aggregate turnover rates.

[12]See Appendix B for more details about the labor market flows.

4.1. *Parameterization*

We first calibrate the model to be consistent with the U.S. economy during the period 1976-1990, which we label *high turnover economy*. In order to bring the model to the data, we consider as young workers those aged between 16 and 34 years old, and as old workers those aged 35 years old and over. With respect to education, high-school dropouts and workers with a high school degree are considered low educated workers, whereas workers with some college or with a a college degree are considered high educated workers. This demographic classification splits the labor force in groups of similar size. In particular, in the CPS microdata for the period 1976-1990, the share of workers aged between 16 and 34 years old in the labor force is 49 percent, and high-school dropouts and workers with a high school degree represent 58 percent of the labor force. Table 2 summarizes the parameter values used to calibrate the baseline economy.

TABLE 2. Parameter values for the high turnover economy

Parameter	Interpretation	Value	Rationale
β	Discount factor	0.9966	Interest rate 4% p.a.
μ	Matching efficiency	0.566	Job finding rate 55.8% (CPS 1976-90)
α	Elasticity of the matching function	0.5	Petrongolo and Pissarides (2001)
η	Worker's bargaining power	0.5	Pissarides (2009)
c	Vacancy posting cost	0.106	1982 EOPP survey
b	Value of being unemployed	0.71	Hall and Milgrom (2008)
μ_a	Mean log idiosyncratic productivity	0	Normalization
σ_a	Standard deviation for log idiosyncratic productivity	0.475	Separation rate 4.1% (CPS 1976-90)
λ	Probability of changing idiosyncratic productivity	0.3333	Fujita and Ramey (2012)
τ^L	Training costs for low educated workers	0.516	1982 EOPP survey
τ^H	Training costs for high educated workers	0.847	1982 EOPP survey
κ	Depreciation of skills due to aging	0.065	Wage loss upon displacement for old workers (see text)
ρ	Probability of getting old	0.0042	Young during 20 years on average
δ	Probability of retirement	0.0040	Share of young workers in the labor force 49% (CPS 1976-90)
l^L	Share of low educated workers in the aggregate labor force	0.58	CPS 1976-90

The model is simulated at a monthly frequency. The value of the discount factor is consistent with an interest rate of four percent. The matching efficiency parameter μ targets an aggregate job finding rate of 55.8 percent, consistent with the CPS microevidence for people with 16 years of age and over for the period 1976-1990. The elasticity of the matching function, α, is set to 0.5, following the evidence reported in Petrongolo and Pissarides (2001). For the worker's bargaining power, we follow most of the literature and set it to $\eta = 0.5$, as in Pissarides (2009) for example. The vacancy posting cost is parametrized following the evidence in the 1982 Employment Opportunity Pilot Project (EOPP) survey of employers, see Cairó and Cajner (2011) for more details. We follow Hall and Milgrom (2008) in order to establish a value for the unemployment benefits. Our choice of $b = 0.71$ is also used by Pissarides (2009).

In order to determine the stochastic properties of the idiosyncratic productivity process, we follow standard assumptions in the literature, and assume that the idiosyncratic shocks are independent draws from a lognormal distribution with mean μ_a and standard deviation σ_a. Following Fujita and Ramey (2012), on average, a firm receives a new draw every three months ($\lambda = 1/3$). The parameter μ_a is normalized to zero and the parameter σ_a is chosen to match the aggregate separation rate of 4.1 percent, consistent with the CPS microevidence for people with 16 years of age and over for the period 1976-1990.

In the model, the parameters τ and κ govern the productivity differences between workers of different education level and age. We use the 1982 EOPP survey to parametrize the training cost τ across education groups. In particular, the survey shows considerable differences across education groups in terms of the duration of training received and in terms of the difference between the initial productivity and the productivity achieved by an incumbent worker (the so-called productivity gap). In the data, we see that workers with low education receive training for 2.7 months and have an initial productivity gap of 0.383, whereas high educated workers receive training for 3.7 months and have an initial productivity gap of 0.460.[13] Given that in the model on-the-job training lasts only one period, we consider the present value of the training in order to assign values to τ. The resulting parameter values are $\tau^L = 0.516$ for low educated workers and $\tau^H = 0.847$ for high educated workers.[14]

The parameter κ determines the productivity differences between young and old workers that have suffered a depreciation in their skill level. These productivity differences will translate into differences in labor market experiences and in wage differentials between young and old workers.[15] In order to calibrate κ we use empirical evidence on wage losses upon displacement. A wide literature, starting with Jacobson et al. (1993), has documented high and persistent wage losses upon job displacement. Interestingly, recent contributions by Davis and Wachter (2011) and Farber (2011) document that, even though wage losses at displacement are large for all age groups, there is a strong relationship between age and the losses in earnings, with older workers suffering larger declines. In particular, using data from the Displaced Workers Survey from 1984-2010, Farber (2011) finds that job losers aged 55-64 earn 16 percent less than do job losers aged 25-34. Similarly, Davis and Wachter (2011) document that men aged 31-40 with three or more years of tenure suffer a 7.7 percent decline on average in the present discounted value of earnings at displacement, using longitudinal Social Security records from 1974 to 2008. This number compares to a 15.9 percent decline on average for men aged 41-50 with three of more years of tenure (a difference of 8.2 percentage points). In the model, the parameter κ

[13]Following our previous work Cairó and Cajner (2011), we restrict the EOPP sample to individuals for whom we have information on education and to individuals with 16 years of age and over. Since the distribution of training duration is highly skewed to the right, we eliminate outliers by truncating distribution at its 95th percentile, which corresponds to the training duration of 2 years. The survey question for training duration was: "How many weeks does it take a new employee hired for this position to become fully trained and qualified if he or she has no previous experience in this job, but has had the necessary school-provided training?". In order to compute the productivity gap we combine the survey question on productivity of a "typical worker who has been in this job for 2 years" and the survey question on productivity of a "typical worker during his/her first 2 weeks of employment".

[14]For low educated workers, we compute τ^L as follows. We first notice that an average productivity gap of 0.192 is consistent with an initial gap of 0.383, which is the proportionally diminishing over time. Then, we take into account that this average productivity gap of 0.192 will be present for 2.7 months on average. Thus, $\tau^L = 0.192 + \beta \times 0.192 + \beta^2 \times 0.192 \times 0.7$. Following a similar argument for high educated workers, we have that $\tau^H = 0.230 + \beta \times 0.230 + \beta^2 \times 0.230 + \beta^3 \times 0.230 \times 0.7$.

[15]See Appendix B for the derivation of the wage equations.

represents the wage losses upon displacement suffered by old workers. However, given that only old workers (and not young workers) suffer a loss in general human capital upon displacement, κ also represents the gap between the wage losses upon displacement suffered for old vs. young workers. We set $\kappa = 0.065$, which corresponds to a gap of 9.5 percent between the wage losses suffered by old vs. young workers at displacement.

The parameters ρ and δ jointly determine the share of young workers in the labor force. In order to assign values to them we proceed as follows. First, and according to our definition of young workers, we set the average number of years of being young to 20, thus $\rho = 1/(20 \times 12)$ on a monthly basis. Second, once the parameter ρ is fixed, we determine the value of δ such that the share of young workers in the labor force in the simulated model equals to 49 percent, which corresponds to the empirical value from the CPS microdata for the period 1976-1990. This requires a value of $\delta = 0.004$ on a monthly basis.

Finally, the last parameter to be calibrated is l^L, which corresponds to the share of low educated workers in the labor force and thus governs the size of each segmented labor market. In the CPS microdata, 58 percent of the labor force are low educated workers on average during the period 1976-1990, thus we set $l^L = 0.58$.

4.2. *Unemployment Flow Rates across Demographic Groups*

This section tests our main working hypothesis that human capital accumulation drives differences in labor market experiences across different demographic groups. Table 3 provides simulation results by education and age groups for the high turnover economy. We begin by focusing on the first two columns, which report the data moments and the baseline simulation results for the high turnover economy. As we can see, the model does a reasonably good job in explaining the differences in unemployment flow rates across demographic groups.[16] Particularly, regarding education, the model is able to account for similar job finding rates across groups, while generating the observed differences in separation rates. With respect to age, the model produces higher job finding rates for young workers than for old workers as in the data, even though the magnitude of the differences is somewhat smaller than in the data. The model can also explain the differences in separation rates across age groups, predicting higher separation rates for young workers, even though the values are a bit magnified.

In the model, the parameters τ and κ govern the differences in labor market experiences across education and age groups respectively. In order to highlight their role, we solve the model for two alternative scenarios corresponding to the last two columns in Table 3. In the first scenario, we eliminate the differences in on-the-job training across education groups, while keeping the rest of parameters constant at the baseline level. The results show that the differences in unemployment inflow rates across education groups disappears. Thus, our baseline results show that the differences in training requirements by education group that we see in the data can quantitatively account for the differences in unemployment flow rates across education groups. These results mirror the conclusions reached in our previous work (Cairó and Cajner, 2011), where we show that on-the-job training is the reason behind the

[16] Similar conclusions are reached if we look at the simulation results for the low turnover economy (see Table 9 in Appendix B).

different unemployment dynamics across education groups. The second alternative scenario eliminates the productivity loss that old workers suffer after displacement by setting $\kappa = 0$ and keeping the rest of parameters constant at the baseline level. The results show that the differences in unemployment flow rates across age groups completely disappear when setting $\kappa = 0$. Thus, the fact that old workers lose a higher fraction of their skills than young workers upon displacement, consistent with the evidence on wage losses upon displacement, can rationalize the differences in unemployment flow rates across age groups.

Table 3. Labor market disaggregates: data versus model

		Simulation results for the high turnover economy		
	U.S. data 1976-1990	*Baseline*	*Same training* $(\tau^L = \tau^H = 0.516)$	*No prod. loss for old workers* $(\kappa = 0)$
Panel A: Job finding rate				
By age				
Young	62.3	57.8	56.4	57.0
Old	43.2	51.0	50.8	57.0
Ratio	1.4	1.1	1.1	1.0
By education level				
Low	55.7	55.1	55.1	56.5
High	56.3	60.4	55.1	58.1
Ratio	1.0	0.9	1.0	1.0
Panel B: Separation rate				
By age				
Young	6.6	7.2	9.1	7.7
Old	1.9	1.4	2.1	7.7
Ratio	3.4	5.1	4.3	1.0
By education level				
Low	5.4	5.3	5.3	9.6
High	2.5	2.5	5.3	5.3
Ratio	2.1	2.1	1.0	1.8

Notes: All data variables are constructed from CPS microdata and are averages of monthly data expressed in percentages. Young workers are workers with ages comprises between 16 and 34, whereas old workers are workers with 35 years of age and over. Low educated workers refer to workers with less than high-school or with a high-school degree. High educated workers refer to workers with some years of college or with a college degree.

4.3. *Accounting for the Fading Dynamism of the U.S. Labor Market*

Once the model is able to account for the cross-sectional differences in unemployment flow rates across education and age groups, we then analyze whether an exogenous change in the composition of the labor force towards older and more educated workers can deliver a decline in the aggregate turnover rates. In order to perform this exercise, we keep all parameters fixed at the values for the high turnover economy, except the two parameters that determine the relative importance of young and low educated workers in the labor force (i.e. δ and l^L respectively). To be more specific, we adjust δ so that the share of young workers in the labor force in the simulated model equals to 39 percent, which corresponds to the empirical average from the CPS microdata for the period 1991-2011. This delivers a value for $\delta = 0.0027$. We also set $l^L = 0.44$, given that the average share of low educated workers in the labor force equals to 44 percent during the period 1991-2011 in the CPS. Table 4 presents the main results of this numerical exercise.

Table 4. Labor market aggregates: data versus model

	High turnover economy	*Low turnover economy*
Panel A: U.S. data	*1976-1990*	*1991-2011*
Unemployment rate	7.0	6.0
Job finding rate	55.8	51.4
Separation rate	4.1	3.1
Panel B: Simulation results		
Unemployment rate	7.1	5.2
Job finding rate	56.5	57.4
Separation rate	4.1	3.0

Notes: All data variables in Panel A are constructed from CPS microdata, and are averages of monthly data. All means of rates are expressed in percentages.

The simulation results show that we roughly hit the empirical means of the job finding rate and the separation rates in the high turnover economy, by construction of the exercise. The results for the low turnover economy are the most important ones. Particularly, as we move from an economy with high shares of young and low educated workers towards an economy with small shares of these two types of workers, the separation rate declines substantially and the job finding rate remains nearly unchanged. If we compare these numbers with the empirical counterparts, we see that the observed change in the composition of the labor force towards older and more educated workers can explain virtually all the decline in the separation rate observed during the two sample periods. Therefore, the change in the composition of the labor force is an important factor in order to understand the fading dynamism of the U.S. labor market over the last three decades.

5. Conclusions

This paper investigates the role of demographics in explaining the increasing sluggishness of the U.S. labor market over the last three decades. Population aging and rising educational attainment are found to be the two most important driving forces behind the downward trends in labor market turnover rates. By performing a series of decomposition exercises using microdata from the Current Population Survey, the empirical results show that these two demographic characteristics explain between 75 and 90 percent of the total decline in the aggregate unemployment inflow rate from 1976 to 2011. The effect of demographics in shaping the behavior of the aggregate unemployment outflow rate is limited, given the small differences in outflow rates observed across demographic groups. We examine theoretically why and how age and education affect the dynamism of worker flows. Since older and more educated workers possess more human capital, the compositional shifts in the labor force induce an increase in accumulated human capital. This in turn reduces incentives to destroy jobs and drives the secular trends in labor market fluidity. We show that a relatively stylized search and matching model with endogenous separations, featuring higher amounts of on-the-job training for more educated workers and skill obsolescence for old unemployed workers, can go a long way in quantitatively accounting for the observed empirical patterns.

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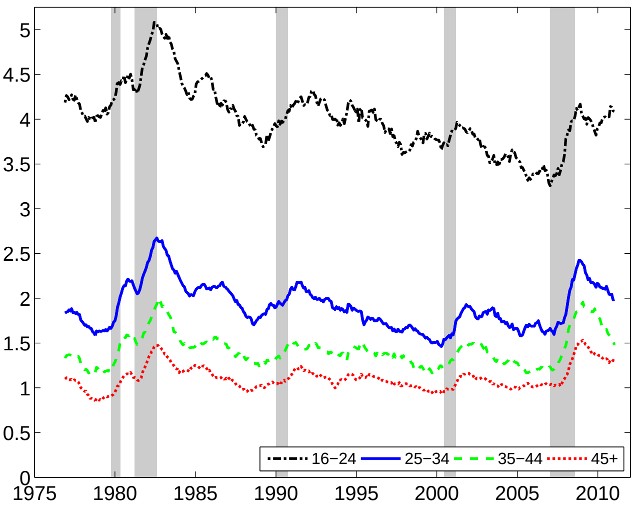
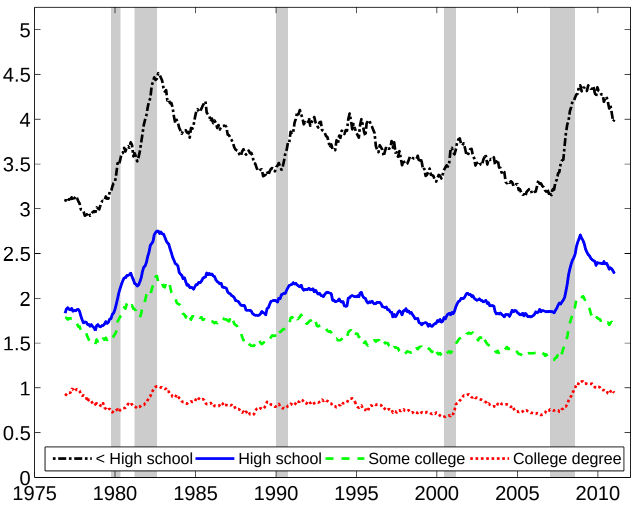
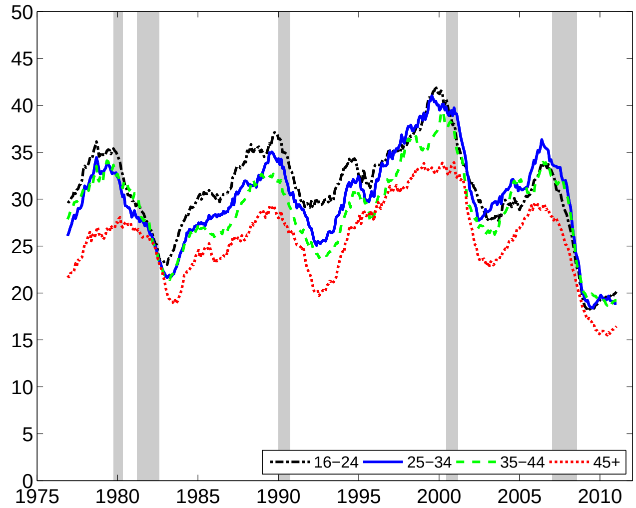
Appendix A. Supplemental Empirical Evidence



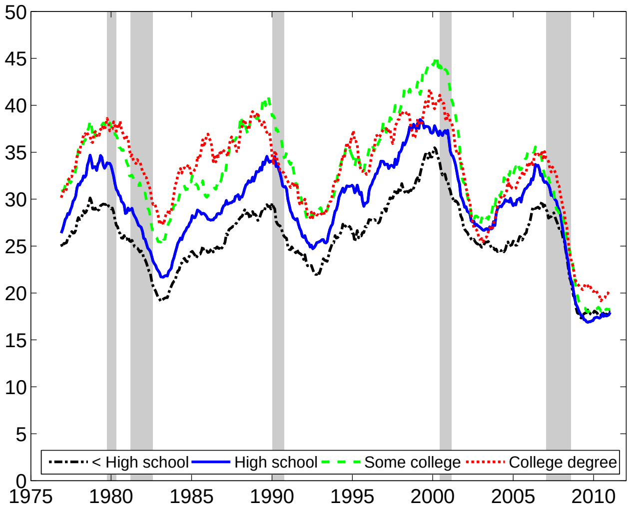
(A) Employment-Unemployment flow hazard rates by age



(B) Employment-Unemployment flow hazard rates by education



(C) Unemployment-Employment flow hazard rates by age



(D) Unemployment-Employment flow hazard rates by education

Figure 6. Description of the U.S. labor market by demographic group

Notes: We plot twelve-month moving averages of monthly data. The sample period is 1976:01 - 2011:12. All variables are constructed from CPS microdata. Shaded areas indicate NBER recessions.

Table 5. Unemployment transition rates by age, 1976-2011 (means, in percent)

	Separation rate		Job finding rate	
	Duration-based	Gross flow	Duration-based	Gross flow
16-24	10.15	4.01	69.71	30.99
25-34	3.23	1.91	50.29	30.00
35-44	2.11	1.42	44.27	28.95
>45	1.55	1.11	39.15	25.58
Aggregate	3.52	1.86	53.28	28.97

Table 6. Unemployment transition rates by education, 1976-2011 (means, in percent)

	Separation rate		Job finding rate	
	Duration-based	Gross flow	Duration-based	Gross flow
< High school	8.32	3.67	59.17	25.99
High school	3.45	2.03	49.58	29.13
Some college	3.05	1.63	56.05	32.71
College degree	1.27	0.83	45.04	32.67
Aggregate	3.52	1.86	53.28	28.97

Table 7. Unemployment inflow rates, 1976-1990 (means, in percent)

	Education level				
Age group	< High school	High school	Some college	College degree	Aggregate
16-24	20.44	8.24	7.85	4.27	10.89
25-34	8.36	4.04	3.01	1.59	3.58
35-44	4.88	2.41	1.95	0.96	2.27
>45	2.78	1.55	1.31	0.69	1.67
Aggregate	8.54	3.72	3.59	1.36	4.12

Table 8. Unemployment inflow rates, 1991-2011 (means, in percent)

	Education level				
Age group	< High school	High school	Some college	College degree	Aggregate
16-24	17.72	8.81	6.31	4.35	9.62
25-34	6.84	3.65	2.75	1.41	2.98
35-44	4.70	2.37	1.83	0.99	1.99
>45	2.85	1.58	1.45	0.89	1.47
Aggregate	8.17	3.25	2.66	1.21	3.10

Appendix B. Supplemental Details on the Model

We can alternatively characterize the equilibrium of the model by first describing the value functions associated with the firm, together with its optimal decision to create and destroy jobs, and then by describing the value functions associated with the unemployed and employed worker.

For people with education level $i \in \{H, L\}$, we have the following Bellman equations for the firm, where subscript t denotes the age of the job match:

$$J_t^{i,Y}(x) = \max\left\{0, a(1-\mathbb{1}_{t=1}\tau^i) - w_t^{i,Y}(x) + \beta\mathbb{E}_x\left\{(1-\rho)J_{t+1}^{i,Y}(x') + \rho J_{t+1}^{i,O}(x')\right\}\right\}, \tag{13}$$

$$J_t^{i,O}(x) = \max\left\{0, a - w_t^{i,O}(x) + \beta(1-\delta)\mathbb{E}_x\left\{J_{t+1}^{i,O}(x')\right\}\right\}, \tag{14}$$

$$J_t^{i,D}(x) = \max\left\{0, a(1-\kappa)(1-\mathbb{1}_{t=1}\tau^i) - w_t^{i,D}(x) + \beta(1-\delta)\mathbb{E}_x\left\{J_{t+1}^{i,D}(x')\right\}\right\}. \tag{15}$$

Equation (13) presents the value of a job filled by a young worker, while equations (14) and (15) refer to the value of a job filled by an old worker. The difference between the last two equations is that in equation (14) the old worker maintains the full value of his general human capital. However, equation (15) presents the value of a job filled by an old worker whose general human capital has depreciated by κ. Note that the training cost τ^i is paid only in the first period of the job match and, importantly, this training cost is non-sunk at the time of wage bargaining. Notice as well that at any point in time the firm can decide to fire its employee and become inactive, in which case it receives a payoff equal to zero. The firm will optimally decide to separate when the idiosyncratic productivity is at or below the reservation productivities $\tilde{a}_t^{i,Y}$, $\tilde{a}_t^{i,O}$ and $\tilde{a}_t^{i,D}$, implicitly defined as the maximum values that make equations (13)-(15) equal to zero.

In order to determine the optimal job creation condition, we assume that there is free entry. Therefore, in equilibrium, the total expected costs of posting a vacancy should be equalized to the total expected benefits of filling it in each segmented labor market i:

$$\frac{c}{q(\theta^i(x))} = \beta\mathbb{E}_x\big\{\gamma^i J_1^{i,Y}(x') + (1-\gamma^i)J_1^{i,D}(x')\big\}, \tag{16}$$

where γ^i is the endogenous share of young among unemployed in the segmented labor market i (i.e. $\gamma^i \equiv u^{i,Y}/u^i$).

An unemployed worker with education level i receives a current payoff of b and meets with a vacancy with probability $p(\theta^i)$. The Bellman equations for the unemployed with education level i are the following:

$$\begin{aligned} U^{i,Y}(x) =& b + p(\theta^i(x))\beta\mathbb{E}_x\big\{(1-\rho)W_1^{i,Y}(x') + \rho W_1^{i,D}(x')\big\} \\ &+ \big[1 - p(\theta^i(x))\big]\beta\mathbb{E}_x\big\{(1-\rho)U^{i,Y}(x') + \rho U^{i,D}(x')\big\}, \end{aligned} \tag{17}$$

$$U^{i,D}(x) = b + p(\theta^i(x))\beta(1-\delta)\mathbb{E}_x\big\{W_1^{i,D}(x')\big\} + \big[1 - p(\theta^i(x))\big]\beta(1-\delta)\mathbb{E}_x\big\{U^{i,D}(x')\big\}. \tag{18}$$

Bellman equations for the worker with education level i are the following:

$$W_t^{i,Y}(x) = \max\left\{U^{i,Y}(x), w_t^{i,Y}(x) + \beta\mathbb{E}_x\left\{(1-\rho)W_{t+1}^{i,Y}(x') + \rho W_{t+1}^{i,O}(x')\right\}\right\}, \tag{19}$$

$$W_t^{i,O}(x) = \max\left\{U^{i,D}(x), w_t^{i,O}(x) + \beta(1-\delta)\mathbb{E}_x\left\{W_{t+1}^{i,O}(x')\right\}\right\}, \tag{20}$$

$$W_t^{i,D}(x) = \max\left\{U^{i,D}(x), w_t^{i,D}(x) + \beta(1-\delta)\mathbb{E}_x\left\{W_{t+1}^{i,D}(x')\right\}\right\}. \tag{21}$$

Note that an old worker who maintains the full value of his formal human capital knows that if he becomes unemployed his general human capital will be depreciated by a factor κ upon re-employment. Thus, the outside option of this worker is $U^{i,D}(x)$ as reflected in equation (20).

We assume that wages are determined through generalized Nash wage bargaining. This means that, at each period, the worker and the firm share the surplus of a job match in fixed proportions, η and $(1-\eta)$ respectively. We define the surplus of a job match with education level $i \in \{H, L\}$ as follows:

$$\begin{aligned} S_t^{i,Y}(x) &= J_t^{i,Y}(x) + W_t^{i,Y}(x) - U^{i,Y}(x), \\ S_t^{i,O}(x) &= J_t^{i,O}(x) + W_t^{i,O}(x) - U^{i,D}(x), \\ S_t^{i,D}(x) &= J_t^{i,D}(x) + W_t^{i,D}(x) - U^{i,D}(x). \end{aligned}$$

Thus, the equilibrium wages $w_t^{i,Y}(x)$, $w_t^{i,O}(x)$ and $w_t^{i,D}(x)$ are determined by the following surplus-splitting conditions:

$$\begin{aligned} (1-\eta)\left[W_t^{i,Y}(x) - U^{i,Y}(x)\right] &= \eta J_t^{i,Y}(x), \\ (1-\eta)\left[W_t^{i,O}(x) - U^{i,D}(x)\right] &= \eta J_t^{i,O}(x), \\ (1-\eta)\left[W_t^{i,D}(x) - U^{i,D}(x)\right] &= \eta J_t^{i,D}(x). \end{aligned}$$

This means that, at each period, both the firm and the worker agree on when to endogenously terminate a job match. Plugging in the value functions in the above equations we find that the equilibrium wages take the following form:

$$w_t^{i,Y}(x) = \eta a(1 - \mathbb{1}_{t=1}\tau^i) + (1-\eta)b + \eta p(\theta^i(x))\beta\mathbb{E}_x\left\{(1-\rho)J_1^{i,Y}(x') + \rho J_1^{i,D}(x')\right\}, \tag{22}$$

$$w_t^{i,O}(x) = \eta a + (1-\eta)b + \eta p(\theta^i(x))\beta(1-\delta)\mathbb{E}_x\left\{J_1^{i,D}(x')\right\}, \tag{23}$$

$$w_t^{i,D}(x) = \eta a(1-\kappa)(1 - \mathbb{1}_{t=1}\tau^i) + (1-\eta)b + \eta p(\theta^i(x))\beta(1-\delta)\mathbb{E}_x\left\{J_1^{i,D}(x')\right\}. \tag{24}$$

Finally, the recursive equilibrium of the model can also be characterized as the solution of equations (1)-(2), (8)-(12) and (13)-(24), for each segmented labor market i. The solution of the model consists of equilibrium labor market tightness $\theta^i(x)$ and reservation productivities $\tilde{a}_t^{i,Y}$, $\tilde{a}_t^{i,O}$ and $\tilde{a}_t^{i,D}$.

Due to the Nash bargaining assumption, we can rewrite the model and express the equilibrium in terms of the surpluses, as we did in the main text of the paper.

B.1. *More on labor market flows*

At the steady state, all labor market flows are constant. Thus, the inflows equalize the outflows for all labor market states. This is illustrated in equations (25)-(29) below, where the left-hand side summarizes the inflows and the right-hand side the outflows, for all types of workers and for all labor market states. Note that all endogenous variables are constant at the steady state.

(1) Employment young $n^{i,Y}$:

$$p(\theta^i)[1 - G(\tilde{a}_1^{i,Y})](1-\rho)u^{i,Y} = \rho n^{i,Y} + s^{i,Y}(1-\rho)n^{i,Y} \tag{25}$$

(2) Employment old $n^{i,O}$:

$$(1 - s^{i,O})\rho n^{i,Y} = \delta n^{i,O} + s^{i,O}(1-\delta)n^{i,O} \tag{26}$$

(3) Employment old depreciated $n^{i,D}$:

$$p(\theta^i)[1 - G(\tilde{a}_1^{i,D})](\rho u^{i,Y} + (1-\delta)u^{i,D}) = \delta n^{i,D} + s^{i,D}(1-\delta)n^{i,D} \tag{27}$$

(4) Unemployment young $u^{i,Y}$:

$$s^{i,Y}(1-\rho)n^{i,Y} + \delta(n^{i,O} + n^{i,D} + u^{i,D}) = p(\theta^i)[1 - G(\tilde{a}_1^{i,Y})](1-\rho)u^{i,Y} + \rho u^{i,Y} \tag{28}$$

(5) Unemployment old $u^{i,D}$:

$$\begin{aligned} &s^{i,O}(\rho n^{i,Y} + (1-\delta)n^{i,O}) + s^{i,D}(1-\delta)n^{i,D} + \left[1 - p(\theta^i)(1 - G(\tilde{a}_1^{i,D}))\right]\rho u^{i,Y} \\ &= \delta u^{i,D} + p(\theta^i)[1 - G(\tilde{a}_1^{i,D})](1-\delta)u^{i,D} \end{aligned} \tag{29}$$

For completeness, Figure 7 summarizes all the worker flows in our model graphically.

B.2. *Computational Strategy*

In order to solve the model numerically we discretize the idiosyncratic productivity shock a by a discrete lognormal distribution with 700 equally spaced grid points. The lognormal distribution is truncated at 0.01 percent and 99.99 percent and then normalize probabilities so that they sum up to one. Given that we analyze an economy on steady-state (we do not introduce aggregate uncertainty into the model), all labor market flows are constant in equilibrium. This greatly simplifies the solution of the model. We proceed as follows: First, we guess an initial share of young workers among unemployed. Second, given this guess we solve the model by value function iteration until convergence. Third, with the obtained solution for labor market tightness and the reservation productivities, we use the law of motion for employment and unemployment to obtain steady state values for all labor market flows. Fourth, if the share of young among unemployed is the same as the initial guess we stop. Otherwise, we use the obtained share as a new guess and repeat the process until convergence.

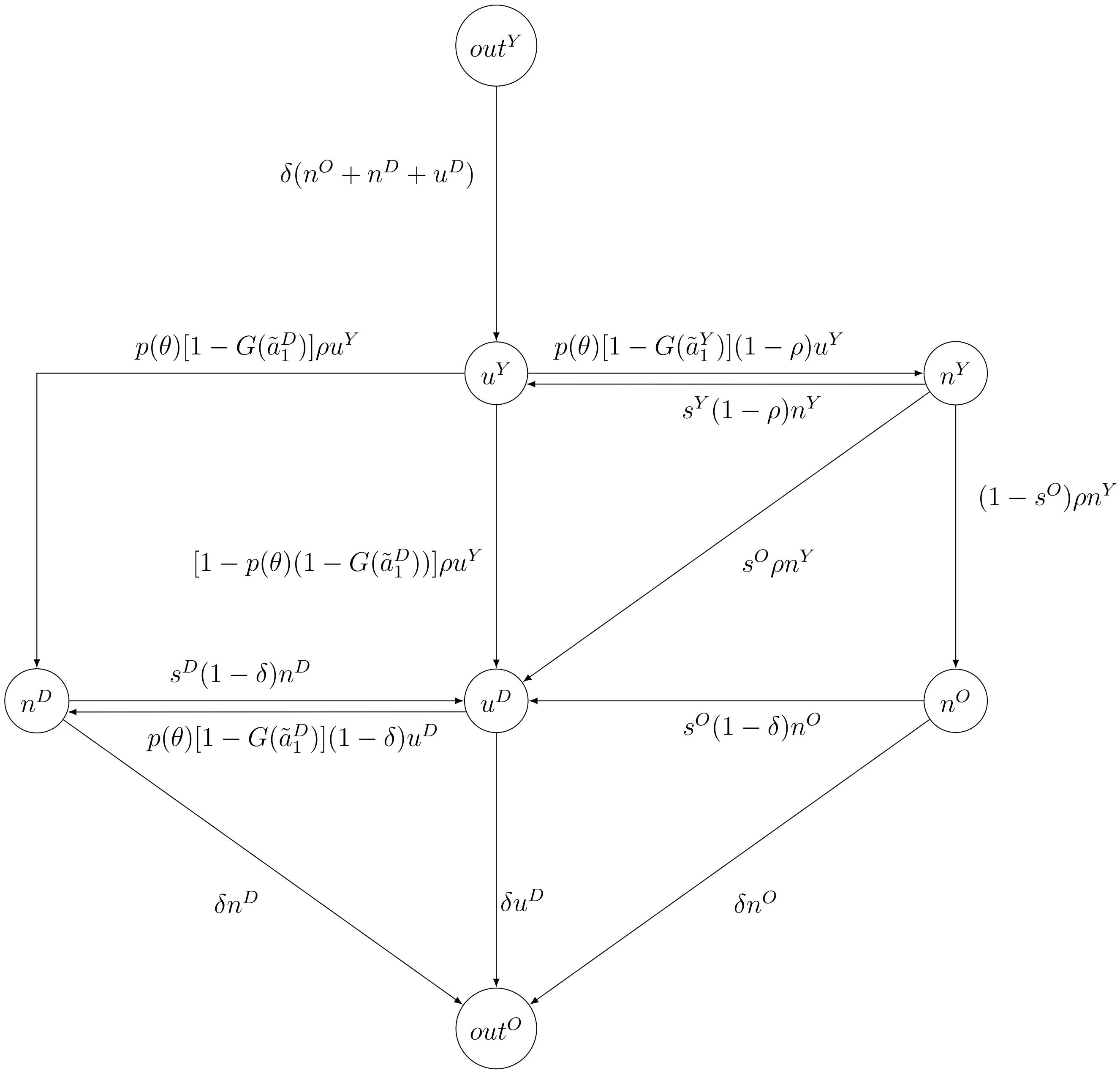


FIGURE 7. Description of labor market flows in the model

B.3. *Additional simulation results*

TABLE 9. Labor market disaggregates: data versus model

	U.S. data 1991-2011	*Simulation results Low turnover economy*
Panel A: Job finding rate		
By age		
Young	60.7	58.8
Old	40.2	51.4
Ratio	1.5	1.1
By education level		
Low	52.7	55.3
High	49.4	60.6
Ratio	1.1	0.9
Panel B: Separation rate		
By age		
Young	5.5	6.6
Old	1.7	0.9
Ratio	3.2	7.7
By education level		
Low	4.6	4.1
High	1.9	2.1
Ratio	2.4	2.0

Notes: All data variables are constructed from CPS microdata and are averages of monthly data expressed in percentages. Young workers are workers with ages comprises between 16 and 34, whereas old workers are workers with 35 years of age and over. Low educated workers refer to workers with less than high-school or with a high-school degree. High educated workers refer to workers with some years of college or with a college degree.