Essays on Human Capital and Labor Market Dynamics

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Als meus pares

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Abstract

This thesis investigates the role of human capital in understanding recent developments in the U.S. labor market. Chapter 1 provides novel empirical evidence suggesting that an increasing importance of on-the-job human capital accumulation is behind the declining dynamism in job turnover. The quantitative results of a theoretical model show that the proposed explanation can account for almost one-third of the decline in job turnover. Chapter 2 shows that population aging and rising educational attainment are two crucial factors behind the downward trend in unemployment flows since mid-1970s. A theoretical model where older and more educated workers posses more job-specific human capital can account for the observed trends. Chapter 3 finds that more educated individuals experience lower and less volatile unemployment due to a lower hazard rate of losing a job. A theoretical model with initial on-the-job training illustrates that accumulation of match-specific human capital can explain this empirical pattern.

Resum

Aquesta tesi investiga el paper del capital humà en la comprensió de certs esdeveniments recents en el mercat de treball dels Estats Units. El capítol 1 proporciona nova evidència empírica que suggereix que la creixent importància de l'acumulació de capital humà en el lloc de treball està darrere de la pèrdua de dinamisme en el mercat laboral. Els resultats quantitatius d'un model teòric mostren que la hipòtesi que es proposa pot explicar gairebé un terç de la pèrdua de dinamisme en el mercat laboral. El capítol 2 mostra que l'envelliment de la població i l'augment del nivell educatiu són dos factors crucials darrere de la tendència a la baixa dels fluxos d'entrada i sortida de l'atur des de mitjans dels anys setanta. Un model teòric en què els treballadors de més edat i més educació tenen un major nivell de capital humà específic pot explicar les tendències observades. El capítol 3 mostra que els individus amb major educació experimenten un nivell de desocupació més baix i menys volàtil, degut a una menor probabilitat de perdre el lloc de treball. Un model teòric que incorpora formació inicial al lloc de treball il·lustra que l'acumulació de capital humà específic pot explicar aquesta regularitat empírica.

Foreword

This thesis examines several macroeconomic aspects of labor markets. It consists of three self-contained chapters that highlight the importance of human capital in understanding recent developments in the U.S. labor market. This thesis uses recent empirical and theoretical advances in the area of labor market flows analysis and search and matching models.

Chapter 1, "The Slowdown in Business Employment Dynamics: The Role of Changing Skill Demands", studies the observed decline in U.S. business employment dynamics over recent decades. I propose and quantitatively evaluate the hypothesis that on-the-job human capital accumulation has become increasingly important over time. Indirect empirical support for this hypothesis relates to secular trends of rising educational attainment and changing skill demands due to technical advances. The chapter also provides more direct and novel empirical evidence, showing that job training requirements have risen over time. I construct a multi-worker search and matching model with endogenous separations, where training investments act as adjustment costs. The model can explain how the increase in training requirements accounts for the decline in job turnover, the increase in inaction, and the evolution towards a more compressed employment growth distribution, all consistent with the data. Quantitatively, the observed increase in training costs can explain almost one-third of the decline in the job reallocation rate over the last few decades. The key mechanism is that higher job training requirements make firms reluctant to hire and fire workers when economic conditions change, resulting in lower labor turnover.

Chapter 2, "The Fading Dynamism of the U.S. Labor Market: The Role of Demographics" (joint with Tomaz Cajner), analyzes the role of demographics for the downward trend in unemployment flows since mid-1970s. We find that population aging and rising educational attainment are two crucial factors behind the observed trend. Empirically, these two demographic characteristics explain about three quarters of the total decline in aggregate unemployment flows from 1976 to 2011. We examine theoretically why and how age and education affect the dynamism of unemployment 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.

Chapter 3, "Human Capital and Unemployment Dynamics: Why Do More Educated Workers Enjoy Greater Employment Stability?" (joint with Tomaz Cajner),

systematically and quantitatively investigates the reasons why employment stability increases with education. The analysis of the U.S. micro data shows that the remarkably divergent patterns in unemployment rates across education groups are almost entirely driven by differences in job separation rates, whereas job finding rates remain surprisingly similar across individuals with different educational attainment. Since existing models fail to account for these stylized facts, we proceed by examining several possible explanations for differences in unemployment dynamics by education with an equilibrium search and matching model that features endogenous job destruction and complementarities between on-the-job training and education. Our main finding is that given the observed differences in on-the-job training by education, the model is able to explain the empirical regularities across education groups on job finding rates, separation rates, and unemployment rates, both in their first and second moments. Other potential explanations for divergent patterns in unemployment by education appear to be less likely when analyzed through the lens of a standard search and matching model.

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Chapter 1

THE SLOWDOWN IN BUSINESS EMPLOYMENT DYNAMICS: THE ROLE OF CHANGING SKILL DEMANDS

1.1 Introduction

The U.S. labor market has been traditionally characterized as highly flexible and dynamic. However, over the recent decades several measures of labor market turnover appear to have been trending down. Diminished labor market dynamism can have profound macroeconomic implications. On the one hand, lower labor market mobility impedes reallocation of labor resources towards their most productive use and could, in theory, result in sluggish labor market recoveries following business cycle downturns. On the other hand, lower job reallocation can also enhance incentives for on-the-job human capital formation, thus leading to productivity gains and possibly higher job stability and reduced joblessness. Which of these opposing forces will prevail, depends to a large extent on the underlying reasons for the secular decline in labor market dynamics. Despite the importance of this question for both employment and productivity dynamics, and also for potential economic policy responses, the existing literature offers little clues on the ultimate source of this decline.

This paper proposes and quantitatively evaluates a novel hypothesis that job training requirements have become increasingly important over time and have resulted in declining labor market turnover. This hypothesis is closely related to several observations about the recent changes in the U.S. labor market: (i) a tremendous increase in educational attainment, that has been associated in the literature with the idea of skill-biased technical change, (ii) job polarization, which refers to the increasing concentration of employment in the highest and lowest skill/wage occupations, as job opportunities in the middle-skill occupations disappear, and (iii) the offshoring of some types of jobs. In order to explain these phenomena, the recent literature links them to technological advances. Major technological innovations of the last decades, such as automation, computerization, and wide diffusion of information and communication technology, seem to have increased the relative demand for skilled workers. Moreover, the change in skill demands has been accompanied by an increase in training requirements. This paper argues that changing skill demands, together with the increase in training requirements, might be behind the declining dynamism of the U.S. labor market.

Empirically, by using the Business Employment Dynamics dataset, I show that job reallocation rates have declined and that the employment growth distribution has become more compressed over time, both at the aggregate level and within industries. At the same time, I document that job training requirements have risen. In particular, combining information on training requirements by occupation from the Dictionary of Occupational Titles with employment data from the Census and the Current Population Survey I find that: (i) the share of workers employed in occupations requiring long training times has steadily increased over time, and (ii) the amount of training required by occupations has also increased. Importantly, most of the increasing importance of training over time is observed within industries. Finally, exploiting evidence at the industry level, I find additional empirical support for the working hypothesis. Specifically, I show that industries with a higher increase in the share of workers employed in long training occupations experience a higher decline in employment dynamics.

Can the observed increases in training requirements account for the decline in labor market dynamism? In order to answer this question I construct a multi-worker search and matching model, where training investments act as adjustment costs. The model economy is calibrated to be consistent with a set of aggregate and distributional moments for the U.S. economy. I then analyze the labor market implications of varying the magnitude of training costs. The model can explain how the increase in training accounts for the decline in job reallocation, the increase in inaction, and the evolution towards a more compressed employment growth distribution, all consistent with the data. Quantitatively, the observed increase in training requirements can explain almost one-third of the decline in the job reallocation rate over the last few decades. The solution of the model is characterized by a region of inaction, given the presence of non-convex hiring costs. Firms only hire when productivity is sufficiently high, and only fire when it is sufficiently low. When training costs rise, the region of inactivity expands and firms become more reluctant to hire and fire workers when economic conditions change.

The introduction of a notion of firm size into a search and matching model allows to analyze a series of cross-sectional implications related to employer size. Particularly, the model predicts that larger firms are more productive and pay higher wages as in the data. More interestingly, the model also predicts that the size-wage differential widens and that wage dispersion raises when training costs increase. While the empirical evidence on changes over time in the size-wage gap is virtually non-existent, there is substantial empirical work documenting an increase in wage inequality in the United States since the late 1970s. Additionally, the model can replicate the empirical fact that larger firms have lower job flow rates, when considering an extension allowing for quadratic vacancy posting costs.

The model is also used to examine a potential alternative explanation for the decline in aggregate labor turnover measures: a decline in the size of shocks faced by firms. The results show that the hypothesis of smaller shocks is consistent with the observed developments in employment dynamics, at least qualitatively, and could complement the explanation analyzed in this paper. However, one of the main challenges for this hypothesis is to find an empirical counterpart for the shocks affecting firms. Finally, other possible explanations behind the decline in labor turnover are briefly discussed at the end of this paper.

Following this introduction, the rest of the paper is organized as follows. Section 1.2 discusses the related literature. Section 1.3 provides the empirical evidence on which this paper builds. Section 1.4 develops the model. Then, Section 1.5 presents the parameterization of the model and the main simulations results, together with a discussion of the model's mechanism. Section 1.6 conducts a sensitivity analysis of the main quantitative results and Section 1.7 examines the cross-sectional implications of the model. A discussion of alternative explanations is contained in Section 1.8. Finally, Section 1.9 concludes with a discussion of possible avenues for further research. I provide data description, some further empirical results, supplementary details on the model and additional robustness checks in Appendix A.

1.2 Related Literature

Several recent papers provide evidence on declining labor market turnover in the United States 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, 2014) 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), Davis et al. (2010), and Decker et al. (2013), 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 have 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 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. The author shows that this mechanism can be behind the decline in the separation rate.

The methodology followed by this paper to document that training has become more important over time is similar to the one in Autor et al. (2003), who argue that the adoption of computer-based technologies is behind the disappearance of routine jobs in the U.S. labor market. Since non-routine tasks are positively correlated with training measures, this enhanced technological sophistication of the production process can also be used as indirect evidence that the importance of training has risen over time. In that respect, this paper is also related to the empirical literature on job polarization as Acemoglu (1999), Autor et al. (2006), Autor and Dorn (2013), Goos and Manning (2007), and Goos et al. (2009).

Additionally, this paper relates to other work that investigates the interaction between labor turnover and training provision. Particularly, chapter 3 of this thesis argues that on-the-job training, being complementary to formal education, is the reason why more educated workers experience lower unemployment rates and lower employment volatility. Wasmer (2006) analyzes the interaction between turnover and specificity of skills in a setting with search frictions and firing costs, and finds that labor market institutions can affect investment decisions between general and specific human capital.

Finally, this paper contributes to the recent theoretical literature on search and matching models that incorporate a notion of firm size. The recent availability of establishment-level data on workers flows and job flows has increased the interest of incorporating firm dynamics and heterogeneity into standard models of search. Contributions to this literature include: Acemoglu and Hawkins (forthcoming), Cooper et al. (2007), Elsby and Michaels (2013), Fujita and Nakajima (2013), Kaas and Kircher (2011), and Schaal (2012). Relative to the existing literature, this paper provides a multi-worker search and matching model with endogenous separations and investments in training, which allows to study the macroeconomic effects of increasing training requirements.

1.3 Empirical Evidence

This section provides the empirical evidence on which this paper builds. First, I show that the declining dynamism of the U.S. labor market manifests itself at the employer level, through lower rates of job gains and losses and through a more compressed distribution of employment growth rates. Second, I provide a novel piece of empirical evidence from the Dictionary of Occupational Titles that training requirements have become more important over time. Then, I examine cross-sectional variation at the industry level to find additional empirical support for the working hypothesis of this paper. Finally, I discuss indirect empirical evidence related to the increasing importance of training over time.

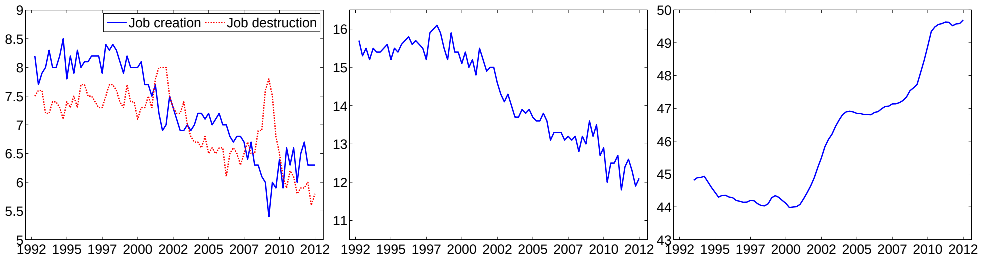
1.3.1 Declining Business Employment Dynamics

This section documents the evolution of job flows in the United States over time. Job flows measure the net change in employment at the establishment level, and they represent a central piece of information for understanding the dynamism of the labor market.

Figures 1.1a and 1.1b depict aggregate quarterly measures of job creation, job destruction, and job reallocation for the nonfarm private sector using data from the Business Employment Dynamics (BED) over time.[1] Job creation is defined as the sum of all jobs added at either opening or expanding establishments, and job destruction includes the sum of all jobs lost in either closing or contracting

[1] The BED data are compiled by the U.S. Bureau of Labor Statistics (BLS) from the administrative records of the Quarterly Census of Employment and Wages program. This program is a quarterly census of all establishments under state unemployment insurance programs, representing about 98 percent of nonfarm payroll employment. The data do not include government employees. All the BED data used in this paper are publicly available through the BLS website: http://www.bls.gov/bdm/.

establishments.[2] In turn, the job reallocation rate is the sum of job creation and destruction rates, and summarizes the restructuring of job opportunities across firms. Two main observations stand out from Figures 1.1a and 1.1b. First, job flows are large in magnitude. For example, in the mid-90s the total number of employment positions that were created and destroyed in a quarter was equal to 15 percent of total employment. Second, both job creation and job destruction rates exhibit a secular decline since the data became available in mid-1992, especially pronounced during the 2000s. Particularly, the average job reallocation rate at the end of the sample period is 20 percent lower than at the beginning of the sample period.[3]



(a) Job flows (b) Job reallocation (c) Inaction rate

Figure 1.1

Notes: All figures plot quarterly data for the nonfarm private sector from the BED for the period 1992:Q3–2012:Q2. Panels A and B plot seasonally adjusted data, while Panel C plots four-quarter moving averages of not seasonally adjusted data.

Even though the BED is only available since mid-1992, job flows from other databases with longer time series also share the same declining pattern. First, the

[2] Job creation and destruction are expressed as rates by dividing their levels by the average of total private employment in the current and the previous quarter. As shown by Davis et al. (1998), this measure provides a symmetric growth rate that offers an integrated framework of births, deaths, and continuing employers.

[3] Importantly, a declining trend is observed not only in quarterly job flows data, but also in annual measures. In particular, the BED *annual* job reallocation rate declined 24 percent between 1994 and 2012, from 27.1 percent to 20.5 percent. There are two main reasons why annualized quarterly flow rates are higher than annual flow rates. First, due to time aggregation, some of the quarterly job gains and job losses at the establishment level are offset during the estimation over the year. Second, as pointed out by Davis et al. (1998), transitory establishment-level employment movements, including seasonal movements, are much more likely to enter into the calculation of gross job flows over three-month, as opposed to twelve-month, intervals. If, for example, the prominence of seasonal jobs or temporary layoffs has declined over time, then we would see stronger declines in quarterly flow measures than in annual measures. The fact that both measures fell by approximately the same amount reassures us that the drop in quarterly measures is not due to changing behavior of transitory movements over time.

slowdown in business employment dynamics can also be observed using annual job flows data from the Business Dynamics Statistics (BDS), which covers the nonfarm private sector for the period 1977–2011 (see Figure A.1 in Appendix A.2). Similar evidence along these lines is provided by Davis et al. (2010) and Decker et al. (2013). Second, Faberman (2008) reports a secular decline in the magnitude of job flows for the manufacturing sector for the entire postwar period.[4] Particularly, the decline in the job reallocation rate in the manufacturing sector between the periods 1947–1983 vs. 1984–2010 is 22 percent (see Table 2 of his paper). Finally, Hyatt and Spletzer (2013) also show declines in job flows for the period 1998–2010 using quarterly employment data from LEHD.

Notice that the job creation and destruction rates are just two summary statistics of the underlying distribution of establishment-level employment growth rates. A closer examination of this distribution using data from the BED shows that it has become more compressed over time. Specifically, Figure 1.1c depicts the evolution of the share of establishments with no employment change from the previous quarter (i.e. the inaction rate). During the 1990s, the share was around 44 percent and it has increased over time, reaching an average close to 50 percent in mid-2012. The inaction rate provides additional information not contained in the job flow measures analyzed so far, as those establishment with unchanged employment contribute to neither job creation nor job destruction. The counterpart of the increasing number of inactive firms is a decline in the share of firms that adjust, visible in nearly all categories by size of change (see Figure A.2 in Appendix A.2). Similar results for the employment-weighted distribution are provided by Davis et al. (2012) and Hyatt and Spletzer (2013), using confidential microdata from the BED and LEHD, respectively.[5] Thus, during the last two decades there has been a narrowing distribution of establishment growth, with more employment in establishments with no change.

Finally, other indicators also point to a secular decline in the variability of establishment-level employment changes. For example, Davis et al. (2010) document a secular decline since the mid-1970s in the cross-sectional dispersion of employment growth rates and in the time-series volatility of establishment growth rates.

[4]The author does so by constructing a consistent time series of quarterly manufacturing job flows for the period 1947–2010 from three different databases: the Longitudinal Research Database, the Labor Turnover Survey and the BED.

[5]Davis et al. (2012) focus on selected periods between 1991 and 2009 (see Figure 5 and Table 1 of their paper) and Hyatt and Spletzer (2013) focus on the period 1998:Q2–2010:Q4 (see Figure 4 of their paper).

The importance of composition shifts for the decline in business employment dynamics

Several possible explanations might be behind the long-term fall in the magnitude of job flows. This paper argues that human capital accumulation in ongoing jobs has become increasingly important over time. Before examining the empirical relevance of this hypothesis, I first analyze whether the changing composition of firms can explain the behavior of aggregate job flows. This exercise has the potential of identifying promising explanations for the decline in turnover. In that respect, one of the first candidates to explain the aggregate trend is the change in the industry composition. Indeed, job flows magnitudes vary greatly among industries, and it is well know that some sectors (e.g. manufacturing) has been shrinking in the United States over the recent years, while others (e.g. health, education and professional and business services) have become more predominant.

Notice that the aggregate job reallocation rate in period t, denoted by r_t, can be computed as the employment-weighted average of job reallocation rates for each industry i as follows:

$$r_t = \sum_{i \in \Omega} z_{it} r_{it}, \tag{1.1}$$

where $z_{it} = (Z_{it}/Z_t)$ is the industry i share of total employment, and Z_{it} and Z_t are the averages of employment in periods t and $t-1$ for industry i and for the aggregate economy, respectively. Finally, Ω represents the set of all industries considered.

With the objective of quantifying the importance of industry changes for the behavior of the aggregate job reallocation rate I decompose the change in the job reallocation rate from period t to the base period t_0 into two terms:

$$\Delta r_t = r_t - r_{t_0} = \sum_{i \in \Omega} \Delta z_{it} \overline{r_i} + \sum_{i \in \Omega} \Delta r_{it} \overline{z_i}, \tag{1.2}$$

where $\overline{r}_i = \frac{1}{2}(r_{it_0} + r_{it})$ and similarly for $\overline{z_i}$. The first term on the right of equation (1.2) measures the change in the composition of the economy between t and t_0, whereas the second term captures the change in the group-specific rate between t and t_0 (the *within* component). Similar equations to (1.1) and (1.2) apply for the job creation and destruction rates. Table 1.1 presents the results of the decomposition for all job flow rates, both for the BDS and BED data, considering the first period of data availability as the base period t_0.[6]

The aggregate job reallocation rate declined by 3.7 percentage points over the sample period, from an average of 15.7 percent in 1992 to an average of 12.1

[6]For the BED data, the decomposition considers 87 3-digit NAICS industries. BDS job flows data at the industry level are only available for 9 industries.

Table 1.1: Decomposition of changes for the job flow rates

	Job reallocation	Job creation	Job destruction
Panel A: BED data 1992:Q2–2012:Q2			
Change over period	-3.7	-2.0	-1.7
Composition	0.4	0.2	0.2
Within	-4.1	-2.2	-1.9
Panel B: BDS data 1977–2011			
Change over period	-12.4	-8.8	-3.6
Composition	1.7	1.1	0.6
Within	-14.1	-9.8	-4.2

Notes: The decomposition considers 87 3-digit NAICS industries for the BED data, and 9 industries for the BDS data.

percent in 2012. However, the industry shifts observed during this period have actually contributed to *increase* the aggregate job reallocation rate. The same result is found for the job creation and destruction rates. Thus, the decomposition exercise informs us that the slowdown in business employment dynamics is observed within industries, and that it is not a result of industry composition shifts.[7] Indeed, virtually all industries experience declines in the reallocation rates and increases in the inaction rates during the sample period (see Figure A.3 in Appendix A.2).[8]

Overall, these results are relevant as they imply that any potential explanation about the decline in job turnover needs to apply, at least in part, within industries. This paper argues that human capital accumulation in ongoing jobs has become increasingly important over time. Next, I examine the empirical relevance of this hypothesis, and I also study whether this is observed across and/or within industries.

[7] Hyatt and Spletzer (2013) find a similar result for the job creation and job destruction rates using BED data from 12 industries for the period 1998:Q2–2010:Q4. Decker et al. (2013), with access to BDS microdata, quantify the contribution of compositional shifts by firm age, firm size, industry, geographic location and multi-unit status to the changing patterns of business dynamics. The authors find that compositional effects explain no more than a quarter of the decline in dynamism between 1982 and 2011. These results lead them to conclude that the real driving force behind the aggregate decline is to be found in factors working within detailed industry, firm size, age, and geographical groupings.

[8] For the BED data, 97 percent of the 87 3-digit NAICS industries experienced a decline in the job reallocation rate between 1993 and 2011. Regarding inaction, 95 percent of the 87 3-digit NAICS industries experienced an increase in the inaction rate over the same period.

1.3.2 The Importance of Training Over Time

This section presents novel empirical evidence on the importance of training investments by occupation and their evolution over time. In order to compute measures of training requirements by occupation I use the information contained in the Fourth Edition of the Dictionary of Occupational Titles (DOT) published in 1977 by the U.S. Department of Labor. This section provides a summary of the data construction process; for a complete description of the process and the datasets used in the analysis see Appendix A.1.

The DOT is a classification of more than 12,000 occupations, with quantitative information about task requirements by occupation. The variable of interest for my analysis is Specific Vocational Preparation (SVP). SVP is defined as the amount of time required by a typical worker to learn the techniques, acquire the information and develop the facility needed for average performance in a specific job-worker situation. SVP includes training acquired in a school, work, military, institutional, or vocational environment, but excludes schooling without specific vocational content. SVP does not include the orientation time required by a fully qualified worker to become accustomed to the special conditions of any new job. Occupations are rated on a nine-point scale, with higher values representing longer training times (see Table 1.2).

Table 1.2: Scale for Specific Vocational Preparation

Level	Description
1	Short demonstration only
2	Anything beyond short demonstration up to and including 30 days
3	Over 30 days up to and including 3 months
4	Over 3 months up to and including 6 months
5	Over 6 months up to and including 1 year
6	Over 1 year up to and including 2 years
7	Over 2 years up to and including 4 years
8	Over 4 years up to and including 10 years
9	Over 10 years

Given that the classification of occupations by the DOT is much more disaggregated than the classification provided by the Census, I follow the methodology proposed by Autor et al. (2003) to aggregate these detailed occupations into 3-digit Census Occupation Codes. This results in a dataset on measures of training requirements by 329 occupations and by gender corresponding to year 1977 (658 observations overall). Some examples of occupations that require very short training times (up to 3 months of training) are graders and sorters of agricultural products, janitors, cashiers, waiters, and textile sewing machine operators. Some examples of occupations that require medium training times (over 3 months up to and including 2 years) are cooks, dental assistants, aircraft mechanics, bank tellers, retail salespersons and sales clerks. Finally, some examples of occupations requiring more than two years of training are: computer software developers, managers and specialists in marketing, lawyers and judges, financial managers, physician, economists, market and survey researchers.

Next, I combine the information on training requirements by occupation with employed workers between 18 and 64 years of age from two data sources: (i) the Census one-percent extracts for 1970, 1980, 1990 and 2000 provided by the Integrated Public Use Microdata Series (Ruggles et al., 2010); and (ii) the yearly Current Population Survey (CPS) Merged Outgoing Rotation Groups (MORG) data files from 1979 until 2010.

In what follows, I study two dimensions of variation in the measure for training requirements over time. The first one considers the change over time in the distribution of employment across occupations requiring different degrees of training, keeping constant training requirements by occupation at the 1977 level. Following Autor et al. (2003), I label these cross-occupation employment changes as "extensive" margin. The second dimension of analysis, labeled "intensive" margin, considers changes in training requirements within occupations between 1977 and 1991. For the intensive margin analysis, I use the information contained in the Revised Fourth Edition of the DOT released in 1991.[9] In particular, I match occupations between the Fourth Edition and the Revised Fourth Edition of the DOT and I examine if there has been any substantial change over time in training requirements within occupations. Note that I only consider changes in training requirements experienced by occupations observed in 1977. Therefore, new occupations that appeared in the DOT 1991 are left aside at this point of the analysis.[10] All observations are weighted by the individual Census or CPS sampling weights. Similar results are obtain when using full-time equivalent hours of labor supply as weights (see Appendix A.2.3).

Aggregate trends in training requirements, 1970–2010

This section presents the results on changes over time in the distribution of employment across occupations requiring different degrees of training. First, I present results on the extensive margin, where I keep training requirements by occupation constant at the 1977 level. Table 1.3 presents the share of employ-

[9] This is the last year for which the DOT database is available. More recent information on task requirements is provided by the O*NET database, the successor of the DOT database. However, note that the O*NET database is not particularly designed to perform time-series analysis of occupation requirements over time.

[10] See Appendix A.1.3 for further details.

ment by level of SVP, separately for the Census sample and for the CPS MORG sample.[11] As it can be seen, there is a shift of employment from occupations requiring low amounts of training (low levels of SVP) to occupations requiring high amounts of training (high levels of SVP).

Table 1.3: Distribution of employment by level of SVP (DOT 1977, in %)

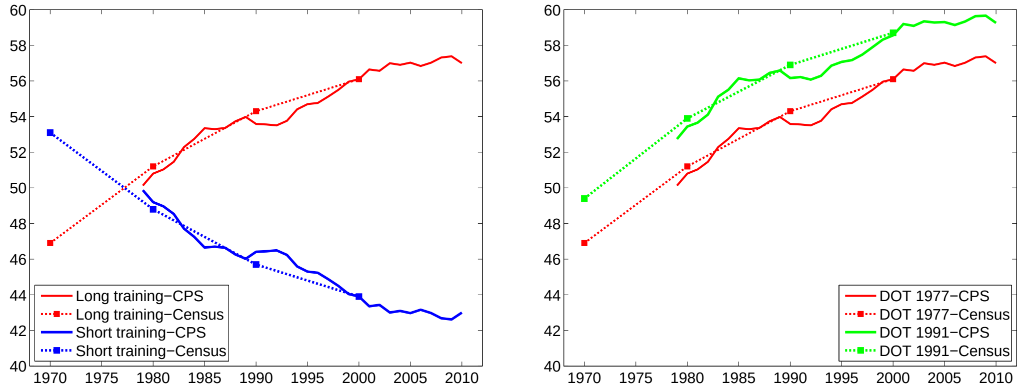
	1	2	3	4	5	6	7	8
Panel A: Census								
1970	0.2	8.3	20.3	11.3	12.9	13.4	20.8	12.8
1980	0.2	7.7	18.8	9.8	12.4	14.1	23.7	13.3
1990	0.2	7.4	17.4	8.6	12.0	14.4	25.8	14.2
2000	0.3	6.0	16.8	8.9	12.0	13.6	26.9	15.6
Diff. 1970–2000	**0.1**	**-2.3**	**-3.5**	**-2.5**	**-1.0**	**0.2**	**6.2**	**2.8**
Panel B: CPS MORG								
1980	0.2	7.5	19.4	9.6	12.4	13.0	22.7	15.0
1990	0.2	8.0	17.4	8.7	12.0	12.8	26.6	14.1
2000	0.3	6.4	16.9	8.9	11.3	12.7	27.4	15.9
2010	0.3	6.6	16.0	9.3	10.9	12.7	27.7	16.6
Diff. 1980–2010	**0.1**	**-0.9**	**-3.4**	**-0.3**	**-1.6**	**-0.3**	**4.9**	**1.6**

In order to graphically summarize Table 1.3, I aggregate occupations in two groups: occupations requiring short training times (up to 1 year of training, corresponding to levels of SVP between 1 and 5) and occupations requiring long training times (over 1 year up to over 10 years of training, corresponding to levels of SVP between 6 and 9). The choice of 1 year of training splits total employment in groups of similar size. Figure 1.2a presents the evolution over the time of the share of workers employed in occupations requiring short and long training times. The figure clearly illustrates that the share of workers employed in occupations requiring high degrees of training has steadily increased over the last years, from 46.9 percent in 1970 to 56.1 percent in 2010.[12]

The analysis so far has kept training requirements by occupation fixed at the 1977 level. Next, I turn to the analysis of the intensive margin, where I exam-

[11] The fact that I do not observe any occupation with SVP equal to 9 is the result of aggregating the detailed DOT occupations into the 3-digit Census Occupation Codes.

[12] Some of the occupations requiring long training times that show the highest increase in employment during the period of analysis are: computer software developers; computer systems analysts and computer scientists; chief executives, public administrators, and legislators; financial managers; office supervisors; and registered nurses. Some of the occupations requiring short training times that show the highest decline in employment during the period of analysis are: assemblers of electrical equipment; bookkeepers and accounting and auditing clerks; laborers, freight, stock, and material handlers; machine operators; textile sewing machine operators; and typists.



(a) Composition of the employment pool (in %)

(b) Share of workers employed in long training occupations (in %)

Figure 1.2

Notes: The dots correspond to the Census samples for each decade between 1970 and 2000, while the solid lines correspond to the CPS MORG samples for each year between 1979 and 2010. *Short training* refers to occupations requiring up to 1 year of training (corresponding to levels of SVP between 1 and 5) and *long training* refers to occupations requiring over 1 year of training (corresponding to levels of SVP between 6 and 9). Training requirements by occupation are kept fixed at the DOT 1977 level in Panel A.

ine the changes in training requirements within occupations between 1977 and 1991. The results are presented in Figure 1.2b, where the green line represents the share of workers employed in occupations requiring long training times using training requirements from 1991, and the red line the same share but using training requirements for 1977. As it can be seen, if the training requirements by occupations from the DOT 1991 are used, I find a higher share of workers employed in long training occupations than if I use the DOT 1977. This provides evidence that training requirements within occupations have risen over time.[13]

To summarize, both the extensive and the intensive margin point to the same conclusion: an increased prevalence of training investments over time. In particular, taking into account both margins, the share of workers employed in occupations requiring high degrees of training has increased 11.8 percentage points over the last years, from 46.9 percent in 1970 to 58.7 percent in 2010. Similar results are obtained when using full-time equivalent hours to weight the observations (see Appendix A.2.3).

Finally, Figure 1.3 shows the evolution of training over time expressed in average training duration. To do that, I first assign an average training time to each

[13]Table A.1 in Appendix A presents the detailed results on the distribution of employment by level of SVP using training requirements from 1991. The observed empirical patterns are similar to the ones presented in Table 1.3.

occupation, which I consider it to be the mid-point of the interval for each level of SVP.[14] Then, I compute the average training times for each year in the sample period, again weighting by the individual Census or CPS sampling weights. As it can be seen in the figure, the average training duration increased by about 5 months or a bit less than 25 percent over the last four decades.

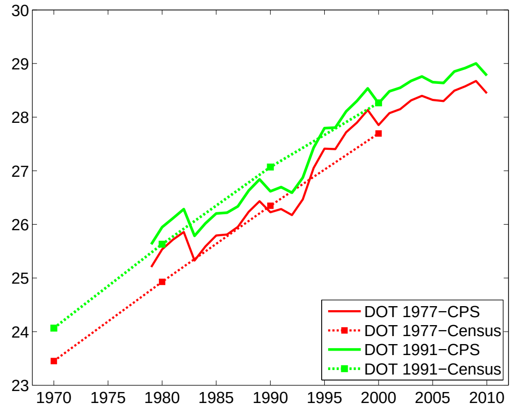


Figure 1.3: Average training times (in months)

Notes: The dots correspond to the Census samples for each decade between 1970 and 2000, while the solid lines correspond to the CPS MORG samples for each year between 1979 and 2010.

Changes in training requirements within and between industries, 1983–2010

In this section I analyze the importance of industry shifts for the aggregate trends in training requirements. The objective here is to know whether the increased importance of training requirements at the aggregate level is due to higher training investments within industries and/or due to a shift of employment from industries that require short training times to industries that require long training times. The answer to this question is relevant given that, as shown in Section 1.3.1, the slowdown in business employment dynamism is observed within industries. Thus, if one would like to argue that the trends in training are related to the trends in job flows, one would also like to see that the aggregate increase in training requirements is at least partly observed also within industries.

Note that the share of workers employed in long training occupations, denoted by γ_t, can be computed as the employment-weighted average of the shares for industry group i as follows:

[14]For the first SVP category the average training time is assumed to be zero, and for the last category I consider it to be equal to 10 years.

$$\gamma_t = \sum_{i \in \Omega} n_{it} \gamma_{it},$$

where $n_{it} = (N_{it}/N_t)$ is the industry i share of employment, and N_{it} and N_t are employment levels in periods t for industry i and for the aggregate economy, respectively. Next I decompose the change in the share of workers employed in long training occupations from period t to the base period t_0 into two terms:

$$\Delta\gamma_t = \gamma_t - \gamma_{t_0} = \sum_{i \in \Omega} \Delta n_{it} \overline{\gamma_i} + \sum_{i \in \Omega} \Delta \gamma_{it} \overline{n_i}, \tag{1.3}$$

where $\overline{\gamma_i} = \frac{1}{2}(\gamma_{it_0} + \gamma_{it})$ and similarly for $\overline{n_i}$. As before, the first term on the right of equation (1.3) measures the change in the composition of the employed workers between t and t_0, whereas the second term captures the change in the group-specific share of workers employed in long training occupations between t and t_0. The results of this decomposition exercise are summarized in Table 1.4.[15] Note that the bulk of the increase in the aggregate share of workers employed in long training occupations happens within industries. In particular, and depending on the sample and the time period analyzed, between 61.6 percent and 73.5 percent of the increase in the aggregate share of workers employed in long training occupations is due to employment shifts from short to long training occupations within industries.

Examining the link between job flows and training requirements at the industry level

This section examines the link between job flows and training requirements at the industry level. In order to do that, I combine two pieces of data at the 3-digit NAICS industry level: (i) job flow rates from the BED for the period 1993 to 2010; and (ii) the share of workers employed in long training occupations from the CPS MORG using training requirements from the DOT 1991, available from 1983 to 2010. Overall, the final dataset contains information on 83 industries.

The analysis of the cross-sectional relationship between jobs flows and training requirements shows that industries with a higher share of workers employed in long training occupations tend to have lower job flow rates and higher inaction rates (see Figure A.6 in Appendix A). This is consistent with the hypothesis suggested by this paper. Nevertheless, given that the cross-industry relationship can

[15] A total of 14 industries are considered for the Census sample and a total of 224 industries for the CPS MORG sample, covering all sectors of the economy in each year of the sample period.

Table 1.4: Decomposition of changes for the share of workers employed in long training occupations

	Census 1970–2000	CPS MORG 1983–2010
Panel A: Extensive margin		
Change over period	8.1	4.9
Composition (in %)	36.0	38.4
Within (in %)	64.0	61.6
Panel B: Extensive and intensive margin		
Change over period	10.7	7.2
Composition (in %)	27.7	26.5
Within (in %)	72.3	73.5

Notes: The decomposition considers 14 industries for the Census sample and a total of 224 industries for the CPS MORG sample.

be confounded by omitted variables, I proceed to analyze whether those industries which experienced higher increases in the share of workers employed in long training occupations also experienced higher declines in job reallocation. One important issue in such analysis is that those industries that need to change their composition of jobs might also need to undertake some degree of additional job creation and destruction. Thus, even if a higher increase in the share of long training jobs might lead to lower employment dynamics in the industry in the long run, it can also induce a short-term boost on job flows. As a result, I run the following regression:

$$\Delta r_{i,93-10} = \alpha + \beta_1 \Delta\gamma_{i,83-92} + \beta_2 \Delta\gamma_{i,93-10} + \epsilon_i, \tag{1.4}$$

where $\Delta r_{i,93-10}$ is the change in the reallocation rate in industry i between periods 2010 and 1993, and γ_i is the share of workers employed in long training (i.e. over 1 year of training) occupations in industry i. The results are presented in Table 1.5.

The results are consistent with the discussion above. Particularly, there is a positive and significant relationship between the increase in the share of workers employed in long training occupations during the period 1983-1992 and the subsequent decrease in the job reallocation rate in the following decade.[16] This is consistent with the hypothesis of this paper that the declining business employment dynamics is related to the increasing share of workers employed in long training occupations. However, increases in the share of workers employed in long

[16]Similar results are obtained when considering as a dependent variable the change in the job creation and destruction rates. See Tables A.4 and A.5 in Appendix A.2.

Table 1.5: Job reallocation and training requirements

	(1)	(2)	(3)
$\hat{\alpha}$	-0.194***	-0.220***	-0.197***
	(0.025)	(0.022)	(0.024)
$\hat{\beta}_1$	-0.318*		-0.363**
	(0.173)		(0.170)
$\hat{\beta}_2$		0.099*	0.141**
		(0.054)	(0.064)
Observations	82	83	82
R-squared	0.072	0.021	0.111

Notes: Dependent variable: Difference in the job reallocation rate between 1993 and 2010. Robust standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

training occupations are found to have a contemporaneous effect of *increasing* the rates of job reallocation. This opposite result could be explained by a mechanical effect: changing the composition of jobs in a particular industry might entail a raise in job reallocation in the short-run.

Overall, I view the industry-level results as suggestive of a link between job flows and training requirements in line with the thesis argued in this paper. However, the results are not conclusive and further research is needed. In particular, more disaggregate data at the level of establishments would be helpful to better identify the mechanisms at work.

1.3.3 Additional Aggregate Trends Related to the Importance of Training

Concurrently to the decline in labor market turnover measures, the U.S. labor market has also seen the emergence of two particular phenomena, that are arguably related to the working hypothesis of this paper that human capital accumulation in ongoing jobs has become increasingly important over time.

First, as documented by Autor et al. (2003), the U.S. labor market has seen the disappearance of routine jobs due to the adoption of computer-based technologies. This enhanced technological sophistication of the production process is consistent with the fact that the importance of training has risen over time, given that non-routine tasks are positively correlated with training measures. Particularly, the correlation between the level of SVP and the measure of routine task-intensity introduced by Autor and Dorn (2013) is equal to -0.17. Thus, routine occupations are characterized by low training requirements. In order to shed additional light into this issue, Table 1.6 presents the share of employment and the average level of SVP by major occupation group for the Census sample.[17]

Table 1.6: Levels and changes in employment share from Census and mean SVP by major occupation group

	Share of Employment (in %)					Mean SVP
					Diff.	
	1970	1980	1990	2000	1970-2000	
Managers/Prof/Tech/Finance/Public Safety	26.2	31.3	37.4	39.1	**12.8**	**7.1**
Production/Craft	4.6	4.5	3.3	3.4	**-1.2**	**6.8**
Transport/Construct/Mech/Mining/Farm	21.1	20.3	18.3	17.2	**-3.9**	**5.0**
Machine/Operators/Assemblers	13.2	9.8	7.3	5.6	**-7.6**	**4.0**
Clerical/Retail Sales	24.7	24.6	24.0	23.7	**-1.0**	**4.4**
Service Occupations	10.2	9.5	9.8	11.1	**0.9**	**3.9**

As we can see, there has been a substantial increase in the share of workers employed in the first occupation group formed by executive and managerial occupations, professional specialty occupations, technicians and related support occupations, financial sales and related occupations, and fire fighting, police, and correctional institutions' workers. As shown in Autor and Dorn (2013), these occupations are characterized by low values of routine-task intensity. Importantly, the level of training that these occupations require is the highest one. At the same time, there has been a noticeable decline in occupations as machine operators, assemblers, and inspectors. These are occupations with a high intensity of routine tasks and, as shown in the table, they are among the occupations with lowest degrees of training requirements. Table A.6 in Appendix A repeats the exercise for the CPS MORG sample, and shows that the observed trends have continued until 2010. Therefore, these results are indicative that the composition of jobs is changing, and that high training jobs are becoming more important over time.

Second, there has been a tremendous increase in educational attainment over the last decades. In particular, Figure 1.4 shows that high school dropouts were the largest education group in the population until the 1970s, while nowadays nearly 60 percent of the population have spent at least some years in college. Existing empirical studies of training overwhelmingly suggest the presence of strong complementarities between education and on-the-job training (see chapter 3 of this thesis and references therein). For example, data on initial on-the-job training from the Employer Opportunity Pilot Project (EOPP) survey shows that highly educated workers receive greater amounts of training than low educated workers, both in terms of the duration of the training received and the subsequent increase in productivity. One interpretation of this stylized fact is that more educated individuals engage in more complex job activities for which they need more initial

[17]The classification into six major occupation groups is to facilitate comparison with the work by Autor and Dorn (2013) on polarization of the U.S. labor market (see Table 1 of their paper). Occupations are ordered by average wage level.

training. The link between education and training can be also analyzed using data on training requirements by occupation from the DOT. Further empirical exploration of these data by education group reveals that the share of workers employed in long training occupations (and also the average training time) is increasing in the level of education, consistent with the evidence on complementarities between education and training.[18] Therefore, if the labor force has become more educated over time, the importance of training should have also increased correspondingly.

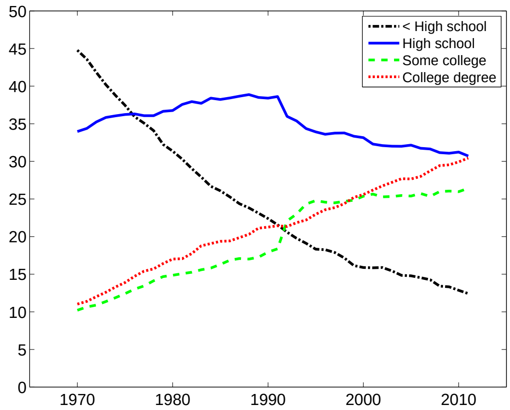


Figure 1.4: Structure of the U.S. population by educational attainment

Notes: The graph plots yearly data for the period 1970–2011. The data correspond to people with 25 years of age and over and is provided by the Census Bureau.

1.4 Model

This section presents a search and matching model with multi-worker firms and endogenous separations. The model builds on the important contributions of Mortensen and Pissarides (1994) and Elsby and Michaels (2013). I extend the existing framework by adding investments in training and idiosyncratic productivity shocks that follow an AR(1) process. I show that the resulting model accounts for the empirical firm-size and employment growth rate distributions, and allows to study the macroeconomic effects of increasing training requirements.

[18] Particularly, 33 percent of workers with less than high school are employed in occupations requiring long training times. The same proportion is 43 percent for high school graduates, 53 percent for those with some college, and 82 percent for college graduates. In terms of average training duration, high school dropouts work in occupations requiring on average 15 months of training, 20 months for high school graduates, 25 months for those with some college and 45 for college graduates. See Figure A.7 in Appendix A.

1.4.1 Environment

I consider a discrete time economy, with a mass of potential workers equal to the labor force L and a fixed mass of firms normalized to one. The model abstracts from entry and exit of firms.[19] Workers are risk-neutral, infinitively-lived, and 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 are ex-ante homogeneous and can be either employed or unemployed. Employed workers earn a wage w, while unemployed workers have access to home production technology, which generates b consumption units per time period. All unemployed workers are looking for a job, thus I abstract from modeling labor force participation decisions.

Firms are risk-neutral and maximize their profits. Firms use labor, n, to produce output according to the following decreasing returns to scale production function:

$$y(\chi, a, n) = \chi a n^{\phi},$$

where χ is a time-invariant firm-specific productivity and a is an idiosyncratic productivity shock. The motivation for introducing a firm-specific fixed effect χ is to account for permanent heterogeneity in firm's productivity that is reflected in the firm-size distribution that we observe in the data. The framework considered in this paper abstracts from aggregate shocks and focuses on steady-state analysis. Thus, all aggregate variables are constant over time. The only source of uncertainty for the firm is the idiosyncratic productivity a. In that respect, job creation and destruction arise in the model only as a result of idiosyncratic factors. This view is consistent with the evidence provided by Davis and Haltiwanger (1999) who show that job flows are largely driven by firm-level heterogeneity in labor demand changes. The stochastic process for the idiosyncratic productivity a is assumed to be an AR(1) process in logs as in Cooper et al. (2007):[20]

[19] In the BED data, 80 percent of total job creation and destruction comes from expansions and contractions of continuing establishments, with the rest being accounted for by openings and closings of establishments. Importantly, the pace of job creation and destruction in the United States has experienced a secular decline over the recent decades both at continuing establishments and also at entering and exiting establishments (see Figure A.4 in Appendix A). A possible future extension of the model could allow for endogenous firm entry and exit.

[20] The specification of the idiosyncratic productivity shocks as an AR(1) process differs from the one adopted by Elsby and Michaels (2013). In particular, the previous paper assumes that a firm retains its idiosyncratic productivity until it is hit by a shock λ, in which case the firm draws a new idiosyncratic productivity from a certain cumulative distribution function G. A similar process is used in the seminal work of Mortensen and Pissarides (1994). The drawback of this process is that all the persistence in the idiosyncratic productivity is in the arrival rate λ, as the process has no memory at the firm level.

$$\ln a = \rho_a \ln a_{-1} + \epsilon, \quad \epsilon \sim \mathcal{N}(0, \sigma_a).$$

Given that the model is formulated recursively, I drop time subscripts from all variables and adopt the convention of using the subscript $_{-1}$ to denote lagged values and to use the prime to denote tomorrow's values.

Firms post vacancies in order to hire workers in the labor market, at a flow cost κ_v per vacancy. Due to the presence of search and matching frictions in the labor market, only a fraction of the posted vacancies will be filled by unemployed workers. Importantly, apart from the vacancy posting cost, I consider a fixed matching cost per hire κ_f, that I interpret as a training cost. This component of hiring cost is independent of the duration of vacancies and, similar to the vacancy posting cost, it is sunk at the time of wage bargaining as in Pissarides (2009).[21] I abstract from incorporating firing costs into the analysis, thus firing workers is costless for the firm.

The timing of events in the model is summarized as follows. At the beginning of the period, a firm's idiosyncratic productivity a is realized, and the firm is characterized by a triplet (χ, a, n_{-1}), where χ is the time-invariant productivity and n_{-1} is the firm's employment level in the previous period. After the realization of the idiosyncratic productivity the firm makes the hiring or firing decision. The hiring decision is subject to search and matching frictions and it is assumed that the vacancies posted at the beginning of the period (after a is realized) can be filled in the same period before production takes place. If the firm is hiring, it has to pay the training cost κ_f per each new hire after the matching process takes place. If the firm decides to fire part of its workforce, the separated workers enter the unemployment pool in the subsequent period. Thus, a worker that is separated will at least spend one period unemployed. After the matching process is complete, the wage negotiation is performed. Finally, production takes place and wages are paid.

1.4.2 Labor Markets

The matching process between vacancies and unemployed workers is assumed to be governed by a constant returns to scale matching function:

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

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

[21] Pissarides (2009) studies the implications of adding fixed matching costs to the proportional vacancy posting cost for the canonical search and matching model, in terms of increasing the cyclical volatility of unemployment.

elasticity of the matching function with respect to unemployment. The matching function is assumed to be concave and increasing in both of its arguments. Labor market tightness is defined as $\theta \equiv v/u$. The endogenous probability for an unemployed worker to meet a vacancy is given by:

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

and the endogenous probability for a vacancy to meet with an unemployed worker is:

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

Note that firms consider these flow probabilities as given when deciding their optimal level of employment.

1.4.3 Characterization of Recursive Equilibrium

In order to analyze the model's equilibrium I characterize the value functions associated to firms and workers. I start by analyzing the behavior of a firm. At the beginning of the period, a typical firm observes the realization of its idiosyncratic productivity shock a and decides, given its fixed productivity χ and its previous level of employment n_{-1}, the employment level that maximizes its profits. In particular, the expected present discounted value of firm's profits can be characterized as:

$$\begin{aligned}\Pi(\chi, a, n_{-1}) = \max_{n,v} \Big\{ &\chi a n^{\phi} - w(\chi, a, n)n - \kappa_v v - \kappa_f \max\{0, \Delta n\} \\ &+ \beta \mathbb{E}_a \{\Pi(\chi, a', n)\} \Big\},\end{aligned} \tag{1.5}$$

where $w(\chi, a, n)$ is the equilibrium bargained wage in a firm with time-invariant productivity χ, idiosyncratic productivity a and n employees. Note that $\Delta n \equiv n - n_{-1}$, given that there are no exogenous separations in the model. Due to the presence of labor market frictions, each vacancy that a firm posts is going to be filled with probability $q(\theta)$. Therefore, if the firm is hiring, the number of hires is given by:

$$\Delta n = vq(\theta). \tag{1.6}$$

Additionally, if the firm is hiring, it will have to pay the training costs κ_f for each newly recently hired worker. Substituting equation (1.6) into equation (1.5) allows to rewrite the firm's problem as follows:

$$\Pi(\chi, a, n_{-1}) = \max_{n} \Big\{ \chi a n^{\phi} - w(\chi, a, n)n - \left(\frac{\kappa_v}{q(\theta)} + \kappa_f \right) \max \{0, \Delta n\}$$
$$+ \beta \mathbb{E}_a \{ \Pi(\chi, a', n) \} \Big\}. \tag{1.7}$$

In order to determine the wage, I adopt the Stole and Zwiebel (1996) bargaining solution, which generalizes the Nash solution to a setting with diminishing returns. In particular, under the Stole and Zwiebel (1996) solution, the wage is the result of Nash bargaining between workers and firms over the total marginal surplus of a firm-worker relationship.

The firm's marginal surplus at the time of wage setting (hiring costs are sunk) is given by:

$$J(\chi, a, n) = \chi a \phi n^{\phi-1} - w(\chi, a, n) - w_n(\chi, a, n)n + \beta \mathbb{E}_a \{ \Pi_n(\chi, a', n) \}.$$

The value to a worker of being employed in a firm characterized by a time-invariant productivity χ, an idiosyncratic productivity level a and n employees is given by:

$$W(\chi, a, n) = w(\chi, a, n) + \beta \mathbb{E}_a \{ sU' + (1-s)W(\chi, a', n') \}.$$

Thus, an employed worker receives a wage $w(\chi, a, n)$ and next period he might be endogenously separated from the firm with probability s, in which case he would become unemployed and receive a value U' defined below. If the worker is not endogenously separated from the firm he will continue being employed tomorrow, enjoying a value $W(\chi, a', n')$.

An unemployed worker receives a current payoff of b and has a probability $p(\theta)$ to find a job next period:

$$U = b + \beta \mathbb{E} \{ (1 - p(\theta))U' + p(\theta)W(\chi, a', n') \}.$$

I can now define the total marginal surplus of a firm-worker relationship as follows:

$$S(\chi, a, n) \equiv \quad J(\chi, a, n) + W(\chi, a, n) - U.$$

Under the generalized Nash wage bargaining rule, the equilibrium wage $w(\chi, a, n)$ is determined by the following surplus-splitting condition, where η stands for the bargaining power of the worker:

$$W(\chi, a, n) - U = \eta S(\chi, a, n),$$

or equivalently:

$$(1-\eta)\left(W(\chi,a,n)-U\right) = \eta J(\chi,a,n).$$

Plugging in the value functions in the above equation, I find that the wage is given by the differential equation:[22]

$$w(\chi,a,n)=\eta\left(\chi a\phi n^{\phi-1}-w_n(\chi,a,n)n+\beta\theta\kappa_v+\beta p(\theta)\kappa_f\right)+(1-\eta)b. \tag{1.8}$$

Several characteristics of the wage equation resemble the standard search and matching model. First, the wage is increasing in the marginal product of labor and in the worker's unemployment income. Second, the worker is rewarded for the saving of hiring costs that the firm enjoys when the match is formed. In the current setup, the hiring costs include both the vacancy posting costs and the training costs. Third, aggregate labor market conditions influence the wage only through labor market tightness. There is, however, a new term in the wage equation, $w_n(\chi,a,n)n$, not present in a standard search and matching model. As mentioned by Stole and Zwiebel (1996), this term represents the incentives of the firm for "overemployment". This is due to the fact that by employing more workers the firm is able to reduce the marginal product of labor, and thus to reduce the wage bill. Solving the differential equation (1.8) yields:

$$w(\chi,a,n)=\eta\left(\frac{\chi a\phi n^{\phi-1}}{1-\eta(1-\phi)}+\beta\theta\kappa_v+\beta p(\theta)\kappa_f\right)+(1-\eta)b. \tag{1.9}$$

Plugging in the wage equation (1.9) into the firm's problem (1.7), I can solve for the policy function for employment $n^* = \Phi(\chi,a,n_{-1})$, given labor market tightness θ. Total employment is defined as the average employment level across firms (again, given θ):

$$N=\int \Phi(\chi,a,n_{-1})dF(\chi,a,n),$$

where $f(\chi,a,n)$ represents the stationary distribution of firms over the time-invariant productivity χ, the idiosyncratic productivity a and the level of employment n. In turn, total separations are defined as:

$$S=\int \max\left\{0,n_{-1}-\Phi(\chi,a,n_{-1})\right\}dF(\chi,a,n).$$

[22]Further details on the derivations can be found in Appendix A.3.

Finally, the labor market tightness is determined by the following two conditions:

$$U(\theta) = L - N, \tag{1.10}$$

$$S = p(\theta)U(\theta). \tag{1.11}$$

Equation (1.10) is the definition of the level of unemployment, and equation (1.11) is the steady state condition for unemployment. In the steady state, the unemployment level remains constant and the total number of separations, S, equal the total number of hires, $p(\theta)U(\theta)$. Appendix A.3.3 describes the computational strategy used to solve the model.

1.5 Simulation Results

This section presents the main simulation results of the paper. First, I calibrate a benchmark economy characterized by a positive value of training costs, consistent with a set of aggregate and distributional moments for the U.S. economy. Second, I analyze the labor market implications of varying the magnitude of training costs, keeping the rest of parameters constant at the benchmark level. Third, I discuss the main mechanism of the model. Finally, I quantify the role that increasing training requirements play in accounting for the observed decline in job turnover.

1.5.1 Calibration

The parameter values used in order to calibrate the benchmark economy are summarized in Table 1.7.

Table 1.7: Parameter values for the benchmark economy

Parameter	Interpretation	Value	Rationale
β	Discount factor	0.9898	Interest rate 4% p.a.
L	Labor force	18.82	Labor market tightness (Pissarides, 2009)
μ	Matching efficiency	1.02	Job finding rate (CPS 1976–2011)
α	Elasticity of the matching function	0.5	Petrongolo and Pissarides (2001)
η	Worker's bargaining power	0.5	Pissarides (2009)
b	Value of being unemployed	0.82	Job turnover (BED 1993)
ϕ	Decreasing returns to scale parameter	0.65	Cooper et al. (2004)
κ_v	Vacancy posting cost	0.10	1982 EOPP survey
κ_f	Training cost	0.08	1982 EOPP survey
μ_χ	Mean fixed prod. (Pareto distr.)	2.44	Establishment size distr. (CBP 1993)
σ_χ	Std. dev. for fixed prod.	1.8	Establishment size distr. (CBP 1993)
ρ_a	AR(1) parameter for log id. prod.	0.73	Employment growth distr. (BED 1993)
σ_a	Std. dev. for id. prod.	0.25	Employment growth distr. (BED 1993)

The model is simulated at a quarterly frequency. The value of the discount factor is consistent with an annual interest rate of four percent. The labor force is set to match a value for labor market tightness θ equal to 0.72, as in Pissarides (2009). The matching efficiency parameter μ targets an aggregate quarterly job finding rate of 86.2 percent, consistent with the CPS microevidence for people with 16 years of age and over for the period 1976–2011.[23] 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, I follow most of the literature and set it to $\eta = 0.5$, as in Pissarides (2009) for example. Given that I analyze an economy in steady state, the level of job creation is the same as the level of job destruction in equilibrium. Thus, the choice of the value for the unemployment benefits $b = 0.82$ targets an aggregate quarterly job destruction rate of 7.7 percent, consistent with the average job reallocation rate of 15.4 percent in 1993 from BED. The decreasing returns to scale parameter is based on plant-level estimates from Cooper et al. (2004). A similar value is also used by Cooper et al. (2007), Elsby and Michaels (2013) and Fujita and Nakajima (2013).

The level of hiring costs, both the vacancy posting cost κ_v and the training cost κ_f, are set following the evidence contained in the 1982 EOPP survey of employers summarized in chapter 3 of this thesis. Particularly, the vacancy posting cost is set to equal 10.4 percent of the average worker's marginal output in the simulated model. Regarding the parameterization of the training cost, an analysis of the 1982 EOPP survey shows that the average duration of on-the-job training is roughly equal to one quarter (3.1 months) and that, on average, trainees are roughly 20 percent less productive than skilled workers. To be conservative, I consider that the firm pays half of this training cost, thus I set an initial value of $\kappa_f = 0.08$ that represents roughly 10 percent of the average worker's marginal output.[24] Nevertheless, Section 1.6.1 contains a robustness check where the initial value of κ_f set to 15 percent of the average worker's marginal output.

In order to determine the parameter values for the fixed firm-specific productivity and for the idiosyncratic productivity I follow the calibration strategy proposed by Elsby and Michaels (2013). In particular, the time-invariant firm-specific productivity follows a Pareto distribution with mean μ_χ and standard deviation σ_χ. The parameters are selected in order to match the empirical establishment-size distribution in 1993 coming from the County Business Patterns (CBP) data.[25] The

[23]The quarterly job finding rate (i.e. the probability that a worker who is unemployed at the beginning of the quarter finds a job at the end of the quarter) is given by $f = f_m(1-s_m)^2 + (1-f_m)f_m(1-s_m) + (1-f_m)^2 f_m + f_m^2 s_m$, where f_m and s_m are the monthly job finding rate and the monthly separation rate, respectively. Using CPS microdata for people with 16 years of age and over for the period 1976–2011, the monthly job finding rate equals 53.3 percent and the monthly separation rate equals 4.1 percent.

[24]Due to the presence of decreasing returns to scale, average and marginal products differ. A value of $\kappa_f = 0.08$ is equal to 6.5 percent of average labor productivity, while a value of $\kappa_v = 0.10$ is equal to 6.7 percent of average labor productivity.

[25]The CBP is an annual series that provides subnational economic data by industry. The data

idiosyncratic productivity shock a is approximated with 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 $\pi^a_{jk} = \mathbb{P}\{a' = a_k \mid a = a_j\}$. I apply the Tauchen method for finite state Markov-chain approximations of AR(1) processes. The parameters for the Markov chain, ρ_a and σ_a, are calibrated to match the distribution of employment changes in 1993 from the BED. More precisely, the parameter ρ_a influences the rate of firms that do not change employment from quarter to quarter (i.e. the inaction rate), while σ_a determines the dispersion of employment changes.

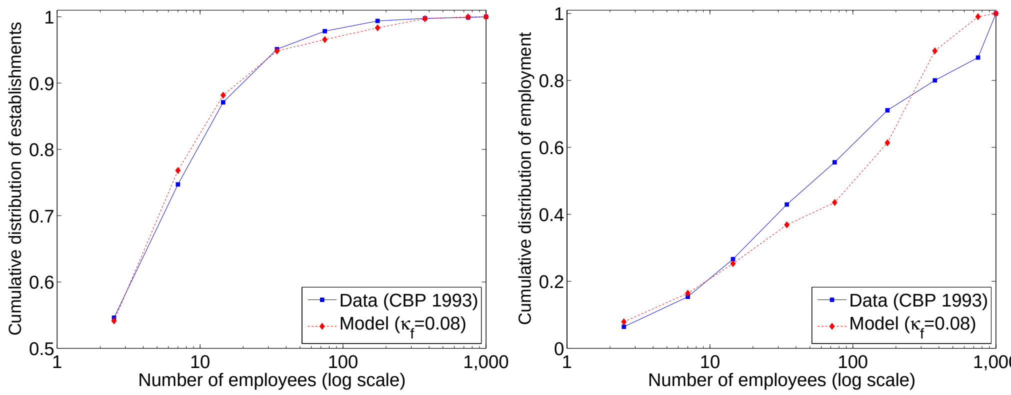
1.5.2 Baseline Simulation Results

I first solve the model parameterized at the benchmark calibration with training costs $\kappa_f = 0.08$. Figure 1.5 and Table 1.8 show that, by construction of the exercise, the model matches reasonably well the empirical establishment size distribution and the employment change distribution, respectively. In particular, Figure 1.5 depicts the establishment size distribution, both in terms of the number of establishments (Panel A) and also in terms of the level of employment at those establishments (Panel B). As it can be seen, a key characteristic of the empirical establishment size distribution in the United States is that there are a large number of establishments that account for a small number of employees, and a small number of establishments that account for a large number of employees. It is important that the model matches this important feature of the data in order to draw conclusions for the aggregate economy.

Table 1.8: Employment change distribution – model vs. data

	Model ($\kappa_f = 0.08$)	Data (BED 1993)
Loss: 20+	1.1	0.8
Loss: 5-19	2.8	3.8
Loss: 1-4	22.7	22.0
No change	47.3	44.9
Gain: 1-4	22.2	23.3
Gain: 5-19	2.8	4.3
Gain: 20+	1.1	0.9

on the establishment-size distribution are publicly available from 1986 to 2011 through the U.S. Census Bureau website: http://www.census.gov/econ/cbp. The data are classified in nine size classes: 1 to 4 employees, 5 to 9 employees, 10 to 19 employees, 20 to 49 employees, 50 to 99 employees, 100 to 249 employees, 250 to 499 employees, 500 to 999 employees, and 1000 and more employees. I consider the distribution in 1993 because the BED dataset starts in 1993. However, the establishment-size distribution in 1993 is very close to the average for the period 1993–2011 and also close to the average for the whole period of data availability 1986–2011.



(a) Number of establishments (b) Employment

Figure 1.5: Establishment size distribution – model vs. data

Notes: The data for the establishment size distribution come from the County Business Patterns published by the U.S. Census Bureau.

I then proceed to analyze the labor market implications of higher training costs. In particular, I keep the parameters constant at the benchmark level and I exogenously increase the parameter κ_f. Table 1.9 presents the main results of this exercise. Panel A presents the parameter values for the training costs used in each of the economies considered in the analysis and Panel B reports the statistics of interest. The simulation results show that, as I increase the level of training costs, firms have less incentives to adjust their employment level. Thus, the rate of job creation (which equals the rate of job destruction given that I analyze an economy in steady state) declines as the level of training costs rises. This in turn lowers the number of vacancies that firms are willing to post, which puts downward pressure

Table 1.9: Baseline simulation results

Panel A: Parameter values				
Training cost (κ_f)	0.08	0.10	0.15	0.20
Panel B: Simulated statistics				
Job creation/destruction rate	7.7	7.3	6.3	5.4
Job reallocation rate	15.4	14.5	12.5	10.8
Labor market tightness	0.72	0.61	0.41	0.28
Job finding rate	86.2	79.3	64.8	53.9
Unemployment rate	8.2	8.4	8.8	9.2
Total hiring costs (in % of output)	1.00	1.02	1.07	1.09
Training costs (in % of output)	0.49	0.58	0.75	0.86

on the labor market tightness and on the job finding rate. The unemployment rate slightly increases when I increase the level of training costs, given that the decline in the job finding rate is only partly offset by a decline in the job separation rate. In the data, we observe a decline in the job reallocation rate from an average of 15.4 percent in 1993 to an average of 12.3 percent in 2011. In the model, in order to account for this decline, the training cost parameter κ_f needs to increase from a value of 0.08 to a value of 0.15, which corresponds to an increase from 10 percent to 20 percent in terms of worker's average marginal output.

Additionally, Table 1.9 reports information on total hiring costs effectively paid by firms.[26] The results show that the total amount of hiring costs (in terms of aggregate output) paid by firms remains nearly unchanged, as the amount of training costs faced by firms increases. Thus, the increase in training cost is partly compensated by the decline in vacancy posting costs, as labor turnover decreases and firms are less willing to post vacancies. Notice as well that the training costs effectively paid by the firm increase by much less than the increase in the parameter κ_f, again due to the decline in labor turnover.

Lastly, changes in the level of labor adjustment costs have clear implications for the employment change distribution (see Table 1.10). In particular, high levels of adjustment costs increase the share of firms that optimally decide to keep constant their level of employment, regardless of the idiosyncratic productivity shocks received, and generate a narrowing employment change distribution.

Table 1.10: Employment change distribution – model vs. data

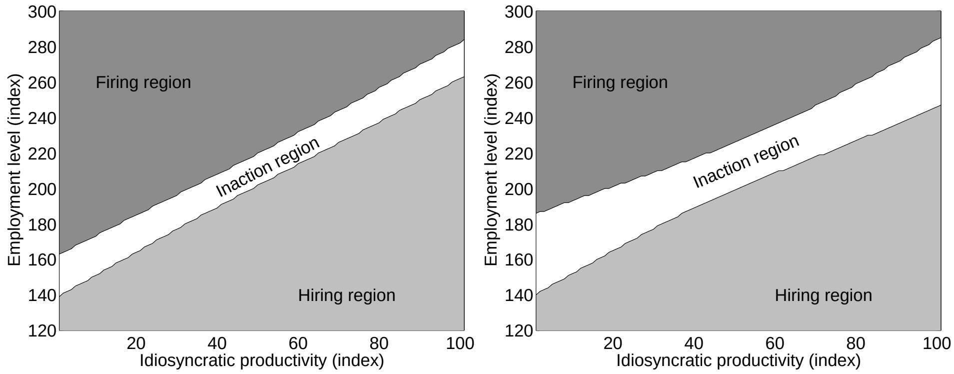
	Simulated statistics		*Data (BED)*	
	Training cost (κ_f)			
	0.08	0.15	1993	2011
Loss: 20+	1.1	0.9	0.8	0.5
Loss: 5-19	2.8	2.3	3.8	3.1
Loss: 1-4	22.7	20.2	22.0	21.3
No change	47.3	53.9	44.9	49.6
Gain: 1-4	22.2	19.6	23.3	21.5
Gain: 5-19	2.8	2.3	4.3	3.4
Gain: 20+	1.1	0.9	0.9	0.6

Summing up, the results presented in Tables 1.9 and 1.10 confirm that increasing training costs lead to a decline in job reallocation, an increase in inaction, and a more compressed employment growth distribution, all consistent with the empirical evidence presented in Section 1.3.1.

[26]Total hiring costs are equal to the sum of training costs and vacancy posting costs, and are computed as the total number of hires in the economy multiplied by $\left(\frac{\kappa_v}{q(\theta)} + \kappa_f\right)$.

1.5.3 Examining the Model's Mechanism

The solution of the model is characterized by a region of inaction delimited by two reservation thresholds in the (χ, a, n_{-1}) space that determine the optimal employment policy of a firm: a hiring threshold above which firms start hiring workers, and a firing threshold below which firms start firing workers. When training costs increase, the central region of inaction expands, and firms become more reluctant to change employment. In order to provide a graphical representation of the mechanism at work in the model, Figure 1.6 plots the values of the hiring and firing reservation thresholds for low training costs (Panel A) and for high training costs (Panel B), for a particular value of the time-invariant productivity χ.[27] In both panels, the x-axis contains the current value of idiosyncratic productivity and the y-axis contains the employment level in the previous period.



(a) Low training cost (b) High training cost

Figure 1.6: Hiring and firing reservation thresholds

Notes: Panel A plots the simulated hiring and firing reservation thresholds for training costs equal to 5.2 percent of average marginal output ($\kappa_f = 0.065$), while Panel B does the same for training costs equal to 33.3 percent of average marginal output ($\kappa_f = 0.40$). A time-invariant productivity χ equal to 4.72 is considered in both panels, which corresponds to an average firm size of 50 employees.

Focusing on Figure 1.6a, we can see that the model delivers a central area of inactivity, given the presence of non-convex hiring costs. In particular, firms only hire when the value of idiosyncratic productivity is sufficiently high (hiring region) and they only fire when the value of idiosyncratic productivity is sufficiently low (firing region). If the idiosyncratic productivity lies in the region of

[27] For illustrative purposes, I consider a time-invariant productivity χ equal to 4.72, which corresponds to an average firm size of 50 employees. Low training costs correspond to 5.2 percent of average marginal output ($\kappa_f = 0.065$) and high training costs correspond to 33.3 percent of average marginal output ($\kappa_f = 0.40$).

inaction, the firm optimally decides to remain inactive. The reason is that given that hiring is costly, firms optimally decide not to adjust the employment level and postpone their decision until the idiosyncratic productivity is sufficiently high to start hiring or sufficiently low to start firing employees. Importantly, when training costs increase the region of inactivity expands, as shown Figure 1.6b. Thus, the higher are the training costs that firms need to pay when hiring workers, the more insensitive the firm will be to changes in idiosyncratic productivity.

Finally, Figure 1.7 provides a different look at the optimal employment policy of a firm. In particular, it plots a one-dimensional cut of each panel in Figure 1.6, where the x-axis is again the current value of idiosyncratic productivity and the y-axis is the (current) optimal employment level of a firm, characterized by a time-invariant productivity $\chi = 4.72$ and with 50 employees in the previous period. As it can be seen, the higher is the amount of training costs that firms need to pay, the larger is the region of inaction where the firm maintains its 50 employees regardless of the changes in idiosyncratic productivity. Additionally, the pace at which the firms hires workers when idiosyncratic productivity improves slows down when training costs are higher. The same happens with the pace of firing, even though to a lesser extent and difficult of being discerned in the figure.

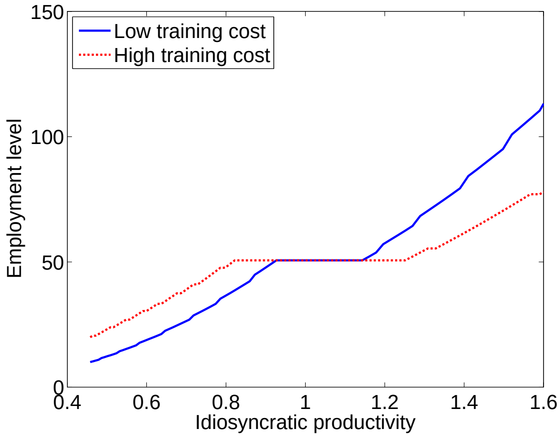


Figure 1.7: The optimal employment policy of the firm

Notes: Low training costs correspond to 5.2 percent of average marginal output ($\kappa_f = 0.065$) and high training costs correspond to 33.3 percent of average marginal output ($\kappa_f = 0.40$). The optimal employment policy of the firm corresponds to a firm characterized by a time-invariant productivity $\chi = 4.72$ and with 50 employees in the previous period.

1.5.4 Accounting for the Decline in Business Employment Dynamics

In this section, I quantify the role that increasing training requirements play in accounting for the decline in job turnover. I view the accounting exercise conducted here as an approximation to the question about how much of the decline in business employment dynamics can be explained by the technology-training hypothesis. In order to answer this question, I first need to have an estimate of the increase in training costs that occurred at the aggregate level. From the DOT evidence presented in Section 1.3.2, the average training duration increased by 23 percent over the period 1970 to 2010 (from 23.5 months in 1970 to 28.8 in 2010). Note that the increase in the average duration is reduced by half if we consider the subperiod 1990 to 2010. Given that longer training times on average might be associated to higher productivity gaps between new hires and incumbents on average, I assume that concurrently to the increase in the training duration there was a similar increase in the productivity gap. Therefore, from the DOT evidence and focusing first in the subperiod 1990–2010, I estimate an increase in training costs from the baseline value of 10 percent of average marginal output to 12.4 percent of average marginal output. In the model, this is achieved by rising the training parameter κ_f from 0.08 to 0.10. A similar argument is used to estimate the increase in training costs for the period 1970–2010. More precisely, and with the objective of maintaining the baseline calibration unaltered, I estimate an increase in training costs from 8.0 to 12.4 percent of average marginal output. In the model, this is achieved by rising the training parameter κ_f from 0.065 to 0.10. Tables 1.11 and 1.12 present the results of this accounting exercise for the job reallocation rate, comparing the simulated results with data from the BED for the period 1993–2011 and data from the BDS for the period 1977–2011.

Table 1.11 analyses how much of the decline in the job reallocation rate over the period 1993–2011 can be explained by the training hypothesis. Notice that this is the period of data availability for the BED database. In the data, the job reallocation rate declined by 20.1 percent, from an average of 15.4 in 1993 to an average of 12.3 in 2011. Using the observed increase in training costs during the same period of analysis, the model predicts a decline of the job reallocation rate of 5.7 percent, from 15.4 percent to 14.5 percent. Thus, the increase in training costs that we observe using evidence from the DOT can explain 28.4 percent of the decline in the job reallocation rate over the period 1993–2011. As a robustness check, I exclude the Great Recession from the analysis and I repeat the same exercise. Particularly, the observed job reallocation rate declined by 14.0 percent during the period 1993 to 2006, from an average of 15.4 percent in 1993 to an average of 13.3 percent in 2006. Clearly, the decline in job turnover accelerated during the recent recession. Using the same predicted decline of 5.7 percent from the model, the increase in training costs that we observe using evidence from the DOT can now explain 42.0 percent of the decline in the job reallocation rate over the period 1993–2006.

Table 1.11: Accounting for the decline in job reallocation over 1993–2011

	High turnover	Low turnover	Change (in %)	% of change explained
Panel A: BED data				
Year	1993	2011		
Job reallocation (quarterly)	15.4	12.3	-20.1	
Panel B: Simulated statistics				
Training cost (κ_f)	0.08	0.10		
Job reallocation (quarterly)	15.4	14.5	-5.7	28.4

Similarly, Table 1.12 analyses how much of the decline in the job reallocation rate over the period 1997–2011 can be explained by the training hypothesis. In this case I draw on evidence on annual job flows from the BDS, which allows to analyze a longer time period. The observed decline in the annual job reallocation rate between 1977 and 2011 was close to 32 percent. Using the increase in training costs that we observe from the DOT for the whole period 1970–2010, the model predicts a decline of the *annual* job reallocation rate of 5.7 percent, from 44.2 percent to 41.7 percent.[28] This implies that the observed increase in training costs can explain 18.0 percent of the decline of the annual job reallocation rate over the period 1977–2011. If I exclude again the Great Recession from the analysis, and focus on the period 1977–2006, the observed increase in training costs can explain 27.6 percent of the observed decline in the annual job reallocation rate (from a value of 37.0 percent in 1977 to a value of 29.3 percent in 2006).

Finally, it is important to notice that the model presented in this paper does not feature worker flows in excess of job flows. In other words, the model features a tight link between worker flows and job flows, as hires are fully linked to job creation and separations to job destruction. This view of the labor market is

[28]The annual job reallocation rates from the BDS are not directly comparable in magnitude to the annual simulated job reallocation rates from the model. The first reason is that the model is calibrated to match quarterly job turnover rates in 1993 from the BED, and it is known that the annual job flows from the BED and the BDS differ in magnitude. See Spletzer et al. (2009) for a discussion on the plausible explanations for these differences in magnitude. The second reason relates to the fact that in the data, transitory establishment-level employment changes explain why the sum of four quarterly gross job gains or losses does not equal annual gross job gains or losses. Some of these transitory factors are not present in the model. This might explain why in the model the ratio of the annual job flows versus quarterly job flows is greater than the observed ratio in the data.

Table 1.12: Accounting for the decline in job reallocation over 1977–2011

	High turnover	Low turnover	Change (in %)	% of change explained
Panel A: BDS data				
Year	1977	2011		
Job reallocation (yearly)	37.0	25.2	-31.9	
Panel B: Simulated statistics				
Training cost (κ_f)	0.065	0.10		
Job reallocation (yearly)	44.2	41.7	-5.7	18.0

broadly consistent with the evidence presented in Davis et al. (2012). However, quits are also an important component of separations in the data. This means that firms need to hire workers if they want to maintain their workforce unchanged. In that respect, the data point to a departure from the iron-link relationship between worker flows and job flows, that the model in this paper abstracts from.[29] The presence of quits might pose an extra burden to the firm, as the firm needs to go again under the costly process of searching for a new worker and, importantly, has to pay again the training cost. As training cost increase over time, it might be costlier for the firm to deal with quits. Therefore, the analysis done in the paper might underestimate the total amount of training costs that firms face in reality.[30]

1.6 Sensitivity Analysis of the Baseline Simulation Results

This section provides a sensitivity analysis of the main quantitative results presented in Section 1.5.2. Two types of robustness checks are performed. First, I explore the role of the value of the training cost parameter in the benchmark calibration. Second, I consider a different specification for training costs. Simulations results for all robustness checks are summarized in Table 1.13.

[29]See the work of Fujita and Nakajima (2013), who extend the model in Elsby and Michaels (2013) to incorporate on-the-job search in order to endogeneize quits and investigate the sources of differences in the cyclicality of worker flows and job flows.

[30]Note the difference with firing costs in this case, where labor attrition might instead help the firm to shrink without relying on costly separations.

Table 1.13: Sensitivity analysis of the main quantitative results

	Higher training cost in benchmark calibration			Training costs as % of marginal output		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Parameter values						
Training cost (κ_f)	0.10	0.125	0.155	0.08	0.10	0.124
Panel B: Simulated statistics						
Job reallocation rate (quarterly)	16.4	15.4	14.2	16.1	15.3	14.5
Job reallocation rate (yearly)	45.6	43.8	41.5	42.8	41.4	40.0
Job finding rate	94.6	86.2	77.5	89.3	86.2	81.5
Unemployment rate	8.0	8.2	8.4	8.3	8.2	8.2
Total hiring costs (in % of output)	1.20	1.23	1.24	1.02	1.07	1.12
Training costs (in % of output)	0.63	0.74	0.84	0.46	0.55	0.65
Employment change distribution						
Loss 5+	4.1	3.8	3.5	4.0	3.9	3.6
Loss 1-4	21.3	21.0	19.5	24.4	23.7	22.7
Inaction rate	49.8	51.0	54.5	43.4	45.0	47.4
Gain 1-4	20.9	20.4	19.1	24.2	23.6	22.7
Gain 5+	4.0	3.8	3.5	4.0	3.9	3.6

1.6.1 Initial Value for Training Costs

For the baseline simulation results, the training cost parameter κ_f was set to 0.08, representing roughly 10 percent of the average worker's marginal output. In this section I solve again the model by setting the training parameter in the benchmark calibration to 15 percent of the average worker's marginal output (i.e. by setting κ_f equal to 0.125). This implies recalibrating some parameter values, in order to be consistent with the calibration strategy described in the text.[31] The results are presented in column 2 of Table 1.13. I then vary the level of training costs (keeping the rest of the parameters constant) consistent with the observed changes in training requirements discussed in Section 1.5.4. The simulation results of this exercise are reported in columns 1 and 3. Overall, the results remain qualitatively unchanged with respect to ones in the main text. Thus, increasing training requirements continue to lead to a decline in the job reallocation rate, an increase in inaction, and a more compressed employment change distribution. Quantitatively, given the observed increase in training costs, the model explains now 40.0 percent of the decline in the job reallocation rate over the period 1993–2011 and 28.2 percent over the period 1977–2011. These numbers compare with 28.4 percent and

[31]In particular, the following parameters need to be re-calibrated: $L = 19.34$, $\mu_\chi = 2.35$, and $\sigma_a = 0.228$. The rest of the parameters remain unchanged at their values in Table 1.7.

18.0 percent, respectively, obtained for the baseline simulation results.[32] Thus, the higher is the initial level of training costs, the larger is the decline in job turnover that the model can explain.

1.6.2 Structure of Training Costs

In the model presented in Section 1.4 I have considered training costs that are independent of firm size or productivity. This implies that training costs per hire are, in relative terms, smaller for large firms than for small firms. The reason is that larger firms have higher marginal product of labor.[33] However, large firms end up paying higher training costs than small firms in equilibrium, given that they have higher turnover in absolute terms.[34] As a robustness check, I consider that training costs are equal to a fraction of the firm's marginal output. Therefore, the training cost of each recently hired worker is now dependent on the productivity of the firm and of its size. Changing the structure of the training cost parameter implies recalibrating some parameter values, in order to be consistent with the calibration strategy described in the text.[35] The results of this exercise are presented in column 5 of Table 1.13. Similarly as before, I then vary the level of training costs (keeping the rest of the parameters constant) consistent with the observed changes in training requirements discussed in Section 1.5.4. The simulation results are reported in columns 4 and 6. Again, the results remain qualitatively unchanged with respect to the main calibration. Increasing training requirements continue to lead to a decline in the job reallocation rate, an increase in inaction, and a more compressed employment growth distribution. Quantitatively, given the observed increase in training costs, the model explains now 26.6 percent of the decline in the job reallocation rate over the period 1993–2011 and 20.7 percent over the period 1977–2011. These numbers compare with 28.4 percent and 18.0 percent, respectively, obtained for the baseline simulation results.[36] Therefore, the sim-

[32]If I exclude the Great Recession from the analysis, the model can now explain 59.0 percent of the decline in the job reallocation rate over the period 1993–2006 and 43.2 percent over the period 1977-2006. These numbers compare with 42.0 percent and 27.6 percent, respectively, obtained for the baseline simulation results.

[33]For example, training costs represent, on average, 10.4 percent of marginal output for firms with 1 to 4 employees in the benchmark calibration, while it represents 9.4 percent for firms with 500 to 999 employees.

[34]For example, firms with 1 to 4 employees pay 0.3 percent of output in training costs in the benchmark calibration, while firms with 500 to 999 employees pay 0.7 percent.

[35]In particular, the following parameters need to be re-calibrated: $L = 18.76$, $b = 0.85$, $\mu_\chi = 2.40$, and $\sigma_a = 0.24$. The rest of the parameters remain unchanged at their values in Table 1.7.

[36]If I exclude the Great Recession from the analysis, the model can now explain 39.3 percent of the decline in the job reallocation rate over the period 1993–2006 and 31.6 percent over the period 1977–2006. These numbers compare with 42.0 percent and 27.6 percent, respectively, obtained

ulation results are robust when considering training costs as a percentage of the productivity of the firm.

1.7 Cross-sectional Implications of the Model

The introduction of a notion of firm size into a search and matching model allows to analyze a series of cross-sectional implications related to employer size. In this section I show that the model of this paper, which is augmented with training costs, retains the prediction of Elsby and Michaels (2013) that larger firms are more productive and pay higher wages, as in the data. More interestingly, the model also predicts that the size-wage differential widens and that wage dispersion raises when training costs increase. While the empirical evidence on changes over time in the size-wage gap is virtually non-existent, there is substantial empirical work documenting an increase in wage inequality in the United States since the late 1970s. Additionally, the model can also replicate the empirical fact that larger firms have lower job flow rates, when considering an extension allowing for quadratic vacancy posting costs.

1.7.1 Relationship between Firm Size and Wages

Using a variety of datasets, Brown and Medoff (1989) find a substantial wage differential associated with establishment size, even in the presence of controls that would be expected to capture much of the cross-employer differences in labor quality.[37] Elsby and Michaels (2013) show that their model is able to reproduce this empirical fact. In what follows, I show that the extensions considered in this paper do not alter this result. Thus, large firms pay higher wages than small firms, as they are more productive. I then evaluate what happens with the wage gap between large and small firms when training cost increase.

In order to investigate whether the model presented in this paper can replicate the positive relationship between the firm size and wages, I follow Schaal (2012) and run the following regression:

$$\log(\text{wage}) = \alpha + \beta \log(\text{employment}) + \epsilon,$$

where I use the simulated wages and employment from the benchmark calibration. Note that in the model there is no worker heterogeneity ex-ante. Thus, the heterogeneity in wages observed in equilibrium is the result of workers randomly

for the baseline simulation results.

[37]There is a large literature in economics that studies the wage gap due to firm size. See the survey article by Oi and Idson (1999).

matching to heterogeneous firms, that differ in terms of productivity (both the time-invariant productivity parameter χ and the idiosyncratic productivity a) and level of employment. Recall that all workers in the same firm receive the same wage. In order to quantify the size-wage differential, I follow Brown and Medoff (1989) and compute by how much higher is the wage of an employee working at a firm with log employment one standard deviation above average compared to the one of a similar employee at a firm with log employment one standard deviation below average. This value is between 6 and 15 percent in the data. In the model, I find a size-wage differential equal to 2.2 percent.[38] Thus, the model predicts a positive relationship between employer size and wages and explains around one fifth of the observed average value in the data.

I then proceed to analyze what happens with the size-wage differential when training cost increase. The results in Table 1.14 show that, as training cost increase, the size-wage differential rises. Analyzing the wage equation, this is due to the fact that the difference in marginal output between large and small firms widens when training costs increase.

Table 1.14: Wage implications of the model

Panel A: Parameter values				
Training cost (κ_f)	0.08	0.10	0.15	0.20
Panel B: Simulated statistics				
Size-wage differential	2.18	2.23	2.33	2.41
Std. Dev. of Log Wages	5.35	5.60	6.21	6.79
Mean-Min Ratio	1.14	1.14	1.16	1.18

1.7.2 Wage Dispersion

In this section I analyze the degree of wage dispersion that the model can generate, and how does it vary with training costs. In particular, as a measure of wage dispersion I consider both the standard deviation of log wages and the mean-min wage ratio proposed by Hornstein et al. (2011). Using the benchmark calibration, the model predicts a standard deviation of log wages equal to 5.35 percent and a mean-min wage ratio of 1.14. These values are relatively low when compared with their empirical counterparts, consistent with other search models that do not incorporate on-the-job search (Hornstein et al., 2011). I then analyze what happens with wage dispersion when training costs increase. As shown in Table 1.14,

[38]Elsby and Michaels (2013) find a value of 2.3 percent and Kaas and Kircher (2011) a value of 2.5 percent.

the standard deviation of log wages increases with training costs. A similar result is found for the mean-min ratio, even though the increase is somewhat more limited. These result seems consistent with existing empirical research (see the survey article by Katz and Autor (1999)), which documents that the U.S. wage structure has become more unequal since the late 1970s.

1.7.3 Job Flows by Firm Size

In this section I consider an extension of the model presented in Section 1.4 to allow for convex vacancy posting costs. Specifically, I assume that vacancy posting costs are quadratic in the number of vacancies posted, i.e. $c(v) = \frac{\kappa_v}{2}v^2$, instead of being linear. This convexity prevents the firm from posting many vacancies to immediately grow to its optimal employment level.[39] I show next that this extension allows the model to generate declining job flows by firm size, as observed in the data. Also, I explain why the benchmark model is not able to generate the observed empirical pattern.

To solve the model, I first calibrate the new parameter κ_v so that total vacancy posting costs effectively paid by firms in equilibrium equal the corresponding value in the benchmark calibration.[40] The rest of parameter values are set following the calibration strategy in Section 1.5.1.[41] Figure 1.8 shows the simulated job reallocation rates by firm size when solving the model with quadratic vacancy posting costs and with training costs set at the benchmark level $\kappa_f = 0.08$.[42] The figure also plots data on job reallocation rates by firm size from the BED dataset in 1993. As it can be seen, the model does remarkably well in reproducing the empirical pattern that job reallocation rates decline with firm size. The introduction

[39] Yashiv (2000) provides empirical evidence in favor of convex vacancy hiring costs. Other papers that include convex vacancy posting costs in search and matching models with multi-worker firms are Cooper et al. (2007), Fujita and Nakajima (2013), and Kaas and Kircher (2011).

[40] In the benchmark calibration, 0.5 percent of output is devoted to pay vacancy posting costs. This implies setting $\kappa_v = 0.012$ in the setup with convex vacancy posting costs.

[41] Particularly, the labor force is set to 20.33 to match a value for labor market tightness equal to 0.72. The value for the unemployment benefits is set to $b = 0.85$ to match an aggregate quarterly job reallocation rate of 15.4 percent in 1993 from BED. Moreover, I also need to adjust the mean of the time-invariant firm-specific productivity ($\mu_\chi = 2.38$) and the values of the idiosyncratic productivity shock a ($\rho_a = 0.83$ and $\sigma_a = 0.33$) to match the establishment size distribution and the employment change distribution, respectively. The rest of parameters remain unchanged at the benchmark calibration (see Table 1.7).

[42] The BED reports job flows by size on nine firm-size categories: 1 to 4 employees, 5 to 9 employees, 10 to 19 employees, 20 to 49 employees, 50 to 99 employees, 100 to 249 employees, 250 to 499 employees, 500 to 999 employees, and 1000 and more employees. In the model, I compute job flows by size as in the data, i.e. following the dynamic-sizing methodology when firms change size class as a result of job creation and destruction. See Butani et al. (2005) for details on the methodology.

of convex vacancy posting costs implies that those firms that would like to adjust employment by a greater amount (i.e. large firms) find it increasingly costly to post vacancies. Thus, the pace at which they hire slows down and turnover is reduced. This mechanism is absent in the benchmark model developed in Section 1.4. The reason is that, in the benchmark model, both the vacancy posting cost and the training cost are linear in the number of hires. Thus, the marginal costs of adjusting employment are constant and the model does not feature significant differences in job flow rates across firm sizes.

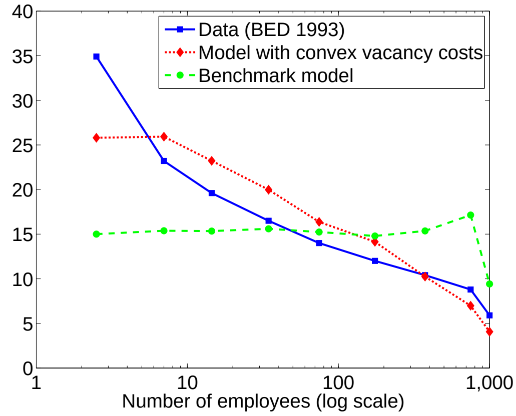
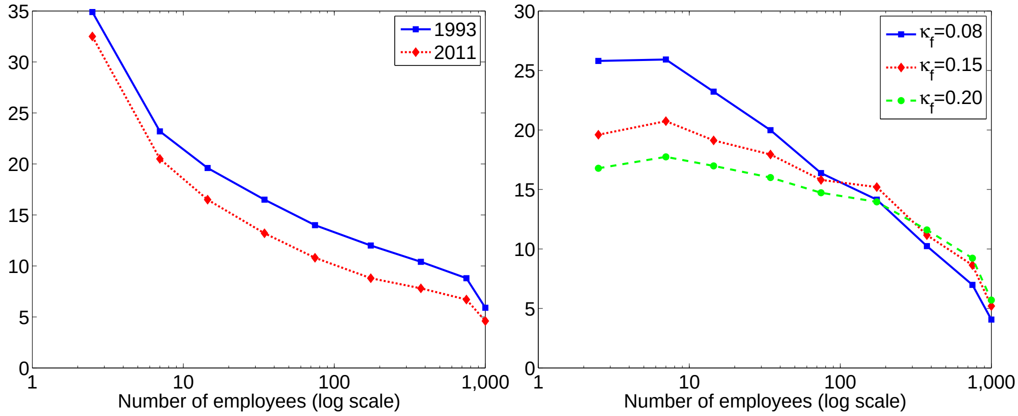


Figure 1.8: Job reallocation rate by firm size

Notes: Data are yearly averages of quarterly job reallocation rates by firm size from the BED, based on nine reported firm-size categories. The simulated job reallocation rates by firm size are computed as in the data, i.e. following the dynamic-sizing methodology when firms change size class as a result of job creation and destruction.

I proceed now to analyze the labor market implications of higher training costs. In particular, I keep the parameters constant at the values described above and I exogenously increase the parameter κ_f. The simulation results show that the introduction of convex vacancy posting costs does not alter the conclusions reached for the baseline simulation results. More specifically, the increase in training costs generates a decline in job turnover, an increase in inaction, and a more compressed employment change distribution, as in the baseline simulation results (see Table A.7 in Appendix A). More interestingly, Figure 1.9 examines the implications of higher training costs for the job flow rates across firm-size categories, and compares the results with the data. Panel A shows that, in the data, all size classes experience a decline in the job reallocation rates over time. Panel B shows that the model can reproduce this pattern for the first six firm-size classes (i.e. for firms up to 249 employees). However, the model counterfactually predicts relatively constant or increasing job reallocation rates for very large firms, when training costs increase. In order to understand this result recall that firms become more insensitive to changes in idiosyncratic productivity when training costs are high. Thus, firms are more reluctant to change employment and, when they decide to do so, they do it at a lower pace. As a result, an increase in training costs implies less willingness to perform big employment adjustments, and thus convex vacancy posting costs are less harmful. This is specially important for large firms, as they are the ones that need to adjust employment to a greater amount. In other words, an increase in training costs reduces somehow the convexity in vacancy posting costs that firms face, as their incentives to adjust employment are reduced. This in turn narrows the gap in job flow rates between small and large firms.



(a) Data from BED (b) Model

Figure 1.9: Job reallocation rates by firm size

Notes: Data are yearly averages of quarterly job reallocation rates by firm size from the BED, based on nine reported firm-size categories. The simulated job reallocation rates by firm size are computed as in the data, i.e. following the dynamic-sizing methodology when firms change size class as a result of job creation and destruction.

1.8 Discussion of Alternative Explanations

This paper evaluates the hypothesis that increasing training requirements have contributed to the decline in aggregate labor turnover measures. While the results show that the observed increase in training costs can account for a significant part of the slowdown, other factors are also likely to be present. In this section, I examine a potential alternative explanation based on smaller shocks, and I briefly discuss some other potential explanations that have been proposed in the literature.

A first alternative explanation relates to a secular decline in the size of shocks faced by firms. This is, for example, the interpretation adopted by Davis et al. (2010) to understand the decline in the job destruction intensity. In what follows, I use the model from Section 1.4 to analyze the macroeconomic implications of lower dispersion of idiosyncratic productivity shocks. More precisely, column 2 in Table 1.15 presents the simulation results when σ_a is reduced from 0.25 to 0.219, while the rest of the parameter values are kept fixed at the benchmark calibration (see Table 1.7). The size of the decline in σ_a is chosen to match the observed decline in the job reallocation rate in the data. In order to facilitate comparisons, column 3 reports the simulation results of increasing the training cost parameter κ_f until reaching the same decline in the job reallocation rate (again, the rest of parameter values are kept fixed at the benchmark calibration). As an additional exercise, I consider a combination of the two potential explanations. Specifically, in column 4 the training cost parameter κ_f is increased from 0.08 to 0.10, as observed in the DOT data, and the standard deviation of idiosyncratic productivity of shocks is decreased up to the point where the model matches the decline in turnover observed in the data (this implies reducing σ_a from 0.25 to 0.226).

Table 1.15: Evaluating alternative explanations

	Benchmark calibration (1)	Smaller shocks (2)	Higher training (3)	Smaller shocks and higher training (4)
Panel A: Parameter values				
Training cost (κ_f)	0.08	0.08	0.155	0.10
Std. Dev. for id. prod. (σ_a)	0.25	0.219	0.25	0.226
Panel B: Simulated statistics				
Job reallocation rate	15.4	12.3	12.3	12.3
Job finding rate	86.2	81.6	63.5	75.9
Unemployment rate	8.2	7.0	8.8	7.5
Total hiring costs (in % of output)	1.0	0.8	1.1	0.9
Employment change distribution				
Loss 5+	3.9	3.2	3.1	3.2
Loss 1-4	22.7	21.8	20.0	21.3
Inaction rate	47.3	50.4	54.4	51.6
Gain 1-4	22.2	21.4	19.4	20.8
Gain 5+	3.9	3.2	3.1	3.2
Size-wage differential	2.18	1.78	2.34	1.89
Std. Dev. of Log Wages	5.35	5.01	6.28	5.31
Mean-Min Ratio	1.15	1.13	1.17	1.14

Comparing columns 1 and 2 of Table 1.15, a decline in the dispersion of shocks generates a decline in job turnover rates, an increase in inaction and a more compressed employment change distribution. The results are qualitatively consistent with the data, and also with the results of increasing training costs (see column 3). Some differences between the two alternative explanations are worth mentioning. First, a lower dispersion of shocks generates a small decline in the job finding rate which, together with the decline in the job destruction rate, imply a fall in the unemployment rate. This contrasts with what happens to the unemployment rate when training costs increase. Particularly, the unemployment rate slightly raises when training costs go up, given that the job finding rate is much more affected. Second, the total amount of hiring costs effectively paid by firms decreases with lower dispersion of shocks, due to the decline in labor turnover. Finally, a reduction in the variance of shocks diminishes both the degree of wage dispersion and the size-wage gap between big firms and small firms. This is in contrast with the predictions of the model when training costs increase.

Overall, the hypothesis of smaller shocks seems to be consistent with the observed developments in employment dynamics, at least qualitatively, and could complement the explanation analyzed in this paper. Recalling the existing literature on the sources behind the Great Moderation, smaller shocks resemble the "good luck" explanation (see, e.g., Stock and Watson (2003)). However, one of the main challenges for this hypothesis is to find an empirical counterpart for the shocks affecting firms. Still, less severe aggregate shocks over time might also be a possibility.[43] In that respect, early findings on the Great Moderation find an abrupt drop in the volatility of U.S. GDP growth in early 1980s (see Kim and Nelson (1999) and Perez-Quiros and McConnell (2000)).[44] However, the decline in the magnitudes of job creation and destruction exhibit a steady trend that begins in the early 1960 (Faberman, 2008).

A second group of hypothesis, as the one analyzed in this paper, proposes instead a change in the transmission mechanism from shocks to macroeconomic outcomes. Fujita (2012) argues that an increase in turbulence, i.e. an increase in the probability of skill obsolescence during unemployment, can be one of the sources of the secular decline in the aggregate transition rate from employment to unemployment. Particularly, if the risk of skill obsolescence during unemployment has increased, then workers should be less willing to separate and accept lower wages in exchange for keeping the job. As mentioned by the author, 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

[43]Recent research suggests that aggregate and idiosyncratic shocks might instead be intimately related. Particularly, Acemoglu et al. (2012) show that microeconomic idiosyncratic shocks may lead to aggregate fluctuations, in the presence of interconnections between different sector, and Carvalho and Gabaix (2013) find that changes in the microeconomic composition of the economy during the post-war period can account for the Great Moderation and its undoing.

[44]Blanchard and Simon (2001) document instead that output volatility experienced a steady decline over several decades, starting in the 1950s, but that was interrupted in the 1970s and early 1980s, and returned to trend in the late 1980s and the 1990s.

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. Finally, another potential explanation conjectured by Davis and Kahn (2008) and Davis et al. (2010) relates to greater compensation flexibility over time. Champagne and Kurmann (2013) and Galí and van Rens (2010) provide empirical evidence that wage volatility has increased over time in the United States. Greater wage flexibility offers an additional margin to the firm to respond to shocks. Thus, firms might be less forced to hire and fire workers when conditions change. One potential avenue for further research could analyze the quantitative relevance of this hypothesis in explaining the decline in business employment dynamics.

1.9 Conclusions

This paper investigates the hypothesis that the slowdown in business employment dynamics observed in the United States over the recent decades can be a result of changing skill demands due to technological advances. In particular, the paper evaluates the hypothesis that on-the-job human capital accumulation has become increasingly important over time. Empirically, I provide evidence that job reallocation has declined and employment change distribution has become more compressed over time using data from the Business Employment Dynamics. At the same time, job training requirements, as measured in the data from the Dictionary of Occupational Titles, have risen. Additional empirical evidence using industry-level data provides further empirical support for the working hypothesis. Theoretically, I construct a multi-worker search and matching model, where training investments act as adjustment costs. The model can explain how the increase in training accounts for the decline in job reallocation, the increase in inaction, and the evolution towards a more compressed employment growth distribution, all consistent with the data.

This paper has modeled the provision of training as a fixed cost with no direct impact on the productivity of the firm. This simplification has allowed to study the macroeconomic effects of increasing training requirements in a setup with firm heterogeneity and rich cross-sectional implications. However, in reality the provision of training might translate into productivity gains. Thus, the observation that training requirements have become more prevalent over time can be interpreted positively, as it represents higher human capital accumulation and additional productivity gains. On the other hand, several studies have highlighted the crucial role that job and worker reallocation plays in enhancing economy-wide productivity growth. In that respect, lower labor market turnover can be considered a matter of great concern, as it can potentially have adverse effects on productivity and growth in the long-run. I view the results of this paper on the importance of training for labor market mobility trends as an important stepping stone towards a more complete study of productivity implications. Endogenizing training investment decisions and the consideration of productivity effects stemming from training would allow to investigate the ultimate consequences of the slowdown in business employment dynamics on productivity. I leave this analysis for future research.

Chapter 2

THE FADING DYNAMISM OF THE U.S. LABOR MARKET: THE ROLE OF DEMOGRAPHICS

(written jointly with Tomaz Cajner)

2.1 Introduction

The important role of demographics for the labor market and other economic outcomes has been long recognized. Many studies have convincingly documented that the baby boom generation has profoundly altered the U.S. aggregate unemployment path during the post-war period (Perry, 1970, Shimer, 1999, Barnichon and Figura, 2010). Aaronson et al. (2006) and Fallick et al. (2010) have shown that demographics have notably affected the U.S. aggregate labor force participation rate. Moreover, Lugauer (2012) finds state-level evidence that the age distribution affects cyclical output volatility in the United States. More generally, Jaimovich and Siu (2009) use panel-data methods to show that changes in the age composition of the labor force account for a significant fraction of the variation in business cycle volatility observed not only in the United States but also in the rest of the G7 economies.

However, much less is known about the effect of demographics on worker flows over time. By using state-level data for the U.S. manufacturing between 1973 and 1988, Shimer (2001) finds that an increase in the youth share of the population raises *job* flows. Hyatt and Spletzer (2013) investigate the recent decline in employment dynamics and find that age and education can each explain about one quarter of the decline in hires and separations between 2001 and 2010 as measured in the Current Population Survey (CPS). In this paper, we analyze the CPS unemployment flows data from 1976 to 2011. This period includes the time when demographics are typically thought of as having the most profound effect on the labor market and is at the same time long enough to reliably distinguish between secular trends and business cycle dynamics.

We document that population aging and rising educational attainment play a crucial role in explaining the downward trend in aggregate unemployment flows, primarily since older and more educated workers experience lower inflows into unemployment. The decomposition exercises performed using microdata from the CPS show that about three quarters of the total decline in aggregate unemployment flows from 1976 to 2011 can be attributed to demographics.

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 lower unemployment inflows in the first place. We argue that older workers on average posses more job-specific human capital, which is also true for 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.

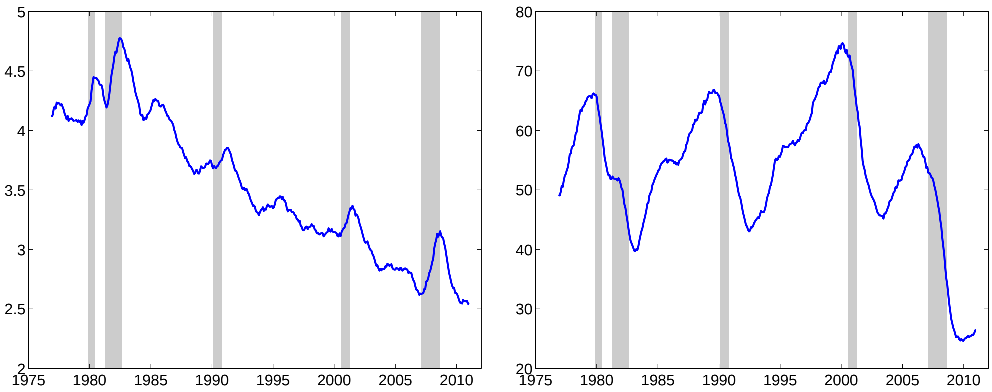
Our findings show that a relatively stylized search and matching model with endogenous separations, featuring higher amounts of on-the-job training for more educated workers and skill obsolescence for old unemployed workers, can go a long way in quantitatively accounting for the observed empirical patterns. 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 flows by education and age. Moreover, the model also demonstrates that the observed changes in the composition of the labor force towards older and more educated workers can account for the decline in the unemployment flows that we observe in the data.

Following this introduction, Section 2.2 provides empirical evidence on the importance of demographics in shaping the behavior of aggregate unemployment flows. Section 2.3 presents the model. Section 2.4 contains the parameterization of the model and presents the simulations results. Finally, Section 2.5 concludes.

2.2 Empirical Evidence

We focus our analysis on the period since 1976 onwards, guided by the availability of CPS microdata. Our preferred empirical measure of unemployment flows is calculated from unemployment inflow and outflow rates, which themselves 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 B.1, our main empirical findings are robust to both the two-state and the three-state decomposition of worker flows.

Figure 2.1 summarizes the evolution of the aggregate unemployment inflow (s_t, left panel) and outflow (f_t, right panel) rate since 1976 onwards. One can observe a stark secular decline in the unemployment inflow rate, which dropped by almost two percentage points over last three decades.[1] On the other hand, a trend in the unemployment outflow rate is less obvious in the data.[2]



(a) Unemployment inflow rate

(b) Unemployment outflow rate

Figure 2.1: Unemployment transition rates (in percent)

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.

However, given that the unemployment outflow rate is strongly inversely related to the unemployment rate, periods of low unemployment might mask ongoing secular trends. Thus, following Davis et al. (2006), we provide additional evidence on unemployment flows, recalling that the unemployment rate (u) in period $t+1$ is equal to the unemployment rate in period t, plus all the inflows into

[1]Downward trends in unemployment flows as measured by the CPS unemployment duration data have been also documented by Davis et al. (2010). Davis et al. (2006) and Fujita (2012) show that these trends are also present in the CPS gross flows data.

[2]As shown by Abraham and Shimer (2001) and 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.

unemployment minus all the outflows from unemployment that occurred during period t:

$$u_{t+1} \equiv u_t + \underbrace{s_t(1-u_t)}_{\text{inflows}} - \underbrace{f_t u_t}_{\text{outflows}}$$

Figure 2.2 depicts the evolution of unemployment flows and shows a clear downward trend in both unemployment inflows and outflows observed over the last few decades.

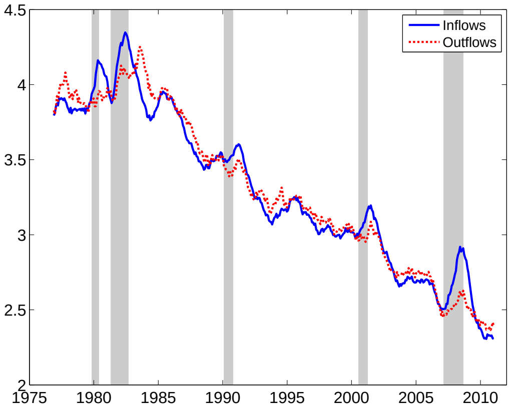
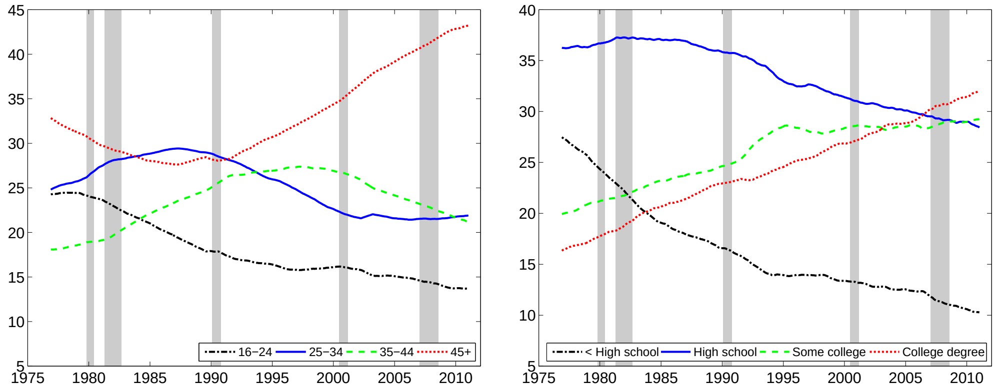


Figure 2.2: Unemployment inflows and outflows (as a percent of labor force)

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.

One likely explanation for the observed secular decline in unemployment flows 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.[3] 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 2.3a). 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 2.3b).

[3]Note that our main focus of analysis here is on compositional changes in the labor force. These changes can occur either due to compositional changes in population or due to changes in group-specific labor force participation rates. See section 2.2.2 for a further dicussion.



(a) Age (b) Education

Figure 2.3: Structure of the U.S. labor force (in percent)

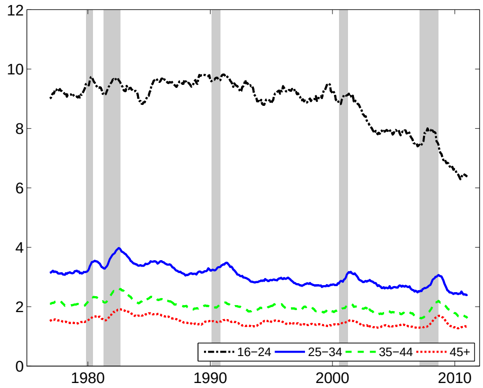
Notes: We plot twelve-month moving averages of monthly data. The sample period is 1976:01 - 2011:12. All variables are constructed from CPS microdata. Shaded areas indicate NBER recessions.

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.[4]

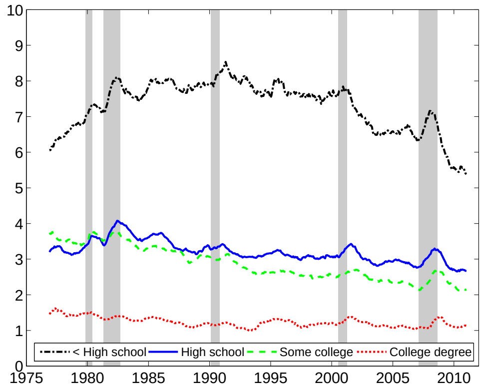
Figure 2.4 reveals substantial differences in the unemployment inflows and outflows by age and education. In particular, both unemployment flows are decreasing in both dimensions and the differences are sizable and persistent over time.[5]

[4]Elsby et al. (2010) report relatively modest heterogeneity in unemployment inflows and outflows by gender – for this reason, we decided to abstract from that demographic characteristic. For a recent analysis of the gender gap in the unemployment rate, see Albanesi and Şahin (2012).

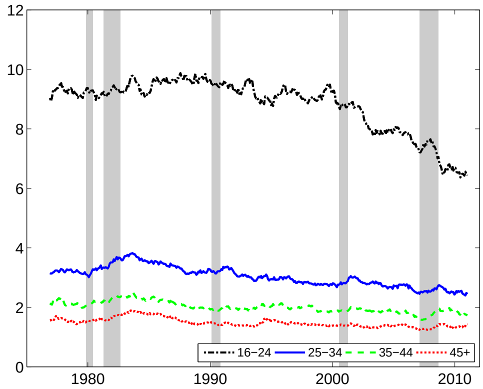
[5]For completeness, Figure B.1 in Appendix B plots similar graphs for the inflow and outflow rate. The results reveal substantial differences in the unemployment inflow rate by age and education. In particular, the inflow rate is decreasing in both dimensions and the differences are sizable and persistent 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.



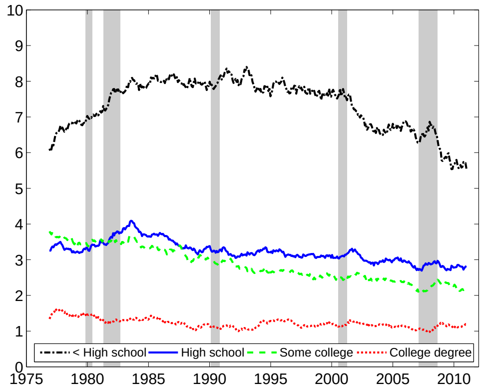
(a) Inflows by age



(b) Inflows by education



(c) Outflows by age



(d) Outflows by education

Figure 2.4: Unemployment flows 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. Unemployment flows are defined relative to the group-specific labor force levels (in percent).

2.2.1 Importance of Demographic Shifts for Aggregate Unemployment Flows

In this section we examine the role of changing composition of the U.S. labor force in explaining the behavior of aggregate unemployment flows, by performing two decomposition exercises.

First, notice that theoretical aggregate unemployment inflows, $s_t(1-u_t)$, can be computed as the labor-force-weighted average of unemployment inflows for each demographic group. In particular, let S_t be the aggregate number of separations, E_t the aggregate number of employed, and LF_t the aggregate number of individuals in the labor force in period t. With index i denoting group-specific variables, we get:

$$s_t(1-u_t) \equiv \frac{S_t}{E_t}\frac{E_t}{LF_t} = \sum_{i\in\Omega} \omega_{it}^{LF} s_{it}^{LF},$$

where ω_{it}^{LF} stands for the group's i labor force share at time t and s_{it}^{LF} is the group-specific unemployment inflow rate, expressed as a percent of the group's labor force.

Similarly, the theoretical aggregate unemployment outflows, $f_t u_t$, can be computed as the labor-force-weighted average of unemployment outflows for each demographic group as follows. Let H_t be the aggregate number of hires and U_t the aggregate number of unemployed. Then:

$$f_t u_t \equiv \frac{H_t}{U_t}\frac{U_t}{LF_t} = \sum_{i\in\Omega} \omega_{it}^{LF} f_{it}^{LF},$$

where f_{it}^{LF} is the group-specific unemployment outflow rate, expressed as a percent of the group's labor force.

The first counterfactual exercise then consists of computing the genuine unemployment inflows and outflows by using *fixed labor force weights* – in calculations we use the average of 1976 as our base period t_0.[6] The main advantage of this decomposition is its straightforward interpretation, as it allows us to answer the following question: "How would have aggregate unemployment inflows and outflows behaved, if the composition of the labor force had remained unchanged over time?". The underlying assumption is that, if the structure of the labor force had remained unchanged at some initial shares $\left\{\omega_{it_0}^{LF}\right\}_{i\in\Omega}$, the behavior of the group-specific inflow and outflow rate, expressed as a percent of the group's labor force levels $\left\{s_{it}^{LF}, f_{it}^{LF}\right\}_{i\in\Omega}$, would have been the same as the ones that we observe

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

from t_0 to t_1. Thus, we define genuine unemployment inflows at time t_1 as:

$$\sum_{i \in \Omega} \omega_{it_0}^{LF} s_{it_1}^{LF},$$

and genuine unemployment outflows at time t_1 as:

$$\sum_{i \in \Omega} \omega_{it_0}^{LF} f_{it_1}^{LF}.$$

The second counterfactual exercise consists of *decomposing changes* in aggregate unemployment inflows and outflows between periods t_0 (in calculations we again use the average of 1976 as our base period) and t_1 into two terms:

$$s_{t_1}(1-u_{t_1}) - s_{t_0}(1-u_{t_0}) = \sum_{i \in \Omega} \Delta\omega_{it_1}^{LF} \bar{s}_i^{LF} + \sum_{i \in \Omega} \bar{\omega}_i^{LF} \Delta s_{it_1}^{LF}, \tag{2.1}$$

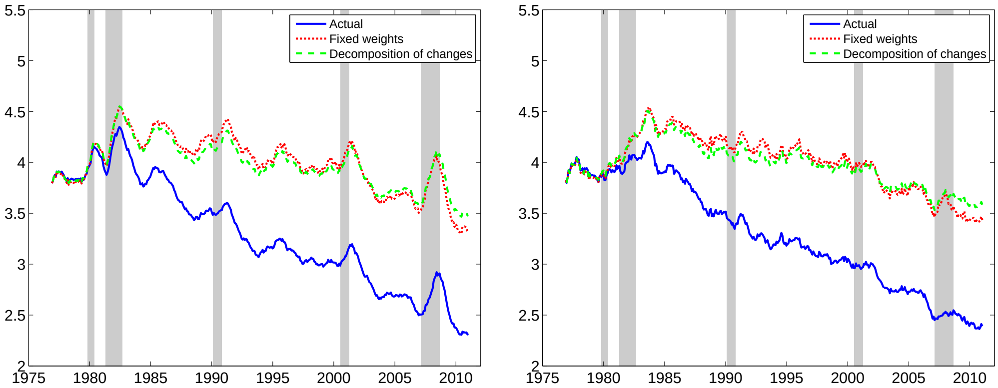
$$f_{t_1}u_{t_1} - f_{t_0}u_{t_0} = \sum_{i \in \Omega} \Delta\omega_{it_1}^{LF} \bar{f}_i^{LF} + \sum_{i \in \Omega} \bar{\omega}_i^{LF} \Delta f_{it_1}^{LF}, \tag{2.2}$$

where $\Delta\omega_{it_1}^{LF} = \omega_{it_1}^{LF} - \omega_{it_0}^{LF}$, $\bar{\omega}_i^{LF} = \frac{1}{2}\left(\omega_{it_0}^{LF} + \omega_{it_1}^{LF}\right)$, and similarly for $\bar{s}_i^{LF}$ and $\bar{f}_i^{LF}$.[7] The first term on the right of equations (2.1) and (2.2) 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 and outflow rates between t_0 and t_1.

Figure 2.5 summarizes the results of the counterfactual exercises for both unemployment inflows and outflows.[8] In particular, Figure 2.5a depicts the evolution of actual aggregate unemployment inflows together with the two counterfactual inflows, which keep the demographic structure of the labor force constant over time. As it can be inferred from this figure, the behavior of aggregate unemployment inflows during the recent decades has been highly influenced by the changes in the age and education composition of the labor force. Once we control for the demographics shifts, the downward trend in unemployment inflows nearly vanishes. Similar results are found for unemployment outflows (see Figure 2.5b). To sum up, both decomposition exercises suggest that demographics play a pivotal role in explaining the downward trend in aggregate unemployment flows over the last three decades, explaining about three quarters of the total decline from 1976 to 2011.

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

[8] For completeness, Appendix B.1.3 examines the importance of demographic shifts for the aggregate unemployment transition rates, by performing similar counterfactual exercises.



(a) Unemployment inflows (b) Unemployment outflows

Figure 2.5: The effect of demographics on unemployment flows: Actual *vs.* counterfactuals

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 respective actual aggregate unemployment flows in the first period.

2.2.2 Discussion of Empirical Findings

Our empirical findings show that demographic shifts in the composition of the U.S. labor force have importantly influenced the behavior of aggregate unemployment flows since 1976. As mentioned above, one important assumption underlying our counterfactual decompositions was that changes in the labor force composition have had no effect on group-specific unemployment inflows and outflows. Such an assumption is common to demographic adjustments of the unemployment rate and other labor market variables in the literature. Moreover, as Figure 2.4 shows, despite huge demographic shifts observed over the last three decades, group-specific unemployment flows have remained strikingly stable over time.[9] Nevertheless, we cannot rule out completely that group-specific unemployment flows have changed over time due to demographic shifts. One possibility is that the changing demographic composition of the U.S. population might have affected group-specific flows; in this respect, Shimer (2001) finds evidence in the state-level data that an increase if the share of youth in the working age population leads to an increase in the (group-specific) unemployment rates. Second possibil-

[9]Similarly, Daly et al. (2007) find that for demographic groups defined jointly by age and education (as in this paper), there is very little correlation between changes in their labor force shares and their changes in unemployment rates.

ity is that shifts in the labor force composition are originating from changes in labor force participation rates. Given that the latter are generally an equilibrium outcome of changes in worker flows across all labor market states, they could be related to changes in unemployment flows as well.

One could also ask whether we can meaningfully distinguish between relative contribution of age and education in accounting for the observed secular trends in unemployment flows. Such an exercise is generally difficult because of the mix effects.[10] For example, one of the main reasons why teenagers experience high unemployment inflows, is precisely because teenagers on average have lower education – and lower education leads by itself to higher unemployment inflows. Our analysis of the data indicates that both age and education are roughly equally important for demographic adjustments of unemployment flows – for example, even after controlling for one characteristic, the other characteristic still results in substantial heterogeneity in unemployment inflows (see Table B.1 in Appendix B).[11] Finally, note that our results are also consistent with the ones obtained in the existing literature. Fujita (2012) shows that roughly one-half of the decline in the gross flow hazard from employment to unemployment can be accounted for by the aging of the labor force (he abstracts from adjusting for the education composition). Moreover, Hyatt and Spletzer (2013) find that age and education can each explain about one quarter of the decline in hires and separations between 2001 and 2010, consistent with our results that during this period unemployment flows adjusted for changes in demographic composition of the labor force have been declining – see the counterfactual unemployment flows in Figure 2.5.

2.3 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

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

[11]Similarly, we calculated fixed 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; the results are not reported for brevity).

capital.[12] The 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 work in chapter 3 of this thesis 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.[13]

2.3.1 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.[14]

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

[12]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.

[13]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.

[14]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.

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.[15]

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 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.[16] 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.[17]

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 $\pi^a_k = \mathbb{P}\{a' = a_k\}$.

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

[16] 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.

[17] 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.

2.3.2 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

$$p(\theta) = \frac{m(u,v)}{u} = \mu\theta^{1-\alpha}, \tag{2.3}$$

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

$$q(\theta) = \frac{m(u,v)}{v} = \mu\theta^{-\alpha}. \tag{2.4}$$

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 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.

2.3.4 Characterization of Recursive Equilibrium

We write the model in terms of the standard match surplus equations (see Appendix B.2 for details on the derivation), where subscript t denotes the age of the job match:

$$\begin{aligned} S_t^{i,Y}(x) = \max\Big\{0, a(1-\mathbb{1}_{t=1}\tau^i) - b \\ &- \beta\eta p(\theta^i(x))\mathbb{E}_x\Big\{(1-\rho)S_1^{i,Y}(x') + \rho S_1^{i,D}(x')\Big\} \\ &+ \beta\mathbb{E}_x\Big\{(1-\rho)S_{t+1}^{i,Y}(x') + \rho S_{t+1}^{i,O}(x')\Big\}\Big\}, \end{aligned} \tag{2.5}$$

$$\begin{aligned} S_t^{i,O}(x) = \max\Big\{0, a - b - \beta(1-\delta)\eta p(\theta^i(x))\mathbb{E}_x\big\{S_1^{i,D}(x')\big\} \\ &+ \beta(1-\delta)\mathbb{E}_x\big\{S_{t+1}^{i,O}(x')\big\}\Big\}, \end{aligned} \tag{2.6}$$

$$\begin{aligned} S_t^{i,D}(x) = \max\Big\{0, a(1-\kappa)(1-\mathbb{1}_{t=1}\tau^i) - b \\ &- \beta(1-\delta)\eta p(\theta^i(x))\mathbb{E}_x\big\{S_1^{i,D}(x')\big\} \\ &+ \beta(1-\delta)\mathbb{E}_x\big\{S_{t+1}^{i,D}(x')\big\}\Big\}. \end{aligned} \tag{2.7}$$

Equation (2.5) presents the surplus that a job filled by a young worker produces, while equations (2.6) and (2.7) are the corresponding ones for a job filled by an old worker. The difference between the last two equations is that in equation (2.6) the old worker maintains the full value of his general human capital, while in equation (2.7) 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.[18] 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:

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

$$\frac{c}{q(\theta^i(x))} = \beta(1-\eta)\mathbb{E}_x\Big\{\gamma^i S_1^{i,Y}(x') + (1-\gamma^i)S_1^{i,D}(x')\Big\}, \tag{2.8}$$

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:

$$(n^{i,Y})' = (1-\rho)(1-s^{i,Y})n^{i,Y} + p(\theta^i)(1-G(\tilde{a}_1^{i,Y}))(1-\rho)u^{i,Y}, \tag{2.9}$$

$$(u^{i,Y})' = \Big[1-p(\theta^i)(1-G(\tilde{a}_1^{i,Y}))\Big](1-\rho)u^{i,Y} + s^{i,Y}(1-\rho)n^{i,Y} + \delta(n^{i,O}+n^{i,D}+u^{i,D}), \tag{2.10}$$

$$(n^{i,O})' = (1-\delta)(1-s^{i,O})n^{i,O} + \rho(1-s^{i,O})n^{i,Y}, \tag{2.11}$$

$$(n^{i,D})' = (1-\delta)(1-s^{i,D})n^{i,D} + p(\theta^i)(1-G(\tilde{a}_1^{i,D}))(\rho u^{i,Y} + (1-\delta)u^{i,D}), \tag{2.12}$$

$$(u^{i,D})' = \Big[1-p(\theta^i)(1-G(\tilde{a}_1^{i,D}))\Big](\rho u^{i,Y} + (1-\delta)u^{i,D}) \tag{2.13}$$

$$+ s^{i,O}(\rho n^{i,Y} + (1-\delta)n^{i,O}) + s^{i,D}(1-\delta)n^{i,D}, \tag{2.14}$$

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.[19] Aggregate employment and unemployment are defined, respectively, as:

$$\begin{aligned} n^i &= n^{i,Y} + n^{i,O} + n^{i,D}, \\ u^i &= u^{i,Y} + u^{i,D}. \end{aligned}$$

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 (2.3)-(2.14), 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.2 describes the computational strategy used to solve the model.

[19] See Appendix B.2 for more details about the labor market flows.

2.4 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.

2.4.1 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 2.1 summarizes the parameter values used to calibrate the baseline economy.

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 chapter 3 of this thesis for more details. We follow Hall and Milgrom (2008) in order to establish a value for the unemployment benefits. Our choice of

Table 2.1: 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

$b = 0.71$ 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.[20]

[20] Following our work in chapter 3 of this thesis, 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

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.[21]

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.[22] 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, Davis and Wachter (2011) find 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 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

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".

[21]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 $\tau^H = 0.230 + \beta \times 0.230 + \beta^2 \times 0.230 + \beta^3 \times 0.230 \times 0.7$.

[22]See Appendix B.2 for the derivation of the wage equations.

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 $l^L = 0.58$.

2.4.2 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 2.2 provides simulation results by education and age groups for the high turnover economy.

Table 2.2: 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 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.

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.[23] 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 2.2. 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 chapter 3 of this thesis, where we show that on-the-job training is the reason behind the 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.

2.4.3 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

[23]Similar conclusions are reached if we look at the simulation results for the low turnover economy (see Table B.2 in Appendix B.2).

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 2.3 presents the main results of this numerical exercise.

Table 2.3: 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
Unemployment outflows	3.9	3.1
Unemployment inflows	3.8	2.9
Panel B: Simulation results		
Unemployment rate	7.1	5.2
Job finding rate	56.5	57.4
Separation rate	4.1	3.0
Unemployment outflows	4.0	3.0
Unemployment inflows	3.8	2.8

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 unemployment inflows and outflows decline substantially. 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 most of the decline in the unemployment flows 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.

2.5 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 unemployment flows. By performing a series of decomposition exercises using microdata from the Current Population Survey, the empirical results show that these two demographic characteristics explain about three quarters of the total decline in aggregate unemployment flows 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 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.

Chapter 3

HUMAN CAPITAL AND UNEMPLOYMENT DYNAMICS: WHY DO MORE EDUCATED WORKERS ENJOY GREATER EMPLOYMENT STABILITY?

(written jointly with Tomaz Cajner)

3.1 Introduction

> "*Employees with specific training have less incentive to quit, and firms have less incentive to fire them, than employees with no training or general training, which implies that quit and layoff rates are inversely related to the amount of specific training.*" (Becker, 1964)

More educated individuals fare much better in the labor market than their less educated peers. For example, when the U.S. aggregate unemployment rate hit 10 percent during the recent recession, high school dropouts suffered from unemployment rates close to 20 percent, whereas college graduates experienced unemployment rates of only 5 percent. As can be inferred from Figure 3.1, educational attainment appears to have been a good antidote to joblessness for the whole period of data availability. Moreover, the volatility of employment decreases with education as well. Indeed, enhanced job security arguably presents one of the main benefits of education. This paper systematically and quantitatively investigates possible explanations for greater employment stability of more educated people by using recent empirical and theoretical advances in the area of worker flow analysis and search and matching models.

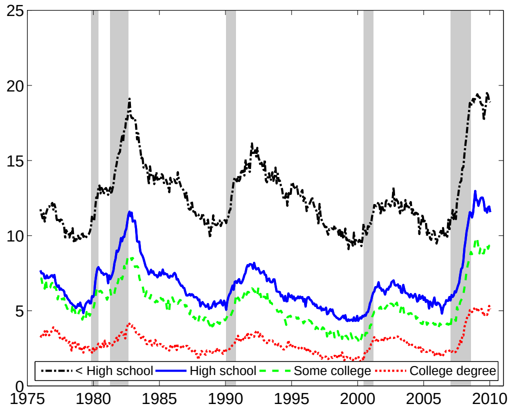


Figure 3.1: U.S. unemployment rate by educational attainment

Notes: The sample period is 1976:01 - 2010:12. Monthly data for the working-age population constructed from CPS microdata and seasonally adjusted. Shaded areas indicate NBER recessions.

Theoretically, differences in unemployment across education groups can arise either because the more educated find jobs faster, because the less educated get fired more often, or due to a combination of the two factors. Empirically, the worker flow analysis in this paper finds that different education groups face roughly the same unemployment outflow rate (loosely speaking, the job finding rate). What creates the remarkably divergent patterns in unemployment by education is the unemployment inflow rate (the job separation rate). Why is it then that more educated workers lose their jobs less frequently and experience lower turnover rates?

This paper provides a theoretical model in which higher educational attainment leads to greater employment stability. The model is based on vast empirical evidence showing that on-the-job training is strongly and positively related to education. As argued already by Becker (1964), higher amounts of specific training should reduce incentives of firms and workers to separate.[1] We build on this insight and formalize it within a search and matching framework with endogenous separations in the spirit of Mortensen and Pissarides (1994). In our model, all new hires lack some job-specific skills, which they obtain through the process of initial on-the-job training. More educated workers engage in more complex job activities, which necessitate more initial on-the-job training. After gaining job-specific human capital, workers have less incentives to separate from their jobs, with these incentives being stronger for more educated workers. We parameterize the model by using detailed micro evidence from the Employment Opportunity Pilot Project (EOPP) survey. In particular, our empirical measure of training for each education

[1]Similar arguments were also put forward by Oi (1962) and Jovanovic (1979).

group is based on the duration of initial on-the-job training and the productivity gap between new hires and incumbent workers.

The simulation results demonstrate that, given the observed empirical differences in initial on-the-job training, the model is able to explain the empirical regularities across education groups on job finding, separation, and unemployment rates, both in their first and second moments. This cross-sectional quantitative success of the model is quite remarkable, especially when compared to the well-documented difficulties of the canonical search and matching model to account for the main time-series properties of aggregate labor market data (Shimer, 2005), and thus represents the main contribution of this paper.

Perhaps the most interesting is the ability of the model to generate vast differences in the separation rate, whereas at the same time the job finding rate remains very similar across education groups. The result that on-the-job training leaves the job finding rate unaltered reflects two opposing forces. On the one hand, higher training costs lower the value of a new job, leading to less vacancy creation and a lower job finding rate. On the other hand, higher training costs reduce the probability of endogenously separating once the worker has been trained, implying a higher value of a new job and a higher job finding rate. The simulation results reveal that both effects cancel out, thus an increase in training costs leaves the job finding rate virtually unaffected. This result is important, because it cannot be obtained with standard models in the literature. Indeed, because the job creation equation represents one of the central building blocks for any search and matching model, it is very likely that alternative explanations for different unemployment dynamics by education will be inconsistent with the empirical observation of almost negligible variation in job finding rates by education.

The model in this paper can be also used to quantitatively evaluate several alternative explanations for differences in unemployment dynamics by education. In particular, the model nests the following alternative explanations: i) differences in the size of job profitability (match surplus heterogeneity); ii) differences in hiring costs; iii) differences in the frequency of idiosyncratic productivity shocks; iv) differences in the dispersion of idiosyncratic productivity shocks; and v) differences in the matching efficiency. We simulate the model under each of these alternative hypotheses and then use empirical evidence in order to discriminate between them. According to our findings, none of the economic mechanisms behind the competing explanations can generate unemployment dynamics by education that we observe in the data.[2]

[2] One alternative hypothesis that we cannot directly test with our model relates to minimum-wage floors, which are more likely to be binding for less educated workers, thus potentially explaining their higher unemployment rates. Nevertheless, the empirical research following Card and Krueger (1994) finds conflicting evidence on the effect of minimum wages on employment. If anything, the employment effects of minimum wages appear to be empirically modest – see, e.g.,

As a final test of the theoretical mechanism embedded in our model, we provide novel empirical evidence on unemployment dynamics by required job training. In particular, we construct unemployment rates, job finding rates and separation rates by specific vocational preparation as measured in the Dictionary of Occupational Titles. This new evidence shows that occupations with higher specific vocational training experience substantially lower unemployment rates, which are predominantly due to lower separation rates. More strikingly, even after we condition for educational attainment, for example by focusing on high school graduates only, we find that higher specific vocational training leads to lower separation rates, but almost indistinguishable job finding rates, consistent with the theoretical mechanism advocated in this paper.

Our paper contributes to three strands of literature. First, it contributes to the theoretical literature of business cycle fluctuations that attempts to move beyond the representative agent framework. The aim of this literature is twofold: first, to test the plausibility of different theories by taking advantage of cross-sectional data, and second, to further our understanding of business cycle fluctuations by studying the heterogeneous impact of aggregate shocks on different demographic groups, which seems particularly relevant for fluctuations in the labor market. Relative to the existing contributions (Kydland, 1984, Gomme et al., 2005), we carry out our analysis within the equilibrium search and matching framework and find that the inability of this class of models to explain aggregate unemployment fluctuations at business cycle frequencies (Shimer, 2005) is not due to a failure of these models to account for fluctuations experienced by some particular education group, but instead this models' failure pertains equally to all education groups. Moreover, this paper shows that a tractable extension of the benchmark search and matching model delivers a framework that can account well for the cross-sectional differences in unemployment fluctuations by education and can be thus fruitfully utilized for studying cross-sectional labor market phenomena.

Second, our paper contributes to the theoretical literature on search and matching models with worker heterogeneity. Contributions in this literature include Gautier (2002), Albrecht and Vroman (2002), Pries (2008), Dolado et al. (2009), Gonzalez and Shi (2010), and Krusell et al. (2010). However, in these papers the worker's exit to unemployment is assumed to be exogenous, hence they cannot be used to explain why the empirical unemployment inflow rate differs dramatically by education. Bils et al. (2011, 2009) allow for endogenous separations and heterogeneity in the rents from being employed; however, the latter assumption generates a substantial variation in the job finding rate and thus cannot be used to explain why the unemployment outflow rate empirically exhibits low variation by education. Relative to the existing literature, this paper provides a search and

Dube et al. (2010) for some recent U.S. empirical evidence.

matching model with endogenous separations and on-the-job training, which can generate substantial variability in job separation rates and at the same time small differences in job finding rates, which was a challenge for existing models.

Third, our paper contributes to the empirical literature that studies cross-sectional differences in unemployment dynamics by education. Using Panel Study of Income Dynamics (PSID) data, Mincer (1991) finds that the incidence of unemployment is far more important than the reduced duration of unemployment in creating the educational differentials in unemployment rates; he attributes this finding to higher amount of on-the-job training for more educated workers. Our paper confirms this finding by using representative Current Population Survey (CPS) microdata, by constructing both duration-based and gross-flow labor market transition rates, and by controlling for possible biases (for example, duration dependence). Moreover, we use a combination of microdata and a theoretical model of equilibrium unemployment in order to interpret empirical evidence and to quantitatively discriminate among several possible explanations for observed empirical patterns.

Following this introduction, Section 3.2 provides some empirical evidence on unemployment, its inflows and outflows, and on-the-job training by education. Section 3.3 outlines the model, which is then calibrated in Section 3.4. Section 3.5 contains the main simulation results of the model and a discussion of the mechanism driving the results. Novel empirical evidence on unemployment dynamics by required job training is provided in Section 3.6. In Section 3.7 we quantitatively explore other possible explanations for differences in unemployment dynamics by education. Finally, Section 3.8 concludes with a discussion of possible avenues for further research. We provide data description, some further empirical results, analytical proofs, sensitivity analysis, and additional robustness checks in Appendix C.

3.2 Empirical Evidence

3.2.1 Unemployment Rates

It is a well-known and documented empirical fact that the unemployment rate differs by education level (recall Figure 3.1). In the United States, the jobless rate of the least educated (high school dropouts) is roughly four times greater than that of the most educated (college graduates), and this difference has been maintained since the data are available.

Table 3.1 tabulates the unemployment rate across four education groups by using the standard demographic controls (i.e., by showing the largest demographic group). As it turns out, substantial unemployment differentials across education

Table 3.1: U.S. unemployment rates by educational attainment (in percent)

	16 years and over	25 years and over	males, prime age (25-54)	males, prime age, white	males, prime age, white, married
Less than high school	12.6	9.0	9.3	8.5	7.1
High school	6.7	5.4	5.9	5.2	3.9
Some college	5.3	4.4	4.5	4.0	2.9
College degree	2.8	2.6	2.4	2.2	1.5
All individuals	6.4	4.9	5.0	4.5	3.4
Ratio LHS/CD	4.5	3.5	3.9	3.9	4.6

Notes: The sample period is 1976:01 - 2010:12. All variables are constructed from CPS microdata. LHS stands for less than high school and CD for college degree.

groups represent a robust empirical finding that cannot be explained by usual demographic controls (age, gender, race, marital status). This is confirmed by results from a somewhat more formal regression analysis, which controls for individual characteristics, industry, and occupation, and includes time dummies – these results can be found in Appendix C (Table C.1).

For the rest of the paper, we focus our analysis on individuals with 25 years of age and older for the following two reasons. First, by the age of 25 most individuals have presumably finished their studies, hence we avoid the possibility that our conclusions regarding unemployment properties for low educated workers could be driven by differential labor market behavior of young people. Second, further empirical exploration of unemployment rates by age reveals that young people experience somehow higher unemployment rates for all education groups, which could be related to their labor market entry that may start with an unemployment spell.[3]

3.2.2 Unemployment Flows

Theoretically, a higher unemployment rate may be a result of a higher probability of becoming unemployed – a higher incidence of unemployment – or a lower probability of finding a job – higher duration of the unemployment spell.[4] In order to distinguish between these possibilities, we follow the recent approach in the literature by calculating empirical unemployment flows.[5] In particular, we

[3]See Figure C.1 in Appendix C.

[4]Acknowledging a slight abuse of terminology, we use in this paper interchangeably expressions “inflow rates”, “separation rates” and “unemployment incidence” to denote flow rates into unemployment. Similarly, we refer to “outflow rates” and “job finding rates” to denote flow rates out of unemployment, whereas “unemployment duration” is the inverse of the latter.

[5]This approach has been used by Shimer (2012), Elsby et al. (2009), and Fujita and Ramey (2009) for the analysis of aggregate data, and by Elsby et al. (2010) for decompositions along

decompose unemployment rates for people with 25 years of age and over into unemployment inflow and outflow rates.[6] As can be seen from Figure 3.2, we find that outflow rates from unemployment are broadly similar across education groups, whereas inflow rates differ considerably.[7] Furthermore, we exploit the steady state unemployment approximation $u_t^* \approx s_t/(s_t + f_t)$, which has been found in the literature to replicate well the actual unemployment rates (s_t stands for the separation rate and f_t denotes the job finding rate). In Figure 3.3 we construct two types of counterfactual unemployment rates to analyze separately the role of outflows and inflows in explaining the differences in unemployment rates across education groups. In particular, in the left panel of Figure 3.3 we calculate the counterfactual unemployment rate series for each group by taking its actual outflow rate series, but keeping the inflow rate series at the value for the aggregate economy. Analogously, in the right panel of Figure 3.3 we calculate the counterfactual unemployment rate series for each group by taking its actual inflow rate series, but keeping the outflow rate series at the value for the aggregate economy. These two counterfactuals clearly demonstrate that the observable differences in job finding rates have a negligible effect on unemployment rates, with separation rates accounting for almost all variability in unemployment rates across education groups.[8] Moreover, the observed differences in outflow rates actually go in the wrong direction as they predict (slightly) higher unemployment rates for highly educated workers.

various demographic groups. Note that there exists an older literature, which is not based on empirical unemployment flows, that also tries to identify the reason behind the observed differences in unemployment rates across education levels. It is a robust finding in this literature that lower incidence of unemployment within the more educated is the main contributor to differences in unemployment rates (Ashenfelter and Ham, 1979, Nickell, 1979, Mincer, 1991). Indeed, empirical evidence on the effect of education on unemployment duration is mixed, with some studies finding a negative effect (Nickell, 1979, Mincer, 1991), some negligible effect (Ashenfelter and Ham, 1979), and some positive effect (Moffitt, 1985, Meyer, 1990).

[6] Details of the procedure can be found in Appendix C. The Appendix C also provides analogous analysis for people with 16 years of age and over.

[7] Similar findings of nearly identical outflow rates and different inflow rates across education groups are provided by Elsby et al. (2010).

[8] Note that our focus here is primarily on cross-sectional variation, as opposed to time variation in unemployment rates. Therefore, we avoid the critique of Fujita and Ramey (2009) on using counterfactual unemployment rates to assess the role of inflow rates and outflow rates in explaining unemployment fluctuations over time. Their critique stressed the importance of accounting for dynamic interactions, which imply that fluctuations in the separation rate are negatively correlated with future changes in the job finding rate.

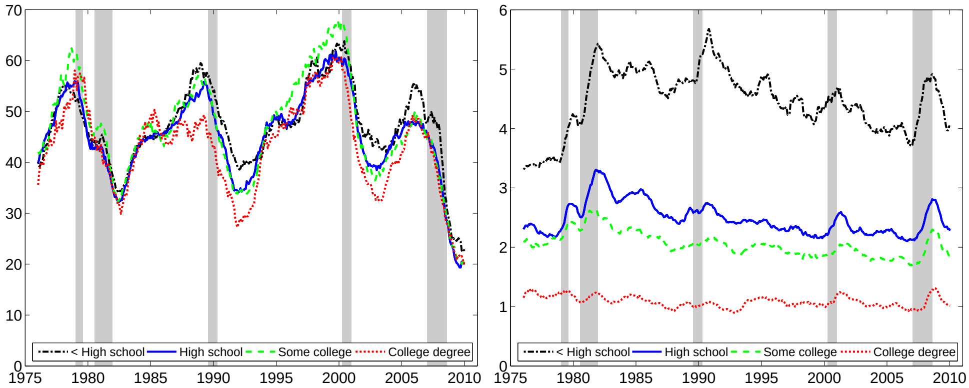


Figure 3.2: Unemployment flow rates

Notes: 12-month moving averages for individuals with 25 years of age and over.

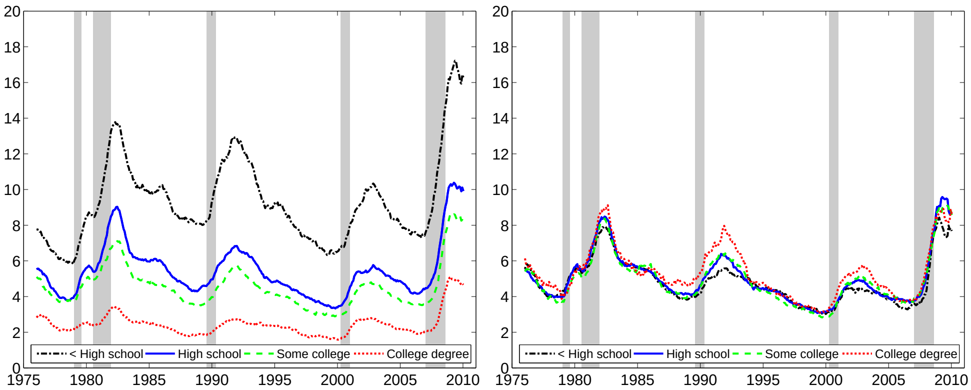


Figure 3.3: Counterfactual unemployment rates

Notes: The left panel shows the counterfactual unemployment rate series for each group by taking its actual outflow rate series, but keeping the inflow rate series at the values for the aggregate economy. The right panel shows the counterfactual unemployment rate series for each group by taking its actual inflow rate series, but keeping the outflow rate series at the values for the aggregate economy. 12-month moving averages for individuals with 25 years of age and over.

In Appendix C we further check for two possible biases regarding our conclusion that inflow rates drive the differences in unemployment rates by education. First, the procedure to calculate outflow rates might be biased due to duration dependence. Figure C.2 in Appendix C illustrates that all education groups are roughly equally represented over the whole unemployment duration spectrum, hence duration dependence is not likely to bias our conclusion that outflow rates are similar by education. Second, so far we have neglected transitions in and out of the labor force. Figures C.3 and C.4 in Appendix C show that the findings of similar job finding rates and vastly different separation rates across education groups remain valid when considering a three-state decomposition of unemployment flows.

To sum up, in order to understand why the least educated workers have unemployment rates nearly four times greater than the most educated workers, one has to identify the economic mechanisms that create a gap in their inflow rates to unemployment.

3.2.3 Labor Market Volatility

Table 3.2 summarizes volatility measures for the main labor market variables of interest. In particular, we report two sets of volatility statistics. First, absolute volatilities are defined as standard deviations of the data expressed in deviations from an HP trend with smoothing parameter 10^5.[9] Second, relative volatilities are defined analogously, except that all variables are initially expressed in natural logarithms.[10] Both sets of volatility statistics are reported in order to facilitate the comparison with the existing literature. More precisely, on the one hand macroeconomists typically avoid taking logarithms of rates and thus prefer to report absolute volatilities. On the other hand, some of the recent literature on quantitative performance of search and matching models puts more emphasis on relative volatilities, because what matters from the viewpoint of the canonical search and matching model are relative changes in unemployment.

Our preferred volatility measure corresponds to the concept of absolute volatility. To understand why, notice that in the case of employment rates, the distinction between relative and absolute volatilities becomes immaterial.[11] As the numbers in Table 3.2 clearly illustrate, more educated workers enjoy greater employment stability. Employment stability is arguably also the concept that matters from the welfare perspective of an individual. However, if we compare absolute and relative volatilities for unemployment rates, the numbers lead to contradictory conclusions – while absolute volatilities agree with employment volatilities by definition, relative volatilities in contrast suggest that the most educated group experiences higher unemployment volatility than the least educated group. The reason why the more educated have more volatile unemployment rates in terms of log deviations, despite having less volatile employment rates, is clearly related to their lower un-

[9] For example, absolute volatility of 1.05 for the aggregate unemployment rate implies that the aggregate unemployment rate varies +/- 1.05 percentage points around its mean of 4.89.

[10] For example, relative volatility of 20.07 for the aggregate unemployment rate implies that the aggregate unemployment rate roughly varies +/- 20.07 percent around its mean of 4.89.

[11] This naturally follows as $\log(1+x) \approx x$ for x close to zero.

Table 3.2: Labor market volatility by education level

	Absolute volatility				Relative volatility			
	n	u	f	s	n	u	f	s
Less than high school	1.78	1.78	7.62	0.42	1.99	18.66	17.45	9.23
High school	1.26	1.26	7.48	0.24	1.35	20.83	18.62	9.09
Some college	1.02	1.02	8.96	0.18	1.08	21.32	20.48	8.28
College degree	0.55	0.55	8.55	0.11	0.57	20.16	21.39	9.87
All individuals	1.05	1.05	7.49	0.18	1.12	20.07	17.99	7.57
Ratio LHS/CD	3.22	3.22	0.89	3.87	3.47	0.93	0.82	0.93

Notes: Quarterly averages of seasonally-adjusted monthly data for individuals with 25 years of age and over. Absolute volatilities are defined as standard deviations of the data expressed in deviations from an HP trend with smoothing parameter 10^5. Relative volatilities are defined analogously, except that all variables are initially expressed in natural logarithms. The sample period is 1976:01 - 2010:12. n refers to employment rate, u to unemployment rate, f to job finding rate and s to separation rate.

employment means.[12] To avoid the distorting effect of different means on relative volatility measures, we prefer to focus on absolute volatilities. Note that the more educated experience also lower (absolute) volatility of separation rates, whereas job finding rates exhibit broadly equal variation across education groups.

3.2.4 On-the-Job Training

Economists have long recognized the importance of learning-by-doing, formal and informal on-the-job training for human capital accumulation. Despite the widely accepted importance of on-the-job training in theoretical work, empirical verifications of theoretical predictions remain rare, mainly due to limited data availability. Unlike with formal education, the data on training need to be obtained from scarce and frequently imperfect surveys, with considerable data imperfections being related especially to informal on-the-job training and learning-by-doing.[13] Nevertheless, existing empirical studies of job training overwhelmingly suggest the presence of strong complementarities between education and training. The positive link between formal schooling and job training has been found in data from: i) the CPS Supplement of January 1983, the National Lon-

[12] By definition of the employment and unemployment rates, we have $n_t + u_t = 1$. Taking log-linear approximation yields $\widehat{u}_t = -(n^*/u^*)\widehat{n}_t \approx -(1/u^*)\widehat{n}_t$, where hats denote steady-state deviations. Hence, log deviations in employment are amplified by a factor of roughly $1/u^*$ when one calculates log deviations in unemployment.

[13] Barron et al. (1997) provide a comprehensive comparison of different measures of on-the-job training across datasets and Lynch (1992) discusses shortcomings of various on-the-job training surveys.

gitudinal Surveys (NLS) of Young Men, Older Men and Mature Women, and the 1980 EOPP survey by Lillard and Tan (1986); ii) the NLS of the High School Class of 1972 by Altonji and Spletzer (1991); iii) the Panel Study of Income Dynamics (PSID) by Mincer (1991); and iv) a dataset of a large manufacturing firm by Bartel (1995).

In what follows we provide some further evidence on training by education level from the 1982 EOPP survey, which will form the empirical basis for the parameterization of our model. Table 3.3 summarizes the main training variables of the survey with a breakdown by education.[14]

Table 3.3: Measures of training by education level from the 1982 EOPP survey

	Less than high school	High school	Some college	College degree	All individuals
Incidence rate of initial training (mean, in percent)					
Formal	9.5	12.0	18.1	17.9	13.7
Informal by manager	89.7	85.9	89.8	88.5	87.3
Informal by coworkers	56.7	58.0	62.7	53.5	58.1
Informal by watching others	78.1	75.1	81.0	73.9	76.3
Some type of training	94.0	94.5	97.0	95.1	95.0
Time to become fully trained (mean, in weeks)					
Duration	10.2	12.0	15.9	18.2	13.4
Productivity gap (mean, in percent)					
Typical new hire vs. incumbent	32.5	36.2	45.3	48.1	39.1

Notes: The sample includes 1053 individuals with 25 years of age and older, for whom we have information on education. The distribution of training duration is truncated at its 95th percentile. All measures of training correspond to typical new hires.

The EOPP survey is particularly useful to analyze training because it includes measures of both formal and informal training. This is important given that the average incidence rate of receiving initial (i.e. during first three months) formal training in our sample corresponds to 13.7 percent, while the incidence rate of receiving some type of initial training is 95.0 percent. Table 3.3 illustrates two relevant aspects of the data for our paper. First, nearly all new hires receive some

[14]We restrict the EOPP sample to individuals for whom we have information on education and, to be consistent with our data on unemployment, to individuals with 25 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". In Appendix C we provide some additional discussion of the 1982 EOPP survey.

type of initial training, regardless of their level of education. Second, there are considerable differences across education groups in terms of the duration of training received and the corresponding productivity gap (the latter is defined as the percent difference in productivity of an incumbent worker with 2 years of experience and a new hire). For example, a newly hired college graduate needs 18.2 weeks on average to become fully trained, which is nearly two times the time needed for a newly hired high school dropout. Moreover, the difference between the initial productivity and the productivity achieved by an incumbent worker increases with the education level as well, from one third to one half.

The objective of this paper is to study whether the observed differences in on-the-job training are able to explain the observed differences in unemployment rates across education groups by affecting the job destruction margin. In particular, the paper's hypothesis claims that higher investments in training reduce incentives for job destruction. However, according to the argument of Becker (1964) incentives for job destruction crucially depend on the portability of training across different jobs. As we argue below, there exist strong reasons to believe that our empirical measure of on-the-job training can indeed be interpreted as being largely job-specific and hence unportable across jobs.

First, the appropriate theoretical concept of specificity in our case is not whether a worker can potentially use his learned skills in another firm. What matters for our analysis is whether after going through an unemployment spell, a worker can still use his past training in a new job. To give an example, a construction worker might well be able to take advantage of his past training in another construction firm, but if after becoming unemployed he cannot find a new job in the construction sector and is thus forced to move to another sector, where he cannot use his past training, then his training should be viewed as specific. Industry and occupational mobility are not merely a theoretical curiosity but, as shown by Kambourov and Manovskii (2008), a notable feature of the U.S. labor market. These authors also find that industry and occupational mobility appears to be especially high when workers go through an unemployment spell.[15] Similarly, by analyzing the National Longitudinal Survey of Youth (NLSY) data Lynch (1991) reaches the conclusion that on-the-job training in the United States appears to be unportable from employer to employer. In the same vein, Lynch (1992) finds that on-the-job training with the current employer increases wages, while spells of on-the-job training acquired before the current job have no impact on current wages.

Second, the EOPP was explicitly designed to measure the initial training at the start of the job (as opposed to training in ongoing job relationships), which is more likely to be of job-specific nature. Moreover, the EOPP also provides data on the

[15] See Figure 10a of their paper.

productivity difference between the *actual* new hire during his first two weeks and the typical worker who has been in this job for two years. For the actual new hire the EOPP also reports months of relevant experience.[16] Table 3.4 summarizes the productivity differences between the actual new hire and the typical incumbent for three age groups and also for two subsamples of new hires with at least 1 and 5 years of relevant experience. Note that one would expect to observe in the data a rapidly disappearing productivity gap (between incumbents and new hires) with rising age of workers and months of relevant experience, if this measure of on-the-job training were capturing primarily general human capital. However, the results in Table 3.4 indicate that initial on-the-job training remains important also for older cohorts of workers and for workers with relevant experience. Crucially for our purposes, the relative differences across education groups remain present and even increase a bit. Overall, this suggests that initial on-the-job training, at least as measured by the EOPP survey, contains primarily specific human capital.

Table 3.4: Productivity gap between incumbents and new hires by education level from the 1982 EOPP survey

	Less than high school	High school	Some college	College degree	All individuals
Productivity gap (mean, in percent)					
16 years and over	32.2	35.4	37.9	43.9	36.4
25 years and over	24.6	29.3	37.9	39.3	31.8
35 years and over	20.2	29.3	31.7	38.6	29.6
25 years and over and at least					
- 1 year of relevant experience	22.7	24.5	34.4	41.7	28.8
- 5 years of relevant experience	18.2	22.6	26.6	38.9	25.0

Notes: The productivity gap is calculated as the difference in productivity between the actual new hire and the typical incumbent. We restrict the sample to individuals for whom we have information on education.

Third, Figure 3.4 depicts the incidence rate of formal training from the NLSY cohort.[17] The analysis of these data shows that the incidence rate of formal training differs across education groups, with more educated workers receiving more training and the numbers being comparable to the ones for formal training from the EOPP survey (see Table 3.3). Moreover, Figure 3.4 shows that incidence rates of training across education groups do not exhibit a notable downward trend with aging of the 1979 NLSY cohort, consistent with the argument of the previous paragraph.

Finally, the traditional approach in the literature to distinguish between general

[16]The exact survey question was "How many months of experience in jobs that had some application to the position did (NAME) have before (he/she) started working for your company?"

[17]A short description of this survey is available in Appendix C.

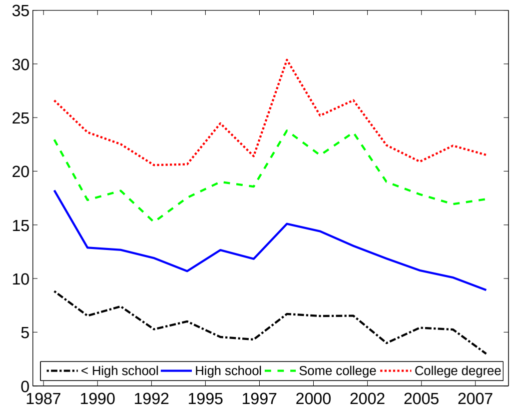


Figure 3.4: Incidence rate of formal training from the 1979 NLSY cohort

and specific human capital has been to associate the wage return to overall work experience as an indication of the presence of general human capital, whereas the wage return to tenure has been typically interpreted as evidence of specific human capital. In an influential paper, Topel (1991) estimates that 10 years of job tenure raise the wage by over 25 percent, with wage growth being particularly rapid during an initial period of job, hence suggesting the presence of specific human capital.[18] Moreover, Brown (1989) shows that firm-specific wage growth occurs almost exclusively during periods of on-the-job training, lending further support to the argument that on-the-job training is mostly specific.

3.3 The Model

This section presents the model, which is an extension of the canonical search and matching model with endogenous separations (Mortensen and Pissarides, 1994). In our setting workers initially lack some job-specific skills, which they obtain during a period of on-the-job training. The model allows for worker heterogeneity in terms of productivity, directly related to their formal education. Moreover, different levels of education require different amounts on-the-job training for exogenous, technological reasons, which may reflect variety in job complexity. Intuitively, more educated workers engage in more complex job activities, which necessitate a higher degree of initial on-the-job training.

[18]Evidence from displaced workers, as reported by Jacobson et al. (1993), and Couch and Placzek (2010), also indicates the importance of specific human capital.

3.3.1 Environment

The discrete-time model economy contains a finite number of segmented labor markets, indexed by $h \in \{1, 2, ..., h^{max}\}$, where h represents different levels of formal educational attainment. Workers in each of these markets possess a certain amount of formal human capital, denoted by $H \in \{H_1, H_2, ..., H_{h^{max}}\}$, directly related to their education. Moreover, firms in each of these markets provide initial on-the-job training to their new hires, with the amount of training depending on worker's education. The assumption of segmented labor markets is chosen because education is an easily observable and verifiable characteristic of workers, hence firms can direct their search towards desired education level for their new hires.[19]

Each segmented labor market features a continuum of measure one of risk-neutral and infinitely-lived workers. These workers 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. Employed workers earn wage w_t, whereas unemployed workers have access to home production technology, which generates b_h consumption units per time period. In general, b_h also includes potential unemployment benefits, leisure, saved work-related expenditures and is net of job-searching costs. Importantly, it depends on worker's education. We abstract from labor force participation decisions, therefore all unemployed workers are assumed to be searching for jobs.

A large measure of risk-neutral firms, which maximize their profits, is trying to hire workers by posting vacancies. We follow the standard approach in search and matching literature by assuming single-worker production units. In other words, each firm can post only one vacancy and for this it pays a vacancy posting cost of c_h units of output per time period. Here we allow this vacancy posting cost to vary across segmented labor markets, reflecting potentially more costly searching process in labor markets that require higher educational attainment. After a match between a firm and a worker with education H is formed, they first draw an idiosyncratic productivity a. If the latter is above a certain threshold level, described more in detail below, they start producing according to the following technology:

$$y(H, A, a) = (1 - \tau_h)HAa.$$

Note that workers are initially untrained, thus they produce only $(1-\tau_h)$ of regular output, where τ_h measures the extent of job-specific skills (i.e., the productivity

[19] In a somewhat related setting with direct search, Mortensen and Pissarides (1999) show that even if one allows for the possibility of overqualification, whereby workers can apply for jobs that require lower formal education than their own, workers optimally self-select themselves into appropriate educational sub-markets, yielding a perfectly segmented equilibrium. For the contrasting case with random search, see for example Pries (2008).

gap between a new hire and a skilled worker). In each period untrained workers experience a probability ϕ_h of being upgraded to a skilled worker. Note that $1/\phi_h$ yields the average duration of on-the-job training.[20] A firm with a skilled worker of education H produces a regular output level of HAa, where A denotes the aggregate productivity and a the idiosyncratic productivity. Both aggregate and idiosyncratic productivity are assumed to be stochastic, evolving over time according to two independent Markov chains $\{\mathbf{A}, \mathbf{\Pi^A}\}$ and $\{\mathbf{a}, \mathbf{\Pi^a}\}$, with finite grids $\mathbf{A} = \{A_1, A_2, ..., A_n\}$ and $\mathbf{a} = \{a_1, a_2, ..., a_m\}$, transition matrices $\mathbf{\Pi^A}$ being composed of elements $\pi^A_{ij} = \mathbb{P}\{A' = A_j \mid A = A_i\}$ and $\mathbf{\Pi^a}$ being composed of elements $\pi^a_{ij} = \mathbb{P}\{a' = a_j \mid a = a_i\}$, and the initial probability vector being composed of elements $\pi^a_j = \mathbb{P}\{a' = a_j\}$.

3.3.2 Labor Markets

The matching process between workers and firms is formally depicted by the existence of a constant returns to scale matching function:

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

where the parameter γ stands for matching efficiency, the parameter α for the elasticity of the matching function with respect to unemployment, u denotes the measure of unemployed and v denotes the measure of vacancies. Each segmented labor market h features such a matching function. We can define labor market tightness as $\theta(H, A) \equiv v(H, A)/u(H, A)$ and derive the endogenously determined vacancy meeting probability, $q(\theta(H, A))$, and job meeting probability, $p(\theta(H, A))$, as:

$$q(\theta(H, A)) = \frac{m(u(H, A), v(H, A))}{v(H, A)} = \gamma\theta(H, A)^{-\alpha}, \tag{3.1}$$

$$p(\theta(H, A)) = \frac{m(u(H, A), v(H, A))}{u(H, A)} = \gamma\theta(H, A)^{1-\alpha}. \tag{3.2}$$

[20] Related modeling approaches are adopted in Silva and Toledo (2009) and Kambourov and Manovskii (2009). Silva and Toledo (2009) model on-the-job training without workers' heterogeneity in order to examine the issue of aggregate volatilities in the search and matching model. In addition to on-the-job training, they also assume that upon firing a skilled worker firms need to pay a firing cost. Kambourov and Manovskii (2009) abstract from business cycle fluctuations and use their occupation-specific human capital model with experienced and inexperienced workers in order to investigate occupational mobility and wage inequality.

3.3.3 Characterization of Recursive Equilibrium

Bellman equations for the firm in labor market h with required education H that is employing a trainee and a skilled worker are, respectively:

$$
\begin{aligned}
J^T(H,A,a) = &\max\big\{0,(1-\tau_h)HAa - w^T(H,A,a) \\
&+ \beta(1-\delta)\mathbb{E}_{A,a}\big\{\phi_h J^S(H,A',a') + (1-\phi_h)J^T(H,A',a')\big\}\big\},
\end{aligned} \tag{3.3}
$$

$$
J^S(H,A,a) = \max\big\{0, HAa - w^S(H,A,a) + \beta(1-\delta)\mathbb{E}_{A,a}\big\{J^S(H,A',a')\big\}\big\}. \tag{3.4}
$$

Equation (3.4) is standard in search and matching models with endogenous separations. Observe that we also allow for exogenous separations at rate δ, which are understood to be other types of separations that are not directly related to the productivity of a job. As explained above, equation (3.3) in addition involves the lost output τ_h that is due to initial lack of job-specific skills and the probability ϕ_h of becoming a skilled worker. $\mathbb{E}_{A,a}$ denotes expectations conditioned on the current values of A and a. Note that at any point in time, a firm can also decide to fire its employee and become inactive in which case it obtains a zero payoff. The firm optimally chooses to endogenously separate at and below the reservation productivities $\tilde{a}^T(H,A)$ and $\tilde{a}^S(H,A)$, which are implicitly defined as the maximum values that satisfy:

$$
J^T(H,A,\tilde{a}^T(H,A)) = 0, \tag{3.5}
$$

$$
J^S(H,A,\tilde{a}^S(H,A)) = 0. \tag{3.6}
$$

The free entry condition equalizes the costs of posting a vacancy (recall that c_h is per period vacancy posting cost and $1/q(\theta(H,A))$ is the expected vacancy duration) with the expected discounted benefit of getting an initially untrained worker:

$$
\frac{c_h}{q(\theta(H,A))} = \beta\mathbb{E}_A\big\{J^T(H,A',a')\big\}. \tag{3.7}
$$

The unemployed worker enjoys utility b_h and with probability $p(\theta(H,A))$ meets with a vacancy:

$$
\begin{aligned}
U(H,A) = &b_h + p(\theta(H,A))\beta\mathbb{E}_A\big\{W^T(H,A',a')\big\} \\
&+ (1-p(\theta(H,A)))\beta\mathbb{E}_A\big\{U(H,A')\big\}.
\end{aligned} \tag{3.8}
$$

Note that the unemployed worker always starts a job as a trainee, due to the initial lack of job-specific skills.[21] Bellman equations for the worker are analogous to

[21]The model could be extended to allow for heterogeneity in the loss of specific human capital upon becoming unemployed, as for example in Ljungqvist and Sargent (1998, 2007). Such an

the firm's ones, with his outside option being determined by the value of being unemployed:

$$W^T(H,A,a) = \max\big\{U(H,A), w^T(H,A,a) + \beta\delta\mathbb{E}_A\big\{U(H,A')\big\} \\ + \beta(1-\delta)\mathbb{E}_{A,a}\big\{\phi_h W^S(H,A',a') + (1-\phi_h)W^T(H,A',a')\big\}\big\}, \tag{3.9}$$

$$W^S(H,A,a) = \max\big\{U(H,A), w^S(H,A,a) + \beta\delta\mathbb{E}_A\big\{U(H,A')\big\} \\ + \beta(1-\delta)\mathbb{E}_{A,a}\big\{W^S(H,A',a')\big\}\big\}. \tag{3.10}$$

Under the generalized Nash wage bargaining rule the worker gets a fraction η of total match surplus, defined as:

$$S^T(H,A,a) \equiv J^T(H,A,a) + W^T(H,A,a) - U(H,A),$$
$$S^S(H,A,a) \equiv J^S(H,A,a) + W^S(H,A,a) - U(H,A),$$

for the job with a trainee and a skilled worker, respectively. Hence:

$$W^T(H,A,a) - U(H,A) = \eta S^T(H,A,a),$$
$$W^S(H,A,a) - U(H,A) = \eta S^S(H,A,a).$$

Observe that the above equations imply that the firm and the worker both want a positive match surplus. Therefore, there is a mutual agreement on when to endogenously separate. From the above surplus-splitting equations it is straightforward to show that the wage equations are given by:

$$w^T(H,A,a) = \eta((1-\tau_h)HAa + c_h\theta(H,A)) + (1-\eta)b_h, \tag{3.11}$$
$$w^S(H,A,a) = \eta(HAa + c_h\theta(H,A)) + (1-\eta)b_h, \tag{3.12}$$

for the trainee and the skilled worker, respectively. The wage equations imply that the worker and the firm share the cost of training in accordance with their bargaining powers.

The model features a recursive equilibrium, with its solution being determined by equations (3.1)-(3.12). The solution of the model consists of equilibrium labor market tightness $\theta(H,A)$ and reservation productivities $\tilde{a}^T(H,A)$ and $\tilde{a}^S(H,A)$. Next, the following proposition establishes an important neutrality result.

Proposition 1. *Under the assumptions $c_h = cH$ and $b_h = bH$ with $c, b, H > 0$ the solution of the model is independent of H.*

---

extension would be valuable for analyzing issues like long-term unemployment (where the loss of specific human capital is likely to be larger) and sectoral worker mobility (where the loss of specific human capital is likely to be larger when an unemployed worker finds a job in a new sector). We leave these extensions for further research.

Proof. We can combine the equilibrium conditions and write the surpluses as:

$$\begin{aligned}
S^T(H,A,a) = &\max\big\{0,(1-\tau_h)HAa - b_h - \beta\eta p(\theta(H,A))\mathbb{E}_A\big\{S^T(H,A',a')\big\} \\
&+ \beta(1-\delta)\mathbb{E}_{A,a}\big\{\phi_h S^S(H,A',a') + (1-\phi_h)S^T(H,A',a')\big\}\big\}, \\
S^S(H,A,a) = &\max\big\{0,HAa - b_h - \beta\eta p(\theta(H,A))\mathbb{E}_A\big\{S^T(H,A',a')\big\} \\
&+ \beta(1-\delta)\mathbb{E}_{A,a}\big\{S^S(H,A',a')\big\}\big\}.
\end{aligned}$$

Moreover, the free entry condition can be written in terms of the surplus as:

$$\frac{c_h}{q(\theta(H,A))} = \beta(1-\eta)\mathbb{E}_A\big\{S^T(H,A',a')\big\}.$$

Introducing the free entry condition in the expressions for the surpluses we obtain the following:

$$\begin{aligned}
S^T(H,A,a) = &\max\Big\{0,(1-\tau_h)HAa - b_h - \theta(H,A)\left(\frac{c_h\eta}{1-\eta}\right) \\
&+ \beta(1-\delta)\mathbb{E}_{A,a}\left\{\phi_h S^S(H,A',a') + (1-\phi_h)S^T(H,A',a')\right\}\Big\}, \\
S^S(H,A,a) = &\max\Big\{0,HAa - b_h - \theta(H,A)\left(\frac{c_h\eta}{1-\eta}\right) \\
&+ \beta(1-\delta)\mathbb{E}_{A,a}\big\{S^S(H,A',a')\big\}\Big\}.
\end{aligned}$$

Substituting recursively, it is straightforward to check that the solution of the model is equivalent for $\forall H > 0$ iff $c_h = cH$ and $b_h = bH$ with $c, b > 0$. □

The usefulness of Proposition 1 will become clear in the following two sections with calibration and numerical results of the model. In particular, the proposition's result enables a transparent comparison of the model results across different education groups h, with the only parameters affecting results being on-the-job training parameters. Notably, by using the proposition we avoid changing the surpluses by magnifying the difference between the firm's output and the value of being unemployed. We believe that the model's implications when changing the value of being unemployed relative to output have been well explored in the recent literature.[22] Indeed, by assuming that more educated workers enjoy higher match surplus (with b_h being lower relative to output than in the case of less educated workers) it is well documented that the model would predict a decrease in the unemployment and the separation rate, but at the same time it would also predict an increase in the job finding rate. The latter prediction strongly contradicts the

[22]See, e.g., Mortensen and Nagypál (2007), Costain and Reiter (2008), and Hagedorn and Manovskii (2008).

empirical evidence across education groups, as documented in Section 3.2. Further discussion of these issues together with some empirical evidence justifying the assumptions of proportionality in c_h and b_h is provided in the next section.

With the obtained solution of the model we can generate numerical results by simulating it, using the law of motion for trainees and skilled workers. The mass of trainees next period with idiosyncratic productivity a_j is given by:

$$\begin{aligned}(n^T)'(a_j) =& \mathbb{1}\left\{a_j > \tilde{a}^T(H, A')\right\} \Bigg[(1-\delta)(1-\phi_h)\sum_{i=1}^{m} \pi^a_{ij} n^T(a_i) \\ &+ p(\theta(H,A))\pi^a_j u(H,A)\Bigg].\end{aligned}$$

First notice that if $a_j \leq \tilde{a}^T(H, A')$ then the mass of trainees with idiosyncratic productivity a_j is zero, given that it is not optimal to produce at this productivity. If $a_j > \tilde{a}^T(H, A')$, the mass of trainees tomorrow with idiosyncratic productivity a_j is composed of two groups: the mass of trainees today that survive exogenous separations and that are not upgraded to skilled workers, and the mass of new matches that are created with productivity a_j.

Similarly, the mass of skilled workers next period with idiosyncratic productivity a_j is given by:

$$\begin{aligned}(n^S)'(a_j) =& \mathbb{1}\left\{a_j > \tilde{a}^S(H, A')\right\} \Bigg[(1-\delta)\sum_{i=1}^{m} \pi^a_{ij} n^S(a_i) \\ &+ (1-\delta)\phi_h \sum_{i=1}^{m} \pi^a_{ij} n^T(a_i)\Bigg].\end{aligned}$$

Again, notice that if $a_j \leq \tilde{a}^S(H, A')$, the mass of skilled workers with idiosyncratic productivity a_j is zero, given that these matches are endogenously destroyed. However, if $a_j > \tilde{a}^S(H, A')$, the mass of skilled workers tomorrow with idiosyncratic productivity a_j is again composed of two groups: the mass of previously skilled workers that survive exogenous separations and the mass of upgraded trainees that were not exogenously destroyed.

Finally, the aggregate employment rate n and unemployment rate u are defined as:

$$\begin{aligned} n(H,A) =& \sum_{i=1}^{m} \left(n^T(a_i) + n^S(a_i)\right), \\ u(H,A) =& 1 - n(H,A), \end{aligned}$$

respectively. Labor productivity is defined as total production (Y) over total employment (n), where

$$Y(H, A) = \quad (1 - \tau_h) HA \sum_{i=1}^{m} a_i n^T(a_i) + HA \sum_{i=1}^{m} a_i n^S(a_i).$$

3.3.4 Efficiency

The canonical search and matching model features search externalities. It is well-known that the equilibrium of this model yields a socially efficient outcome, provided that the Hosios condition is satisfied (Hosios, 1990). This condition equalizes the worker's bargaining power to the elasticity of the matching function with respect to unemployment. Does the same condition also apply to our model or is there some role for policy?

Proposition 2. *Abstracting from aggregate productivity shocks and assuming that idiosyncratic productivity shocks are being drawn in each period from a continuous distribution $G(a)$, the model's equilibrium is constrained-efficient iff $\eta = \alpha$.*

The proof of the above proposition is given in Appendix C. Hence, the standard Hosios condition applies also to our setting where workers are initially untrained. In other words, there are no additional inefficiencies specific to our model, except from the standard search externalities. Therefore, differential unemployment outcomes, which are related to differential training requirements, are efficient in our model if the Hosios condition is satisfied. This result is intuitive, because training requirements in our model are merely a technological constraint. Finally, we show in Appendix C that the job destruction is maximized when the Hosios condition holds.[23]

3.4 Calibration

We proceed by calibrating the model. First, we discuss the calibration of parameter values that are consistent with empirical evidence at the aggregate level. Second, we specify the on-the-job training parameter values that are specific to each education group.

[23] Whether violation of the Hosios condition affects more the job destruction margin for trainees or for skilled workers depends on parameter values. The exact analytical condition is given in Appendix C, where we also provide a numerical example for our original model (with aggregate productivity shocks and some persistence in idiosyncratic productivity), showing that the job destruction is maximized when the worker's bargaining power is equal to the elasticity of the matching function with respect to unemployment.

3.4.1 Parameter Values at the Aggregate Level

The model is simulated at monthly frequency. Table 3.5 summarizes the parameter values at the aggregate level.

Table 3.5: Parameter values at the aggregate level

Parameter	Interpretation	Value	Rationale
β	Discount factor	0.9966	Interest rate 4% p.a.
γ	Matching efficiency	0.45	Job finding rate 45.3% (CPS)
α	Elasticity of the matching function	0.5	Petrongolo and Pissarides (2001)
η	Worker's bargaining power	0.5	Hosios condition
c	Vacancy posting cost	0.106	1982 EOPP survey
b	Value of being unemployed	0.82	See text
σ_A	Standard deviation for log aggregate productivity	0.0064	Labor productivity (BLS)
ρ_A	Autoregressive parameter for log aggregate productivity	0.98	Labor productivity (BLS)
μ_a	Mean log idiosyncratic productivity	0	Normalization
σ_a	Standard deviation for log idiosyncratic productivity	0.249	Separation rate 2.24% (CPS)
λ	Probability of changing idiosyncratic productivity	0.3333	Fujita and Ramey (2012)
δ	Exogenous separation rate	0.0075	JOLTS data
ϕ	Probability of training upgrade	0.3226	1982 EOPP survey
τ	Training costs	0.196	1982 EOPP survey
H	Worker's productivity	1	Normalization

The value of the discount factor is consistent with an annual interest rate of four percent. The efficiency parameter γ in the matching function targets a mean monthly job finding rate of 45.3 percent, consistent with the CPS microevidence for people with 25 years and over as described in Section 3.2.2. For the elasticity of the Cobb-Douglas matching function with respect to unemployment we draw from the evidence reported in Petrongolo and Pissarides (2001) and accordingly set $\alpha = 0.5$. Absent any further microevidence, we follow most of the literature and put the workers' bargaining power equal to $\eta = 0.5$.[24] As we show in Section 3.3.4, this guarantees efficiency of the equilibrium, consistent with the Hosios condition.

For the parameterization of the vacancy posting cost we take advantage of the EOPP data, which contain information on vacancy duration and hours spent dur-

[24]The same value is used by Pissarides (2009). The calibration in the credible bargaining model of Hall and Milgrom (2008) implies that the worker's share of the joint surplus is 0.54.

ing the recruitment process.[25] In our sample it took on average 17.8 days to fill the vacancy, with 11.3 hours being spent during the whole recruitment process.[26] Note that the expected recruitment cost in the model is equal to the product of the flow vacancy posting cost and the expected duration of the vacancy, $c \times (1/q)$. Hence, we have on a monthly basis $c \times (17.8/30) = 11.3/180$, which gives us the flow vacancy posting cost $c = 0.106$.[27] The vacancy posting cost equals 10.5 percent of average worker's productivity in our simulated model, which also appears to be broadly consistent with other parameter values for the vacancy posting cost used in the literature.[28]

The flow value of non-market activities b in general consists of: i) unemployment insurance benefits; ii) home production and self-employment; iii) value of leisure and disutility of work; iv) expenditures saved by not working; and v) is net of job-searching costs. The literature has demonstrated that this parameter value crucially affects the results of the model. Low values of b, such as in Shimer (2005) who uses $b = 0.40$, imply large surpluses and low volatilities of labor market variables. High values of b, such as in Hagedorn and Manovskii (2008) who use $b = 0.955$, instead generate high volatilities, but as shown by Costain and Reiter (2008) also imply unrealistic responses of unemployment levels to policy changes in unemployment benefits. Here, we decided to choose an intermediate level of $b = 0.82$, which imply 81.2 percent of average labor productivity in our simulated model. As shown in Appendix C, our main results remain unaffected if we set $b = 0.71$ as in Hall and Milgrom (2008) and Pissarides (2009).

Parameters for the Markov chain governing the aggregate productivity process are calibrated to match the cyclical properties of the quarterly average U.S. labor productivity between 1976 and 2010.[29] After taking logs and deviations from

[25] The survey questions were "Approximately how many days was between the time you started looking for someone to fill the opening and the time *new hire* started to work?" and "While hiring for this position, what was the total number of man hours spent by your company personnel recruiting, screening, and interviewing all applicants?"

[26] We restrict the sample to individuals with 25 years of age and older, for whom we have information on education. Because of positive skewness, the vacancy duration and the hours spent distributions are truncated at their 99th percentiles, which correspond to 6 months and 100 hours, respectively.

[27] This value of the vacancy posting cost might be too low for two reasons. First, the EOPP survey asked questions related to the *last hired* worker, so it is very likely to overrepresent vacancies with shorter durations. Second, it might well be that the hiring personnel consists of managers and supervisors, who are paid more than the hired worker in question. Nevertheless, as shown in Appendix C, our results are robust to different parameterizations of the vacancy posting cost.

[28] Hagedorn and Manovskii (2008) argue that the flow labor cost of posting a vacancy equals to 11.0 percent of average labor productivity. Fujita and Ramey (2012) use the value of $c = 0.17$, Pissarides (2009) $c = 0.356$ and Hall and Milgrom (2008) $c = 0.43$.

[29] Following Shimer (2005), the average labor productivity is the seasonally adjusted real average output per employed worker in the nonfarm business sector. These data are provided by the

an HP trend with smoothing parameter 10^5, the standard deviation of quarterly labor productivity is equal to 0.018 and its quarterly autocorrelation is equal to 0.90. We apply the Rouwenhorst (1995) method for finite state Markov-chain approximations of AR(1) processes, which has been found to generate accurate approximations to highly persistent processes (Kopecky and Suen, 2010).

In choosing the Markov chain for the idiosyncratic productivity process, we follow the standard assumption in the literature by assuming that idiosyncratic shocks are independent draws from a lognormal distribution with parameters μ_a and σ_a. As in Fujita and Ramey (2012), these draws occur on average every quarter ($\lambda = 1/3$), governing the persistence of the Markov chain. In order to determine the parameters of the lognormal distribution and the exogenous separation rate we match the empirical evidence on separation rates. The CPS microevidence for people with 25 years of age and over gives us a mean monthly inflow rate to unemployment of 2.24 percent. The recent Job Openings and Labor Turnover Survey (JOLTS) data, available from December 2000 onwards, tell us that the mean monthly layoff rate is equal to 1.5 percent. The layoffs in JOLTS data correspond to involuntary separations initiated by the employer, hence we take these to be endogenous separations. Accordingly, we set the exogenous monthly separation rate to $\delta = 0.75$ percent, and adjust σ_a in order that the simulated data generate mean monthly inflow rates to unemployment of 2.24 percent. The parameter μ_a is normalized to zero.

We select parameters regarding on the-job-training from the 1982 EOPP survey as summarized in Table 3.3 of Section 3.2.4. To calibrate the duration of on-the-job training we consider the time to become fully trained in months. In particular, under the baseline calibration we parameterize the average duration of on-the-job training to 3.10 months ($13.4 \times (12/52)$), which yields the value for ϕ equal to $1/3.10$. To calibrate the extent of on-the-job training we use the average productivity gap between a typical new hire and a typical fully trained worker. In reality, we would expect that workers obtain job-specific skills in a gradual way, i.e. shrinking the productivity gap due to lack of skills proportionally with the time spent on the job. Our parameterization of training costs for the aggregate economy, $\tau = 0.196$, implies that trainees are on average 19.6 percent less productive than skilled workers. This is consistent with an average initial gap of 39.1 percent, which is then proportionally diminishing over time. Finally, the worker's productivity parameter H is normalized to one.

Bureau of Labor Statistics (BLS), series PRS85006163.

3.4.2 Parameter Values Specific to Education Groups

Next we turn to parameterizing the model across education groups. We keep fixed all the parameter values at the aggregate level as reported in Table 3.5, with the only exception being the training parameters (ϕ and τ). In particular, we assume that $c_h = cH$ and $b_h = bH$, making applicable the neutrality result of Proposition 1, according to which the parameterization for H is irrelevant. We argue below that this is not only desirable from the model comparison viewpoint as we can completely isolate the effects of on-the-job training, but it is also a reasonable thing to do given available empirical evidence. Note also that a neutrality result similar to Proposition 1 would obtain if we were to assume a standard utility function in macroeconomic literature, featuring disutility of labor and offsetting income and substitution effects.[30]

Regarding the parameterization of parameter b_h, recall that this parameter should capture several elements, including unemployment insurance benefits, home production, disutility of work, expenditures saved by not working, and job-searching costs. Intuitively, higher educational attainment could lead to higher b_h through all of the mentioned elements. More educated workers typically earn higher salaries and are hence also entitled to higher unemployment insurance benefits (albeit the latter are usually capped at some level). Higher educational attainment presumably not only increases market productivity, but also home production, which incorporates the possibility of becoming self-employed. Jobs requiring more education could be more stressful, leading to higher disutility of work, and might require higher work-related expenditures (e.g., commuting, meals, clothing). Finally, more educated workers might be able to take advantage of more efficient job-searching methods, lowering their job-searching costs. Overall, there seems to be little a priori justification to simply assume that more educated workers enjoy higher job surplus.

To proceed further, we turn to empirical evidence reported in Aguiar and Hurst (2005), who among other things measure food consumption and food expenditure changes during unemployment. Focusing on food items (which include eating in restaurants) is a bit restrictive for our purposes, but the results are nevertheless illustrative. Aguiar and Hurst (2005) report their estimates separately for the whole sample and for the "low-education" subsample, which consist of individuals with 12 years or less of schooling. They find that during unemployment food expenditure falls by 19 percent for the whole sample and by 21 percent for the low-education sample, with the difference not being statistically significant. The drop in food consumption amounts to 5 percent for the whole sample and 4 percent for the low-education sample, with the numbers being statistically significant

[30]See Blanchard and Galí (2010).

from zero, but not from each other.[31] Based on this micro evidence and the reasoning given above, we take $b_h = bH$ to be a reasonable assumption. Results from robustness checks on this assumption are provided in Appendix C.

The proportionality assumption on flow vacancy posting cost would follow directly if we were to assume that hiring is a labor intensive activity as in Shimer (2009). Moreover, the textbook matching model also assumes proportionality of hiring costs to productivity (Pissarides, 2000). Nevertheless, we perform the sensitivity analysis of the quantitative results with respect to different specification of vacancy posting cost and report them in Appendix C.

For the parameters regarding on-the-job training we refer the reader to Table 3.3 in Section 3.2.4. Moreover, we will report all on-the-job training parameter values for different education groups in the tables with simulation results.

3.5 Simulation Results

The main results of the paper are presented in this section. First, we report baseline simulation results for the aggregate economy. Second, the model is solved and simulated for each education group. This exercise is done by changing the parameters ϕ_h and τ_h related to on-the-job training for each education group, while keeping the rest of parameters fixed at the aggregate level. Finally, we discuss the main mechanism of the model, by exploring how simulation results depend on each training parameter. This section reports simulation results with the calibration for the age group of 25 years and older. As shown in Appendix C, our conclusions remain unaffected if we calibrate the model for the whole working-age population.

3.5.1 Baseline Simulation Results

We begin by simulating the model, parameterized at the average aggregate level for duration of training and training costs ($1/\phi = 3.10$ and $\tau = 0.196$). Table 3.6 reports the baseline simulation results together with the actual data moments for the United States during 1976-2010. In particular, we report means, absolute and relative volatilities for the key variables of interest. The reported model statistics are means of statistics computed from 100 simulations. In each simulation, 1000 monthly observations for all variables are obtained. The first 580 months are discarded and the last 420 months, corresponding to data from 1976:01 to 2010:12, are used to compute the statistics in the same way as we do for the data. In order to assess the precision of the results, standard deviations of simulated statistics are computed across simulations.

[31] See Table 6 of their paper.

Table 3.6: Labor market variables: data versus model

	y	n	u	f	s
Panel A: U.S. data, 1976 - 2010					
Mean	-	95.11	4.89	45.26	2.24
Absolute volatility	-	1.05	1.05	7.49	0.18
Relative volatility	1.78	1.12	20.07	17.99	7.57
Panel B: Baseline simulation results					
Mean	-	95.14	4.86	45.24	2.25
		(0.61)	(0.61)	(2.39)	(0.16)
Absolute volatility	-	0.80	0.80	3.22	0.23
		(0.28)	(0.28)	(0.64)	(0.07)
Relative volatility	1.78	0.85	15.47	7.28	9.64
	(0.34)	(0.31)	(3.55)	(1.65)	(2.18)

Notes: All data variables in Panel A are seasonally-adjusted. y is quarterly real average output per employed worker in the nonfarm business sector, provided by the BLS. The rest of variables are constructed from CPS microdata and are quarterly averages of monthly data. Statistics for the model in Panel B are means across 100 simulations, standard deviations across simulations are reported in parentheses. All means of rates are expressed in percentages.

The baseline simulation results show that the model performs reasonably well at the aggregate level. It essentially hits the empirical means of the unemployment rate, the job finding rate and the separation rate by construction of the exercise. More notably, it also mirrors well the empirical volatilities. Two main reasons why the model does not suffer from an extreme unemployment volatility puzzle as in Shimer (2005) relate to a bit higher flow value of being unemployed and the inclusion of endogenous separations.[32] The latter are also the reason why the model matches the volatility of the separation rate quite well.[33] The model underpredicts the volatility of the job finding rate and to a somewhat lesser extent the volatility of the unemployment rate, which should not be surprising given that in this model productivity shocks are the only cause of fluctuations in vacancies.[34]

[32] Hagedorn and Manovskii (2008) claim that the unemployment volatility puzzle can be resolved by a calibrating higher flow value of being unemployed. Note that our value for this parameter ($b = 0.82$) is considerably below the one used in Hagedorn and Manovskii (2008). As shown in Appendix C, our main results remain unaffected if we set $b = 0.71$ as in Hall and Milgrom (2008) and Pissarides (2009).

[33] Fujita and Ramey (2012) also find that the inclusion of endogenous separations can help in increasing volatilities of search and matching models.

[34] Mortensen and Nagypál (2007) argue that the empirical correlation between labor productivity and labor market tightness is 0.396, thus substantially below the model's correlation of close to 1.

3.5.2 Unemployment Rates across Education Groups

Next, we turn to the simulation results across different education groups. We keep fixed all the parameter values at the aggregate level and only vary the training parameters across education groups. Table 3.7 shows the simulation results for the means. As we can see, the model is able to explain the differences in unemployment rates across education groups that we observe in the data. In particular, the ratio of unemployment rates of the least educated group to the most educated group is 3.5 in the data and 3.4 in the model. Moreover, the model accounts for the observable differences in separation rates across groups, while keeping similar job finding rates. The ratio of separation rates of the least educated group to the most educated group is 4.1 in the data and 3.6 in the model. In general, the greater is the degree of on-the-job training (longer training periods and higher productivity gaps), the lower is the separation rate and the lower is the unemployment rate. Therefore, the observed variation in training received across education groups can explain most of the observed differences in separation rates and unemployment rates.

Table 3.7: Education, training and unemployment properties - means (in percent)

	Data			Parameters		Model		
	u	f	s	$1/\phi_h$	τ_h	u	f	s
Less than high school	8.96	46.85	4.45	2.35	0.163	7.93	45.51	3.83
						(0.75)	(2.08)	(0.21)
High school	5.45	45.02	2.48	2.78	0.181	6.09	45.53	2.88
						(0.71)	(2.38)	(0.20)
Some college	4.44	46.34	2.05	3.67	0.227	3.02	45.08	1.36
						(0.32)	(2.35)	(0.08)
College degree	2.56	42.80	1.09	4.19	0.240	2.35	45.27	1.06
						(0.25)	(2.38)	(0.05)

Notes: Data moments are quarterly averages of monthly seasonally-adjusted data constructed from CPS microdata. The sample period is 1976:01 - 2010:12. Statistics for the model are means across 100 simulations, with standard deviations across simulations reported in parentheses.

Table 3.8 presents a more detailed view of the results, offering a breakdown of separation rates and employment rates for trainees and for skilled workers. As it can be seen, separation rates of trainees are roughly similar across education groups and trainees represent a small share of employment for all four education groups. Therefore, differences in separation rates for skilled workers are the main reason why more educated workers enjoy lower separation rates.

Table 3.8: Separation and employment rates for trainees and skilled workers - means (in percent)

	s	s^T	s^S	n	n^T	n^S
Less than high school	3.83	7.83	3.63	92.07	7.47	84.60
High school	2.88	7.69	2.65	93.91	6.59	87.32
Some college	1.36	7.32	1.18	96.98	4.05	92.94
College degree	1.06	7.13	0.89	97.65	3.54	94.11
All individuals	2.25	7.59	2.02	95.14	5.70	89.45

Notes: Statistics are means across 100 simulations. s^T and s^S refer to separation rates of trainees and skilled workers respectively, n^T and n^S to employment rate of trainees and skilled workers respectively.

3.5.3 Unemployment Volatility across Education Groups

Panel A of Table 3.9 reports the simulation results for absolute volatilities. As mentioned in Section 3.5.1, the model underpredicts the volatilities of the job finding and the unemployment rates. This property of the model is also inherited here. Nevertheless, the model replicates well the relative differences in volatilities across education groups. In the data, the volatility of the unemployment rate for high school dropouts is 3.2 times higher than the corresponding volatility for college graduates, whereas the same ratio in the model stands at 3.7. Something similar is true for volatilities of separation rates (the ratio is 3.9 in the data and 5.5 in the model), where additionally the model also explains volatility levels quite well. The model can also account for the observed similar values of volatilities in job finding rates across education groups.

Panel B of Table 3.9 reports the simulation results for relative volatilities. The model succeeds in replicating the ratio of relative employment volatility of the least educated group to the most educated group (the ratio is 3.5 in the data and 3.9 in the model). This finding is not surprising given the results of Panel A of Table 3.9, which show that the model is able to replicate the ratio of absolute employment volatility. The model also accounts well for the empirical finding that relative volatilities in unemployment, job finding, and separation rates are similar across education groups.

3.5.4 Unemployment Dynamics across Education Groups

To provide another view of the model's results we conduct the following experiment. Using the model's original solution for the aggregate economy and the actual data on the aggregate unemployment rate we back out the implied realizations of the aggregate productivity innovations. Then, we feed this implied

Table 3.9: Education, training and unemployment properties - volatilities

	Data				Parameters		Model			
	n	u	f	s	$1/\phi_h$	τ_h	n	u	f	s
Panel A: Absolute volatilities										
Less than high school	1.78	1.78	7.62	0.42	2.35	0.163	1.14	1.14	3.07	0.34
							(0.28)	(0.28)	(0.63)	(0.07)
High school	1.26	1.26	7.48	0.24	2.78	0.181	0.91	0.91	3.07	0.27
							(0.27)	(0.27)	(0.57)	(0.07)
Some college	1.02	1.02	8.96	0.18	3.67	0.227	0.48	0.48	3.34	0.12
							(0.14)	(0.14)	(0.54)	(0.03)
College degree	0.55	0.55	8.55	0.11	4.19	0.240	0.31	0.31	3.30	0.06
							(0.12)	(0.12)	(0.68)	(0.02)
Panel B: Relative volatilities										
Less than high school	1.99	18.66	17.45	9.23	2.35	0.163	1.25	13.65	6.88	8.55
							(0.32)	(2.87)	(1.47)	(1.66)
High school	1.35	20.83	18.62	9.09	2.78	0.181	0.98	14.36	6.86	9.04
							(0.30)	(2.96)	(1.43)	(1.79)
Some college	1.08	21.32	20.48	8.28	3.67	0.227	0.49	14.67	7.55	8.20
							(0.15)	(2.93)	(1.35)	(1.75)
College degree	0.57	20.16	21.39	9.87	4.19	0.240	0.32	12.13	7.47	5.51
							(0.13)	(3.21)	(1.69)	(1.70)

Notes: Absolute volatilities are defined as standard deviations of the data expressed in deviations from an HP trend with smoothing parameter 10^5. Relative volatilities are defined analogously, except that all variables are initially expressed in natural logarithms. The sample period is 1976:01 - 2010:12, with all data being seasonally adjusted. Statistics for the model are means across 100 simulations, with standard deviations across simulations reported in parentheses.

aggregate productivity series to the model's original solution for each education group. The simulated unemployment rate series for each group are shown in Figure 3.5, together with the actual unemployment rates. Again, the model replicates the data remarkably well, both in terms of capturing the differences in means and volatilities across groups.

3.5.5 Discussion of the Model's Mechanism

In order to highlight the mechanism at work in our model, two more exercises are conducted. In particular, we analyze separately the effects of training duration and productivity gap of new hires to demonstrate that both of them quantitatively play almost equally important roles for our results. In the left panel of Figure 3.6 we study the role of the average duration of on-the-job training, keeping the rest of the parameters constant at the aggregate level. Analogously, the right panel of Figure 3.6 studies the role of the productivity gap of new hires, keeping the rest of the parameters constant at the aggregate level. In both cases, we observe a decrease in the mean of the unemployment rate as we increase the degree of on-the-job training (longer training periods and higher productivity gaps). This decrease in the unemployment rate is completely driven by the decrease in the separation rate,

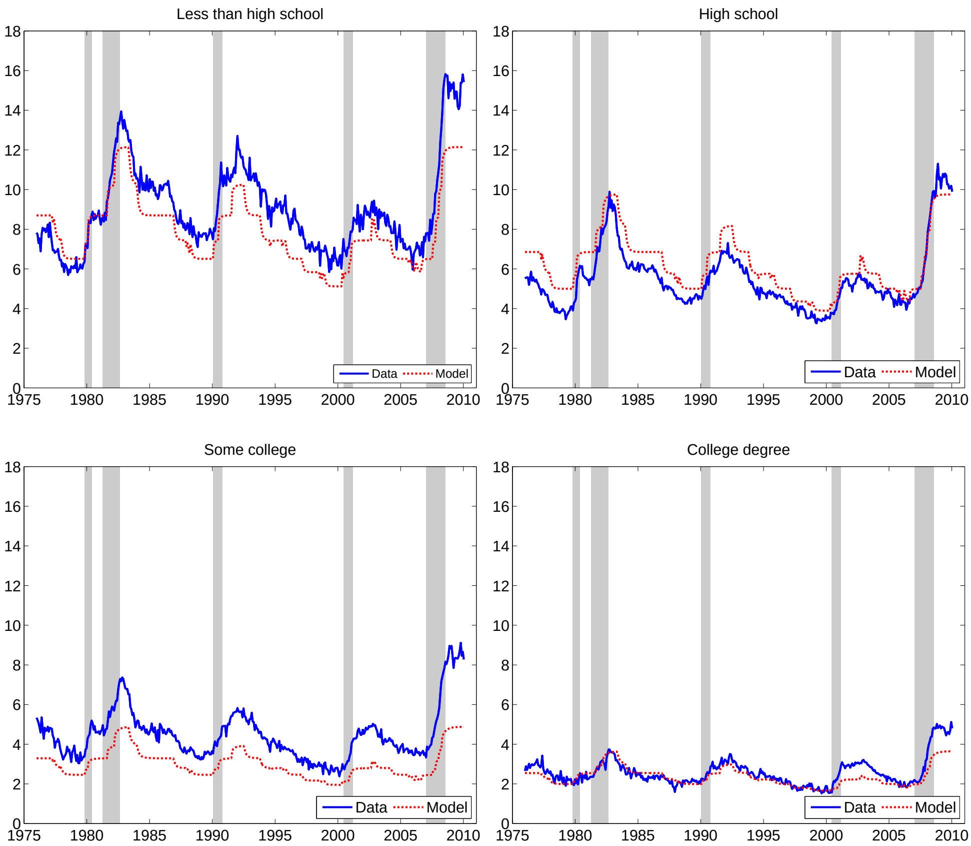


Figure 3.5: Unemployment rates across education groups: model versus data

Notes: Actual unemployment rates are quarterly averages of monthly seasonally-adjusted data constructed from CPS microdata. The simulated unemployment rates are generated by solving and simulating the model for each education group using the implied realizations of the aggregate productivity innovations as explained in the text.

given that the job finding rate remains roughly constant as we vary the degree of on-the-job training.[35]

Let's consider first why the job finding rate virtually does not move with the average duration of on-the-job training. One would expect that an increase in the average duration of on-the-job training reduces the value of a new job, since the worker spends more time being less productive. Consequently, firms' incentives

[35]In fact, the simulation results reveal that the job finding rate decreases by roughly 2 percentage points as we increase either the training duration or the productivity gap of new hires. Such a decrease leads to approximately 0.5 percentage points higher unemployment rate, which quantitatively represents a modest effect, given the observed declines in the unemployment rate in Figure 3.6.

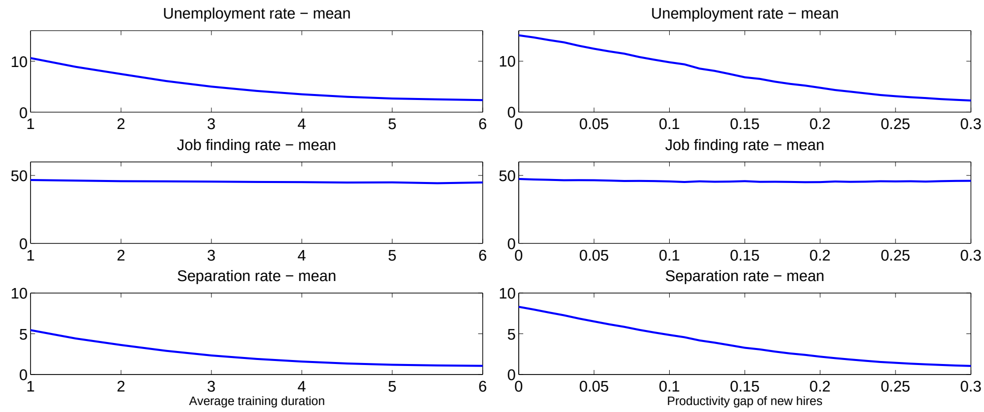


Figure 3.6: The role of training parameters

Notes: Statistics are means (in percent) across 100 simulations. The left panel studies the role of the average duration of on-the-job training, keeping the rest of parameters constant at the aggregate level. The right panel studies the role of the productivity gap of new hires, keeping the rest of parameters constant at the aggregate level.

to post vacancies should decrease, leading to a decrease in the job finding rate. However, an increase in the average duration of on-the-job training also reduces the probability of separating endogenously once the worker becomes skilled. This second effect increases the value of a new job, and hence incentives for vacancy posting go up. It turns out that these two effects cancel out and the job finding rate hence remains almost unaffected. The same reasoning holds for the productivity gap of new hires, which measures the extent of on-the-job training. Again, we have two effects at work, which cancel each other out – a higher extent of on-the-job training by itself decreases the value of a new job, but at the same time the latter increases through lower endogenous separations of skilled workers.

In order to understand why separation rates decrease with the degree of on-the-job training, we analyze match incentives to separate. Figure 3.7 shows the reservation productivities for trainees and skilled workers for different degrees of on-the-job training. As we can see, investments in match-specific human capital do not significantly affect the incentives of trainees to separate, while they clearly reduce skilled workers' incentives to separate. The intuition for this result is that skilled workers know that upon a job loss they will have to undergo first, a period of searching for a new job and second, a period of on-the-job training with a lower wage. Hence, reservation productivity levels drop for skilled workers as we increase the degree of on-the-job training, implying a lower rate of endogenous separations.

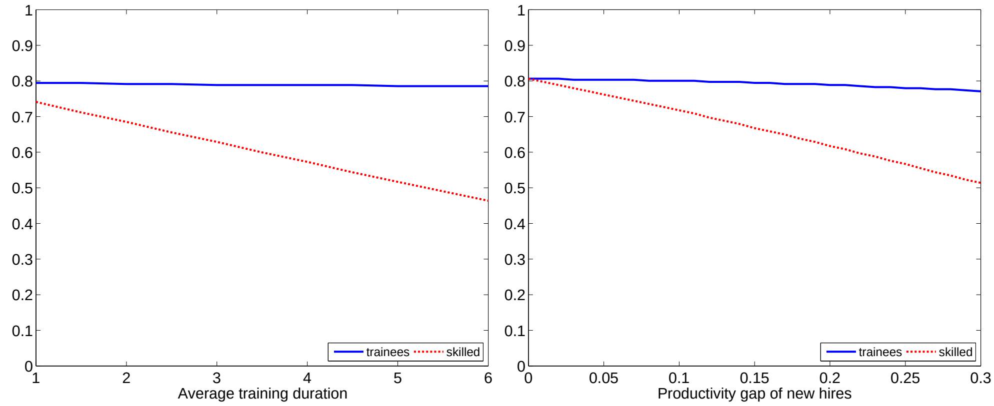


Figure 3.7: The effects of on-the-job training on reservation productivities

Notes: The left panel plots reservation productivities for trainees and skilled workers for different training durations, keeping the rest of parameters constant at the aggregate level. The right panel plots reservation productivities for trainees and skilled workers for different productivity gaps of new hires, keeping the rest of parameters constant at the aggregate level.

3.6 Unemployment Dynamics by Training Requirements

One direct testable implication of our model is that on-the-job training itself leads to greater employment stability by resulting in lower separation rates (and similar job finding rates). In order to test this prediction of the model, we provide in this section novel empirical evidence on unemployment dynamics by training requirements. The measure of training we use here is specific vocational preparation as measured in the Fourth Edition of the Dictionary of Occupational Titles (provided by the US Department of Labor). The Dictionary of Occupational Titles (DOT) defines specific vocational preparation as “the amount of lapsed time required by a typical worker to learn the techniques, acquire the information, and develop the facility needed for average performance in a specific job-worker situation.” Following the methodology of Autor et al. (2003), we aggregate detailed occupations from DOT into three-digit Census occupation codes. We then merge training data from these aggregated occupations with the CPS microdata and construct unemployment rates, job finding rates, and separation rates by training.

Figure 3.8 depicts unemployment rates by training requirements for all individuals with 25 years of age and over (left panel) and for high school graduates with 25 years and over (right panel). Given the strong complementaries between education and job training (see the discussion in Section 3.2.4) it is not surprising to see that higher training requirements are associated with lower unemployment rates. What is more striking is that even after we control for education, for ex-

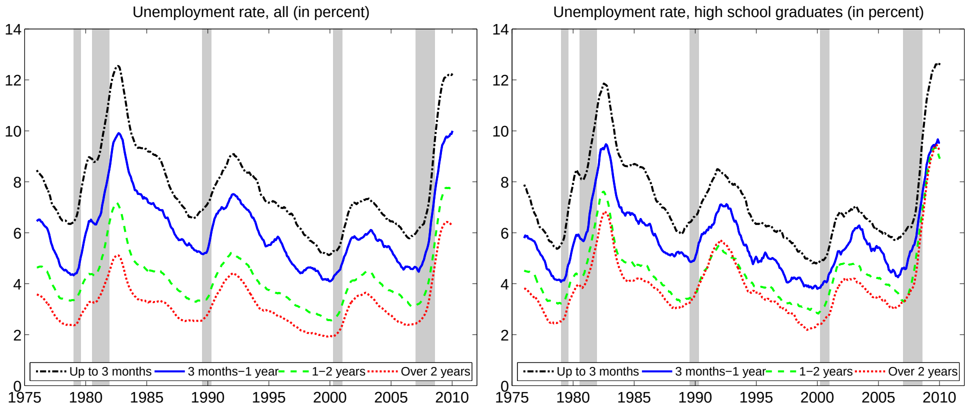


Figure 3.8: Unemployment rate by training requirements

Notes: 12-month moving averages for individuals with 25 years of age and over.

ample by focusing on high school graduates as in the right panel of Figure 3.8, higher training levels remain to be related to more stable employment. Furthermore, even after we condition for education attainment, job training leads to empirically lower separation rates and similar job finding rates as shown in Figure 3.9. We view this novel empirical evidence, which shows that occupations with higher specific vocational training experience substantially lower unemployment rates, predominantly through lower separation rates, as an external validation of the theoretical mechanism advocated in this paper.

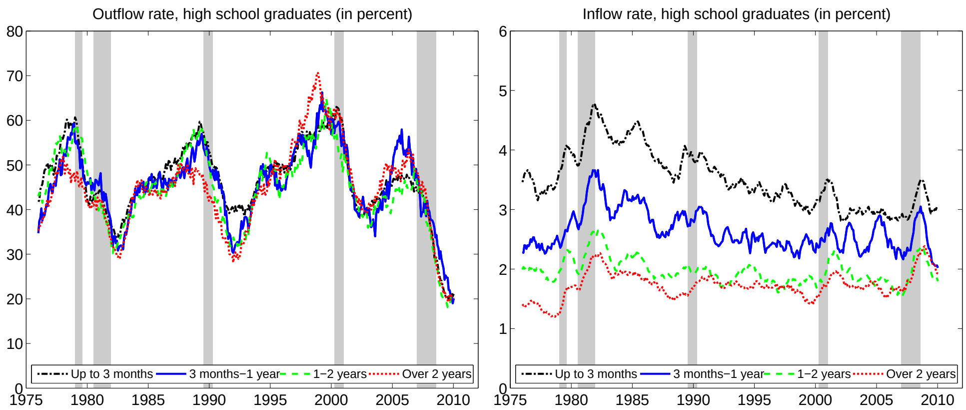


Figure 3.9: Unemployment flow rates by training requirements, high school graduates

Notes: 12-month moving averages for individuals with 25 years of age and over.

3.7 Evaluating Other Potential Explanations

This section evaluates the plausibility of other potential explanations for differential unemployment dynamics by education. In particular, our model can encompass the following alternative hypotheses: i) differences in the size of match surplus ; ii) differences in hiring costs; iii) differences in frequency of idiosyncratic productivity shocks; iv) differences in dispersion of idiosyncratic productivity shocks; and v) differences in matching efficiency. We simulate the model under each of these alternative hypotheses and then confront the obtained simulation results with empirical evidence. In particular, for these simulations we use the parameter values for the aggregate level as given in Table 3.5, whereas across education groups we only allow to vary the parameter that is crucial for each alternative hypothesis. This helps us to highlight economic mechanisms behind the alternative hypotheses. Simulations results are summarized in Table 3.10.

3.7.1 Differences in the Size of Match Surplus

One possibility why more educated workers enjoy higher employment stability might be related to higher profitability of their jobs. In the terminology of search and matching framework, more educated workers might be employed in jobs yielding a higher match surplus. The latter crucially depends on the worker's outside option, which is in turn governed by the flow value of being unemployed. In our main simulation results as reported in Section 3.5, we ruled out this possibility by assuming that the flow value of being unemployed is proportional to the market labor productivity coming from education, i.e. $b_h = bH$.

Here we relax the proportionality assumption and instead assume $b_1 = 0.90$, $b_2 = 0.85$, $b_3 = 0.80$, $b_4 = 0.75$. In other words, the size of match surplus is now increasing with education. The simulation results, reported in Panel B of Table 3.10, indicate that the unemployment rate decreases with education under this alternative parameterization, as in the data. However, the model now counterfactually predicts higher job finding rates for more educated workers. Intuitively, since jobs with more educated workers yield higher surplus, firms are willing to post more vacancies in this segment of the labor market, leading in turn to higher labor market tightness and job finding rates. Additionally, further simulation results reveal exaggerated employment stability for highly educated workers; indeed, due to greater surplus the simulation results for college graduates now suffer from extreme unemployment volatility puzzle, as their unemployment rate remains virtually constant over the business cycle. [36]

[36]The detailed simulation results on volatilities are available from authors upon request.

Table 3.10: Other potential explanations (means, in percent)

	u	f	s
Panel A: U.S. data, 1976 - 2010			
Less than high school	8.96	46.85	4.45
High school	5.45	45.02	2.48
Some college	4.44	46.34	2.05
College degree	2.56	42.80	1.09
Panel B: Size of Match Surplus			
$b_1 = 0.90$	14.37	29.28	4.61
$b_2 = 0.85$	7.12	39.31	2.89
$b_3 = 0.80$	3.89	49.20	1.95
$b_4 = 0.75$	2.43	58.29	1.44
Panel C: Hiring Costs			
$c_1 = 0.05$	8.76	55.26	5.19
$c_2 = 0.10$	5.13	46.06	2.42
$c_3 = 0.15$	3.58	40.83	1.48
$c_4 = 0.20$	2.91	37.25	1.09
Panel D: Idiosyncratic Shocks – Frequency			
$\lambda_1 = 1/6$	15.62	33.64	6.16
$\lambda_2 = 1/4$	10.24	39.80	4.46
$\lambda_3 = 1/3$	4.80	45.47	2.23
$\lambda_4 = 1/2$	1.52	53.22	0.81
Panel E: Idiosyncratic Shocks – Dispersion			
$\sigma_1 = 0.35$	14.12	39.41	6.38
$\sigma_2 = 0.30$	9.40	41.57	4.22
$\sigma_3 = 0.25$	5.01	45.05	2.31
$\sigma_4 = 0.20$	2.32	49.27	1.14
Panel F: Matching Efficiency			
$\gamma_1 = 0.60$	7.74	53.14	4.35
$\gamma_2 = 0.50$	5.78	48.32	2.89
$\gamma_3 = 0.40$	3.92	42.45	1.69
$\gamma_4 = 0.30$	2.70	34.78	0.95

Notes: Data moments are quarterly averages of monthly seasonally-adjusted data constructed from CPS microdata. The sample period is 1976:01 - 2010:12. Statistics for the model are means across 100 simulations.

Overall, the simulation results show that one cannot explain differences in unemployment dynamics across education groups by assuming higher match surplus for more educated. As discussed in Section 3.4.2, such an assumption also lacks empirical support, at the least for the case of the United States.

Interestingly though, Gomes (2012) finds empirical evidence that in the UK both the differences in job finding and separation rates contribute roughly equally towards generating differences in unemployment rates by education.[37] Moreover,

[37] In the UK, high school dropouts experience approximately four times higher unemployment rates than college graduates, with their separation rates being higher by a factor of two and their

the OECD data show that the average of net replacement rates over 60 months of unemployment is roughly twice as high in the United Kingdom as in the United States. To the extent that this difference in net replacement rates reflects more generous welfare policies in the UK, which would in turn invalidate our baseline assumption of proportionality between market and non-market returns, differences in the size of match surplus might play a role for explaining unemployment dynamics by education in countries with similar or even more generous welfare policies as in the UK.

3.7.2 Differences in Hiring Costs

Another possibility for differences in unemployment dynamics by education might be due to hiring costs. One could imagine that hiring costs are greater for highly skilled individuals and anecdotal evidence about head hunters in some top-skill occupations is indeed consistent with such a story. In our main simulation results in Section 3.5 we already assumed that flow vacancy posting costs are growing proportionally with productivity. However, it might be that this assumption understates the true differences in hiring costs by education.

In what follows, we assume the following values for vacancy posting costs, which are expressed in terms of output: $c_1 = 0.05$, $c_2 = 0.10$, $c_3 = 0.15$, $c_4 = 0.20$. Hence, hiring somebody with a college degree is now four times costlier than hiring a high school dropout in terms of their output. Acknowledging differences in their productivity, this implies that in absolute terms, hiring costs are more than six times higher for the most educated group relative to the least educated group. The simulation results, reported in Panel C of Table 3.10, reveal that under the assumed differences in hiring costs the model replicates the unemployment rates by education. However, the model now predicts sharply decreasing job finding rates with education, which is in contrast with the empirical evidence for the U.S. as presented in Section 3.2.2 and even more at odds with the empirical evidence for the UK found by Gomes (2012). What is the economic mechanism behind these simulation results? Because it is costlier to hire college graduates, firms will post fewer vacancies in this labor market segments. As a consequence, the job finding rate drops. Highly educated workers that are currently employed know that upon a job loss they will face a lower job finding rate, hence they are less likely to get separated than less educated workers. The less educated workers are instead facing high job finding rates, hence they are more willing to leave their employer in the case of low idiosyncratic productivity shock.

As mentioned, the problem with this explanation lies in the fact that there is no empirical evidence that job finding rate for the most educated workers would be

job finding rates being lower by half.

substantially lower, or in other words, that their unemployment duration would be longer. Moreover, the parameterization of the flow vacancy posting cost assumes that it is extremely expensive to hire a college graduate, whereas this cannot be seen from the EOPP data (see Appendix C for further discussion).

3.7.3 Differences in Frequency of Idiosyncratic Productivity Shocks

Individuals with different educational attainment might work in different industries and occupations – the classical distinction between blue-collar and white-collar workers comes to mind. Therefore, it might be that differences in unemployment dynamics by education are due to industry and/or occupation specific factors. Results from estimated regression equations, as reported in Appendix C (Table C.1), indicate that this might indeed be part of the story. But then the natural question is in what sense industries and occupations differ. It is quite likely that they differ in terms of initial on-the-job training requirements and this would be consistent with our main story, according to which differences in training lead to differences in unemployment. However, it might also be the case that industries and occupations are subject to heterogeneous dynamics of idiosyncratic shocks. For example, industries and occupations with predominantly low educated workers might be subject to more frequent shocks.

The simulation results reported in Panel D of Table 3.10 illustrate what happens when we vary the Poisson arrival rate of idiosyncratic productivity shocks from every 6 months ($\lambda = 1/6$) to every 2 months ($\lambda = 1/2$). It turns out that the faster the arrival rate of idiosyncratic productivity shocks, the lower will be the separation rate. The intuition behind this result is straightforward: if new shocks arrive often, then it is better to stay in the match even in the case of a very low idiosyncratic productivity shock, since you avoid the unemployment spell.[38] But these results are then not consistent with the notion that it should be the industries and occupations with low educated workers that are facing more frequent shocks – historically, blue-collar jobs are more cyclical. Additionally, the model cannot generate different unemployment rates and similar job-finding rates.

3.7.4 Differences in Dispersion of Idiosyncratic Productivity Shocks

Still another possibility, related to the story from the previous subsection, is that the dispersion of idiosyncratic productivity shocks varies across industries and

[38]Note that nonlinearities are present here – after some point, lower frequency of idiosyncratic productivity shocks leads to slowly declining separation rates.

occupations (or more generally, across jobs with different proportions of workers by education). This possibility is explored in Panel E of Table 3.10. The results show that higher dispersion of idiosyncratic productivity shocks generates more separations and leads to higher unemployment. But this would then imply that low educated workers should exhibit higher wage dispersion than high educated workers, which is at odds with the empirical evidence. In particular, the evidence provided in Lemieux (2006) for the U.S. shows that highly educated workers have higher variance of wages than less educated workers, and these differences are present in both 1973–1975 and 2000–2002 time periods.[39] Furthermore and similar to before, this model specification also cannot generate similar job finding rates in the presence of different unemployment rates.

3.7.5 Differences in Matching Efficiency

Finally, imagine a situation where the extent of labor market frictions differs by education. This situation is explored in Panel F of Table 3.10. The simulation results show that better matching efficiency creates higher labor turnover rates. Hence, while higher matching efficiency generates higher unemployment, it also creates higher job finding rates – and both facts cannot be consistent with the empirical evidence for the U.S. Additionally, higher matching efficiency for less educated is in sharp contrast with the anecdotal evidence that more educated workers take greater advantage of modern techniques for job search.

3.8 Conclusions

In this paper we build a theoretical search and matching model with endogenous separations and initial on-the-job training. We use the model in order to explain differential unemployment properties across education groups. The model is parameterized by taking advantage of detailed micro evidence from the EOPP survey on the duration of on-the-job training and the productivity gap between new hires and incumbent workers across four education groups. In particular, the applied parameter values reflect strong complementarities between educational attainment and on-the-job training. The simulation results reveal that the model almost perfectly captures the empirical regularities across education groups on job finding rates, separation rates and unemployment rates, both in their first and second moments.

The analysis of this paper views training requirements as a technological constraint, inherent to the nature of the job. We believe that such a view is appropriate

[39] See Table 1A of his paper.

for the initial on-the-job training, for which we also have exact empirical measures that are used in the paper for the parameterization of the model. However, in reality firms provide training also to their workers in ongoing job relationships. To investigate such cases it would be worthwhile to endogenize the training decisions and examine interactions between training provision and job separations. Furthermore, one could take advantage of cross-country variation in labor market institutions that are likely to affect incentives for training provision. This could provide a new explanation for differential unemployment dynamics across countries, based on supportiveness of their respective labor market institutions to on-the-job training. We leave these extensions for future research.

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Appendix A

THE SLOWDOWN IN BUSINESS EMPLOYMENT DYNAMICS: THE ROLE OF CHANGING SKILL DEMANDS

A.1 Data Description

A.1.1 Employment Data from the Census and the CPS MORG

I consider employed workers between 18 and 64 years of age from two data sources. The first one is the Census one-percent extracts for 1970, 1980, 1990 and 2000 provided by the Integrated Public Use Microdata Series (IPUMS, see Ruggles et al. (2010)), accessed through http://usa.ipums.org/usa. The second one is the Current Population Survey (CPS) Merged Outgoing Rotation Groups (MORG) data files from 1979 until 2010, available at the NBER website http://www.nber.org/data/morg.html.

All observations are weighted by the individual Census or CPS sampling weights. However, as a robustness exercise, I redo all the analysis using full-time equivalent hours of labor supply as weights. In particular, and following Autor et al. (2003), full-time equivalent hours of labor supply are computed as the product of the individual Census or individual CPS sampling weight times weeks of work for the Census sample or hours of work per week for the CPS sample. The variable weeks of work used for the Census samples is *wkswork2*, which reports the number of weeks that the respondent worked for profit, pay, or as an unpaid family worker during the reference period (the previous calendar year). For the CPS, I use the variable *hourslw*, which is the number of hours worked during the last week at all jobs. The results in Section 1.3.2 remain virtually unchanged when using the variable *uhourse* for the CPS, which is the number of hours per week usually work at the main job.

A.1.2 Computing Training Requirements by Occupation

To merge information on training requirements by occupation from the Dictionary of Occupational Titles (DOT) with employed workers from the Census and the CPS MORG, I need to aggregate the detailed DOT occupations into three-digit Census Occupation Codes (COC). In order to do that I follow the methodology used by Autor et al. (2003) to compute measures of job tasks by occupation. In particular, I use the April 1971 Current Population Survey (CPS) issued by the national academy of Sciences (1984). In this monthly file, members of the Committee on Occupational Classification and Analysis of the National Academy of Sciences assigned individual DOT occupation codes corresponding to the 1977 Fourth Edition of the DOT, and the corresponding occupation characteristics, to the 60,441 individuals in the sample. To this dataset I append the 1980 COC using the crosswalk between the DOT occupations and the 1980 COC provided by the National Crosswalk Service Center from its website http://www.xwalkcenter.org. The April 1971 CPS file contains 3886 unique 1977 DOT occupations associated to 419 1970 COC and to 471 1980 COC. With this information I can compute SVP means by occupation and by gender, using the individual CPS sampling weight. As in Autor et al. (2003), in cases where an occupation has information on SVP only for males or females, I assigned the occupation mean to both genders.

The next step in the process of computing training requirements by occupation is to link occupations over time. The Census Bureau has modified its classification systems every decade, thus to reconcile COC over time I need to use appropriate crosswalks. The CPS MORG samples also use the three-digit COC classification to categorize occupations. In particular, the 1970 COC classification is used for years 1979 to 1982, the 1980 COC classification is used for the period 1983–1991, the 1990 COC classification is used for the period 1992–1999, and the 2000 COC classification is used for the period 2000–2010. To consistently link occupations over time, I use the crosswalks developed by Autor and Dorn (2013) which provide a balanced panel of occupation covering the 1980, 1990, and 2000 COC classifications, with the creation of a new occupation system with 330 “occ1990dd” codes. The occupation categories of the 1970 Census are also matched to this occupation system. Details of the construction of the consistent occupation scheme developed by Autor and Dorn (2013) can be find in Dorn (2009). Note that these crosswalks represent a modified version of the ones developed by Meyer and Osborne (2005) to create time-consistent occupation categories. As a robustness exercise, I have also used the crosswalks from Meyer and Osborne (2005) and I found very similar results to the ones presented in this paper.[1]

Finally, using the April 1971 CPS file augmented with COC 1980 codes, together with the crosswalk from COC 1980 to occ1990dd, I can thus compute a dataset of 658 observations on SVP means corresponding to the DOT released in 1977 (329 occ1990dd occupation codes by gender).[2] This is the data set on SVP means by occupation and gender that is merged with employed workers from the Census and the CPS MORG.

A.1.3 Computing Changes in Training Requirements within Occupations between 1977 and 1991

In order to consider changes in training requirements within occupations, I use the 1991 Revised Fourth Edition of the DOT. In this edition, occupational analysts revised 646, combined 136, and deleted 75 occupational codes and titles, based on evaluations of new source material. Thus, the revision affected those occupations that seem to have had the most significant changes over time. I start by constructing a crosswalk between the DOT codes for 1977 and the DOT codes for 1991. To do that I use the Conversion Tables contained in the Document 6100 distributed by the Inter-university Consortium for Political and Social Research. It is important to notice that I only consider occupational code and/or title changes from 1977 DOT codes, and occupations deleted from the Fourth Edition of the DOT or combined with another in the Revised Fourth Edition of the DOT. Therefore, new DOT occupations that appear in the 1991 edition are not considered. I do so for two reasons. First, because I use the CPS sampling weight from the 1971 April CPS file to construct means of each SVP measure by occupation and gender, and this file only contains DOT codes for 1977. Second, because I want to provide a conservative measure of changes in training requirements over time. Particularly, a closer look at the 570 new codes that appeared in the DOT 1991 reveals that these occupations have on average a higher level of SPV than the average occupation in the DOT 1977. Therefore, in the intensive margin analysis I examine changes in training requirements within occupations matched between the 1977

[1] The occupation coding scheme developed by Meyer and Osborne (2005) is implemented in the IPUMS samples. Additionally, crosswalks between this classification system and the Census classification from 1950 to 2000 are also available at the IPUMS website, see http://usa.ipums.org/usa/volii/occ_ind.html.

[2] In the April 1976 there is no individual performing occupation 106 in the occ1990dd system. The title of this occupation is physicians' assistants. Thus, I cannot compute SVP means by this occupation. Nevertheless, this occupation represents a very small share of total employment during my sample period. Particularly, for the Census sample, it represents 0.03% percent of total employment in weighted terms in 1980, 0.02% in 1990 and 0.05% in 2000. I do not observe this occupation in 1970. Therefore, I decided not to impute an SVP mean to this category, and lose it from the analysis.

Fourth Edition and the 1991 Revised Fourth Edition of the DOT. Also, I assume that the occupations that were not revised in the 1991 DOT experienced no change in training requirements. This is consistent with the fact that the revision affected those occupations that seem to have had the most significant changes over time. Finally, I append the information on training requirements from the 1991 DOT to the 1971 April CPS file and compute means of each SVP measure by occ1990dd occupation and gender using the individual CPS sampling weight. This generates the second dataset of 658 observations on SVP means corresponding to the DOT released in 1991 (329 occ1990dd occupation codes by gender).

A.1.4 Computing Training Requirements by Industry

To compute training requirements by industry, I first assign an SVP mean by occupation and gender to each employed individual in the Census and the CPS MORG samples. Then, I aggregate the observations to the level of consistent Census Industry Codes (CIC) and I compute the share of workers employed in long training occupations by industry using the Census and CPS MORG sampling weights. It is also important to notice that the Census Bureau has change its industry classification system over time. Particularly, for the CPS MORG samples, the 1980 CIC classification is used for the period 1979–1982, the 1990 CIC classification is used for the period 1983–2001, and the 2002 CIC classification is used for the period 2002–2010. Thus I need to use appropriate crosswalks to reconcile CIC over time.

In performing the decomposition exercise by industry in Section 1.3.2, I focus on the period 1983–2010 and use the CPS MORG sample. I adopt the 1990 CIC as the benchmark classification to link occupations over time. To make 1980 CIC compatible to 1990 CIC I use the corresponding crosswalk provided by http://www.unionstats.com. To make 2002 CIC compatible with 1990 CIC I use the corresponding crosswalk provided by the Census Bureau, available at http://www.census.gov/people/io/methodology. A total of 224 industries have employment over the whole period of analysis. I lose twelve industries for which I do not have employment over the sample period. These industries account for less than 2 percent of total employment.

A.2 Supplementary Empirical Evidence

A.2.1 Business Dynamics Statistics

The Business Dynamics Statistics (BDS) annual data series describes establishment-level business dynamics along dimensions absent from similar databases including firm age and firm size. The BDS dataset is created from the Longitudinal Business Database, a confidential database available only to qualified researchers through secure Census Bureau Research Data Centers.

(a) Job flows

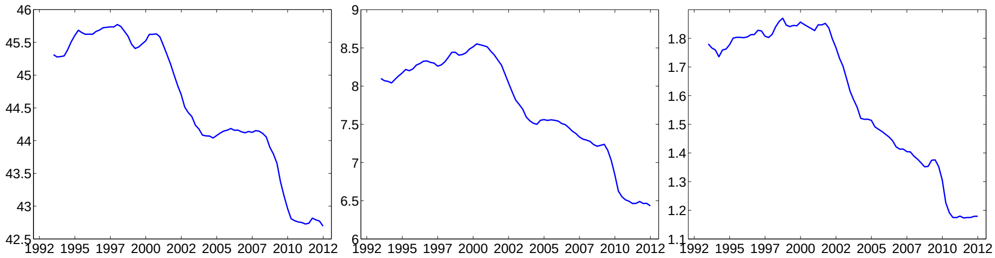
(b) Job reallocation rate

Figure A.1

Notes: All figures plot yearly data from the BDS. The sample period is 1977–2011.

A.2.2 Business Employment Dynamics

Employment change distribution

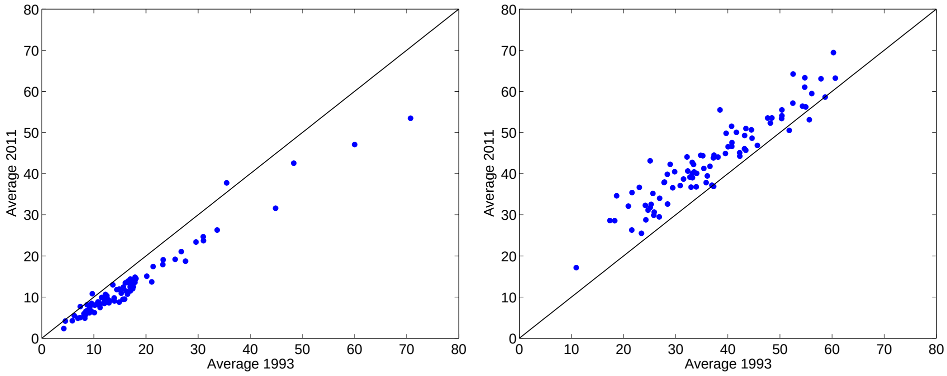


(a) Size of change 1-4 jobs (b) Size of change 5-19 jobs (c) Size of change 20+ jobs

Figure A.2: Employment change distribution (in percentage)

Notes: All figures plot four-quarter moving averages of not seasonally adjusted quarterly data from the BED. The sample period is 1992:Q3–2012:Q2.

Job Reallocation and Inaction Rates Across Industries and Over Time



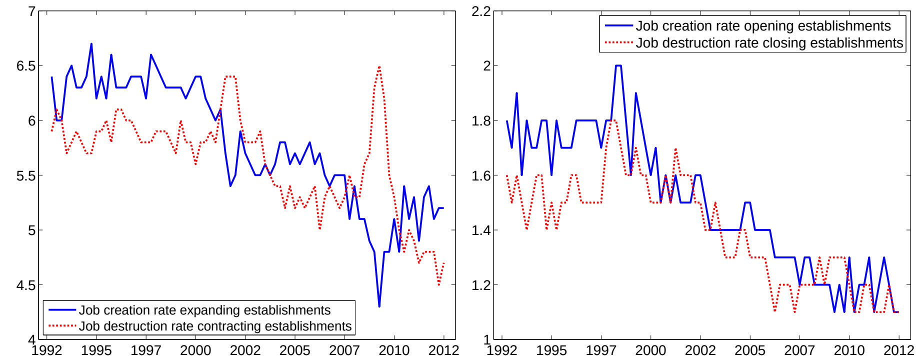
(a) Job reallocation rate (b) Inaction rate

Figure A.3

Notes: Data are yearly averages of quarterly data from the BED. Each dot corresponds to one industry. There are 87 3-digit NAICS industries considered in both panels. The line corresponds to the 45 degree line.

Job flows: Continuing establishments vs. Openings and Closings

Figure A.4a shows evidence on job flow rates by continuing establishments, while Figure A.4b focuses on the job flow rates of opening and closing establishments. In both cases, we observe a decline in job flow rates over time.



(a) Continuing establishments (b) Openings and closings

Figure A.4: Job flow rates

Notes: All figures plot seasonally adjusted quarterly data for the nonfarm private sector from the BED for the period 1992:Q3–2012:Q2.

A.2.3 The Importance of Training Over Time

In this section I present supplemental empirical evidence, that complements the discussion in Section 1.3.2.

Aggregate trends in training requirements using DOT 1991

Table A.1 presents the distribution of employment by level of SVP using training requirements from 1991. The observed empirical patterns are similar to the ones presented in Table 1.3. In particular, there is a shift of employment from occupations requiring low amounts of training to occupations requiring high amounts of training.

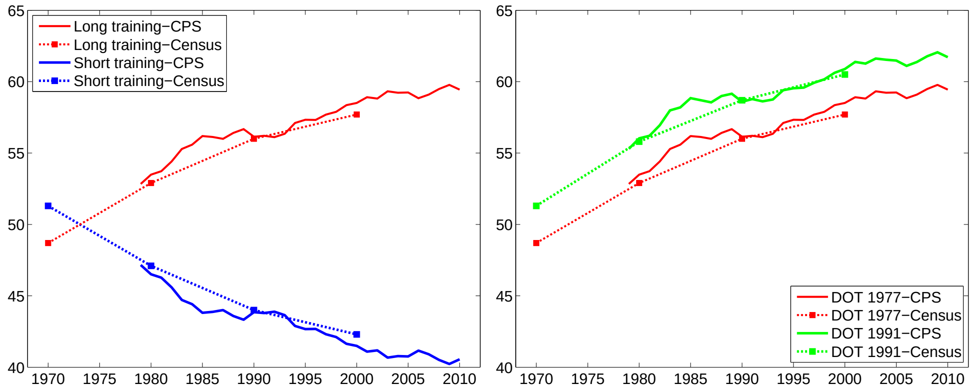
Table A.1: Distribution of employment by level of SVP (DOT 1991, in %)

	1	2	3	4	5	6	7	8
Panel A: Census								
1970	0.2	8.2	19.7	12.5	10.0	13.7	22.9	12.8
1980	0.2	7.5	18.4	11.0	9.0	14.2	26.3	13.4
1990	0.2	7.3	17.0	10.1	8.5	14.2	28.4	14.4
2000	0.3	5.8	16.8	9.8	8.5	13.7	29.8	15.3
Diff. 1970–2000	**0.1**	**-2.4**	**-2.9**	**-2.6**	**-1.5**	**-0.1**	**6.9**	**2.5**
Panel B: CPS MORG								
1980	0.2	7.4	19.1	10.8	9.0	13.9	24.6	14.9
1990	0.2	7.9	17.3	10.0	8.4	14.1	28.0	14.1
2000	0.3	6.2	17.0	9.9	7.9	13.3	29.7	15.6
2010	0.3	6.4	16.4	10.1	7.5	12.9	30.2	16.2
Diff. 1980–2010	**0.1**	**-1.0**	**-2.7**	**-0.7**	**-1.5**	**-1.0**	**5.6**	**1.3**

Robustness regarding the weights used in the analysis

This section performs a robustness exercise of Section 1.3.2 regarding the use of sampling weights in computing aggregate measures. In particular, in the analysis performed in the main text all the observations are weighted by the individual Census or CPS sampling weights. I repeat here the exercise by using full-time equivalent hours of labor supply as weights. Following Autor et al. (2003), full-time equivalent hours of labor supply are defined as the product of the individual Census or CPS sampling weight times weeks of work for the Census sample or hours of work per week for the CPS sample.

Figure A.5 and Tables A.2 and A.3 show the composition of the employment pool by level of SVP, considering both the extensive and intensive margin of analysis. The results are similar to the ones presented in the text: the rise in the share of workers employed in long training occupations is also 11.8 percentage points, from 48.7 percent in 1970 to 60.5 percent in 2010, when considering both margins.



(a) Composition of the employment pool (in %)

(b) Share of workers employed in long training occupations (in %)

Figure A.5

Notes: The dots correspond to the Census samples for each decade between 1970 and 2000, while the solid lines correspond to the CPS MORG samples for each year between 1979 and 2010. *Short training* refers to occupations requiring up to 1 year of training (corresponding to levels of SVP between 1 and 5) and *long training* refers to occupations requiring over 1 year of training (corresponding to levels of SVP between 6 and 9). Training requirements by occupation are kept fixed at the DOT 1977 level in Panel A. In both panels, full-time equivalent hours of labor supply are used as weights.

Table A.2: Distribution of employment by level of SVP using FTE as weights (DOT 1977, in %)

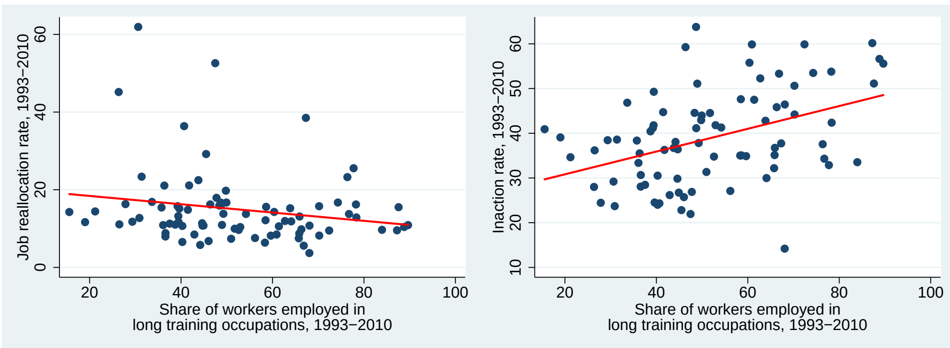
	1	2	3	4	5	6	7	8
Panel A: Census								
1970	0.2	7.7	18.8	11.2	13.4	13.2	21.6	13.9
1980	0.2	7.0	17.6	9.6	12.8	14.0	24.6	14.3
1990	0.2	6.8	16.4	8.4	12.3	14.2	26.7	15.1
2000	0.3	5.5	15.7	8.6	12.2	13.5	27.7	16.5
Diff. 1970–2000	**0.1**	**-2.2**	**-3.1**	**-2.7**	**-1.1**	**0.3**	**6.1**	**2.7**
Panel B: CPS MORG								
1980	0.2	6.7	17.6	9.6	12.4	12.6	23.6	17.3
1990	0.2	7.1	16.0	8.6	12.0	12.3	27.8	16.0
2000	0.3	5.9	15.5	8.6	11.2	12.3	28.3	17.9
2010	0.3	5.9	14.5	8.8	11.0	12.4	28.5	18.5
Diff. 1980–2010	**0.1**	**-0.8**	**-3.1**	**-0.7**	**-1.4**	**-0.2**	**4.9**	**1.3**

Table A.3: Distribution of employment by level of SVP using FTE as weights (DOT 1991, in %)

	1	2	3	4	5	6	7	8
Panel A: Census								
1970	0.2	7.7	18.1	12.3	10.4	13.9	23.5	13.9
1980	0.2	6.9	17.2	10.7	9.3	14.4	27.0	14.4
1990	0.2	6.6	15.9	9.8	8.8	14.4	29.0	15.3
2000	0.3	5.4	15.7	9.5	8.7	13.9	30.4	16.2
Diff. 1970–2000	**0.1**	**-2.3**	**-2.5**	**-2.8**	**-1.7**	**0.0**	**7.0**	**2.3**
Panel B: CPS MORG								
1980	0.2	6.6	17.5	10.4	9.3	13.7	25.2	17.2
1990	0.2	7.0	16.0	9.5	8.7	13.7	28.9	16.0
2000	0.3	5.7	15.7	9.4	8.0	13.0	30.4	17.5
2010	0.3	5.7	14.9	9.5	7.8	12.8	30.8	18.2
Diff. 1980–2010	**0.1**	**-0.9**	**-2.5**	**-0.9**	**-1.5**	**-0.9**	**5.6**	**1.0**

Additional evidence on the link between job flows and training requirements at the industry level

First, I present results on the cross-industry relationship between job flows and training requirements at the industry level. Figure A.6 shows that industries with a high share of workers employed in long training occupations tend to have lower job reallocation rates and higher inaction rates. In order to construct these graphs, I average quarterly job reallocation rates and inaction rates over the period 1993–2010, and the same is done for the yearly share of workers employed in long training occupations. The patterns for the job creation and destruction rates are very similar to the ones observed for the reallocation rate and thus are not shown. Even though the cross-industry relationship can be confounded by omitted variables, the observed patterns are consistent with the hypothesis that a higher importance of training requirements in the job leads to lower job reallocation and higher inaction.



(a) Job reallocation rate (b) Inaction rate

Figure A.6: Job flows and training requirements by industry, averages 1993–2010

Second, Tables A.4 and A.5 show the results of running similar regressions to (1.4) for the job creation and destruction rate, respectively.

Table A.4: Job creation and training requirements

	(1)	(2)	(3)
$\hat{\alpha}$	-0.209***	-0.238***	-0.214***
	(0.028)	(0.022)	(0.027)
$\hat{\beta}_1$	-0.322*		-0.394**
	(0.185)		(0.175)
$\hat{\beta}_2$		0.185*	0.228**
		(0.069)	(0.074)
Observations	82	83	82
R-squared	0.059	0.057	0.141

Notes: Dependent variable: Difference in the job creation rate between 1993 and 2010. Robust standard errors in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.5: Job destruction and training requirements

	(1)	(2)	(3)
$\hat{\alpha}$	-0.173***	-0.195***	-0.174***
	(0.024)	(0.022)	(0.023)
$\hat{\beta}_1$	-0.335*		-0.351**
	(0.187)		(0.191)
$\hat{\beta}_2$		0.010	0.052
		(0.065)	(0.075)
Observations	82	83	82
R-squared	0.067	0	0.071

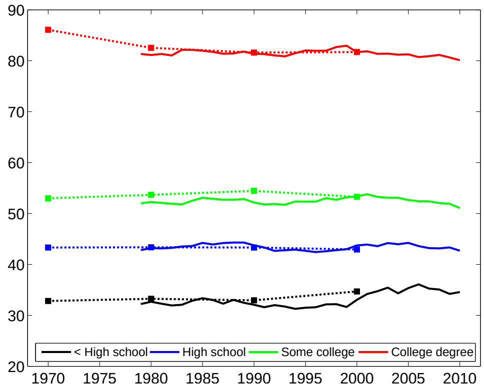
Notes: Dependent variable: Difference in the job destruction rate between 1993 and 2010. Robust standard errors in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

A.2.4 Additional Aggregate Trends Related to the Importance of Training

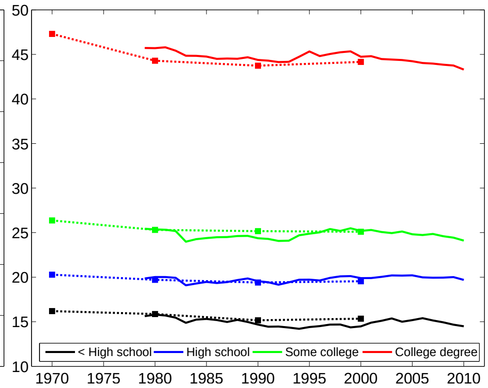
In this section I present supplemental empirical evidence, that complements the discussion in Section 1.3.3.

Table A.6: Levels and changes in employment share from CPS MORG and mean SVP by major occupation group

	Share of Employment (in %)					Mean SVP
	1980	1990	2000	2010	Diff. 1980-2010	
Managers/Prof/Tech/Finance/Public Safety	31.0	36.3	39.4	42.5	**11.5**	**7.1**
Production/Craft	4.2	3.3	3.4	2.6	**-1.5**	**6.8**
Transport/Construct/Mech/Mining/Farm	19.9	19.0	17.3	16.1	**-3.7**	**5.0**
Machine/Operators/Assemblers	10.3	7.4	5.6	3.6	**-6.6**	**4.0**
Clerical/Retail Sales	24.4	23.6	23.1	21.2	**-3.2**	**4.4**
Service Occupations	10.3	10.4	11.3	13.9	**3.6**	**3.9**



(a) Share of workers employed in long training occupations (in %)



(b) Average training times (in months)

Figure A.7: Training requirements by educational attainment

Notes: The dots correspond to the Census samples for each decade between 1970 and 2000, while the solid lines correspond to the CPS MORG samples for each year between 1979 and 2010. Training requirements within occupations correspond to the DOT 1977 level in both panels.

A.3 Supplementary Details on the Model

This appendix presents the details on the derivation of the optimal employment policy of the firm and on the derivation of the wage equation. I also describe here the computational strategy used to solve the model.

A.3.1 Optimal Employment Policy of the Firm

In order to characterize the firm's optimal employment policy I start by taking the first-order condition for hires and separations from the firm's problem defined in equation (1.7):

$$\chi a \phi n^{\phi-1} - w(\chi,a,n) - w_n(\chi,a,n)n - \mathbb{1}^{+}\left(\frac{\kappa_v}{q(\theta)} + \kappa_f\right) + \beta \mathbb{E}_a\left\{\Pi_n(\chi,a',n)\right\} = 0,$$

where $\mathbb{1}$ is an indicator function that equals one if the firm is hiring and zero otherwise, and $\mathbb{E}_a\left\{\Pi_n(\chi,a',n)\right\}$ captures the marginal effect of current employment decisions on the future value of the firm.

The optimal employment decision of the firm is characterized by two reservation thresholds $\tilde{a}^F(\chi,n)$ and $\tilde{a}^H(\chi,n)$, implicitly defined by the following two equations:

$$\chi \tilde{a}^F(\chi,n)\phi n^{\phi-1} - w(\chi,\tilde{a}^F(\chi,n),n) - w_n(\chi,\tilde{a}^F(\chi,n),n)n + \beta\mathbb{E}_a\left\{\Pi_n(\chi,a',n)\right\} = 0,$$
$$\chi \tilde{a}^H(\chi,n)\phi n^{\phi-1} - w(\chi,\tilde{a}^H(\chi,n),n) - w_n(\chi,\tilde{a}^H(\chi,n),n)n + \beta\mathbb{E}_a\left\{\Pi_n(\chi,a',n)\right\} = \left(\frac{\kappa_v}{q(\theta)} + \kappa_f\right),$$

where

$$\Pi_n(\chi,a',n) = \begin{cases} 0 & \text{if } a' < \tilde{a}^F(\chi,n), \\ \chi a'\phi n^{\phi-1} - w(\chi,a',n) - w_n(\chi,a',n)n + \beta\mathbb{E}_a\left\{\Pi_n(\chi,a'',n)\right\} & \text{if } a' \in \left[\tilde{a}^F(\chi,n),\tilde{a}^H(\chi,n)\right], \\ \frac{\kappa_v}{q(\theta)} + \kappa_f & \text{if } a' > \tilde{a}^H(\chi,n). \end{cases}$$

In particular, consider a firm characterized by a time-invariant productivity χ that enters the current period with n_{-1} employees and receives an idiosyncratic productivity shock a. Its optimal employment level in the current period is thus characterized by the following policy function:

$$\Phi(\chi,a,n_{-1}) = \begin{cases} \tilde{n}^F(\chi,a) & \text{if } a < \tilde{a}^F(\chi,n_{-1}), \\ n_{-1} & \text{if } a \in \left[\tilde{a}^F(\chi,n_{-1}),\tilde{a}^H(\chi,n_{-1})\right], \\ \tilde{n}^H(\chi,a) & \text{if } a > \tilde{a}^H(\chi,n_{-1}), \end{cases}$$

where $\tilde{n}^F(\chi,a)$ and $\tilde{n}^H(\chi,a)$ refer to the optimal employment level satisfying equations (A.1) and (A.2) below:

$$\chi a\phi(\tilde{n}^F)^{\phi-1} - w(\chi,a,\tilde{n}^F) - w_n(\chi,a,\tilde{n}^F)\tilde{n}^F + \beta\mathbb{E}_a\left\{\Pi_n(\chi,a',\tilde{n}^F)\right\} = 0, \tag{A.1}$$

$$\chi a\phi(\tilde{n}^H)^{\phi-1} - w(\chi,a,\tilde{n}^H) - w_n(\chi,a,\tilde{n}^H)\tilde{n}^H + \beta\mathbb{E}_a\left\{\Pi_n(\chi,a',\tilde{n}^H)\right\} = \left(\frac{\kappa_v}{q(\theta)} + \kappa_f\right). \tag{A.2}$$

In words, if the idiosyncratic productivity a is below the reservation threshold $\tilde{a}^F(\chi, n_{-1})$ the firm will fire workers until condition (A.1) is satisfied. If instead the idiosyncratic productivity a is above the reservation threshold $\tilde{a}^H(\chi, n_{-1})$ the firm will hire workers until condition (A.2) is satisfied. However, if the idiosyncratic productivity a is between the two reservation thresholds (i.e. if $a \in \left[\tilde{a}^F(\chi, n_{-1}), \tilde{a}^H(\chi, n_{-1})\right]$) then the firm will remain inactive and will keep its employment level unchanged, thus $n = n_{-1}$.

A.3.2 Wage Determination

The Stole and Zwiebel (1996) bargaining solution is used in order to determine the wage in the model. In particular, under this solution, the wage is the result of Nash bargaining between workers and firms over the total marginal surplus of a firm-worker relationship.

First, let's analyze the firm's marginal surplus at the time of wage setting which is given by

$$J(\chi,a,n) = \chi a\phi n^{\phi-1} - w(\chi,a,n) - w_n(\chi,a,n)n + \beta\mathbb{E}_a\left\{\Pi_n(\chi,a',n)\right\}.$$

Using the optimal employment policy of the firm derived above, the previous expression can be written as:

$$\begin{aligned} J(\chi,a,n) =& \chi a\phi n^{\phi-1} - w(\chi,a,n) - w_n(\chi,a,n)n \\ &+ \beta\int_{\tilde{a}^F(\chi,n)}^{\tilde{a}^H(\chi,n)} J(\chi,a',n)dG(a'|a) \\ &+ \beta\int_{\tilde{a}^H(\chi,n)}^{\infty}\left(\frac{\kappa_v}{q(\theta)} + \kappa_f\right)dG(a'|a). \end{aligned} \tag{A.3}$$

Second, let's analyze the value to a worker of being employed in a firm characterized by a time-invariant productivity χ, an idiosyncratic productivity level a, and n employees, which is given by:

$$W(\chi,a,n) = w(\chi,a,n) + \beta\mathbb{E}\left\{sU' + (1-s)W(\chi,a',n')\right\}.$$

This can be rewritten as:

$$W(\chi,a,n) = w(\chi,a,n) + \beta\int_0^{\tilde{a}^F(\chi,n)} \left(\delta U' + (1-\delta)W(\chi,a',\tilde{n}^F(\chi,a'))\right) dG(a'|a)$$
$$+ \beta\int_{\tilde{a}^F(\chi,n)}^{\tilde{a}^H(\chi,n)} W(\chi,a',n)dG(a'|a)$$
$$+ \beta\int_{\tilde{a}^H(\chi,n)}^{\infty} W(\chi,a',\tilde{n}^H(\chi,a'))dG(a'|a).$$

An employed worker receives a wage $w(\chi,a,n)$ in the current period. In the next period, his employment situation will be dependent on the idiosyncratic productivity draw that the firm gets. First, if the firm receives an idiosyncratic productivity below the reservation threshold $\tilde{a}^F(\chi,n)$, the firm will fire workers until condition (A.1) is satisfied. That is, until the firm equals its marginal surplus to zero (i.e. $J(\chi,a',\tilde{n}^F(\chi,a')) = 0$). Given the Nash-sharing rule, this means that the value for an employed worker that stays in the firm is equal to U' (i.e. $W(\chi,a',\tilde{n}^F(\chi,a')) = U'$). Thus, a worker in a firm that is firing workers has two options in the next period, with some probability δ he might stay in the firm and with probability $(1-\delta)$ he might become unemployed, but in either case the worker will receive a value equal to U'. Second, if the firm receives an idiosyncratic productivity between the two reservation thresholds (i.e. if $a' \in \left[\tilde{a}^F(\chi,n), \tilde{a}^H(\chi,n)\right]$), the firm keeps its employment level unchanged, and the worker receives a value equal to $W(\chi,a',n)$ which, given the Nash-sharing rule it is equal to $U' + \frac{\eta}{1-\eta}J(\chi,a',n)$. Third, if the firm receives an idiosyncratic productivity above the reservation threshold $\tilde{a}^H(\chi,n)$, the firm will hire workers until condition (A.2) is satisfied. Thus, the worker will receive a value equal to $W(\chi,a',\tilde{n}^H(\chi,a'))$ which, given the Nash-sharing rule it is equal to $U' + \frac{\eta}{1-\eta}\left(\frac{\kappa_v}{q(\theta)} + \kappa_f\right)$. All this allows to rewrite the value to a worker of being employed as:

$$W(\chi,a,n) = w(\chi,a,n) + \beta U' + \beta\frac{\eta}{1-\eta}\int_{\tilde{a}^F(\chi,n)}^{\tilde{a}^H(\chi,n)} J(\chi,a',n)dG(a'|a)$$
$$+ \beta\frac{\eta}{1-\eta}\int_{\tilde{a}^H(\chi,n)}^{\infty}\left(\frac{\kappa_v}{q(\theta)} + \kappa_f\right)dG(a'|a). \tag{A.4}$$

Third, let's analyze the value to a worker of being unemployed, which is given by:

$$U = b + \beta\mathbb{E}\left\{(1-p(\theta))U' + p(\theta)W(\chi,a',n')\right\}.$$

An unemployed worker receives a current payoff of b and has a probability $p(\theta)$ to find a job next period. Notice that the worker can only find a job at those firms that are posting vacancies. That is, at those firms characterized by a time-invariant productivity χ and n employees that receive an idiosyncratic productivity a' above the reservation threshold $\tilde{a}^H(\chi, n)$. Note that those firms will be hiring optimally, thus choosing a level of employment equal to $\tilde{n}^H(\chi, a')$. Therefore, if the worker gets a job in a hiring firm he will receive the value $W(\chi, a', \tilde{n}^H(\chi, a'))$, which, given the Nash-sharing rule it is equal to $U' + \frac{\eta}{1-\eta}\left(\frac{\kappa_v}{q(\theta)} + \kappa_f\right)$. Therefore, we can express the value of being unemployed as follows:

$$U = b + \beta U' + \beta p(\theta)\frac{\eta}{1-\eta}\left(\frac{\kappa_v}{q(\theta)} + \kappa_f\right). \tag{A.5}$$

Fourth, the surplus of a worker of being employed is obtained by subtracting equation (A.5) from (A.4):

$$\begin{aligned} W(\chi, a, n) - U =& w(\chi, a, n) - b - \beta p(\theta)\frac{\eta}{1-\eta}\left(\frac{\kappa_v}{q(\theta)} + \kappa_f\right) \\ &+ \beta\frac{\eta}{1-\eta}\int_{\tilde{a}^F(\chi,n)}^{\tilde{a}^H(\chi,n)} J(\chi, a', n)dG(a'|a) \\ &+ \beta\frac{\eta}{1-\eta}\int_{\tilde{a}^H(\chi,n)}^{\infty}\left(\frac{\kappa_v}{q(\theta)} + \kappa_f\right)dG(a'|a). \end{aligned} \tag{A.6}$$

Finally, under the generalized Nash wage bargaining rule, the wage $w(\chi, a, n)$ is determined by the following surplus-splitting condition:

$$(1-\eta)\left(W(\chi, a, n) - U\right) = \eta J(\chi, a, n).$$

Thus, plugging in the surplus of the worker given by equation (A.6) and the surplus for the firm given by equation (A.3), the wage is equal to

$$w(\chi, a, n) = \eta\left(\chi a \phi n^{\phi-1} - w_n(\chi, a, n)n + \beta\theta\kappa_v + \beta p(\theta)\kappa_f\right) + (1-\eta)b.$$

A.3.3 Computational Strategy

In order to solve the model numerically I discretize the time-invariant firm-specific productivity χ with 30 grid points, equally spaced in terms of the probability density function. The idiosyncratic productivity shock a is also discretized using 101 equally spaced gridpoints, whereas the employment level is discretized using a log-spaced grid with 377 points. Then, I proceed as follows: First, I guess an initial value for the labor market tightness. Second, given the labor market tightness I find the optimal employment policy with policy function iteration (Howard improvement algorithm). Third, I calculate the steady state employment distribution by means of Monte Carlo simulation. I choose a sample size of 22500 firms and 1100 periods and discard the first 500 periods to remove the effect of initial conditions. Fourth, I update the value for the labor market tightness. Fifth, if the new value for the labor market tightness is sufficiently close to the initial guess I stop. Otherwise, I use the obtained labor market tightness as a new guess and repeat the process until convergence.

A.4 Supplementary Results of the Model

Table A.7: Simulation results with convex vacancy posting costs

Panel A: Parameter values				
Training cost (κ_f)	0.08	0.10	0.15	0.20
Panel B: Simulated statistics				
Job creation/destruction rate	7.7	7.6	7.3	6.8
Job reallocation rate	15.4	15.2	14.5	13.6
Labor market tightness	0.72	0.57	0.34	0.22
Job finding rate	86.2	76.7	59.3	47.9
Unemployment rate	8.2	9.1	11.0	12.6
Total hiring costs (in % of output)	1.05	1.11	1.25	1.38
Training costs (in % of output)	0.50	0.62	0.87	1.08
Employment change distribution				
Loss 5+	5.7	5.4	4.7	4.1
Loss 1-4	18.1	17.2	15.2	13.7
Inaction rate	47.8	51.5	58.5	63.7
Gain 1-4	21.0	19.1	15.9	3.8
Gain 5+	7.4	6.9	5.8	4.8

Appendix B

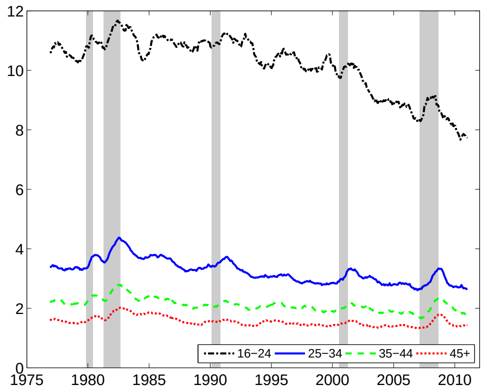
THE FADING DYNAMISM OF THE U.S. LABOR MARKET: THE ROLE OF DEMOGRAPHICS

B.1 Supplemental Empirical Evidence

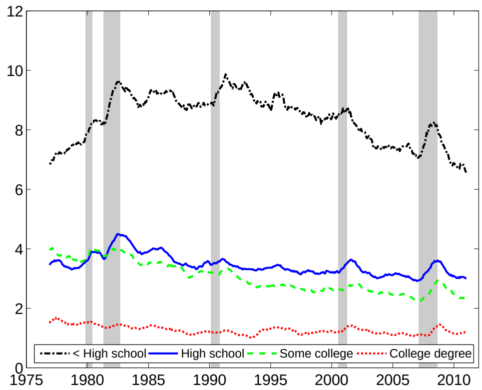
B.1.1 Unemployment Transition Rates by Demographic Group

Table B.1: Unemployment inflow rates, 1976-2011 (means, in percent)

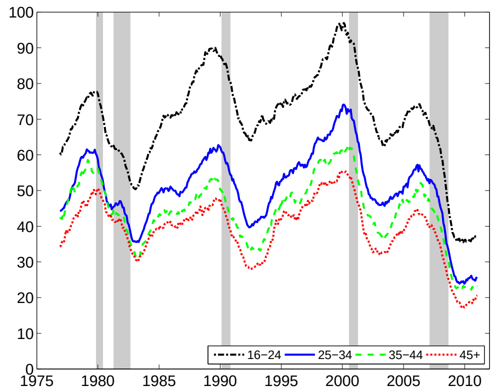
	Education level				
Age group	$<$ High school	High school	Some college	College degree	Aggregate
16-24	18.85	8.57	6.95	4.32	10.15
25-34	7.47	3.81	2.86	1.49	3.23
35-44	4.77	2.39	1.88	0.98	2.11
$>$45	2.82	1.57	1.39	0.81	1.55
Aggregate	8.32	3.45	3.05	1.27	3.52



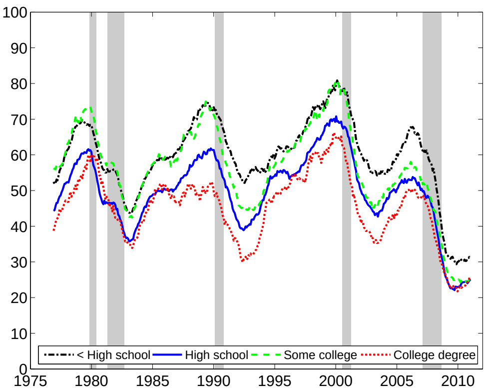
(a) Inflow rates by age



(b) Inflow rates by education



(c) Outflow rates by age

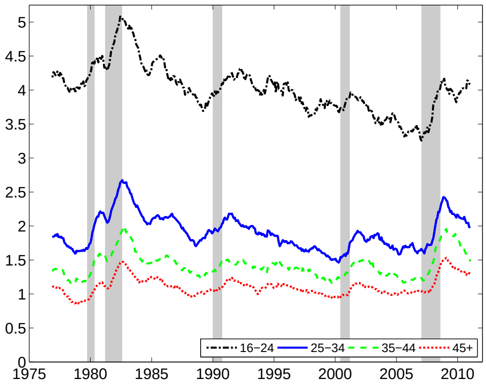


(d) Outflow rates by education

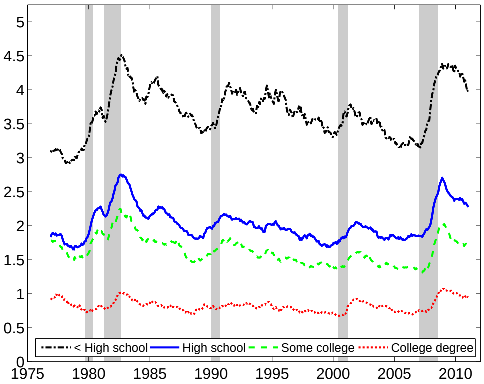
Figure B.1: Unemployment transition rates by demographic group

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.

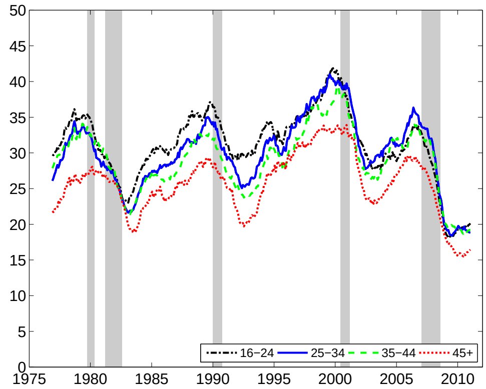
B.1.2 Unemployment Gross Flow Rates by Demographic Group



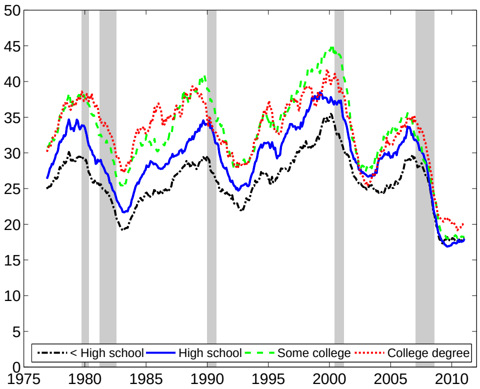
(a) Employment-Unemployment flow hazard rates by age



(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 B.2: Unemployment gross flow rates 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.

B.1.3 Importance of Demographic Shifts for the Aggregate Unemployment Transition Rates

In this section, we examine the role of changing demographic structure in explaining the behavior of the aggregate unemployment transition rates by performing two decomposition exercises. We proceed analogously as with the analysis for unemployment flows performed in Section 2.2.1.

First, 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:

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

where ω_{it}^E stands for the fraction of employed workers in group i at time t.

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

$$\sum_{i\in\Omega} \omega_{it_0}^E s_{it_1}.$$

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) and t_1 into two terms:

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

where $\bar{s}_i = \frac{1}{2}\left(s_{it_0} + s_{it_1}\right)$ and $\bar{\omega}_i^E = \frac{1}{2}\left(\omega_{it_0}^E + \omega_{it_1}^E\right)$. 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.

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:

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

where ω_{it}^U 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):

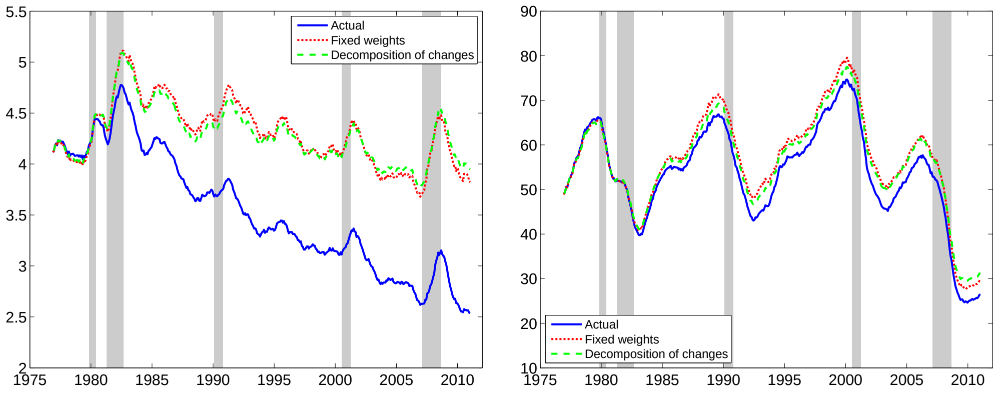
$$\sum_{i \in \Omega} \omega_{it_0}^U f_{it_1}.$$

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

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

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

Figure B.3 summarizes the results. In particular, Figure B.3a depicts the evolution of the actual aggregate unemployment inflow rate together with the two 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. Thus, both counterfactual exercises 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. In turn, Figure B.3b depicts the evolution of the actual aggregate unemployment outflow rate together with the two counterfactual outflow rates. 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.



(a) Unemployment inflow rate

(b) Unemployment outflow rate

Figure B.3: The effect of demographics on aggregate unemployment transition rates: Actual *vs.* counterfactual

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 respective actual aggregate unemployment transition rate in the first period.

B.2 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:

$$\begin{aligned} J_t^{i,Y}(x) = \max\Big\{&0, a(1 - \mathbb{1}_{t=1}\tau^i) - w_t^{i,Y}(x) \\ &+ \beta\mathbb{E}_x\Big\{(1-\rho)_{t+1}^{i,Y}(x') + \rho J_{t+1}^{i,O}(x')\Big\}\Big\}, \end{aligned} \tag{B.1}$$

$$J_t^{i,O}(x) = \max\Big\{0, a - w_t^{i,O}(x) + \beta(1-\delta)\mathbb{E}_x\Big\{J_{t+1}^{i,O}(x')\Big\}\Big\}, \tag{B.2}$$

$$J_t^{i,D}(x) = \max\Big\{0, a(1-\kappa)(1 - \mathbb{1}_{t=1}\tau^i) - w_t^{i,D}(x) + \beta(1-\delta)\mathbb{E}_x\Big\{J_{t+1}^{i,D}(x')\Big\}\Big\}. \tag{B.3}$$

Equation (B.1) presents the value of a job filled by a young worker, while equations (B.2) and (B.3) refer to the value of a job filled by an old worker. The difference between the last two equations is that in equation (B.2) the old worker maintains the full value of his general human capital. However, equation (B.3) 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 (B.1)-(B.3) 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:

$$\frac{c}{q(\theta^i(x))} = \beta\mathbb{E}_x\big\{\gamma^i J_1^{i,Y}(x') + (1-\gamma^i)J_1^{i,D}(x')\big\}, \tag{B.4}$$

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:

$$U^{i,Y}(x) = b + p(\theta^i(x))\beta\mathbb{E}_x\big\{(1-\rho)W_1^{i,Y}(x') + \rho W_1^{i,D}(x')\big\} \\ + \big[1 - p(\theta^i(x))\big]\,\beta\mathbb{E}_x\big\{(1-\rho)U^{i,Y}(x') + \rho U^{i,D}(x')\big\}, \tag{B.5}$$

$$U^{i,D}(x) = b + p(\theta^i(x))\beta(1-\delta)\mathbb{E}_x\big\{W_1^{i,D}(x')\big\} + \\ \big[1 - p(\theta^i(x))\big]\,\beta(1-\delta)\mathbb{E}_x\big\{U^{i,D}(x')\big\}. \tag{B.6}$$

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

$$W_t^{i,Y}(x) = \max\left\{U^{i,Y}(x), w_t^{i,Y}(x) + \beta\mathbb{E}_x\left\{(1-\rho)W_{t+1}^{i,Y}(x') + \rho W_{t+1}^{i,O}(x')\right\}\right\}, \tag{B.7}$$

$$W_t^{i,O}(x) = \max\left\{U^{i,D}(x), w_t^{i,O}(x) + \beta(1-\delta)\mathbb{E}_x\left\{W_{t+1}^{i,O}(x')\right\}\right\}, \tag{B.8}$$

$$W_t^{i,D}(x) = \max\left\{U^{i,D}(x), w_t^{i,D}(x) + \beta(1-\delta)\mathbb{E}_x\left\{W_{t+1}^{i,D}(x')\right\}\right\}. \tag{B.9}$$

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 (B.8).

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:

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

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:

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

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:

$$\begin{aligned} w_t^{i,Y}(x) =& \eta a(1-\mathbb{1}_{t=1}\tau^i) + (1-\eta)b \\ &+ \eta p(\theta^i(x))\beta \mathbb{E}_x\left\{(1-\rho)J_1^{i,Y}(x') + \rho J_1^{i,D}(x')\right\}, \end{aligned} \tag{B.10}$$

$$w_t^{i,O}(x) = \eta a + (1-\eta)b + \eta p(\theta^i(x))\beta(1-\delta)\mathbb{E}_x\left\{J_1^{i,D}(x')\right\}, \tag{B.11}$$

$$\begin{aligned} w_t^{i,D}(x) =& \eta a(1-\kappa)(1-\mathbb{1}_{t=1}\tau^i) + (1-\eta)b \\ &+ \eta p(\theta^i(x))\beta(1-\delta)\mathbb{E}_x\left\{J_1^{i,D}(x')\right\}. \end{aligned} \tag{B.12}$$

Finally, the recursive equilibrium of the model can also be characterized as the solution of equations (2.3)-(2.4), (2.10)-(2.14) and (B.1)-(B.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 $\tilde{a}_t^{i,D}$.

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.2.1 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 (B.13)-(B.17) 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 $n^{i,Y}$:

$$p(\theta^i)[1-G(\tilde{a}_1^{i,Y})](1-\rho)u^{i,Y} = \rho n^{i,Y} + s^{i,Y}(1-\rho)n^{i,Y} \tag{B.13}$$

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

$$(1-s^{i,O})\rho n^{i,Y} = \delta n^{i,O} + s^{i,O}(1-\delta)n^{i,O} \tag{B.14}$$

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

$$p(\theta^i)[1-G(\tilde{a}_1^{i,D})](\rho u^{i,Y} + (1-\delta)u^{i,D}) = \delta n^{i,D} + s^{i,D}(1-\delta)n^{i,D} \tag{B.15}$$

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

$$\begin{aligned} &s^{i,Y}(1-\rho)n^{i,Y} + \delta(n^{i,O} + n^{i,D} + u^{i,D}) \\ &= p(\theta^i)[1-G(\tilde{a}_1^{i,Y})](1-\rho)u^{i,Y} + \rho u^{i,Y} \end{aligned} \tag{B.16}$$

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

$$\begin{aligned}
& s^{i,O}(\rho n^{i,Y} + (1-\delta)n^{i,O}) + s^{i,D}(1-\delta)n^{i,D} \\
& + \left[1 - p(\theta^i)(1 - G(\tilde{a}_1^{i,D}))\right] \rho u^{i,Y} \\
& = \delta u^{i,D} + p(\theta^i)[1 - G(\tilde{a}_1^{i,D})](1-\delta)u^{i,D} \qquad \text{(B.17)}
\end{aligned}$$

For completeness, Figure B.4 summarizes all the worker flows in our model graphically.

B.2.2 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.

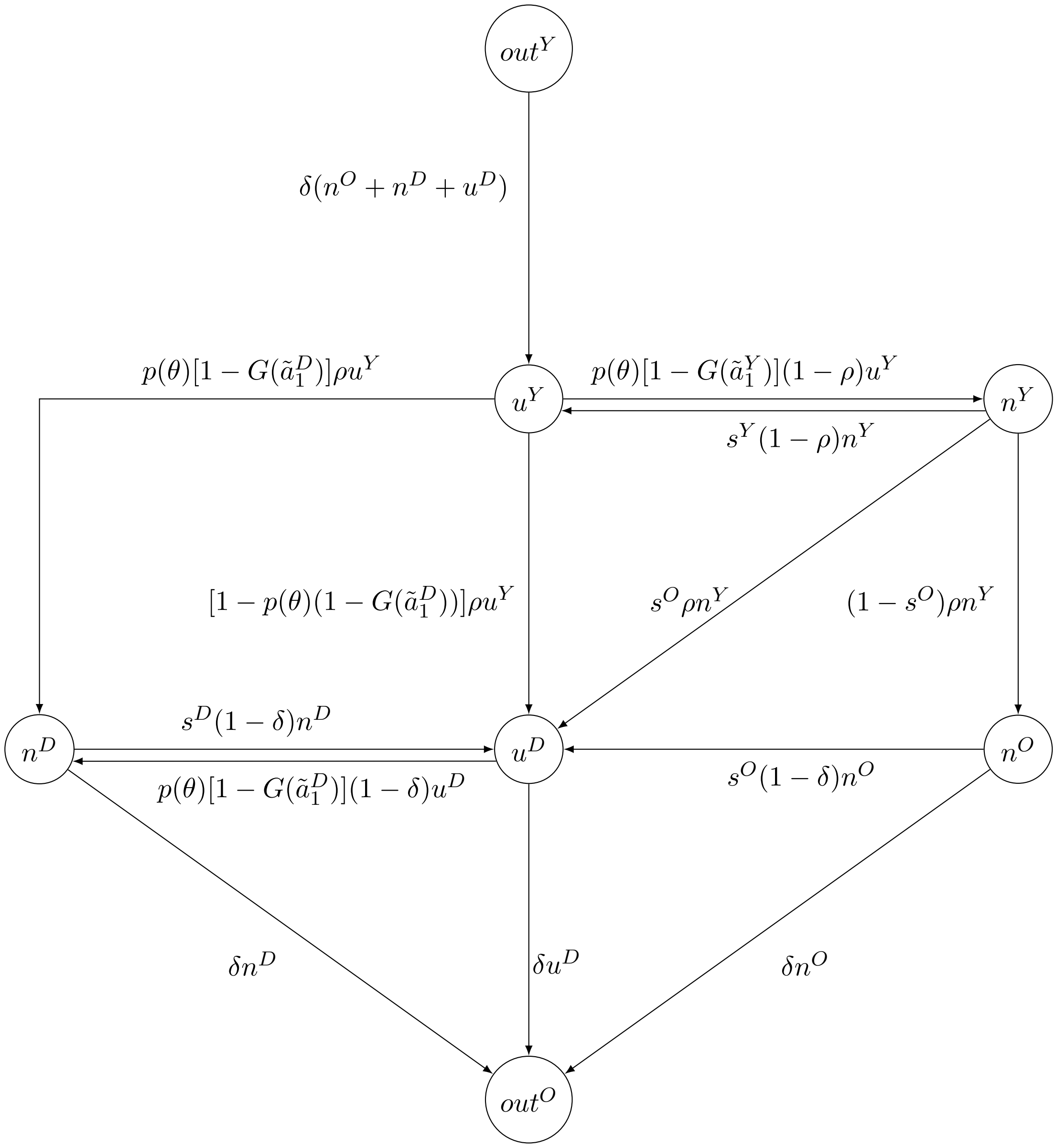


Figure B.4: Description of labor market flows in the model

B.2.3 Additional Simulation Results

Table B.2: 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 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.

Appendix C

HUMAN CAPITAL AND UNEMPLOYMENT DYNAMICS: WHY DO MORE EDUCATED WORKERS ENJOY GREATER EMPLOYMENT STABILITY?

C.1 Data Description

C.1.1 Current Population Survey

In order to construct unemployment rates, inflows, and outflows by education group we use the Current Population Survey (CPS) basic monthly data files from January 1976 until December 2010, accessed through http://www.nber.org/cps/. From these data we obtain the total number of employed, the total number of unemployed and the number of short-term (less than 5 weeks) unemployed for each education group. The calculation of unemployment rates follows the usual definition (unemployed/labor force).

In January 1992 the U.S. Census Bureau modified the CPS question on educational attainment. In particular, before 1992 the question was about the highest grade attended and completed (years of education), whereas after that the question has been about the highest degree received. We broadly follow suggestions by Jaeger (1997) on categorical recoding schemes for old and new education questions. Our education groups consist of: i) less than high school (0-12 years uncompleted according to the old question; at most 12th grade, no diploma according to the new question); ii) high school graduates (12 years completed; high school graduates); iii) some college (13-16 years uncompleted; some college, associate's degrees); iv) college graduates (16 years completed and more; bachelor's, master's, professional school and doctoral degrees).

Moreover, due to the January 1994 CPS redesign there is a discontinuity in the short-term unemployment series.[1] More precisely, from 1994 onwards the CPS does not ask about unemployment duration a worker who is unemployed in consecutive months, but instead his duration is calculated as the sum of unemployment duration in the previous month plus the intervening number of weeks. Nevertheless, workers in the incoming rotation groups (1st and 5th) are always asked about unemployment duration, even after 1994. This allows to calculate the ratio of the short-term unemployed share for the 1st and 5th rotation groups relative to the short-term unemployed share in the full sample. One can then multiply the short-term unemployment series after 1994 by this ratio. Since the ratio turns out to be quite volatile over time, we follow the suggestion by Elsby et al. (2009) and multiply the series by the average value of the ratio for the period February 1994 - December 2010. We apply this correction for each education group separately, although the ratios are very similar across groups. More precisely, the ratio equals to 1.14 (1.17 when limiting the sample to 16 years of age and over) for high school dropouts, 1.14 (1.16) for high school graduates, 1.14 (1.14) for people with some college, 1.13 (1.15) for college graduates, and 1.14 (1.16) for aggregate numbers. Note that the aggregate number for the whole sample is very close to the one calculated by Elsby et al. (2009), who find an average ratio of 1.15 for the period February 1994 - January 2005.

Next, we seasonally adjust the series using the X-12-ARIMA seasonal adjustment program (version 0.3), provided by the U.S. Census Bureau. Then we compute the monthly outflow and inflow rates. The outflow rate can be obtained from the equation describing the law of motion for unemployment: $u_{t+1} = (1 - F_t)u_t + u^s_{t+1}$, where u_t denotes unemployed, u^s_t short-term unemployed and F_t the monthly outflow probability. The latter is hence given by $F_t = 1 - (u_{t+1} - u^s_{t+1})/u_t$, with the outflow hazard rate being $f_t = -\log(1 - F_t)$. To calculate inflow rates, we use the continuous-time correction for time aggregation bias from Shimer (2012), which takes into account that some workers who become unemployed, manage to find a new job before the next CPS survey arrives.

C.1.2 Employment Opportunity Pilot Project Survey

The 1982 Employment Opportunity Pilot Project (EOPP) was a survey of employers in the United States conducted between February and June 1982. The survey had three parts. The first part collected information on general hiring practices,

[1]See also Shimer (2012) and references therein.

the second part asked the employer about the last hired worker and the last part dealt with government programs. We focus only on the central part of the survey, given that it provides specific information about the relationship between education and the degree of on-the-job training. In particular, employers were asked to think about the last new employee the company hired prior to August 1981 regardless of whether that person was still employed by the company at the time of the interview. A series of specific questions were asked about the training received by the new employee during the first three months in the company.

The main advantage of the 1982 EOPP survey is that it includes both measures of formal and informal training. Nevertheless, some drawbacks of the 1982 EOPP survey need to be mentioned as well. First, the sample of employers interviewed is not representative. In particular, the sample was intentionally designed to overrepresent low-paid jobs. Second, given that questions were related to the last hire in the company, the sample also most likely overrepresents workers with higher turnover rates. Finally, although the survey has been widely used to study several aspects of on-the-job training, it is becoming outdated and thus perhaps less relevant. To overcome some of these concerns, we use the data from the 1979 National Longitudinal Survey of Youth as a supplementary data source on (formal) on-the-job training.

C.1.3 National Longitudinal Survey of Youth

The 1979 National Longitudinal Survey of Youth (NLSY) contains a nationally representative sample of 12,686 young men and women who were 14-22 years old when they were first surveyed in 1979. These individuals were interviewed annually through 1994 and are currently interviewed on a biennial basis. The measure of training incidence used in the text comes from the following question in the survey: “Since [date of the last interview], did you attend any training program or any on-the-job training designed to improve job skills, help people find a job, or learn a new job?”. Notice that this question has a 1-year reference period in 1989-1994, while it has a 2-year reference period in 1988 and from 1996 onwards. As mentioned in the text, the analysis of the NLSY data supports the main empirical findings from the 1982 EOPP data regarding the existence of on-the-job training differences across education groups.

C.2 Supplementary Results

C.2.1 Unemployment Rates by Education

Table C.1 shows results from estimated regression equations, where the probability of being unemployed is being regressed on the standard set of controls. These results show that education remains an important predictor of the probability of being unemployed, even when controlling for demographic characteristics, industry, occupation, and including time dummies.

Table C.1: Unemployment and education

	(1)	(2)	(3)	(4)	(5)	(6)
Less Than High School	0.0986***	0.0749***	0.0764***	0.0487***	0.0402***	0.0372***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
High School	0.0430***	0.0327***	0.0334***	0.0233***	0.0165***	0.0152***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Some College	0.0253***	0.0137***	0.0140***	0.0108***	0.0068***	0.0061***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Individual controls		yes	yes	yes	yes	yes
Time dummies			yes	yes	yes	yes
Industry controls				yes		yes
Occupation controls					yes	yes
Observations	6,701,078	6,701,078	6,701,078	6,670,335	6,670,335	6,670,335
R-squared	0.015	0.0321	0.0385	0.0367	0.0355	0.0389

Notes: Dependent variable: probability of being unemployed. The omitted education dummy corresponds to college graduates. The sample period is 2003:01 - 2010:12. All variables are obtained from CPS microdata. Individual controls: age, age squared, gender, marital status, race. Time dummies: month and year. Industry controls: 52 2-digit industries. Occupation controls: 23 2-digit occupations. Robust standard errors in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

C.2.2 Unemployment Rates by Age

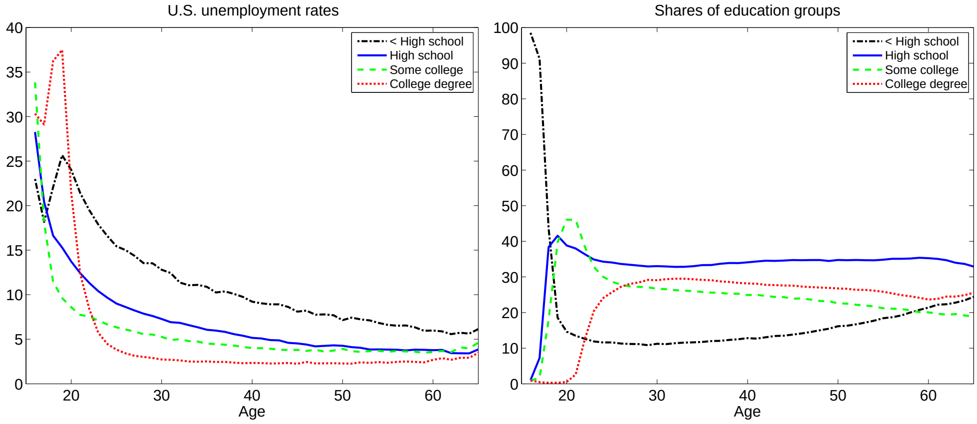


Figure C.1: U.S. unemployment rates, educational attainment and age

Notes: The sample period is 1976:01-2010:12. All variables are constructed from CPS microdata.

C.2.3 Unemployment Duration Shares by Education Groups

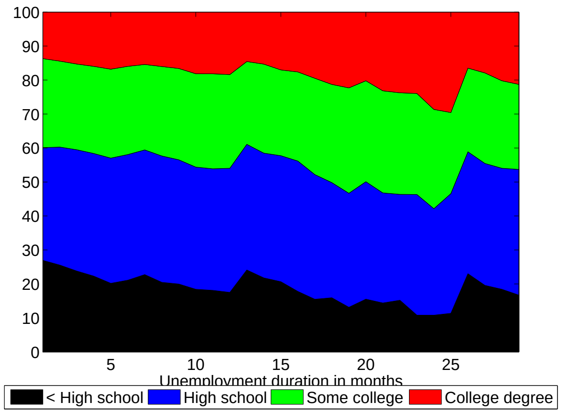


Figure C.2: Unemployment duration shares by education groups

Notes: The sample period is 2003:01-2010:12. All variables are constructed from CPS microdata.

C.2.4 Unemployment Gross Flows

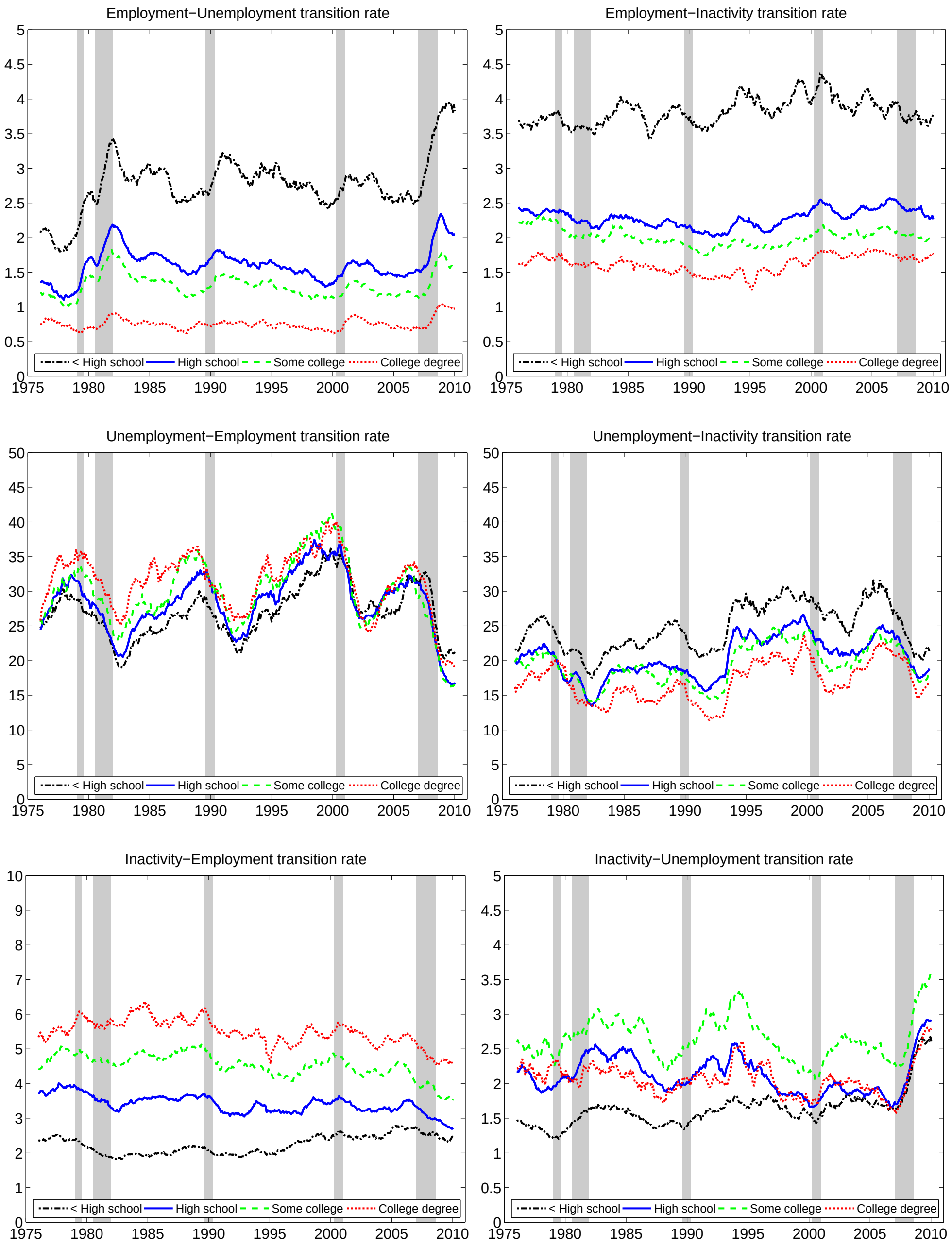


Figure C.3: Gross flow rates (25+ years of age)

Notes: 12-month moving averages.

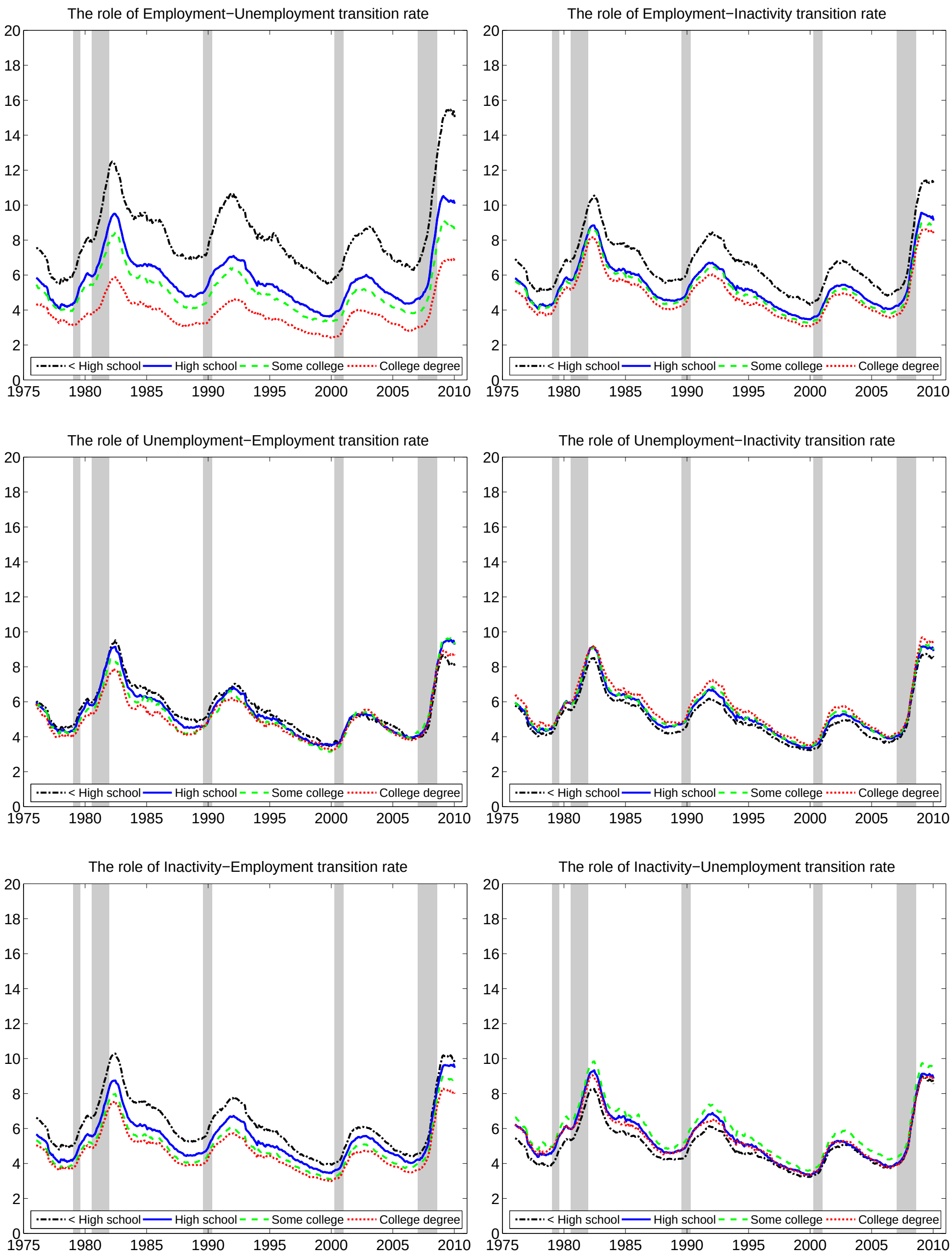


Figure C.4: Counterfactual unemployment rates (25+ years of age)

Notes: The top left panel shows the counterfactual unemployment rate series for each group by taking its actual employment-unemployment transition rate series, but keeping the rest of transition rates series at the values for the aggregate economy. The rest of the panels are constructed analogously, but analyzing the role of different transition rates. 12-month moving averages.

C.2.5 Unemployment Flows for Working-Age Population

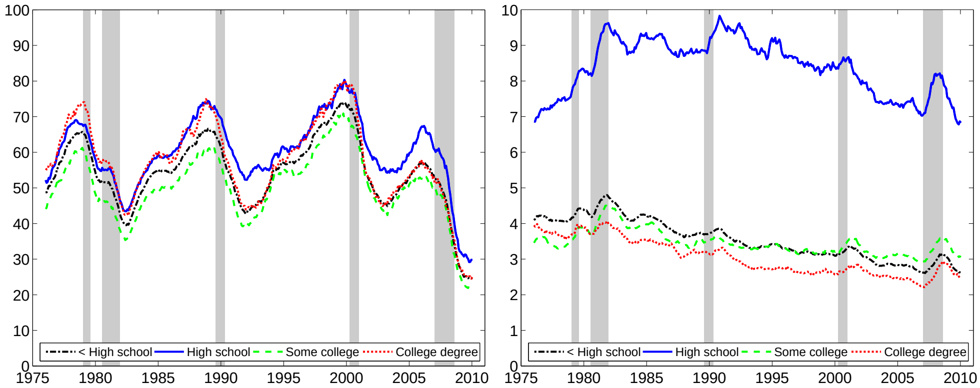


Figure C.5: Unemployment flow rates (16+ years of age)

Notes: 12-month moving averages.

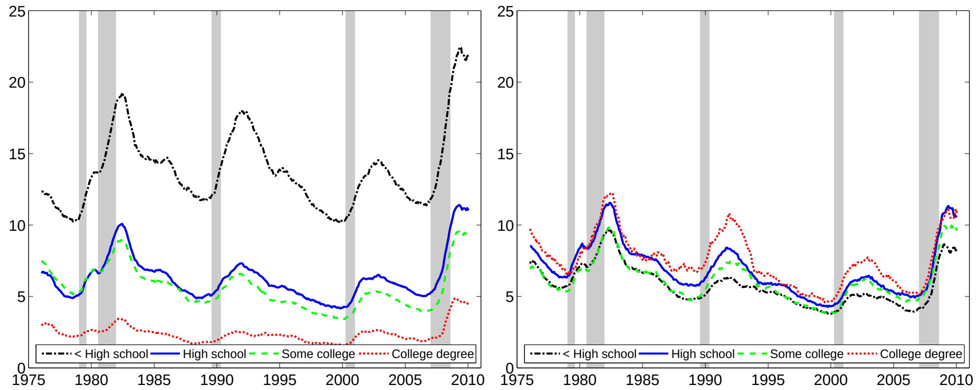


Figure C.6: Counterfactual unemployment rates (16+ years of age)

Notes: The left panel shows the counterfactual unemployment rate series for each group by taking its actual outflow rate series, but keeping the inflow rate series at the value for the aggregate economy. The right panel shows the counterfactual unemployment rate series for each group by taking its actual inflow rate series, but keeping the outflow rate series at the value for the aggregate economy. 12-month moving averages.

C.3 Proofs and Computational Strategy

C.3.1 Proof of Proposition 2

The Constrained-Efficient Allocation

In order to investigate the efficiency properties of the model, we derive the constrained-efficient allocation by solving the problem of a benevolent social planner. Given the assumption on risk neutrality of agents in the model, we naturally abstract from distributive inefficiency and instead examine inefficiency arising exclusively due to search externalities. The social planner takes as given the search frictions and the training requirements. We abstract from aggregate productivity shocks and assume that idiosyncratic shocks are being drawn in each period from a continuous distribution $G(a)$, which simplifies some of the derivations.

The benevolent social problem chooses θ, $\tilde{a}^T$ and $\tilde{a}^S$ in order to maximize the utility of the representative worker by solving the following Bellman equation for each submarket h:

$$\begin{aligned} V\Big(N^T(x), N^S(x)\Big) = \max_{\theta,\tilde{a}^T,\tilde{a}^S} \Big\{ & (1-\tau_h)HA\int_{\tilde{a}^T}^{\infty} an^T(a)dG(a) \\ & + HA\int_{\tilde{a}^S}^{\infty} an^S(a)dG(a) + (1-n)b_h - \theta(1-n)c_h \\ & + \beta V\Big((N^T)'(x), (N^S)'(x)\Big)\Big\}, \end{aligned}$$

with

$$\begin{aligned} N^T(x) = \int_{-\infty}^{x} n^T(a)dG(a), \quad N^S(x) = \int_{-\infty}^{x} n^S(a)dG(a), \\ n = \int_{\tilde{a}^T}^{\infty} n^T(a)dG(a) + \int_{\tilde{a}^S}^{\infty} n^S(a)dG(a), \end{aligned}$$

subject to the following laws of motion for employment:

$$\begin{aligned} (N^T)'(x) &= \left[(1-\delta)(1-\phi_h)\int_{\tilde{a}^T}^{\infty} n^T(a)dG(a) + \gamma\theta^{1-\alpha}(1-n)\right] G(x), \\ (N^S)'(x) &= \left[(1-\delta)\int_{\tilde{a}^S}^{\infty} n^S(a)dG(a) + (1-\delta)\phi_h\int_{\tilde{a}^T}^{\infty} n^T(a)dG(a)\right] G(x). \end{aligned}$$

Note that $N^T(x)$ and $N^S(x)$ denote employment distributions after idiosyncratic productivity shocks take place and before the social planner decides the optimal destruction thresholds.

The first order conditions are:

$$
\begin{aligned}
0 =& - c_h(1-n) + \beta \frac{\partial V'(\cdot)}{\partial (N^T)'(x)} \gamma(1-\alpha)\theta^{-\alpha}(1-n)G(x), \\
0 =& (1-\tau_h)HA(-\tilde{a}^T n^T(\tilde{a}^T)) - b_h(-n^T(\tilde{a}^T)) + c_h\theta(-n^T(\tilde{a}^T)) \\
&+ \beta \frac{\partial V'(\cdot)}{\partial (N^T)'(x)} \Big((1-\delta)(1-\phi_h)(-n^T(\tilde{a}^T) - \gamma\theta^{1-\alpha}(-n^T(\tilde{a}^T))\Big)G(x) \\
&+ \beta \frac{\partial V'(\cdot)}{\partial (N^S)'(x)} (1-\delta)\phi_h(-n^T(\tilde{a}^T))G(x), \\
0 =& HA(-\tilde{a}^S n^S(\tilde{a}^S)) - b_h(-n^S(\tilde{a}^S)) + c_h\theta(-n^S(\tilde{a}^S)) \\
&+ \beta \frac{\partial V'(\cdot)}{\partial (N^T)'(x)} \Big(-\gamma\theta^{1-\alpha}(-n^S(\tilde{a}^S))\Big)G(x) \\
&+ \beta \frac{\partial V'(\cdot)}{\partial (N^S)'(x)} (1-\delta)(-n^S(\tilde{a}^S))G(x).
\end{aligned}
$$

The envelope conditions are:

$$
\begin{aligned}
\frac{\partial V(\cdot)}{\partial (N^T)(x)} G(x) =& (1-\tau_h)HA \int_{\tilde{a}^T}^{\infty} a dG(a) - b_h(1-G(\tilde{a}^T)) + c_h\theta(1-G(\tilde{a}^T)) \\
&+ \beta \frac{\partial V'(\cdot)}{\partial (N^T)'(x)} \Big((1-\delta)(1-\phi_h) - \gamma\theta^{1-\alpha}\Big)(1-G(\tilde{a}^T))G(x) \\
&+ \beta \frac{\partial V'(\cdot)}{\partial (N^S)'(x)} (1-\delta)\phi_h(1-G(\tilde{a}^T))G(x), \\
\frac{\partial V(\cdot)}{\partial (N^S)(x)} G(x) =& HA \int_{\tilde{a}^S}^{\infty} a dG(a) - b_h(1-G(\tilde{a}^S)) + c_h\theta(1-G(\tilde{a}^S)) \\
&+ \beta \frac{\partial V'(\cdot)}{\partial (N^T)'(x)} (-\gamma\theta^{1-\alpha})(1-G(\tilde{a}^S))G(x) \\
&+ \beta \frac{\partial V'(\cdot)}{\partial (N^S)'(x)} (1-\delta)(1-G(\tilde{a}^S))G(x).
\end{aligned}
$$

After some rearrangements, the following optimal job creation condition can be obtained:

$$
\begin{aligned}
\frac{c_h}{\gamma\theta^{-\alpha}} =& \beta(1-\alpha) \int_{\tilde{a}^T}^{\infty} \Big\{(1-\tau_h)HAa - b_h - \frac{\alpha}{1-\alpha}c_h\theta \\
&+ \frac{(1-\delta)(1-\phi_h)c_h}{(1-\alpha)\gamma\theta^{-\alpha}} + \frac{\beta(1-\delta)\phi_h}{1-\beta(1-\delta)(1-G(\tilde{a}^S))} \\
&\int_{\tilde{a}^S}^{\infty} \Big\{HAa - b_h - \frac{\alpha}{1-\alpha}c_h\theta\Big\}dG(a)\Big\}dG(a).
\end{aligned}
\tag{C.1}
$$

Similarly, the optimal job destruction conditions are given by:

$$\begin{aligned} 0 =& (1-\tau_h)HA\tilde{a}^T - b_h - \frac{\alpha}{1-\alpha}c_h\theta + \frac{(1-\delta)(1-\phi_h)c_h}{(1-\alpha)\gamma\theta^{-\alpha}} \\ &+ \frac{\beta(1-\delta)\phi_h}{1-\beta(1-\delta)(1-G(\tilde{a}^S))}\int_{\tilde{a}^S}^{\infty}\Big\{HAa - b_h - \frac{\alpha}{1-\alpha}c_h\theta\Big\}dG(a), \end{aligned} \tag{C.2}$$

$$\begin{aligned} 0 =& HA\tilde{a}^S - b_h - \frac{\alpha}{1-\alpha}c_h\theta \\ &+ \frac{\beta(1-\delta)}{1-\beta(1-\delta)(1-G(\tilde{a}^S))}\int_{\tilde{a}^S}^{\infty}\Big\{HAa - b_h - \frac{\alpha}{1-\alpha}c_h\theta\Big\}dG(a). \end{aligned} \tag{C.3}$$

Decentralized Allocation

Again, we abstract from aggregate productivity shocks and assume that idiosyncratic shocks are being drawn in each period from a continuous distribution $G(a)$. The main equilibrium conditions are:

$$\begin{aligned} S^T(H,A,a) =& (1-\tau_h)HAa - b_h - \beta\eta\gamma\theta^{1-\alpha}\int_{\tilde{a}^T}^{\infty} S^T(H,A,a)dG(a) \\ &+ \beta(1-\delta)\phi_h\int_{\tilde{a}^S}^{\infty} S^S(H,A,a)dG(a) \\ &+ \beta(1-\delta)(1-\phi_h)\int_{\tilde{a}^T}^{\infty} S^T(H,A,a)dG(a), \\ S^S(H,A,a) =& HAa - b_h - \beta\eta\gamma\theta^{1-\alpha}\int_{\tilde{a}^T}^{\infty} S^T(H,A,a)dG(a) \\ &+ \beta(1-\delta)\int_{\tilde{a}^S}^{\infty} S^S(H,A,a)dG(a), \\ \frac{c_h}{\gamma\theta^{-\alpha}} =& \beta(1-\eta)\int_{\tilde{a}^T}^{\infty} S^T(H,A,a)dG(a). \end{aligned}$$

Notice that we can write:

$$\big(1-\beta(1-\delta)(1-G(\tilde{a}^S))\big)\int_{\tilde{a}^S}^{\infty} S^S(H,A,a)dG(a) = \\ \int_{\tilde{a}^S}^{\infty}\Big\{HAa - b_h - \frac{\eta}{1-\eta}c_h\theta\Big\}dG(a).$$

So, we have the following job creation condition:

$$\begin{aligned}\frac{c_h}{\gamma\theta^{-\alpha}} =&\beta(1-\eta)\int_{\tilde{a}^T}^{\infty}\Big\{(1-\tau_h)HAa - b_h - \frac{\eta}{1-\eta}c_h\theta \\ &+ \frac{(1-\delta)(1-\phi_h)c_h}{(1-\eta)\gamma\theta^{-\alpha}} + \frac{\beta(1-\delta)\phi_h}{1-\beta(1-\delta)(1-G(\tilde{a}^S))} \\ &\int_{\tilde{a}^S}^{\infty}\Big\{HAa - b_h - \frac{\eta}{1-\eta}c_h\theta\Big\}dG(a)\Big\}dG(a).\end{aligned} \tag{C.4}$$

The job destruction conditions can be derived as:

$$\begin{aligned}0 =&(1-\tau_h)HA\tilde{a}^T - b_h - \frac{\eta}{1-\eta}c_h\theta + \frac{(1-\delta)(1-\phi_h)c_h}{(1-\eta)\gamma\theta^{-\alpha}} \\ &+ \frac{\beta(1-\delta)\phi_h}{1-\beta(1-\delta)(1-G(\tilde{a}^S))}\int_{\tilde{a}^S}^{\infty}\Big\{HAa - b_h - \frac{\eta}{1-\eta}c_h\theta\Big\}dG(a),\end{aligned} \tag{C.5}$$

$$\begin{aligned}0 =&HA\tilde{a}^S - b_h - \frac{\eta}{1-\eta}c_h\theta \\ &+ \frac{\beta(1-\delta)}{1-\beta(1-\delta)(1-G(\tilde{a}^S))}\int_{\tilde{a}^S}^{\infty}\Big\{HAa - b_h - \frac{\eta}{1-\eta}c_h\theta\Big\}dG(a).\end{aligned} \tag{C.6}$$

By comparing the constrained-efficient equilibrium conditions (C.1)-(C.3) with the decentralized equilibrium conditions (C.4)-(C.6) it follows that the decentralized allocation replicates the constrained-efficient allocation when $\eta = \alpha$, reflecting the standard Hosios condition.

Worker's bargaining power and job destruction - analytical results

Subtracting $S^T(H,A,\tilde{a}^T) = 0$ from $S^T(H,A,a)$ and $S^S(H,A,\tilde{a}^S) = 0$ from $S^S(H,A,a)$ we get:

$$\begin{aligned}S^T(H,A,a) =&(1-\tau_h)HA(a-\tilde{a}^T), \\ S^S(H,A,a) =&HA(a-\tilde{a}^S).\end{aligned}$$

Using the above in the job creation condition gives:

$$\frac{c_h}{\gamma\theta^{-\alpha}} = \beta(1-\eta)(1-\tau_h)HA\int_{\tilde{a}^T}^{\infty}(a-\tilde{a}^T)dG(a).$$

Taking derivative of the above job creation with respect to η yields:

$$\frac{\partial\theta}{\partial\eta} = \frac{-\theta}{\alpha(1-\eta)} - \frac{\gamma\theta^{1-\alpha}}{c_h\alpha}\beta(1-\eta)(1-\tau_h)HA(1-G(\tilde{a}^T))\frac{\partial\tilde{a}^T}{\partial\eta}.$$

Making an analogous substitutions and taking derivative of the job destruction condition for trainees with respect to η yields:

$$
\begin{aligned}
&(1-\tau_h)HA\left(1-\beta(1-\phi_h)(1-\delta)(1-G(\tilde{a}^T))\right)\frac{\partial \tilde{a}^T}{\partial \eta} = \\
&\frac{1}{1-\eta}\left(\frac{c_h\theta}{1-\eta}+\eta c_h\frac{\partial\theta}{\partial\eta}\right)+\beta(1-\delta)\phi_h HA(1-G(\tilde{a}^S))\frac{\partial \tilde{a}^S}{\partial \eta}.
\end{aligned}
$$

Making an analogous substitutions and taking derivative of the job destruction condition for skilled workers with respect to η yields:

$$
HA\left(1-\beta(1-\delta)(1-G(\tilde{a}^S))\right)\frac{\partial \tilde{a}^S}{\partial \eta} = \frac{1}{1-\eta}\left(\frac{c_h\theta}{1-\eta}+\eta c_h\frac{\partial\theta}{\partial\eta}\right).
$$

Combining the above and rearranging gives:

$$
\begin{aligned}
\frac{\partial \tilde{a}^T}{\partial \eta} &= \frac{c_h\theta}{(1-\eta)^2}\left(\frac{\alpha-\eta}{\alpha}\right)\frac{\Theta}{\Delta}, \\
\frac{\partial \tilde{a}^S}{\partial \eta} &= \frac{c_h\theta}{(1-\eta)^2}\left(\frac{\alpha-\eta}{\alpha}\right)\frac{\Psi}{\Delta},
\end{aligned}
$$

where:

$$
\begin{aligned}
\Theta &\equiv \frac{1-\beta(1-\phi_h)(1-\delta)(1-G(\tilde{a}^S))}{1-\beta(1-\delta)(1-G(\tilde{a}^S))}, \\
\Psi &\equiv \frac{(1-\tau_h)\left(1-\beta(1-\phi_h)(1-\delta)(1-G(\tilde{a}^T))\right)}{1-\beta(1-\delta)(1-G(\tilde{a}^S))}, \\
\Delta &\equiv (1-\tau_h)HA\Big\{\left(1-\beta(1-\phi_h)(1-\delta)(1-G(\tilde{a}^T))\right) \\
&\quad + \frac{\gamma\theta^{1-\alpha}}{\alpha}\eta\beta(1-G(\tilde{a}^T))\Theta\Big\}.
\end{aligned}
$$

Note that Δ, Θ and Ψ are all positive. Hence $\frac{\partial \tilde{a}^S}{\partial \eta}$ and $\frac{\partial \tilde{a}^T}{\partial \eta}$ reach their maximum when $\eta = \alpha$.

As we move away from the Hosios efficiency condition, we have:

$$
\frac{\partial \tilde{a}^T}{\partial \eta} = \frac{\partial \tilde{a}^S}{\partial \eta}\frac{1-\beta(1-\phi_h)(1-\delta)(1-G(\tilde{a}^S))}{(1-\tau_h)\left(1-\beta(1-\phi_h)(1-\delta)(1-G(\tilde{a}^T))\right)}.
$$

Thus, whether search externalities impose greater inefficiencies on job destruction of jobs with trainees or jobs with skilled workers depends on parameter values.

Worker's bargaining power and job destruction - numerical results

Figure C.7 illustrates how different values of bargaining power affect both job destruction margins under our baseline calibration. Note that in this numerical exercise we allow for aggregate productivity shocks and some persistence in idiosyncratic productivity shocks.

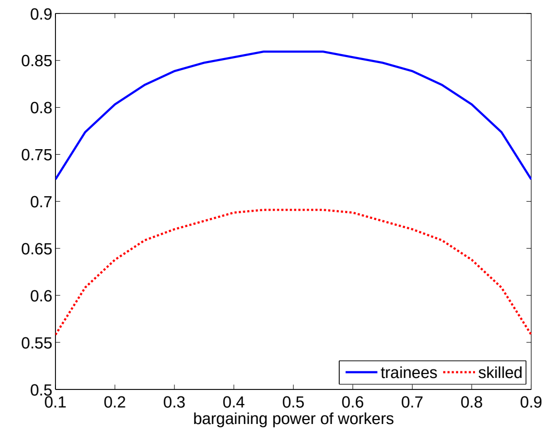


Figure C.7: The effects of workers' bargaining power on reservation productivities

Notes: Results from solving the model for different values of workers' bargaining power, keeping the rest of parameters constant at the aggregate level.

C.3.2 Computational Strategy

In order to solve the model numerically, we discretize the state space. In particular, the aggregate shock A is approximated with a Markov chain of 11 equally spaced gridpoints, whereas the idiosyncratic shock a is approximated by a discrete lognormal distribution with its support having 700 equally spaced gridpoints. We truncate the lognormal distribution at 0.01 percent and 99.99 percent and then normalize probabilities so that they sum up to one. The solution algorithm consists of value function iteration until convergence. The final model's solution consists of equilibrium labor market tightness $\theta(H, A)$ and reservation productivities $\tilde{a}^T(H, A)$ and $\tilde{a}^S(H, A)$. This solution is then used to simulate the model.

C.4 Sensitivity Analysis of the Quantitative Results

Here we provide the sensitivity analysis of our main quantitative results from Section 3.5 of the paper where differences in unemployment dynamics by education are explained by differences in on-the-job training. We perform two types of robustness checks for our quantitative results. First, we explore the role of parameter for the flow value when being unemployed, both regarding its overall level and differences across education groups. Second, we consider different specification for the flow vacancy posting costs. Simulations results for all robustness checks are summarized in Table C.2.

C.4.1 Value of Being Unemployed

Value of being unemployed - overall level

Here we set $b = 0.71$ as in Hall and Milgrom (2008) and Pissarides (2009). Consistent with our calibration procedure we adjust the matching efficiency parameter to $\gamma = 0.33$ in order to target the average job finding rate and we adjust the standard deviation of idiosyncratic productivity shocks to $\sigma_a = 0.385$ in order to hit the average separation rate. The rest of the numerical exercise follows the same steps as in Section 3.5, including the same parameter values for on-the-job training by education. The simulation results are provided in Panel B of Table C.2 and are to be compared with results in Table 3.7. Note that with $b = 0.71$ our results remain basically unchanged with respect to our baseline calibration. The unemployment ratio between high school dropouts and college graduates was 3.4 under our baseline calibration, whereas with $b = 0.71$ it is 3.2 (to be compared with 3.5 in the data). The only noticeable difference concerns the volatility results. In particular, now the aggregate volatilities of labor market variables are lower by half – the unemployment volatility puzzle becomes more evident and this is also the only reason that we chose a somewhat higher b in our baseline calibration. Nevertheless, also with $b = 0.71$ the relative differences in volatilities across education groups remain present; the unemployment volatility ratio between high school dropouts and college graduates was 3.7 under our baseline calibration, whereas now it is 3.2, the same as in the data.[2]

[2]The detailed simulation results on volatilities are available from authors upon request.

Table C.2: Sensitivity analysis of the main quantitative results - means (in percent)

	Parameters			u	f	s
Panel A: U.S. data, 1976 - 2010						
Less than high school				8.96	46.85	4.45
High school				5.45	45.02	2.48
Some college				4.44	46.34	2.05
College degree				2.56	42.80	1.09
Panel B: Value of being unemployed – level						
	$1/\phi_h$	τ_h	b			
Less than high school	2.35	0.163	0.71	7.26	45.32	3.52
High school	2.78	0.181	0.71	5.89	45.06	2.80
Some college	3.67	0.227	0.71	2.98	45.51	1.38
College degree	4.19	0.240	0.71	2.27	45.75	1.06
Panel C: Constant value of being unemployed						
	$1/\phi_h$	τ_h	b_h			
Less than high school	2.35	0.163	0.82	39.98	17.29	10.98
High school	2.78	0.181	0.82	12.16	34.24	4.52
Some college	3.67	0.227	0.82	1.91	54.79	1.05
College degree	4.19	0.240	0.82	0.98	80.05	0.79
Panel D: Actual vacancy posting costs						
	$1/\phi_h$	τ_h	c_h			
Less than high school	2.35	0.163	0.090	7.67	45.89	3.73
High school	2.78	0.181	0.104	5.93	44.77	2.74
Some college	3.67	0.227	0.121	2.87	44.12	1.27
College degree	4.19	0.240	0.128	2.47	46.60	1.15
Panel E: Constant vacancy posting costs						
	$1/\phi_h$	τ_h	c_h			
Less than high school	2.35	0.163	0.106	6.79	43.69	3.11
High school	2.78	0.181	0.106	5.67	44.82	2.63
Some college	3.67	0.227	0.106	3.12	46.19	1.45
College degree	4.19	0.240	0.106	2.76	49.12	1.35
Panel F: Vacancy posting costs – level						
	$1/\phi_h$	τ_h	c_h			
Less than high school	2.35	0.163	0.212	7.79	45.67	3.78
High school	2.78	0.181	0.212	6.14	45.37	2.89
Some college	3.67	0.227	0.212	2.99	45.13	1.35
College degree	4.19	0.240	0.212	2.34	45.32	1.06

Notes: Data moments are quarterly averages of monthly seasonally-adjusted data constructed from CPS microdata. The sample period is 1976:01 - 2010:12. Statistics for the model are means across 100 simulations.

Constant value of being unemployed across education groups

Below we present a robustness check when we deviate from the proportionality assumption and we keep b_h constant at 0.82 for all four education groups. As the result of Proposition 1 does not apply anymore, we need to parameterize differences in the market labor productivity across education groups, H. We do so by taking advantage of the 1982 EOPP data, which contain information on hourly wage. Hourly wage data allow us to impute productivity differences H, which are reported in Table C.3. The parametrized productivity differences are broadly in line with estimates obtained by the literature on returns to schooling.[3] After simulating the model, we can express the flow value of being unemployed relative to the effective productivity. The obtained values for the effective flow value of being unemployed are 88.7 percent for high school dropouts, 85.0 percent for high school graduates, 77.2 percent for people with some college, and 61.2 percent for college graduates. In short, the size of match surplus is now increasing with education.

Table C.3: Productivity (H) by education

	Hourly Wage	Implied Productivity H
Less than high school	5.60	0.84
High school	6.21	0.93
Some college	7.07	1.06
College degree	8.96	1.35
All individuals	6.65	1

Notes: Productivity differences, H, are imputed from the hourly wage data in the 1982 EOPP survey. We normalize the average productivity in the economy to 1.

Panel C of Table C.2 presents the simulation results. In particular, we solve and simulate the model for each education group, by using the corresponding training parameters (ϕ_h and τ_h), the constant flow value of being unemployed ($b_h = 0.82$) and productivity parameters (H) for each education group, while keeping the rest of parameters constant at the aggregate level. It turns out that when we deviate from the proportionality assumption $b_h = bH$, the model yields highly counterfactual predictions. In particular, the job finding rate for college graduates is now more than four times higher than the one for high school

[3] In a search and matching model, the wage depends on productivity, hiring costs and the value of being unemployed, with weights determined by the worker's bargaining power – c.f. the wage equation (3.12). The imputation procedure adopted here is thus likely to understate the true differences in productivity to the extent that hiring costs and the value of being unemployed are not proportional to productivity.

dropouts, whereas in the data they are practically identical. Additionally, the simulation results for college graduates suffer from extreme unemployment volatility puzzle, as their unemployment rate remains virtually constant over the business cycle.[4] The simulation results with constant absolute flow value of being unemployed also severely overpredict differences in unemployment and separation rates across education groups.

C.4.2 Vacancy Posting Costs

Next, we examine the quantitative implications of the model when considering different assumptions regarding the vacancy costs. In particular, three robustness exercises will be carried out. The first one considers the actual data from the 1982 EOPP survey to infer the vacancy posting cost for each education group. The second exercise considers the same absolute value of vacancy posting costs for all education groups. In the last exercise we double the vacancy posting cost used in our baseline calibration.

Actual vacancy posting costs from the 1982 EOPP survey

The 1982 EOPP data contain evidence on vacancy duration and recruitment costs. Table C.4 summarizes these data across education groups.[5] The column denoted "c" presents vacancy posting costs expressed in terms of output for each corresponding education group. As it can be seen, the vacancy posting costs across education groups remain close to the aggregate level, which is consistent with our assumption $c_h = cH$. The calculated vacancy posting costs exhibit very little variation across education groups due to two counteracting effects in the data. On the one hand, recruitment costs in terms of hours spent are indeed much higher for more educated workers. On the other hand, the 1982 EOPP data also show higher vacancy duration for more educated workers. Note that the latter observation is inconsistent with the empirical evidence of similar job finding rates across education groups, under the assumption of identical matching efficiency across groups. However, longer vacancy duration for more educated workers might not be due to lower vacancy meeting probability, but might simply reflect that the recruitment process itself is longer for this group of workers, perhaps for administrative reasons. In this respect, van Ours and Ridder (1993) provide evidence that the vacancy duration consists of an application period, during which applicants arrive,

[4] The detailed simulation results on volatilities are available from authors upon request.

[5] As before, we restrict the sample to individuals with 25 years of age and older, for whom we have information on education. Because of positive skewness, the vacancy duration and the hours spent distributions are truncated at their 99th percentiles, which correspond to 6 months and 100 hours, respectively.

and a selection period, during which a new employee is chosen from the pool of applicants. They conclude that the mean selection period increases with the required level of education, while required education has no effect on the applicant arrival rate. The applicant arrival rate is arguably the empirical counterpart for the vacancy meeting probability of a theoretical search model. Finally note that in the calibration of search and matching models, vacancy duration is merely a normalization, as its changes can be undone by adjusting the flow vacancy posting cost and matching efficiency.[6]

Table C.4: Vacancy posting cost by education level from the 1982 EOPP survey

	Vacancy duration (in days)	Recruitment costs (in hours)	c	Wage	H	$c_h = cH$
Less than high school	12.2	7.8	0.107	5.60	0.84	0.090
High school	14.2	9.4	0.111	6.21	0.93	0.104
Some college	20.2	13.9	0.114	7.07	1.06	0.121
College degree	33.8	19.3	0.095	8.96	1.35	0.128
All individuals	17.8	11.3	0.106	6.65	1	0.106

Since some differences in flow vacancy posting costs are present across education groups, we use the exact information on these costs to parameterize our model as a robustnesses check. In order to do that, we express all flow vacancy posting costs in terms of aggregate output and again parameterize differences in productivity across education groups. The column denoted "Wage" corresponds to the 1982 EOPP hourly wage, from which we impute productivity differences H. The last column of Table C.4 gives us the parameter values to use in the simulations for each education group. We solve and simulate the model for each education group, by using the corresponding training parameters (ϕ_h and τ_h), actual vacancy posting cost (c_h) and productivity parameters (H) for each education group, while keeping the rest of parameters constant at the aggregate level.[7] Panel D of Table C.2 reports the simulation results and, as we can see, they do not differ much from our simulation results in Section 3.5. Therefore, our simulation results are robust when considering the actual vacancy posting costs from the 1982 EOPP survey.

Constant vacancy posting costs across education groups

Panel E of Table C.2 reports simulation results when we set $c_h = 0.106$ for all four education groups, hence deviating from the assumption of proportionality in vacancy posting costs. We solve and simulate the model for each education group,

[6] See Costain and Reiter (2008).

[7] We would obtain the same numerical results by using c, the flow vacancy posting cost expressed in terms of output for each corresponding education group, and setting $H = 1$.

by using the corresponding training parameters (ϕ_h and τ_h), vacancy posting cost ($c_h = 0.106$) and productivity parameters (H) for each education group, while keeping the rest of parameters constant at the aggregate level. Note that this exercise presents an extreme case, in the sense that the vacancy posting cost is the same in absolute value across education groups, implying that in terms of output it is decreasing with education. The simulation results remain virtually unchanged, implying again that the parameterization of c is not crucial for our conclusions.

Doubling vacancy posting costs

In the last robustness exercise with respect to the vacancy posting cost we double the value used in our baseline calibration, increasing c from 0.106 to 0.212. Following the discussion of calibration strategy in the text (see Section 3.4), changing the vacancy posting cost affects the calibration of the matching efficiency in order to maintain a mean monthly job finding rate of 45.3 percent. Therefore, under the alternative calibration of $c = 0.212$, the efficiency parameter γ is set to 0.635. The rest of parameters remain unchanged at the aggregate level (see Table 3.5). Panel F of Table C.2 reports simulation results for all four education groups. Again, the simulation results remain consistent with the ones under our baseline calibration.

Overall, the simulation results for different specifications of the flow vacancy posting cost illustrate that our proportionality assumption $c_h = cH$ is not crucial for our conclusions.

C.4.3 Working-Age Population

Here we investigate if observed differences in training can also explain unemployment patterns across education groups, when we consider the whole working-age population (persons with 16 years of age and older). Two main reasons, why we focused our main analysis on persons with 25 years of age and older, are the following: first, by that age most individuals finish their formal schooling, and second, we avoid new labor market entrants who might exhibit different unemployment dynamics. However, such an approach also has a drawback, because high school dropouts have on average higher overall labor market experience as we disregard their initial labor market period by construction.

In order to proceed, we calibrate the training parameters using the 1982 EOPP survey, restricting the sample to individuals with 16 years and over. In particular, under the baseline calibration we parameterize the average duration of on-the-job training to 3.00 months ($13.0 \times (12/52)$), which yields the value for ϕ equal to $1/3.00$. Our parameterization of training costs for the aggregate economy is $\tau = 0.203$, which implies that trainees are on average 20.3 percent less productive than skilled workers. This is consistent with an average initial gap of 40.6 percent, which is then proportionally diminishing over time.

Following the calibration strategy in Section 3.4, we also need to adjust the efficiency parameter in the matching function (from 0.45 to 0.59) to target a mean monthly job finding rate of 53.9 percent, consistent with the CPS microevidence for people with 16 years of age and over. Moreover, we also need to adjust the standard deviation of the distribution of idiosyncratic productivity (from 0.249 to 0.237) in order that the simulated data generate mean monthly inflow rates to unemployment of 3.55 percent, consistent with the CPS microevidence for people with 16 years of age and over. The rest of parameters remain unchanged at the aggregate level (see Table 3.5).

As in Section 3.5, we first present baseline simulation results for the aggregate economy and then the model is solved and simulated for each education group. The last exercise is done by changing the parameters ϕ_h and τ_h related to on-the-job training for each group, while keeping the rest of parameters fixed.

Panel A of Table C.5 presents the actual data moments for the United States during 1976-2010 for people with 16 years of age and older, which can be compared with the simulation results for the aggregate economy presented in Panel B of the same Table C.5.

Table C.5: Labor market variables: data versus model

	y	n	u	f	s
Panel A: U.S. data, 1976 - 2010					
Mean	-	93.64	6.36	53.93	3.55
Absolute volatility	-	1.17	1.17	8.40	0.20
Relative volatility	1.78	1.26	17.34	16.92	5.56
Panel B: Baseline simulation results					
Mean	-	93.52	6.48	53.24	3.59
		(0.79)	(0.79)	(3.20)	(0.25)
Absolute volatility	-	0.99	0.99	3.95	0.31
		(0.27)	(0.27)	(0.63)	(0.07)
Relative volatility	1.78	1.06	14.61	7.56	8.52
	(0.28)	(0.31)	(2.63)	(1.40)	(1.48)

Notes: All data variables in Panel A are seasonally-adjusted. y is quarterly real average output per employed worker in the nonfarm business sector, provided by the BLS. The rest of variables are constructed from CPS microdata for individuals with 16 years of age and older, and are quarterly averages of monthly data. Statistics for the model in Panel B are means across 100 simulations, standard deviations across simulations are reported in parentheses. All means of rates are expressed in percentages.

Table C.6 reports simulation results on unemployment levels across education groups. As we can see, the observed variation in training received across education groups can explain most of the observed differences in separation rates and unemployment rates. In particular, the ratio of unemployment rates of the least educated group to the most educated group is 4.5 in the data and 4.0 in the model and the ratio of separation rates of the least educated group to the most educated group is 6.6 in the data and 4.5 in the model. Thus, the observed differences in training can also explain unemployment patterns across education groups for the whole working-age population.

Table C.6: Education, training and unemployment properties - means (in percent)

	Data			Parameters		Model		
	u	f	s	$1/\phi_h$	τ_h	u	f	s
Less than high school	12.58	59.75	8.36	2.16	0.172	9.72	54.48	5.75
						(0.82)	(2.60)	(0.25)
High school	6.72	50.13	3.46	2.83	0.196	6.98	54.05	3.95
						(0.73)	(2.83)	(0.23)
Some college	5.29	57.00	3.06	3.38	0.218	4.83	53.48	2.63
						(0.47)	(2.30)	(0.14)
College degree	2.80	45.91	1.27	4.25	0.254	2.43	53.27	1.29
						(0.28)	(3.22)	(0.07)

Notes: Data moments are quarterly averages of monthly seasonally-adjusted data constructed from CPS microdata for individuals with 16 years of age and over. The sample period is 1976:01 - 2010:12. Statistics for the model are means across 100 simulations, standard deviations across simulations are reported in parentheses.

Panel A of Table C.7 reports simulation results on absolute volatilities across education groups. As in Section 3.5, the model underpredicts the volatilities of the job finding rate and unemployment rates. However, the model can replicate remarkably well the relative differences in volatilities across education groups, even when considering the whole working-age population. In particular, the volatility of the unemployment rate for high school dropouts is 3.4 times higher than the corresponding volatility for college graduates, whereas the same ratio in the model also stands at 3.4. Something similar holds for volatilities of separation rates (the ratio is 4.0 in the data and 4.3 in the model), where the model can also account reasonably well for volatility levels. The model delivers also similar volatilities for the job finding rate across education groups, as in the data. Panel B of Table C.7 presents the simulation results for relative volatilities. Also here the results are broadly consistent with the ones from Section 3.5.

Overall, the simulation results for the whole working-age population are consistent with the ones for individuals with 25 years of age and older.

Table C.7: Working-age population - volatilities

	Data				Parameters		Model			
	n	u	f	s	$1/\phi_h$	τ_h	n	u	f	s
Panel A: Absolute volatilities										
Less than high school	1.97	1.97	8.61	0.48	2.16	0.172	1.18	1.18	3.79	0.37
							(0.27)	(0.27)	(0.69)	(0.08)
High school	1.40	1.40	8.13	0.26	2.83	0.196	0.99	0.99	3.85	0.32
							(0.29)	(0.29)	(0.67)	(0.08)
Some college	1.07	1.07	10.00	0.20	3.38	0.218	0.79	0.79	3.94	0.25
							(0.23)	(0.23)	(0.81)	(0.06)
College degree	0.58	0.58	8.80	0.12	4.25	0.254	0.35	0.35	4.00	0.09
							(0.12)	(0.12)	(0.73)	(0.03)
Panel B: Relative volatilities										
Less than high school	2.29	14.83	15.65	5.73	2.16	0.172	1.32	11.78	7.08	6.36
							(0.31)	(2.23)	(1.35)	(1.15)
High school	1.53	18.80	18.00	7.26	2.83	0.196	1.08	13.58	7.27	7.76
							(0.32)	(2.65)	(1.43)	(1.51)
Some college	1.14	19.08	18.52	6.63	3.38	0.218	0.83	15.35	7.51	9.06
							(0.25)	(3.33)	(1.65)	(1.89)
College degree	0.60	19.53	20.48	9.41	4.25	0.254	0.36	13.33	7.68	6.46
							(0.13)	(3.14)	(1.59)	(1.73)

Notes: Absolute volatilities are defined as standard deviations of the data expressed in deviations from an HP trend with smoothing parameter 10^5. Relative volatilities are defined analogously, except that all variables are initially expressed in natural logarithms. The sample period is 1976:01 - 2010:12, with all data being seasonally adjusted. Statistics for the model are means across 100 simulations, with standard deviations across simulations reported in parentheses.