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

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Abstract. This paper studies the observed slowdown 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 paper 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.

Keywords: employment, labor demand, on-the-job training, specific human capital, turnover
JEL Classification: E24, J23, J24, J63

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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 2 discusses the related literature. Section 3 provides the empirical evidence on which this paper builds. Section 4 develops the model. Then, Section 5 presents the parameterization of the model and the main simulations results, together with a discussion of the model's mechanism. Section 6 conducts a sensitivity analysis of the main quantitative results and Section 7 examines the cross-sectional implications of the model. A discussion of alternative explanations is contained in Section 8. Finally, Section 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 the Appendix.

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, 2013) and by the Longitudinal Employer-Household Dynamics (LEHD) data (Hyatt and McEntarfer, 2012). Additionally, Mukoyama and Şahin (2009) report a substantial increase in the average duration of unemployment relative to the unemployment rate, whereas Lazear and Spletzer (2012) 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, Cairó and Cajner (2013) argue 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.

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.

3.1. *Declining Business Employment Dynamics*

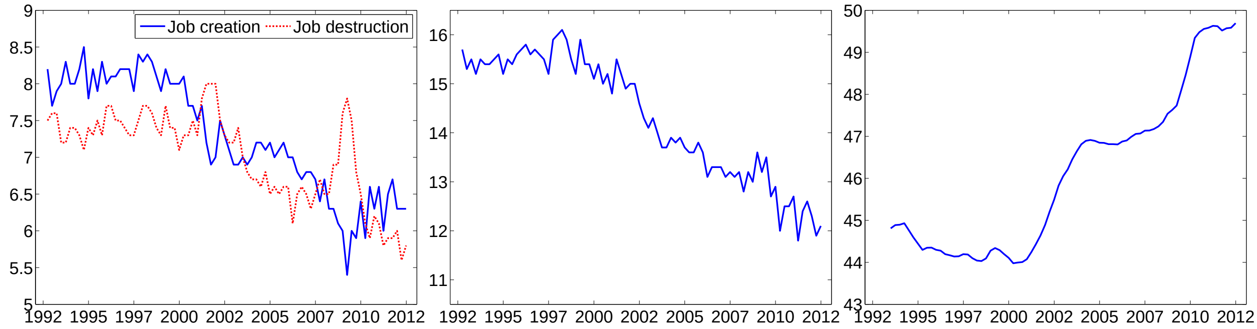
This section documents the evolution of job flows in the United States over time. Job flows measure the net change in employment at the establishment level, and they represent a central piece of information for understanding the dynamism of the labor market.

Figures 1a and 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 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 1a and 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]

[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/`.

[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



(A) Job flows (B) Job reallocation (C) Inaction rate

FIGURE 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 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 10 in Appendix B). 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 the Longitudinal Employer-Household Dynamics (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 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 11 in Appendix B). Similar results for the employment-weighted distribution

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.

[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.

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.

3.1.1. *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:

$$r_t = \sum_{i \in \Omega} z_{it} r_{it}, \tag{1}$$

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:

$$\Delta r_t = r_t - r_{t_0} = \sum_{i \in \Omega} \Delta z_{it} \overline{r_i} + \sum_{i \in \Omega} \Delta r_{it} \overline{z_i}, \tag{2}$$

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 (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) and (2) apply for the job creation and destruction rates. Table 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]

[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).

[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. 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.

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 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 12 in Appendix B).[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.

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.

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

[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.

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 2).

TABLE 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 B.3.2).

3.2.1. *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 3 presents the share of employment 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).

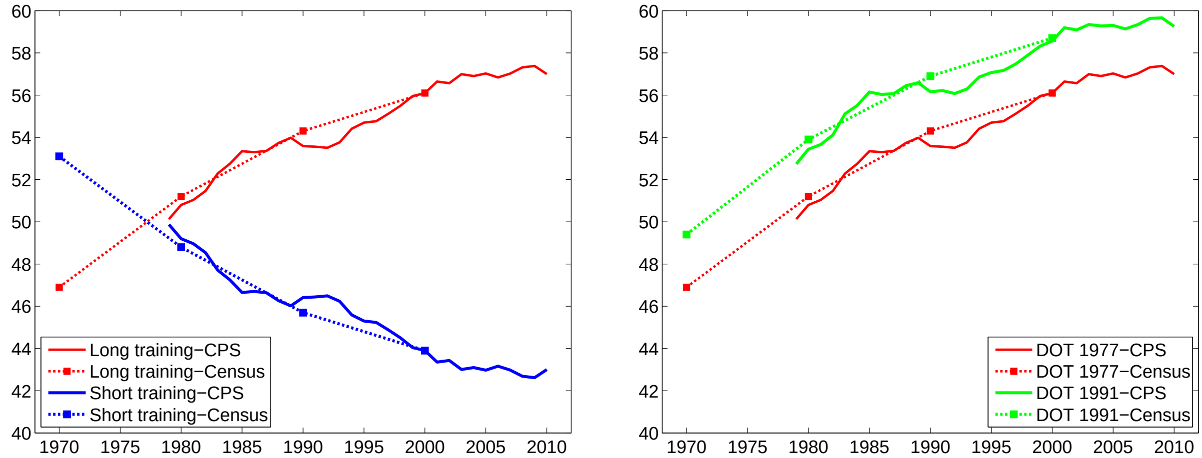
TABLE 3. Distribution of employment by level of SVP (DOT 1977, in %)

	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 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 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

[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.3 for further details.
[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.

degrees of training has steadily increased over the last years, from 46.9 percent in 1970 to 56.1 percent in 2010.[12]



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

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

FIGURE 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.

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 examine the changes in training requirements within occupations between 1977 and 1991. The results are presented in Figure 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

[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.

[13]Table 16 in the Appendix 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 3.

percent in 2010. Similar results are obtained when using full-time equivalent hours to weight the observations (see Appendix B.3.2).

Finally, Figure 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 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.

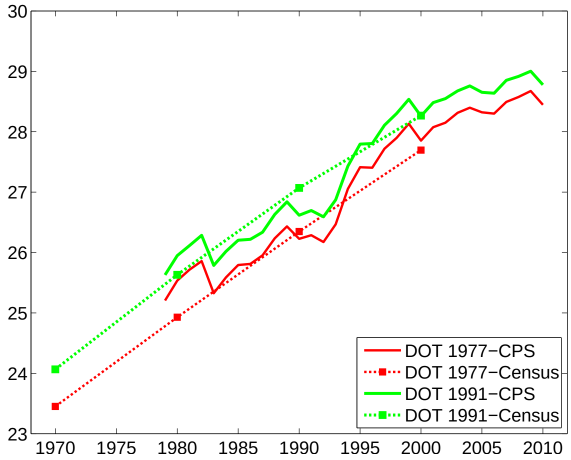


FIGURE 3. Average training times (in months)

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.

3.2.2. *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 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:

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

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

[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.

the change in the share of workers employed in long training occupations from period t to the base period t_0 into two terms:

$$\Delta\gamma_t = \gamma_t - \gamma_{t_0} = \sum_{i\in\Omega} \Delta n_{it}\overline{\gamma_i} + \sum_{i\in\Omega} \Delta\gamma_{it}\overline{n_i}, \tag{3}$$

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 (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 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.

Table 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.

3.2.3. *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 15 in the Appendix). This is consistent with the hypothesis suggested by this paper. Nevertheless, given that the cross-industry relationship can be confounded by omitted variables, I proceed to analyze whether

[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.

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:

$$\Delta r_{i,93-10} = \alpha + \beta_1 \Delta\gamma_{i,83-92} + \beta_2 \Delta\gamma_{i,93-10} + \epsilon_i, \tag{4}$$

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 5.

Table 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.

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 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.

[16]Similar results are obtained when considering as a dependent variable the change in the job creation and destruction rates. See Tables 19 and 20 in Appendix B.

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 6 presents the share of employment and the average level of SVP by major occupation group for the Census sample.[17]

Table 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 21 in the Appendix 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 4 shows that high school dropouts were the largest education group

[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.

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 Cairó and Cajner (2013) 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 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.

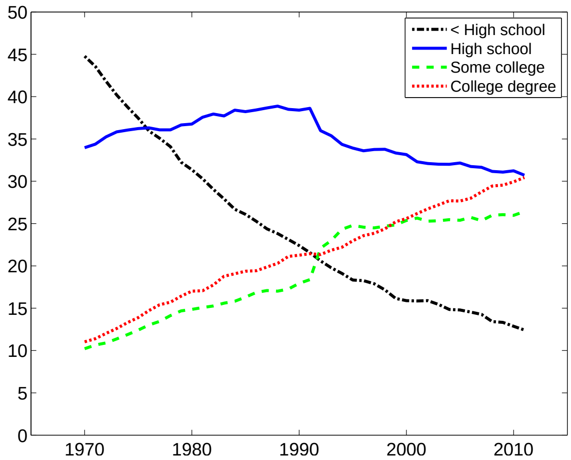


FIGURE 4. Structure of the U.S. population by educational attainment

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.

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 16 in the Appendix.

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]

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

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

[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 13 in the Appendix). 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.

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.

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 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.

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

[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.

maximizes its profits. In particular, the expected present discounted value of firm's profits can be characterized as:

$$\Pi(\chi, a, n_{-1}) = \max_{n,v} \left\{ \chi a n^{\phi} - w(\chi, a, n)n - \kappa_v v - \kappa_f \max\{0, \Delta n\} + \beta \mathbb{E}_a \{\Pi(\chi, a', n)\} \right\}, \quad (5)$$

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:

$$\Delta n = vq(\theta). \quad (6)$$

Additionally, if the firm is hiring, it will have to pay the training costs κ_f for each newly recently hired worker. Substituting equation (6) into equation (5) allows to rewrite the firm's problem as follows:

$$\begin{aligned} \Pi(\chi, a, n_{-1}) = \max_{n} \Big\{ \chi a n^{\phi} - w(\chi, a, n)n - \left(\frac{\kappa_v}{q(\theta)} + \kappa_f \right) \max\{0, \Delta n\} \\ + \beta \mathbb{E}_a \{\Pi(\chi, a', n)\} \Big\}. \end{aligned} \quad (7)$$

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:

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

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]

$$w(\chi, a, n) = \eta\left(\chi a \phi n^{\phi-1} - w_n(\chi, a, n)n + \beta\theta\kappa_v + \beta p(\theta)\kappa_f\right) + (1-\eta)b. \tag{8}$$

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 (8) yields:

$$w(\chi, a, n) = \eta\left(\frac{\chi a \phi n^{\phi-1}}{1-\eta(1-\phi)} + \beta\theta\kappa_v + \beta p(\theta)\kappa_f\right) + (1-\eta)b. \tag{9}$$

Plugging in the wage equation (9) into the firm's problem (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:

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

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

$$U(\theta) = L - N, \tag{10}$$

$$S = p(\theta)U(\theta). \tag{11}$$

Equation (10) is the definition of the level of unemployment, and equation (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 C.3 describes the computational strategy used to solve the model.

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

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.

5.1. *Calibration*

The parameter values used in order to calibrate the benchmark economy are summarized in Table 7.

Table 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

[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.

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 Cairó and Cajner (2013). 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 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 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.

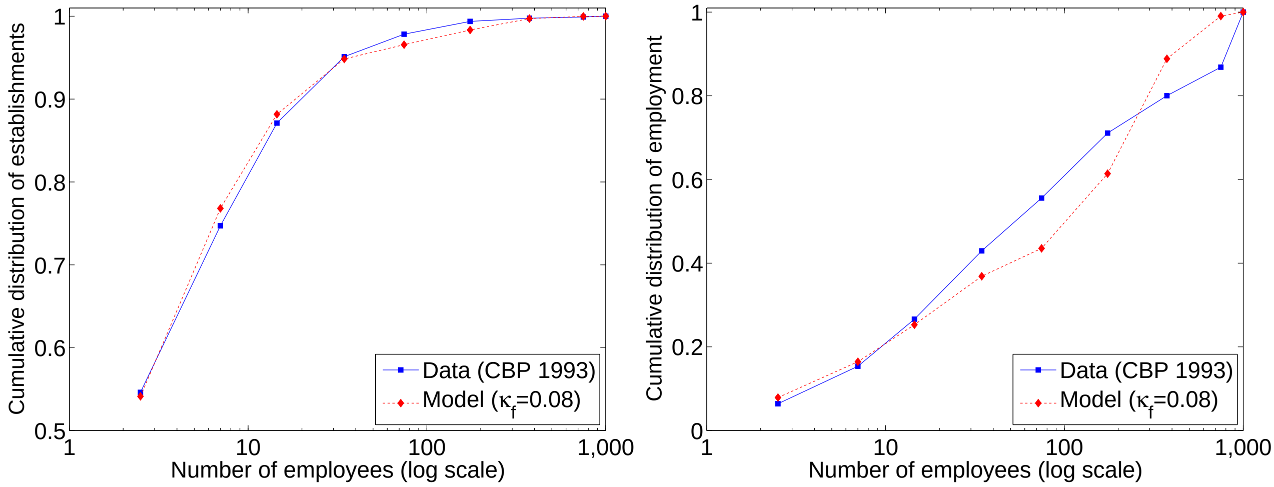
5.2. *Baseline Simulation Results*

I first solve the model parameterized at the benchmark calibration with training costs $\kappa_f = 0.08$. Figure 5 and Table 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 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

[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 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.

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.



(A) Number of establishments (B) Employment

FIGURE 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.

TABLE 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

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 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 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

Table 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

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 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 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 10. Employment change distribution – model vs. data

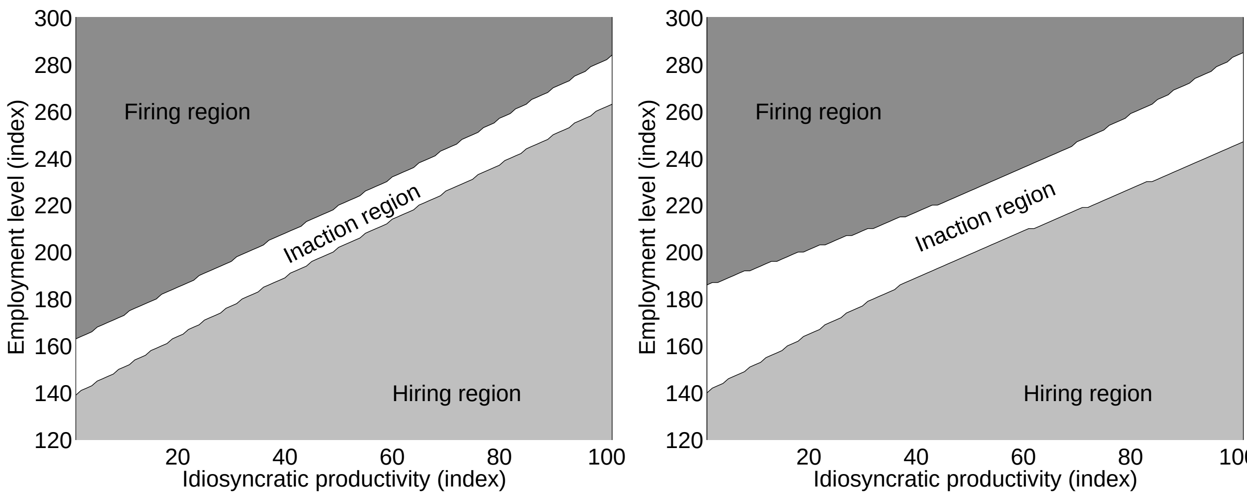
	Simulated statistics		*Data (BED)*	
	Training cost (κ_f)			
	0.08	0.15	1993	2011
Loss: 20+	1.1	0.9	0.8	0.5
Loss: 5-19	2.8	2.3	3.8	3.1
Loss: 1-4	22.7	20.2	22.0	21.3
No change	47.3	53.9	44.9	49.6
Gain: 1-4	22.2	19.6	23.3	21.5
Gain: 5-19	2.8	2.3	4.3	3.4
Gain: 20+	1.1	0.9	0.9	0.6

Summing up, the results presented in Tables 9 and 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 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 $\left(\frac{\kappa_v}{q(\theta)} + \kappa_f\right)$.

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 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 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 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 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 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.

[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 ($\kappa_f = 0.40$).

Finally, Figure 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 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.

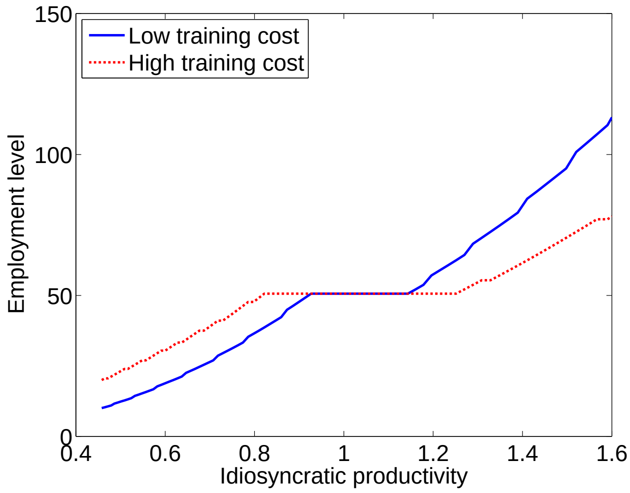


FIGURE 7. The optimal employment policy of the firm

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.

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 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 11 and 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 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 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 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

[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

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).

Table 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

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 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]

6. Sensitivity Analysis of the Baseline Simulation Results

This section provides a sensitivity analysis of the main quantitative results presented in Section 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 13.

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.

[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 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

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 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 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 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.

6.2. *Structure of training costs*

In the model presented in Section 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

[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 7.

[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.

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

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.

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

[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 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 for the baseline simulation results.

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 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 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 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

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

[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).

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

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 14, 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.

7.3. *Job flows by firm size*

In this section I consider an extension of the model presented in Section 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 5.1.[41] Figure 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 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 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

[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 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.

employment are constant and the model does not feature significant differences in job flow rates across firm sizes.

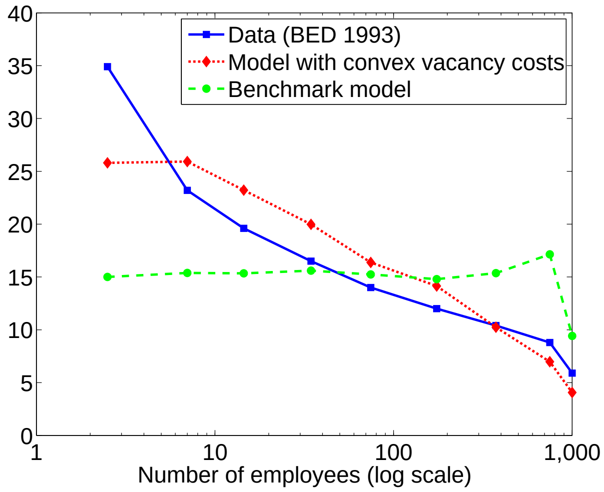
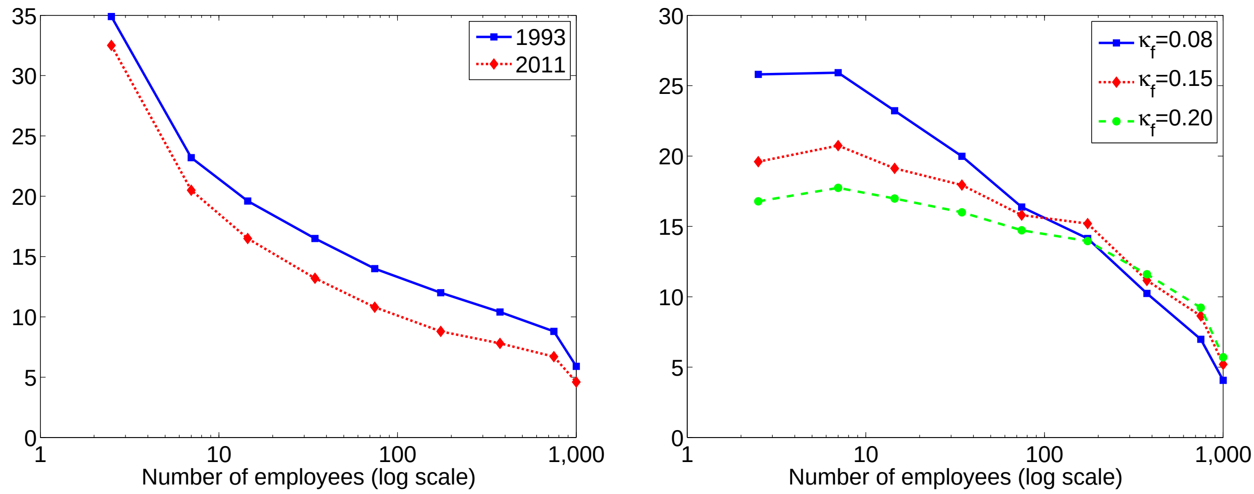


FIGURE 8. Job reallocation rate by firm size

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 22 in the Appendix). More interestingly, Figure 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 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.

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 4 to analyze the macroeconomic implications of lower dispersion of idiosyncratic productivity shocks. More precisely, column 2 in Table 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 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).

Comparing columns 1 and 2 of Table 15, a decline in the dispersion of shocks generates a decline in job turnover rates, an increase in inaction and a more compressed employment

TABLE 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

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

[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.

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 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.

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

[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.

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.

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Appendix A. Data Description

A.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 3.2.1 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.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.[45]

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).[46] 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.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

[45]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.

[46]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.

the intensive margin analysis I examine changes in training requirements within occupations matched between the 1977 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.4. *Computing Training Requirements by Industry*

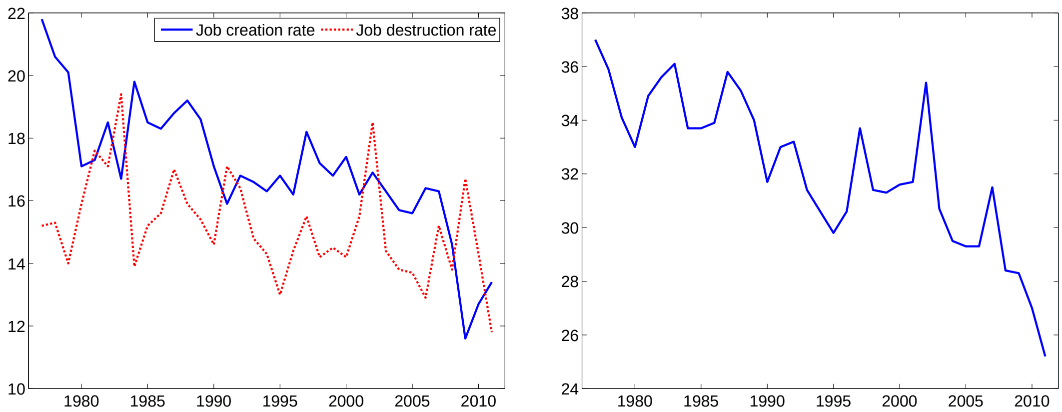
To compute training requirements by industry, I first assign an SVP mean by occupation and gender to each employed individual in the Census and the CPS MORG samples. Then, I aggregate the observations to the level of consistent Census Industry Codes (CIC) and I compute the share of workers employed in 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 3.2.2, 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.

Appendix B. Supplementary Empirical Evidence

B.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 (LBD), a confidential database available only to qualified researchers through secure Census Bureau Research Data Centers.



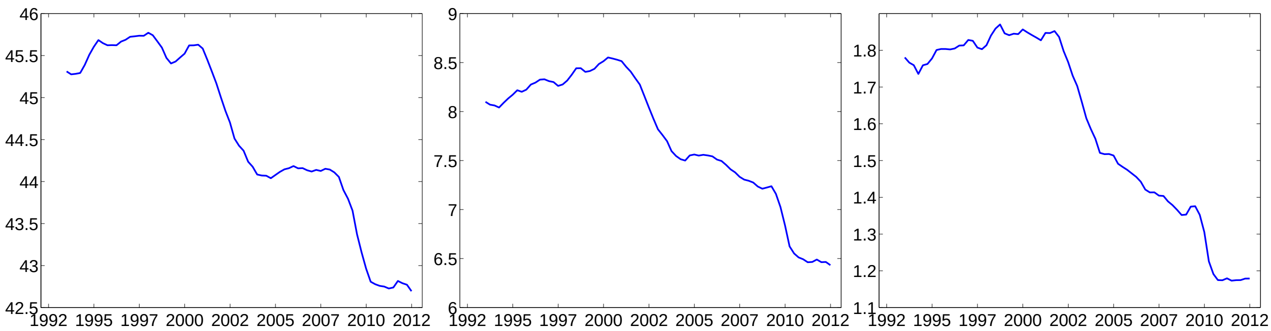
(A) Job flows (B) Job reallocation rate

Figure 10

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

B.2. *Business Employment Dynamics*

B.2.1. *Employment change distribution*

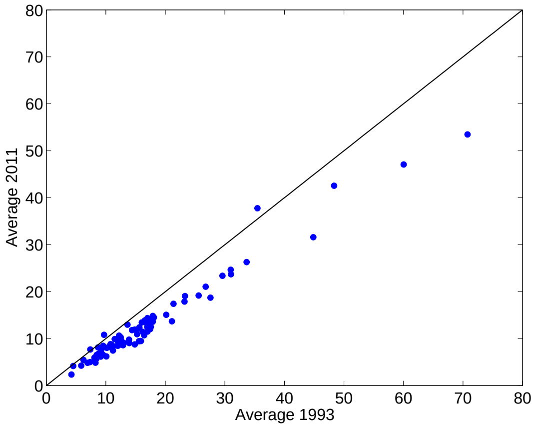


(A) Size of change 1-4 jobs (B) Size of change 5-19 jobs (C) Size of change 20+ jobs

Figure 11. Employment change distribution (in percentage)

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

B.2.2. *Job Reallocation and Inaction Rates Across Industries and Over Time*



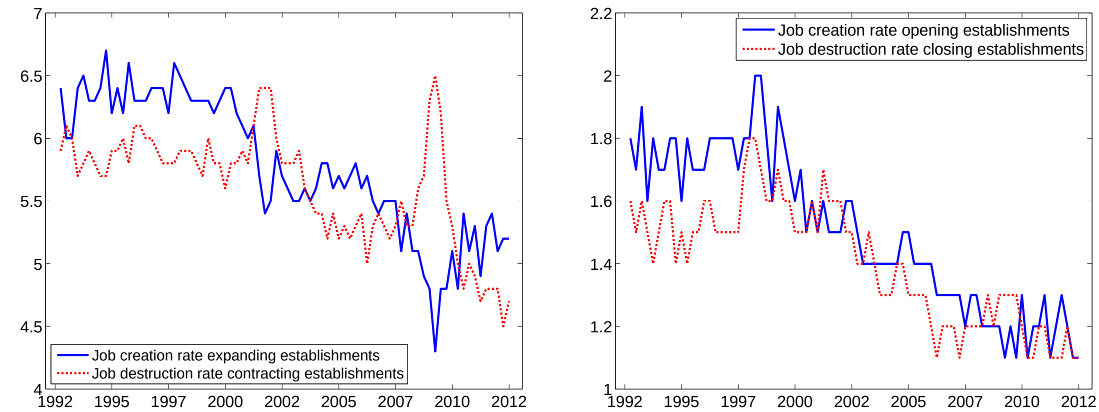
(A) Job reallocation rate (B) Inaction rate

FIGURE 12

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.

B.2.3. *Job flows: Continuing establishments vs. Openings and Closings*

Figure 13a shows evidence on job flow rates by continuing establishments, while Figure 13b 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 13. Job flows

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

B.3. *The Importance of Training Over Time*

In this section I present supplemental empirical evidence, that complements the discussion in Section 3.2.

B.3.1. *Aggregate trends in training requirements using DOT 1991*

Table 16 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 3. In particular, there is a shift of employment from occupations requiring low amounts of training to occupations requiring high amounts of training.

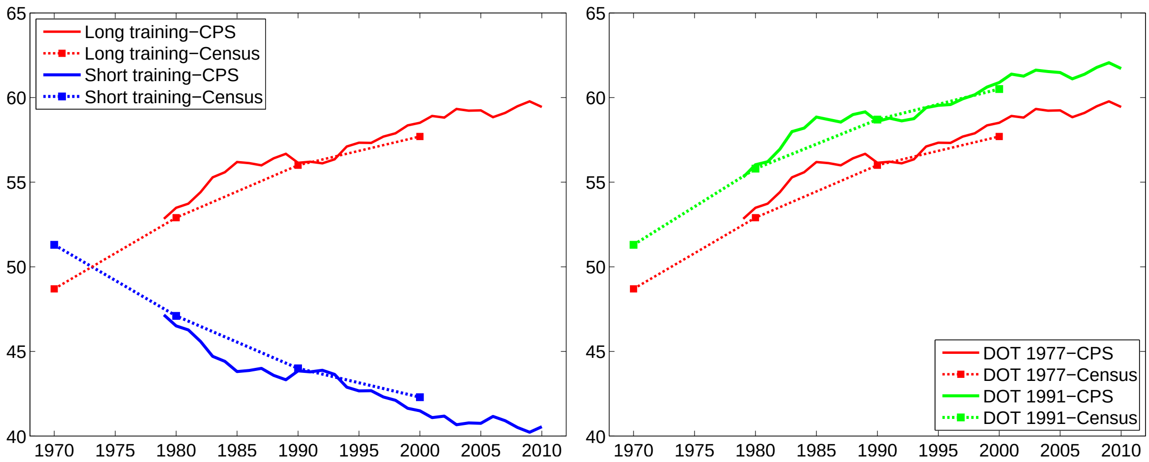
Table 16. Distribution of employment by level of SVP (DOT 1991, in %)

	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**

B.3.2. *Robustness regarding the weights used in the analysis*

This section performs a robustness exercise of Section 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 14 and Tables 17 and 18 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 14

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 17. Distribution of employment by level of SVP using FTE as weights (DOT 1977, in %)

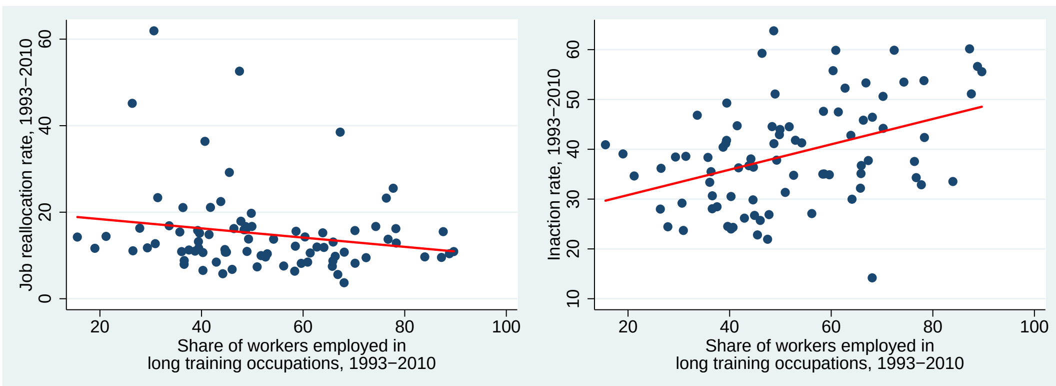
	1	2	3	4	5	6	7	8
Panel A: Census								
1970	0.2	7.7	18.8	11.2	13.4	13.2	21.6	13.9
1980	0.2	7.0	17.6	9.6	12.8	14.0	24.6	14.3
1990	0.2	6.8	16.4	8.4	12.3	14.2	26.7	15.1
2000	0.3	5.5	15.7	8.6	12.2	13.5	27.7	16.5
Diff. 1970–2000	**0.1**	**-2.2**	**-3.1**	**-2.7**	**-1.1**	**0.3**	**6.1**	**2.7**
Panel B: 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 18. 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**

B.3.3. *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 15 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 15. Job flows and training requirements by industry, averages 1993–2010

Second, Tables 19 and 20 show the results of running similar regressions to (4) for the job creation and destruction rate, respectively.

Table 19. 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 20. 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

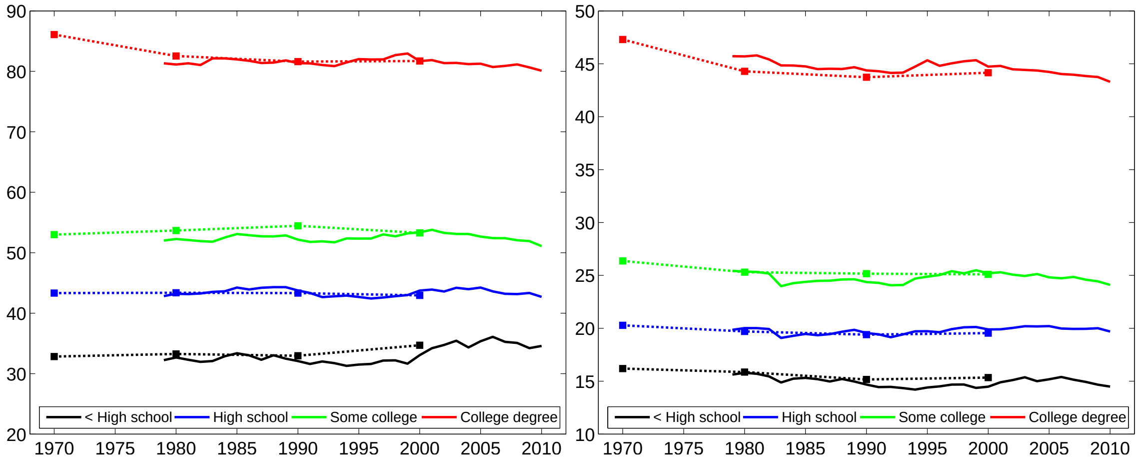
Notes: Dependent variable: Difference in the job destruction rate between 1993 and 2010. Robust standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

B.4. *Additional Aggregate Trends Related to the Importance of Training*

In this section I present supplemental empirical evidence, that complements the discussion in Section 3.3.

Table 21. 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 16. 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.

Appendix C. 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.

C.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 (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 (12) and (13) below.

$$\chi a\phi(\tilde{n}^F)^{\phi-1} - w(\chi,a,\tilde{n}^F) - w_n(\chi,a,\tilde{n}^F)\tilde{n}^F + \beta\mathbb{E}_a\left\{\Pi_n(\chi,a',\tilde{n}^F)\right\} = 0, \tag{12}$$

$$\chi a\phi(\tilde{n}^H)^{\phi-1} - w(\chi,a,\tilde{n}^H) - w_n(\chi,a,\tilde{n}^H)\tilde{n}^H + \beta\mathbb{E}_a\left\{\Pi_n(\chi,a',\tilde{n}^H)\right\} = \left(\frac{\kappa_v}{q(\theta)} + \kappa_f\right). \tag{13}$$

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 (12) 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 (13) 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 $n = n_{-1}$.

C.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:

$$\begin{aligned} J(\chi, a, n) =& \chi a \phi n^{\phi-1} - w(\chi, a, n) - w_n(\chi, a, n)n + \beta \int_{\tilde{a}^F(\chi,n)}^{\tilde{a}^H(\chi,n)} J(\chi, a', n) dG(a'|a) \\ &+ \beta \int_{\tilde{a}^H(\chi,n)}^{\infty} \left(\frac{\kappa_v}{q(\theta)} + \kappa_f \right) dG(a'|a). \end{aligned} \tag{14}$$

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:

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

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 (12) 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 (13) 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:

$$\begin{aligned} W(\chi, a, n) =& w(\chi, a, n) + \beta U' + \beta \frac{\eta}{1-\eta} \int_{\tilde{a}^F(\chi,n)}^{\tilde{a}^H(\chi,n)} J(\chi, a', n) dG(a'|a) \\ &+ \beta \frac{\eta}{1-\eta} \int_{\tilde{a}^H(\chi,n)}^{\infty} \left(\frac{\kappa_v}{q(\theta)} + \kappa_f\right) dG(a'|a). \end{aligned} \tag{15}$$

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:

$$U = b + \beta U' + \beta p(\theta) \frac{\eta}{1-\eta}\left(\frac{\kappa_v}{q(\theta)} + \kappa_f\right). \tag{16}$$

Fourth, the surplus of a worker of being employed is obtained by subtracting equation (16) from (15):

$$\begin{aligned} W(\chi, a, n) - U =& w(\chi, a, n) - b - \beta p(\theta)\frac{\eta}{1-\eta}\left(\frac{\kappa_v}{q(\theta)} + \kappa_f\right) \\ &+ \beta \frac{\eta}{1-\eta} \int_{\tilde{a}^F(\chi,n)}^{\tilde{a}^H(\chi,n)} J(\chi, a', n) dG(a'|a) + \beta \frac{\eta}{1-\eta} \int_{\tilde{a}^H(\chi,n)}^{\infty} \left(\frac{\kappa_v}{q(\theta)} + \kappa_f\right) dG(a'|a). \end{aligned} \tag{17}$$

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 (17) and the surplus for the firm given by equation (14), the wage is equal to

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

C.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.

Appendix D. Supplementary Results of the Model

Table 22. 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