Essays on the Macroeconomics of Labor Markets

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TESI DOCTORAL UPF / ANY 2012

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To the memory of my grandparents who passed away during the course of my graduate studies

Acknowledgments

Several extremely rational economic agents made this thesis possible. First and foremost, I wish to express my deepest gratitude to my advisor Jordi Galí for his guidance, advice, and encouragement at all stages of this project. Special thanks also go to Thijs van Rens for countless discussions that greatly improved this thesis. Additionally, I benefited tremendously from insightful conversations with Vasco Carvalho.

For further comments on different parts of this thesis I thank Regis Barnichon, Andrea Caggese, Fabio Canova, Juan Carlos Conesa, Nir Jaimovich, Oleksiy Kryvtsov, Christian Merkl, Pascal Michaillat, Kristoffer Nimark, Eran Yashiv, and participants of the CREI Macroeconomics Breakfast, the Macro Workshop at the UAB, the XV Workshop on Dynamic Macroeconomics in Vigo, the XXth Aix-Marseille Doctoral Spring School in Aix-en-Provence, the 2011 SED Annual Meeting in Ghent, the 2011 EEA Annual Congress in Oslo, the 13th IZA/CEPR European Summer Symposium in Labour Economics in Buch am Ammersee, and the 2011 SAEe in Málaga. I also thank seminar participants at the IIES, IESE, the ECB, the Bank of Canada, the Federal Reserve Board, and the Bank of Spain. Finally, I would like to thank my co-author, Jan Grobovšek, for his collaboration on a chapter of this thesis.

I am grateful to Laura Agustí, Marta Araque, Mariona Novoa, and Carolina Rojas for their patience and help with all the bureaucratic burdens. I am also indebted to the Generalitat de Catalunya and the European Social Fund for their financial support, without which this thesis would not have been feasible. Furthermore, I would like to thank Catalunya for being my country over the past – and hopefully not the last – six years.

Finally, I wish to thank my family and my extended Catalan family for their love and unconditional support. Last but certainly not the least, I would like to thank Isabel, for being much more than a co-author. Gràcies per estar aquí, per ajudar-me a començar cada dia amb il·lusió i per fer que aquest camí hagi estat tan especial.

Abstract

This thesis investigates several macroeconomic aspects of labor markets. First chapter finds that in the US more educated individuals experience lower and less volatile unemployment due to a lower hazard rate of losing a job. A theoretical model with initial on-the-job training illustrates that accumulation of match-specific human capital can explain this empirical pattern. Second chapter develops a theoretical model with state-dependent wage setting. The model predicts that higher wage bargaining costs lead to higher and more volatile unemployment, consistent with some cross-country empirical evidence. Third chapter proposes a method to indirectly measure job-embodied technical change by using data on job tenure. The results show that job-embodied technical change has increased substantially since the mid-nineties.

Resum

Aquesta tesi investiga diversos aspectes dels mercats de treball. El primer capítol troba que, als Estats Units, els individus amb un nivell d'educació més elevat experimenten un nivell de desocupació més baix i menys volàtil, degut a una menor probabilitat de perdre el lloc de treball. Un model teòric que incorpora formació inicial al lloc de treball il·lustra que l'acumulació de capital humà específic pot explicar aquesta regularitat empírica. El segon capítol desenvolupa un model teòric amb un mecanisme de fixació de salaris que depèn de l'estat de l'economia. El model prediu que uns costos de negociació salarial més elevats comporten un nivell de desocupació més elevat i més volàtil, de forma consistent amb l'evidència empírica entre països. El tercer capítol proposa un mètode per mesurar, de forma indirecta, el canvi tecnològic incorporat als llocs de treball, mitjançant l'ús de dades sobre l'antiguitat al lloc de treball. Els resultats mostren que el canvi tecnològic incorporat als llocs de treball ha augmentat considerablement des de mitjans dels anys noranta.

Foreword

This thesis is concerned with the macroeconomics analysis of labor markets. It is mostly set within the search and matching paradigm, which by now constitutes one of the three standard frameworks in modern macroeconomic theory. The thesis contains three largely self-contained chapters.

Chapter 1, "Human Capital and Unemployment Dynamics", is a joint work with Isabel Cairó. This chapter addresses the question why more educated workers experience lower unemployment rates and lower employment volatility. A closer look at the US data reveals that these workers have similar job finding rates, but much lower and less volatile separation rates than their less educated colleagues. We argue that on-the-job training, being complementary to formal education, is the reason for this pattern. Using a search and matching model with endogenous separations and initial on-the-job training, we show that investments in match-specific human capital reduce the outside option of workers, implying less incentives to separate and thus longer job spells. The model is calibrated by taking advantage of detailed micro evidence on training by education group. The simulation results reveal that, given the observed differences in training, the model is able to explain the empirical regularities across education groups on job finding rates, separation rates and unemployment rates, both in their first and second moments. We also quantitatively evaluate alternative explanations for differences in unemployment dynamics by education and use empirical evidence in order to discriminate among them. According to our findings, none of the economic mechanisms behind the competing explanations is likely to generate unemployment dynamics by education that we observe in the data.

Chapter 2, "Labor Market Frictions and Bargaining Costs", develops a search and matching model with endogenous separations and costly wage bargaining. In particular, I introduce into an otherwise standard model a fixed wage bargaining cost, which endogenously generates infrequent wage adjustments, but nevertheless leaves wages in new job matches perfectly flexible, consistent with some recent microeconometric evidence. The steady-state version of the model provides a theoretical link between wage bargaining institutions and the unemployment level, illustrating how higher wage bargaining costs lead to higher unemployment. The dynamic version of the model shows how unemployment volatility increases with wage bargaining costs, primarily due to enhanced volatility at the job destruction margin. The model can thus explain why job destruction plays a bigger role for unemployment fluctuations in Continental Europe than in the United States. Finally, the model can rationalize the empirical observation that many firms in recessions do not avoid layoffs by cutting pay.

Chapter 3, "Job-Embodied Growth and Decline of Job Tenure" (joint with Jan Grobovšek), argues that a fraction of the increase in aggregate productivity

is related to productivity growth embodied in new job vintages. We propose a model economy to measure indirectly the rate of job-embodied technical change by linking it to job tenure. We find that in the US, job-embodied technical change is an important component of aggregate growth, and that its growth rate must have significantly increased in the mid-nineties to match the concomitant sharp drop in job tenure over the last two decades. Our measure appears robust in the sense that it replicates the decline in job tenure in Europe over the same time period, which we do not target. We also show that labor market frictions present a larger obstacle to productivity growth the higher is the rate of job-embodied technical change, but that their quantitative impact is negligible and hence unlikely to explain the large productivity gap that has opened up between Europe and the US since the mid-nineties.

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Chapter 1

HUMAN CAPITAL AND UNEMPLOYMENT DYNAMICS
(written jointly with Isabel Cairó)

1.1 Introduction

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

More educated individuals fare much better in the labor market than their less educated colleagues. For example, when the U.S. aggregate unemployment rate hit 10 percent during the recent recession, high school dropouts suffered from unemployment rates close to 20 percent, whereas college graduates experienced unemployment rates of 5 percent only. As can be inferred from Figure 1.1, educational attainment seems to have been a good antidote to joblessness for the whole period of data availability. Moreover, the volatility of employment decreases with education as well. Indeed, enhanced job security arguably presents one of the main benefits of education. This paper sheds some light on why more educated people enjoy greater employment stability.

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

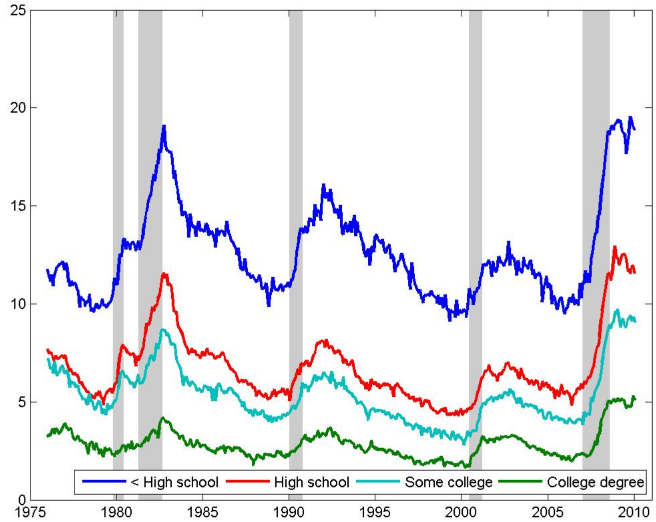

Figure 1.1: U.S. unemployment rates by educational attainment (16+ years of age)

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

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

We parameterize our model by using detailed micro evidence from the Employment Opportunity Pilot Project (EOPP) survey. In particular, our empirical measure of training for each education group is based on the duration of initial on-the-job training and the productivity gap between new hires and incumbents. The simulation results reveal that, given the observed differences in training, the model is able to explain the empirical regularities across education groups on job finding rates, separation rates and unemployment rates, both in their first and

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

second moments. This cross-sectional quantitative success of the model is quite remarkable, especially when compared to the well-documented difficulties of the canonical search and matching model to account for the main time-series properties of aggregate labor market data.

Two main alternative explanations for greater employment stability of more educated workers relate to greater job surplus and minimum-wage floors. First, if more educated workers engage in more profitable jobs that yield higher match surplus, for example due to their lower relative economic value of unemployment as assumed by Mortensen and Pissarides (1999), then a standard search and matching model will also predict lower separation and unemployment rates for the more educated. However, in this case firms will be willing to post more vacancies in the labor market segment for more educated workers, additionally leading to higher job finding rates for more educated workers, which is at odds with empirical evidence. Second, minimum wages are more likely to be binding for less educated workers, potentially explaining their higher unemployment rates. Nevertheless, the empirical research following Card and Krueger (1994) finds conflicting evidence on the effect of minimum wages on employment. If anything, the employment effects of minimum wages appear to be empirically modest.[2] In the paper, we also quantitatively evaluate the following possible explanations for differences in unemployment dynamics by education: i) differences in the size of match surplus ; ii) differences in hiring costs; iii) differences in frequency of idiosyncratic productivity shocks; iv) differences in dispersion of idiosyncratic productivity shocks; v) differences in matching efficiency. Since our model nests all these alternative explanations, we simulate the model under each of the hypotheses and then use empirical evidence in order to discriminate between them. According to our findings, none of the economic mechanisms behind the competing explanations is likely to generate unemployment dynamics by education that we observe in the data.

Search and matching models with worker heterogeneity include Albrecht and Vroman (2002), Gautier (2002), Pries (2008), Dolado et al. (2009), Krusell et al. (2010), and Gonzalez and Shi (2010). However, in these models the worker's exit to unemployment is assumed to be exogenous, hence they cannot be used to explain why unemployment inflow rates differ dramatically by education. Bils et al. (2009, 2011) allow for endogenous separations and heterogeneity in the rents from being employed, but as already discussed above, the latter assumption generates counterfactual predictions for unemployment dynamics by education. Nagypál (2007) investigates the decline in separation rate with job tenure.

[2] See, e.g., Dube et al. (2010) for some recent U.S. empirical evidence. Note also that some theoretical models, like the one by Burdett and Mortensen (1998), provide rationale for positive effects of minimum wages on employment.

Analyzing French data, she emphasizes learning about match quality, but also finds that learning-by-doing plays an important role during the first six months of an employment relationship, consistent with our story. The interaction between turnover and specificity of skills in a setting with search frictions and firing costs is also explored by Wasmer (2006), who argues that labor market institutions can affect investment decisions between general and specific human capital. Finally, Elsby and Shapiro (2012) study the interplay between the return to experience and labor supply in order to explain long-run trends in nonemployment by skill group.

Following this introduction, Section 1.2 provides some empirical evidence by education on unemployment, its inflows and outflows, and on-the-job training. Section 1.3 outlines the model, which is then calibrated in Section 1.4. Section 1.5 contains the main simulation results of the model and a discussion of the mechanism driving the results, while Section 1.6 explores other possible explanations for differences in unemployment dynamics by education. The main simulation results are presented for the population with 25 years of age and older. Section 1.7 shows that our conclusions remain unaffected when considering the whole working-age population and Section 1.8 conducts a further sensitivity analysis of the main quantitative results. Finally, Section 1.9 concludes with a discussion of possible avenues for further research. We provide data description, some further empirical checks, analytical proofs and additional robustness checks in the Appendix.

1.2 Empirical Evidence

This section documents the empirical evidence on which this paper builds. First, we investigate the reasons behind the observed differences in unemployment rates across education levels by decomposing them into unemployment inflows and outflows. Next, we calculate volatility measures for the main variables of interest. Finally, we summarize the existing evidence on on-the-job training and provide empirical measures of on-the-job training by education group from the EOPP survey.

1.2.1 Unemployment Rates

It is a well-known and documented empirical fact that unemployment rates differ across education levels (Figure 1.1). The jobless rate of the least educated (high school dropouts) is roughly four times greater than that of the most educated (college graduates), and this difference has been maintained since the data are available.[3]

Table 1.1: Unemployment rates by education level (in percent)

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

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

Table 1.1 further tabulates the unemployment rate across education groups controlling for several observable demographic characteristics. As it turns out, substantial unemployment differentials across education groups represent a robust empirical finding that cannot be explained by standard demographic controls (age, gender, race, marital status). This is confirmed by results from estimated regression equations, reported in Table 1.2. These results show that education remains an important predictor of the probability of being unemployed, even when controlling for individual characteristics, industries, occupations and time dummies.

Table 1.2: Unemployment and education

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

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

[3] We construct unemployment rates by education group from the Current Population Survey (CPS) microdata, which are available from 1976 onwards.

For the rest of the paper, we focus our analysis on individuals with 25 years of age and older for the following two reasons. First, by the age of 25 most individuals have presumably finished their studies, hence we avoid that our conclusions regarding unemployment properties for low educated workers would be driven by potentially differential labor market behavior of young people. Second, further empirical exploration of unemployment rates by age reveals that young people experience somehow higher unemployment rates for all education groups, which could be related to their labor market entry that may start with an unemployment spell.[4]

1.2.2 Unemployment Flows

Theoretically, a higher unemployment rate may be the result of a higher probability to become unemployed – a higher incidence of unemployment – or a lower probability to find a job – higher duration of the unemployment spell.[5] There exists an older literature that tries to identify the reason behind the observed differences in unemployment rates across education levels. It is a robust finding in this literature that lower incidence of unemployment within the more educated is the main contributor to differences in unemployment rates (Ashenfelter and Ham, 1979, Nickell, 1979, Mincer, 1991). Indeed, empirical evidence on the effect of education on unemployment duration is mixed, with some studies finding a negative effect (Nickell, 1979, Mincer, 1991), some negligible effect (Ashenfelter and Ham, 1979), and some positive effect (Moffitt, 1985, Meyer, 1990).[6]

More recently, the literature has witnessed a renewed interest in calculating inflow rates to unemployment and outflow rates from unemployment.[7] We decompose unemployment rates for people with 25 years of age and over into unemployment inflow and outflow rates.[8] Our results support earlier findings. As can be seen from Figure 1.2, outflow rates from unemployment are broadly similar across education groups, whereas inflow rates differ considerably.[9] Furthermore,

[4]See Figure 1.8 in the Appendix.

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

[6]The positive effect of education on unemployment duration can be explained by higher reservation wages for more educated workers.

[7]See Shimer (2007), Elsby et al. (2009), and Fujita and Ramey (2009) for the analysis of aggregate data, and Elsby et al. (2010) for decompositions along various demographic groups.

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

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

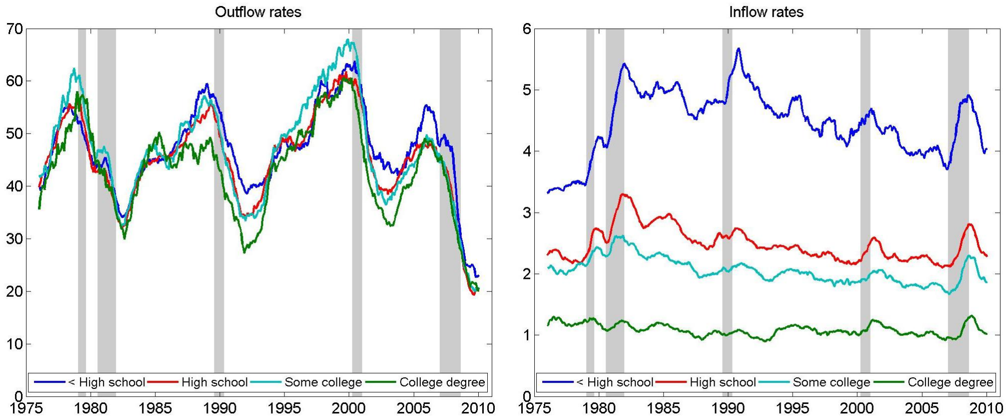

Figure 1.2: Unemployment flows (25+ years of age)

Notes: We plot twelve-month moving averages of seasonally-adjusted monthly data. The sample period is 1976:01 - 2010:12. All variables are constructed from CPS microdata. Shaded areas indicate NBER recessions.

we exploit the steady state unemployment approximation $u_t^* \approx s_t/(s_t+f_t)$, which has been found in the literature to replicate well the actual unemployment rates (s_t stands for the separation rate and f_t denotes the job finding rate). In Figure 1.3 we construct two hypothetical unemployment rates to analyze separately the role of outflows and inflows in explaining the differences in unemployment rates across education groups. In particular, in the left panel of Figure 1.3 we calculate the hypothetical unemployment rate series for each group by taking its actual outflow rate series, but keeping the inflow rate series at the value for the aggregate economy. Analogously, in the right panel of Figure 1.3 we calculate the hypothetical unemployment rate series for each group by taking its actual inflow rate series, but keeping the outflow rate series at the value for the aggregate economy. These two approximations clearly demonstrate that the observable differences in job finding rates have a negligible effect on unemployment rates, with separation rates accounting for almost all variability in unemployment rates across education groups.[10] Moreover, the observed differences in outflow rates go into the wrong direction as they predict (slightly) higher unemployment rates for highly educated workers, consistent with the previously mentioned findings of Moffitt (1985) and

[10]Note that our focus here is primarily on cross-sectional variation, as opposed to time variation in unemployment rates. Therefore, we avoid the critique of Fujita and Ramey (2009) on using hypothetical unemployment rates to assess the role of inflow rates and outflow rates in explaining unemployment fluctuations over time. Their critique stressed the importance of accounting for dynamic interactions, implying that fluctuations in the separation rate are negatively correlated with future changes in the job finding rate. Furthermore, since the unemployment differentials across education groups range up to four times in relative terms, calculating first- or higher-order approximations would be subject to non-negligible approximation errors.

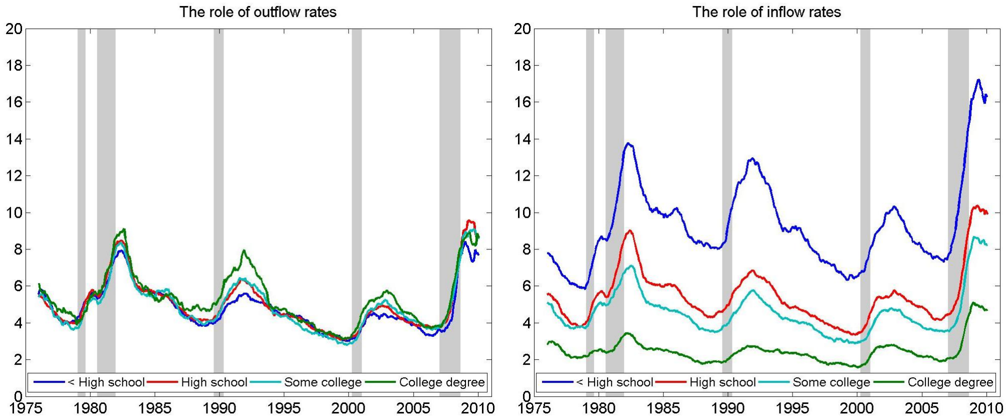

Figure 1.3: Hypothetical unemployment rates (25+ years of age)

Notes: The left panel shows the unemployment rate series for each group by taking its actual outflow rate series, but keeping the inflow rate series at the value for the aggregate economy. The right panel shows the unemployment rate series for each group by taking its actual inflow rate series, but keeping the outflow rate series at the value for the aggregate economy. We plot twelve-month moving averages of seasonally-adjusted monthly data. The sample period is 1976:01 - 2010:12. All variables are constructed using CPS microdata. Shaded areas indicate NBER recessions.

Meyer (1990).

In the Appendix we check for two possible biases regarding the conclusion that inflow rates drive the differences in unemployment rates by education. First, the procedure to calculate outflow rates might be biased due to duration dependence. Figure 1.9 in the Appendix illustrates that all education groups are roughly equally represented over the whole unemployment duration spectrum, hence duration dependence cannot bias our conclusion that outflow rates do not differ by education. Second, so far we neglected transitions in and out of the labor force. Figures 1.10 and 1.11 in the Appendix show that the findings of equal job finding rates and vastly different separation rates across education groups remain valid when considering a three-state decomposition of unemployment flows.

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

1.2.3 Labor Market Volatility

Table 1.3 summarizes volatility measures for the main labor market variables of interest. In particular, we report two sets of volatility statistics. First, absolute volatilities are defined as standard deviations of the data expressed in deviations from an HP trend with smoothing parameter 10^5.[11] Second, relative volatilities are defined analogously, except that all variables are initially expressed in natural logarithms.[12] Both sets of volatility statistics are reported in order to facilitate the comparison with the existing literature. More precisely, on the one hand macroeconomists typically avoid taking logarithms of rates and thus prefer to report absolute volatilities. On the other hand, some of the recent literature on quantitative performance of search and matching models puts more emphasis on relative volatilities, because what matters from the viewpoint of the canonical search and matching model are relative changes in unemployment.

Table 1.3: Labor market volatility by education level

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

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

Our preferred volatility measure corresponds to the concept of absolute volatility. To understand why, notice that in the case of employment rates, the distinction between relative and absolute volatilities becomes immaterial.[13] As the numbers in Table 1.3 clearly illustrate, more educated workers enjoy greater employment stability. Employment stability is arguably also the concept that matters from the welfare perspective of an individual. However, if we compare absolute and relative volatilities for unemployment rates, the numbers lead to contradictory conclusions – while absolute volatilities agree with employment volatilities by definition, relative volatilities in contrast suggest that the most educated group experiences higher unemployment volatility than the least educated group. The reason why the more educated have more volatile unemployment rates in terms of log deviations, despite having less volatile employment rates, is clearly related to their lower unemployment means.[14] To avoid the distorting effect of different means on relative

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

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

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

[14]By definition of the employment and unemployment rates, we have $n_t + u_t = 1$. Taking

volatility measures, we prefer to focus on absolute volatilities. Note that the more educated experience also lower (absolute) volatility of separation rates, whereas job finding rates exhibit broadly equal variation across education groups.

1.2.4 On-the-Job Training

Economists have long recognized the importance of learning-by-doing, formal and informal on-the-job training for human capital accumulation. Despite the widely accepted importance of on-the-job training in theoretical work, empirical verifications of theoretical predictions remain scarce, mainly due to limited data availability. Unlike with formal education, the data on training need to be obtained from scarce and frequently imperfect surveys, with considerable data imperfections being related especially to informal on-the-job training and learning-by-doing.[15] Nevertheless, existing empirical studies of training overwhelmingly suggest the presence of strong complementarities between education and training. The positive link between formal schooling and job training has been found on data from: i) the CPS Supplement of January 1983, the National Longitudinal Surveys (NLS) of Young Men, Older Men and Mature Women, and the 1980 EOPP survey by Lillard and Tan (1986); ii) the NLS of the High School Class of 1972 by Altonji and Spletzer (1991); iii) the Panel Study of Income Dynamics (PSID) by Mincer (1991); and iv) a dataset of a large manufacturing firm by Bartel (1995).

In what follows we provide some further evidence on training by education level from the 1982 EOPP survey, which will form the empirical basis for the parameterization of our model. Table 1.4 summarizes the main training variables of the survey with a breakdown by education.[16]

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log-linear approximation yields $\widehat{u}_t = -(n^*/u^*)\widehat{n}_t \approx -(1/u^*)\widehat{n}_t$, where hats denote steady-state deviations. Hence, log deviations in employment are amplified by a factor of roughly $1/u^*$ when one calculates log deviations in unemployment.

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

[16] We restrict the EOPP sample to individuals for whom we have information on education and, to be consistent with our data on unemployment, to individuals with 25 years of age and over. Since the distribution of training duration is highly skewed to the right, we eliminate outliers by truncating distribution at its 95th percentile, which corresponds to the training duration of 2 years. The survey question for training duration was: "How many weeks does it take a new employee hired for this position to become fully trained and qualified if he or she has no previous experience in this job, but has had the necessary school-provided training?" In order to compute the productivity gap we combine the survey question on productivity of a "typical worker who has been in this job for 2 years" and the survey question on productivity of a "typical worker during his/her first 2 weeks of employment". In the Appendix we describe the relevant features of the 1982 EOPP survey in detail and provide some further tabulations of training by education.

Table 1.4: Measures of training by education level from the 1982 EOPP survey

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

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

The EOPP survey is particularly useful to analyze training because it includes measures of both formal and informal training. This is important given that the average incidence rate of receiving initial (i.e. during first three months) formal training in our sample corresponds to 13.7 percent, while the incidence rate of receiving some type of initial training is 95.0 percent. Table 1.4 illustrates two relevant aspects of the data for our paper. First, nearly all new hires receive some type of initial training, regardless of their level of education. Second, there are considerable differences across education groups in terms of the duration of training received and the corresponding productivity gap. For example, a newly hired college graduate needs 18.2 weeks on average to become fully trained, which is nearly two times the time needed for a newly hired high school dropout. Moreover, the difference between the initial productivity and the productivity achieved by an incumbent worker increases with the education level, from one third to one half.

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

First, the appropriate theoretical concept of specificity in our case is not whether a worker can potentially use his learned skills in another firm. What matters for our analysis is whether after going through an unemployment spell, a worker can still use his past training in a new job. To give an example, a construction worker might well be able to take advantage of his past training in another construction firm, but if after becoming unemployed he cannot find a new job in the construction sector and is thus forced to move to another sector, where he cannot use his past training, then his training should be viewed as specific. Industry and occupational mobility are not merely a theoretical curiosity but, as shown by Kambourov and Manovskii (2008), a notable feature of the U.S. labor market. These authors also find that industry and occupational mobility appears to be especially high when workers go through an unemployment spell.[17] Similarly, by analyzing the National Longitudinal Survey of Youth (NLSY) data Lynch (1991) reaches the conclusion that on-the-job training in the United States appears to be unportable from employer to employer. In the same vein, Lynch (1992) finds that on-the-job training with the current employer increases wages, while spells of on-the-job training acquired before the current job have no impact on current wages.

Second, the EOPP was explicitly designed to measure the initial training at the start of the job (as opposed to training in ongoing job relationships), which is more likely to be of job-specific nature. Moreover, the EOPP also provides data on the productivity difference between the *actual* new hire during his first two weeks and the typical worker who has been in this job for two years. For the actual new hire the EOPP also reports months of relevant experience.[18] Table 1.5 summarizes the productivity differences between the actual new hire and the typical incumbent for three age groups and also for two subsamples of new hires with at least 1 and 5 years of relevant experience. Note that one would expect to observe in the data a rapidly disappearing productivity gap with rising age of workers and months of relevant experience, if this measure of on-the-job training were capturing primarily general human capital. However, the results in Table 1.5 indicate that on-the-job training remains important also for older cohorts of workers and for workers with relevant experience. Crucially for our purposes, the relative differences across education groups remain present and even increase a bit. Overall, this suggests that on-the-job training, at least as measured by the EOPP survey, contains primarily specific human capital.

Third, Figure 1.4 depicts the incidence rate of formal training from the NLSY cohort.[19] The analysis of these data, available until 2008, shows that the incidence rate of formal training differs across education groups, with more educated workers receiving more training and the numbers being comparable to the ones for formal training from the EOPP survey (see Table 1.4). Moreover, Figure 1.4 shows that incidence rates of training across education groups do not exhibit a

[17] See Figure 10a of their paper.

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

[19] A short description of this survey is available in the Appendix.

Table 1.5: Measures of training by education level from the 1982 EOPP survey

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

Notes: All measures of training compare productivity between the actual new hire and the typical incumbent. We restrict the sample to individuals for whom we have information on education.

notable downward trend with aging of the cohort, consistent with the argument of the previous paragraph.

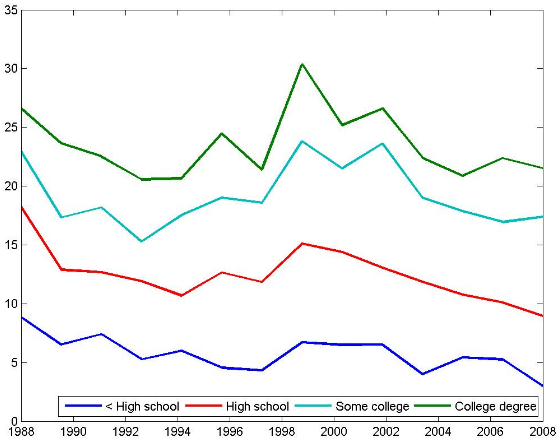


Figure 1.4: Incidence rate of formal training from the 1979 NLSY

Finally, the traditional approach in the literature to distinguish between general and specific human capital has been to associate the wage return to overall work experience as an indication of the presence of general human capital, whereas the wage return to tenure has been typically interpreted as evidence of specific human capital. In an influential paper, Topel (1991) estimates that 10 years of job tenure raise the wage by over 25 percent, with wage growth being particularly rapid during an initial period of job, hence suggesting the presence of specific human capital.[20] Moreover, Brown (1989) claims that firm-specific wage growth occurs

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

almost exclusively during periods of on-the-job training, lending further support to the argument that on-the-job training is mostly specific.

1.3 The Model

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

1.3.1 Environment

The discrete-time model economy contains a finite number of segmented labor markets, indexed by $h \in \{1, 2, ..., h^{max}\}$, where h represents different levels of formal educational attainment. Workers in each of these markets possess a certain amount of formal human capital, denoted by $H \in \{H_1, H_2, ..., H_{h^{max}}\}$, directly related to their education. Moreover, firms in each of these markets provide initial on-the-job training to their new hires, with the amount of training depending on worker's education. The assumption of segmented labor markets is chosen because education is an easily observable and verifiable characteristic of workers, hence firms can direct their search towards desired education level for their new hires.[21]

Each segmented labor market features a continuum of measure one of risk-neutral and infinitely-lived workers. These workers maximize their expected discounted lifetime utility defined over consumption, $\mathbb{E}_t \sum_{k=0}^{\infty} \beta^k c_{t+k}$, where $\beta \in (0, 1)$ represents the discount factor. Workers can be either employed or unemployed. Employed workers earn wage w_t, whereas unemployed workers have access to home production technology, which generates b_h consumption units per time period. In general, b_h also includes potential unemployment benefits, leisure, saved work-related expenditures and is net of job-searching costs. Importantly, it

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

depends on worker's education. We abstract from labor force participation decisions, therefore all unemployed workers are assumed to be searching for jobs.

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

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

Note that workers are initially untrained, thus they produce only $(1-\tau_h)$ of regular output, where τ_h measures the extent of job-specific skills (i.e., the productivity gap between a new hire and a skilled worker). In each period untrained workers experience a probability ϕ_h of being upgraded to a skilled worker. Note that $1/\phi_h$ yields the average duration of on-the-job training.[22] A firm with a skilled worker of education H produces a regular output level of HAa, where A denotes the aggregate productivity and a the idiosyncratic productivity. Both aggregate and idiosyncratic productivity are assumed to be stochastic, evolving over time according to two independent Markov chains $\{\mathbf{A}, \mathbf{\Pi^A}\}$ and $\{\mathbf{a}, \mathbf{\Pi^a}\}$, with finite grids $\mathbf{A} = \{A_1, A_2, ..., A_n\}$ and $\mathbf{a} = \{a_1, a_2, ..., a_m\}$, transition matrices $\mathbf{\Pi^A}$ being composed of elements $\pi^A_{ij} = \mathbb{P}\{A' = A_j \mid A = A_i\}$ and $\mathbf{\Pi^a}$ being composed of elements $\pi^a_{ij} = \mathbb{P}\{a' = a_j \mid a = a_i\}$, and the initial probability vector being composed of elements $\pi^a_j = \mathbb{P}\{a' = a_j\}$.

1.3.2 Labor Markets

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

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

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

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

$$q(\theta(H, A)) = \frac{m(u(H, A), v(H, A))}{v(H, A)} = \gamma\theta(H, A)^{-\alpha}, \tag{1.1}$$

$$p(\theta(H, A)) = \frac{m(u(H, A), v(H, A))}{u(H, A)} = \gamma\theta(H, A)^{1-\alpha}. \tag{1.2}$$

1.3.3 Characterization of Recursive Equilibrium

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

$$\begin{aligned} J^T(H, A, a) = &\max \big\{0, (1-\tau_h)HAa - w^T(H, A, a) \\ &+ \beta(1-\delta)\mathbb{E}_{A,a}\left\{\phi_h J^S(H, A', a') + (1-\phi_h)J^T(H, A', a')\right\}\big\}, \end{aligned} \tag{1.3}$$

$$\begin{aligned} J^S(H, A, a) = &\max \big\{0, HAa - w^S(H, A, a) \\ &+ \beta(1-\delta)\mathbb{E}_{A,a}\left\{J^S(H, A', a')\right\}\big\}. \end{aligned} \tag{1.4}$$

Equation (1.4) is standard in search and matching models with endogenous separations. Observe that we also allow for exogenous separations at rate δ, which are understood to be other types of separations that are not directly related to the productivity of a job. As explained above, equation (1.3) in addition involves the lost output τ_h that is due to initial lack of job-specific skills and the probability ϕ_h of becoming a skilled worker. $\mathbb{E}_{A,a}$ denotes expectations conditioned on the current values of A and a. Note that at any point in time, a firm can also decide to fire its employee and become inactive in which case it obtains a zero payoff. The firm optimally chooses to endogenously separate at and below the reservation productivities $\tilde{a}^T(H, A)$ and $\tilde{a}^S(H, A)$, which are implicitly defined as the maximum values that satisfy:

$$J^T(H, A, \tilde{a}^T(H, A)) = 0, \tag{1.5}$$

$$J^S(H, A, \tilde{a}^S(H, A)) = 0. \tag{1.6}$$

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

$$\frac{c_h}{q(\theta(H,A))} = \beta\mathbb{E}_A\big\{J^T(H,A',a')\big\}. \tag{1.7}$$

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

$$\begin{aligned} U(H,A) =& b_h + p(\theta(H,A))\beta\mathbb{E}_A\big\{W^T(H,A',a')\big\} \\ &+ (1-p(\theta(H,A)))\beta\mathbb{E}_A\big\{U(H,A')\big\}. \end{aligned} \tag{1.8}$$

Note that the unemployed worker always starts a job as a trainee, due to the initial lack of job-specific skills.[23] Bellman equations for the worker are analogous to the firm's ones, with his outside option being determined by the value of being unemployed:

$$\begin{aligned} W^T(H,A,a) =& \max\big\{U(H,A), w^T(H,A,a) + \beta\delta\mathbb{E}_A\big\{U(H,A')\big\} \\ &+ \beta(1-\delta)\mathbb{E}_{A,a}\big\{\phi_h W^S(H,A',a') + (1-\phi_h)W^T(H,A',a')\big\}\big\}, \end{aligned} \tag{1.9}$$

$$\begin{aligned} W^S(H,A,a) =& \max\big\{U(H,A), w^S(H,A,a) + \beta\delta\mathbb{E}_A\big\{U(H,A')\big\} \\ &+ \beta(1-\delta)\mathbb{E}_{A,a}\big\{W^S(H,A',a')\big\}\big\}. \end{aligned} \tag{1.10}$$

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

$$\begin{aligned} S^T(H,A,a) &\equiv J^T(H,A,a) + W^T(H,A,a) - U(H,A), \\ S^S(H,A,a) &\equiv J^S(H,A,a) + W^S(H,A,a) - U(H,A), \end{aligned}$$

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

$$\begin{aligned} W^T(H,A,a) - U(H,A) &= \eta S^T(H,A,a), \\ W^S(H,A,a) - U(H,A) &= \eta S^S(H,A,a). \end{aligned}$$

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

$$w^T(H,A,a) = \eta((1-\tau_h)HAa + c_h\theta(H,A)) + (1-\eta)b_h, \tag{1.11}$$

$$w^S(H,A,a) = \eta(HAa + c_h\theta(H,A)) + (1-\eta)b_h, \tag{1.12}$$

[23] The model could be extended to allow for heterogeneity in the loss of specific human capital upon becoming unemployed, as for example in Ljungqvist and Sargent (1998), and Ljungqvist and Sargent (2007). Such an extension would be valuable for analyzing issues like long-term unemployment (where the loss of specific human capital is likely to be larger) and sectoral worker mobility (where the loss of specific human capital is likely to be larger when an unemployed worker finds a job in a new sector). We leave these extensions for further research.

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

The model features a recursive equilibrium, with its solution being determined by equations (1.1)-(1.12). The solution of the model consists of equilibrium labor market tightness $\theta(H, A)$ and reservation productivities $\tilde{a}^T(H, A)$ and $\tilde{a}^S(H, A)$. Next, the following proposition establishes an important neutrality result.

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

Proof 1 *We can combine the equilibrium conditions and write the surpluses as:*

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

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

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

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

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

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

The usefulness of Proposition 1 will become clear in the following two sections with calibration and numerical results of the model. In particular, the proposition's result enables a transparent comparison of the model results across different education groups h, with the only parameters affecting results being on-the-job training parameters. Notably, by using the proposition we avoid changing the surpluses by magnifying the difference between firm's output and value of being unemployed. We believe that the model's implications when changing the value of being unemployed relative to output have been well explored in the recent literature.[24] Indeed, by assuming that more educated workers enjoy higher match surplus (with b_h being lower relative to output than in the case of less educated workers) it is well documented that the model would predict a decrease in the unemployment and the separation rate, but at the same time it would also predict an increase in the job finding rate. The latter prediction strongly contradicts the empirical evidence across education groups, as documented in Section 1.2. Further discussion of these issues together with some empirical evidence justifying the assumptions of proportionality in c_h and b_h is provided in the next section.

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

$$(n^T)'(a_j) = \mathbb{1}\{a_j > \tilde{a}^T(H, A')\}\Bigg[(1-\delta)(1-\phi_h)\sum_{i=1}^{m}\pi_{ij}^a n^T(a_i) + p(\theta(H, A))\pi_j^a u(H, A)\Bigg] \quad \forall j.$$

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

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

$$(n^S)'(a_j) = \mathbb{1}\{a_j > \tilde{a}^S(H, A')\}\Bigg[(1-\delta)\sum_{i=1}^{m}\pi_{ij}^a n^S(a_i) + (1-\delta)\phi_h\sum_{i=1}^{m}\pi_{ij}^a n^T(a_i)\Bigg] \quad \forall j.$$

Again, notice that if $a_j \leq \tilde{a}^S(H, A')$, the mass of skilled workers with idiosyncratic productivity a_j is zero, given that these matches are endogenously destroyed. However, if $a_j > \tilde{a}^S(H, A')$, the mass of skilled workers tomorrow with idiosyncratic productivity a_j is again composed of two groups: the mass of

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

previously skilled workers that survive exogenous separations and the mass of upgraded trainees that were not exogenously destroyed.

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

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

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

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

1.3.4 Efficiency

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

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

The proof of the above proposition is given in the Appendix. Hence, the standard Hosios condition applies also to our setting where workers are initially untrained. In other words, there are no additional inefficiencies specific to our model, except from the standard search externalities. Therefore, differential unemployment outcomes, which are related to differential training requirements, are efficient in our model if the Hosios condition is satisfied. This result is intuitive, because training requirements in our model are merely a technological constraint. Finally, we show in the Appendix that the job destruction is maximized when the Hosios condition holds.[25]

[25] Whether violation of the Hosios condition affects more the job destruction margin for trainees or for skilled workers depends on parameter values. The exact analytical condition is given in

1.4 Calibration

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

1.4.1 Parameter Values at the Aggregate Level

The model is simulated at monthly frequency. Table 1.6 summarizes the parameter values at the aggregate level.

Table 1.6: Parameter values at the aggregate level

Parameter	Interpretation	Value	Rationale
β	Discount factor	0.9966	Interest rate 4% p.a.
γ	Matching efficiency	0.45	Job finding rate 45.26% (CPS)
α	Elasticity of the matching function	0.5	Petrongolo and Pissarides (2001)
η	Worker's bargaining power	0.5	Hosios condition
c	Vacancy posting cost	0.106	1982 EOPP survey
b	Value of being unemployed	0.82	See text
σ_A	Standard deviation for log aggregate productivity	0.0064	Labor productivity (BLS)
ρ_A	Autoregressive parameter for log aggregate productivity	0.98	Labor productivity (BLS)
μ_a	Mean log idiosyncratic productivity	0	Normalization
σ_a	Standard deviation for log idiosyncratic productivity	0.249	Separation rate 2.24% (CPS)
λ	Probability of changing idiosyncratic productivity	0.3333	Ramey (2008)
δ	Exogenous separation rate	0.0075	JOLTS data
ϕ	Probability of training upgrade	0.3226	1982 EOPP survey
τ	Training costs	0.196	1982 EOPP survey
H	Worker's productivity	1	Normalization

The value of the discount factor is consistent with an annual interest rate of four percent. The efficiency parameter γ in the matching function targets a mean monthly job finding rate of 45.26 percent, consistent with the CPS microevidence for people with 25 years and over as described in Section 1.2.2. For the elasticity of the Cobb-Douglas matching function with respect to unemployment we draw from the evidence reported in Petrongolo and Pissarides (2001) and accordingly set $\alpha = 0.5$. Absent any further microevidence, we follow most of the literature and put the workers' bargaining power equal to $\eta = 0.5$.[26] As we show in Section

the Appendix, where we also provide a numerical example for our original model (with aggregate productivity shocks and some persistence in idiosyncratic productivity), showing that the job destruction is maximized when the worker's bargaining power is equal to the elasticity of the matching function with respect to unemployment.

[26]The same value is used, for example, by Pissarides (2009). The calibration in the credible

1.3.4, this guarantees efficiency of the equilibrium, consistent with the Hosios condition.

For the parameterization of the vacancy posting cost we take advantage of the EOPP data, which contain information on vacancy duration and hours spent during the recruitment process.[27] In our sample it took on average 17.8 days to fill the vacancy, with 11.3 hours being spent during the whole recruitment process.[28] Note that the expected recruitment cost in the model is equal to the product of the flow vacancy posting cost and the expected duration of the vacancy, $c \times (1/q)$. Hence, we have on a monthly basis $c \times (17.8/30) = 11.3/180$, which gives us the flow vacancy posting cost $c = 0.106$.[29] The vacancy posting cost equals 10.5 percent of average worker's productivity in our simulated model, which also appears to be broadly consistent with other parameter values for the vacancy posting cost used in the literature.[30]

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

bargaining model of Hall and Milgrom (2008) implies that the worker's share of the joint surplus is 0.54.

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

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

[29]This value of the vacancy posting cost might be too low due to two reasons. First, the EOPP survey asks questions related to the *last hired* worker, so it is very likely to overrepresent vacancies with shorter durations. Second, it might well be that the hiring personnel consist of managers and supervisors, who are paid more than the hired worker in question. Section 1.8.2 discusses the robustness of the quantitative results with respect to higher values of c.

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

simulated model.[31]

The parameters for the Markov chain governing the aggregate productivity process are calibrated to match the cyclical properties of the quarterly average U.S. labor productivity between 1976 and 2010.[32] After taking logs and deviations from an HP trend with smoothing parameter 10^5 the standard deviation of quarterly labor productivity is equal to 0.0178 and its quarterly autocorrelation is equal to 0.8962. We apply the Rouwenhorst (1995) method for finite state Markov-chain approximations of AR(1) processes, which has been found to generate accurate approximations to highly persistent processes (Kopecky and Suen, 2010).

In choosing the Markov chain for the idiosyncratic productivity process, we follow the standard assumption in the literature by assuming that idiosyncratic shocks are independent draws from a lognormal distribution with parameters μ_a and σ_a. Following Ramey (2008), these draws occur on average every quarter ($\lambda = 1/3$), governing the persistence of the Markov chain. In order to determine the parameters of the lognormal distribution and the exogenous separation rate we match the empirical evidence on separation rates. The CPS microevidence for people with 25 years of age and over gives us a mean monthly inflow rate to unemployment of 2.24 percent. The recent Job Openings and Labor Turnover Survey (JOLTS) data, available from December 2000 onwards, tell us that the mean monthly layoff rate is equal to 1.5 percent. The layoffs in JOLTS data correspond to involuntary separations initiated by the employer, hence we take these to be endogenous separations. Accordingly, we set the exogenous monthly separation rate to $\delta = 0.75$ percent, and adjust σ_a in order that the simulated data generate mean monthly inflow rates to unemployment of 2.24 percent. The parameter μ_a is normalized to zero.

We select parameters regarding on the-job-training from the 1982 EOPP survey as summarized in Table 1.4 of Section 1.2.4. To calibrate the duration of on-the-job training we consider the time to become fully trained in months. In particular, under the baseline calibration we parameterize the average duration of on-the-job training to 3.10 months ($13.4 \times (12/52)$), which yields the value for ϕ equal to $1/3.10$. To calibrate the extent of on-the-job training we use the average productivity gap between a typical new hire and a typical fully trained worker. In reality, we would expect that workers obtain job-specific skills in a gradual way, i.e. shrinking the productivity gap due to lack of skills proportionally with the time spent on the job. Our parameterization of training costs for the aggregate economy, $\tau = 0.196$, implies that trainees are on average 19.6 percent less pro-

[31] Hall and Milgrom (2008) suggest the value of $b = 0.71$.

[32] Following Shimer (2005), the average labor productivity is the seasonally adjusted real average output per employed worker in the nonfarm business sector. These data are provided by the Bureau of Labor Statistics (BLS), series PRS85006163.

ductive than skilled workers. This is consistent with an average initial gap of 39.1 percent, which is then proportionally diminishing over time. Finally, the worker's productivity parameter H is normalized to one.

1.4.2 Parameter Values Specific to Education Groups

Next we turn to parameterizing the model across education groups. We keep fixed all the parameter values at the aggregate level as reported in Table 1.6, with the only exception being the training parameters (ϕ and τ). In particular, we assume that $c_h = cH$ and $b_h = bH$, making applicable the neutrality result of Proposition 1, according to which the parameterization for H is irrelevant. We argue below that this is not only desirable from the model comparison viewpoint as we can completely isolate the effects of on-the-job training, but it is also a reasonable thing to do given available empirical evidence. Note also that a neutrality result similar to Proposition 1 would obtain if we were to assume a standard utility function in macroeconomic literature, featuring disutility of labor and offsetting income and substitution effects.[33]

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

To proceed further, we turn to empirical evidence reported in Aguiar and Hurst (2005), who among other things measure food consumption and food expenditure changes during unemployment. Focusing on food items (which include eating in restaurants) is a bit restrictive for our purposes, but the results are nevertheless illustrative. Aguiar and Hurst (2005) report their estimates separately for the whole sample and for the "low-education" subsample, which consist of individuals with 12 years or less of schooling. They find that during unemployment food

[33] See Blanchard and Galí (2010).

expenditure falls by 19 percent for the whole sample and by 21 percent for the low-education sample, with the difference not being statistically significant. The drop in food consumption amounts to 5 percent for the whole sample and 4 percent for the low-education sample, with the numbers being statistically significant from zero, but not from each other.[34] Based on this micro evidence and the reasoning given above, we take $b_h = bH$ to be a reasonable assumption. Results from robustness checks on this assumption are reported in 1.8.1.

The proportionality assumption on flow vacancy posting cost would follow directly if we were to assume that hiring is a labor intensive activity as in Shimer (2009).[35] Nevertheless, we perform the sensitivity analysis of the quantitative results with respect to different specification of vacancy posting cost in Section 1.8.2.

For the parameters regarding on-the-job training we refer the reader to Table 1.4 in Section 1.2.4. Moreover, we will report all on-the-job training parameter values for different education groups in the tables with simulation results.

1.5 Simulation results

The main results of the paper are presented in this section. First, we report baseline simulation results for the aggregate economy. Second, the model is solved and simulated for each education group. This exercise is done by changing the parameters ϕ_h and τ_h related to on-the-job training for each education group, while keeping the rest of parameters fixed at the aggregate level. Finally, we discuss the main mechanism of the model, by exploring how simulation results depend on each training parameter. This section reports simulation results with the calibration for the age group of 25 years and older. As shown in Section 1.7, our conclusions remain unaffected if we calibrate the model for the whole working-age population.

1.5.1 Baseline Simulation Results

We begin by simulating the model, parameterized at the average aggregate level for duration of training and training costs ($1/\phi = 3.10$ and $\tau = 0.196$). Table 1.7 reports the baseline simulation results together with the actual data moments for the United States during 1976-2010. In particular, we report means, absolute and relative volatilities for the key variables of interest. The reported model statistics are means of statistics computed from 100 simulations. In each simulation, 1000

[34]See Table 6 of their paper.

[35]The textbook matching model also assumes proportionality of hiring costs to productivity (Pissarides, 2000).

monthly observations for all variables are obtained. The first 580 months are discarded and the last 420 months, corresponding to data from 1976:01 to 2010:12, are used to compute the statistics in the same way as we do for the data. In order to assess the precision of the results, standard deviations of simulated statistics are computed across simulations.

Table 1.7: Labor market variables: data versus model

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

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

The baseline simulation results show that the model performs reasonably well at the aggregate level. It essentially hits the empirical means of unemployment rate, job finding rate and separation rate by construction of the exercise. More notably, it also mirrors well the empirical volatilities. Two main reasons why the model does not suffer from extreme unemployment volatility puzzle as in Shimer (2005) relate to a bit higher flow value of being unemployed and the inclusion of endogenous separations.[36] The latter are also the reason why the model matches the volatility of the separation rate quite well. The model underpredicts the volatility of the job finding rate and to a somewhat lesser extent the volatility of the unemployment rate, which should not be surprising given that in this model productivity shocks are the only cause of fluctuations in vacancies.[37]

[36]Hagedorn and Manovskii (2008) claim that the unemployment volatility puzzle can be resolved by calibrating higher flow value of being unemployed. Note that our value for this parameter is considerably below Hagedorn and Manovskii (2008) and closer to the value used in Hall and Milgrom (2008). Ramey (2008) also finds that the inclusion of endogenous separations can help in increasing volatilities of search and matching models.

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

1.5.2 Unemployment Rates across Education Groups

Next, we turn to the simulation results across different education groups. We keep fixed all the parameter values at the aggregate level and only vary the training parameters across education groups. Table 1.8 shows the simulation results for the means. As we can see, the model is able to explain the differences in unemployment rates across education groups that we observe in the data. In particular, the ratio of unemployment rates of the least educated group to the most educated group is 3.50 in the data and 3.37 in the model. Moreover, the model accounts for the observable differences in separation rates across groups, while keeping similar job finding rates. The ratio of separation rates of the least educated group to the most educated group is 4.10 in the data and 3.60 in the model. In general, the greater is the degree of on-the-job training (longer training periods and higher productivity gaps), the lower is the separation rate and the lower is the unemployment rate. Therefore, the observed variation in training received across education groups can explain most of the observed differences in separation rates and unemployment rates.

Table 1.8: Education, training and unemployment properties - means (in percent)

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

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

Table 1.9 presents a more detailed view of the results, offering a breakdown of separation rates and employment rates for trainees and for skilled workers. As it can be seen, separation rates of trainees are roughly similar across education groups and trainees represent a small share of employment for all four education groups. Therefore, differences in separation rates for skilled workers are the main reason why more educated workers enjoy lower separation rates.

1.5.3 Unemployment Volatility across Education Groups

Panel A of Table 1.10 reports the simulation results for absolute volatilities. As mentioned in Section 1.5.1, the model underpredicts the volatilities of the job find-

Table 1.9: Separation and employment rates for trainees and skilled workers - means (in percent)

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

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

ing and the unemployment rates. This property of the model is also inherited here. Nevertheless, the model replicates well relative differences in volatilities across education groups. In the data, the volatility of the unemployment rate for high school dropouts is 3.22 times higher than the corresponding volatility for college graduates, whereas the same ratio in the model stands at 3.67. Something similar is true for volatilities of separation rates (the ratio is 3.87 in the data and 5.47 in the model), where additionally the model also explains volatility levels quite well. The model can also account for the observed similar values of volatilities in job finding rates across education groups.

Panel B of Table 1.10 reports the simulation results for relative volatilities. The model succeeds in replicating the ratio of relative employment volatility of the least educated group to the most educated group (the ratio is 3.47 in the data and 3.92 in the model). This finding is not surprising given the results of Panel A of Table 1.10, which show that the model is able to replicate the ratio of absolute employment volatility. The model also accounts well for the empirical finding that relative volatilities in unemployment, job finding, and separation rates remain similar across education groups.

1.5.4 Unemployment Dynamics across Education Groups

To provide another view of the model's results we conduct the following experiment. Using the model's original solution for the aggregate economy and the actual data on the aggregate unemployment rate we back out the implied realizations of the aggregate productivity innovations. Then, we feed this implied aggregate productivity series to the model's original solution for each education group. The simulated unemployment rate series for each group are shown in Figure 1.5, together with the actual unemployment rates. Again, the model replicates the data remarkably well, both in terms of capturing the differences in means and volatilities across groups.

Table 1.10: Education, training and unemployment properties - volatilities

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

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

1.5.5 Discussion of the Model's Mechanism

In order to highlight the mechanism at work in our model, two more exercises are conducted. In particular, we analyze separately the effects of training duration and productivity gap of new hires to demonstrate that both of them quantitatively play almost equally important role for our results. In the left panel of Figure 1.6 we study the role of the average duration of on-the-job training, keeping the rest of parameters constant at the aggregate level. Analogously, the right panel of Figure 1.6 studies the role of the productivity gap of new hires, keeping the rest of parameters constant at the aggregate level. In both cases, we observe a decrease in the mean of the unemployment rate as we increase the degree of on-the-job training (longer training periods and higher productivity gaps). This decrease in the unemployment rate is completely driven by the decrease in the separation rate, given that the job finding rate remains roughly constant as we vary the degree of on-the-job training.[38]

Let's consider first why the job finding rate virtually does not move with the

[38] In fact, the simulation results reveal that the job finding rate decreases by roughly 2 percentage points as we increase either the training duration or the productivity gap of new hires. Such a decrease leads to approximately 0.5 percentage points higher unemployment rate, which quantitatively represents a modest effect, given the observed declines in unemployment rate in Figure 1.6.

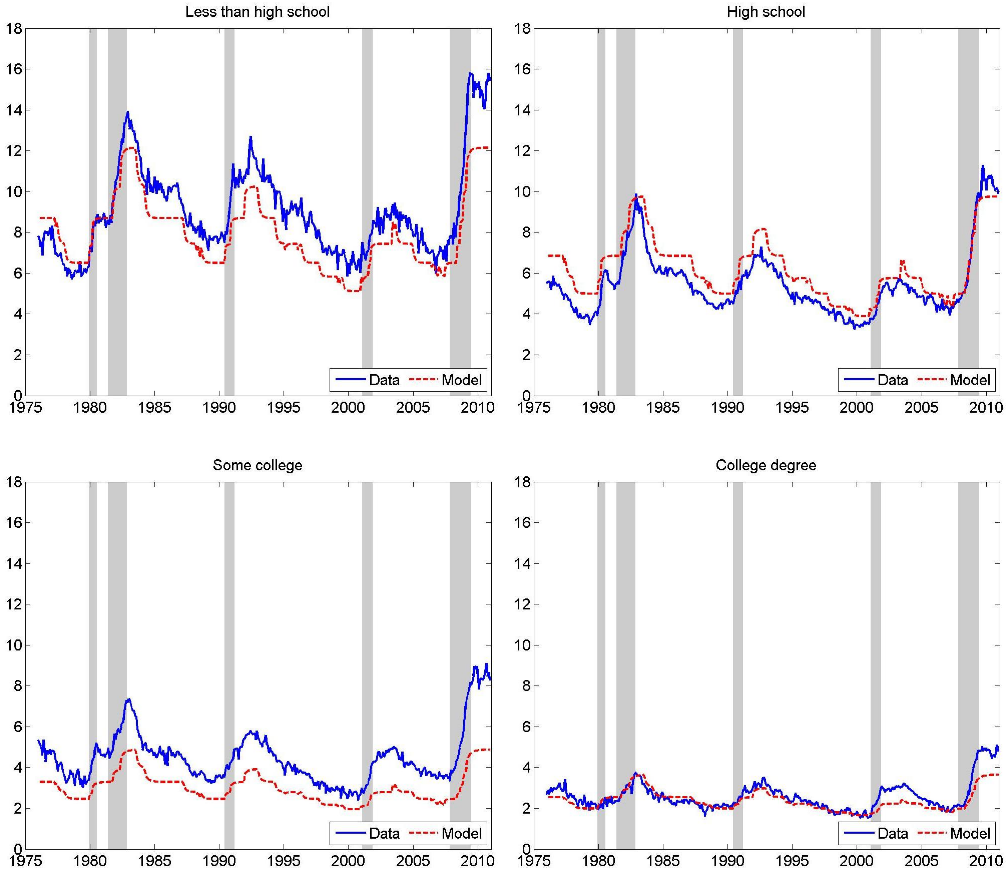


Figure 1.5: Unemployment rates across education groups: model versus data

Notes: Actual unemployment rates are quarterly averages of monthly seasonally-adjusted data constructed from CPS microdata. The sample period is 1976:01 - 2010:12. The simulated unemployment rates are generated by solving and simulating the model for each education group using the implied realizations of the aggregate productivity innovations as explained in the text. Shaded areas indicate NBER recessions.

average duration of on-the-job training. One would expect that an increase in the average duration of on-the-job training reduces the value of a new job, since the worker spends more time being less productive. Consequently, firms' incentives to post vacancies should decrease, leading to a decrease in the job finding rate. However, an increase in the average duration of on-the-job training also reduces the probability to separate endogenously once the worker becomes skilled. This second effect increases the value of a new job, and hence incentives for vacancy posting go up. It turns out that these two effects cancel out and the job finding rate hence remains almost unaffected. The same reasoning holds for the productivity gap of new hires, which measures the extent of on-the-job training. Again, we have two effects at work, which cancel each other out – a higher extent of on-the-

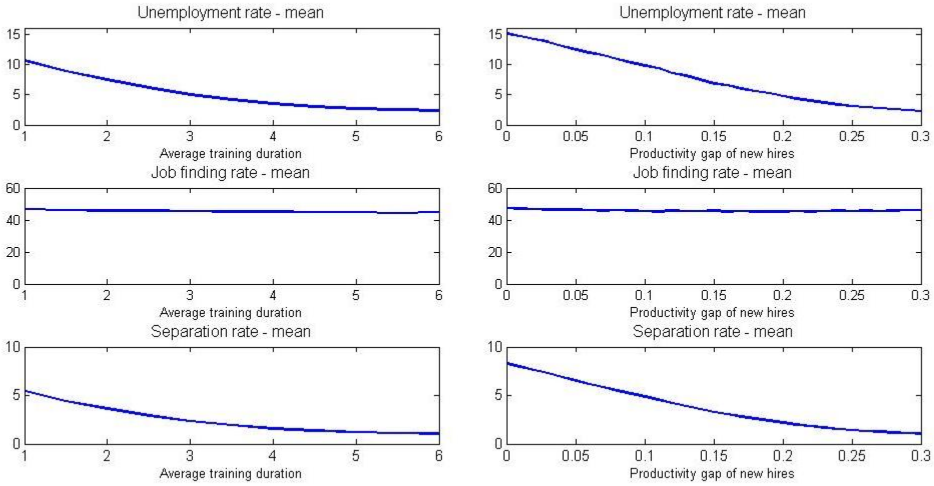


Figure 1.6: The role of training parameters

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

job training by itself decreases the value of a new job, but at the same time the latter increases through lower endogenous separations of skilled workers.

In order to understand why separation rates decrease with the degree of on-the-job training, we analyze match incentives to separate. Figure 1.7 shows the reservation productivities for trainees and skilled workers for different degrees of on-the-job training. As we can see, investments in match-specific human capital do not significantly affect the incentives of trainees to separate, while they clearly reduce skilled workers' incentives to separate. The intuition for this result is that skilled workers know that upon a job loss they will have to undergo first, a period of searching for a new job and second, a period of on-the-job training with a lower wage. Hence, reservation productivity levels drop for skilled workers as we increase the degree of on-the-job training, implying a lower rate of endogenous separations.

1.6 Evaluating Other Potential Explanations

In this section we evaluate how plausible are other potential explanations for differential unemployment dynamics across education groups. In particular, our model can encompass the following alternative hypotheses: i) differences in the size of match surplus ; ii) differences in hiring costs; iii) differences in frequency of idiosyncratic productivity shocks; iv) differences in dispersion of idiosyncratic

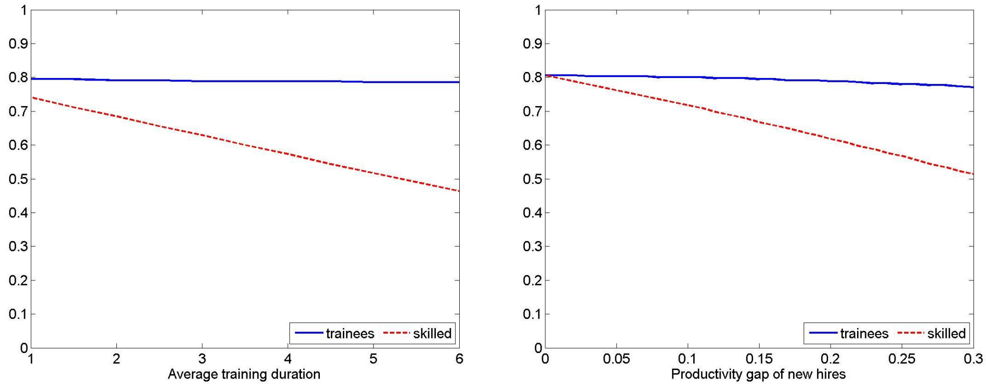


Figure 1.7: The effects of on-the-job training on reservation productivities

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

productivity shocks; v) differences in matching efficiency. We simulate the model under these alternative hypotheses and then confront the obtained simulation results with empirical evidence. In particular, for these simulations we use the parameter values for the aggregate level as given in Table 1.6, whereas across education groups we only allow to vary the parameter that is crucial to each alternative hypothesis. This helps us to highlight economic mechanisms behind the alternative hypotheses. Simulations results are summarized in Table 1.11.

1.6.1 Differences in the Size of Match Surplus

One possibility why more educated workers enjoy higher employment stability might be related to higher profitability of their jobs. In the terminology of search and matching framework, more educated workers might be employed in jobs yielding a higher match surplus. The latter crucially depends on the worker's outside option, which is in turn governed by the flow value of being unemployed. In our main simulation results as reported in Section 1.5, we ruled out this possibility by assuming that the flow value of being unemployed is proportional to the market labor productivity coming from education, i.e. $b_h = bH$.

Here we relax the proportionality assumption and instead assume $b_1 = 0.90$, $b_2 = 0.85$, $b_3 = 0.80$, $b_4 = 0.75$. In other words, the size of match surplus is now increasing with education. The simulation results, reported in Panel B of Table 1.11, indicate that the unemployment rate also rises under this alternative explanation. However, the model now counterfactually predicts higher job finding rates for more educated workers. Intuitively, since jobs with more educated

Table 1.11: Evaluating other potential explanations - means (in percent)

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

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

workers yield higher surplus, firms are willing to post more vacancies in this segment of the labor market, leading in turn to higher labor market tightness and job finding rates. Additionally, the simulation results reveal exaggerated employment stability for highly educated workers.[39] Indeed, due to greater surplus the simulation results for college graduates suffer from extreme unemployment volatility puzzle, as their unemployment rate remains virtually constant over the business cycle. Overall, the simulation results show that one cannot explain differences in unemployment dynamics across education groups by assuming higher match surplus for more educated. As discussed in Section 1.4.2, such an assumption also lacks empirical support, at the least for the case of the US.

Interestingly though, Gomes (2011) finds empirical evidence that in the UK both the differences in job finding and separation rates contribute roughly equally

[39]See Table 1.20 in the Appendix.

towards generating differences in unemployment rates by education.[40] Moreover, OECD calculates that the average of net replacement rates over 60 months of unemployment is roughly twice as high in the UK as in the US.[41] To the extent that this difference in net replacement rates reflects more generous welfare policies in the UK, which would in turn invalidate our baseline assumption on proportionality between market and non-market returns, differences in the size of match surplus might play a role for explaining unemployment dynamics by education in countries with similar or even more generous welfare policies as in the UK.

1.6.2 Differences in Hiring Costs

Another possibility for differences in unemployment dynamics by education might be due to hiring costs. One could imagine that hiring costs are bigger for highly skilled individuals and anecdotal evidence about head hunters in some top-skill occupations is indeed consistent with such a story. In our main simulation results in Section 1.5 we already assumed that flow vacancy posting costs are growing proportionally with productivity. However, it might be that this assumption understates the true differences in hiring costs by education.

In what follows, we assume the following values for vacancy posting costs, which are expressed in terms of output: $c_1 = 0.05$, $c_2 = 0.10$, $c_3 = 0.15$, $c_4 = 0.20$. Hence, hiring somebody with a college degree is now four times costlier than hiring a high school dropout in terms of their output. Acknowledging differences in their productivity, this implies that in absolute terms, hiring costs are more than six times higher for the most educated group relative to the least educated group. The simulation results, reported in Panel C of Table 1.11, reveal that under the assumed differences in hiring costs the model replicates the unemployment rates by education. However, the model now predicts sharply decreasing job finding rates with education, which is in contrast with the empirical evidence for the US as presented in Section 1.2.2 and even more at odds with the empirical evidence for the UK found by Gomes (2011). What is the economic mechanism behind these simulation results? Because it is costlier to hire college graduates, firms will post less vacancies in this labor market segments. As a consequence, the job finding rate drops. Highly educated workers that are currently employed know that upon a job loss they will face a lower job finding rate, hence they are less likely to get separated then less educated workers. The less educated workers are instead facing high job finding rates, hence they are more willing to leave their employer in the case of low idiosyncratic productivity shock.

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

[41]See http://www.oecd.org/dataoecd/16/42/48911290.xls.

As mentioned, the problem with this explanation lies in the fact that there is no empirical evidence that job finding rate for the most educated workers would be substantially lower, or in other words, that their unemployment duration would be longer. Moreover, the parameterization of the flow vacancy posting cost assumes that it is extremely expensive to hire a college graduate, whereas this cannot be seen from the EOPP data – see Section 1.8.2.

1.6.3 Differences in Frequency of Idiosyncratic Shocks

Individuals with different educational attainment might work in different industries and occupations – the classical distinction between blue-collar and white-collar workers comes to mind. Therefore, it might be that differences in unemployment dynamics by education are due to industry and/or occupation specific factors. Results from estimated regression equations, as reported in Table 1.2, indicate that this might indeed be part of the story. But then the natural question is in what sense industries and occupations differ among them. It is quite likely that they differ in terms of initial on-the-job training requirements and this would be consistent with our main story, according to which differences in training lead to differences in unemployment. However, it might also be the case that industries and occupations are subject to heterogeneous dynamics of idiosyncratic shocks. For example, industries and occupations with predominantly low educated workers might be subject to more frequent shocks.

The simulation results, reported in Panel C of Table 1.11, illustrate what happens when we vary the Poisson arrival rate of idiosyncratic productivity shocks from every 6 months ($\lambda = 1/6$) to every 2 months ($\lambda = 1/2$). It turns out that the faster the arrival rate of idiosyncratic productivity shocks, the lower will be the separation rate. The intuition behind this result is straightforward: if new shocks arrive often, then it is better to stay in the match even in the case of a very low idiosyncratic productivity shock, since you avoid the unemployment spell.[42] But these results are then not consistent with the notion that it should be the industries and occupations with low educated workers that are facing more frequent shocks – historically, blue-collar jobs are more cyclical. Additionally, the model cannot generate different unemployment rates and similar job-finding rates.

1.6.4 Differences in Dispersion of Idiosyncratic Shocks

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

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

occupations (or more generally, across jobs with different proportions of workers by education). This possibility is explored in Panel D of Table 1.11. The results show that higher dispersion of idiosyncratic productivity shocks generates more separations and leads to higher unemployment. But this would then imply that low educated workers should exhibit higher wage dispersion than high educated workers, which is at odds with the empirical evidence. In particular, the evidence provided in Lemieux (2006) for the US shows that highly educated workers have higher variance of wages than less educated workers, and these differences are present in both 1973-1975 and 2000-2002 time periods.[43] Furthermore and similar as before, this model specification also cannot generate similar job finding rates in the presence of different unemployment rates.

1.6.5 Differences in Matching Efficiency

Finally, imagine the situation where the extent of labor market frictions differs by education. This situation is explored in Panel E of Table 1.11. The simulation results show that better matching efficiency creates higher labor turnover rates. Hence, while higher matching efficiency generates higher unemployment, it also creates higher job finding rates – and both facts cannot be consistent with the empirical evidence for the US. Additionally, higher matching efficiency for less educated is in sharp contrast with the anecdotal evidence that more educated workers take greater advantage of modern techniques for job search.

1.7 Working-Age Population

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

In order to proceed, we calibrate the training parameters using the 1982 EOPP survey, restricting the sample to individuals with 16 years and over. The latter data are summarized in the Appendix, Table 1.18. In particular, under the baseline calibration we parameterize the average duration of on-the-job training to

[43] See Table 1A of his paper.

3.00 months $(13.0 \times (12/52))$, which yields the value for ϕ equal to $1/3.00$. Our parameterization of training costs for the aggregate economy is $\tau = 0.203$, which implies that trainees are on average 20.3 percent less productive than skilled workers. This is consistent with an average initial gap of 40.6 percent, which is then proportionally diminishing over time.

Following the calibration strategy in Section 1.4, we also need to adjust the efficiency parameter in the matching function (from 0.45 to 0.592) to target a mean monthly job finding rate of 53.93 percent, consistent with the CPS microevidence for people with 16 years of age and over. Moreover, we also need to adjust the standard deviation of the distribution of idiosyncratic productivity (from 0.249 to 0.237) in order that the simulated data generate mean monthly inflow rates to unemployment of 3.55 percent, consistent with the CPS microevidence for people with 16 years of age and over. The rest of parameters remain unchanged at the aggregate level (see Table 1.6).

As in Section 1.5, we first present baseline simulation results for the aggregate economy and then the model is solved and simulated for each education group. The last exercise is done by changing the parameters ϕ_h and τ_h related to on-the-job training for each group summarized in Table 1.18 of the Appendix, while keeping the rest of parameters fixed.

Panel A of Table 1.12 presents the actual data moments for the United States during 1976-2010 for people with 16 years of age and older, which can be compared with the simulation results for the aggregate economy presented in Panel B of the same Table 1.12.

Table 1.12: Labor market variables: data versus model

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

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

Table 1.13 reports simulation results on unemployment levels across education groups. As we can see, the observed variation in training received across education groups can explain most of the observed differences in separation rates and unemployment rates. In particular, the ratio of unemployment rates of the least educated group to the most educated group is 4.50 in the data and 4.00 in the model and the ratio of separation rates of the least educated group to the most educated group is 6.56 in the data and 4.47 in the model. Thus, the observed differences in training can also explain unemployment patterns across education groups for the whole working-age population.

Table 1.13: Education, training and unemployment properties - means (in percent)

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

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

Panel A of Table 1.19 in the Appendix reports simulation results on absolute volatilities across education groups. As in Section 1.5, the model underpredicts the volatilities of the job finding rate and unemployment rates. However, the model can remarkably well replicate the relative differences in volatilities across education groups, also when considering the whole working-age population. In particular, the volatility of the unemployment rate for high school dropouts is 3.41 times higher than the corresponding volatility for college graduates, whereas the same ratio in the model stands at 3.39. Something similar holds for volatilities of separation rates (the ratio is 4.01 in the data and 4.28 in the model), where the model can also account reasonably well for volatility levels. The model delivers also similar volatilities for the job finding rate across education groups, as in the data. Panel B of Table 1.19 in the Appendix presents the simulation results for relative volatilities. Also here the results are broadly consistent with the ones from Section 1.5.

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

1.8 Sensitivity Analysis of the Main Quantitative Results

In this section, we provide the sensitivity analysis of our main quantitative results from Section 1.5 where differences in unemployment dynamics by education are explained by differences in on-the-job training. We perform two types of robustness checks for our quantitative results. First, we explore the role of parameter for the flow value when being unemployed, both regarding its overall level and differences across education groups. Second, we consider different specification for the flow vacancy posting costs. Simulations results for all robustness checks are summarized in Table 1.14.

Table 1.14: Sensitivity analysis of the main quantitative results - means (in percent)

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

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

1.8.1 Value of Being Unemployed

Value of being unemployed - overall level

Here we set $b = 0.71$ as in Hall and Milgrom (2008) and Pissarides (2009). Consistent with our calibration procedure we adjust the matching efficiency parameter to $\gamma = 0.33$ in order to target the average job finding rate and we adjust the standard deviation of idiosyncratic productivity shocks to $\sigma_a = 0.385$ in order to hit the average separation rate. The rest of the numerical exercise follows the same steps as in Section 1.5, including the same parameter values for on-the-job training by education. The simulation results are provided in Panel B of Table 1.14 and are to be compared with results in Table 1.8. Note that with $b = 0.71$ our results remain basically unchanged with respect to our baseline calibration. The unemployment ratio between high school dropouts and college graduates was 3.37 under our baseline calibration, whereas with $b = 0.71$ it decreases only slightly to 3.20. The only noticeable difference concerns the volatility results. Now the aggregate volatilities of labor market variables are lower by half – the unemployment volatility puzzle becomes more evident and this is also the only reason that we chose a somewhat higher b in our baseline calibration. Nevertheless, also with $b = 0.71$ the relative differences in volatilities across education groups remain present; the unemployment volatility ratio between high school dropouts and college graduates was 3.67 under our baseline calibration, whereas now it decreases only slightly to 3.25.

Constant value of being unemployed across education groups

Below we present a robustness check when we deviate from the proportionality assumption and we keep b_h constant at 0.82 for all four education groups. As the result of Proposition 1 does not apply anymore, we need to parameterize differences in the market labor productivity across education groups, H. We do so by taking advantage of the 1982 EOPP data, which contain information on hourly wage. Hourly wage data allow us to impute productivity differences H, which are reported in Table 1.15. The parametrized productivity differences are broadly in line with estimates obtained by the literature on returns to schooling.[44] After simulating the model, we can express the flow value of being unemployed relative to the effective productivity. The obtained values for the effective flow value of being unemployed are 88.7 percent for high school dropouts, 85.0 percent for

[44] In a search and matching model, the wage depends on productivity, hiring costs and the value of being unemployed, with weights determined by the worker's bargaining power – c.f. the wage equation (1.12). The imputation procedure adopted here is thus likely to understate the true differences in productivity to the extent that hiring costs and the value of being unemployed are not proportional to productivity.

high school graduates, 77.2 percent for people with some college, and 61.2 percent for college graduates. In short, the size of match surplus is now increasing with education.

Table 1.15: Productivity (H) by education

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

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

Panel C of Table 1.14 presents the simulation results. In particular, we solve and simulate the model for each education group, by using the corresponding training parameters (ϕ_h and τ_h), the constant flow value of being unemployed ($c_h = 0.82$) and productivity parameters (H) for each education group, while keeping the rest of parameters constant at the aggregate level. It turns out that when we deviate from the proportionality assumption $b_h = bH$, the model yields highly counterfactual predictions. In particular, the job finding rate for college graduates is now more than four times higher than the one for high school dropouts, whereas in the data they are practically identical. Additionally, the simulation results for college graduates suffer from extreme unemployment volatility puzzle, as their unemployment rate remains virtually constant over the business cycle.[45] The simulation results with constant absolute flow value of being unemployed also severely overpredict differences in unemployment and separation rates across education groups.

1.8.2 Vacancy Posting Costs

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

[45] See Table 1.22 in the Appendix.

Actual vacancy posting costs from the 1982 EOPP survey

The 1982 EOPP data contain evidence on vacancy duration and recruitment costs. Table 1.16 summarizes these data across education groups.[46] The column denoted "c" presents vacancy posting costs expressed in terms of output for each corresponding education group. As it can be seen, the vacancy posting costs across education groups remain close to the aggregate level, which is consistent with our assumption $c_h = cH$. The calculated vacancy posting costs exhibit very little variation across education groups due to two counteracting effects in the data. On the one hand, recruitment costs in terms of hours spent are indeed much higher for more educated workers. On the other hand, the 1982 EOPP data also show higher vacancy duration for more educated workers. Note that the latter observation is inconsistent with the empirical evidence of similar job finding rates across education groups, under the assumption of identical matching efficiency across groups. However, longer vacancy duration for more educated workers might not be due to lower vacancy meeting probability, but might simply reflect that the recruitment process itself is longer for this group of workers, perhaps for administrative reasons. In this respect, van Ours and Ridder (1993) provide evidence that a vacancy duration consists of an application period, during which applicants arrive, and a selection period, during which a new employee is chosen from the pool of applicants. They conclude that the mean selection period increases with the required level of education, while required education has no effect on the applicant arrival rate. The applicant arrival rate is arguably the empirical counterpart for the vacancy meeting probability of a theoretical search model. Finally note that in the calibration of search and matching models, vacancy duration is merely a normalization, as its changes can be undone by adjusting the flow vacancy posting cost and matching efficiency.[47]

Table 1.16: Vacancy posting cost by education level from the 1982 EOPP survey

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

Since some differences in flow vacancy posting costs are present across ed-

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

[47] See Costain and Reiter (2008).

ucation groups, we use the exact information on these costs to parameterize our model as a robustnesses check. In order to do that, we express all flow vacancy posting costs in terms of aggregate output and again parameterize differences in productivity across education groups. The column denoted "Wage" corresponds to the 1982 EOPP hourly wage, from which we impute productivity differences H. The last column of Table 1.16 gives us the parameter values to use in the simulations for each education group. We solve and simulate the model for each education group, by using the corresponding training parameters (ϕ_h and τ_h), actual vacancy posting cost (c_h) and productivity parameters (H) for each education group, while keeping the rest of parameters constant at the aggregate level.[48] Panel D of Table 1.14 reports the simulation results and, as we can see, they do not differ much from our simulation results in Section 1.5. Therefore, our simulation results are robust when considering the actual vacancy posting costs from the 1982 EOPP survey.

Constant vacancy posting costs across education groups

Panel E of Table 1.14 reports simulation results when we set $c_h = 0.106$ for all four education groups, hence deviating from the assumption of proportionality in vacancy posting costs. We solve and simulate the model for each education group, by using the corresponding training parameters (ϕ_h and τ_h), vacancy posting cost ($c_h = 0.106$) and productivity parameters (H) for each education group, while keeping the rest of parameters constant at the aggregate level. Note that this exercise presents an extreme case, in the sense that the vacancy posting cost is the same in absolute value across education groups, implying that in terms of output it is decreasing with education. The simulation results remain virtually unchanged, implying again that the parameterization of c is not crucial for our conclusions.

Doubling vacancy posting costs

In the last robustness exercise with respect to the vacancy posting cost we double the value used in our baseline calibration, increasing c from 0.106 to 0.212. Following the discussion of calibration strategy in the text (see Section 1.4), changing the vacancy posting cost affects the calibration of the matching efficiency in order to maintain a mean monthly job finding rate of 45.26 percent. Therefore, under the alternative calibration of $c = 0.212$, the efficiency parameter γ is set to 0.635. The rest of parameters remain unchanged at the aggregate level (see Table 1.6). Panel F of Table 1.14 reports simulation results for all four education groups. Again, the simulation results remain consistent with the ones under our baseline calibration.

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

Overall, the simulation results for different specifications of the flow vacancy posting cost illustrate that our proportionality assumption $c_h = cH$ is not crucial for our conclusions. The same holds for the results on absolute and relative volatilities, which we report in Tables 1.22 and 1.23 in the Appendix.

1.9 Conclusions

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

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

1.10 Appendix

1.10.1 Data Description

Current Population Survey

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

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

Moreover, due to the January 1994 CPS redesign there is a discontinuity in the short-term unemployment series.[49] More precisely, from 1994 onwards the CPS does not ask about unemployment duration a worker who is unemployed in consecutive months, but instead his duration is calculated as the sum of unemployment duration in the previous month plus the intervening number of weeks. Nevertheless, workers in the "incoming rotation groups" (1st and 5th) are always asked about unemployment duration, even after 1994. This allows to calculate the ratio of the short-term unemployment share for the 1st and 5th rotation groups to the full sample's short-term unemployment share. One can then multiply the short-term unemployment series after 1994 by this ratio. Since the ratio turns out to be quite volatile over time, we follow the suggestion by Elsby et al. (2009) and multiply the series by the average value of the ratio for the period February 1994 - December 2010. We apply this correction for each education group separately, although the ratios are very similar across groups. More precisely, the ratio equals to 1.144 (1.167 when limiting the sample to 16 years of age and over) for high school dropouts, 1.144 (1.163) for high school graduates, 1.141 (1.139) for peo-

[49] See also Shimer (2007) and references therein.

ple with some college, 1.133 (1.147) for college graduates, and 1.142 (1.157) for aggregate numbers. Note that the aggregate number for the whole sample is very close to the one calculated by Elsby et al. (2009), who find an average ratio of 1.1549 for the period February 1994 - January 2005.

Next, we seasonally adjust the series using the X-12-ARIMA seasonal adjustment program (version 0.3), provided by the U.S. Census Bureau. Then we compute the monthly outflow and inflow rates. The outflow rate can be obtained from the equation describing the law of motion for unemployment: $u_{t+1} = (1 - F_t)u_t + u^s_{t+1}$, where u_t denotes unemployed, u^s_t short-term unemployed and F_t the monthly outflow probability. The latter is hence given by $F_t = 1 - (u_{t+1} - u^s_{t+1})/u_t$, with the outflow hazard rate being $f_t = -\log(1 - F_t)$. To calculate inflow rates, we use the discrete-time correction for time aggregation bias of Elsby et al. (2009), which takes into account that some workers who become unemployed managed to find a new job before the next CPS survey arrives. In particular, we impute discrete weekly hazard rates by noting that on a weekly basis we have: $u_{t+\tau+1/4} = u_{t+\tau} + s^w_t e_{t+\tau} - f^w_t u_{t+\tau} = s^w_t l_t + (1 - s^w_t - f^w_t)u_{t+\tau}$, where superscript w denotes weekly probabilities, assumed to be constant within a month, l_t denotes labor force, also assumed to be constant within a month, and e_t employment, with the following identity holding $l_t \equiv e_t + u_t$. The weekly inflow rates can be solved for from the following nonlinear equation $u_{t+1} = s^w_t l_t \sum^3_{n=0}(1 - s^w_t - f^w_t)^n + (1 - s^w_t - f^w_t)^4 u_t$.

Employment Opportunity Pilot Project Survey

The 1982 Employment Opportunity Pilot Project (EOPP) is a survey of employers conducted between February and June 1982 in the United States. The survey has three parts. The first one concerns information on general hiring practices, the second part asks the employer about the last hired worker and the last part deals with government programs. We focus only on the central part of the survey, given that it provides specific information about the relationship between education and the degree of on-the-job training. In particular, employers were asked to think about the last new employee the company hired prior to August 1981 regardless of whether that person was still employed by the company at the time of the interview. A series of specific questions were asked about the training received by the new employee during the first three months in the company.

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

National Longitudinal Survey of Youth

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

1.10.2 Supplementary Empirical Evidence

Unemployment Rates by Age

Here we provide a further empirical exploration of unemployment rates by age. In particular, the left panel of Figure 1.8 displays the unemployment rate across education groups for each age group. As we can see, young people (below 25 years of age) experience somehow higher unemployment rates for all education groups. This could be related to their labor market entry, that may start with an unemployment spell. This is one of the reasons why we decide to focus the analysis in the text on individuals with 25 years of age and older. The second reason is that by the age of 25 most individuals have finished their studies. This can be inferred from the right panel of Figure 1.8, where we plot, for each age category, the share of individuals in each education group. As we can see, by the age of 25, the shares start stabilizing.

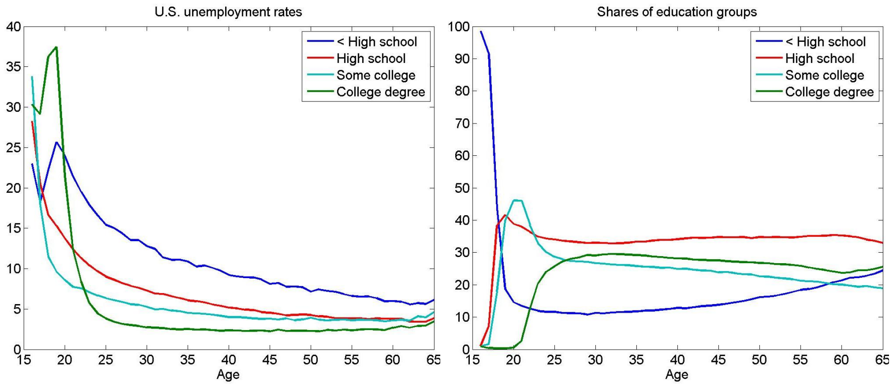


Figure 1.8: U.S. unemployment rates, educational attainment and age

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

Unemployment Duration Shares by Education Groups

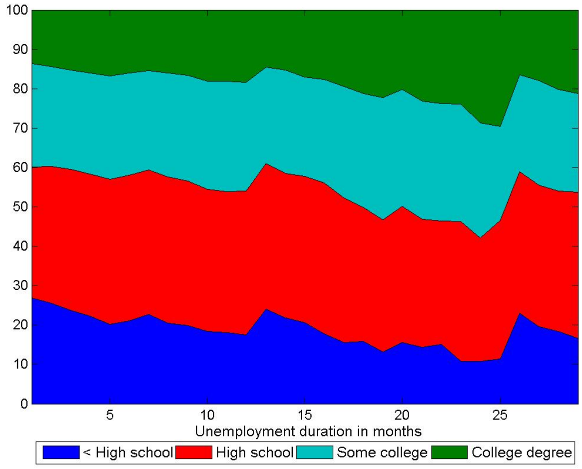


Figure 1.9: Unemployment duration shares by education groups

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

Unemployment Gross Flows

Figure 1.10: Gross flows (25+ years of age)

Notes: We plot twelve-month moving averages of seasonally-adjusted monthly data. The sample period is 1976:01 - 2010:12. All variables are constructed from CPS microdata. Shaded areas indicate NBER recessions.

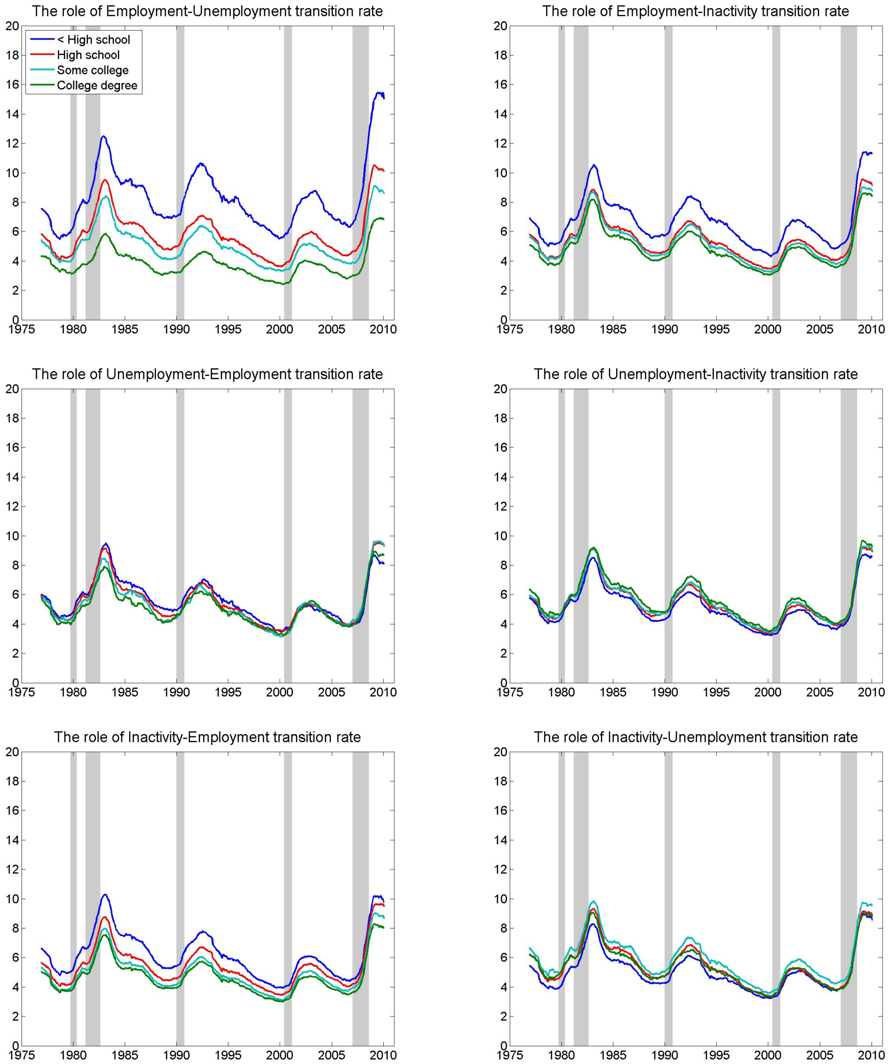


Figure 1.11: Hypothetical unemployment rates (25+ years of age)

Notes: The top left panel shows the unemployment rate series for each group by taking its actual employment-unemployment transition rate series, but keeping the rest of transition rates series at the value for the aggregate economy. The rest of the panels are constructed analogously, but analyzing the role of different transition rates. We plot twelve-month moving averages of seasonally-adjusted monthly data. The sample period is 1976:01 - 2010:12. All variables are constructed using CPS microdata. Shaded areas indicate NBER recessions.

Unemployment Flows for Working-Age Population

Here we provide an analogous analysis to the one in Section 1.2.2 for the whole working-age population. Figure 1.12 presents outflow rates from unemployment and inflow rates to unemployment for people with 16 years of age and over, equivalent to Figure 1.2 in the text. Figure 1.13 plots the hypothetical unemployment rates that allow us to assess separately the role of outflows and inflows in explaining unemployment rate differences across education groups, equivalent to Figure 1.3 in the text. The same conclusion as in the text applies also here: separation rates are responsible for creating the differences in unemployment rates across education groups.

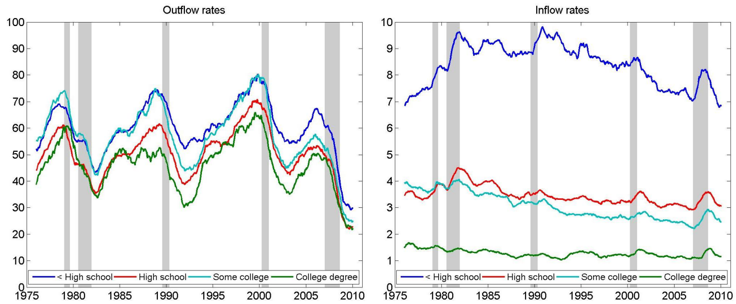


Figure 1.12: Unemployment flows (16+ years of age)

Notes: We plot twelve-month moving averages of seasonally-adjusted monthly data. The sample period is 1976:01 - 2010:12. All variables are constructed from CPS microdata. Shaded areas indicate NBER recessions.

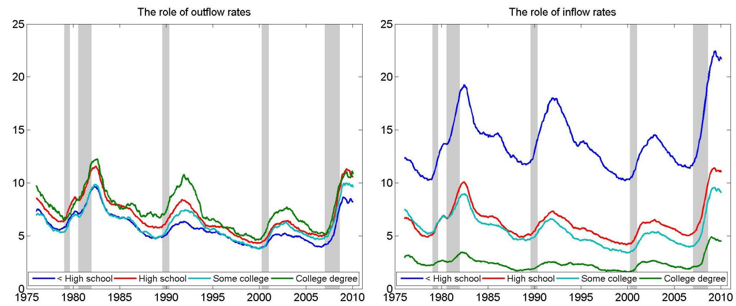


Figure 1.13: Hypothetical unemployment rates (16+ years of age)

Notes: The left panel shows the unemployment rate series for each group by taking its actual outflow rate series, but keeping the inflow rate series at the value for the aggregate economy. The right panel shows the unemployment rate series for each group by taking its actual inflow rate series, but keeping the outflow rate series at the value for the aggregate economy. We plot twelve-month moving averages of seasonally-adjusted monthly data. The sample period is 1976:01 - 2010:12. All variables are constructed using CPS microdata. Shaded areas indicate NBER recessions.

The 1982 EOPP Survey

Here we provide some further tabulations of training by education level from the 1982 EOPP survey. Table 1.17 summarizes the main training variables of the survey with a breakdown by education, when we do not restrict the sample by age and we do not remove the outliers from the top 5 percent of the training duration distribution.

Table 1.17: Measures of training by education level from the 1982 EOPP survey

	Less than high school	High school	Some college	College degree	All individuals
Incidence rate of initial training (in percent)					
Formal training	10.2	11.9	17.2	18.7	13.4
Informal training by manager	88.8	85.9	89.1	88.0	87.1
Informal training by coworkers	63.6	59.4	61.9	54.3	59.9
Informal training by watching others	77.8	75.7	81.1	73.4	76.8
Some type of training	94.8	94.1	97.4	93.7	94.8
Time to become fully trained					
In weeks	15.9	21.3	23.1	30.2	21.9
Productivity gap (in percent)					
Typical new hires versus incumbents	34.6	39.1	43.3	50.3	40.5

Notes: The sample includes 2530 individuals. All measures of training correspond to typical new hires.

Table 1.18 summarizes the main training variables of the survey when we restrict the sample to individuals with 16 years of age and over, for whom we have information on education. Moreover, since the distribution of training duration is highly skewed to the right, we eliminate outliers by truncating distribution at its 95th percentile. The data from this table are going to be used for parameterization of training when we perform the sensitivity analysis of the quantitative results for the whole working-age population.

Table 1.18: Measures of training by education level from the 1982 EOPP survey

	Less than high school	High school	Some college	College degree	All individuals
Incidence rate of initial training (in percent)					
Formal training	9.1	11.4	16.5	20.1	13.0
Informal training by manager	89.4	86.8	89.8	88.4	87.8
Informal training by coworkers	63.7	61.7	64.4	56.5	62.0
Informal training by watching others	79.8	78.1	83.5	74.9	79.1
Some type of training	95.4	94.6	97.9	93.8	95.3
Time to become fully trained					
In weeks	9.4	12.3	14.7	18.4	13.0
Productivity gap (in percent)					
Typical new hires versus incumbents	34.4	39.1	43.6	50.8	40.6

Notes: The sample includes 2164 individuals with 16 years of age and older, for whom we have information on education. The distribution of training duration is truncated at its 95th percentile. All measures of training correspond to typical new hires.

1.10.3 Proofs and Computational Strategy

Proof of Proposition 2

The Constrained-Efficient Allocation

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

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

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

with

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

subject to the following laws of motion for employment:

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

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

The first order conditions are:

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

The envelope conditions are:

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

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

$$
\begin{aligned}
\frac{c_h}{\gamma\theta^{-\alpha}} =&\beta(1-\alpha)\int_{\tilde{a}^T}^{\infty}\Big\{(1-\tau_h)HAa - b_h - \frac{\alpha}{1-\alpha}c_h\theta \\
&+\frac{(1-\delta)(1-\phi_h)c_h}{(1-\alpha)\gamma\theta^{-\alpha}} + \frac{\beta(1-\delta)\phi_h}{1-\beta(1-\delta)(1-G(\tilde{a}^S))}\\
&\int_{\tilde{a}^S}^{\infty}\Big\{HAa - b_h - \frac{\alpha}{1-\alpha}c_h\theta\Big\}dG(a)\Big\}dG(a).
\end{aligned} \tag{1.13}
$$

Similarly, the optimal job destruction conditions are given by:

$$
\begin{aligned}
0 =&(1-\tau_h)HA\tilde{a}^T - b_h - \frac{\alpha}{1-\alpha}c_h\theta + \frac{(1-\delta)(1-\phi_h)c_h}{(1-\alpha)\gamma\theta^{-\alpha}}\\
&+\frac{\beta(1-\delta)\phi_h}{1-\beta(1-\delta)(1-G(\tilde{a}^S))}\int_{\tilde{a}^S}^{\infty}\Big\{HAa - b_h - \frac{\alpha}{1-\alpha}c_h\theta\Big\}dG(a),
\end{aligned} \tag{1.14}
$$

$$
\begin{aligned}
0 =&HA\tilde{a}^S - b_h - \frac{\alpha}{1-\alpha}c_h\theta\\
&+\frac{\beta(1-\delta)}{1-\beta(1-\delta)(1-G(\tilde{a}^S))}\int_{\tilde{a}^S}^{\infty}\Big\{HAa - b_h - \frac{\alpha}{1-\alpha}c_h\theta\Big\}dG(a).
\end{aligned} \tag{1.15}
$$

Decentralized Allocation

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

The main equilibrium conditions are:

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

Notice that we can write:

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

So, we have the following job creation condition:

$$
\begin{aligned}
\frac{c_h}{\gamma\theta^{-\alpha}} =&\beta(1-\eta)\int_{\tilde{a}^T}^{\infty}\Big\{(1-\tau_h)HAa - b_h - \frac{\eta}{1-\eta}c_h\theta \\
&+ \frac{(1-\delta)(1-\phi_h)c_h}{(1-\eta)\gamma\theta^{-\alpha}} + \frac{\beta(1-\delta)\phi_h}{1-\beta(1-\delta)(1-G(\tilde{a}^S))} \\
&\int_{\tilde{a}^S}^{\infty}\Big\{HAa - b_h - \frac{\eta}{1-\eta}c_h\theta\Big\}dG(a)\Big\}dG(a).
\end{aligned} \tag{1.16}
$$

The job destruction conditions can be derived as:

$$
\begin{aligned}
0 =&(1-\tau_h)HA\tilde{a}^T - b_h - \frac{\eta}{1-\eta}c_h\theta + \frac{(1-\delta)(1-\phi_h)c_h}{(1-\eta)\gamma\theta^{-\alpha}} \\
&+ \frac{\beta(1-\delta)\phi_h}{1-\beta(1-\delta)(1-G(\tilde{a}^S))}\int_{\tilde{a}^S}^{\infty}\Big\{HAa - b_h - \frac{\eta}{1-\eta}c_h\theta\Big\}dG(a),
\end{aligned} \tag{1.17}
$$

$$
\begin{aligned}
0 =&HA\tilde{a}^S - b_h - \frac{\eta}{1-\eta}c_h\theta \\
&+ \frac{\beta(1-\delta)}{1-\beta(1-\delta)(1-G(\tilde{a}^S))}\int_{\tilde{a}^S}^{\infty}\Big\{HAa - b_h - \frac{\eta}{1-\eta}c_h\theta\Big\}dG(a).
\end{aligned} \tag{1.18}
$$

By comparing the constrained-efficient equilibrium conditions (1.13)-(1.15) with the decentralized equilibrium conditions (1.16)-(1.18) it follows that the decentralized allocation replicates the constrained-efficient allocation when $\eta = \alpha$, reflecting the standard Hosios condition.

Worker's bargaining power and job destruction - analytical results

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

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

Using the above in the job creation condition gives:

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

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

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

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

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

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

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

Combining the above and rearranging gives:

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

where:

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

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

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

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

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

Worker's bargaining power and job destruction - numerical results

Figure 1.14 illustrates how different values of bargaining power affect both job destruction margins under our baseline calibration. Note that in this numerical exercise we allow for aggregate productivity shocks and some persistence in idiosyncratic productivity shocks.

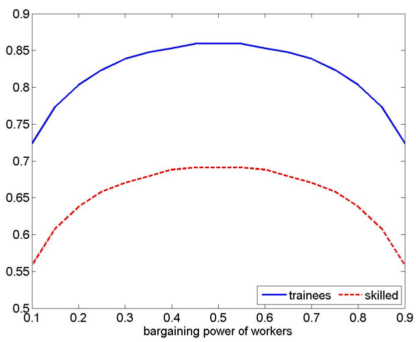


Figure 1.14: Workers' bargaining power and reservation productivity

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

Computational Strategy

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

1.10.4 Sensitivity Analysis of Quantitative Results - Volatilities

Table 1.19: Working-age population - volatilities

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

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

Table 1.20: Evaluating other potential explanations - absolute volatilities

	n	u	f	s
Panel A: U.S. data, 1976 - 2010				
Less than high school	1.78	1.78	7.62	0.42
High school	1.26	1.26	7.48	0.24
Some college	1.02	1.02	8.96	0.18
College degree	0.55	0.55	8.55	0.11
Panel B: Size of Match Surplus				
$b_1 = 0.90$	3.52	3.52	3.77	0.75
$b_2 = 0.85$	1.40	1.40	3.40	0.36
$b_3 = 0.80$	0.53	0.53	3.06	0.16
$b_4 = 0.75$	0.24	0.24	2.75	0.08
Panel C: Hiring Costs				
$c_1 = 0.05$	1.13	1.13	3.89	0.37
$c_2 = 0.10$	0.85	0.85	3.31	0.25
$c_3 = 0.15$	0.59	0.59	2.82	0.15
$c_4 = 0.20$	0.41	0.41	2.50	0.09
Panel D: Idiosyncratic Shocks – Frequency				
$\lambda_1 = 1/6$	1.17	1.17	2.07	0.21
$\lambda_2 = 1/4$	1.19	1.19	2.69	0.29
$\lambda_3 = 1/3$	0.79	0.79	3.27	0.22
$\lambda_4 = 1/2$	0.14	0.14	3.56	0.02
Panel E: Idiosyncratic Shocks – Dispersion				
$\sigma_1 = 0.35$	1.49	1.49	2.51	0.40
$\sigma_2 = 0.30$	1.32	1.32	2.95	0.36
$\sigma_3 = 0.25$	0.80	0.80	3.15	0.23
$\sigma_4 = 0.20$	0.34	0.34	3.43	0.09
Panel F: Matching Efficiency				
$\gamma_1 = 0.60$	1.06	1.06	3.77	0.34
$\gamma_2 = 0.50$	0.87	0.87	3.34	0.26
$\gamma_3 = 0.40$	0.66	0.66	3.02	0.17
$\gamma_4 = 0.30$	0.34	0.34	2.23	0.06

Notes: Absolute volatilities are defined as standard deviations of the data expressed in deviations from an HP trend with smoothing parameter 10^5. Data moments are quarterly averages of monthly seasonally-adjusted data constructed from CPS microdata. The sample period is 1976:01 - 2010:12. Statistics for the model are means across 100 simulations.

Table 1.21: Evaluating other potential explanations - relative volatilities

	n	u	f	s
Panel A: U.S. data, 1976 - 2010				
Less than high school	1.99	18.66	17.45	9.23
High school	1.35	20.83	18.62	9.09
Some college	1.08	21.32	20.48	8.28
College degree	0.57	20.16	21.39	9.87
Panel B: Size of Match Surplus				
$b_1 = 0.90$	4.30	23.22	13.53	15.38
$b_2 = 0.85$	1.53	18.37	8.90	11.82
$b_3 = 0.80$	0.56	13.24	6.31	7.97
$b_4 = 0.75$	0.25	9.65	4.76	5.44
Panel C: Hiring Costs				
$c_1 = 0.05$	1.25	12.63	7.14	7.07
$c_2 = 0.10$	0.90	15.59	7.33	9.72
$c_3 = 0.15$	0.61	15.06	7.06	9.34
$c_4 = 0.20$	0.42	13.11	6.84	7.45
Panel D: Idiosyncratic Shocks – Frequency				
$\lambda_1 = 1/6$	1.40	7.42	6.22	3.28
$\lambda_2 = 1/4$	1.34	11.23	6.88	6.32
$\lambda_3 = 1/3$	0.83	15.60	7.32	9.70
$\lambda_4 = 1/2$	0.14	8.54	6.85	2.10
Panel E: Idiosyncratic Shocks – Dispersion				
$\sigma_1 = 0.35$	1.75	10.37	6.45	6.14
$\sigma_2 = 0.30$	1.47	13.52	7.21	8.33
$\sigma_3 = 0.25$	0.85	15.14	7.15	9.46
$\sigma_4 = 0.20$	0.35	13.43	7.12	7.18
Panel F: Matching Efficiency				
$\gamma_1 = 0.60$	1.16	13.29	7.22	7.59
$\gamma_2 = 0.50$	0.93	14.40	7.03	8.82
$\gamma_3 = 0.40$	0.69	15.84	7.24	9.95
$\gamma_4 = 0.30$	0.35	11.48	6.57	6.02

Notes: Relative volatilities are defined as standard deviations of the natural logarithm of the data expressed in deviations from an HP trend with smoothing parameter 10^5. Data moments are quarterly averages of monthly seasonally-adjusted data constructed from CPS microdata. The sample period is 1976:01 - 2010:12. Statistics for the model are means across 100 simulations.

Table 1.22: Sensitivity analysis of the main quantitative results - absolute volatilities

	Parameters			n	u	f	s
Panel A: U.S. data, 1976 - 2010							
Less than high school				1.78	1.78	7.62	0.42
High school				1.26	1.26	7.48	0.24
Some college				1.02	1.02	8.96	0.18
College degree				0.55	0.55	8.55	0.11
Panel B: Value of being unemployed – level							
	$1/\phi_h$	τ_h	b				
Less than high school	2.35	0.163	0.71	0.57	0.57	1.76	0.17
High school	2.78	0.181	0.71	0.50	0.50	1.76	0.15
Some college	3.67	0.227	0.71	0.25	0.25	1.83	0.07
College degree	4.19	0.240	0.71	0.18	0.18	1.90	0.04
Panel C: Constant value of being unemployed							
	$1/\phi_h$	τ_h	b_h				
Less than high school	2.35	0.163	0.82	6.60	6.60	3.08	1.31
High school	2.78	0.181	0.82	2.43	2.43	3.46	0.58
Some college	3.67	0.227	0.82	0.19	0.19	3.03	0.05
College degree	4.19	0.240	0.82	0.03	0.03	2.12	0.00
Panel D: Actual vacancy posting costs							
	$1/\phi_h$	τ_h	c_h				
Less than high school	2.35	0.163	0.090	1.04	1.04	3.01	0.31
High school	2.78	0.181	0.104	0.91	0.91	3.04	0.26
Some college	3.67	0.227	0.121	0.43	0.43	3.10	0.10
College degree	4.19	0.240	0.128	0.34	0.34	3.40	0.07
Panel E: Constant vacancy posting costs							
	$1/\phi_h$	τ_h	c_h				
Less than high school	2.35	0.163	0.106	0.99	0.99	2.98	0.28
High school	2.78	0.181	0.106	0.87	0.87	3.06	0.25
Some college	3.67	0.227	0.106	0.50	0.50	3.38	0.13
College degree	4.19	0.240	0.106	0.42	0.42	3.70	0.10
Panel F: Vacancy posting costs – level							
	$1/\phi_h$	τ_h	c_h				
Less than high school	2.35	0.163	0.212	1.09	1.09	3.07	0.33
High school	2.78	0.181	0.212	0.97	0.97	3.21	0.28
Some college	3.67	0.227	0.212	0.47	0.47	3.29	0.12
College degree	4.19	0.240	0.212	0.30	0.30	3.34	0.06

Notes: Absolute volatilities are defined as standard deviations of the data expressed in deviations from an HP trend with smoothing parameter 10^5. Data moments are quarterly averages of monthly seasonally-adjusted data constructed from CPS microdata. The sample period is 1976:01 - 2010:12. Statistics for the model are means across 100 simulations.

Table 1.23: Sensitivity analysis of the main quantitative results - relative volatilities

	Parameters			n	u	f	s
Panel A: U.S. data, 1976 - 2010							
Less than high school				1.99	18.66	17.45	9.23
High school				1.35	20.83	18.62	9.09
Some college				1.08	21.32	20.48	8.28
College degree				0.57	20.16	21.39	9.87
Panel B: Value of being unemployed – level							
	$1/\phi_h$	τ_h	b				
Less than high school	2.35	0.163	0.71	0.62	7.70	3.91	4.78
High school	2.78	0.181	0.71	0.53	8.28	3.94	5.29
Some college	3.67	0.227	0.71	0.26	8.39	4.05	4.98
College degree	4.19	0.240	0.71	0.18	7.54	4.19	3.86
Panel C: Constant value of being unemployed							
	$1/\phi_h$	τ_h	b_h				
Less than high school	2.35	0.163	0.82	12.02	16.81	18.86	11.80
High school	2.78	0.181	0.82	2.85	18.85	10.49	12.20
Some college	3.67	0.227	0.82	0.19	9.41	5.61	4.28
College degree	4.19	0.240	0.82	0.03	2.77	2.65	0.17
Panel D: Actual vacancy posting costs							
	$1/\phi_h$	τ_h	c_h				
Less than high school	2.35	0.163	0.090	1.14	13.00	6.70	7.97
High school	2.78	0.181	0.104	0.98	14.57	6.94	9.20
Some college	3.67	0.227	0.121	0.44	13.71	7.18	7.58
College degree	4.19	0.240	0.128	0.35	12.78	7.44	6.18
Panel E: Constant vacancy posting costs							
	$1/\phi_h$	τ_h	c_h				
Less than high school	2.35	0.163	0.106	1.07	14.12	6.92	8.86
High school	2.78	0.181	0.106	0.93	14.71	6.94	9.29
Some college	3.67	0.227	0.106	0.51	14.80	7.48	8.40
College degree	4.19	0.240	0.106	0.43	14.10	7.69	7.29
Panel F: Vacancy posting costs – level							
	$1/\phi_h$	τ_h	c_h				
Less than high school	2.35	0.163	0.212	1.19	13.58	6.83	8.49
High school	2.78	0.181	0.212	1.04	15.01	7.20	9.42
Some college	3.67	0.227	0.212	0.49	14.72	7.44	8.35
College degree	4.19	0.240	0.212	0.31	11.97	7.50	5.27

Notes: Relative volatilities are defined as standard deviations of the natural logarithm of the data expressed in deviations from an HP trend with smoothing parameter 10^5. Data moments are quarterly averages of monthly seasonally-adjusted data constructed from CPS microdata. The sample period is 1976:01 - 2010:12. Statistics for the model are means across 100 simulations.

Chapter 2

LABOR MARKET FRICTIONS AND BARGAINING COSTS

2.1 Introduction

The canonical Diamond-Mortensen-Pissarides search and matching model of unemployment is based on three main building blocks: the matching function, the job creation condition, and the wage equation. Among these, the wage equation that splits the monopoly rents inherent to any job match due to search frictions remains probably the least investigated and the least understood.[1] Most papers in the literature simply assume period-by-period Nash wage bargaining protocol. While this assumption facilitates the model's tractability, it is unfortunately also the main source for much of the recent criticism pointed at search and matching models, because it leads to the unemployment volatility puzzle (Shimer, 2005). Moreover, a perfectly flexible wage is inconsistent with vast empirical evidence on wage stickiness.

Another important element of the labor market analysis that has been recently largely ignored in the search and matching literature relates to job destruction. Whereas the seminal contribution by Mortensen and Pissarides (1994) included a proper theoretical modelling of job destruction decisions, many subsequent papers simply assumed an exogenously given and constant probability of match separation. The main justification for this recent trend in macroeconomic modelling of the labor market originates in the empirical work of Shimer (2007), who finds that the employment exit probability has accounted only for 25 percent of unemployment fluctuations in the United States over the post-war period, with the share dropping to merely 5 percent during last two decades. These findings have been

[1]In his Nobel prize lecture, Pissarides (2011) recently argued that wage determination in search and matching models presents an area of research that should attract a lot of attention in the future.

challenged by Fujita and Ramey (2009), who by using a different decomposition method attribute more than 40 percent of unemployment fluctuations in the United States to the time variation in the separation rate.[2] Perhaps even more importantly, Elsby et al. (2012) provide evidence that compared to the Anglo-Saxon countries, the job destruction margin plays a bigger role in Continental Europe and Nordic countries, where it contributes roughly half to unemployment fluctuations. Hence, if we want to understand unemployment fluctuations in the latter set of countries, we cannot proceed with a constant separation rate assumption. Additionally, theoretical models with a constant separation rate are at odds with empirical evidence that recessions start with a burst of job destruction (i.e., changes in separation rate lead changes in unemployment) and that gross worker flows increase during a downturn (Elsby et al., 2012).

This paper develops a search and matching model with an explicit theoretical link between wage stickiness and job destruction. This task has proved to be a difficult one in the existing literature, as one needs to deal with the criticism of Barro (1977), directed at the allocational effects of wage stickiness. In particular, Barro argued that job separations due to wage stickiness violate rationality as the worker and the firm have an ongoing relationship and should therefore be able to exploit all potential gains from mutual trade. The model developed here avoids this criticism by relying on microeconomic foundations for wage stickiness. More precisely, the model explicitly acknowledges that wage bargaining takes time and other resources, and thus relates the origins of infrequent wage adjustments to a fixed wage bargaining cost. Firms and workers are thus free to renegotiate the wage at any point in time, but need to pay a fixed bargaining cost whenever such wage negotiations occur. Whether it is optimal to renegotiate or not, will depend on aggregate and idiosyncratic productivity shocks experienced, with wage inertia emerging as an endogenous outcome of the model. Crucially, in recessionary periods characterized by low aggregate productivity some firms and workers will find it optimal to separate instead of renegotiating the wage and paying the fixed wage bargaining cost. In this sense, the model rationalizes the empirical observation that many firms in recessions do not avoid layoffs by cutting pay (Bewley, 1998, 1999).

Two main predictions of the model concern the relationship between wage rigidities and job destruction. First, already the steady-state version of the model provides a theoretical link between wage bargaining institutions and the unemployment level, illustrating how higher wage bargaining costs lead to higher unemployment. Second, the dynamic version of the model shows how unemployment volatility increases with wage bargaining costs, primarily due to enhanced volatility at the job destruction margin. The model can thus explain why Euro-

[2] Elsby et al. (2009) make a similar point.

pean countries on average experience higher unemployment with a bigger role of job destruction for unemployment fluctuations than the United States, given that European countries have labor market institutions that are associated with higher wage bargaining costs (higher presence of unions, higher share of employees covered by wage bargaining agreements, higher coordination of wage bargaining).

The main assumption of this paper is that wage bargaining represents a costly activity, captured in the model by a fixed bargaining cost. The modelling device of a fixed bargaining cost has some natural economic interpretations. Evidence suggests that the bargaining process between firms and workers is frequently accompanied by strikes and other disruptions of production, leading to lower productivity and quality of production (Kleiner et al., 2002, Krueger and Mas, 2004, Mas, 2008). Similarly, wage negotiations can result in harmed workers' morale and lower subsequent work effort, which is especially true when workers share the impression that the negotiated wage outcome is too low or when the wage is reduced (Greenberg, 1990, Mas, 2006). Finally, wage bargaining might entail costly information gathering, for example measuring the worker's productivity or forecasting the firm's future profitability which determines the extent of match surplus to be shared.[3]

Shimer (2005) noted that the main reason for the unemployment volatility puzzle in search and matching models relates to excessive wage fluctuations. In a boom, wages absorb most of the productivity gains, thus discouraging vacancy creation. In reaction to that, ad hoc wage rigidity in the sense of a wage norm was proposed by Hall (2005) as a solution to augment labor market volatilities in models with labor market frictions. The issue of labor market volatilities was also studied by Gertler and Trigari (2009), who developed a search and matching model with time-dependent staggered wage setting. Blanchard and Galí (2010) construct a utility-based model of fluctuations with reduced-form wage rigidity and unemployment in order to analyze monetary policy implications. Michaillat (2012) combines wage rigidities with diminishing marginal returns to labor, which allows him to introduce a concept of job rationing into a search and matching model. All these models assume an exogenous and constant separation rate. Therefore, the effect of wage stickiness works through the job creation margin with the crucial assumption being the presence of wage stickiness in new job matches.[4] Indeed, as shown for example by Shimer (2004), wage stickiness present only in exist-

[3]Pissarides (2009) introduces in his model a fixed matching cost that leads to higher model-generated unemployment volatility and at the same time preserves wage flexibility. One of his interpretations for this cost includes (one-off) negotiation costs.

[4]Moreover, since in these type of models the wage always needs to remain within the bargaining set to prevent inefficient separations, only small shocks can affect the employment relationships of workers and firms, as pointed out by Mortensen and Nagypál (2007). In practice, this rules out the introduction of idiosyncratic productivity shocks, at least of the size typically calibrated.

ing jobs bears no effects on unemployment dynamics in a standard search and matching model. Some recent empirical evidence seems to be contradicting the assumption that wages of new hires are rigid (Haefke et al., 2008, Pissarides, 2009, Kudlyak, 2011).[5] As a result, Pissarides (2009) concluded that wage stickiness cannot provide an answer to the unemployment volatility puzzle. In contrast with the existing literature on wage stickiness in search and matching models, this paper explores the effects of wage stickiness on endogenous job destruction. Importantly, the wage always needs to be negotiated in the initial period of a job match, which yields a perfectly flexible wage for new hires, consistent with the empirical microevidence reviewed above.

The rest of the paper is organized as follows. Section 2.2 develops the main theoretical framework – it constructs a model with endogenous separations and costly wage bargaining, and then establishes its block recursivity. The choice of parameters for numerical simulations is discussed in Section 2.3. Section 2.4 provides a steady state analysis, while an analysis of full dynamic version of the model can be found in Section 2.5. Section 2.6 considers two applications of the model and Section 2.7 concludes with a discussion of possible avenues for future research.

2.2 The Model

This section develops a stochastic version of the Diamond-Mortensen-Pissarides search and matching model with endogenous separations and the main novel modification of introducing costly wage bargaining that gives rise to endogenous wage rigidities. In particular, the firm and the worker are free to renegotiate their wage at any point in time, but need to pay a fixed bargaining cost in order to do so. As a consequence, the wage endogenously remains unchanged when shocks are small, with wage rebargaining occurring only when the state of the economy changes sufficiently to justify the payment of the fixed cost.

2.2.1 Environment

The discrete-time model economy contains a continuum of measure one of risk-neutral, infinitely-lived workers. Each worker maximizes his expected discounted lifetime consumption, $\mathbb{E}_t \sum_{k=0}^{\infty} \beta^k c_{t+k}$, where $\beta \in (0, 1)$ represents the usual discount factor. Workers can be either employed or unemployed. Employed workers

[5] Some controversy regarding wage stickiness for new hires remains present due to the possibility of changing worker composition over the cycle – see Gertler and Trigari (2009) for a further discussion of this issue and Carneiro et al. (2012) for some related empirical evidence from a longitudinal matched employer-employee data set for Portugal.

earn real wage $w_{t+k|t}$, where the subscript indicates that the wage for the period $t+k$ was last renegotiated in period t. Unemployed workers have access to a home production technology, which generates b consumption units per time period (b can in general also include potential unemployment benefits). By assumption all unemployed search for jobs, hence I abstract from the labor force participation decision.

There is also a continuum of a large measure of risk-neutral firms, which maximize profits. In order to produce, firms need to hire workers by posting vacancies. Each firm can post one vacancy only and for this it pays a vacancy posting cost of c units of output per period. Moreover, each firm can have at most one employee and can always freely choose to shut down and become inactive.[6] After a firm meets with a worker, they first draw an idiosyncratic productivity a from a lognormal distribution $F(a)$. If the drawn idiosyncratic productivity level is high enough in the sense described more in detail later on, they start producing according to the following technology:

$$y_t = A_t a_t.$$

In the equation above, A_t denotes aggregate productivity, which is assumed to be stochastic, evolving over time according to a Markov chain $\{\mathbf{A}, \mathbf{\Pi^A}\}$, with the grid $\mathbf{A} = \{A_1, A_2, ..., A_n\}$ and the transition matrix $\mathbf{\Pi^A}$ being composed of elements $\pi_{ij}^A = \mathbb{P}\{A' = A_j \mid A = A_i\}$. Similarly, the evolution of idiosyncratic productivity is in general described by a Markov chain $\{\mathbf{a}, \mathbf{\Pi^a}\}$ with the finite grid $\mathbf{a} = \{a_1, a_2, ..., a_m\}$, the transition matrix $\mathbf{\Pi^a}$ being composed of elements $\pi_{ij}^a = \mathbb{P}\{a' = a_j \mid a = a_i\}$, and the initial probability vector being composed of elements $\pi_j^a = \mathbb{P}\{a' = a_j\}$. For the numerical results, I will assume that idiosyncratic productivity shocks follow a Poisson process with arrival rate λ and are being independently drawn from a fixed lognormal distribution $F(a)$. In this case the arrival rate λ determines the persistence of idiosyncratic productivity shocks.

[6]The assumption of one worker per firm, which is common in the standard search and matching literature, serves here a particular technical purpose. When wage rigidities are present in a setting with many workers per firm, wage dispersion leads to dispersion in incentives for posting vacancies, implying that only the firm with the lowest wage is posting vacancies in equilibrium. To get around this problem, Thomas (2008) assumes convex vacancy-posting costs, Gertler and Trigari (2009) deal with quadratic costs of adjusting employment, while Galí (2011) works with the production technology featuring decreasing returns. Instead, I restrict firms to have at most one employee. The assumption of single-worker production units is simply a technical modelling device and should not be interpreted too narrowly. Indeed, it can be easily extended to the case where real-world firms are composed of several modelled single-worker production units.

2.2.2 Labor Markets

Workers and firms interact in the labor market. The matching process between both types of agents is formally depicted by the existence of a matching function $m(v_t, u_t)$, where v_t and u_t are measures of vacancies and unemployed workers, respectively. The matching function is assumed to be homogeneous of degree one with $m'(\cdot) > 0$ and $m''(\cdot) < 0$. Letting $\theta_t \equiv v_t/u_t$ denote the labor market tightness, we can express the probability for the searching firm to meet a worker as $q_t = m(v_t, u_t)/v_t = m(1, \theta_t^{-1})$, and the corresponding probability for the searching worker to find a job as $p_t = m(v_t, u_t)/u_t = m(\theta_t, 1)$. The probabilities are decreasing in the measures of vacancies and unemployed workers, respectively, i.e. $\partial q_t/\partial v_t < 0$ and $\partial p_t/\partial u_t < 0$. For the numerical results, I will assume a standard Cobb-Douglas matching function with elasticity α and matching efficiency γ:

$$m(u_t, v_t) = \gamma u_t^{\alpha} v_t^{1-\alpha}$$

Finally, the timing assumption is such that an unemployed worker in period $t-1$ can start working at the earliest in period t. This reflects the intuitive notion of the search and matching paradigm that it takes time before a worker can be met with a firm and become fully productive. For simplicity, I abstract from the possibility of on-the-job search.

2.2.3 Characterization of Recursive Equilibrium

The behavior of firms and workers can be summarized by a set of Bellman equations. The block of Bellman equations for the firm is:

$$V^{JN}(A, a) = Aa - (1-\eta)\kappa_0 - w + \beta(1-\delta)\mathbb{E}_{A,a}\{V^J(A', a', w'_{-1})\} \tag{2.1}$$

$$V^{JR}(A, a) = Aa - (1-\eta)\kappa - w + \beta(1-\delta)\mathbb{E}_{A,a}\{V^J(A', a', w'_{-1})\} \tag{2.2}$$

$$V^{JO}(A, a, w_{-1}) = Aa - w_{-1} + \beta(1-\delta)\mathbb{E}_{A,a}\{V^J(A', a', w'_{-1})\} \tag{2.3}$$

with the following optimal choice at the beginning of each period for continuing job matches:

$$\begin{aligned} V^J(A, a, w_{-1}) = \max\{0, & \\ & V^{JR}\mathbb{1}\{V^{ER} > V^U\}, \\ & V^{JO}\mathbb{1}\{V^{EO} = \max\{V^U, V^{ER}, V^{EO}\}\}\} \end{aligned} \tag{2.4}$$

Equation (2.1) gives the (present-discounted) value of a new job with an initially set wage. The current value consists of firm's output minus the initial bargaining costs and the wage. The initial fixed bargaining costs amounts to κ_0 and the firms needs to pay a share $(1-\eta)$ of this cost, where η stands for the worker's bargaining power in the surplus splitting equation as will become clear later on.[7] The continuation value depends on possible evolution of shocks, with $\mathbb{E}_{A,a}$ denoting expectations conditioned on the current values of A and a. For generality, existing job matches are also subject to an exogenously given and constant probability of separation in each period, δ. Equation (2.2) summarizes the value of a job when the renegotiation occurs. Note that the bargaining cost κ for the case of renegotiation differs from the initial bargaining costs. If one's interpretation for the bargaining cost includes an output loss due to strikes, then it is clear that the initial bargaining costs should be lower, as obviously strikes are impossible before the job match is formed. Another thing to notice is that the wage, which is an endogenously determined object that depends both on aggregate and idiosyncratic productivity, is the same for the initial bargaining and rebargaining, despite the difference in bargaining costs; this follows as the bargaining cost will cancel out from the wage equation that will be derived later on. Equation (2.3) describes the value of a job with an old wage, in which case the firm avoids paying the fixed bargaining cost. Finally, equation (2.4) says that in the beginning of each continuation period the firm has the option of choosing between: i) closing down and obtaining a zero payoff, ii) continuing with the job relationship and renegotiating the wage, and iii) continuing with the job relationship under the existing wage. Clearly, the firm's choice has to be mutually consistent with the worker's choice as denoted by the indicator function $\mathbb{1}\{\cdot\}$. The tie-breaking rule stipulates that in the case of equivalent values, the firm and the worker prefer to choose their outside option, which slightly facilitates the subsequent analysis. Moreover, any agent can initiate the wage renegotiation process, provided that the other party is still better off than in the case of ending the job match. Thus, the decision matrix for both agents has the following form: i) separate if at least one agent wants to separate; ii) rebargain if at least one agent wants to rebargain, but nobody wants to separate; and iii) continue with the old wage only if both agents prefer to do so.

[7] It would be straightforward to generalize the setting in order to allow for differences in sharing arrangements for bargaining costs and for the surplus. Notice, however, that the current assumption on sharing of bargaining costs is intuitive in the following sense. When the worker's bargaining power equals to zero, the worker always consumes according to his outside option, b. Thus, in this case the firm cannot inflict any amount of bargaining costs whatsoever on the worker.

An analogous block of Bellman equations applies to the worker:

$$V^{EN}(A,a) = w - \eta\kappa_0 + \beta\delta\mathbb{E}_A\{V^U(A')\} + \beta(1-\delta)\mathbb{E}_{A,a}\{V^E(A',a',w'_{-1})\} \tag{2.5}$$

$$V^{ER}(A,a) = w - \eta\kappa + \beta\delta\mathbb{E}_A\{V^U(A')\} + \beta(1-\delta)\mathbb{E}_{A,a}\{V^E(A',a',w'_{-1})\} \tag{2.6}$$

$$V^{EO}(A,a,w_{-1}) = w_{-1} + \beta\delta\mathbb{E}_A\{V^U(A')\} + \beta(1-\delta)\mathbb{E}_{A,a}\{V^E(A',a',w'_{-1})\} \tag{2.7}$$

with the following optimal choice at the beginning of each period for continuing job matches:

$$\begin{aligned} V^E(A,a,w_{-1}) = \max\{ & V^U, \\ & V^{ER}\mathbb{1}\{V^{JR} > 0\}, \\ & V^{EO}\mathbb{1}\{V^{JO} = \max\{0, V^{JR}, V^{JO}\}\}\} \end{aligned} \tag{2.8}$$

and the value of being unemployed:

$$\begin{aligned} V^U(A) = & b + p(\theta(A))\beta\mathbb{E}_A\{\max\{V^U(A'), V^{EN}(A',a')\}\} \\ & + (1 - p(\theta(A)))\beta\mathbb{E}_A\{V^U(A')\} \end{aligned} \tag{2.9}$$

Equation (2.5) gives the value of new employment with an initially negotiated wage, in which case the worker earns w and needs to pay a share η of the fixed initial bargaining cost κ_0. Similarly as above, the worker can be exogenously separated from the match and become unemployed with probability δ, whereas the continuation value depends on the evolution of shocks. Next, equation (2.6) describes the value of employment with a renegotiated wage, equation (2.7) summarizes the value of employment with an old wage, whereas equation (2.9) gives the value for unemployed workers. Recall that the latter enjoy utility flow b and are met with the firm at endogenously determined probability $p(\theta(A))$. Finally, as implicit in equation (2.8), in the beginining of each period the employed workers can choose between: i) quitting and becoming unemployed, ii) continuing with the employment relationship and renegotiating the wage, and iii) continuing with the employment relationship under the existing wage. Again, the worker's and the firm's choice on whether and how to continue the job match must be mutually consistent.

Searching firms find a worker with endogenously determined probability, denoted by $q(\theta(A))$. Assuming free entry, the standard job creation condition corresponds to:

$$\frac{c}{q(\theta(A))} = \beta\mathbb{E}_A\{\max\{0, V^{JN}(A',a')\}\} \tag{2.10}$$

All existing jobs with idiosyncratic productivity below threshold $\tilde{a}(A, w_{-1})$ are endogenously destroyed, with this threshold being implicitly defined as the maximum value that satisfies:

$$V^J(A, \tilde{a}, w_{-1}) = 0 \tag{2.11}$$

A similar threshold $\tilde{a}^N(A)$ exists for newly formed jobs:

$$V^{JN}(A, \tilde{a}^N) = 0 \tag{2.12}$$

Whether the worker and the firm prefer to continue with their existing job relationship crucially depends on the wage negotiation process, which is discussed next.

2.2.4 Wage Determination

Due to the presence of search and matching frictions, there exist monopoly rents in every job relationship. These rents need to be shared between the worker and the firm through a wage contract. I first define the bounds of the wage bargaining set implicitly by[8]:

$$\begin{aligned} w^{UB}: &\quad V^{JR} = 0 \\ w^{LB}: &\quad V^{ER} = V^U \end{aligned}$$

Thus the firm's and the worker's reservation wage can be defined as, respectively:

$$\begin{aligned} w^{UB} =& Aa - (1-\eta)\kappa + \beta(1-\delta)\mathbb{E}_{A,a}\{V^J(A', a', w'_{-1})\} \\ w^{LB} =& b + \eta\kappa + p(\theta(A))\beta\mathbb{E}_A\{\max\{V^U(A'), V^{EN}(A', a')\}\} \\ &+ (1 - p(\theta(A)))\beta\mathbb{E}_A\{V^U(A')\} \\ &- \beta\delta\mathbb{E}_A\{V^U(A')\} - \beta(1-\delta)\mathbb{E}_{A,a}\{V^E(A', a', w'_{-1})\} \end{aligned}$$

Denoting with η the worker's bargaining power we obtain:

$$w = \eta w^{UB} + (1-\eta)w^{LB} \tag{2.13}$$

This implies that the wage bargaining rule is assumed to split the match surplus in fixed proportions whenever the agents negotiate about the wage. Notice also that the bargaining costs cancel out from the wage equation (2.13), hence the wage formed in the initial bargaining period and the rebargained wage are the same, conditional on aggregate and idiosyncratic shocks.

[8]For brevity, I only describe the wage bounds for the case of renegotiations. The wage bounds for the initial bargaining are analogous, with κ_0 instead of κ.

2.2.5 Block Recursive Equilibrium

This subsection gives a definition for a particular type of equilibrium and establishes its existence. The main theoretical challenge for determination of equilibrium originates in the endogenous nondegenerate joint distribution of wages and idiosyncratic productivities across firm-worker pairs, $G_t(w, a)$, which is in general part of the state of the economy and could thus in principle affect the vacancy posting decisions and job destruction decisions.

I show that it is possible to solve the model with costly wage bargaining and endogenous separations in two steps. First, one can determine the equilibrium path for individuals' optimal decisions and labor market tightness. In particular, the solution of the model consists of: i) equilibrium labor market tightness $\theta(A)$; ii) job destruction thresholds $\tilde{a}(A, w_{-1})$ and $\tilde{a}^N(A)$ for existing and new matches, respectively; and iii) wage renegotiation thresholds $\tilde{a}^{JR}(A, w_{-1})$ and $\tilde{a}^{ER}(A, w_{-1})$ for the firm and the worker, respectively. This solution can be obtained independently of the joint distribution of wages and idiosyncratic productivities across job matches. Second, after having computed the equilibrium agents' decisions and labor market tightness, one can simulate the economy and by keeping track of the evolution of the joint wage and idiosyncratic productivities distribution (which is now a discrete distribution in the space spanned by the grids for aggregate and idiosyncratic productivity shocks) determine the unemployment dynamics. The key property of the equilibrium that allows for solving the model in two steps ("blocks") is block recursivity.

Note that at the beginning of each period, the state of the economy is given by the triple $(A_t, u_t, G_t) = \psi_t$, i.e. by the current level of aggregate productivity, the current measure of unemployed workers, and the current joint distribution of workers across different wages and idiosyncratic productivities, $G_t(w, a)$. Using the terminology of Menzio and Shi (2010), I define a block recursive equilibrium (BRE). In this type of equilibrium, the agents' value and policy functions, and the labor market tightness do not depend on the distribution of workers across different employment states (employment at different wages and idiosyncratic productivities, and unemployment).[9]

[9] In the context of models with directed on-the-job search, Shi (2009) establishes the existence of a BRE for the deterministic case, Menzio and Shi (2011) consider a BRE in the case of a stochastic model with complete employment contracts, while Menzio and Shi (2010) deal with a more general stochastic environment and incomplete employment contracts. Schaal (2010) shows that the property of block recursivity also holds for multiworker firms with decreasing returns under some conditions. All mentioned papers differ importantly from the setting adopted here, as they involve an additional complication due to on-the-job search. With the assumption of directed on-the-job search, each worker chooses to search for a job that he will always accept, which in turn simplifies the exposition. Nevertheless, because of the existence of a continuum of labor submarkets, these papers need to utilize different fixed point theorems to establish equilibrium

Definition 1 *A block recursive equilibrium is a recursive equilibrium such that the equilibrium objects in* (2.1)-(2.13) *depend on the aggregate state of the economy, ψ_t, only through aggregate productivity, A_t, and not trough the joint distribution of wages and idiosyncratic productivities, $G_t(w, a)$, nor the unemployment rate, u_t.*

The existence of equilibrium can be established by applying the standard fixed point arguments. The existence and uniqueness of V^U given some V^E and V^J follows since V^U is a contraction from the space of functions $V^U : \mathbf{A} \to \mathbb{R}$, with the corresponding contraction mapping satisfying Blackwell's sufficient conditions (Stokey and Lucas (1989), Theorem 3.3, p.54). The existence and continuity of the value functions V^E and V^J from the spaces of functions $V^E : (\mathbf{A} \times \mathbf{A} \times \mathbf{a} \times \mathbf{a}) \to \mathbb{R}$ and $V^J : (\mathbf{A} \times \mathbf{A} \times \mathbf{a} \times \mathbf{a}) \to \mathbb{R}$, respectively, can be established by using standard theorems as well.[10] Notice that due to a fixed bargaining cost these value functions are not concave. Nevertheless, following the literature on the optimality of (S,s) policies, the concept of K-concavity by Scarf (1959) can be invoked (see also a discussion in Bertsekas (1976), p.81-89, and Aguirregabiria (1999) for an economic application with menu costs). In turn, K-concavity guarantees uniqueness of the optimal decision rules. Finally, given the assumed restrictions for the matching function, the job creation condition 2.10 uniquely determines the equilibrium labor market tightness, $\theta(A)$.

An important feature of a block recursive equilibrium is that the joint distribution of workers across different wages and idiosyncratic productivities, $G_t(w, a)$, and the unemployment rate in the current period, u_t, together with the realization of aggregate productivity in the next period, A_{t+1}, uniquely determine $G_{t+1}(w, a)$ and u_{t+1}, i.e. the joint distribution of workers across different wages and idiosyncratic productivities, and the unemployment rate in the next period. I exploit this feature when simulating the model in order to obtain simulated employment and unemployment series.

Two assumptions are crucial for the above fixed-point arguments to be valid: constant returns to scale matching function and the free entry condition. With a *non-constant* returns to scale matching function, the current unemployment rate would affect the equilibrium labor market tightness. Moreover, since the current distribution of workers across wages affects tomorrow's unemployment rate, the worker's decision to quit would be affected by both the current unemployment rate and the current distribution of workers across wages. On the other hand, the free entry condition guarantees that the value of a vacancy is driven down to zero

existence from the ones used in the present paper.

[10]The notation adopted here takes into account that the past wage is a function of past aggregate and idiosyncratic productivities, i.e. $w_{-1}(A_{-1}a,_{-1})$.

at any point in time, i.e. that the firm's benefit and cost of creating a vacancy are always equalized in expectations.

The only remaining non-standard element of the model involves a non-convex wage bargaining set, which is again due to a fixed wage bargaining cost. This implies a departure from the standard axiomatic approach to bargaining by Nash (1953). The most common remedy is to convexify the set of feasible payoffs by introducing a wage lottery. However, since under the current calibration with relatively small wage bargaining costs departure from convexity is quantitatively minor, such a generalization would not affect the results obtained in the paper. Gertler and Trigari (2009), who also construct a model with a non-convex wage bargaining set, show that the gains from the lottery are small in their case and could be easily offset by small transaction costs of running and enforcing the lottery.

2.2.6 Comparison with the Existing Literature

It was argued already by Hall (2005) that the employment rents due to searching frictions determine a wage bargaining set and any wage within this set implies private efficiency in the worker-firm match. The worker and the firm thus must agree on a specific wage from the bargaining set. Hall (2005) assumes a constant wage rule, which can be interpreted as a wage norm, and shows that such a rule might address the unemployment volatility puzzle. In addition to arbitrariness, there are two particular problems associated with a constant wage contract. First, it is assumed that the wage always remains within the bargaining set, even though the wage never adjusts. As pointed out by Mortensen and Nagypál (2007), to maintain that the rigid wage is jointly rational, only small shocks can affect the employment relationship of workers and firms in the economy, as otherwise the wage will leave the bargaining set. In particular, this in practice rules out the possibility of idiosyncratic productivity shocks in the spirit of Mortensen and Pissarides (1994), at least of the size that is typically calibrated. Second, perfect wage rigidity lacks empirical support. In this respect, Gertler and Trigari (2009) provide a model with staggered multiperiod wage contracting of the Calvo (1983) type, which allows wages to be changed occasionally. Still, their model is inconsistent with some empirical evidence that wages in new matches are completely flexible.[11]

A specific class of models argues that wage rigidity might arise in the context of risk-averse workers and risk-neutral firms. In a seminal contribution, Thomas and Worrall (1988) develop a model with self-enforcing wage contracts whereby risk-neutral firms provide insurance to risk-averse workers. In their model agents

[11] See Haefke et al. (2008), Kudlyak (2011), Pissarides (2009), and references therein.

cannot commit, but contacts are nevertheless self-enforcing due to an extreme reputation assumption, according to which an agent who reneges on a contract is forced to trade on the spot market forever after. Efficient contracts are contained in a certain interval and whenever the wage leaves this interval, the agents update the wage by the smallest possible change that puts the wage back into the interval (i.e., on the bounds of the interval). Rudanko (2009) embeds this kind of model into an equilibrium model of directed search with aggregate shocks. In her model a constant wage emerges if both agents can fully commit, in which case the risk-neutral firms provide insurance to risk averse workers through optimal long-term wage contracting. In contrast to Hall (2005), her micro-founded model of perfect wage rigidity does not lead to a substantial increase in the cyclical volatility of unemployment.

Galí and van Rens (2010) use a wage determination mechanism, where the wage is more likely to adjust when it is closer to the bounds of the bargaining set. In their model the wage is never allowed to leave the wage bargaining set, following a similar argument as in Thomas and Worrall (1988). Moreover, since the size of the bargaining set is determined by the size of match surplus, whereas the latter is determined by the extent of labor market frictions, the model of Galí and van Rens (2010) yields predictions on the relationship between labor market frictions and wage rigidities. Kennan (2010) develops a model, in which wage rigidities arise due to private information. In particular, in his model only the firm observes idiosyncratic shocks and due to the assumption that the worker always finds it optimal to demand the low surplus, the firms obtains an informational rent and wage rigidities emerge.

2.3 Calibration

The calibrated frequency is monthly. Table 2.1 gives the parameter values used in the baseline simulations. The discount factor β is consistent with an annual interest rate of four percent. The matching efficiency parameter γ targets the average job finding rate during the period 1976-2010, which corresponds to 53.9 percent. The matching function is assumed to be of the Cobb-Douglas form with the unemployment elasticity α of 0.5, consistent with the evidence in Petrongolo and Pissarides (2001). The worker's bargaining power η is also set to 0.5, implying that the total match surplus is split in equal proportions between the worker and the firm. The flow vacancy posting cost c is parametrized to 0.20 or roughly 20 percent of monthly output, consistent with the evidence from the 1982 Employment Opportunity Pilot Project (EOPP) survey and values used in the literature. For the flow value when being unemployed I follow Hall and Milgrom (2008) and accordingly set b to 0.71.

Table 2.1: Parameter values

Parameter	Interpretation	Value	Rationale
β	Discount factor	0.9966	Interest rate 4% p.a.
γ	Matching efficiency	0.555	Job finding rate 53.9% (CPS)
α	Elasticity of match. funct.	0.5	Petrongolo and Pissarides (2001)
η	Worker's bargaining power	0.5	Symmetric surplus splitting
c	Vacancy posting cost	0.20	1982 EOPP survey, literature
b	Value of being unemployed	0.71	Hall and Milgrom (2008)
σ_A	Standard deviation for log aggregate productivity	0.006	Labor productivity (BLS)
ρ_A	Autoregressive parameter for log aggregate prod.	0.975	Labor productivity (BLS)
μ_a	Mean log idiosyncratic prod.	0	Normalization
σ_a	Standard dev. for log idiosyncratic prod.	0.10	Separation rate 3.55% (CPS)
λ	Probability of changing idiosyncratic prod.	1/6	Semi-annual
δ	Exogenous separation rate	0.01	JOLTS data
κ	Bargaining cost	0.20	Wage change prob. of 5.0%
κ_0	Initial bargaining cost	0	Baseline case

The Markov chain for the aggregate productivity process is meant to match the cyclical properties of the quarterly average U.S. labor productivity between 1976 and 2010, which determines values for the standard deviation of log aggregate productivity, σ_A, and for the autoregressive parameter of log aggregate productivity, ρ_A.[12] For the idiosyncratic shocks, I assume that they occur on average every six months. Mean log idiosyncratic productivity is normalized to zero, whereas the corresponding standard deviation targets endogenous separations in the model and is set accordingly to 0.10. Notice that the average monthly separation rate during the period 1976-2010 was 3.55 percent. I set the exogenous separation rate to 1 percent, whereas the remaining part of separations is accounted for by endogenous separations. This is roughly consistent with the recent Job Openings and Labor Turnover Survey (JOLTS) data, available from December 2000 onwards, and with the calibration strategy of den Haan et al. (2000).

Fixed bargaining cost, κ, determines the frequency of wage renegotiations. Barattieri et al. (2010) estimate the quarterly probability of a nominal wage change to be between 5 and 18 percent, which is at the monthly level around 2 to 6 percent. Consequently, I set κ to 0.20 of quarterly output, which implies a monthly probability of changing the wage of 5.0 percent (3.95 percent in the model without aggregate shocks).[13] In the baseline scenario I set the initial bargaining cost, κ_0,

[12]Following Shimer (2005), the average labor productivity is the seasonally adjusted real average output per employed worker in the nonfarm business sector, i.e. the Bureau of Labor Statistics (BLS) series PRS85006163.

[13]This value is also close to the evidence from a case study of labor unrest in Caterpillar, analyzed by Mas (2008). For plants affected by labor disputes, he finds a 12 percent reduction in output and a 5 percent reduction in product quality, as implied by resale prices.

equal to 0.

2.3.1 Computational Strategy

In order to solve the model numerically, I discretize the state space. In particular, the aggregate shock A is approximated by a Markov chain of 5 equally spaced gridpoints, whereas the idiosyncratic shock a is approximated by a discrete lognormal distribution with its support having 100 equally spaced gridpoints. I truncate the lognormal distribution at 0.1 percent and 99.9 percent and then normalize probabilities so that they sum up to one. The solution algorithm consists of value function iterations until convergence. The final model's solution consists of: i) equilibrium labor market tightness $\theta(A)$; ii) job destruction thresholds $\tilde{a}(A, w_{-1})$ and $\tilde{a}^N(A)$ for existing and new matches, respectively; and iii) wage renegotiation thresholds $\tilde{a}^{JR}(A, w_{-1})$ and $\tilde{a}^{ER}(A, w_{-1})$ for the firm and the worker, respectively. This solution is then used to simulate the model.

2.4 Steady State Analysis

Before considering the business cycle implications of the model, it is instructive to perform a steady state analysis. In order to do so, I shut down the aggregate shocks; i.e. I set $\sigma_A = 0$, whereas A is normalized to 1. All the remaining parameters are the same as in Table 2.1. The steady state analysis yields the first important theoretical implication of the model: higher wage bargaining costs lead to higher unemployment.

2.4.1 Wage Bargaining Costs and Unemployment

Table 2.2: Wage bargaining costs and unemployment

Initial bargaining cost - κ_0	0	0	0	0	0
Wage bargaining cost - κ	0	0.10	0.20	0.30	∞
Unemployment (in %)	2.93	4.05	5.16	6.83	5.41
Job finding rate (in %)	62.21	60.18	58.58	56.65	63.11
Separation rate (in %)	1.87	2.51	3.14	4.05	3.54
Labor market tightness (v/u)	1.40	1.34	1.29	1.27	1.37
Share of wage renegotiations (in %)	15.32	13.39	10.84	8.03	0

Table 2.2 shows simulation results for different values of wage bargaining costs. The results suggest that lower wage bargaining costs imply a lower unemployment rate, which happens mostly due to a lower separation rate. Intuitively, if wage bargaining costs are low, the firm and the worker are more likely to adjust their wage and thus avoid separations. Indeed, as wage bargaining costs

decrease, the wage renegotiations occur more frequently.[14] According to this result, countries with higher bargaining costs will experience higher unemployment rates, more rigid wages and higher separation rates *relative* to job finding rates.[15]

2.4.2 The Role of Initial Bargaining Costs

Table 2.3 illustrate the role of initial bargaining costs. Note that a higher initial bargaining cost, κ_0, decreases the unemployment rate and decreases the separation rate. Intuitively, if initial bargaining is costly, whereas ongoing bargaining is costless, then the firm and the worker prefer to stay in the match even in the case of a very low idiosyncratic productivity shock, leading to longer job spells and less separations. Nevertheless, when both bargaining costs increase to 0.30, this leads to higher unemployment and more separations as before.

Table 2.3: The role of initial bargaining costs

Initial bargaining cost - κ_0	0	0	0.30	0.30
Wage bargaining cost - κ	0	0.30	0	0.30
Unemployment (in %)	2.93	6.83	1.93	3.94
Job finding rate (in %)	62.21	56.65	61.05	56.29
Separation rate (in %)	1.87	4.05	1.20	2.29
Labor market tightness (v/u)	1.40	1.27	1.37	1.22
Share of wage renegotiations (in %)	15.32	8.03	16.00	9.91

2.4.3 Renegotiation Inactivity Band

Figure 2.1 depicts graphically the wage bargaining process. The x-axis contains the value of idiosyncratic productivity at the time, when the existing wage was agreed. The y-axis contains the current value of idiosyncratic productivity. Since bargaining is costly ($\kappa = 0.20$), the firm and the worker prefer to continue the match relationship with the existing wage, provided that the values of current and initial idiosyncratic productivity remain close. The region of inactivity is thus represented by the white area on the figure. However, if the shock is big enough, the renegotiation might occur. The green area above the inactivity region corresponds

[14]The share of wage renegotiations does not converge to 100 percent when the wage bargaining costs go to zero, because in the case of no idiosyncratic shock occuring there is no need to change the wage anyway.

[15]In the last statement the word "relative" is crucial. We know that European labor markets are sclerotic in the sense that they exhibit lower turnover rates as compared to the United States, which could be simply a manifestation of higher labor market frictions in Europe. The statement here argues that European countries with higher wage bargaining costs will experience a higher separation rate/job finding rate ratio.

to the cases where wage is rebargained, with the rebargaining process being initiated by the worker, who wants to benefit from the higher productivity than the one that was present at the time of the initial wage bargain. The blue area below the inactivity region depicts cases where the wage is rebargained downwards, hence the rebargaining process was initiated by the firm. Finally, the red area at the bottom shows the cases where the match output is too low, hence the match is endogenously destroyed. The red area with job destruction is larger in the case with costly wage bargaining than in the case with costless wage bargaining.

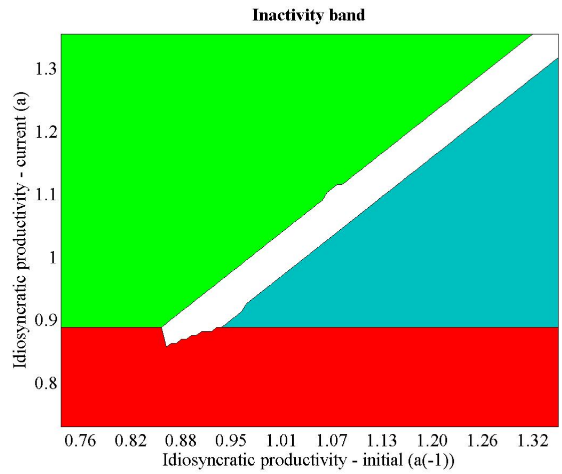


Figure 2.1: Wage bargaining areas, $\kappa = 0.20$

2.5 Dynamic Analysis

This section presents the simulation results for the full dynamic model and discusses the model implication for labor market volatility. The second important theoretical implication of the model is obtained: unemployment volatility increases with wage bargaining costs, primarily due to enhanced volatility at the job destruction margin.

2.5.1 Wage Bargaining Costs and Labor Market Volatility

Existing literature argues that exogenously imposed (perfect) wage rigidity can amplify unemployment volatility (Hall, 2005), whereas endogenous wage rigidity originating in optimal long-term wage contracts between risk neutral firms and risk averse workers does not amplify unemployment volatility (Rudanko, 2009). Simulation results in Table 2.4 suggest that wage bargaining costs increase the model's generated fluctuations in unemployment. For example, with $\kappa = 0.20$ the model's unemployment volatility increases by roughly one third as compared to the case with costless wage bargaining. This happens despite wages in new job matches being completely flexible. Most of the increase in volatility results from the job destruction margin.

Table 2.4: Wage bargaining costs and labor market volatility

Initial bargaining cost - κ_0	0	0	0	0	0	0.10
Wage bargaining cost - κ	0	0.10	0.20	0.30	∞	0.30
Means						
Unemployment (in %) - data: 6.4	3.11	4.23	5.51	7.07	8.56	5.84
Job finding rate (in %) - data: 53.9	61.62	59.43	57.76	56.61	59.38	55.71
Separation rate (in %) - data: 3.55	1.95	2.58	3.29	4.16	5.30	3.38
Share of wage reneg. (in %) - data: 2-6	19.66	15.65	12.01	8.53	0	8.85
Standard deviations						
Unemployment (HP log) - data: 17.3	7.68	8.69	9.91	10.74	31.94	9.08
Job finding rate (HP log) - data: 16.9	3.81	3.80	4.12	4.23	6.05	4.39
Separation rate (HP log) - data: 5.6	4.80	6.08	7.46	8.81	33.82	6.11

2.6 Applications of the Model

This section discusses how the theoretical implications of the model line up with empirical evidence. In particular, two applications of the model are considered. First, I examine whether the model can be used in order to explain the differential labor market behavior between Anglo-Saxon and Continental Europe countries. Second, I compare the model's predictions with the recent trends in wage volatility and employment volatility in the United States.

2.6.1 Labor Markets in Continental Europe

Dismal performance of labor markets in Continental Europe has been emphasized by several observers. The most common finding is that European labor markets are "sclerotic" in the sense that they exhibit lower labor turnover rates. Another, possibly related, characteristic is the average unemployment level, which has been systematically above the level of the United States during the last three decades. Recently, Elsby et al. (2012) also showed that Continental European and Nordic countries experience a bigger importance of the job destruction margin for unemployment fluctuations.

Lower labor turnover rates and lower reallocation of labor in Europe at least partly, if not mostly, result from employment protection legislation.[16] But why is it

[16] Another possibility is a higher degree of labor market frictions in Europe, for example due to lower geographical and occupational mobility.

then that European labor markets also suffer from higher unemployment rates and higher importance of job destruction for unemployment fluctuations? After all, there are at least some theoretical contributions, arguing that firing costs should have a positive employment effect (Bentolila and Bertola, 1990).[17]

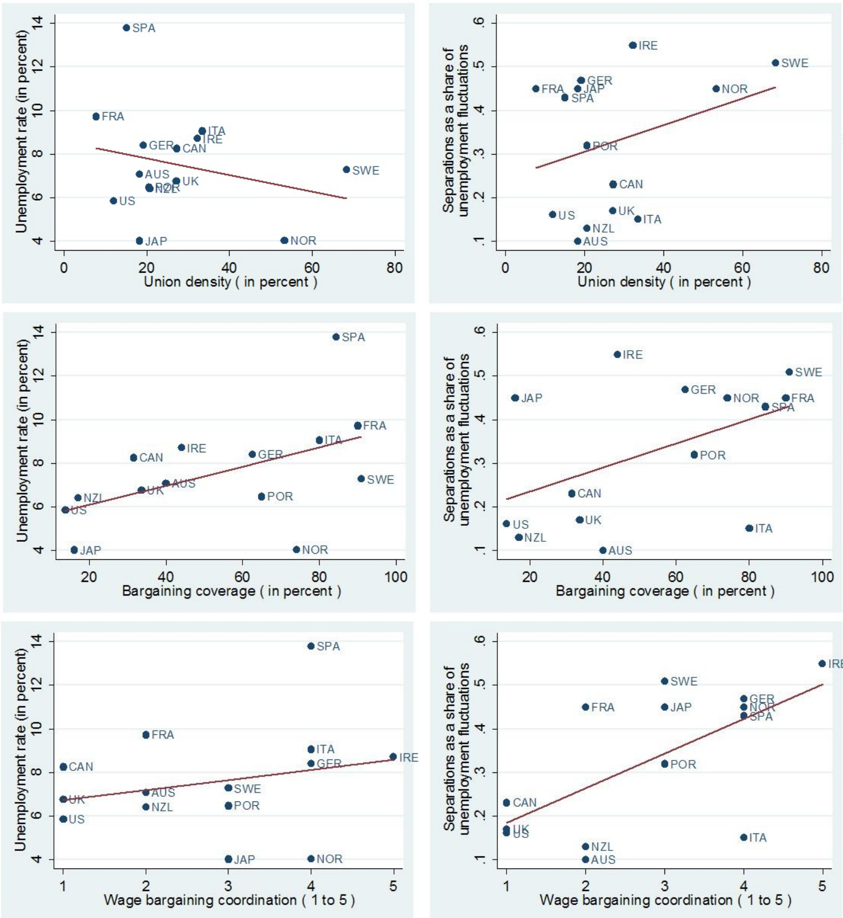


Figure 2.2: Wage bargaining costs and unemployment

Notes: Unemployment rate refers to the average annual harmonized unemployment rate over the period 1991-2010; data provided by OECD. *Separations as share of unemployment fluctuations* are measured over period 1968/1986-2009 and were take from Elsby et al. (2012). *Union density* corresponds to the ratio of wage and salary earners that are trade union members, divided by the total number of wage and salary earners in 2008; data provided by the OECD. *Bargaining coverage* stands for employees covered by wage bargaining agreements as a proportion of all wage and salary earners in employment with the right to bargaining in 2008; data provided by Visser (2011). *Wage bargaining coordination* measures enforceability of wage agreement in 2008 – 5 stands for economy-wide bargaining, 1 for bargaining at the company level; data provided by Visser (2011).

The theoretical analysis of this paper implies that higher wage bargaining costs

[17]Ljungqvist (2002) offers a detailed analysis on the employment effects of firing costs and explains under which circumstances theoretical models can also deliver a negative employment effect of firing costs.

lead to higher unemployment levels and greater importance of the job destruction margin. Figure 2.2 compares some indirect proxies for wage bargaining costs with the unemployment level and the importance of separation rate for unemployment fluctuations. The data include 14 countries: Australia, Canada, France, Germany, Ireland, Italy, Japan, New Zealand, Norway, Portugal, Spain, Sweden, the United Kingdom, and the United States. Three indirect proxies for wage bargaining costs consist of: union density, bargaining coverage, and bargaining coordination. A higher value for any of these three proxies indicates higher wage bargaining costs.

Figure 2.2 suggests that there seems to be a link between wage bargaining costs and unemployment outcomes. This is particularly the case when bargaining coverage and bargaining coordination are used as a proxy for wage bargaining costs, whereas union density appears to have less predicting power for unemployment properties.

2.6.2 Wage Bargaining Costs and the Decline in Unemployment Volatility Over Time

During the last 30 years we observe the following two macroeconomic trends in the United States. First, business cycle volatility of the aggregate wage has increased (Galí and van Rens, 2010, Champagne and Kurmann, 2010). Second, business cycle volatility of the unemployment rate has declined. Could these two structural changes in US macroeconomic dynamics be related? In principle, higher wage flexibility could be a result of diminished influence of labor unions (or wage bargaining costs in general).[18] But then the results of this paper imply that lower bargaining costs (higher wage flexibility) will lead to lower unemployment volatility (see Table 2.4). In this sense, implications of the model are consistent with the recent macroeconomics trends in the United States.

2.7 Conclusions

Sluggish adjustment of wages plays a central role in several classes of economic models. Thus, it comes as a bit of surprise that the existing literature has little to say about microfounded models of wage inertia, which is in sharp contrast with a relatively rich literature on microfounded "menu costs" models of price inertia. This paper tries to fill this gap in the literature by providing a microfounded model of wage rigidities based on wage bargaining costs.

[18] Galí and van Rens (2010) argue that a decline in labor market frictions implies a smaller match surplus, which in their case endogenously leads to higher wage flexibility, as the wage needs to adjust whenever it approaches the bands of the bargaining set. They relate lower labor market frictions to the empirical evidence on the decline of unionization.

The model of the present paper is set in the standard search and matching framework. This framework offers a natural interpretation on why wage inertia emerges and on the implications of wage inertia for macroeconomic outcomes. In particular, as it is widely known labor market frictions generate rents for existing job matches that need to be shared between the firm and the worker. The paper retains the assumption that the wage contract splits the match surplus, but dispenses with the assumption that bargaining is costless. The final result is a theoretical model with rich predictions, which can be used in order to investigate the linkages between bargaining costs and unemployment dynamics.

For future research, one natural extension would be to allow for nominal rigidities. In particular, a monetary business cycle model with state-dependent wage setting, could be used in order to investigate the classic macroeconomics question of monetary non-neutralities. Such a model would provide a wage counterpart to the price stickiness analysis of Golosov and Lucas (2007). Additionally, the model could be enriched by introducing many workers per firm and multiworker bargaining, very much in the spirit of another price-setting analysis provided by Midrigan (2011).

Chapter 3

JOB-EMBODIED GROWTH AND DECLINE OF JOB TENURE

(written jointly with Jan Grobovšek)

3.1 Introduction

One economic phenomenon that has received increasing attention over the last two decades has been the perceived drop in employment security in the developed world. The notion of the disappearing lifetime job has been vocalized by the popular press to the point of becoming a commonplace. At the same time, the developed world, and in particular the US, has experienced a significant acceleration in its productivity growth around the mid-nineties. This paper is concerned with linking these two phenomena. In particular, we claim that the nature of the productivity rise has manifested itself disproportionately as embodied in new jobs. As such, it has increased the incentive to reallocate jobs more often, resulting in a smaller share of long-term jobs.

Indirect evidence for the increase in job-embodied technical change can be found in several structural changes that took place worldwide since the 1990s. Examples of such changes include the digital revolution that vastly improved computing and communication technologies, the globalization process that induced higher international trade flows and outsourcing of some jobs, and financial market innovations. Our view is that this increase in the microeconomic dynamics is not only a one-off event. Rather, we think of it as a medium-term regime switch in the economic environment, characterized broadly by a higher level of competition and innovation. The main issue here is to quantify empirically the rate of job-embodied technical change.

That a part of technological progress can be embodied was proposed already fifty years ago by Solow (1959) and Johansen (1959), who developed first capital vintage models. However, it was not until the 1990s that the capital vintage theory received some empirical validation. Building on the work of Gordon (1990), who constructed a quality-adjusted price index for producer's durable equipment, Hulten (1992), Greenwood et al. (1997), and Cummins and Violante (2002) provide explicit estimates of investment-embodied technical change.[1] Aghion and Howitt (1994) consider a setup where the introduction of new technologies requires labor reallocation for their implementation, which gives rise to the Schumpeterian notion of "creative destruction." Mortensen and Pissarides (1998) provide a theoretical analysis of the effect that job-embodied growth has a on unemployment when firms are allowed to upgrade their technology at a cost rather than destroy the match. Despite these important theoretical contributions, to the best of our knowledge the existing literature lacks empirical estimates of job-embodied technical change.[2]

To make some progress in terms of measuring job-embodied technical change, we propose a model economy where jobs are losing their productivity edge over time. The model is set within a standard search and matching framework, which further allows us to investigate the implications of differential labor market frictions on economic outcomes. Such a theoretical model predicts that faster job-embodied technical change leads to fewer long-term jobs. Next, we confront the model with the data on job tenure. We find that to match our empirical measure of long-term jobs in the US around 1995 and to be compatible with standard values governing the process of labor dynamics, the annual rate of job-embodied growth should be around 0.31 percent. The ensuing decline in the job tenure by 2007 requires an increase in the annual rate of job-embodied growth by approximately

[1]Measuring investment-embodied technical change through a quality-adjusted price index is known in the literature as the price-side approach. Sakellaris and Wilson (2004) instead rely on the production-side approach, whereby they use data on productivity, current and past investment in order to quantify investment-embodied technical change. The latter approach yields somewhat higher estimates of embodied technical change.

[2]A possible exception is Pissarides and Vallanti (2007), who find that unemployment is negatively related to TFP and from this finding make the inference that technology should be completely disembodied. Such a conclusion could be premature for several reasons. First, establishing a causal link between technology shocks and unemployment (or employment) has proved to be a difficult task – see Galí and Rabanal (2005) and references therein for an excellent review of the empirical work and its possible pitfalls at business cycle frequencies. When it comes to medium/long-run frequencies, the sign of relationship between TFP and unemployment seems to be uncertain – see Bean and Pissarides (1993) for some evidence from OECD countries. Moreover, the results of a negative relationship between TFP and unemployment appear to be mostly obtained for the 1970s and 1980s, i.e. one particular period characterized by productivity slowdown and high unemployment. Second, the findings of Prat (2007) show that for plausible parameter values also disembodied technological progress increases the rate of unemployment. Third, our results in this paper indicate that for empirically reasonable changes in rates of job-embodied technical change over time, the effect on unemployment is relatively small, less than 0.5 percentage point, and could be thus hard to discern in the data.

80 percent, that is to about 0.58 percent. For external validation we turn to the data for Europe. We consider its job-embodied technical growth to have been the same as the one in the US in both 1995 and 2007, and change its matching efficiency (a proxy for labor market frictions) so as to hit its tenure length in 1995. The predicted decrease in job tenure by 2007 closely matches the one observed in the data.

In the second part of the paper, we examine the productivity effects of faster job-embodied technical change under different labor market regimes. We find that higher labor market frictions theoretically lead to more misallocation and a lower productivity level. However, when we use our calculated rates of job-embodied technical change, it turns out that the empirically reasonable effect of job-embodied growth on productivity is rather low. Lower labor market turnover rates in Europe generate a productivity lag of about 7 percent relative to the US. The estimated increase in job-embodied growth in the mid 1990s had a negligible productivity effect of about 0.2 percent.

3.1.1 Relationship to the Literature

It can be argued that one of the most distinctive characteristics of developed economies is the functioning of their labor markets. The typical classification of countries into a group with "fluid" labor markets and a group with "sclerotic" labor markets is usually obtained by evaluating labor market institutions like firing costs, unemployment benefits, bargaining arrangements, minimum wages, and labor taxes. Perhaps surprisingly, neither the theoretical nor the empirical literature has managed to establish a clear link between labor market institutions and labor market outcomes.[3] In this paper, we investigate the effects of labor market fluidity on the prevalence of long-term jobs and on labor productivity. The main focus is put on the experience of the four large continental EU countries (Germany, France, Italy, Spain), the UK, and the US over the years 1995-2007, which is a period that can be arguably described as a period with a very dynamic economic environment.

This paper is also about misallocation due to labor market distortions. While the idea that misallocation of resources can affect aggregate TFP and thus aggregate output in a quantitatively important way has featured prominently in recent work, most of these papers focus either on capital misallocation or the related

[3] Ljungqvist (2002) shows how firing costs can either increase or decrease employment, depending on the theoretical framework used. Ljungqvist and Sargent (1998, 2008) and den Haan et al. (2005) obtain opposite results for the effects of high unemployment benefits on unemployment in the presence of turbulence, which makes skill obsolescence more likely. Nickell and Layard (1999) even claim that "time spent worrying about strict labor market regulations, employment protection and minimum wages is probably time largely wasted".

misallocation due to financial frictions, abstracting from labor market distortions. However, some papers do address the theoretical and empirical interplay between labor market institutions and aggregate productivity. Hopenhayn and Rogerson (1993) provide a general equilibrium model with heterogeneous firms and use it to evaluate the consequences of labor adjustment costs. They find that a tax on job destruction lowers employment and labor productivity. Lagos (2006) obtains a theoretical aggregation result by deriving an aggregate production function from fixed-proportions micro-level production technologies combined with a search and matching model of Mortensen and Pissarides (1994). His model predicts that employment subsidies and firing taxes reduce TFP, whereas hiring subsidies and unemployment benefits increase TFP. More relatedly, Kambourov (2009) studies the sectoral reallocation of labor for the case of trade reforms. He argues that firing costs hinder the intersectoral reallocation of labor after trade liberalization reforms. His island-economy model à la Lucas and Prescott (1974) shows that the foregone benefits of not liberalizing the labor market are quantitatively substantial. His focus is on firing costs exclusively and his empirical motivation comes from the episodes of Latin American countries (case studies for Chile and Mexico). Our contribution here is to emphasize an additional channel working through obsolescence and the entry/exit decision. Foster et al. (2006) find that in the US retail trade sector most of the productivity gains in the 1990s occurred precisely due to high-productivity entering establishments replacing low-productivity exiting establishments.

Finally, the present paper paper fits into the literature on the “shocks-and-institutions hypothesis”, according to which some common shock can lead to differential labor market responses when labor market institutions differ across countries.[4] That a common shock could be propagated differently because of differences in institutions was argued already by Blanchard and Wolfers (2000). Examples of papers which explore this hypothesis include Ljungqvist and Sargent (1998, 2007, 2008), who claim that increased microeconomic turbulence in connection with stronger employment protection and more generous unemployment benefits resulted in systematically higher unemployment in Europe since the 1970s; Mortensen and Pissarides (1999) who propose that a skill-biased technology shock could explain the rise in unemployment in Europe due to differential labor market policy regimes; and Hornstein et al. (2007) who investigate how capital-embodied technological change can shape labor market outcomes. In our paper, the common shock is represented by job-embodied technological change. More precisely, in our model the adoption of the latest vintage of embodied technology requires reallocation of labor. Sclerotic labor markets hinder that realloca-

[4]We borrow the term from Rogerson and Shimer (2011).

tion, resulting in lower productivity growth.[5]

3.2 Empirical Evidence

This section firstly provides data on the decline of long-term jobs since the mid-1990s in Europe and in the US. We subsequently use these data in order to infer the rate of job-embodied technical change. Secondly, this section examines the evidence on the extent of labor market frictions in Europe and in the US, and the evidence on the widening of the labor productivity gap between Europe and the US since the mid-1990s. The paper seeks to explore to what extent the increase in job-embodied technical change could contribute to the increasing productivity gap due to differential labor market fluidity.

3.2.1 Long-term Jobs

The basic piece of evidence motivating this paper is the observation that the share of long-term jobs has decreased substantially since the mid-1990s. In particular we focus on jobs with at least 10 years of tenure, which we define to be long-term jobs. Figure 3.1 and Table 3.1 summarize the evolution of long-term employment over the last two decades. We focus on men to avoid confounding effects of increased female labor force participation in some countries, which could distort the picture. We also present data by age intervals to control for the fact that older workers are more likely to hold long-term jobs and that some countries experienced substantial aging of their population. Our preferred measure of a change in long-term jobs, which we use later on for the calibration purposes, corresponds to the change in the share of long-term jobs for prime age males between 35-54 years from 1995 to 2007. We use this interval as it ensures that all sampled workers can possibly have been tenured for at least 10 years since the onset of prime age at 25. The observation period ends just before a full-blown increase in the recessionary unemployment took place.[6]

Several interesting observations emerge from the data. First, with a possible exception of Germany, all countries experienced a sharp decline in the share of long-term jobs between 1995 and 2007. This is broadly consistent with Kambourov and Manovskii (2008) who find evidence of an upward trend in occupational and industry mobility for the US, and with findings of Farber (2010) on the

[5]Elsby et al. (2012) provide estimates of labor market flows for several countries, indicating that European labor markets are indeed more sclerotic by an order of magnitude.

[6]It is known that in recessions job tenure and the share of long-term jobs typically increase as more fragile, short-term jobs are destroyed first during an economic downturn.

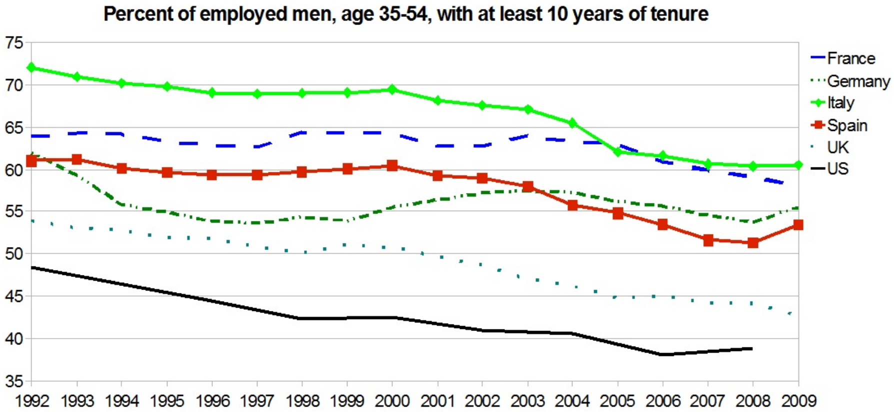


Figure 3.1: Decline in long-term jobs

Source: OECD, `http://stats.oecd.org/wbos/default.aspx?DatasetCode=TENURE_DIS`, for European countries, and BLS, `http://www.bls.gov/news.release/archives/tenure_09142010.htm`, for the US.

decline in long-term employment in the US. Second, continental European countries face a substantially higher proportion of long-term jobs in comparison with the US, with the UK being somewhere in between.

Table 3.1: Share of long-term (> 10year) jobs, men

Age	35 to 39			40 to 44			45 to 49			50 to 54		
Year	1995	2007	Diff	1995	2007	Diff	1995	2007	Diff	1995	2007	Diff
France	49.6	43.6	-6.0	62.1	55.6	-6.5	68.6	65.8	-2.9	72.6	74.4	1.8
Germany	37.5	38.4	0.9	50.7	50.6	0.0	62.7	61.6	-1.0	68.8	67.6	-1.2
Italy	52.7	42.3	-10.4	68.6	58.5	-10.1	77.0	66.9	-10.2	80.8	74.7	-6.1
Spain	43.3	32.0	-11.4	57.8	48.5	-9.4	64.7	59.1	-5.6	72.5	66.9	-5.7
UK	40.9	31.5	-9.4	51.0	41.7	-9.3	56.6	49.3	-7.3	58.9	54.0	-4.9
US*	30.5	25.4	-5.1	41.7	35.8	-5.9	50.8	43.5	-7.3	54.9	50.4	-4.5

Source: OECD, `http://stats.oecd.org/wbos/default.aspx?DatasetCode=TENURE_DIS`, for European countries, and BLS, `http://www.bls.gov/news.release/archives/tenure_09142010.htm`, for the US.
*The data for the US correspond to February 1996 and January 2008, as the Current Population Survey (CPS) includes supplemental questions on employee tenure only every 2 years.

Notice that focusing on long-term jobs is especially suited for our purposes and consistent with our theory. If the economic environment becomes more turbulent and exhibits a higher growth rate of job-embodied technical change, one should expect to see in the data a decline of long-term jobs.[7] Furthermore, accord-

[7]Notice, however, that we avoid referring to the *average* tenure. While in our setup a decline in the share of long-term jobs will invariably involve a decline in average job tenure, the latter is likely to be a less precise measure of job-embodied growth as it is more affected by short-term job switches.

ing to our theory, jobs with outdated technology lead to lower labor productivity if they are not destroyed, for example due to labor market institutions in place. In our theoretical model a higher share of long-term jobs implies a higher number of jobs with technology of older vintages.[8]

Notice, however, that we avoid referring to the average tenure. While in our setup a decline in the share of long-term jobs will invariably involve a decline in average job tenure, the latter is likely to be a less precise measure of job-embodied growth as it is more affected by short-term job switches.

3.2.2 Labor Markets Frictions

Europe and the US have very different labor markets. While the US labor market is relatively fluid, the European one suffers from much lower turnover rates. The latter stylized fact was dubbed as "Eurosclerosis". A recent piece of empirical evidence on this comes from Elsby et al. (2012).[9] They estimate that the monthly unemployment inflow rates (roughly speaking, "job separation rates") among European economies vary between 0.5-1.0 percent, whereas the same hazard rate for the US stands at 3.5 percent (see Figure 3.2). Similarly, the monthly unemployment outflow rates (roughly speaking, "job finding rates") equal to around 10 percent in Europe and almost to 60 percent in the US.[10] In short, the US labor market exhibits remarkably higher dynamics and higher rates of labor reallocation compared to the European labor markets. We interpret this stylized fact broadly as labor market frictions being more binding in Europe. In our theoretical model, higher labor market frictions in Europe will be captured by a lower matching efficiency (e.g., higher matching frictions could be due to lower geographical and occupational mobility).

The UK represents an interesting intermediate case between continental Europe and the US. Whereas the UK labor market used to be more similar to the ones in continental Europe, some recent reforms attempted to move it closer to the US labor market. In particular, the UK Jobseeker's Allowance reform of Oc-

[8]The destruction of jobs with outdated technology is important also in the following sense. Some European countries, most notably Spain, exhibit the so-called dual labor markets with temporary and permanent jobs. A high prevalence of temporary jobs will be in principle manifested in higher job market flows and lower mean tenure. Nevertheless, this does not necessarily imply a lower misallocation if long-term (permanent) jobs with low-productivity are not being destroyed. A development of a full dual labor market model is beyond the scope of this paper.

[9]See also Botero et al. (2004) for other measures of labor market flexibility, showing a similar story.

[10]These numbers correspond to the average values for the period from around 1980 (depending on data availability) to 2009. The authors also report the evolution of the hazard rates from around 1980 onwards. While there exists some time variation, the US hazard rates always exceed the European ones by at least a factor of two.

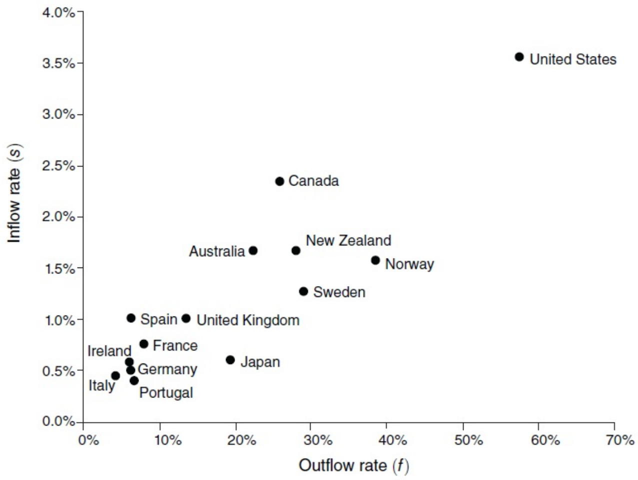


Figure 3.2: Labor market dynamics

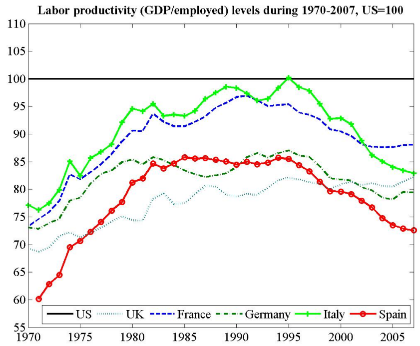
Source: Elsby et al. (2012), Figure 1.

tober 1996, which increased job search requirements for unemployment benefits eligibility, seems to have improved the fluidity of the UK labor market.

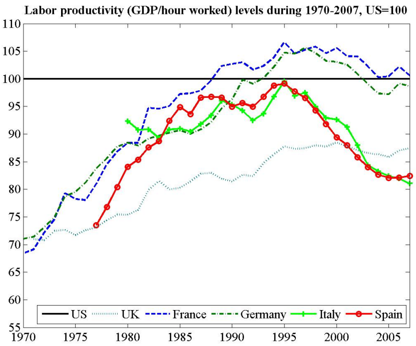
3.2.3 Europe/US Labor Productivity Gap

Figure 3.3 depicts the evolution of the labor productivity level relative to the US for the five largest EU countries from 1970 onwards. In particular, two empirical measures of labor productivity are provided, both converted to US dollars using 2009 purchasing power parities: i) real gross domestic product (GDP) per employed person in panel 3.3a; ii) real GDP per hour worked in panel 3.3b. As it emerges from the figure, Western Europe experienced a relatively rapid catch-up process with respect to the US up to around 1995, when this process suddenly stopped. To be more precise, labor productivity data based on employment as the labor input suggest that Western Europe as a region failed to converge fully to the US, whereas the data based on hours worked indicate that some parts of Western Europe (i.e. France, Germany) actually even managed to overtake the US in terms of productivity. While conceptually the preferred measure of labor productivity corresponds to the GDP per hour worked, empirically this measure suffers from severe data reliability issues. In particular, the estimates of hours worked are obtained through different data sources in different countries, leading to systematic biases in estimated labor input.[11] The literature typically agrees that individuals

[11] Different data sources on hours worked include labor force surveys, establishment surveys, national accounts, and administrative data. Due to the measurement issues, organizations that pro-



(a) GDP/employed



(b) GDP/hour worked

Figure 3.3: Labor productivity levels 1970-2007 (US=100)

Source: BLS, `http://www.bls.gov/fls/intl_gdp_capita_gdp_hour.xls`.

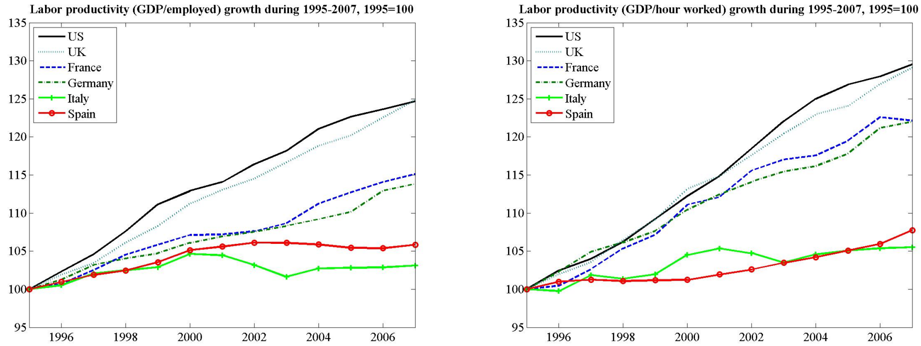
in Western Europe work less hours than people in the US, but estimates of these differences vary substantially, making it difficult to make precise cross-country comparisons of levels of labor productivity per hour worked.

Figure 3.4 focuses on comparisons of labor productivity over time, which is less subject to the aforementioned measurement errors. The figure reveals that the Europe/US labor productivity growth gap opened considerably during the last 12 years.[12] In the case of France and Germany, the gap in cumulative labor productivity growth versus the US over 1995-2007 amounts almost to 10 percentage points, while Italy and Spain experienced a drop in relative productivity of roughly 20 percentage points.[13] Given the short period of time, these differences are striking

vide estimates of hours worked even advise not to compare levels of hours worked across countries and instead rather focus on their growth rates. The estimates of hours worked are regularly produced by the US Bureau of Labor Statistics (BLS), the Organization for Economic Cooperation and Development (OECD), and the Conference Board (CB). For some recent advances in obtaining reliable estimates of hours worked across countries, see Blundell et al. (2011).

[12]We intentionally end the observation period in 2007, which is just before the Great Recession started on both sides of the Atlantic. During the latest recession the Europe/US labor productivity gap widened even further. The latest OECD estimates for 2010 show that relatively to the US, GDP per hour worked amounted to 92.1 percent in France, 89.8 percent in Germany, 79.7 percent in Spain, 78.5 percent in the UK, and 73.2 percent in Italy. While the reasons for the latest increase in the productivity gap are probably closely linked to the hypothesis examined in this paper – in contrast with the US, European labor market institutions prevent the destruction of low-productivity jobs – we leave a more detailed analysis of labor productivity developments during the recent cyclical downturn for future research.

[13]The higher drop in labor productivity for both Mediterranean countries could be related to their increased employment rate during the period under analysis, which might have involved the employment entry of less productive individuals.



(a) GDP/employed (b) GDP/hour worked

Figure 3.4: Labor productivity growth 1995-2007 (1995=100)

Source: BLS, `http://www.bls.gov/fls/intl_gdp_capita_gdp_hour.xls`.

and imply non-negligible effects on standards of living. Interestingly, only the UK seems to have been able to keep pace with the US in terms of labor productivity growth during the recent period. As we argued above, during the same period the UK witnessed labor market reforms, which were intended to increase labor market flexibility. According to the hypothesis of the present paper, this could be the explanation why the UK has performed relatively well in terms of labor productivity growth since mid 1990s.

The converging-diverging productivity patterns have been extensively documented in the literature – see, e.g., van Ark et al. (2008). One potential explanation for these patterns was proposed by Dew-Becker and Gordon (2008), who single out: i) the declining capital-labor ratio in Europe, and ii) the labor force composition effect as the two primary sources for these developments. A decline in the capital-labor ratio could occur due to European labor market policies that promoted employment growth and this could in turn lead to lower productivity. However and as mentioned by Dew-Becker and Gordon (2008), the negative trade-off between productivity and employment growth within Europe can only be of a short-run nature. In the medium run, one should expect that capital adjustments take place through higher investments. A subsequent increase in the capital-labor ratio and in productivity growth should hence follow relatively quickly. In this paper, we are primarily interested in the medium-run productivity growth patterns and would like to explain why the European labor productivity growth failed to recover even after a period of 15 years.[14] The second source, the

[14]This is not to say that there may not have been insufficient capital reallocation in Europe relative to the US over the period of interest. We would only like to argue that rigidities in the reallocation of labor in Europe are more binding, relative to the US, than rigidities in capital

labor force composition effect, stipulates that an increase in employment rate typically implies the inclusion of workers with lower skills into the labor force. This compositional change could be further amplified through the channel of immigration. In our view, this explanation can be mostly confined to Spain and Italy and even in these two cases presents only part of the story. Moreover, the increase in the Spanish employment rate was mostly a consequence of falling unemployment, which decreased from 19 percent in the beginning of 1995 to 8 percent in 2007. This fall was largely of a cyclical nature as it reversed the recessionary run-up in Spanish unemployment during 1991-1994. Again, we would like to focus our analysis on medium-term effects and leave aside cyclical considerations.[15]

3.3 Model

3.3.1 Environment

The model features a continuum of a large measure of risk-neutral firms, maximizing their profits. Before being able to start producing, a firm needs to find a worker in the labor market through a vacancy. The per period vacancy posting cost is $p_t\kappa$ where p_t is the discrete time period t price of the unique consumption good. With some endogenously determined probability $q_t \in (0, 1)$, the vacancy is filled with an unemployed individual. After the pair meet, they draw an idiosyncratic match productivity x from some time-invariant distribution X. If the draw is high enough (as described below), the firm starts producing. In each following period, the idiosyncratic productivity remains unchanged with probability $1 - \lambda$ and with probability λ the pair receive a new idiosyncratic productivity from the distribution X.

We assume that the output of a match depends further on learning-by-doing as well as the quality of the job description (i.e. a job vintage) to which the worker is matched, denoted by $k_{t,a}$, where a stands for the age of a particular vintage. Formally, the output of a match in period t employing a job vintage aged a is given by $y_{x,t,a} = x(1 + a)^{\epsilon}k_{t,a}$, $\epsilon \in [0, 1)$. The second term on the right hand side of the equation captures concave job-specific learning-by-doing in the sense that older matches are more productive as workers become increasingly better at performing their task. Furthermore, the economy experiences job-embodied

reallocation.

[15]If the story was mostly about the compositional effects, then one would expect to observe a dramatic jump in Spanish labor productivity during the recent recession, which sent the Spanish unemployment rate back to levels above 20 percent. While a moderate increase in Spanish labor productivity did occur in 2009, this was clearly not enough to reverse the trends being present since 1995.

technical change at the growth rate γ so that $k_{t,a} = (1+\gamma)^{t-a}$. The effective depreciation rate of job vintages is then given by $(1-\delta) \equiv \frac{1}{(1+\gamma)}$ and thus we have $y_{x,t,a} = x(1+a)^{\epsilon}(1+\gamma)^t(1-\delta)^a$. Differentiation with respect to a gives that output is strictly increasing in age in the interval $a \in \left[0, \frac{\epsilon}{\ln(1+\gamma)} - 1\right)$ as learning-by-doing outweighs effective depreciation. Past the threshold, output is strictly decreasing in age and thus there exists a critical age following which firms using older vintages of jobs in the match produce increasingly less efficiently than firms using the latest job vintage. Note that the threshold is increasing in the coefficient governing learning-by-doing ϵ and decreasing in the rate of job-embodied growth γ.

Period profits are given by $y_{x,t,a} - w_{x,t,a}$ where $w_{x,t,a}$ is the match-specific wage. We assume that a job can be installed at zero cost and that each initial match starts out with the newest vintage type of capital. The firm's value of a match is given by

$$\begin{aligned} J(x,t,a) =& \max\{0, x(1+a)^{\epsilon}(1+\gamma)^t(1-\delta)^a - w_{x,t,a} + \beta(1-\rho) \\ & [\lambda \mathbb{E}_{x'} J(x', t+1, a+1) + (1-\lambda) J(x, t+1, a+1)]\}, \end{aligned} \tag{3.1}$$

where the expectation is over next period's productivity x', ρ is the exogenous job destruction rate and $\beta \in (0,1)$ is the usual time discount factor. A firm in a continuing match thus has two choices. It can produce according to the job blueprint installed a periods ago, or it can dissolve the match.

On the household side, the economy is populated by a continuum of measure one of ex-ante identical workers. Workers are risk-neutral and maximize their expected discounted lifetime utility defined over consumption, $\mathbb{E}_t \sum_{k=0}^{\infty} \beta^k c_{t+k}$. In each time period a given worker can find himself in one of two possible states. Either he is unemployed, in which case he home-produces $b(1+\gamma)^t$ and actively searches for a job. Note that we assume that home production is subject to the same productivity increase as the overall economy. Alternatively, he is matched with a firm of type x and a at the wage $w_{x,t,a}$, which he can either accept or reject in favor of unemployment. Formally, the unemployed worker's value function is given by

$$U(t) = b(1+\gamma)^t + \beta[f_t \mathbb{E}_{x'} W(x', t+1, 0) + (1-f_t) U(t+1)], \tag{3.2}$$

where $f_t \in (0,1)$ is the endogenously determined probability of finding a job and $W(x,t,0)$ is the value of entering a new job match. In general, the value of a job match of type (x,t,a) is given by

$$\begin{aligned} W(x,t,a) =& \max\{U(t), w_{x,t,a} + \beta\rho U(t+1) + \beta(1-\rho) \\ & [\lambda \mathbb{E}_{x'} W(x', t+1, a+1) + (1-\lambda) W(x, t+1, a+1)]\}. \end{aligned} \tag{3.3}$$

Firms and unemployed individuals meet in the aggregate labor market. The matching process is formally depicted by the existence of an aggregate matching function, which brings together the measure of time t unemployed individuals u_t and the measure of posted vacancies v_t. The matching function $m(u_t, v_t)$ is assumed to be Cobb-Douglas, $m(u_t, v_t) = \mu u_t^{\alpha} v_t^{1-\alpha}$. Letting $\theta_t \equiv v_t/u_t$ denote the labor market tightness, we can express the probability for the searching firm to meet a worker as $q_t(\theta_t) = m(u_t, v_t)/v_t = \mu\theta_t^{-\alpha}$, and the corresponding probability for the searching worker to meet a firm as $f_t(\theta_t) = \frac{m(u_t,v_t)}{u_t} = \mu\theta_t^{1-\alpha}$. The meeting probabilities are decreasing in the measures of vacancies and unemployed workers, respectively, i.e. $\partial q/\partial v < 0$ and $\partial f/\partial u < 0$.

Assuming free entry, the job creation condition is given by:

$$p_t\kappa = q_t(\theta_t)\beta\mathbb{E}_{x'}J(x', t+1, 0). \tag{3.4}$$

Finally, we posit that wages are determined by the generalized Nash bargaining rule over the surplus of the match, which is defined as $S(x, t, a) \equiv J(x, t, a) + W(x, t, a) - U(t)$. The bargaining strength of the worker is η, so that we have:

$$W(x, t, a) - U(t) = \eta S(x, t, a). \tag{3.5}$$

3.3.2 Characterization of the Balanced Growth Path

Our interest is centered on the balanced growth path. For this we assume that $p_t = (1+\gamma)^t$, i.e. the period price grows at the rate of aggregate productivity. This just implies that at the balanced growth path costs rise proportionally to wages, given that at the balanced growth path $w_{x,t,a} = (1+\gamma)^t w_{x,a}$.

The balanced growth path equilibrium can now be succinctly summarized by the following equations. Given free entry, the expected gain for firms of posting a vacancy is zero, so job creation is implicitly governed by the expression

$$\kappa = q(\theta)\beta(1+\gamma)\mathbb{E}_{x'}J(x', 0). \tag{3.6}$$

A match is continued if and only if the match productivity x is high enough. Let $\tilde{x}(a)$ be the maximum implicit threshold productivity such that

$$J(\tilde{x}(a), a) = 0. \tag{3.7}$$

Recall that with the generalized Nash bargaining rule, we have that $J(x, a) = (1-\eta)S(x, a)$. Then the match surplus can be expressed as

$$\begin{aligned} S(x, a) = &\max\{0, x(1+a)^{\epsilon}(1-\delta)^a - b - \beta(1+\gamma)\eta f(\theta)\mathbb{E}_{x'}S(x', 0) \\ &+ \beta(1+\gamma)(1-\rho)[\lambda\mathbb{E}_{x'}S(x', a+1) + (1-\lambda)S(x, a+1)]\}. \end{aligned} \tag{3.8}$$

3.4 Qualitative Implications

We proceed by discussing some theoretical implications of changes in the growth rate of job-embodied technical change. The numerical results of this section are of illustrative nature, whereas a more detailed quantitative analysis with the calibrations for the US and European economies can be found in Section 3.5.

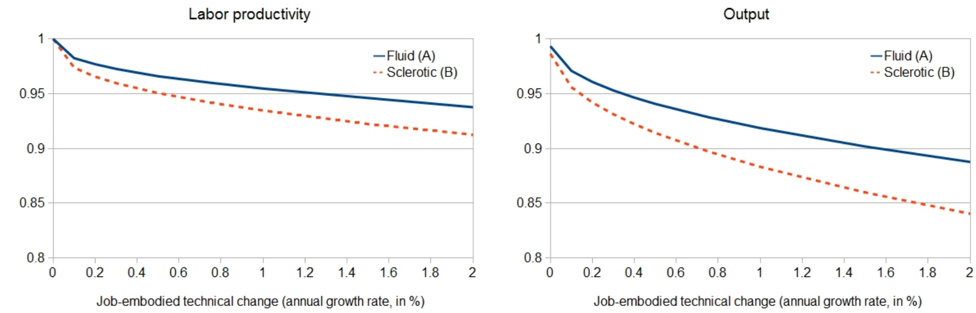
Table 3.2 summarizes the assigned parameter values. The frequency is quarterly. For simplicity we abstract in this section from learning-by-doing ($\epsilon = 0$) and from idiosyncratic productivity shocks (implying a degenerate distribution with all mass at $x = 1$). In order to generate some unemployment even in the case of zero job-embodied technical growth, we set the exogenous separation rate ρ to 0.5 percent. Two scenarios will be examined to highlight the importance of labor market frictions. First, in the "fluid" labor market scenario we set the matching efficiency parameter $\mu^A = 0.75$. Second, in the "sclerotic" labor market scenario we reduce the matching efficiency by half: $\mu^B = 0.75/2$.[16]

Table 3.2: Assigned parameter values

Parameter	Value
Discount factor (β)	0.9873
Value of non-market activities (b)	0.4
Vacancy posting cost (κ)	0.584
Matching function elasticity(α)	0.5
Worker's bargaining power (η)	0.5
Learning-by-doing (ϵ)	0
Mean idiosyncratic productivity ($\bar{x}$)	1
Std. deviation of log idiosyncratic prod. ($\sigma_{\log x}$)	0
Exogenous separation rate (ρ)	0.005
Matching function efficiency A (μ^A)	0.75
Matching function efficiency B (μ^B)	0.75/2

Figure 3.5 illustrates the implications of job-embodied technical change on labor productivity and output. Notice that with zero job-embodied technical change ($\gamma = 0$) and absent idiosyncratic productivity shocks and learning-by-doing all job matches have the same productivity, normalized to one. As we increase the growth rate of job-embodied technical change, the effect of job obsolescence on the average labor productivity in the economy increases, as evident from panel 3.5a. Recall that we define the productivity relative to the productivity frontier, hence the faster is job-embodied technical change, the higher will be the effective depreciation of jobs. Interestingly, the effect on labor productivity is stronger for the case of "sclerotic" labor market. This results indicates that labor market frictions become more binding if job-embodied technical change increases. Indeed, if there were no labor market frictions, all the labor could be instantaneously reallocated to the jobs of the newest technological vintage and there would be no asso-

[16] For a detailed explanation of other chosen parameter values, see Section 3.5.



(a) Labor productivity (b) Output

Figure 3.5: Job-embodied technical change, labor productivity, and output

ciated productivity losses, regardless of the growth rate of job-embodied technical change. In this sense, labor market frictions cause misallocation in the presence of job-embodied technical change.

Panel 3.5b depicts the effect of job-embodied technical change on output. The output effect is larger than the effect on labor productivity and the gap between the "fluid" and the "sclerotic" labor market opens up. The main reason behind this result relates to the evolution of the unemployment rate as shown in Figure 3.6. An increase in the growth rate of job-embodied technical change leads to more endogenous separations due to faster obsolescence and consequently to higher unemployment. The effect is stronger for the case of "sclerotic" labor market with lower matching efficiency.[17]

The qualitative effects of job-embodied technical change on labor productivity, output, and unemployment are theoretically interesting, because they imply that labor market frictions become more binding as the job-embodied technical change becomes faster. But how important are these effects quantitatively? And how large should be an empirically reasonable growth rate of job-embodied technical change for developed economies like the US and Europe? These are the questions that we seek to address in the next section.

[17]Of course, the result that faster embodied technical change can lead to higher unemployment is not new and has been, for example, discussed in Mortensen and Pissarides (1998). Hornstein et al. (2007) develop a vintage capital model to show how differences in taxes, unemployment benefits, and firing costs can lead to differential effects of capital-embodied technical change on unemployment. They show that their model can explain a sizeable fraction of the observed differences in the evolution of unemployment in Europe and in the US for the period 1960-1995.

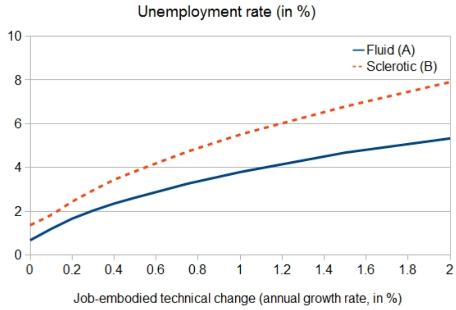


Figure 3.6: Job-embodied technical change and unemployment

3.5 Quantitative Analysis

3.5.1 Model-Implied Job-Embodied Technical Change in the US

In this section we calibrate and simulate the model for the US. Table 3.3 summarizes the chosen parameter values under the baseline US parametrization. The calibrated frequency is quarterly.[18] The discount factor is consistent with the annual interest rate of 5 percent. The flow value of non-market activities is set to 0.4 units of output as in Shimer (2005).[19] The flow vacancy posting cost is set to 0.584 units of output as in Hagedorn and Manovskii (2008), who take into account the capital cost of vacancies. To parametrize the matching function elasticity we draw from the evidence summarized in Petrongolo and Pissarides (2001) and hence put $\alpha = 0.5$. Absent microeconomic evidence on bargaining power, we assume that the surplus is split in equal shares, which also guarantees efficiency despite the presence of searching externalities since $\eta = \alpha = 0.5$ and hence the Hosios condition is satisfied. The learning-by-doing coefficient ϵ is set to 0.06. This is consistent with match-specific output becoming 24.8 percent more efficient after 10 years. Topel (1991) estimates that, everything else equal, workers' job-specific (i.e. not transferable) wages grow by a cumulative 24.6 percent in an uninterupted match over 10 years. Our parsimonious representation of learning-by-doing cap-

[18]We check that the job-meeting and vacancy-meeting probabilities are properly defined, i.e. being between 0 and 1.

[19]Some papers in the literature on business cycle fluctuations of unemployment set this parameter higher - see, e.g., Hall and Milgrom (2008), and Hagedorn and Manovskii (2008). In our model this parameter should also capture the cost of updating workers' skills, as workers get separated from a job with outdated technology and then subsequently find a job with the newest technology available. Indeed, in our case it is not even clear, whether this parameter should be positive. Section 3.5.3 considers a calibration with a different parameter value for the flow value of non-market activities.

Table 3.3: Baseline parameter values for the US

Parameter of interest	Value	Source/Target
Discount factor (β)	0.9873	5% interest rate p.a.
Value of non-market activities (b)	0.4	Shimer (2005)
Vacancy posting cost (κ)	0.584	Hagedorn and Manovskii (2008)
Matching function efficiency (μ)	0.631	job-finding rate of 72.1%
Matching function elasticity(α)	0.5	Petrongolo and Pissarides (2001)
Worker's bargaining power (η)	0.5	$\eta = \alpha$ (efficiency)
Learning-by-doing (ϵ)	0.06	Topel (1991)
Mean idiosyncratic productivity ($\bar{x}$)	1	normalization
Std. deviation of log idiosyncratic prod. ($\sigma_{\log x}$)	0.273	separation rate of 3.79%
Prob. of changing idiosyncratic prod. (λ)	1/24	business cycle duration
Exogenous separation rate (ρ)	0	baseline
Job-embodied technical change (γ^{1995}) in %	0.311	Empl. share of 10y jobs - 1995 (44.5 %)
Job-embodied technical change (γ^{2007}) in %	0.576	Empl. share of 10y jobs - 2007 (38.8 %)

tures pretty well the concave earnings progression estimated by Topel as it also translates to job-specific efficiency increases of 14.8, 27.8 and 30.1 percent over, respectively, 5, 15 and 20 years, which are to be compared with the estimations of 17.9, 28.3 and 33.8 percent computed by Topel.

According to Auer et al. (2005), the average tenure in the US was 6.6 years in 1998. This implies the average quarterly separation rate of $s^{US} = \frac{1}{4*6.6} = 3.79$ percent for the US. Notice that our calibration strategy differs from the typical calibration of search and matching models in the business cycle literature, which is due to the well-known heterogeneity in separation rates. In particular, the separation rate is decreasing with the time of job duration.[20] Thus, the labor market includes individuals with very high turnover rates, frequently switching between unemployment and employment, and these particular individuals are the main focus of the literature on unemployment fluctuations over the business cycle. Here, we are instead interested in an average individual job spell, hence we find it more appropriate to calibrate our model to the statistics on average job duration. Next, according to the OECD data the US unemployment rate over the period 1995-2007 averaged 4.99 percent. Using the steady state decomposition, $u = \frac{s}{s+f}$ and the above calculated separation rate, we get the average quarterly job-finding rate of $f^{US} = 72.1$ percent. We calibrate the matching efficiency parameter, μ, in order to target the quarterly job-finding rate, whereas the dispersion of idiosyncratic productivity distribution, $\sigma_{\log a}$, is chosen so that the quarterly separation rate is matched. For the frequency of idiosyncratic shocks, we assume that they arrive on average every 6 years (24 quarters), which matches the average business cycle duration over the post-war period, as measured by the NBER's Business Cycle Dating Committee.[21] Finally, the exogenous separation rate is set to zero in the

[20]See Nagypál (2007) for some recent evidence and a possible explanation for this empirical regularity.

[21]Duration of the average cycle, defined as trough from previous trough is 73 months – see

baseline calibration.

Regarding the growth rate of job-embodied technical change, γ, we back it out from the model by targeting the share of long-term jobs. In particular, in February 1996 the share of prime age males between 35-54 years with a job duration of at least 10 years was 44.5 percent. The model implies that the growth rate of job-embodied technical change consistent with this share was 0.31 percent on a yearly basis. On the other hand, the same share in January 2008 was 38.8 percent, which implies a γ of 0.58 percent. In other words, the growth rate of job-embodied technical change increased by roughly 80 percent in the period 1995-2007.

How do we interpret these numbers? With a $\gamma = 0.311$ percent and absent learning-by-doing, an individual performing the same job over the whole of his working life (45 years) will be roughly 12.5 percent less productive at the end of his career when compared to the jobs at the technological frontier. With a $\gamma = 0.576$ percent, the productivity penalty for continuing the same job blueprint for the whole career will amount to roughly 22.4 percent. This difference might be substantial enough to explain the recent disappearance of life-long jobs.

At this point we also need to mention the likely presence of heterogeneity across different types of jobs. Indeed, there are jobs that have existed for centuries without noticeable changes – some service jobs, like a teacher or a barber, come to mind. Arguably, job-embodied technical change for this type of jobs is close to zero. On the other hand, some jobs experience a very rapid job-embodied technical change, meaning that they are quickly losing their productivity edge and becoming obsolete – bank tellers and telephone operators, for example. Indeed, there are even jobs that did not even exist 50 years ago and are now at the verge of extinction – e.g., VCR and TV repair technicians. Thus, our aggregate numbers for job-embodied technical change hide important heterogeneity across jobs.

Table 3.4 contains more detailed simulation results.[22] Notice that a higher job-embodied technical change also implies a slightly lower job-finding rate and a slightly higher separation rate, implying together and increase in the unemployment rate of about 0.6 percentage point. While we do not observe in the US data an increase in the aggregate separation rate (and hence unemployment rate) during the last 15 years, this could be due to demographic trends: older and more educated individual experience lower separation rates.

`http://www.nber.org/cycles/cyclesmain.html`.

[22]The simulations use the model specification where in the initial period of the job match there is always production. Only after one period the match can be destroyed. Intuitively, production must take place for at least one period before the idiosyncratic match quality is known and hence the endogenous separation decision can take place. Moreover, we restrict the maximum duration of a job to 40 years, which is consistent with the standard duration of an individual's active working life.

Table 3.4: Baseline simulation results for the US

	US 1995	US 2007
Implied job-embodied technical growth (%)	0.311	0.576
Labor market tightness	1.301	1.266
Job-finding rate (%)	72.0	71.0
Separation rate (%)	3.78	4.23
Average job age (quarters)	43.5	23.0
Employment share 10y jobs (%)	44.4	38.8
Unemployment (%)	4.99	5.62
Output (in efficiency units)	1.239	1.210
Labor productivity (in efficiency units)	1.304	1.282

3.5.2 US versus Europe

We know that compared to the US, European labor markets are sclerotic. One way to introduce this into the model is to assume a lower matching efficiency for European labor markets. Intuitively, individuals in Europe might be less willing to move geographically and/or across occupations, which implies a higher degree of labor market frictions. Table 3.5 gives the simulation results, when we choose μ^{EU} for Europe of 0.296, a bit less than half of the US value. This number was chosen in order to target the share of long-term jobs for prime age males between 35-54 years in Europe in 1995, which was 59.9 percent.[23]

What are predictions of the model given $\mu^{EU} = 0.296$ for Europe? First, notice that the quarterly job-finding rate is now 31.8 percent and the quarterly separation rate is 1.51 percent, a bit less than half of the US values. This is consistent with the business cycle evidence on relative magnitudes in job-finding and separation rates in Europe and the US, as depicted in Figure 3.2. Moreover, Auer et al. (2005) estimate that the average tenure in 1997 for five European countries (France, Germany, Italy, Spain, UK) was 10.2 years. This implies the average quarterly separation rate of $s^{EU} = \frac{1}{4*10.2} = 2.45$, which is not far away from the number obtained in the simulation results.[24] More generally, our model predicts that a labor market with lower matching efficiency will generate lower labor market turnover flows (job-finding and separation rates) and a higher share of long-term jobs. The empirical evidence from Section 3.2 supports such a relationship for Europe and the US. Second, the labor productivity falls, yielding a significant gap versus the US of 7.1 percent. The lower labor productivity in Europe is due to lower matching efficiency, which makes the outside option of the match less attractive as the matching process takes longer. Because of that the average age

[23] We define Europe as the unweighted sum of the five largest economies of the EU.

[24] We could target the separation rate in Europe directly by adjusting the standard deviation of idiosyncratic shocks as we did before for the case of the US. However, in order to make the comparison of simulation results as clear as possible, we prefer to adjust only one parameter – matching efficiency.

Table 3.5: Baseline simulation results for Europe

	EU 1995	EU 2007
Matching function efficiency (μ^{EU})	0.296	0.296
Implied job-embodied technical growth (%)	0.311	0.576
Labor market tightness	1.155	1.113
Job-finding rate (%)	31.8	31.2
Separation rate (%)	1.51	1.84
Average job age (quarters)	58.2	50.2
Employment share 10y jobs (%)	59.9	53.0
Unemployment (%)	4.54	5.56
Output (in efficiency units)	1.156	1.226
Labor productivity (in efficiency units)	1.211	1.189
Labor productivity gap versus the US (%)	-7.08	-7.29

of matches is 43.5 quarters in the US and 58.2 quarters in Europe. In short, job matches with obsolete technology are inefficiently not destroyed in Europe. Third, the unemployment rate is, counterfactually, slightly lower at 4.54 percent.

Next, we take the implied job-embodied technical growth for the US in 2007. The model predicts that the share of long-term jobs in Europe should fall to 53.0 percent in 2007, whereas the actual number in the data for 2007 stands at 54.1 percent. We view this surprisingly good match as an external validation of our calibration exercise, since we do not target in any way the share of long-term jobs in Europe in 2007. Furthermore, the labor productivity gap opens, although the effect is quantitatively minor: from 7.1 percent in 1995 to 7.3 percent in 2007. With faster job-embodied technical growth, the destruction of job matches with obsolete technology becomes more important, thus the matching frictions become more binding.

3.5.3 Robustness

Worker's bargaining power

In our baseline calibration, the unemployment rates for the US and Europe are very close to each other, which is not consistent with the data. Here we show that the higher unemployment rate for Europe can be obtained if we assume that the worker's bargaining power is higher in Europe (e.g., due to higher presence of unions, centralized wage bargaining, etc.). Moreover, the rest of our results remain unaffected.

Table 3.6 shows the results when we set the worker's bargaining power in EU to $\eta^{EU} = 0.888$. At the same time we need to adjust the matching function efficiency by targeting the share of long-term jobs. Accordingly we set $\mu^{EU} = 0.468$. The job-finding rate drops to 17.9 percent, yielding an unemployment rate of 7.8 percent in 1995. The results regarding the labor market productivity remain almost unaffected.

Table 3.6: Simulation results with higher worker's bargaining power

	EU 1995	EU 2007
Matching function efficiency (μ^{EU})	0.468	0.468
Worker's bargaining power (η^{EU})	0.888	0.888
Implied job-embodied technical growth (%)	0.311	0.576
Labor market tightness	0.146	0.140
Job-finding rate (%)	17.9	17.5
Separation rate (%)	1.51	1.83
Average job age (quarters)	58.2	50.3
Employment share 10y jobs (%)	59.9	53.1
Unemployment (%)	7.79	9.47
Output (in efficiency units)	1.117	1.076
Labor productivity (in efficiency units)	1.211	1.188
Labor productivity gap versus the US (%)	-7.10	-7.30

Flow value of non-market activities

One of the crucial parameters in search and matching models is the flow value of non-market activities. The literature on business cycle fluctuations of unemployment has shown that this parameter influences the model's generated unemployment volatility – see Hagedorn and Manovskii (2008). In our case, the value of non-market activities affects the incentives to separate and hence the productivity of the marginal match with the oldest vintage. For the baseline calibration we follow Shimer (2005) and set $b = 0.4$. However, we already acknowledged that for our model this parameter should also capture the costly updating of worker's skills, as the worker gets separated from a job with outdated technology and then subsequently finds a job with the newest technology available. In other words, our value of non-market activities would better be represented by expression $b = \bar{b} - \chi$, where $\bar{b}$ stands for the usual "unemployment benefits" and χ stands for costly human capital investments.

In what follows, we perform a robustness check where $\bar{b} = 0.4$ and $\chi = 0.4$,

Table 3.7: Simulation results with costlier updating of skills

	US 1995	US 2007	EU 1995	EU 2007
Matching efficiency (μ)	0.526	0.526	0.278	0.278
Std. dev. idiosyncratic ($\sigma_{\log a}$)	0.400	0.400	0.400	0.400
Unemployment benefits (b)	0	0	0	0
Implied job-embodied technical growth (%)	0.158	0.534	0.158	0.534
Labor market tightness	1.882	1.836	1.706	1.651
Job-finding rate (%)	72.2	71.3	36.3	35.7
Separation rate (%)	3.86	4.35	1.58	1.95
Average job age (quarters)	44.1	38.1	58.6	50.1
Employment share 10y jobs (%)	44.7	38.8	59.9	52.5
Unemployment (%)	5.08	5.75	4.17	5.19
Output (in efficiency units)	1.244	1.207	1.135	1.094
Labor productivity (in efficiency units)	1.311	1.281	1.184	1.154
Labor productivity gap versus the US (%)			-9.69	-9.92

yielding the value of non-market activities equal to $b = 0$. In order to match the job finding and the separation rate, we now set the matching efficiency for the US to $\mu^{US} = 0.526$ and for Europe to $\mu^{EU} = 0.278$, whereas the standard deviation of idiosyncratic shocks is now $\sigma_{\log a} = 0.400$ for both regions. Under this calibration, the model-implied growth rate of job-embodied technical change, which again targets the share of prime age male between 35-54 years with a job duration of at least 10 years of 44.5 percent, is now $\gamma^{1995} = 0.16$ percent for the US in 1995. The growth rate of job-embodied technical change then increased to $\gamma^{2007} = 0.53$ percent in the US in 2007, being consistent with the drop in the share of long-term jobs. Assigning the same growth rates of job-embodied technical change to the EU, we can again match the evolution of long-term jobs in the EU, confirming the robustness of our numerical exercise. Note that although we obtain significantly lower growth rates of job-embodied technological change with the calibration when the value of non-market activities is set to zero, the relative increase of that growth rate remains substantial.

When it comes to the labor productivity gap between the US and Europe, we obtain now somewhat bigger differences: 9.7 percent in 1995 and 9.9 percent in 2007. With zero flow value of non-market activities the scrapping age increases both in the US and Europe, but the obsolescence effect that lowers the average labor productivity is bigger in Europe.

Modest Learning-By-Doing

There exists some controversy surrounding the quantitative significance of job-specific learning-by-doing and returns to tenure in general. As discussed in Altonji and Williams (2005), the estimates in Topel (1991) may exaggerate the importance of job-specific human capital. The estimates of Altonji and Williams (2005) suggest a value closer to half of the returns estimated by Topel. To check for this, we repeat the above calibration exercise with the coefficient of learning parameter equal to half the previous value, $\epsilon = 0.03$, which translates to slightly less than a 12 percent job-specific cumulative return to 10-year tenure.

Table 3.8 presents the results for the four cases of interest, i.e. the US and Europe, respectively, in 1995 and 2007. Compared to the benchmark case, the implied rate of job-embodied technical growth is much lower now. This results from the fact that lower on-the-job learning makes matches less interesting to continue so that the implied effective depreciation of job blueprints must be lower to arrive at the same proportion of long-term jobs. For the US in 2005 the implied rate is now 0.09 percent, i.e. less than a third of the value found in the benchmark calibration. Turning to 2007 we can observe that the implied rate now increases to 0.32 percent, which is to say by a much larger factor than previously. This is necessary in order to account for the sharp drop in long-term jobs starting with an

Table 3.8: Simulation results with modest learning-by-doing

	US 1995	US 2007	EU 1995	EU 2007
Matching efficiency (μ)	0.668	0.668	0.324	0.324
Std. dev. idiosyncratic ($\sigma_{\log a}$)	0.244	0.244	0.244	0.244
Learning-by-doing (ϵ)	0.03	0.03	0.03	0.03
Implied job-embodied technical growth (%)	0.093	0.324	0.093	0.324
Labor market tightness	1.163	1.136	1.040	1.001
Job-finding rate (%)	72.0	71.1	33.0	32.5
Separation rate (%)	3.71	4.16	1.51	1.83
Average job age (quarters)	43.8	38.1	58.7	50.8
Employment share 10y jobs (%)	44.4	38.8	59.9	53.1
Unemployment (%)	4.90	5.53	4.36	5.33
Output (in efficiency units)	1.145	1.122	1.076	1.048
Labor productivity (in efficiency units)	1.204	1.187	1.125	1.107
Labor productivity gap versus the US (%)			-6.56	-6.74

extremely low rate of embodied growth. Importantly, note that the calibration for Europe suggests that the implied increase in job-embodied growth should have shortened the share of long-term jobs to 53.1 percent, virtually the same as the prediction from the benchmark calibration and very much in line with the data. We take from this that while the rate of on-the-job learning is quite crucial in determining the actual rate of job-embodied growth, all learning parameter values within a plausible range suggest that the increase in job-embodied growth starting with 1995 was significant. We also note that the lower fluidity of the European labor market as calibrated here has sizeable effects on the level of productivity for lower on-the-job learning as well, and yet that higher job-embodied growth only marginally enhances that productivity loss.

3.6 Conclusions

This paper had two main objectives. The first was to provide an estimate of job-embodied technical change. This estimate was obtained indirectly by using a theoretical model and targeting the share of long-term jobs. As it is the case with estimates of capital-embodied technical change, our estimates need to be viewed merely as an empirical proxy for the theoretical concept of job-embodied growth. Nevertheless, we believe that this proxy is useful and can shed some light on the behavior of job-embodied growth over time.

The second objective of the paper was to investigate the implications of job-embodied growth on misallocation and productivity growth. In this respect, we found that the observed time variation in job-embodied growth most likely has a negligible effect on productivity differences under differential labor market frictions. However, lower labor market turnover does cause lower labor productivity in the level and could be of some importance in sectors with especially fast job-embodied growth.

The main focus of this paper were medium-run effects of job-embodied growth. For future research it would be interesting to investigate the cyclical consequences of faster job-embodied growth. If jobs are becoming obsolete faster nowadays, then this should in principle imply that during a cyclical downturn more jobs will be destroyed permanently, leading to higher structural unemployment. This interesting hypothesis is left for being explored in the near future.

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