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# Essays on the Aggregate Labor Market

Engbom, Niklas

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# Essays on the Aggregate Labor Market

Niklas Valentin Engbom

A Dissertation

Presented to the Faculty

of Princeton University

in Candidacy for the Degree

of Doctor of Philosophy

Recommended for Acceptance

by the Department of

Economics

Adviser: Professor Rogerson

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# Abstract

This collection of essays studies issues related to the aggregate labor market. Chapter 1 documents that life-cycle wage growth and the fluidity of labor markets differ substantially across countries, and that the two strongly co-vary across countries. I propose a model of on-the-job accumulation of human capital in a frictional labor market, which explains this pattern as a result of differences in institutions that impact labor market fluidity and implies an important effect of labor market fluidity on the stock of human capital in the economy.

Chapter 2 assesses the impact of aging of the US labor force over the past decades on the functioning of the labor market as well as aggregate economic outcomes. I develop a novel theory that links firm and worker dynamics to economic growth and demographic change, and use it to argue that aging has led to a large decline in dynamism of the US economy and a quarter of a percentage point decline in annual economic growth.

Chapter 3 develops a model of application flows, worker flows and screening by firms to interpret recent empirical evidence that search behavior differs substantially between the unemployed and employed. The model matches well such empirical patterns, and implies substantially greater amplification of aggregate productivity shocks.

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To my family.

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# Chapter 1

# Worker Flows and Wage Growth over the Life-Cycle: A Cross-Country Analysis

## 1.1 Introduction

A large literature studies differences in labor market flows across countries. This line of research finds that such flows vary markedly between countries, and that policies and institutions that impede such flows may lead to misallocation of factors of production. The literature, however, has tended to focus on the effects of such policies on firms' job creation and destruction decisions, with less attention paid to their impact on worker flows and the behavior of workers. Yet worker responses to such large differences in the functioning of the labor market may have a first-order effect on aggregate economic outcomes. In this paper, I add to the literature by studying the joint behavior of worker flows and life-cycle wage growth across countries.

I analyze wage and employment histories across 12 OECD countries using panel data containing 15 or more years of data per country and over four hundred thousand observations. Based on these unique data, I establish three stylized facts on worker flows and life-cycle wage growth across countries. First, in line with results in the existing literature

(Pries and Rogerson, 2005; Lagakos et al., 2016), life-cycle wage and mobility dynamics differ substantially across countries. Second, *labor market fluidity*, which I define as the fraction of all employed workers who made a voluntary job-to-job (JtJ) transition at some point in the past 12 months, and life-cycle wage growth covary positively across countries. The magnitude of this relationship is economically meaningful, with a two standard deviation difference in the fluidity of a labor market being associated with over 20 log points greater wage growth between age 25 and 50. Third, despite being accompanied by wage growth in all countries, job shopping directly accounts for only a quarter of the cross-country difference in life-cycle wage growth that can be projected on labor market fluidity.

To reconcile these facts and to evaluate their importance for cross-country income differences, the second part of the paper develops a general equilibrium life-cycle search model in the Diamond-Mortensen-Pissarides tradition (Mortensen and Pissarides, 1994). The marginal productivity of a worker's human capital differs across firms, but frictions in the labor market prevent workers from immediately reallocating to their most productive use. I introduce on-the-job accumulation of human capital into this framework, motivated by a literature that emphasizes human capital and job shopping as two key drivers of life-cycle wage growth (Rubinstein and Weiss, 2006). In contrast to recent attempts to combine the two (Yamaguchi, 2010; Bagger et al., 2014), I model on-the-job training as an endogenous choice, thus allowing human capital accumulation to respond to differences in labor market institutions.

Higher vacancy creation increases the rate at which workers expect to climb the job ladder. Since the value of human capital increases with the productivity of the firm (the two are "supermodular"), a faster rate of climbing the job ladder raises the expected value of human capital. As a result, policies that depress firms' incentives to create jobs reduce output for three reasons. First, by reducing the job finding rate from unemployment they increase the unemployment rate. Second, they result in worse matching of workers to

firms, since workers do not climb the job ladder to the same extent. Third, they reduce the stock of human capital by lowering incentives to invest in learning on the job. At the same time, due to their complementarity lower human capital accumulation reduces the value of a vacancy to a firm. This leads to amplification.

I calibrate the model to fit key dimensions of the data for a hypothetical average fluidity country. The model fits the data well and suggests that human capital accounts for the majority of life-cycle wage growth. Subsequently, in order to understand the impact of labor market fluidity on worker behavior, I introduce *wedges* to firms' cost of creating jobs such that the model reproduces empirical differences in fluidity across countries. Holding all other parameters fixed, I evaluate the implication of such wedges for life-cycle growth in human capital, match productivity and wages, as well as cross-country income differences.

Such wedges to firms' cost of creating jobs generate a substantial effect on life-cycle wage growth and output by affecting workers' optimal behavior. A two standard deviation increase in the empirical measure of fluidity results in a steepening of life-cycle wage growth by over 20 log points. The model replicates 98–99 percent of the empirical covariation between labor market fluidity, on the one hand, and life-cycle wage growth and output per capita, on the other, and 43–45 percent of the overall empirical variation in these moments. Differences in the stock of human capital account for two thirds of this.

The final part of the paper verifies two key predictions of the model using standardized data on on-the-job training and search across countries. First, as predicted by the model the data display a distinct positive correlation between labor market fluidity and on-the-job training. Second, in line with the model a higher share of workers search actively on the job in more fluid labor markets. The model quantitatively matches well both the cross-country patterns and the life-cycle profiles of each of these two moments, which is a validation of the model given that none were targeted in the calibration.

### 1.1.1 Previous literature

I contribute to three strands of the literature. First, an empirical literature characterizes differences across countries in wage and mobility dynamics. Several papers conduct a two-country comparison, including Schönberg (2007) for the U.S. and Germany, Dustmann and Pereira (2008) for the U.K. and Germany, and Guvenen et al. (2013) for the U.S. and Germany. The first two document substantially higher mobility and wage growth in the U.K./U.S. relative to Germany, while the latter only discuss the steeper wage growth in the U.S. Hobijn and Sahin (2009) use duration data to document large differences in reentry rates from unemployment across 27 OECD countries, but much smaller variation in separation rates. Jolivet et al. (2006) construct measures of JtJ mobility across several OECD countries, but only for the 1994–1997 period and not with a life-cycle perspective. Lagakos et al. (2016) find large dispersion in life-cycle wage growth across rich and poor countries.

Relative to these authors, I contribute a life-cycle perspective on worker flows—including JtJ mobility—across 12 OECD countries. Furthermore, I show that large differences in life-cycle wage growth exist also among developed countries, and I leverage the longitudinal aspect of my data to alleviate concerns that such differences are driven by selection. Finally, I document the wage impact of mobility across countries and I construct a measure of the direct contribution of job shopping to wage growth across countries.

Second, I contribute to a largely theoretical, qualitative literature on training in frictional labor markets. Pigou (1912) argues that since workers may leave their firm, employers do not have the right incentives to train their workers. Hence, training subsidies may be warranted. Becker (1964) casts doubt on this conclusion by showing that in a competitive setting, workers bear the full burden of investment in general human capital and achieve the efficient level of investment. Acemoglu (1997) shows that when labor markets are imperfect, the equilibrium features underinvestment. Acemoglu and Pischke

(1998, 1999) argue that in the presence of imperfections in the labor market, training may decrease with mobility. Laing et al. (1995) show that a complementarity between individuals' schooling decisions and firms' vacancy posting decisions may give rise to multiple equilibria. Wasmer (2006) considers a frictional labor market with endogenous formation of two types of human capital—firm-specific and general—to show that higher turnover increases incentives to accumulate general rather than specific skills (which in turn may raise turnover).

I expand upon this literature in three ways. First, I incorporate on-the-job search. As it turns out, an increase in the chance of such mobility has a qualitatively different effect on incentives to accumulate human capital than an increase in turnover through unemployment.[1] Second, I investigate empirically the cross-country link between labor market fluidity and training on the job, which has largely bypassed this primarily theoretical literature.[2] Third, I quantify the dynamic effect of frictions on life-cycle human capital accumulation.

Finally, I add to a literature that uses quantitative models to understand life-cycle income and mobility dynamics. Huggett et al. (2006, 2011) use a human capital model in the spirit of Ben-Porath (1967) in a frictionless labor market to understand life-cycle dynamics in the U.S. Guvenen et al. (2013) study the implication of taxation for inequality across countries and time, also in a frictionless life-cycle setting. Lack of data restricts the latter authors to only evaluate the model's life-cycle predictions against Germany and the U.S. Bagger et al. (2014) introduce exogenous on-the-job accumulation of human capital into the setting of Cahuc et al. (2006), and find that human capital accumulation is the most important source of life-cycle wage growth in Denmark. Yamaguchi (2010) also estimates a version of the Cahuc et al. (2006) model with exogenous human capital accumulation, and concludes that human capital is the most important source of wage

[1] Rubinstein and Weiss (2006) note in a highly stylized, partial-equilibrium setting that a greater chance of JtJ mobility increases incentives to invest in human capital.

[2] Bassanini et al. (2005) present evidence on workplace training in Europe and discuss informally how it relates to institutional differences such as unions, employment protection and product market competition.

growth also in the U.S. Bowlus and Liu (2013) model endogenous on-the-job training in a partial equilibrium search model, but do not attempt to understand cross-country differences. Finally, Menzio et al. (2016) construct a directed search model with exogenous human capital accumulation and estimate it on U.S. data.

Relative to this literature, I incorporate endogenous human capital accumulation in a general equilibrium framework and evaluate to what extent it can reproduce key differences in life-cycle dynamics across 12 developed economies.

This paper is organized as follows. Section 1.2 outlines the data sources, variable definitions and sample restrictions that I use to derive my empirical results. Section 1.3 presents three stylized facts on life-cycle mobility and wage dynamics across countries. Section 2.3 develops a structural search model with endogenous training on the job, which Section 2.5 brings to the data. Section 1.6 presents quantitative results on the impact of policies that affect vacancy creation on life-cycle outcomes of workers and aggregate outcomes for the economy, and Section 2.8 concludes.

## 1.2 Data and methodology

The following section first discusses how I construct my data set, and second the methodology used to establish three key stylized facts on life-cycle wage growth and labor market fluidity across countries.

### 1.2.1 Data

**Sources** I base my empirical analysis on the following data sources: the 1990–2013 U.S. Panel Study of Income Dynamics (PSID); the 1994–2001 European Community Household Panel (ECHP); the 2004–2014 European Union Survey of Income and Living Conditions (EU-SILC); the 1994–2014 German Socio-Economic Panel (GSOEP); and the 1992–2008 British Household Panel Survey (BHPS). These surveys have in common that (a)

they are longitudinal, allowing me to follow the same individual over time; (b) they provide at least 15 years of data per country between 1990–2014; and (c) they follow a similar design, simplifying the task of making them comparable.

The combination of data sources provides four hundred thousand observations on individuals that can be followed over time for the following 12 countries: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Spain, the United Kingdom,[3] and the United States. I combine this with aggregate economic outcomes from the Organization of Economic Co-operation and Development (OECD). Appendix B.1 provides more details on these data sources and how I clean and standardize them across countries.

**Sample selection** I focus on male workers who are either employed and working at least 15 hours a week, or unemployed. The model I construct in Section 2.3 is not well-suited to understand the non-participation margin, and hence I focus my empirical analysis on a group of workers with a strong attachment to the labor force. For the same reason, I exclude women and those not in the labor force. The 15 hours a week threshold is additionally required since the ECHP/EU-SILC only contains information on hours worked for those working more than 15 hours a week at the time of the survey.

To avoid issues related to the timing of entry into the labor market and early retirement, which I do not model, I focus on males age 25–55. I also exclude self-employed workers because my model is not built to capture the forces determining self-employment. Finally, I drop workers with missing year of birth, year and month of survey, employment status and income.

**Variable definitions** The wage is total annual labor income divided by annual hours. Income is measured prior to taxes and social security contributions of the worker and

[3]Strictly speaking Great Britain since the BHPS only contains respondents living in Great Britain during the 1991–1998 period.

is broadly defined, including bonuses and other forms of compensation. Appendix B.1 provides greater detail, including how I convert nominal local currencies to real 2004 U.S. dollars. I define a worker as employed if he works at least 15 hours a week.

As noted above, my measure of labor market fluidity is the fraction of employed workers who switched voluntarily directly from one employer to another at some point in the past 12 months. Appendix A.2 alternatively derives a set of flow-balance equations that allow me to use the available data to estimate monthly JtJ, EU and UE mobility hazard rates. The measure of fluidity is strongly positively correlated with both the monthly JtJ hazard and the monthly UE hazard across countries, and uncorrelated with the EU hazard.

### 1.2.2 Methodology

**Life-cycle wage profiles and labor market fluidity** To study the relationship between fluidity and life-cycle wage growth, I regress the annual average log wage of individual $i$ in year $t$ on an interaction between the average labor market fluidity of individual $i$'s country and a polynomial in age, a set of age dummies common to all countries, $\Xi_{a(i,t)}$, individual fixed effects, $\Phi_i$, and country-year effects, $\Psi_{c(i)t}$,

$$wage_{it} = \phi(a_{it}) \times fluidity_{c(i)} + \Xi_{a(i,t)} + \Phi_i + \Psi_{c(i)t} + \varepsilon_{it} \tag{1.1}$$

subject to an assumption that wages do not grow at the end of careers,

$$\Xi_a = (1-\eta)^{a-\bar{a}}\Xi_{\bar{a}}, \quad \forall a > \bar{a} \tag{1.2}$$

where $\bar{a}$ is some upper age threshold beyond which wages are assumed to fall by $\eta$ annually. All regressions are weighted using the provided survey weights adjusted such that

each country receives an equal weighting. Standard errors are clustered at the country level.

As is well known in the literature, some restriction is necessary in order to separate individual, age and time effects. I follow Lagakos et al. (2016) to impose the restriction that wages fall at some predetermined rate after some age, which implies that time effects are identified off the behavior of wages within an individual late in life.[4] This assumption is motivated by the predictions of the theory developed in Section 2.3, which suggests that average wage growth late in life should be small.[5] In my baseline specification, I assume no depreciation, $\eta = 0$, and that wages do not grow after age 50, $\bar{a} = 50$, but I present multiple robustness specifications with respect to these assumptions. I also alternatively impose the restriction proposed by Hall (1968) and Deaton (1997), or include measures of labor productivity to control for the impact of economic growth on wages.

In order to study to what extent differences in educational attainment account for the cross-country differences in life-cycle wage growth, I include a separate linear age trend for high-school graduates and one for college graduates. I also consider a version with a separate linear in age fully interacted with 10 broad occupations groups. Alternatively, I reestimate the model for college graduates only (including reestimating the measure of fluidity). To the extent that minimum wages is a key factor behind cross-country differences in life-cycle wage growth and college graduates are less bound by the minimum, one would expect smaller cross-country differences in wage growth for college graduates.

Finally, to address concerns about omitted variable bias in the cross-country regressions, I exploit within-country variation in fluidity and wage growth. Specifically, I com-

[4]This approach was originally proposed by Heckman et al. (1998).

[5]Another approach sometimes taken by the literature is to produce separate results under a "cohort effects" and a "time effects" view, and argue that to the extent that these specifications produce similar conclusions, the analysis is robust. There is, however, no sense in which the results under these two specifications are at the two extremes of a spectrum, and hence the fact that the two produce qualitatively similar results is no guarantee that another, equally plausible and similarly arbitrary normalization of cohort and time effects would not produce qualitatively different results. The problem is particularly relevant for the cross-country comparison since the same normalization might be differentially good across countries. Hence, I pursue an approach grounded in economic theory.

pute fluidity separately for college and non-college graduates within a country and substitute this for the country-wide measure of fluidity in the above regressions together with a country-specific quadratic in age and a full set of college-age interactions. This regression thus relates the relative steepness of the life-cycle wage profile of college graduates within a country to their relative fluidity within that country.

**The contribution of search to life-cycle wage growth** To study the impact of mobility on wages, I borrow from the literature on displaced workers (Jacobson et al., 1993).[6] Specifically, I estimate by OLS the current log wage on indicators for whether the worker moved voluntarily from one employer to another up to seven years prior to the current date and up to two years into the future, as well as whether he separated involuntarily up to seven years prior to the current date as well as up to two years into the future,[7]

$$wage_{it} = \sum_{\tau=-2}^{7} \left\{ \xi_\tau JtJ_{it-\tau} + v_\tau EU_{it-\tau} \right\} + age_{it} \left\{ \zeta \overline{JtJ}_{it} + \kappa \overline{EU}_{it} \right\} + \mathbb{X}_{it}\beta + \varepsilon_{it} \tag{1.3}$$

where $JtJ_{it-\tau}$ takes value one if individual $i$ made a voluntary JtJ transition in year $t - \tau$, $\overline{JtJ}_{it}$ takes value one if individual $i$ made a voluntary JtJ transition at some point in year $t-7$ to $t$, and $\mathbb{X}$ includes a full set of individual effects and country-year effects. I also consider versions that allow me to test for differences in the return to mobility across countries. The $\xi$ and $v$ coefficients capture the dynamic impact of a labor market transition on wages up to seven years after the transition and up to two years prior to the transition, while $\zeta$ and $\kappa$ allow it to differ by age.[8] Weights are adjusted such that

[6] This part of the analysis is based on the ECHP, the 1990–1997 PSID, the 1994–2001 GSOEP, and the 1994–2001 BHPS. The EU-SILC does not provide a wage measure whose timing aligns with the mobility measures, while the bi-annual PSID post 1997 misses any mobility taking place in off survey years. Hence, I restrict this analysis to the 1990–2001 period.

[7] I use the wage at the time of the interview since the mobility measures cover the time between the interview and the previous interview, while the average annual wage is the average wage during the prior calendar year.

[8] The advantage of this approach, relative to for instance differencing the data and relating annual wage growth to mobility, is that it allows a characterization of the behavior of wages pre-mobility and in the years after mobility.

each country receives the same aggregate weight, and standard errors are clustered at the individual level.

Using the above estimates of the return to mobility as well as the frequency of mobility at each age, I construct the predicted average life-cycle profile of wages due to search in the following way. I first assign the estimated gain from mobility two years after the event relative to right before the event as the return to mobility at age $a$, $gain_a = \hat{\xi}_2 - \hat{\xi}_{-1} + \hat{\zeta} \times a$. Subsequently, I compute the job shopping component of wages at age $a$ as the cumulative sum of wage gains up to age $a$

$$\widehat{wage}_{c,a}^{Search} = \sum_{s=26}^{a} gain_s \times fluidity_{c,s}$$

where $fluidity_{c,s}$ is the fraction of employed $s$ year olds in country $c$ who made a voluntary JtJ transition in the past year.[9]

## 1.3 Empirical facts

This section establishes three empirical facts characterizing cross-country differences in labor market mobility, life-cycle wage growth, and the importance of job shopping for wage growth differences.

### 1.3.1 Fact 1: Fluidity and life-cycle wage growth differ substantially across countries

Figure 1.1 plots the fraction of employed who made a voluntary JtJ transition at some point in the past year over the life-cycle across the 12 OECD countries in my sample. In all countries, it displays a distinct life-cycle pattern. There are substantial differences across

[9]The measure of fluidity is relative to employed workers and not the workforce, which implies that this procedure slightly overstates the contribution of search to life-cycle wage growth. Given that the employment rate of prime age males is very high across all countries the error due to this is arguably second order.

countries in the levels of voluntary mobility. For instance, American and Danish men are twice as likely to make a voluntary JtJ switch compared to their French and Italian peers throughout their careers. Appendix A.2 presents estimated life-cycle profiles of monthly JtJ, EU and UE transition rates based on these data.

Figure 1.2 contains estimated life-cycle wage profiles across the 12 OECD countries in my sample. It is assuming that wages do not grow past age 50. Wage growth varies substantially across countries, with the U.S., Ireland, the U.K. and the Netherlands displaying the greatest growth in wages and France, Austria and Belgium having the weakest wage growth over careers.

### 1.3.2 Fact 2: Fluidity and life-cycle wage growth are positively correlated

Figure 1.3 plots wage growth between age 25 and 50 against labor market fluidity across these 12 countries. Life-cycle wage growth is positively correlated with labor market fluidity and the relationship is economically meaningful.

Figure 1.1: Fraction of employed who made a voluntary JtJ move in past year

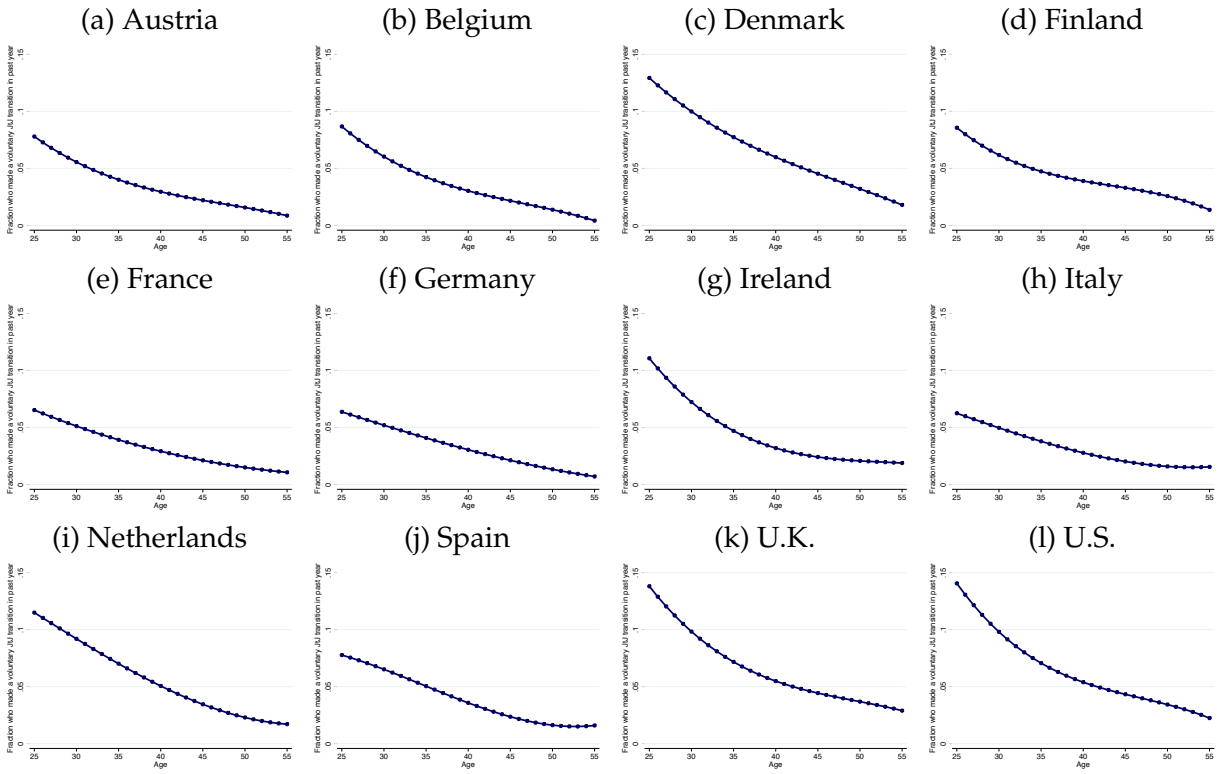
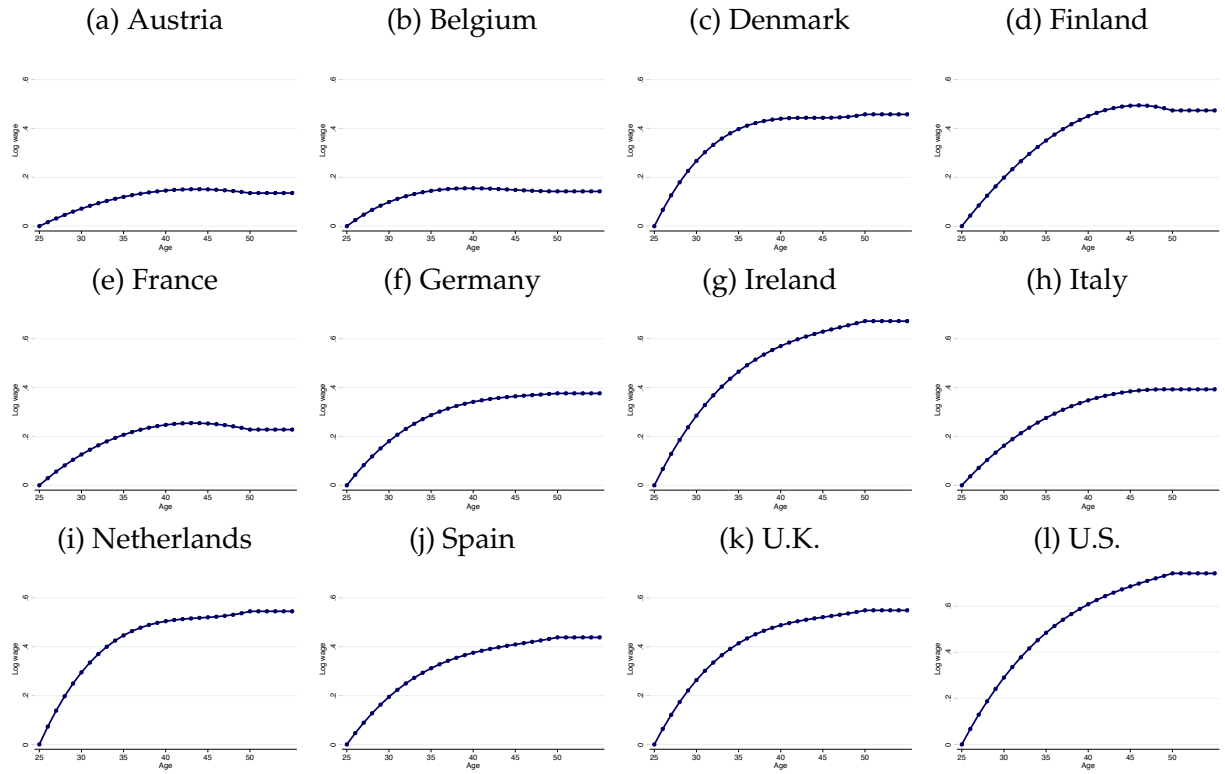
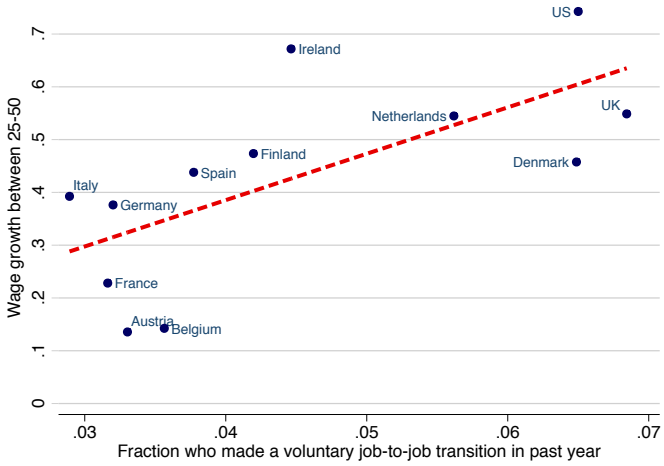


Figure 1.2: Estimated life-cycle wage profiles




Note: ECHP (1994–2001), EU-SILC (2004–2014), PSID (1990–2013), GSOEP (1990–2011), and BHPS (1991–2008). See text for further details.

Figure 1.3: Fluidity and life-cycle wage growth across 12 OECD countries




Note: ECHP (1994–2001), EU-SILC (2004–2014), PSID (1990–2013), GSOEP (1991–2011), and BHPS (1992–2008). See text for further details.

One potential explanation behind the steeper growth in high fluidity countries would be if labor force composition covaries with fluidity and different types of workers have different wage growth. To investigate this, Table 1.1 presents regression results based on equation (1.1) on the correlation between the steepness of life-cycle wage profiles and labor market fluidity. I use for $\phi(age)$ a third order polynomial in age and restrict as above wages to not grow past age 50.

Column 2 allows for a different life-cycle slope by three broad education groups. College graduates have substantially steeper wage profiles than the less educated, while there is no statistically significant difference between high-school graduates and those with less than high-school. Column 3 does the same but with a separate linear age trend for 10 broad occupation groups. These specifications suggest that the steeper wage growth in higher fluidity countries is not primarily due to differences in the educational or occupational composition of the workforce.

Column 4 shows results for college graduates only, with similar results. This casts doubt on for instance differences in the minimum wage being the main explanation be-

hind the positive correlation between fluidity and wage growth, given that it arguably applies less to college graduates. Finally, column 5 relates the relative difference in life-cycle wage growth between college and non-college graduates to the relative difference in fluidity between college and non-college graduates within a country. The estimated coefficient is positive, suggesting that the greater is the difference in fluidity between college graduates and non-college graduates within a country, the greater is the relative wage growth of college graduates to non-college graduates within that country.

Table 1.1: Fluidity and life-cycle wage growth

| | (1) Baseline | (2) Education slopes | (3) Occupation slopes | (4) College only | (5) Within country |
|---|---|---|---|---|---|
| Fluidity $\times$Age | 0.817*** | 0.771*** | 0.801*** | 0.923* | 0.985** |
| | (0.171) | (0.176) | (0.172) | (0.438) | (0.452) |
| Fluidity $\times$Age$^2$ | -0.039*** | -0.039*** | -0.039*** | -0.045** | |
| | (0.009) | (0.009) | (0.008) | (0.020) | |
| Fluidity $\times$Age$^3$ | 0.001*** | 0.001*** | 0.001*** | 0.001* | |
| | (0.000) | (0.000) | (0.000) | (0.000) | |
| High-school $\times$Age | | -0.001 | | | |
| | | (0.003) | | | |
| College $\times$Age | | 0.017** | | | |
| | | (0.006) | | | |
| N | 401,945 | 400,364 | 379,350 | 120,384 | 400,364 |
| R2 | 0.812 | 0.812 | 0.816 | 0.804 | 0.815 |

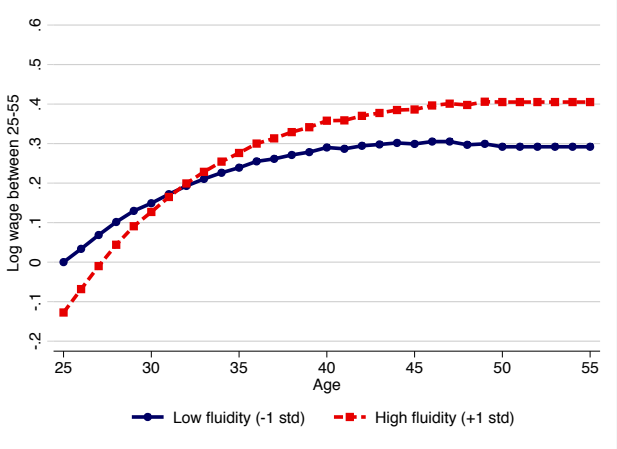
ECHP (1994–2001), EU-SILC (2004–2014), PSID (1990–2013), GSOEP (1991–2011), and BHPS (1992–2008); *10%; **5%; ***1%; see text for further detail.

To illustrate the magnitude of these differences, Figure 1.4 plots the predicted wage profile for a country with a one standard deviation higher fluidity (red with squares) and a one standard deviation lower fluidity (blue with circles) based on the estimates from the first column. Wages grow by 30 log points between age 25–50 in the low fluidity country and 53 log points in the high-fluidity country. Furthermore, wages are initially lower in high fluidity countries and gradually overtake those in low fluidity countries.

Figure A.4 in Appendix A.3 plots the predicted life-cycle wage profile for a high and low fluidity country based on the estimates with education or occupation controls in column 2–3, while Figure A.5 plots that based on the estimates for college graduates only in column 4. The predicted difference in wage growth remains roughly as large under each specification.

Appendix A.3 reports similar results under several robustness specifications, including different assumptions on the depreciation rate of wages late in life. These results suggest that although different assumptions on the magnitude of depreciation changes the estimated overall growth in wages, the cross-country difference remains the same (up to what appears like estimation error). Hence to the extent that wages change by the same amount late in life across countries, the exact magnitude of this change does not seem to matter for the cross-country comparison. Appendix A.3 also reports results under the normalization advocated by Deaton (1997), using labor productivity to control for time trends, or with potential experience substituted for age. These alternatives suggest as large or a larger difference in wage growth associated with fluidity.

Figure 1.4: Predicted life-cycle wage growth, high and low fluidity country

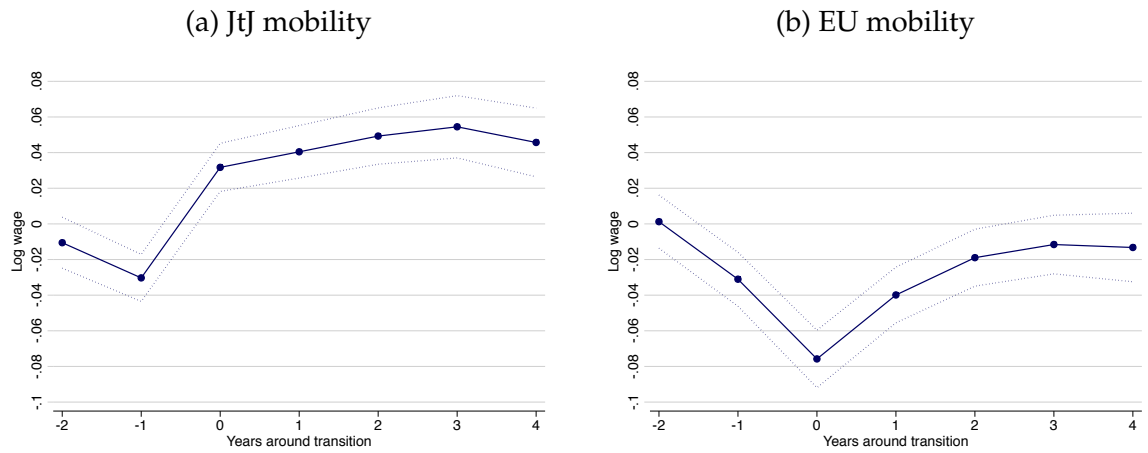



Note: ECHP (1994–2001), EU-SILC (2004–2014), PSID (1990–2013), GSOEP (1991–2011), and BHPS (1992–2008). See text for further details.

### 1.3.3 Fact 3: Job shopping directly accounts for a quarter of the difference in wage growth

Figure 1.5 plots the estimated wage impact of mobility up to two years prior to the transition and up to four years after the transition. A JtJ transition is associated with a six log point gain in wages on impact.[10] The gains continue to accrue for up to three years after the transition. As discussed in further detail in Appendix A.4, there is only weak support for the hypothesis that these gains differ across countries and no support for the hypothesis that they covary systematically with fluidity. The wage loss from an EU transition is eight log points on impact and almost disappears within three years after the event. The loss is larger in more fluid labor markets.[11] Appendix A.4 provides additional results and regression tables.

Figure 1.5: Estimated wage changes associated with mobility




Note: ECHP (1994–2001), PSID (1990–1997), GSOEP (1994–2001) and BHPS (1994–2001). See text for further detail.

[10] For comparison, Topel and Ward (1992) report a 10 log point gain for young American men.

[11] The estimated loss from job loss is smaller then what is typically reported by the displaced worker literature (Jacobson et al., 1993). That literature, however, tends to be based on workers with long tenures at their pre-displacement employer. Furthermore, I use hourly wages instead of income, and the literature typically finds smaller wage losses. Finally, I find larger losses in more fluid labor markets, and most of the displaced worker literature tends to focus on the U.S. (which is a high fluidity country). Available evidence from less fluid labor markets suggest lower losses from displacement there (Burda and Mertens, 2001).

To what extent can the direct effect of job shopping account for the differences in life-cycle wage growth? Figure 1.6 plots the predicted cumulative growth in wages between age 25–55 implied by the estimated return to mobility as well as the frequency of such switches for a one standard deviation higher and a one standard deviation lower fluidity country. Job switching is predicted to contribute six log points to wage growth in the low-fluidity country (blue with circles) and 12 log points in the high-fluidity country (red with squares), or roughly a quarter of life-cycle wage growth.[12] Job shopping also directly accounts for about a quarter of the difference in overall wage growth across countries. Although substantial, it hence falls short of explaining the entire cross-country differences in wage growth.[13]

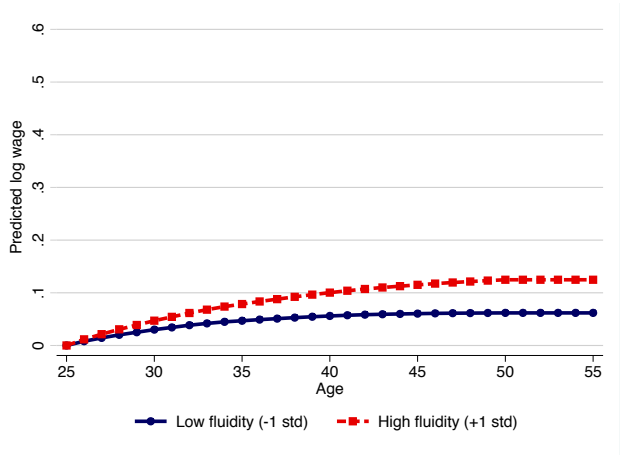
### 1.3.4 Summary of empirical evidence

The above analysis establishes three facts on life-cycle labor market outcomes across countries. First, life-cycle wage growth and labor market fluidity differ substantially even within a group of relatively homogeneous, developed economies. Second, wage growth and labor market fluidity are positively correlated across countries, and the relationship is quantitatively meaningful. Finally, the direct effect of job shopping accounts for a quarter of the difference in life-cycle wage growth that can be projected on fluidity. Thus, job shopping directly only explains a fraction of the covariance between wage growth and fluidity in the data. Motivated by this, I proceed to analyze the equilibrium impact of differences in labor market fluidity on human capital accumulation.

[12] For comparison, Topel and Ward (1992) attribute about a third of wage growth during the first 10 years of careers to job switching for American men.

[13] Measurement error in the classification of who made a transition during the prior year will bias both overall growth due to search as well as the predicted cross-country difference due to search towards zero. Such measurement error, however, would have to be implausibly large in order to account for the entire difference in life-cycle wage growth. For example, the true return to voluntary mobility would have to be four times what I estimate it to be, or close to 40 percent. This is much higher than what any study has found.

Figure 1.6: Wage growth due to job shopping, high and low fluidity country




Note: ECHP (1994–2001), EU-SILC (2004–2014), PSID (1990–2013), GSOEP (1991–2011), and BHPS (1992–2008). See text for further details.

## 1.4 Model

The following section develops a general equilibrium search model with endogenous training on the job in order to study the equilibrium implication of differences in labor market fluidity for human capital accumulation on the job, life-cycle wage growth, and cross-country income differences.

### 1.4.1 Environment

Time is discrete and lasts forever. There are no aggregate shocks and I restrict attention to the long-run steady-state. The economy consists of a unit mass of young workers, a unit mass of old workers and a positive mass of firms who meet in a frictional labor market to produce a single good. They have the same linear preferences over the single good of the economy, and I abstract for now from discounting.

### 1.4.2 Workers

Workers live for two periods. At each point in time, old workers exit the labor market permanently with continuation value zero, young workers become old, and an equal mass of new workers enter as young. Entrants start out in a random draw of jobs at age one and firms compete only for young workers. These assumptions are made for tractability and will be relaxed in the quantitative analysis.

**Search** The assumption that workers search from employment is motivated by the finding in Section 1.3 that voluntary mobility of workers directly from one employer to another is a robust feature of the data, and that workers typically enjoy wage gains in conjunction with this. It differs from that made in Acemoglu (1997) and Acemoglu and Pischke (1998), and it will turn out to have a qualitatively different effect on the marginal value of human capital than turnover through unemployment.

**Human capital** Workers may grow their human capital by investing in learning on the job. The assumption of endogenous accumulation of human capital differs from that in recent quantitative life-cycle models such as Bagger et al. (2014). While their purpose is to understand the sources of life-cycle wage growth within a country, my objective is to understand the determinants of cross-country differences in life-cycle wage growth. For that purpose, it appears important to allow human capital accumulation to respond to economic incentives. Section 1.6 presents evidence that on-the-job training varies both over the life-cycle and across countries.

To increase his human capital to $h' = h + i$ a worker has to pay cost $c(i)$,[14] where

$$c(i) = \frac{c_h}{\gamma} i^{\gamma}, \quad \gamma > 1$$

I assume that human capital does not depreciate.

[14] An earlier version of this paper considered a Ben-Porath (1967) specification with similar results.

### 1.4.3 Firms

A firm may be producing or recruiting, and it may employ at most one worker. Hence a firm is really a match. An infinite supply of potential entrepreneurs may become recruiting firms by paying flow cost $c_v$, which gives a chance to meet with a worker. If a recruiting firm meets a worker, the two draw low, $p_1$, or high, $p_2$, productivity with equal probability. If a firm fails to either recruit or retain a worker, it permanently exit and gets continuation value zero.

If $h$ is the human capital of that worker, the match's output of the single good of the economy is $y = ph$. This implies that human capital and productivity are complements in production. Although this is key for generating a feedback from the labor market to incentives to accumulate skills on the job, there is substantial empirical support for a complementarity between technology and workforce skill going back at least to Griliches (1969). The assumption that human capital is general is motivated by a recent literature that casts doubt on the importance of firm-specific human capital (Kambourov and Manovskii, 2009). Appendix A.9 presents empirical evidence on the behavior of mobility around on-the-job training that is consistent with human capital being general.

### 1.4.4 The labor market

**Matching** An aggregate matching function, $m(v, S)$, produces meetings out of recruiting firms $v$ and the efficiency-mass of searching workers, $S$. As is standard in the literature, I assume a Cobb-Douglas functional form,

$$m(v, S) = \chi v^{\alpha} S^{1-\alpha}$$

where $\chi$ captures matching efficiency and $\alpha \in [0, 1]$ denotes the elasticity of meetings with respect to vacancies. As discussed in greater detail in Section 2.5, without data on

vacancies $\chi$ is not separately identified from the cost of creating jobs, $c_v$, and hence I normalize $\chi = 1$ to save on notation.

Denote by $\theta = v/S$ aggregate labor market tightness, by $\lambda(\theta)$ the job finding rate of young workers, and by $q(\theta)$ the worker finding rate of firms,

$$\lambda(\theta) = \theta^{\alpha}, \qquad q(\theta) = \theta^{\alpha-1}$$

**Contracting** I assume that there are no constraints on the type of contracts and payments the parties of a match can commit to, while all future employers cannot contract with the current match. The first part of this assumption is different from that in Acemoglu and Pischke (1998), who assume that the worker and current firm cannot contract on investment. As a result, in their environment a worker would never take a wage cut in return for higher promised training, since the firm will renege on that promise. This implies that investment is dictated by the incentives of the firm, and a higher probability that the worker leaves the firm reduces investment. Under my assumption, on the other hand, the match will undertake the bilaterally optimal investment. Given that it is not clear ex ante which assumption is the more realistic, it seems valuable to consider the implications of relaxing their assumption.

Under this assumption it is irrelevant whether the worker or the firm actually pays for investment. The match choses investment to maximize its bilateral surplus and splits the maximized value. The bilateral surplus, however, need not equal social surplus. In fact, as noted by Acemoglu (1997) in a similar setting, investment of the current match has a positive externality on all future matches, and under the second part of the assumption there is no way for future employers to compensate the current match for such investment. This part of the assumption is natural: with random search, all future employers would have to contract with all existing matches prior to creating jobs. This seems like an insurmountable task to achieve for the decentralized economy.

**Bargaining** I assume that the worker and firm split the surplus of the match following the bargaining protocol of Cahuc et al. (2006). Consider a worker without a job who meets a firm $p$. A match is only formed if both parties agree to it. If they agree to match, the worker and firm split the surplus of the match such that the worker gets a share $\beta$ of the surplus.

Consider next a worker employed at $p$ who meets a new firm $p'$. A second price auction starts between $p$ and $p'$ for the worker. This is won by the bidder with the higher valuation, and it leaves the worker with the full value of working for the least productive firm as his outside option. The worker and winning firm bargain over the differential surplus such that the worker receives a slice $\beta$ of the differential surplus.[15] The critical element of this part of the assumption is that when an employed worker meets a new employer, the future firm shares some of the proceeds from the match over and above the maximum value the worker could get in the current match, i.e. $\beta > 0$.

The above bargaining protocol pins down the total payment the worker receives, but not the timing of payments. In lack of a satisfactory model of the timing of payments, I follow the literature and assume that they take the form of a piece rate of net match output, $w \times \left(y - \frac{c_h}{\gamma} i^{\gamma}\right)$ (Barlevy, 2008; Bagger et al., 2014).[16] As I show in Section 1.6, this assumption generates a process for wages that fits the data well.[17]

### 1.4.5 Analysis

**Definition 1** (Stationary search equilibrium)**.** A stationary search equilibrium with positive vacancy creation consists of a value function of the young, $J(p; v)$; an investment

[15] Subject to the constraint that the worker cannot be made worse off by receiving a new offer.

[16] I do not subtract the cost of employed search given my interpretation that such costs are paid in terms of utility.

[17] I have experimented with alternative assumptions on the timing of payment, including a fixed wage (in contrast to a fixed piece rate). This produces a worse fit with the data in terms of wage dynamics, but delivers a similar prediction on cross-country differences in response to different wedges. These results are available on request.

policy of the young, $i(p;v)$; a stock of human capital of the old, $h'(p;v)$; and a mass of recruiting firms, $v(h)$, such that

1. The value function and investment policy solves the problem of the young given a mass of recruiting firms;

2. The stock of human capital of the old is consistent with investment as young;

3. And the mass of recruiting firms is consistent with free entry.

The equilibrium is bilaterally optimal and hence it is sufficient to consider the problem of the match. Specifically, the only interesting problem is that of a low productivity match at age one,[18]

$$J(p_1;v) = \max_{i,h'} \left\{ p_1 h - \frac{c_h}{\gamma} i^\gamma + \left[ p_1 + v^\alpha \beta \frac{1}{2}(p_2 - p_1) \right] h' \right\}$$

subject to $h' = h + i$. At rate $v^\alpha$ a worker initially employed in a low productivity job meets a new firm at age two, and with probability 0.5 the two draw a high productivity. In this case the worker moves to the new firm, and gets a slice $\beta$ of the the differential surplus, $p_2 - p_1$.

The free entry condition of potential entrepreneurs can be written as

$$c_v \quad = \quad v^{\alpha-1} \frac{1}{2} \frac{1}{2} (1-\beta)(p_2 - p_1)\,(h+i)$$

At rate $v^{\alpha-1}$ a recruiting firm gets paired with a young worker, with probability 0.5 that worker is employed in a bad job, and with probability 0.5 the match draws a good job. Only in this case is the recruiting firm successful and it gets a slice $1-\beta$ of the differential value of the match.

[18] High productive matches in period one are unaffected by changes in job creation in period two.

An optimal investment rule satisfies,

$$i^W(v) = \left[\frac{1}{c_h}\left(p_1 + v^\alpha \beta \frac{1}{2}(p_2 - p_1)\right)\right]^{\frac{1}{\gamma-1}} \tag{1.4}$$

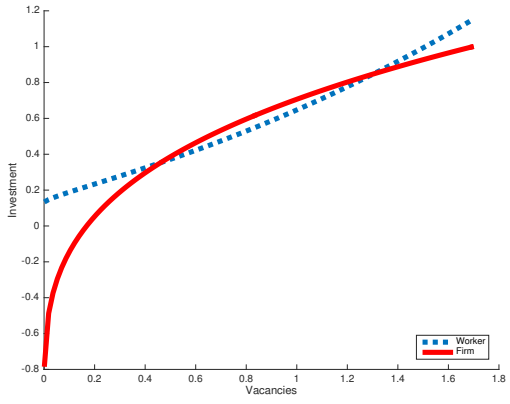
which is increasing in vacancies. We can rewrite the free entry condition as,

$$v(i) = \left[\frac{(1-\beta)(p_2-p_1)\,(h+i)}{4c_v}\right]^{\frac{1}{1-\alpha}} \iff i^F(v) = \frac{4c_v v^{1-\alpha}}{(1-\beta)(p_2-p_1)} - h \tag{1.5}$$

and hence entry is increasing in the investment of workers. This reflects the fact that investment and job creation are complements: if more jobs are created by firms, the value to workers of human capital increases, while if workers invest more the value of an open job increases to firms.

Figure 1.7 plots the *v*-*i* combinations that are consistent with optimal behavior as characterized by (1.4)–(1.5). For these particular parameter choices, the two lines cross twice, reflecting a multiplicity of equilibria. In one equilibrium, investment is high and so is vacancy creation, while in the other both investment and job creation are low.

Figure 1.7: Best response functions




The key parameters governing whether multiplicity may arise are the elasticity of matches with respect to vacancies, $\alpha$, and the curvature of the cost of investing in human capital, $\gamma$. If vacancy creation or investment can be scaled up easily, a given increase

in investment (vacancies) of workers (firms) leads to a stronger optimal increase in vacancies (investment) of firms (workers), strengthening feedback. The following proposition shows that for low (high) enough values of $\alpha$ ($\gamma$), a unique equilibrium exists,

**Proposition 1.** *If* $\gamma(1-\alpha) > 1$, *or if* $\gamma(1-\alpha) = 1$ *and* $2c_h(4c_v)^{\gamma-1} > \beta(1-\beta)^{\gamma-1}(p_2-p_1)^{\gamma}$, *the economy admits a unique equilibrium.*

*Proof.* See appendix A.5. □

The next proposition shows that, although as in Acemoglu and Pischke (1998) a higher probability that the worker meets a new employer lowers the value of human capital to the firm, the option to leave the firm voluntarily increases the value of human capital to the worker. When the worker's bargaining power is strictly positive, the latter effect outweighs the former. As a result, the match invests more in response to a higher arrival rate of outside offers, and the worker compensates the firm for higher investment through a lower initial wage. Allowing for JtJ mobility is critical to this argument as it gives the worker the chance to re-bargain using the value of the current match as benchmark and not the value out of unemployment.

**Proposition 2.** *Suppose parameter values are such that there exists a unique equilibrium and* $\beta > 0$. *In this equilibrium, an increase in the cost of posting vacancies reduces the amount of vacancies in the economy and the amount of on-the-job training.*

*Proof.* See appendix A.5. □

A similar result extends to cases where multiple equilibria exist: in the lowest $v$ equilibrium, an increase in the cost of posting vacancies reduces investment.

The next proposition demonstrates how endogenous human capital accumulation amplifies the impact of changes in the cost of creating jobs on vacancy creation.

**Proposition 3.** *Suppose parameter values are such that there exists a unique equilibrium and* $\beta > 0$. *In this equilibrium, the less convex is the cost function of human capital investment—the*

*lower is $\gamma$—the larger is the percentage fall in investment and vacancies in response to an increase in the cost of creating jobs*

*Proof.* See appendix A.5. □

We can think of the case with exogenous investment as corresponding to $\gamma \to \infty$, in which case investment does not change in response to changes in labor market conditions. In this case, the equilibrium fall in vacancies in response to an increase in the cost of creating jobs is minimized.

Finally, I briefly comment on the welfare properties of the unique equilibrium under the special assumption that $\gamma = 2$ and $\alpha = 0.5$.

**Proposition 4.** *Suppose $\gamma = 2$, $\alpha = 0.5$ and $8c_v c_h - (p_2 - p_1)^2 > 0$. There exists no $\beta \in [0, 1]$ such that the unique decentralized equilibrium achieves the level of training in the constrained optimal allocation, and the degree of underinvestment is minimized for $\beta = 0.5$. If $\beta \geq 0.5$, the unique equilibrium features too few vacancies relative to the constrained optimum.*

*Proof.* See appendix A.5. □

For the same reason as in Acemoglu (1997), namely a positive externality of investment on future employers, the competitive economy features under-investment in human capital relative to the social optimum. While $\beta = 0.5$ minimizes the deviation in investment between the competitive equilibrium and the constrained first best, such a high bargaining power of workers is inconsistent with vacancies being at their constrained optimum.

### 1.4.6 Extended model

Before bringing the model to the data, I make five extensions. First, I assume that workers live for $A$ periods and that firms and workers discount at rate $\rho$. Second, I assume that matches sample from a continuous distribution, $F(p)$.

**Unemployment** Third, I allow for unemployment. Workers enter the labor market as unemployed, which pays flow utility $b$ denominated in the single good of the economy. Denote by $U$ the total mass of unemployed workers and $u_a$ the unemployment rate of an age $a$ worker.

**Endogenous separations** Fourth, I introduce productivity shocks and allow for endogenous separations. Denote by $G(\cdot|p)$ the distribution of productivity in the next period given that current productivity is $p$. A match terminates if the productivity of the firm falls below a threshold such that it is in the worker-firm's mutual best interest to terminate the match. Endogenous separations allow the model to match the decline in the EU hazard with age: because workers gradually climb a job ladder as they age, a given magnitude shock is more likely to result in a separation when a worker is young.[19]

**Endogenous search** Finally, I introduce endogenous search, motivated by the following observations. First, it seems realistic that workers have some control over whether they search or not. Second, data presented in Section 1.6 suggest that search effort does vary both across countries and over the life-cycle. For the question at hand, it appears relevant to ask the model to replicate this. Third, with exogenous search the model cannot match the magnitude of the fall with age in the JtJ and UE hazards.[20]

If an employed (unemployed) worker exerts search effort $s$ he meets a job at rate $s\lambda$, but it comes at utility cost $c_e(s)$ ($c_u(s)$). The cost function differs between unemployed and employed workers in order to match the much higher job finding rate of unemployed

[19] In addition, the endogenous separation threshold falls as the worker accumulates human capital due to the assumption that the value of leisure does not scale in human capital. Appendix A.9 presents evidence supporting this assumption.

[20] Exogenous search does generate a fall in the JtJ hazard as workers climb the job ladder. However, the magnitude of the fall with age is much greater in the data than what the model with exogenous search can account for.

workers in the data. I assume the following functional forms

$$c_i(s,h) = \frac{c_i h}{\eta_i} s^{\eta_i}, \quad \eta_i > 1,\ i \in \{u,e\}$$

I interpret the search cost to be in terms of opportunity time, which motivates the assumption that it scales in human capital. Without this assumption, search intensity increases over the life-cycle since flow output increases in human capital, which is at odds with the data presented in Section 1.6.

Denote by $S_u$ aggregate search intensity of the unemployed, by $S_e$ aggregate search intensity of the employed, by $\lambda(s;\theta)$ the rate at which a worker who searches with intensity $s$ receives an offer, by $q_0(S_e,S_u,\theta)$ the rate at which a recruiting firm contacts an unemployed worker, and by $q(S_e,S_u,\theta)$ the rate at which a recruiting firm contacts an employed worker. The meeting rates satisfy,

$$\lambda(s,\theta) = s\theta^{\alpha}, \quad q_0\left(S_e,S_u,\theta\right) = \frac{S_u}{S_u+S_e}\theta^{\alpha-1}, \quad q\left(S_e,S_u,\theta\right) = \frac{S_e}{S_u+S_e}\theta^{\alpha-1}$$

### 1.4.7 Value functions

Let $W_a(h)$ be the value function of an unemployed worker of age $a$ with human capital $h$. Denote by $V_a(h,p,w)$ the value function of an age $a$ employed worker with human capital $h$ who is employed in a match with productivity $p$ and who is paid wage $w$. Finally, let $J_a(h,p)$ be the value of a match between an age $a$ worker with human capital $h$ and a firm with productivity $p$. All value functions in addition depend on the aggregate states of the economy.

**Match** The value function of the match satisfies

$$\tilde{J}_a(h,p) = \max_{i,h',s}\left\{ph - \frac{c_h}{\gamma}i^{\gamma} + \rho\left[-\frac{c_e h'}{\eta_e}s^{\eta_e} + \int_{\underline{p}}^{\bar{p}}\left(J_{a+1}(h',\tilde{p}) + s\lambda\beta\int_{\tilde{p}}^{\bar{p}}[J_{a+1}(h',p') - J_{a+1}(h',\tilde{p})]dF(p')\right)dG(\tilde{p}|p)\right]\right\}$$

subject to $h' = h + i$ and $i \in [0, \bar{I}]$, where $\bar{I}$ is an upper bound on investment that ensures that flow output is always positive,[21] and

$$J_a(h,p) = \max\left\{\tilde{J}_a(h,p), W_a(h)\right\}$$

The cost of searching is assumed to be in terms of next period's human capital because it simplifies the solution algorithm. Denote by $i_a(h,p)$ the optimal investment policy, by $s_a^e(h,p)$ the optimal search policy, and by $\bar{p}_a(h)$ a reservation productivity such that

$$\tilde{J}_a\left(h, \bar{p}_a(h)\right) = W_a(h)$$

**Unemployment** The value function of an unemployed worker satisfies

$$W_a(h) = \max_s \left\{ b + \rho \left[ -\frac{c_u h}{\eta_u} s^{\eta_u} + W_{a+1}(h) + s\lambda\beta \int_{\underline{p}}^{\bar{p}} J_{a+1}(h,p) - W_{a+1}(h) dF(p) \right] \right\} \tag{1.6}$$

which defines an optimal search policy of the unemployed, $s_a^u(h)$.

**Worker** Given optimal investment and search policies, the value function of an employed worker satisfies

$$\begin{aligned}
\tilde{V}_a(h,p,w) \quad = \quad & w\left[ph - \frac{c_h}{\gamma} i_a(h,p)^\gamma\right] + \rho\left[-\frac{c_e h'}{\gamma} s_a^e(h,p) + \int_{\underline{p}}^{\bar{p}} \left\{(1 - s_a^e(h,p)\lambda) V_{a+1}(h',\tilde{p},w) + \right.\right. \\
& + s_a^e(h,p)\lambda \int_{\underline{p}}^{\tilde{p}} \max\left[J_{a+1}(h',p') + \beta\left(J_{a+1}(h',\tilde{p}) - J_{a+1}(h',p')\right), V_{a+1}(h',\tilde{p},w)\right] dF(p') \\
& \left.\left. + s_a^e(h,p)\lambda \int_{\tilde{p}}^{\bar{p}} \left[J_{a+1}(h',\tilde{p}) + \beta\left(J_{a+1}(h',p') - J_{a+1}(h',\tilde{p})\right)\right] dF(p') \right\} dG(\tilde{p}|p) \right]
\end{aligned}$$

subject to $h' = h + i_a(h,p)$.

[21] In the quantitative exercises, this upper bound never binds in optimum for the estimated parameter values.

Since a worker has to at least get his outside option but cannot get more than the full value of the match,

$$V_a(h,p,w) = \min\left\{\max\left[\tilde{V}_a(h,p,w), W_a(h)\right], J_a(h,p)\right\}$$

**Wage policies** Define $\bar{w}_a(h,p)$ as the lowest wage a worker age $a$ with human capital $h$ working for firm $p$ may be paid,

$$\tilde{V}_a(h,p,\bar{w}_a(h,p)) = W_a(h)$$

The maximum piece rate a worker can be paid is one.

Given value functions of the worker and match, define the wage policy out of unemployment, $\phi_a(h,p)$, and the wage policy for a poached worker, $\psi_a(h,p,p')$ as

$$V_a\left(h,p,\phi_a(h,p)\right) = W_a(h) + \beta\left[J_a(h,p) - W_a(h)\right]$$

and

$$V_a(h,p,\psi_a(h,p,p')) = J_a(h,p) + \beta\left[J_a(h,p') - J_a(h,p)\right]$$

### 1.4.8 Equilibrium

Denote by $E_a(h,p)$ the distribution of human capital and productivities across age $a$ employed workers and by $N_a(h)$ the distribution of human capital across age $a$ unemployed workers. Aggregate laws of motion characterize these distributions, and in steady-state the distributions are constant over time. Given these distributions, we can write

$$S_u = \sum_{a\in A} u_a \int_{\underline{h}}^{\bar{h}} s_a^u(h) dN_a(h)$$

and

$$S_e = \sum_{a \in A} (1 - u_a) \int_{\underline{p}}^{\bar{p}} \int_{\underline{h}}^{\bar{h}} s_a^e(h,p) dE_a(h,p)$$

The free entry condition is

$$\begin{aligned} \frac{c_v}{1-\beta} &= q_0 \sum_A \int_{\underline{h}}^{\bar{h}} \int_{\bar{p}_a(h)}^{\bar{p}} \frac{s_a^u(h)}{S_u} \left\{ J_a(h,p) - W_a(h) \right\} dF(p) dN_a(h) + \\ & \quad q \sum_A \int_{\underline{h}}^{\bar{h}} \int_{p'}^{\bar{p}} \frac{s_a^e(h,p')}{S_e} \left\{ J_a(h,p) - J_a(h,p') \right\} dF(p) dE_a(h,p') \end{aligned}$$

An open job meets an unemployed worker at rate $q_0$, who at rate $\frac{s_a^u(h)}{S_u} n_a(h)$ is of age $a$ and has human capital $h$. If the firm draws productivity $p \geq \bar{p}_a(h)$ the match is formed and the firm gets a share $1 - \beta$ of the surplus. The job meets an employed worker at rate $q$ who at rate $\frac{s_a^e(h,p')}{S_e} e_a(h,p')$ is of age $a$, has human capital $h$ and works in a firm $p'$. If the firm draws productivity $p \geq p'$ the match is formed and the firm gets a slice $1 - \beta$ of the differential surplus.

**Definition 2** (Stationary search equilibrium)**.** A stationary search equilibrium with positive vacancy creation consists of value functions $W_a$, $V_a$ and $J_a$; an investment policy $i_a(h,p)$, search policies $s_a^u(h)$ and $s_a^e(h,p)$, and a reservation rule $\bar{p}_a(h)$; wage rules $\phi_a$, $\psi_a$ and $\bar{w}_a$; aggregate masses of searching unemployed and employed workers, $S_u$ and $S_e$; an aggregate tightness, $\theta$; and distributions $N_a(h)$ and $E_a(h,p)$ such that

1. The value functions, investment and search policies, and reservation rule solve the problem of the match, unemployed worker and employed worker;

2. The wage rules are consistent with the sharing assumptions;

3. The mass of searching workers and tightness are consistent with the free entry condition;

4. The distributions $U_a(h)$ and $E_a(h,p)$ are constant over time, as is tightness.

## 1.5 Estimation

The following section discusses how I bring the model to the data. I solve a discretized version of the model numerically by iterating backwards on the derivative of the value function using an endogenous grid point method.[22] By avoiding maximums, this procedure is very fast (solving the model takes less than two seconds, while simulating it takes about 15 seconds). I simulate the model for 10,000 individuals, and apply the same methodology on the simulated data as on the actual data. Appendix A.6 contains further details.

### 1.5.1 Calibration

The model is calibrated at a monthly frequency to match key moments for a hypothetical average fluidity country. I set the monthly discount factor to match a four percent annual interest rate. I normalize initial human capital to one and assume that workers exit permanently after 35 years. Without data on vacancies, match efficiency is not separately identified from the cost of creating jobs and it is hard to identify the elasticity of matches with respect to vacancies. I hence normalize $\chi = 1$ and set $\alpha = 0.6$ based on Petrongolo and Pissarides (2001). The remaining parameters are calibrated internally.

I assume that match productivity is bounded Pareto with shape $\xi$, while productivity follows a Markov process that is the discretized, bounded equivalent of normal shocks with standard deviation $\sigma$.[23] In addition, I assume that at some rate $\delta$ the match gets a very negative shock so that it is destroyed with certainty. The parameters to be estimated are the shape of the match productivity distribution, $\xi$; the bargaining power of workers, $\beta$; the cost of investing in human capital, $c_h$; the convexity of the cost function, $\gamma$; the cost

[22] I use a $20 \times 20 \times 20$ grid for human capital, productivity and the piece rate, respectively. In both solving and simulating the model, I use linear (bilinear, trilinear) interpolation to approximate values between grid points. Results are not sensitive to increasing the number of grid points.

[23] The upper bound for the grid for $p$ is chosen such that the probability of drawing an initial $p$ above the upper bound under the unbounded equivalent Pareto distribution is close to zero. The results are not sensitive to increasing this upper bound.

of searching as employed and unemployed, $c_e$ and $c_u$; the convexity of the two cost functions of search, $\eta_e$ and $\eta_u$; the cost of creating jobs, $c_v$; the exogenous separation hazard, $\delta$; the standard deviation of shocks to productivity, $\sigma$; and the value of unemployment, $b$.

The target moments consist of life-cycle profiles of wages, JtJ, EU and UE mobility, and the dynamics of gains from JtJ mobility. The return to JtJ mobility is informative about the dispersion in match productivity. Intuitively, the greater is the dispersion the larger are the gains from moving between firms. The greater is $\beta$, the more the worker obtains at the time of mobility relative to gradually post-mobility. Hence, the slope of the wage profile after a JtJ move is informative about the bargaining power parameter.

The slope and curvature of the wage profile is informative about the cost function of investment, $c_h$ and $\gamma$. For a given contribution of job shopping to life-time wage growth, $c_h$ is set to target overall wage growth. The smaller is $\gamma$, the more investment is front loaded to early in careers, generating a more concave wage profile.

I target for the cost of creating vacancies a job finding rate of one for someone who searches with unit effort. Under this normalization, the average and curvature of the JtJ hazard is informative about the employed search cost parameters, $c_e$ and $\eta_e$, while the average and curvature of the UE hazard is informative about the unemployed search cost parameters, $c_u$ and $\eta_u$. The average and curvature of the EU hazard is informative about shocks to productivity, $\delta$ and $\sigma$. Given lack of evidence on the value of leisure, I set the value of unemployment such that workers at labor market entry are indifferent between working at the lowest productivity firm in the sampling distribution and unemployment.

### 1.5.2 Parameter values

Table 1.2 presents parameter values. The training cost function is close to linear in order to match the concavity of the wage profile. The data suggests more elastic employed than unemployed search in order to match the larger fall in the JtJ hazard with age. The estimated shape of the match productivity distribution implies a log 25–75 ratio of 0.21.

As a share of average output, the flow value of unemployment is 57 percent, which is within the range of unemployment replacement rates in the countries of study. Primarily two reasons are behind the fact that the model largely overcomes the issue raised by Hornstein et al. (2011). First, it features on-the-job search, and as noted by those authors this lowers the sacrificed option value of moving to employment. Second, the option to accumulate human capital on the job carries value, which tilts the tradeoff in favor of employment.

Table 1.2: Parameter values

| | Parameter | Target | Estimate |
|---|---|---|---|
| Pre-set | $\rho$ | 4% interest rate | 0.9967 |
| | $A$ | 35 years in market | 420 |
| | $\chi$ | Normalization | 1 |
| | $\alpha$ | Petrongolo and Pissarides (2001) | 0.6 |
| Calibrated | $\zeta$ | Mobility gains | 6 |
| | $\beta$ | Post-mobility wage growth | 0.3 |
| | $c_h$ | Life-cycle wage growth | 435 |
| | $\gamma$ | Curvature of wage profile | 1.1 |
| | $c_e$ | Average JtJ | 31 |
| | $\eta_e$ | Curvature of JtJ | 1.6 |
| | $c_u$ | Average UE | 1100 |
| | $\eta_u$ | Curvature of UE | 3 |
| | $\delta$ | Average EU | 0.005 |
| | $\sigma$ | Curvature of EU | 0.016 |
| | $c_v$ | Unit job finding rate | 9.87 |
| | $b$ | Value of leisure | 0.845 |

### 1.5.3 Model fit

Figure 1.8 plots the life-cycle profile of wages in the average fluidity country in the model and in the data. Job shopping contributes mostly to wage growth early in careers, which allows the model to capture well the concavity of the wage profile in the data. In constrast,

models with only human capital accumulation typically struggle to generate enough concavity (see for instance Huggett et al., 2011).

Figure 1.8: Wages in average fluidity country, model vs data

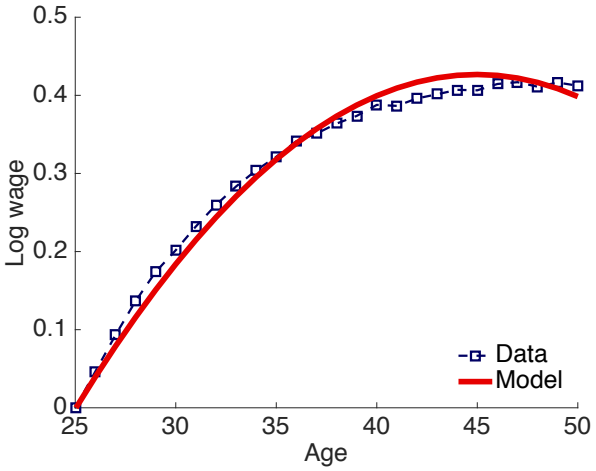



Figure 1.9 shows that the model captures relatively well the life-cycle profiles of worker mobility. The left pane plots the JtJ mobility rate. Three forces contribute to the decline with age in the model. First, young workers are disproportionately employed at the lower end of the job ladder, which makes them more likely to accept a new offer. Second, because of the high expected return to search at the bottom of the ladder, workers employed at the bottom search hard. Third, a horizon effect adds to high search intensity early in careers since workers expect to enjoy the gains for longer.

The middle pane plots the EU hazard. Shocks to productivity result in a high separation rate early in careers, when workers tend to be employed at the bottom of the job ladder. As workers climb the ladder, the probability that a given shock pushes productivity below the threshold declines. Furthermore, the relative value of unemployment declines in human capital, which implies that the endogenous separation rate declines as workers accumulate human capital. The right pane plots the UE hazard. The model cannot replicate the fall with age in this. The only force that leads to a fall in the UE hazard in the model is a horizon effect, but this force is weak until the last few years of careers.

Figure 1.9: Mobility hazards in average fluidity country, model vs data

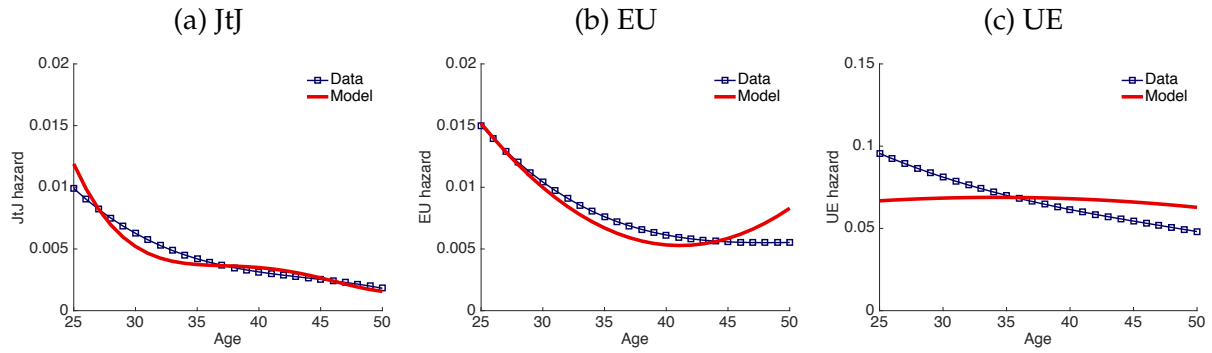
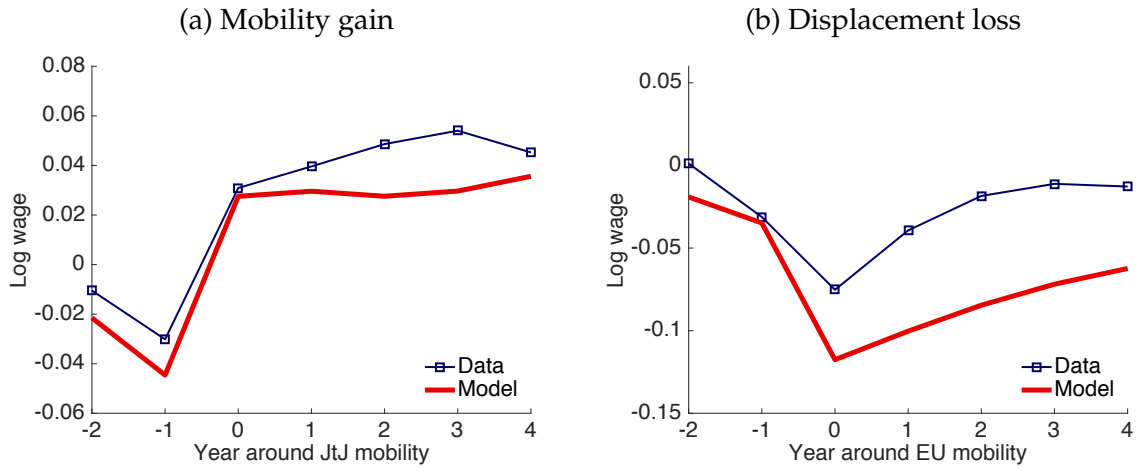



Figure 1.10 plots the wage impact of JtJ mobility and displacement in the model and data. Wages decline relative to counter-factual prior to a JtJ move, driven by the fact that a negative shock to productivity reduces wages and increases employed job search. This biases the pool of searching employed workers towards those who experienced a negative shock. In both the model and data wages trends up relative to counter-factual after a JtJ move. In the model, this is driven by workers gradually recouping more and more of the surplus of the new match as they get outside offers.

Figure 1.10: Returns to mobility in average fluidity country, model vs data




The model captures fairly well the experience of job losers given that this is an untargeted moment. It overpredicts the level but predicts well the dynamics of losses. Two factors are behind the model's ability to generate persistent losses: First, despite no depre-

ciation of human capital, the fact that workers cannot invest when unemployed reduces wage growth relative to counter-factual.[24] Second, displacement brings the worker down the job ladder, which makes it more likely that a shock will cause subsequent displacement (Krolikowski, 2016).

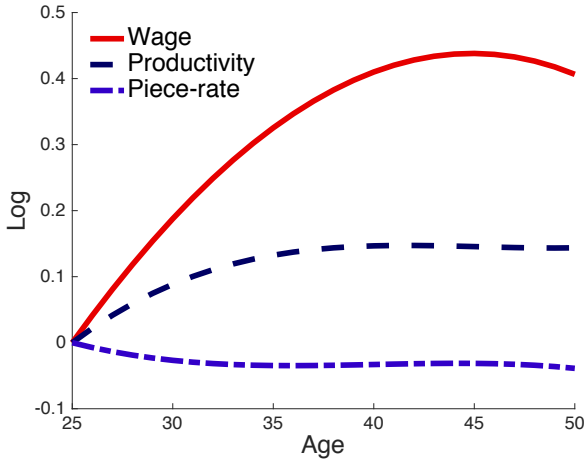
### 1.5.4 Sources of life-cycle wage growth

Figure 1.11 plot life-cycle growth in log wages (solid red), log match productivity (dashed navy blue), and the log piece rate (dash-dotted royal blue). Growth in the piece rate subtracts marginally from life-cycle wage growth. This is the result of the assumption that the value of leisure does not increase in human capital. Under this assumption, workers return from unemployment at an increasingly worse position as they accumulate human capital with age. This assumption receives empirical support from the fact that losses from displacement increase with age and the behavior of mobility around on-the-job training as discussed in Section 1.6.

Match productivity grows by 14 log points and almost all of this takes place during the first 10 years of careers. The remaining growth in wages is due to human capital accumulation, which hence accounts for roughly 70 percent of overall wage growth between age 25 and 50. The prediction that human capital accumulation is the most important source of life-time wage growth corroborates findings in Yamaguchi (2010) and Bagger et al. (2014).

[24] Based on this, one may suspect that the model predicts the largest losses early in careers. Countering this effect, however, are the facts that workers lose more from displacement when they are further up the job ladder and the relative value of unemployment falls as workers accumulate human capital. Quantitatively, the latter effects dominate so that the model matches relatively well the greater losses with age in the data (despite overpredicting the levels). These results are available on request.

Figure 1.11: Decomposition of life-cycle wage growth, model




## 1.6 Results

This section evaluates the impact of introducing wedges to job creation in order to match observed labor market fluidity across countries. I implement the comparison in the following way. Holding all other parameters fixed, I adjust the cost of creating jobs to target higher or lower fluidity, and evaluate its impact on life-cycle wage growth, the stock of human capital, labor productivity and output.

### 1.6.1 Micro-level predictions

Table 1.3 presents the model's predictions for cross-country differences in labor market hazards and returns to mobility. I compute the statistics for an average fluidity country (the target in the estimation), a low fluidity country (minus one standard deviation fluidity) and a high fluidity country (plus one standard deviation fluidity). To achieve a two standard deviation change in the empirical variation in fluidity, the model requires a 35 log point difference in the cost of creating jobs.

By construction, the model matches the level of the JtJ hazard in the high and low fluidity country. The model predicts a somewhat too high (low) EU hazard in the low

(high) fluidity country, yet as in the data variation across countries in the EU hazard is modest. The model replicates about 50 percent of the systematic variation in the UE hazard with fluidity in the data.

Table 1.3: Micro-level outcomes in model versus data

| | Low fluidity | | Average fluidity | | High fluidity | |
|---|---|---|---|---|---|---|
| | Data | Model | Data | Model | Data | Model |
| JtJ hazard | 0.0034 | 0.0034 | 0.0043 | 0.0044 | 0.0054 | 0.0054 |
| *(% of average)* | 79% | 77% | 100% | 100% | 126% | 123% |
| EU hazard | 0.0078 | 0.0084 | 0.0080 | 0.0079 | 0.0082 | 0.0074 |
| *(% of average)* | 98% | 106% | 100% | 100% | 103% | 94% |
| UE hazard | 0.053 | 0.058 | 0.068 | 0.067 | 0.082 | 0.079 |
| *(% of average)* | 78% | 87% | 100% | 100% | 121% | 118% |
| Gain from JtJ | 0.072 | 0.081 | 0.073 | 0.077 | 0.074 | 0.076 |
| *(Log points)* | 99% | 105% | 100% | 100% | 101% | 97% |
| Loss from EU | -0.025 | -0.052 | -0.035 | -0.063 | -0.045 | -0.077 |
| *(Log points)* | 71% | 83% | 100% | 100% | 129% | 122% |

The last four rows in Table 1.3 evaluate the wage impact of mobility. In line with the data, the model predicts essentially no difference in the return to JtJ mobility across countries. Although it overpredicts the level of losses in all countries, it reproduces the empirical fact that losses are higher in more fluid labor markets.

Figure 1.12 plots the wage profiles in the low and high fluidity country in the model and the data. Both are normalized to wages at age 25 in the low fluidity country. In response to the change in fluidity, the model matches well both the differential life-cycle growth in wages as well as the change in levels.

Figure 1.12: Predicted wage profiles in model versus data

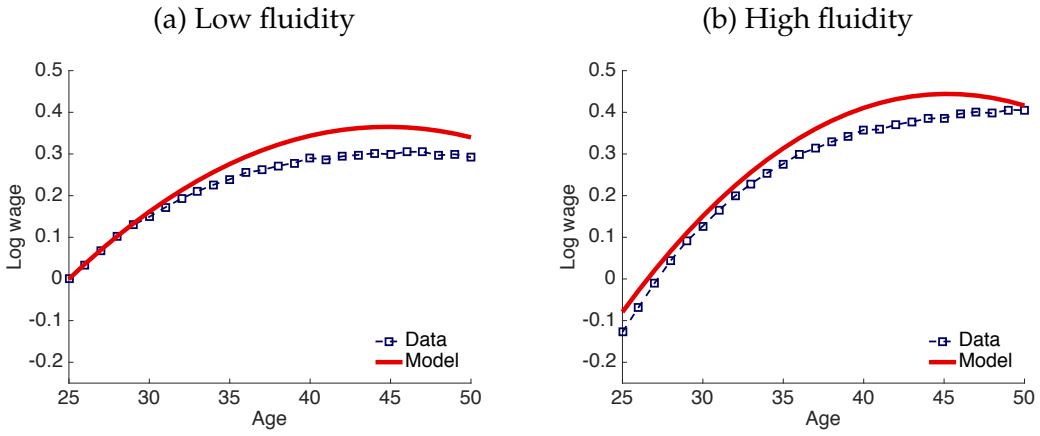
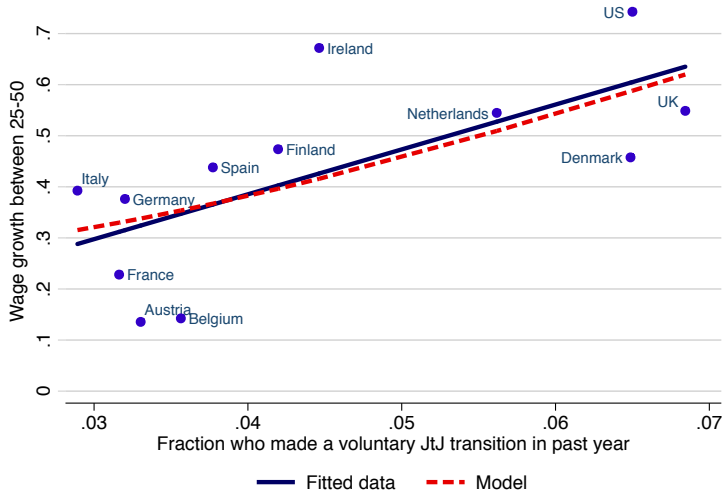



Figure 1.13 plots wage growth between age 25–50 in the model and data against fluidity across the 12 countries. The model captures 98 percent of the systematic relationship between fluidity and wage growth in the data and 43 percent of the overall variation in wage growth. The correlation between wage growth in the data and model is $\rho = 0.66$. Appendix A.7 shows that the model also replicates the modest covariance in the data between fluidity, on the one hand, and residual wage inequality and life-cycle growth in inequality, on the other hand.

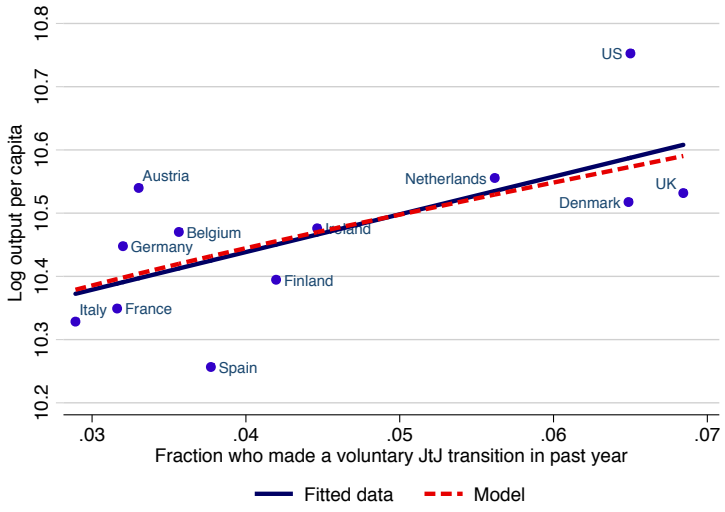
Figure 1.13: Wage growth between 25–50 against fluidity, model versus data



### 1.6.2 Macro-level predictions

Figure 1.14 plots output per capita against fluidity in the model and data. The model quantitatively captures well the positive covariation between fluidity and output per capita in the data. In the model, this is driven by three forces. First, the higher job finding rate in more fluid labor markets drive down unemployment. Second, the faster rate at which workers climb the job ladder result in higher match productivity in more fluid labor markets. Finally, workers accumulate more human capital in more fluid labor markets.

Figure 1.14: Output per capita against fluidity, model versus data

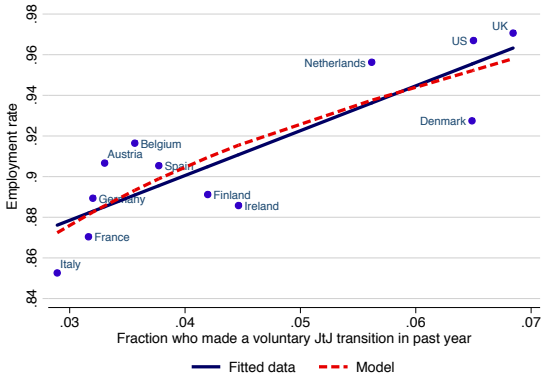



Note: Output per capita from the OECD 1996–2014; cleaned for age, college and year effects following the procedure in Appendix B.1.

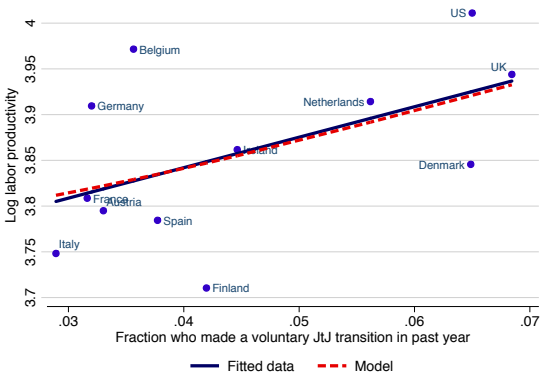
Figure 1.15 breaks down the effect in the model and data on output per capita into the employment margin and the productivity margin. The left pane plots the employment rate against fluidity in the model and data. The model quantitatively matches the relationship well. The right pane plots labor productivity against fluidity. The relationship is noisier in the data. The model fits the positive covariance very well.

Figure 1.15: Macro-level outcomes against fluidity, model versus data

(a) Employment rate, prime age males




(b) Labor productivity




Note: Labor productivity from the OECD 1996–2014, employment rate of males age 25–55 from the micro data; cleaned for age, college and year effects following the procedure in Appendix B.1.

Table 1.4 summarizes the model's explanatory power. The model explains 99 percent of the covariance between output per capita and fluidity in the data, and 45 percent of the overall variation in output per capita. The correlation between model and data generated output per capita is 0.67. It explains 99 percent of the empirical covariance between labor productivity and fluidity and 28 percent of the overall variation, and 99 percent of the covariance between employment rates and fluidity and 74 percent of the overall variation.

Table 1.4: Fraction of covariance and total variation explained by model

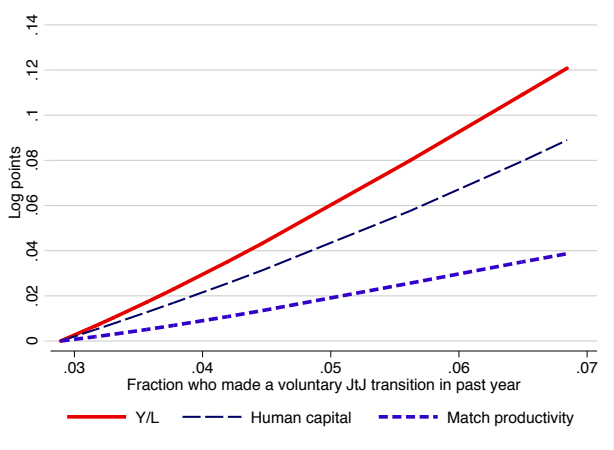
| Moment | % of covariance | % of total | $\rho$(model,data) |
|---|---|---|---|
| Output per capita | 98.7% | 44.8% | 0.673 |
| Labor productivity | 99.3% | 27.7% | 0.528 |
| Employment rate | 98.9% | 73.6% | 0.859 |
| Life-cycle wage growth | 98.4% | 43.2% | 0.660 |

### 1.6.3 The role of human capital

Figure 1.16 plots labor productivity, human capital and match productivity as a function of fluidity in the model. The stock of human capital increases by nine log points going

from the least to the most fluid country, while match productivity increases by four log points. Overall labor productivity increases by 12 log points, with the difference primarily due to the cost of investment.[25]

Figure 1.16: Labor productivity, human capital and match productivity, model




### 1.6.4 Supporting evidence

Two key predictions of the model are that training and search on-the-job covary positively with labor market fluidity. This section uses direct data on on-the-job training and search intensity across countries to evaluate these predictions empirically.

**Training and fluidity** To study the empirical covariation between training on-the-job and fluidity, I rely on standardized questions on on-the-job training asked in the ECHP and BHPS.[26] Before proceeding with this part of the analysis, it is appropriate to recognize that correctly capturing on-the-job training in survey questionnaires is likely difficult. In support of analyzing the available measures, I show below that the empirical life-cycle profile of training matches well that predicted by the structural model (despite not being

[25] A welfare calculation would also have to take into account resources spent on vacancy creation and the utility cost of search. The former is roughly constant with fluidity at about 12 percent of output (a result of higher vacancy creation being offset by a lower cost of a vacancy), while the utility cost of search rises from 1.9 to 2.1 percent of output moving from minus to plus one standard deviation in fluidity.

[26] These questions were incorporated into the entire BHPS to align it with the ECHP subsample of that survey.

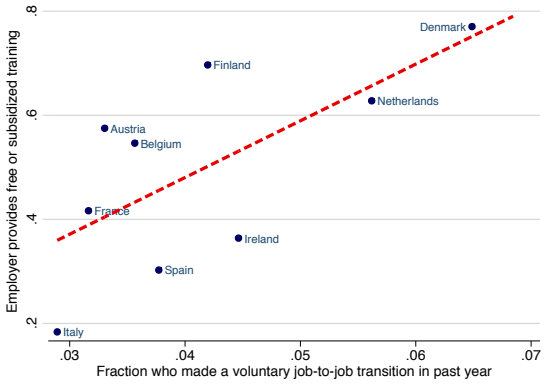
a target in the estimation), and in Appendix A.8 that training is associated with subsequent wage growth conditional on individual and year effects, that college graduates train more, and that the ranking of occupations in terms of training is a mirror image of life-cycle wage growth. To the extent that countries with high levels of reported training also have high levels of unreported training, at least qualitatively the cross-country comparison remains informative.

Figure 1.17 plots the incidence of training on the job against labor market fluidity. The left pane plots the fraction of workers who report that their employer provides "free or subsidized" training, while the right pane graphs number of weeks in on-the-job training since January last year. In both cases, the data display a distinct upward slope, and the relationship is economically meaningful. A two standard deviation difference in fluidity is associated with three more weeks of training. Given that the average number of weeks of training of a 25 year old is just under five, the difference is substantial.

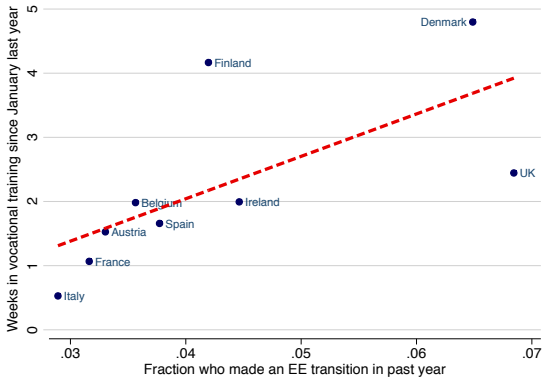
Appendix A.8 confirms that the relationship is statistically significant and that it remains after controlling for worker observables. It also shows that the difference in the incidence of training between college and non-college graduates is the largest in countries where the difference in fluidity between these two groups is the largest. Finally, it presents results on the behavior of job mobility post training that supports two important assumptions in Section 2.3: JtJ mobility is unaffected by on-the-job training, while the risk of displacement falls after training. This is consistent with human capital being general and the outside option not rising with human capital accumulation.

Figure 1.17: On-the-job training across countries

(a) Employer provides free or subsidized training




(b) Weeks in training since january last year



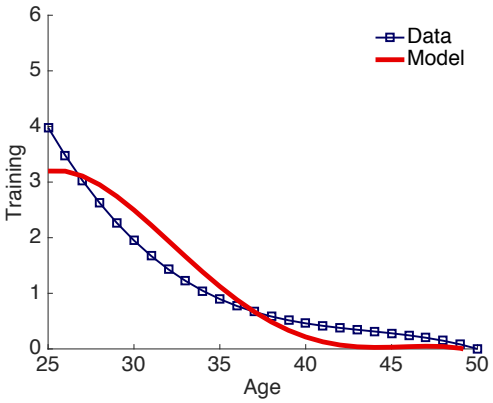

Note: ECHP (1994–2001) and BHPS (1991–1998). Left not available for the U.K., right not for the Netherlands. See text for further details.

Figure 1.18 compares the model's predictions for training with the data. The left pane plots the life-cycle profile of training in the model and data.[27] The model underpredicts the fall in training with age at young ages, and overpredicts the overall fall in training somewhat. Yet given that this is not a target in the estimation, the model does a good job at capturing the data. The right pane of Figure 1.18 plots aggregate training against fluidity in the model and data. The model does a good job at capturing the covariance between the incidence of training on-the-job and fluidity in the data.

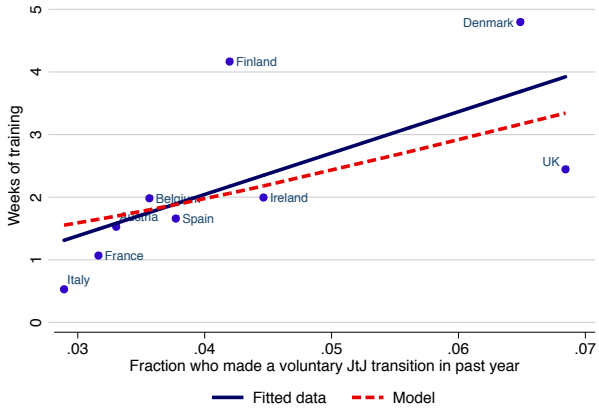
[27] Model moments are rescaled by dividing by the mean over the life-cycle and multiplying by the mean of the empirical profile. Furthermore, in the data a 50 year old on average trains 1.3 weeks, which the model cannot replicate (it is close to zero in the model). I assume that this is due to an exogenously required level of training and subtract it from the empirical life-cycle profile of training.

Figure 1.18: On-the-job training, model versus data

(a) Life-cycle profile

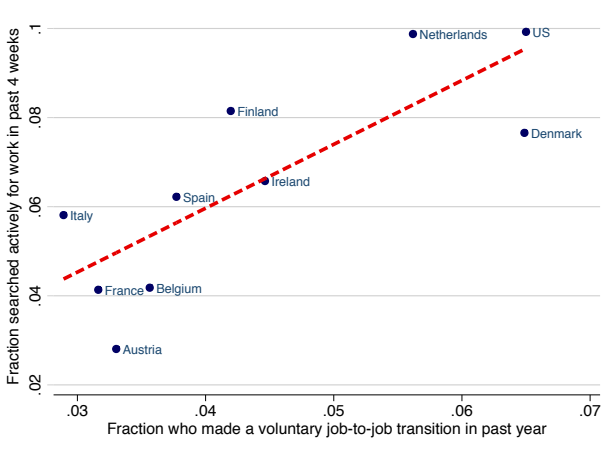



(b) Training and fluidity




**Search and fluidity** To study the relationship between job search and fludidity, I use questions on employed job search from the ECHP and the 1990–1997 PSID. Appendix A.9 shows that the measure of on-the-job search strongly predicts future mobility, lending credibility to interpreting these measures of search. Figure 1.19 plots the fraction of employed workers that searched actively for a new job at some point in the past four weeks against labor market fluidity. The data suggest a strong positive correlation between on-the-job search and labor market fluidity.

Figure 1.19: Fluidity and fraction of employed workers searching for a new job in past 4 weeks



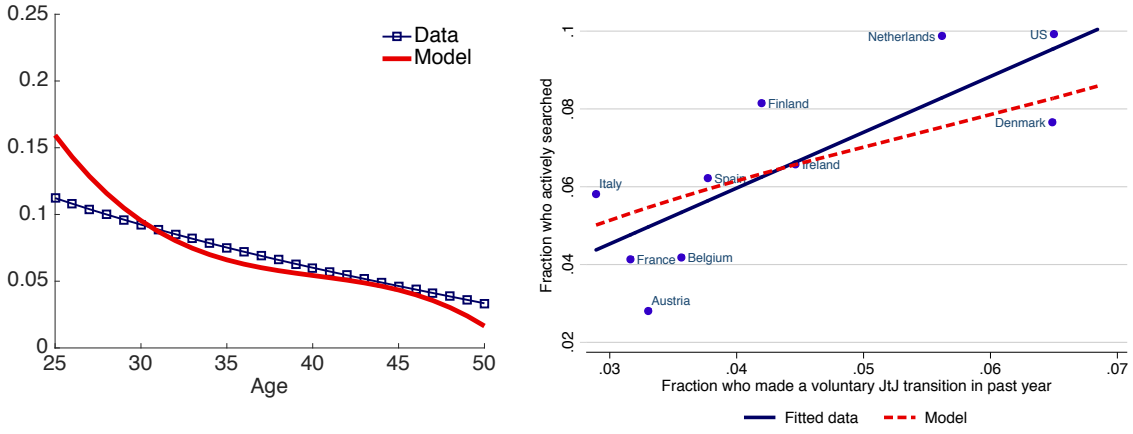

Note: ECHP (1994–2001) and PSID (1990–1997), see text for further details.

Figure 1.20 plots the life-cycle profile of job search in the model and data for the average fluidity country.[28] The model generates a slightly too steep decline in the life-cycle pattern of employed job search in the data. Nevertheless, given that this is not an explicit target in the estimation, the model does a reasonably good job at predicting the life-cycle profile.

Figure 1.20: On-the-job search, model versus data

(a) Life-cycle profile

(b) Search and fluidity




[28]The level in the model is normalized by dividing by the model mean and multiplying by the corresponding empirical mean.

Appendix A.7 shows that the model predicts only a modest fall in unemployed search over the life-cycle and only a small covariance between unemployed search and fluidity, in line with the data.

## 1.7 Conclusion

This paper studies to what extent differences in the fluidity of the labor market affects workers' optimal behavior from a life-cycle perspective. I construct a unique panel data on worker wage and employment histories across 12 OECD countries for 1990–2014, and use it to document three stylized facts on life-cycle labor market outcomes across countries. First, worker flows and life-cycle wage growth differ substantially across countries. Second, the fluidity of a country's labor market covaries positively with life-cycle wage growth of its workers. Finally, the direct effect of job shopping accounts for only a quarter of this.

The structural search model that I develop reproduces the correlations in the data, and suggests that labor market institutions may have an important impact on aggregate economic outcomes by affecting workers' behavior. Particularly, in line with the data workers train less in less fluid labor markets, since a lower rate of climbing the job ladder reduces the return to human capital. An important question that I pursue in ongoing research is what specific policies may give rise to the calibrated wedges to firms' hiring decisions.

# Chapter 2

# Firm and Worker Dynamics in an Aging Labor Market

## 2.1 Introduction

The aging of the labor force is an important phenomenon in many advanced countries. Because older individuals are less mobile, less innovative and less willing to take risk, labor force aging has potentially far-reaching implications for a range of economic outcomes and policy.[1] In this paper, I focus on the impact of an aging US labor force on the operation of the US labor market, and argue that it has lead to a significant decline in firm and worker dynamics and has had a negative effect on economic growth.

I make three contributions: First, I propose a theory that links business dynamism, labor market fluidity and economic growth to the age composition of the labor force. The model embeds endogenous growth through creative destruction in an equilibrium job ladder model, highlighting two-way feedback between the extent of mismatch in the

[1]See Jones (2010) for evidence that older people are less innovative, and Josef et al. (2016) for evidence that older individuals are less willing to take risk. Earlier research has found that, among other things, aging may have significant consequences for unemployment (Shimer, 2001), business cycles (Jaimovich and Siu, 2009), the returns to experience (Jeong et al., 2015), monetary policy (Wong, 2016), and fiscal policy (Mcgrattan and Prescott, 2017).

labor market and incentives to innovate. Second, I apply the theory to the case of the US over the last 30 years in order to provide a quantitative assessment of the impact of aging on dynamism. To that end, I calibrate the model to match aggregate firm and worker reallocation rates, and demonstrate that the model correctly predicts life-cycle firm and worker dynamics in the data, providing confidence in the theory. Subsequently, I evaluate the impact of a change in the age composition of the labor force on four key measures of dynamism—job reallocation, firm turnover, worker flows (employment-to-unemployment and job-to-job mobility) and economic growth—and show that the observed aging of the labor force has contributed to significant declines in each. Third, I use cross-state variation in the incidence of aging and an instrumental variables strategy to lend support to the model's prediction of large effects of aging on dynamism and growth.

I develop a model of joint firm and worker life-cycle dynamics that embeds endogenous growth through creative destruction in an equilibrium job ladder model. Firms are subject to idiosyncratic and permanent shocks to their productivity and hire individuals in a frictional labor market. Individuals search for better employment opportunities both on and off the job and choose when to become entrepreneurs over their life-cycle. A central element of models of creative destruction is that entry of new, more productive entrepreneurs pushes out the least productive incumbent firms, giving rise to a life-cycle of firms. Firms enter small, a few survive and grow large, but eventually all firms are replaced by more productive, new entrants. A key feature of job ladder models is a notion of endogenous labor market mismatch—the equilibrium rate at which individuals move up and down the ladder affects how well individuals are paired with firms. Combining these two properties, individuals' rank on the job ladder gradually deteriorates as their firms fall behind the market leader over time. Through a time-consuming process of on the job search, individuals may offset the negative drift in the relative productivity of their firm by moving to better firms.

In line with robust empirical patterns, older individuals in the model are less likely to both become entrepreneurs and move between employers. This results from older individuals having had more time to find a good match for their skills, thereby raising their opportunity cost of a move. As a consequence, by tilting the workforce toward older, less mobile parts of the population, aging reduces business dynamism and labor market fluidity through a composition effect. Furthermore, the less mobile recruitment pool in the older economy dissuades firms from creating jobs and entrepreneurs from entering by increasing the effective cost of hiring. Finally, aging reduces dynamism through the following equilibrium mechanism. A decline in the entry rate due to the effects highlighted above slows the process of creative destruction. Consequently, individuals do not fall behind on the job ladder as quickly, resulting in less labor market mismatch. This reduces the job-to-job mobility hazard, which discourages entry by again raising the effective cost of recruiting and by increasing the opportunity cost of entry, since potential entrepreneurs would have to sacrifice a more lucrative employment position in order to enter. It also reduces the employment-to-unemployment hazard as fewer firms exit.

I calibrate the model to match salient features of firm and worker dynamics in the US Census Bureau's Business Dynamic Statistics (BDS) and Survey of Income and Program Participation (SIPP). The model fits the data well. On the firm side, I target average firm size, employment shares by firm size, employment shares by firm size among entrant firms, the aggregate entry and exit rate, and estimates of the contribution of firm selection to economic growth. The model predicts as an endogenous equilibrium outcome life-cycle firm dynamics that match the data, including the extent to which older firms are larger, less likely to exit and have lower job reallocation rates conditional on remaining. This suggests that the proposed theory of random growth, firm selection and labor market frictions captures key forces driving life-cycle firm dynamics. On the worker side, I target the aggregate employment-to-unemployment and job-to-job mobility hazards, and show that the model generates life-cycle profiles of these mobility rates that closely mimic

their empirical counterparts as an endogenous equilibrium outcome. This supports the mechanisms proposed by the model as key drivers of life-cycle worker mobility patterns.

I next use the model to quantify the effect of aging on dynamism. To that end, I change the age composition in the model holding all other parameters fixed, and evaluate its effect on the long-run balanced growth path equilibrium. The model implies that the aging of the US labor force has led to quantitatively important declines in business dynamism, labor market fluidity and economic growth. In particular, it explains 39 percent of the decline in job reallocation in the data, 56 percent of the decline in firm turnover, 36 percent of the decline in the employment-to-unemployment hazard, and 48 percent of the decline in the job-to-job mobility hazard. In line with the data, I show that a standard shift-share analysis on model-generated data suggests a much smaller role of aging. I conclude that aging has had important equilibrium effects on dynamism, which such a simple accounting exercise does not capture.

A key question raised by Davis and Haltiwanger (2014) is whether the slowdown in dynamism is cause for concern. The model suggests two opposing effects of aging. On one hand, annual economic growth falls by 0.27 percentage points in response to aging, driven by less creative destruction. On the other hand, the lower unemployment rate and the shift of individuals up the job ladder give rise to a 5.5 percent positive level effect on net output. In addition, reduced dynamism is associated with a lower risk of becoming unemployed and more generally lower income volatility of individuals. This highlights that although the less dynamic environment is worrisome for the long-run macroeconomic performance of the economy, it is associated with fewer adverse shocks at the micro level. In the long run, the growth effect outweighs the level effect so that discounted net output falls by four percent across the two balanced growth path equilibria.

To provide additional support for the hypothesis that aging has had important effects on dynamism, I exploit variation in the magnitude and timing of aging across US states from 1978 to 2014. I correlate the age composition of a state with various measures of

dynamism, controlling for state fixed effects, year effects and growth in state real output per worker. To partly address concerns that workers of different ages may move differentially across states in response to temporary variation in dynamism, I instrument for the current share of older individuals in a state using lagged age shares. I also consider the same regression framework with growth in state real GDP per worker as the outcome variable.

In line with the predictions of the model, the cross-state variation suggests a quantitatively important covariation between aging and dynamism. A higher share of older people is associated with lower dynamism across a range of measures of establishment, firm and worker dynamics, as well as growth in real GDP per worker. This is not primarily the consequence of changes in sectoral composition or state economic policy that are correlated with aging, and I typically find more pronounced results when I instrument for the current age composition using lagged age shares. To the extent that the cross-state variation reflects a causal relationship and is informative about the effect of aging at the national level, the estimates would suggest that aging accounts for 40–50 percent of the large declines in firm and worker dynamism since 1986 and just over a one percentage point decline in growth in real GDP per worker.[2] This lends support to the predicted large equilibrium effects of aging in the model.

**Related literature.** My paper is related to three strands of the literature. First, as in the original Burdett and Mortensen (1998) model and in more recent work by Borovickova (2016), Lise and Robin (2017) and Moscarini and Postel-Vinay (2013, 2016), I study a random search environment in which firms hire multiple workers and workers search on

[2]The estimated relationship between the share of older individuals and the job-to-job mobility hazard, however, is not statistically significant when I instrument for the current share of older workers. As I discuss in greater detail later, data on job-to-job mobility are only available for a much more limited number of years, which may account for the lack of statistical significance. Maestas et al. (2016) also find that growth is negatively correlated with aging across US states using a somewhat different methodology.

the job.[3] I contribute to this literature a model in which firms are subject to idiosyncratic shocks and enter and exit, individuals are characterized by a life-cycle and choose when to become entrepreneurs, and growth is endogenous.

Second, I relate to a literature on growth in an environment with labor marker frictions. Aghion and Howitt (1994) and Mortensen and Pissarides (1998) find that job creation may increase in the rate of economic growth. I reach a similar conclusion, but emphasize a different mechanism behind this outcome, namely a congestion externality in the labor market in the spirit of Diamond (1982). This arises from the introduction of on the job search. Michau (2013) and Miyamoto and Takahashi (2011) also consider models with growth and on the job search to study the relationship between growth and unemployment, but abstract from a life-cycle of individuals and an entrepreneurial choice, and model growth as exogenous.[4] None of the above papers discusses the feedback between labor market mismatch and growth that I emphasize.[5]

Third, a recent and rapidly expanding empirical literature studies changes in US dynamism. Davis and Haltiwanger (2014) provide a comprehensive overview of the declines using a variety of data sources and discuss potential factors behind them.[6] Davis et al. (2010) link the decline in unemployment inflows to declines in job destruction and find that the latter accounts for 28 percent of the secular decline in the former from 1982 to 2005 using cross-industry variation (and 55 percent since 1990). Pugsley and Sahin (2015) suggest that while firm entry has fallen substantially over the past decades, incumbent dynamics have remained the same conditional on firm age. Decker et al. (2017a),

[3]Kaas and Kircher (2015) and Schaal (2016) construct directed search models with multi-worker firms, but abstract from an entrepreneurship decision and growth.

[4]The relationship between growth and unemployment is the subject of a large literature, including Postel-Vinay (2002), Hornstein et al. (2007), Michelacci and Lopez-Salido (2007), Pissarides and Vallanti (2007), and Prat (2007). These papers abstract from on the job search and endogenous growth.

[5]A vast literature studies endogenous growth absent frictional labor markets, including Romer (1990), Grossman and Helpman (1991), Aghion and Howitt (1992); Luttmer (2007), Lucas and Moll (2014), Perla and Tonetti (2014) and Sampson (2016).

[6]To mention a few papers, Shimer (2012) notes the decline in the employment-to-unemployment hazard in the Current Population Survey (CPS), Hyatt (2015) discusses the decline in job-to-job mobility in the CPS, and Bosler and Petrosky-Nadeau (2016) discuss the decline in job-to-job mobility in the SIPP (see also Hyatt and Spletzer, 2013, and Decker et al., 2016).

on the other hand, show that dynamism has fallen also within firm age groups. Furthermore, they argue that the decline in job reallocation is not due to more benign productivity shocks but due to a weaker employment response of firms to shocks. Molloy et al. (2016) discuss potential explanations behind the broad-based declines in job and worker turnover since the early 1980s, but without a formal model. Finally, Decker et al. (2017b) suggest that the decline in reallocation has led to weaker economic growth.

Fewer papers provide a structural model of the declines.[7] In a recent working paper, Karahan et al. (2016) argue that with anticipation effects, the slowdown in labor supply growth over this period can account for up to 25 percent of the decline in start-up activity. My paper differs in two key dimensions. First, we focus on different mechanisms. While they evaluate the importance of labor supply growth on the start-up rate through the lens of a Hopenhayn (1992) industry equilibrium model of firm dynamics, I study the effect of the age composition through a new model of firm and worker dynamics. In my empirical work, I show in a joint framework that both mechanisms receive support in the data, and hence I view our papers as offering complementary explanations for the large decline in dynamism (in fact, even adding both of our mechanisms, an important share of the declines remains unexplained). Second, my model and empirical analysis speak to changes in a range of outcomes over and above the start-up rate that is the focus of their paper, including worker mobility and economic growth. I find that across US states, long-run declines in the various measures of dynamism are strongly positively correlated with each other, which motivates me to develop a unified framework to evaluate the declines.[8]

To summarize, the main contribution of this paper is to develop a theory of joint firm and worker life-cycle dynamics that incorporates entry and exit of firms, on the job search,

[7] See also Kaplan and Schulhofer-Wohl (2017), who provide a structural model of the decline in interstate migration, Liang et al. (2016), who seek to understand the inverse u-shaped entrepreneurship entry rate over the life-cycle as well as the fact that younger countries have higher entrepreneurship entry rates conditional on age, and Shimer (2001), who studies the equilibrium effect of the age composition on unemployment in a frictional labor market.

[8] From an accounting perspective, some of this positive correlation is expected. I show in Appendix B.2 that a strong correlation in long-run secular declines between measures remains after taking out the component that is mechanical.

an entrepreneurship decision, and endogenous growth, and apply the theory to quantitatively assess the impact of aging over the last 30 years in the US on business dynamism, labor market fluidity and economic growth.

**Outline.** The next section summarizes four sets of facts that motivate my study. Section 2.3 develops a theory of joint firm and worker dynamics to interpret these facts, and Section 2.4 outlines the balanced growth path equilibrium of the model. Section 2.5 brings the model to the data to show that it replicates life-cycle firm and worker dynamics as non-targeted equilibrium outcomes, providing confidence in the theory. Section 2.6 uses the model to quantify the equilibrium effect of aging. Section 2.7 provides empirical support for the hypothesis using cross-state variation over this period in aging and dynamism. Finally, Section 2.8 concludes.

## 2.2 Motivating Facts

The analysis of this paper is motivated by four sets of facts. Although each of these has been documented separately by various authors, it is important for my subsequent analysis to establish them in a consistent manner. Hence, I construct these facts using a combination of data from the Bureau of Economic Analysis (BEA), the Bureau of Labor Statistics (BLS), the BDS, the CPS and the SIPP. I briefly report the findings of this analysis here, and provide the details in Appendix B.2. As I define variables in a standard fashion, I refer to Appendix B.1 for the definitions.

First, firm and establishment dynamics have declined substantially over this period, as initially noted by Davis et al. (2006). The employment-weighted turnover rate of firms has declined by 38 percent since 1986. This is driven by declines in both entry and exit; in particular these have declined by 46 percent and 27 percent, respectively. The overall job reallocation rate has declined by 28 percent. Although roughly half of this is accounted for

by the decline in turnover, the other half reflects a fall in job reallocation for incumbents. The declines are not accounted for by sectoral shifts.

Second, worker flows have fallen significantly. The employment-to-unemployment (EU) hazard has declined by 30–40 percent and the job-to-job (JJ) hazard has declined by 25–30 percent since 1986. In contrast, the unemployment-to-employment (UE) hazard showed little evidence of a secular decline until the Great Recession, when it fell substantially. Given that the UE hazard is volatile at business cycle frequencies, it is plausible that the recent decline at least in part is a business cycle phenomenon rather than a secular trend (at the time of this writing, the UE hazard has almost recovered to its pre-Great Recession level).

Third, although uncertainty surrounds the exact magnitude of the slowdown, an emerging consensus finds that trend economic growth has declined (Fernald, 2014). Growth in real GDP per labor force participant has fallen from an average of 2.6 percent per year in 1984–1988 to 1.7 percent in 2012–2016.[9]

Fourth, the US labor force has aged substantially over this period. The share of the labor force that is 40 years of age and older achieved a trough in the mid-1980s and has increased by 15 percentage points since 1986. This is not driven by differential trends in labor force participation by age.

The next section develops an equilibrium job ladder model with endogenous growth driven by creative destruction in order to understand these facts. I return to interpret them through the lens of the structural model in Section 2.6.

[9] Although I report growth in GDP per labor force participant for reasons that will become clear in the model, the drop is similar to the decline in growth in real GDP per hour, which has declined from 1.8 percent annually in 1984–1988 to 0.7 percent annually in 2012–2016.

## 2.3 A Job Ladder with Creative Destruction

This section outlines an equilibrium model of the labor market with the following three features. First, firm productive heterogeneity combined with on-the-job search give rise to a job ladder that individuals gradually climb with time in the market. Second, the presence of a factor in fixed supply implies that entry of new, more productive firms pushes out the least productive incumbent firms, i.e. creative destruction. Third, individuals face a life cycle.

### 2.3.1 Environment

Time is continuous and there are no aggregate shocks. The economy consists of a unit mass of ex-ante identical individuals, who can be one of $A$ ages.[10] They enter the economy as age one and move stochastically to the next age at rate $\kappa(a)$. Once an individual reaches the oldest age group, she dies at rate $\kappa(A)$ and is replaced by her offspring. I assume that individuals are perfectly altruistic in the sense that they care as much about their offspring as themselves. That is, one can think of the economy as being populated by a unit continuum of dynasties.[11] Dynasties value an expected stream of consumption discounted at rate $\tilde{\rho}$, including a consumption equivalent flow value of leisure $B(t)$ enjoyed during periods of unemployment,[12]

$$\mathbb{E}_t \int_t^\infty \exp(-\tilde{\rho}(\tau - t)) \left(c(\tau) + B(\tau)\right) d\tau$$

**Firms.** At each point in time, a positive mass of firms is heterogeneous in current productivity, $Z$, and employment level. When a firm first hires an individual, they draw

[10] The quantitative section typically considers the case of $A = 3$.

[11] With a varying probability of death over the life cycle, the effective discount rate would in general vary. Assuming that individuals are perfectly altruistic with respect to their offspring simplifies by avoiding this.

[12] For reasons that will become clear, I allow $B(t)$ to vary over time to ensure the existence of a balanced growth path.

a match productivity, $x \in \{x_b, x_g\}$ with $x_b < 1 < x_g$ normalized such that $\mathbb{E}(x) = 1$. Match productivity is independent across matches, fixed for the duration of the match, and learned by both parties at rate $\psi$.[13] The purpose of introducing learning is quantitative: it generates worker flows over and above job flows and it allows the model to quantitatively match life cycle mobility.[14] Qualitatively, my results would hold without this ingredient of the model.

Total output of a firm with productivity $Z$ and $e_b$, $e_g$ and $e_u$ of bad, good and unknown quality matches, respectively, is given by

$$y\left(Z, e_b, e_g, e_u\right) = Z(x_b e_b + x_g e_g + e_u)$$

where a law of large numbers implies that the productivity of the mass $e_u$ of matches deterministically equals one. Firm productivity evolves according to a geometric Brownian motion,

$$dZ(t) = \sigma Z(t) dW(t)$$

where $dW(t)$ is the standard Wiener process. These productivity shocks could be viewed as reflecting either TFP shocks, demand shocks or a combination of both.[15]

To expand its workforce, a firm needs to pay a fixed cost $\tilde{r}(t)$ associated with employing a marketing specialist to create new employment opportunities at the firm, as well as a variable cost per vacancy posted. Specifically, a mass $v$ of vacancies comes at strictly

[13] In a discrete time setting, Pries (2004) shows how this outcome can be microfounded by assuming that match output is observed with noise, $x + \varepsilon(t)$, where the noise is uniform $\varepsilon(t) \sim U(-\xi, \xi)$. If observed output is less than $x_g - \xi$, the match infers that it must be low productive, since this outcome can never happen if it were high productive. A symmetric argument implies that a match learns that it is high productive when output is greater than $x_b + \xi$. Any observation of match output in $[x_g - \xi, x_b + \xi]$ is equally likely regardless of underlying match quality and the match learns nothing. Consequently, the rate of learning equals $\psi = (x_g - x_b)/2\xi$.

[14] Without learning, the JJ hazard declines over the life cycle as individuals climb a job ladder, but this mechanism is not strong enough to match the decline in the data. Similarly, the EU hazard falls with age as individuals climb away from firms close to the separation threshold, but again this force only matches part of the empirical decline. Nagypál (2007) finds that such learning is economically significant.

[15] One could add a drift to incumbent growth without impacting the results of this paper, which I hence abstract from for simplicity. I later calibrate parameters to match estimates of the contribution of selection to economic growth.

convex flow cost,

$$c_v(v,t) = c_v \underline{Z}(t) \frac{v^{1+\eta}}{1+\eta}, \qquad c_v, \eta > 0$$

where $\underline{Z}(t)$ denotes the lowest productivity of firms seeking to hire at time $t$. I thus follow a large strand of the literature in assuming that costs grow at the rate of the economy to ensure a balanced growth path (BGP).[16] The total flow cost of posting $v$ vacancies is hence $\tilde{r}(t) + c_v(v,t)$. Following the literature, unfilled vacancies are assumed to be forsaken, and if the firm stops paying the fixed cost it permanently exits the hiring market.

**Entrepreneurial choice.** At rate $\gamma(a)$, an individual gets the opportunity to start a business. I allow this to differ by age to match the inverse u-shaped entrepreneurship entry hazard with age in the data.[17] To pursue the opportunity, she has to pay a cost $c_e \underline{Z}(t)$, where $c_e \sim \Omega$, and quit her job if she is employed. Subsequently, she draws an initial productivity $Z$ from probability density function (pdf) $\tilde{\phi}$,

$$\tilde{\phi}(Z,t) = \zeta \underline{Z}(t) Z^{-(\zeta+1)}$$

I note two things: First, by linking the distribution of innovations to that of incumbent firms, the model features an externality in the sense that entrants benefit from the successes of previous firms. This allows the model to attain perpetual economic growth. Second, innovation on average takes place far from the frontier, in contrast to first-generation

[16] See for instance Romer (1990), Aghion and Howitt (1992), Aghion and Howitt (1994), Kortum (1997), Mortensen and Pissarides (1998), and chapters 13–14 of Acemoglu (2011). Bollard et al. (2016) discuss how such an assumption can be microfounded by viewing costs to be in terms of time, but for simplicity, I follow the standard in the literature and simply assume that such costs grow at the rate of the economy. Although several normalizations are possible, including for instance relative to mean wages, it is particularly tractable to normalize to the lowest productivity.

[17] The literature has yet to reach a definite answer as to why the entry rate behaves as it does over the life cycle, with proposed explanations including changes in risk-aversion, the utility cost of working hard, the ability to conduct critical thinking, and creativity (see for instance Liang et al., 2016, and Acemoglu et al., 2017, for recent papers in economics and Ruth and Birren, 1985, and Ryan et al., 2000, for contributions in other fields). In light of such ambiguity, I take a reduced-form approach. I note that all other life cycle patterns in the model are the outcomes of endogenous, optimal choices.

models of creative destruction (Aghion and Howitt, 1992; Grossman and Helpman, 1991). My approach follows recent contributions such as Luttmer (2012) and is motivated by the empirical observation that entrants typically enter small with a high exit probability. Only through a sequence of favorable shocks does an entrant grow large. Section 2.5 shows that this assumption is consistent with key patterns in the data including exit rates by firm age, firm size by firm age, and employment shares by firm age.[18]

Having come up with an idea (i.e. a productivity $Z$) for a new business, an innovating individual offers it to a mutual fund at a take-it-or-leave-it price and returns to the labor market as unemployed.

**Mutual fund.** A mutual fund owns all ideas in the economy and purchases ideas from innovating individuals at a price such that the individual captures the entire surplus. In this sense, the model is similar to Romer (1990)'s seminal model in which an intermediate goods producer purchases blueprints from a research and development-producing sector such that the inventor captures the entire surplus. This assumption simplifies the problem by avoiding the age of the founder as a state in the firm's problem (and hence also in the employed individual's problem).[19] Following the creative destruction literature, I assume a factor in fixed supply, which implies that entry of new, more productive firms pushes out the least productive incumbents. That is, it gives rise to creative destruction.[20]

[18] Appendix B.2 provides evidence of no systematic differences in post-entry firm performance by age of the founder.

[19] An earlier version of this paper had owner entrepreneurs who bequeathed their firms to their offspring when they died, which complicated the problem but did not change results. I note in particular with respect to this that flows into entrepreneurship are an order of magnitude lower than EU flows in both the model and the data. The mutual fund is assumed to own firms but not be involved in their day-to-day operational decisions (specifically, firms do not internalize the negative effect their vacancy posting decisions have on other firms).

[20] For instance, Klette and Kortum (2004) assume a fixed number of goods and Perla and Tonetti (2014) a fixed stock of entrepreneurs. I think about this fixed factor as marketing specialists, but alternative interpretations may be human or physical capital, land or real estate. I note with respect to this assumption that average firm size has only increased slightly over this period in the data, which the model matches under this assumption (due to a decline in the unemployment rate). I have also considered a version with a fixed cost instead of a fixed factor, but this delivers a counterfactually large change in the number of firms (and an even larger effect of aging). Hence, I assume a fixed factor in the spirit of the creative destruction literature.

Specifically, I assume that the mutual fund possesses $M$ marketing specialists that it rents out to firms in a perfectly competitive market. The mutual fund distributes any profits that it makes as lump sum transfers to all individuals.[21]

**Search and matching.** Since individuals who come up with an idea for a business immediately sell it, an individual may at any point in time be either employed or unemployed. Unemployed and employed individuals search with the same efficiency, which I normalize to one.[22] Following the literature, I assume that if firms post an aggregate amount of vacancies $\bar{v}$, the total number of matches that takes place equals $\chi \bar{v}^{\alpha}$, where $\chi$ is aggregate matching efficiency and $\alpha$ is the elasticity of matches with respect to vacancies. Denote by $\lambda$ the rate at which an individual meets an open vacancy and by $q$ the rate at which an open vacancy contacts an individual,

$$\lambda = \chi \bar{v}^{\alpha}, \qquad \text{and} \qquad q = \chi \bar{v}^{\alpha - 1} \tag{2.1}$$

**Wage setting.** Firms and individuals bargain over the proceeds of their match following Cahuc et al. (2006). When an unemployed individual meets a firm, the two engage in an alternating offers game as in Rubinstein (1982). This results in the individual receiving the full value of unemployment, plus a share $\beta$ of the difference between the value of the match and the value of unemployment. If an employed individual meets a new firm, the current and new firm engage in Bertrand competition for the individual's services. This competition is won by the firm with the higher valuation of the match, and the second highest value becomes the individual's outside option in a new alternating offers game with the winning firm. The individual either switches to the new employer and gets the full value of her previous match plus a share $\beta$ of the differential value between the two

[21] Given that utility is linear, such transfers have no impact on incentives; hence, I abstract from them when formulating the individual's problem for simplicity.

[22] See Faberman et al. (2017) for evidence that although employed workers spend less time searching, this is countered by the fact that they receive more offers per unit of time searched.

matches, or stays with her current employer but potentially gets an updated contract that delivers the value of the poaching match plus a share $\beta$ of the differential surplus. The latter is subject to the individual not being worse off by receiving an outside offer.

The bargaining protocol pins down the split of the surplus, but not the timing of payments. Lacking a satisfactory model of when individuals get paid, I follow Postel-Vinay and Turon (2010) in assuming that individuals are paid a fixed wage in place until either party has a credible threat to force renegotiation. I show in Appendix B.5 that this assumption delivers a process for wages that matches wage dynamics in the data.

In an environment with subsequent shocks, situations may arise in which, for a given payment scheme, one party of a match has a credible threat to abandon the match although there are mutual gains from preserving it. To avoid such bilaterally inefficient separations, I allow for renegotiation in these cases. Specifically, I assume that this delivers an updated contract such that the party that initiated the renegotiation is indifferent between leaving the match and remaining.

## 2.4 Equilibrium with Balanced Growth

This section considers a BGP equilibrium in which the lower threshold, $\underline{Z}(t)$, and the price of a marketing specialist, $\tilde{r}(t)$, grow at endogenous rate $\mu$, while incumbent firm productivity remains fixed in expectation. It is convenient to instead study a transformed economy where the lower threshold and the price of a marketing specialist are constant. To that end, I normalize all relevant variables by the lower threshold, $\underline{Z}(t)$. Denote by $z$ the log of transformed firm productivity, $z = \log(Z(t)/\underline{Z}(t))$, by $r$ the transformed price of a marketing specialist, by $\phi(z)$ the transformed log innovation distribution, and by $\rho$ the difference between the subjective discount rate and the growth rate, $\tilde{\rho} - \mu$. In the

transformed economy, firm productivity drifts downward at rate $\mu$ while $r$ is constant. Finally, I assume that the flow value of unemployment equals $B(t) = b\underline{Z}(t)$.[23]

### 2.4.1 Value functions

I now formulate the three key Bellman equations that characterize optimal behavior. First, $U(a)$ denotes the value of unemployment to an individual of age $a$. Second, $V(z, x, a)$ denotes the value of a match with productivity $x$ between a firm with productivity $z$ and an individual of age $a$, with the convention that $V(z, x_u, a)$ represents the expected value when match productivity is unknown. Third, $J(z)$ denotes the expected value of recruiting to a firm with productivity $z$. Appendix B.3 specifies separately the value to an employed individual of age $a$ of being employed in a firm with productivity $z$ with match productivity $x$ when paid wage $w$, $W^w(z, x, a, w)$, and the value to a firm of the same match, $W^f(z, x, a, w)$, to show that $V(z, x, a) = W^w(z, x, a, w) + W^f(z, x, a, w)$, i.e., the value of the match does not depend on how it is split. As this is a well-known property of this class of offer matching models, I refer a further discussion to the appendix.[24] Consequently, all decisions made by the match are bilaterally optimal and to solve for the equilibrium allocation it suffices to work with the value of the match and of unemployment. Denote also by $E$ the expected value of entry to entrepreneurship.

In order to characterize the value functions, the following four objects are necessary: First, $h(z)$ denotes the pdf of recruiting firms. Second, $f(z)$ denotes the *vacancy-weighted* pdf of recruiting firms. Third, $u(a)$ denotes the mass of unemployed workers of age $a$. Fourth, $g(z, x, a)$ denotes the pdf of employed workers. For all densities, upper case letters denote the corresponding cumulative density functions (cdf).

[23] I numerically find that the model may have several stationary equilibria, where typically one is stable and the other unstable (in the sense that a small deviation from it will lead to either the firm productivity distribution exploding or the stable equilibrium). In these cases, I focus my analysis on the stable equilibrium. Appendix B.4 discusses this in greater detail, as well as potential additional assumptions that could guarantee uniqueness.

[24] See for instance Cahuc et al. (2006), Jarosch (2015) and Borovickova (2016).

**Unemployment.** The value of unemployment solves,

$$\rho U(a) = b + \underbrace{\lambda\beta \int_0^\infty \max\left\{V\left(z, x_u, a\right) - U(a), 0\right\} dF\left(z\right)}_{\text{job offer}} + \underbrace{\kappa(a)\left[U(a+1) - U(a)\right]}_{\text{aging}} + \underbrace{\gamma(a) \int_{\bar{c}}^{\bar{c}} \max\left\{E - c, 0\right\} d\Omega(c)}_{\text{entrepreneurship opportunity}} \tag{2.2}$$

An unemployed individual enjoys flow value $b$ and meets vacancies at rate $\lambda$. If she accepts the job, she starts in a match with unknown quality and gets a slice $\beta$ of the surplus. She ages at rate $\kappa(a)$, with the convention that $U\left(A+1\right) \equiv U(1)$ (since an individual is perfectly altruistic and her offspring enters as unemployed). Finally, at rate $\gamma(a)$ she draws a cost of starting a business. If she pays the cost, she gets the expected value of a new business and returns to unemployment.

An unemployed individual enters employment if she meets a firm, $z > \underline{z}^u(x_u, a)$, where the threshold $\underline{z}^u(x_u, a)$ is defined by,

$$U(a) = V\left(\underline{z}^u(x_u, a), x_u, a\right) \tag{2.3}$$

An unemployed individual attempts entrepreneurship if she draws a sufficiently low cost, $c < \bar{c}^u$, where the threshold $\bar{c}^u$ is defined by,

$$E = \bar{c}^u \tag{2.4}$$

The latter does not depend on age since an innovating individual instantaneously returns to unemployment.

**Match.** The match solves an optimal stopping time problem to determine at what point $\underline{z}^u(x, a)$ to break up the match for unemployment. The value of a match with unknown productivity satisfies for $z > \underline{z}^u\left(x_u, a\right)$,

$$\rho V(z,x_u,a) = e^z - \underbrace{\mu \frac{\partial V(z,x_u,a)}{\partial z}}_{\text{drift in } z} + \underbrace{\frac{\sigma^2}{2}\frac{\partial^2 V(z,x_u,a)}{\partial z^2}}_{\text{shocks to } z} + \underbrace{\kappa(a)\left[\max\left\{V(z,x_u,a+1), U(a+1)\right\} - V(z,x_u,a)\right]}_{\text{individual ages}} +$$

$$+ \underbrace{\lambda\beta \int_0^{\infty} \max\left\{V(z',x_u,a) - V(z,x_u,a), 0\right\} dF(z')}_{\text{new job offer}} + \underbrace{\psi \sum_{i\in\{b,g\}} \pi(x_i) \max\left\{V(z,x_i,a), U(a)\right\} - V(z,x_u,a)}_{\text{match productivity is revealed}} +$$

$$+ \underbrace{\gamma(a) \int_{\underline{c}}^{\bar{c}} \max\left\{E - c - V(z,x_u,a) + U(a), 0\right\} d\Omega(c)}_{\text{entrepreneurship opportunity}} \tag{2.5}$$

I discuss each term of (2.5) in sequence. A match with unknown productivity in expectation produces $e^z$. On the BGP, firm productivity drifts down at rate $\mu$ and is subject to shocks with standard deviation $\sigma$. At rate $\kappa(a)$ the individual ages, with the convention that $V(z,x,A+1) \equiv U(1)$, $\forall z,x$. At rate $\lambda$ the individual gets a new job offer. If she switches employer, she gets the full value of her current match, plus a slice $\beta$ of the surplus. The payoff to the firm in this case is zero, since it would have to pay the flow cost of creating a new vacancy and there is no capacity constraint in production.[25] At rate $\psi$, the match learns its productivity, which with probability $\pi(x_i)$ is productivity $i$, and optimally decides whether to quit. Finally, at rate $\gamma(a)$, the individual draws a cost of entry to entrepreneurship and enters if the cost is sufficiently low. A similar recursion characterizes the value of a match with known match productivity and can be found in Appendix B.3.

The recursions for the match define two reservation policies in addition to the exit boundary. First, an employed individual switches employer if she meets a new firm $z' > \underline{z}^e(z,x,a)$, where,

$$V(\underline{z}^e(z,x,a), x_u, a) = V(z,x,a) \tag{2.6}$$

[25]There is no term for a "loss" to the firm of the worker moving on to a new job. The reason is that the worker obtains the full value of the current match from the new employer.

In the case when an individual is in an unknown quality match, this reduces to simply $\underline{z}^e(z, x_u, a) = z$. $V$ is intuitively increasing in $z$ and $x$. Consequently, $\partial \underline{z}^e(z, x, a)/\partial z > 0$ and $x' > x \implies \underline{z}^e(z, x', a) > \underline{z}^e(z, x, a)$—the higher a person is on the job ladder and the better suited she is for her match, the better the outside offer must be in order for her to accept it. Second, she enters entrepreneurship if she draws $c < \bar{c}^e(z, x, a)$, defined by,

$$E - \bar{c}^e(z, x, a) + U(a) = V(z, x, a) \tag{2.7}$$

It follows that $\partial \bar{c}^e(z, x, a)/\partial z < 0$ and $x' > x \implies \bar{c}^e(z, x', a) < \bar{c}^e(z, x, a)$. The higher up on the job ladder an individual is and the better she knows that her match is, the higher is her opportunity cost. Hence, the lower is the maximum cost she is willing to pay to enter entrepreneurship. Since a match optimally terminates at $\underline{z}^u(x, a)$, for $z < \underline{z}^u(x, a)$, $V(z, x, a) = U(a)$.

**Firm.** The firm solves an optimal stopping time problem of choosing at what point $\underline{z}$ to exit the recruiting market to avoid paying the fixed cost $r$, as well as how many vacancies to post.[26] That is, the firm solves for $z > \underline{z}$,

$$\rho J(z) = \max_{v \geq 0} \left\{ v(1-\beta) q \left[ \sum_a \left( \underbrace{u(a) \max\{V(z, x_u, a) - U(a), 0\}}_{\text{value from meeting unemployed}} \right) + \right. \right. \tag{2.8}$$
$$\left. \left. + \underbrace{(1-u) \int \max\{V(z, x_u, a) - V(z', x, a), 0\} \, dG(z', x, a)}_{\text{value from meeting employed}} \right] - c_v \frac{v^{1+\eta}}{1+\eta} \right\} - \underbrace{r}_{\text{fixed cost}} - \underbrace{\mu J'(z)}_{\text{drift in } z} + \underbrace{\frac{\sigma^2}{2} J''(z)}_{\text{shocks to } z}$$

where $u(a)$ is the mass of unemployed of age $a$ and $u = \sum_a u(a)$ is the aggregate unemployment rate. I discuss each term in (2.8) in sequence. At rate $q$, the vacancy contacts an individual, who with probability $u(a)$ is unemployed of age $a$. With probability $1 - u$ the

[26] Notice that when a firm exits the recruitment market, it does not automatically lead to the termination of previously created matches. Hence size is not a state for $J$.

individual is employed and randomly drawn from the distribution of employed individuals. The individual only accepts the new job if it is better than her previous job. In both cases, the firm gets a slice $1-\beta$ of the differential value. For $z \leq \underline{z}$, $J(z) = 0$.

The optimal vacancy posting rule, $v(z)$, hence solves,

$$v(z)^{\eta} = \frac{(1-\beta)q}{c_v} \left[ \sum_a u(a) \max\left\{V(z, x_u, a) - U(a), 0\right\} + (1-u) \int \max\left\{V(z, x_u, a) - V(z', x, a), 0\right\} dG(z', x, a) \right] \tag{2.9}$$

In the calibrated model, as well as in the data, a large share of a firm's hires comes directly from other employers. Consequently, the distribution of employed workers, $G$, figures prominently in the firm's vacancy posting decision. In particular, if the distribution of employment moves up the job ladder—the labor market becomes less mismatched—that will tend to discourage vacancy creation by increasing the mass of individuals that will reject the job and improving the bargaining position of those that accept it.

**Entrepreneurship.** An individual who enters entrepreneurship draws an initial firm productivity $z$ from cdf $\Phi(\cdot)$. She then gives the mutual fund a take-it-or-leave-it offer to purchase the business idea, whose value equals $J(z)$. Hence the expected value of entry equals,

$$E = \int_0^{\infty} J(z) d\Phi(z) \tag{2.10}$$

### 2.4.2 Laws of motion

Firms drift downward at rate $\mu$ and receive shocks at rate $\sigma$. Those that cross the exit threshold exit the recruiting market, while new recruiting firms enter with a productivity drawn from the innovation distribution $\phi$.[27] That is, $h$ solves the Kolmogorov forward

[27] Note that if a random variable is Pareto with shape $\zeta$ and scale one, its log is exponentially distributed with rate $\zeta$.

equation (KFE),

$$0 = \mu h'(z) + \frac{\sigma^2}{2} h''(z) + e\zeta \exp(-\zeta z), \qquad z > 0 \tag{2.11}$$

subject to,

$$h(0) = 0, \qquad \int_0^\infty h(z)dz = 1, \qquad e = \frac{\sigma^2}{2} h'(0) \tag{2.12}$$

where $e$ is the aggregate entry rate. The density at the boundary is zero since firms exit when they hit it, while by the nature of $h$ being a density it must integrate to one. Finally, the mass of exiting firms equals $\sigma^2 h'(0)/2$, which in the stationary equilibrium has to equal the entry rate. This can be seen by integrating (2.11) from 0 to $\infty$, which gives $0 = -\mu h(0) - \sigma^2/2 h'(0) + e$, and imposing $h(0) = 0$. The equation (2.11) subject to (2.12) is a second-order ordinary differential equation with solution,

$$h(z) = \frac{e}{\mu - \frac{\sigma^2}{2}\zeta} \left[ \exp(-\zeta z) - \exp\left( -\frac{2\mu}{\sigma^2} z \right) \right] \tag{2.13}$$

where the growth rate of the economy is a function of the aggregate entry rate of entrepreneurs,

$$\mu = \frac{e}{\zeta} \tag{2.14}$$

The solution can be verified by substituting (2.13)–(2.14) into (2.11) subject to (2.12).

The vacancy-weighted distribution of firms, $f(z)$, equals the density of recruiting firms at $z$ times the amount of vacancies they post,

$$f(z) = \frac{v(z)h(z)}{\bar{v}}, \qquad \bar{v} = \int_0^\infty v\left(\tilde{z}\right) dh\left(\tilde{z}\right) \tag{2.15}$$

where $v(z)$ is the solution to (2.9).

On the BGP, $g(z, x, a)$ satisfies the KFE

$$
\begin{aligned}
0 =& -\mu \frac{\partial g(z,x,a)}{\partial z} + \frac{\sigma^2}{2}\frac{\partial^2 g(z,x,a)}{\partial z^2} + \underbrace{\lambda \frac{u(a)}{1-u} f(z) \mathbb{1}\{x = x_u\} \mathbb{1}\{z > \underline{z}^u(x_u,a)\}}_{\text{inflow from unemployment}} + \underbrace{\kappa(a-1)\mathbb{1}\{z > \underline{z}^u(x_u,a)\} g(z,x,a-1)}_{\text{inflow from aging}} - \\
& - \underbrace{\kappa(a) g(z,x,a)}_{\text{outflow from aging}} + \underbrace{\lambda f(z) \mathbb{1}\{x = x_u\} \int \mathbb{1}\left\{z > \underline{z}^e(z',x',a)\right\} G(dz',dx',a)}_{\text{inflow from lower rungs in job ladder}} - \underbrace{\lambda \left[1 - F\left(\underline{z}^e(z,x,a)\right)\right] g(z,x,a)}_{\text{outflow to higher rungs in job ladder}} + \\
& + \underbrace{\psi \mathbb{1}\{z > \underline{z}^u(x,a)\} \pi(x) g(z,x_u,a)}_{\text{inflow from learning}} - \underbrace{\psi \mathbb{1}\{x = x_u\} g(z,x,a)}_{\text{outflow from learning}} - \underbrace{\gamma(a) g(z,x,a) \Omega\left(\bar{c}^e(z,x,a)\right)}_{\text{outflow to entrepreneurship}} \qquad (2.16)
\end{aligned}
$$

with the convention that $\pi(x_u) = 0$ and $g(z,x,0) \equiv 0, \forall z, x$, subject to the boundary condition that workers exit at the boundary so that the density is zero and the pdf integrates to one. I discuss the terms on the right-hand side of (2.16) in order. The distribution is subject to the drift $-\mu$ and shocks $\sigma$. At rate $\lambda f(z)$, an unemployed individual receives an offer from a firm with productivity $z$. If she accepts it, she starts out with unknown match productivity. There is a mass $u(a)$ of unemployed individuals of age $a$, which has to be adjusted for the fact that only $1-u$ individuals are employed. There is an inflow of aging individuals at intensity $\kappa(a-1)$ (to the extent that they remain in the market, $z > \underline{z}^u(x,a)$). At rate $\kappa(a)$, individuals flow out due to aging. At rate $\lambda f(z)$, employed individuals not currently working at $z$ receive a job offer from a $z$ firm. The offer is accepted if it is sufficiently better than their previous match, and the new match starts with unknown productivity. Individuals receive new offers at rate $\lambda$ and they move out up the ladder if it is sufficiently good. For match productivities different than $x_u$, there is an inflow of individuals who learn their productivity and do not abandon the match. For match productivities with $x_u$, there is an outflow due to learning at rate $\psi$. Finally, individuals receive the opportunity to enter entrepreneurship at rate $\gamma(a)$. This is accepted if the cost is sufficiently low, leading to an outflow of individuals.

The mass of unemployed of each age group, $u(a)$, satisfies,

$$0 = -\underbrace{\lambda\left[1-F\left(\underline{z}^u(x_u,a)\right)\right]u(a)}_{\text{outflow to employment}} + \underbrace{(1-u(a))\sum_x \frac{\sigma^2}{2}\frac{\partial g(\underline{z}^u(x,a),x,a)}{\partial z}}_{\text{individuals drifting below the threshold}} + \underbrace{(1-u(a))\psi\pi(x_b)G\left(\underline{z}^u(x_b,a),x_u,a\right)}_{\text{individuals jumping below the threshold due to learning}} +$$

$$+\underbrace{\mathbb{1}\{a=1\}\kappa(A)}_{\text{newborn}} - \underbrace{\kappa(a)u(a)}_{\text{outflow from aging}} + \underbrace{\kappa(a-1)\left[u(a-1)+(1-u)\sum_x G\left(\underline{z}^u(x,a),x,a-1\right)\right]}_{\text{inflow from aging}} +$$

$$+\underbrace{(1-u(a))\gamma(a)\int\Omega\left(\bar{c}^e(z,x,a)\right)G(dz,dx,a)}_{\text{entry to entrepreneurship}} \tag{2.17}$$

with the convention that $u(0) = 0$. At offer arrival rate $\lambda$, unemployed individuals meet with hiring firms and enter employment if the firm is sufficiently productive. Employed individuals drift below the separation threshold at rate $\partial g\left(\underline{z}^u(x,a),x,a\right)/\partial z$. Individuals in unknown quality matches learn that their match is low quality at learning rate $\psi\pi(x_b)$, and they separate if their firm productivity is sufficiently low.[28] $\kappa(A)$ of newborn individuals start as unemployed. $\kappa(a)$ individuals age. There is an inflow due to aging of unemployed individuals and employed individuals who endogenously terminate their match as they age. Finally, at rate $\gamma(a)$, employed individuals receive the chance to enter entrepreneurship, which they accept if the associated cost is sufficiently low. They subsequently flow into the pool of unemployed.

It is not possible to derive a closed-form solution to (2.16)–(3.1). However, the quantitative analysis will confirm the natural intuition that a more negative drift, $-\mu$, results in more density in $g$ on lower productivity firms. That is, higher growth results in more labor market mismatch.

**Definition 3** (Stationary equilibrium)**.** *A BGP equilibrium consists of value functions* $\{V, J, E, U\}$*; optimal entry and mobility policies of unemployed and matches,* $\{\bar{c}^u, \underline{z}^u(x,a), \underline{z}^e(z,x,a), \bar{c}^e(z,x,a)\}$

[28] To simplify the notation, I take as given that $V$ is increasing in $x$ so that if a match is viable with unknown quality, it is preserved when the match learns that it is good. This will be true in the quantitative analysis.

*optimal exit and vacancy policies of firms,* $\{\underline{z}, v(z)\}$*; numbers* $\{\lambda, q, \bar{v}, r, e, \mu\}$*; masses of unemployed* $u(a)$*; and distributions* $\{h(z), f(z), g(z, x, a)\}$*; such that*

1. *U solves* (2.2)*, V and* $\underline{z}^u(x, a)$ *solve the stopping time problem of the match* (2.5)*, and the policy functions of the unemployed and the match are given by* (2.3)–(2.4) *and* (2.6)–(2.7)*;*

2. *J and* $\underline{z}$ *solve the stopping time problem of the firm* (2.8) *and* $\underline{z} = 0$*, E is given by* (2.10)*, and the vacancy policy is given by* (2.9)*;*

3. *The aggregate entry rate e is consistent with individual behavior and the growth rate is given by* (2.14)*;*

4. *Aggregate vacancies* $\bar{v}$ *are consistent with firm behavior and the finding rates are given by* (2.1)*;*

5. $h(z)$ *is given by* (2.13)*,* $f(z)$ *by* (2.15)*, and* $u(a)$ *and* $g(z, x, a)$ *solve* (2.16)–(3.1)*.*

### 2.4.3 Intuition

Before bringing the model to the data, I briefly discuss the effect of aging in the model. To that end, denote by $\hat{G}(z, x|a)$ the age-conditional cdf of employment and by $m(a)$ the share of the labor force of age $a$. The aggregate JJ hazard can be written as

$$JJ = \lambda \int \left[1 - F\left(\underline{z}^e(z, x, a)\right)\right] dG(z, x, a) = \sum_a m(a) \frac{1 - \frac{u(a)}{m(a)}}{1 - u} \times \lambda \times \int \left[1 - F\left(\underline{z}^e(z, x, a)\right)\right] d\hat{G}(z, x|a) \tag{2.18}$$

At offer arrival rate $\lambda$, employed individuals receive outside offers sampled from the endogenous, vacancy-weighted distribution of firms $F$. They accept them if they are sufficiently better than their current jobs. This highlights four channels through which the aggregate JJ hazard may be affected by aging. First, a shift in the age distribution, $m(a)$, will affect the aggregate JJ hazard since older individuals typically are better matched and hence have a lower probability of making a JJ move. Second, $\lambda$ may change as firms

respond to the changed economic environment by adjusting vacancy creation. Third, $F$ may change as firms change their vacancy posting decisions, which may or may not be associated with a change in $\lambda$.[29] Fourth, aging may give rise to changes in age-conditional labor market mismatch, $\hat{G}(z, x|a)$.

The aggregate entrepreneurship entry rate equals

$$\begin{aligned} e &= \frac{1}{M}\left\{(1-u)\int \Omega\left[\bar{c}^e(z,x,a)\right]\gamma(a)dG(z,x,a) + \Omega\left(\bar{c}^u\right)\sum_a u(a)\gamma(a)\right\} \\ &= \sum_a m(a)\frac{\gamma(a)}{M}\left\{\left(1-\frac{u(a)}{m(a)}\right)\int \Omega\left[\bar{c}^e(z,x,a)\right]d\hat{G}(z,x|a) + \frac{u(a)}{m(a)}\Omega\left(\bar{c}^u\right)\right\} \end{aligned} \tag{2.19}$$

A mass $m(a)$ of age $a$ individuals receive entrepreneurship opportunities at rate $\gamma(a)$ drawn from $\Omega$. Of these, a fraction $1-u(a)/m(a)$ are employed and enter if the cost is below $\bar{c}^e(z,x,a)$. A fraction $u(a)/m(a)$ are unemployed and enter if the cost is below $\bar{c}^u$. This is all divided by the total mass of recruiting firms, $M$. This highlights three channels through which the aggregate entry rate may be affected by aging. First, a shift in the age distribution, $m(a)$, will affect entry since age groups in general differ in their propensity to enter. Second, a change in the age composition may affect the optimal entry policy, $\bar{c}^e(z,x,a)$, as if for instance an older pool of potential hires discourages entry by driving up the effective cost of recruiting. Finally, through equilibrium effects aging may affect age conditional labor market mismatch, $\hat{G}(z,x|a)$, and unemployment, $u(a)/m(a)$.

Hence, the following takes place in response to aging. It reduces the aggregate JJ and entry hazards by tilting the workforce composition towards older, less mobile parts of the population, i.e., it changes $m(a)$. Moreover, the less mobile recruitment pool dissuades firms from posting vacancies and entrepreneurs from entering by driving up the effective cost of hiring—a change in $\bar{c}^e(z,x,a)$. When the entry rate falls, by (2.14) the process of creative destruction slows and $\mu$ falls. Incumbent firms do not fall behind the market as

[29] Aging may also affect what jobs individuals accept, $\underline{z}^e(z,x,a)$. The quantitative model finds that this effect is very small.

fast as before, which from (2.16)–(3.1) implies that individuals on average are employed higher up the job ladder also conditional on age. The shift in the age conditional distribution of employment, $\hat{G}(z, x|a)$, up the ladder further reduces the JJ and entry hazards by (2.18)–(2.19). The next two sections quantify the importance of these equilibrium mechanisms, highlighting what moments of the data inform their strength.[30]

## 2.5 Firm and Worker Life Cycle Dynamics

A life cycle of both firms and workers plays a prominent role in the theory. This section brings the model to the data to show that it generates as a non-targeted equilibrium outcome life cycle firm and worker dynamics that closely match the corresponding empirical moments, providing confidence in the theory.

### 2.5.1 Strategy

Due to better data availability at the end of my sample period, I calibrate the model to match key moments in 2012–2014. In this sense, I run the experiment in the next section "backwards." Although it simplified the notation to specify the model in continuous time, several of the moments I compute later take complicated forms, such as annual reallocation rates at the firm level and higher-order moments of annual income innovations. This opts me to solve a discretized version of the model to compute these by simulation rather than derive PDEs that characterize them. Appendix B.4 contains a detailed description of the algorithm I use to solve and simulate the model.

The model is solved at a monthly frequency. I first determine a set of standard parameters based on common values in the literature, summarized in Table 3.1. The discount rate is set to the monthly equivalent of a four percent annual real interest rate. Matching efficiency is not separately identified from the cost of vacancy creation, and hence I

[30] Appendix B.3 illustrates this intuition in a highly stylized version of the model.

normalize $\chi$.[31] I set the elasticity of the matching function with respect to vacancies to $\theta = 0.7$, which is a commonly estimated value when one allows for search on the job (Petrongolo and Pissarides, 2001). Finally, I set workers' bargaining power to $\beta = 0.3$, which is the average value across education groups estimated by Bagger et al. (2014). My results are not sensitive to other reasonable values for $\beta$ or $\theta$.[32]

Table 2.1: Pre-set parameter values

| | Description | Target | Value |
|---|---|---|---|
| $\rho$ | Discount rate | Annual interest rate of 4% | 0.0034 |
| $\chi$ | Matching efficiency | Normalization | 0.1 |
| $\alpha$ | Elasticity of matching function | Petrongolo and Pissarides (2001) | 0.7 |
| $\beta$ | Bargaining power | Bagger et al. (2014) | 0.3 |

I approximate the life cycle with three age groups and set the monthly transition rate $\kappa(a)$ such that individuals expect to be young for 15 years (age 20–34), middle age for 10 years (35–44) and older for 15 years (45–59). The three age groups are set to roughly correspond to phases of life cycle dynamics documented in Appendix B.2.

The remaining 12 parameters are calibrated internally to match the 12 moments listed in Table 2.2. I discuss heuristically why these moments are particularly informative about some parameters, but the calibration is joint and hence all moments in general inform all parameters. All statements below should be interpreted as "holding everything else constant, if X is larger..."

As discussed in Section 2.2, the available evidence suggests that the recent decline in the UE hazard may be an artifact of the Great Recession rather than a secular phenomenon. In light of this, I calibrate $c_v$ to target the average UE hazard in 2005–2007, which is 17 percent. The results are not sensitive to the exact value for $c_v$. The aggre-

[31] In the discrete time approximation, the worker finding rate of a vacancy cannot be larger than one. Normalizing $\chi$ to a sufficiently low value ensures this.

[32] Tenure wage profiles and wage gains from JJ mobility are partly informative about $\beta$. I show in Appendix B.4 that the model under this parameter value closely matches empirical estimates of these moments.

gate EU hazard informs the probability that the match is low productive, $\pi(x_b)$. If this is small, the EU hazard is low. The aggregate JJ hazard informs the productivity of high productive matches, $x_g$. If this is high, the JJ hazard is low since individuals who have learned that they are high productive would have to sacrifice more to switch employers. The rate of learning, $\psi$, is informed by the tenure profile of the JJ hazard.[33] If $\psi$ is high, uncertainty about match productivity is rapidly resolved and the JJ hazard falls quickly with tenure. Few good estimates are available on the flow value of leisure. Hence, I set it such that a young individual with unknown match productivity is indifferent between working for the least productive hiring firm and unemployment.

The average firm entry rate informs the average of the arrival rate of entrepreneurship opportunities across age groups. Differences in the arrival rate of opportunities by age are calibrated to match entrepreneurship entry rates by age. As noted in the previous section, this is the only parameter that I allow to vary directly with age. Little evidence is available on the dispersion in the cost of entering entrepreneurship, and hence I assume that it is uniformly distributed between $-C$ and $C$. The dispersion in entry costs, $C$, is informed by the fall in entry with tenure. If the cost distribution is dispersed, large changes in the value of entry are required to achieve a given change in the number of individuals who enter entrepreneurship. With tenure, the opportunity cost of entry increases; hence, the extent to which entry declines with tenure informs $C$. Finally, recall from (2.14) that the growth rate is directly linked to the entry rate and the shape of the innovation distribution, $\zeta$. I calibrate $\zeta$ to Luttmer (2007)'s estimate that 65 percent of growth is due to selection of firms applied to the 1.7 percent growth rate in 2012–2016.[34] I have considered alternative reasonable values for $\zeta$ with similar results.

[33] I construct tenure profiles of mobility using pooled SIPP data from 1996 onwards for which tenure is available, and adjust the level to match that in the late period.

[34] As discussed further below, I additionally introduce a death shock to firms, which implies a slightly more complex mapping between the entry rate and the growth rate than (2.14). Nevertheless, the same intuition holds.

I set the mass of marketing specialists, $M$, to match average firm size, and the elasticity of the vacancy cost function, $\eta$, to match the share of employment of entrant firms in size bins 1–249, 250–499, 500–999, and 1000+ employees. When $\eta$ is high, the cost of creating jobs increases rapidly in vacancy creation. Hence, it is expensive to rapidly increase employment, and entrant firms will be smaller. I introduce a small probability of firm death that is independent of firm productivity for the following reason. The unweighted entry rate is implicitly determined by the entrepreneurship and firm growth parameters discussed above, which pins down the unweighted exit rate (since unweighted entry equals unweighted exit in equilibrium).[35] Without a small death shock destroying some large firms, the weighted exit rate is too low because not enough workers work at firms close to the separation threshold.[36] Finally, $\sigma$ is set to match the the share of employment of all firms in size bins 1–249, 250–499, 500–999, and 1000+ employees. A more volatile productivity process implies greater dispersion in productivity in the stationary economy, which translates into greater dispersion in firm size in equilibrium.

[35]The model somewhat overstates the level of the unweighted entry rate, which is 13.8 percent in the model versus 8.0 percent in the data in the late period. To the extent that some small (typically one worker) firms enter as unincorporated businesses, they would not be captured by the data, which only cover incorporated businesses.

[36]At the calibrated values, about three quarters of the employment-weighted exit rate is due to firms falling below the endogenous separation threshold, and the remaining quarter due to the exogenous death shock (practically all of the unweighted exit rate is due to endogenous exit). Apart from allowing me to match the exit rate, introducing this exogenous death shock has no meaningful impact on results.

Table 2.2: Calibrated parameter values

| | Description | Target | Value |
|---|---|---|---|
| *Panel A: Labor market mobility* | | | |
| $c_v$ | Cost of vacancy creation | Average UE | $4.5 * 10^{-4}$ |
| $\pi(x_b)$ | $P$(match is low productive) | Average EU | 0.5 |
| $x_g$ | Productivity of high prod. match | Average JJ | 1.3 |
| $\psi$ | Rate of learning | Timing of decline in JJ with tenure | 0.043 |
| $b$ | Flow value of unemployment | Indifference at margin | 1.09 |
| *Panel B: Entrepreneurship* | | | |
| $\nu(a)$ | Entrepreneurship opportunity | Entry rate by age | $[4.2; 4.5; 2.1] * 10^{-3}$ |
| $C$ | Dispersion in entry cost | Decline in entry with tenure | 72 |
| $\zeta$ | Innovation distribution | Growth due to selection (Luttmer, 2007) | 20 |
| *Panel C: Incumbent firms* | | | |
| $M$ | Marketing specialists | Average firm size | 0.13 |
| $\eta$ | Curvature of vacancy creation | Size distribution of entrants | 2 |
| $d$ | Exit shock for firms | Average exit rate | $3.8 * 10^{-4}$ |
| $\sigma$ | Shocks to productivity | Size distribution | $7 * 10^{-3}$ |

### 2.5.2 Properties of the calibrated economy

I comment briefly on some of the calibrated parameters and the model fit. The probability that a match is good is calibrated to 0.5, in which case it is 30 percent more productive than expected productivity. The calibrated learning parameter implies that half of matches will have learned their productivity in two years, i.e., learning is quite slow. This is implied by the slow decline in the JJ hazard with tenure. The flow value of unemployment that makes individuals indifferent between entering at the lowest productivity firm and remaining unemployed is high. This results from individuals not giving up any option value to enter employment, but gaining the option value to learn that their match is high productive.

The estimated standard deviation of shocks to firm productivity implies a steady-state standard deviation of marginal productivity of 0.14.[37]

Since the model fits the targeted aggregate firm and worker reallocation rates very well, to avoid repetition I refer to Tables 2.3–2.4 in the next section for the numbers.[38] The top two panels of Figure 2.1 plot the JJ hazard and entrepreneurship entry hazard by tenure in the model and data. Appendix B.4 also shows that the model matches well the tenure profile of the EU hazard. The bottom two panels plot the distribution of employment by firm size of all firms and entrant firms. The model fit is overall good.

Figure 2.2 compares the implied life cycle profiles of the EU and JJ hazards in the model with their empirical counterparts. As individuals age, they climb the job ladder and learn about match quality. It takes time, however, to find a productive employer, and even then it is not guaranteed that the individual will be a good fit with the firm. Furthermore, employers are subject to continuous shocks to their productivity, necessitating constant worker reallocation. It adds up to produce a rather time-consuming process. Recall that the calibration only targets the aggregate EU and JJ hazards.[39] Matching the life cycle profiles of these hazards so well supports the proposed job ladder and learning mechanisms as important factors behind life cycle worker dynamics.[40]

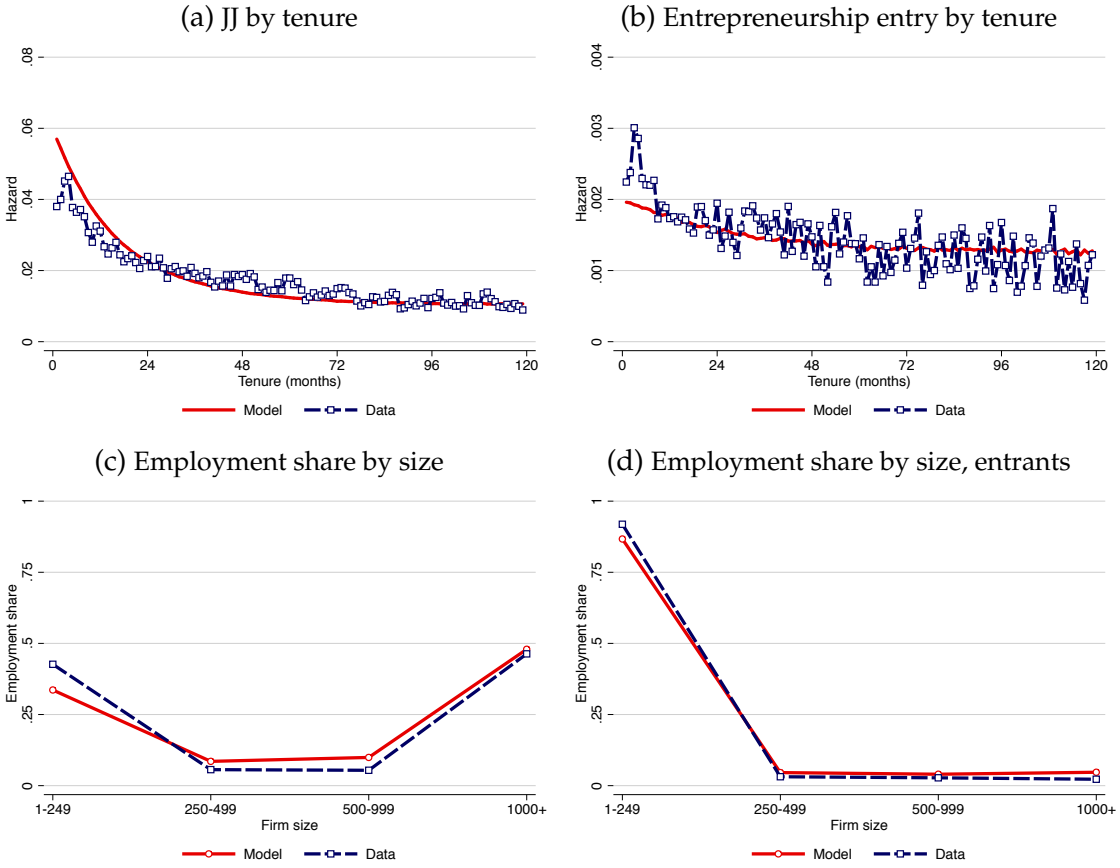
[37] Decker et al. (2017a) report a standard deviation of within-detailed industry dispersion in log TFP of just over 0.4 in 2011 (see their Figure 1). Empirical measures of value added and TFP are known to be plagued by substantial measurement error, which may account for the discrepancy.

[38] Additionally, the model predicts an average firm size of 31.5 versus 33.2 in the data, and a life cycle profile of entrepreneurship entry that matches the data perfectly.

[39] Note the if the JJ hazard falls by $X$ percent between zero and long tenures, the rate of learning, $\psi$, determines how early on in a match the $X$ percent fall takes place. It does not govern the magnitude of the fall, $X$.

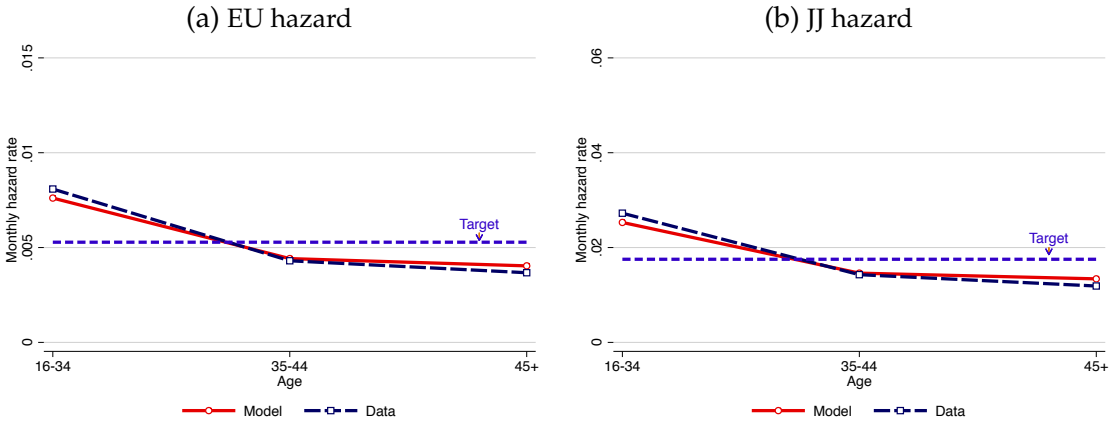
[40] Appendix B.4 shows that the model predicts a flat UE hazard over the life cycle, while the hazard falls modestly in the data. To the extent that individuals become less likely to make an UE move as they age, the fact that the model does not match this will likely lead to an underestimate of the impact of aging. Appendix B.4 also shows that the model matches well empirical wage-tenure profiles, gains from JJ mobility, the variance of annual income, and the second, third and fourth moments of annual income innovations.

Figure 2.1: Model fit: JJ tenure profile, entrepreneurship entry tenure profile, employment share by firm size, and employment share by firm size of entrants



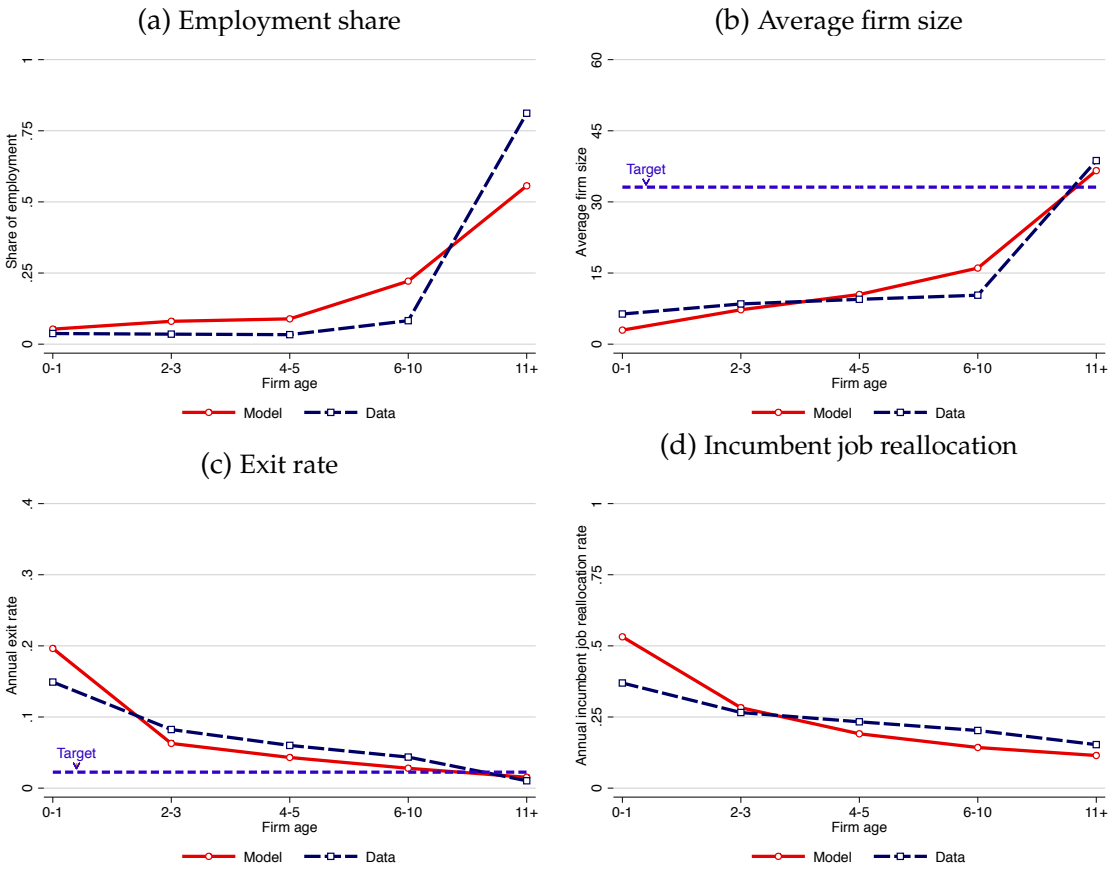

*Note: SIPP 1996–2013 adjusted to the level in 2013 and BDS in 2014 (HP-filtered annual data with smoothing parameter 6.25). JJ: share of employed in $t$ who are with a different employer in $t+1$; entrepreneurship entry: share of employed in month $t$ who are self-employed in $t+1$.*

Figure 2.2: Validation: Life cycle worker dynamics



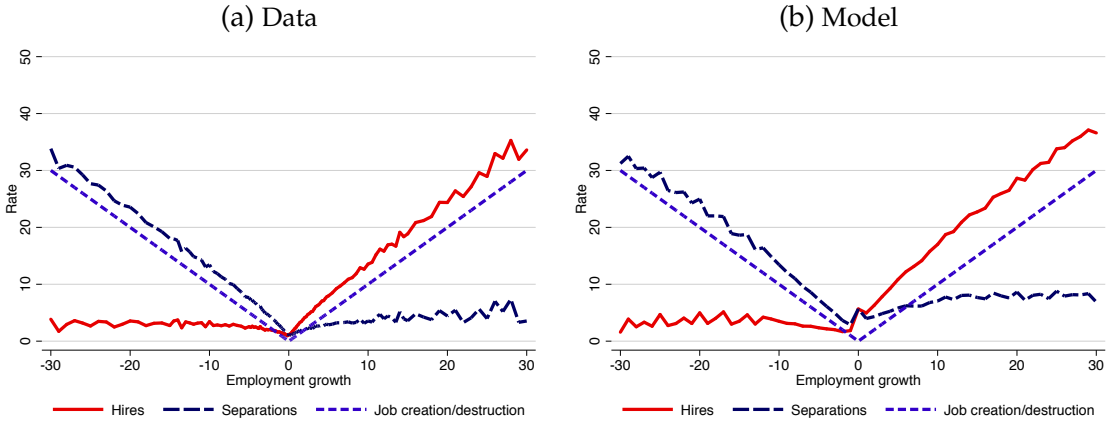

*Note: SIPP 2011–2013 (HP-filtered annual data with smoothing parameter 6.25). JJ: share of employed in $t$ who are with a different employer in $t+1$; EU: share of employed in month $t$ who are unemployed in $t+1$.*

Figure 2.3: Validation: Life cycle firm dynamics




*Note: BDS in 2014 after HP-filtering the data. Exit rate: sum of employment of firms whose employment in the subsequent year is zero; Incumbent job reallocation: sum of job creation of expanding non-entrant establishments and job destruction of contracting non-exiting establishments; Firm age: years lapsed since first year with positive employment. All within firm age groups and divided by total employment in that age group. Exit and firm size are adjusted to match the empirical mean.*

Figure 2.4: Validation: Linking firm and worker dynamics




*Note: Reproduced from Davis et al. (2010) based on JOLTS micro data for 2001–2006. Data are monthly and model-simulated data quarterly. Hiring rate: sum of hires between time t and $t+1$; Separation rate: sum of separations between time t and $t+1$; Employment growth: change in employment between t and $t+1$; all divided by to total employment at time t. Weighted by employment and multiplied by 100.*

The top left panel of Figure 2.3 illustrates that in both the model and the data most individuals work for old firms, with the model understating somewhat the share of employment at very old firms. The next three panels show that the model matches well average firm size by age, the exit rate by age, and job reallocation for incumbents by age.[41] I note that any error in the measurement of firm age will tend to bias the decline with age in the empirical profiles towards zero.

Recall that the calibration targets average firm size, employment shares by firm size, employment shares by firm size of entrants, the aggregate entry and exit rate, and an estimate of the contribution of firm selection to economic growth. Hence, it is not by construction that the model replicates so well life cycle firm dynamics. In particular, the drift and standard deviation of the productivity process are calibrated to match very different moments, yet the model matches well job reallocation for incumbents by firm age. It

[41] Given that the model understates the share of employment at very old firms, these firms are the largest and have the lowest exit rates, and I additionally target average firm size and the average exit rate, I will overstate (understate) somewhat the age-conditional firm size (exit rate) by construction. Figure 2.3 normalizes the average firm size and the exit rate to the average in the data to highlight the pattern with age. I prefer to get the overall average firm size and exit rate right rather than the level of the age-conditional firm size and exit rates, but I have verified that this preference has no meaningful impact on results. Appendix B.4 shows the unadjusted graphs.

suggests that the proposed combination of a geometric Brownian motion for productivity, firm selection through creative destruction, and labor markets frictions captures key stylized facts on life cycle firm dynamics.

Figure 2.4 illustrates that the model captures the hockey stick-like link between the hiring and separation rate at the establishment level and establishment-level employment growth as documented by Davis et al. (2010).[42] I note in particular that in both the model and the data the hiring rate rises more than one-for-one with employment growth. An expanding establishment hires workers whose productivity is unknown, resulting in an elevated churn rate.[43]

## 2.6 Quantifying the Effects of Aging

Having confirmed that the model replicates key features of firm and worker dynamics in the data, I proceed to analyze the impact of aging through the lens of the model. To that end, I change the age composition of the economy and evaluate its implications for business dynamism, labor market fluidity and economic growth. In order to achieve a decrease in the share of older individuals in line with the data, I change the rate at which older individuals exit the market, $\kappa(3)$, from 0.0043 in the late period to 0.0087 in the early period. Changing $\kappa(3)$ while keeping $\kappa(1)$ and $\kappa(2)$ constant leads me to understate the increase in the share of young and overstate the increase in the share of middle aged somewhat. As young individuals are more mobile than middle aged people and have

[42] I use quarterly model-generated data, while the data are monthly. Using a monthly frequency in the model de-emphasizes this pattern since I do not allow an employment spell to start and end in the same month in the model. Supposedly this restriction is not present in the real world. Aggregating to the quarterly level allows for short, within-period transitions.

[43] Appendix B.4 shows that the model fits well a range of additional moments. This includes a fat-tailed distribution of firm quarterly employment changes; hires and separations from and to employment and unemployment, respectively, with firm age; a modestly increasing share of hires that are poached from other firms by firm age; a declining net poaching rate by firm age; an increasing average age of workers by firm age; the decline in the exit rate by firm size; as well as the magnitude of the firm age and firm size pay gradients and between-firm dispersion in pay.

about the same entrepreneurship entry rates, this will result in an underestimate of the effect of aging.[44]

The change in $\kappa(3)$ has two effects: First, it increases the share of young people, and second it shortens the time individuals expect to remain in the market. In the data, on the other hand, the retirement age has not increased over this period, which suggests that individuals did not expect to spend less time in the market in the 1980s. To achieve the first effect while purging the results from the second, I use the original $\kappa(3)$ when solving the value functions, and the new $\kappa(3)$ when computing individual transitions (i.e., in the laws of motion (2.16)–(3.1)). That is, individuals continue to behave as though they expect to spend as much time in each age group as before. Although I believe that this is the most appropriate way to map the non-stationary real world into the model environment, results are effectively the same if I do not offset the direct effect.[45]

### 2.6.1 The decline in business dynamism

Table 2.3 summarizes the predicted effect of aging on firm reallocation rates. According to the model, aging explains 56 percent of the empirical change in firm turnover and 39 percent of the fall in job reallocation over this period. In line with the data, both entry and exit fall substantially.[46] Furthermore, a substantial share of the decline in job reallocation is driven by falling job reallocation for incumbents. These predictions are in line with the first set of empirical facts in Section 2.2.

Figure 2.5 illustrates that aging in the model explains key changes in the life cycle dynamics of firms over this period. The left panel shows that employment has shifted

[44] I have also considered a specification where I also adjust $\kappa(2)$ to fully match the change in the age distribution, with modestly more pronounced results. Table B.6 in Appendix B.5 summarizes the age distribution in the model and the data in the early and late period.

[45] This is not surprising given the dynastic preference structure, which assumes that older individuals are perfectly altruistic with respect to their offspring. In ongoing work, I am pursuing an extension to study the transition path.

[46] Given that I assume that the exogenous death shock remains fixed, it is not surprising that as a fraction the model explains less of the change in the exit rate than in the entry rate.

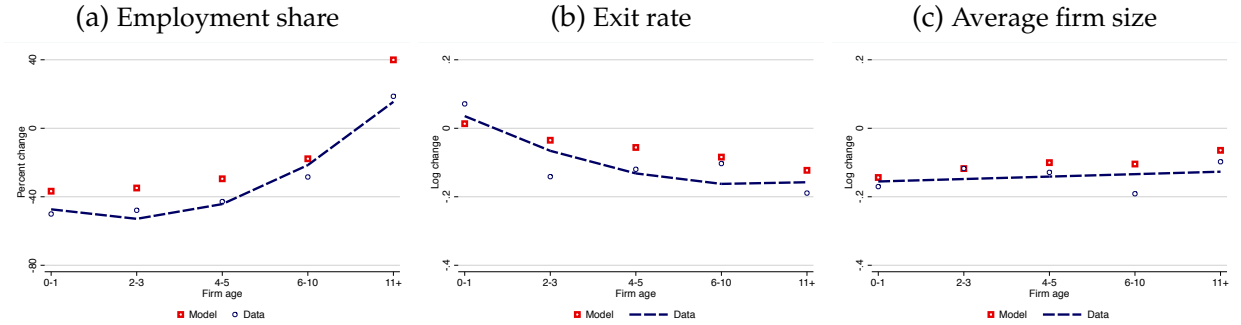
substantially towards older firms as the turnover rate of firms has slowed. Since older firms are less dynamic, from an accounting perspective, the shift towards older firms accounts for some of the decline in firm dynamics. I show in Appendix B.5 that aging in the model replicates the empirical fact that the shift towards older firms accounts for all (or more) of the decline in exit and a substantial share of the decline in job reallocation for incumbents. While in both the model and the data the weighted exit rate did not fall conditional on firm age, the unweighted exit rate has declined within firm age groups. The middle panel shows that aging in the model reproduces the empirical pattern that the exit rate has declined by more in relative terms for old firms. The right panel shows that firm size has fallen the most for young firms over this period, which aging in the model largely replicates. The harder recruiting environment hampers firm growth, resulting in smaller firms conditional on age. In contrast, average firm size has increased modestly in both the model and the data due to the rapid shift towards older firms, which are on average larger.

Table 2.3: Impact of aging on business dynamics

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Early | | Late | | Change | | |
| | Data | Model | Data | Model | Data | Model | Share |
| Entry | 0.037 | 0.033 | 0.020 | 0.021 | -0.018 | -0.012 | 65.4 |
| Exit | 0.028 | 0.021 | 0.019 | 0.018 | -0.009 | -0.003 | 35.6 |
| Turnover | 0.065 | 0.054 | 0.039 | 0.039 | -0.026 | -0.015 | 55.8 |
| Incumbent | 0.213 | 0.176 | 0.166 | 0.152 | -0.046 | -0.024 | 52.7 |
| Job | 0.345 | 0.231 | 0.246 | 0.191 | -0.100 | -0.039 | 39.2 |

*Note: Annual firm reallocation rates from the BDS in 1986 and 2014 after HP-filtering with smoothing parameter 6.25.*

Figure 2.5: Change in firm life cycle dynamics




*Note: Data from the BDS in 1988 and 2014 after HP-filtering the annual data with smoothing parameter 6.25. Employment share: sum of employment by firms in that age group divided by total employment; Exit rate: number of exiting firms divided by total number of firms in that age group; Average firm size: sum of employment at firms in that age group divided by number of firms in that age group. Difference between late and early period.*

Job reallocation may be viewed as the second moment of employment changes at the firm level. Based on this, Decker et al. (2017a) document four empirical patterns over this period. First, the fall in job reallocation is not due to a more benign economic environment facing firms. Second, older firms adjust employment less in response to productivity shocks. Third, employment has shifted towards older firms, accounting for some of the decline in the response of firm employment to firm productivity shocks. Fourth, the response has fallen within firm age groups. The model replicates this pattern. First, the variance of underlying productivity shocks is held constant. Second, firms' employment response to changes in idiosyncratic productivity is (partly) tied to the number of ranks a firm moves in the ladder in response to a shock. If a firm changes many ranks, this has a large effect on the number of workers it loses and gains for a given number of vacancies posted, which is amplified through its effect on optimal vacancy creation.[47] The (log) productivity distance between ranks of firms is larger further up the ladder, and hence a given magnitude productivity shock does not move a firm as many ranks at the top of the

[47] Additionally, vacancies respond proportionally less at the top of the ladder due to the strict convexity of the cost function.

ladder, leading to a smaller employment response.[48] Older, surviving firms are on average further up the ladder, resulting in them endogenously having a lower pass-through. Third, as noted above, aging in the model leads to a substantial shift of employment towards older firms. Fourth, employment has also shifted up the ladder within firm age groups, leading to a decline in the pass-through conditional on firm age. Table B.7 in Appendix B.5 provides more details.

### 2.6.2 The fall in labor market fluidity

Table 2.4 summarizes the predicted effect of aging on worker flows. Aging explains 36 percent of the change in the EU hazard and 48 percent of the change in the JJ hazard in the data.[49] The decline in worker reallocation is only partly due to the decline in job reallocation, with also a significant fall in churn.[50] In contrast, the UE hazard only declines slightly. This is in line with the set of facts on worker flows presented in Section 2.2.

Table 2.4: Impact of aging on labor market fluidity

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Early | | Late | | Change | | |
| | Data | Model | Data | Model | Data | Model | Share |
| EU | 0.009 | 0.006 | 0.005 | 0.005 | -0.003 | -0.001 | 35.7 |
| JJ | 0.023 | 0.020 | 0.018 | 0.017 | -0.005 | -0.002 | 47.6 |
| UE | 0.175 | 0.169 | 0.170 | 0.168 | -0.005 | -0.001 | 24.8 |

*Note: Monthly worker reallocation rates from SIPP in 1986 and 2012–2013 (2005–2007 for UE), first converted to annual averages and then HP-filtered with smoothing parameter 6.25.*

[48] Given that higher-ranked firms are typically larger, an implication of this is that the variance of growth rates is higher for small firms. This is a robust feature of the data (Sutton, 1997; Caves, 1998). Despite all firms being subject to the same proportional productivity process, the model generates this as an endogenous equilibrium outcome arising from the presence of labor market frictions.

[49] In light of the fact that the SIPP experienced a break in the JJ series in 1996, the exact empirical decline in the JJ hazard is somewhat uncertain. See Appendix B.1 for a further discussion and robustness.

[50] The model accounts for 38 percent of the decline in quarterly churn in the QWI from 1993–2014.

The model reconciles the difference in behavior between the JJ and UE hazards through the following mechanism.[51] Conditional on productivity, firms post fewer vacancies in the older economy as they face a better matched labor market. On the other hand, the slower turnover rate of firms implies that the distribution of firms has shifted to the right, and more productive firms post more vacancies. The net effect is only a small decline in the job finding rate (Appendix B.5 illustrates this). In contrast, the less dynamic economy implies that employment has shifted up the ranks of firms and a higher share of matches have learned that they are high productive. As individuals higher up the ladder and who know that they are in a high-productive match are less likely to accept a job offer, this has reduced the JJ hazard over and above the modest decline in the offer arrival rate.

Figure 2.6 plots the relative decline in the EU, JJ and UE hazards by age in the model in red squares. The model suggests a relatively larger effect on mobility rates late in careers when individuals have moved up the ladder. In the next section, I use cross-state variation to find a pattern in the data that corresponds to what the model suggests. This is plotted in dashed blue.[52]

To relate my structural analysis to a literature that typically finds a limited role of aging in the slowdown in worker reallocation, I employ a commonly used shift-share analysis on model-generated and actual data. That is, I compute age conditional mobility rates in a late period, $\beta_a^{\text{late}}$, and change the age composition assuming that age-conditional mobility rates remain constant,

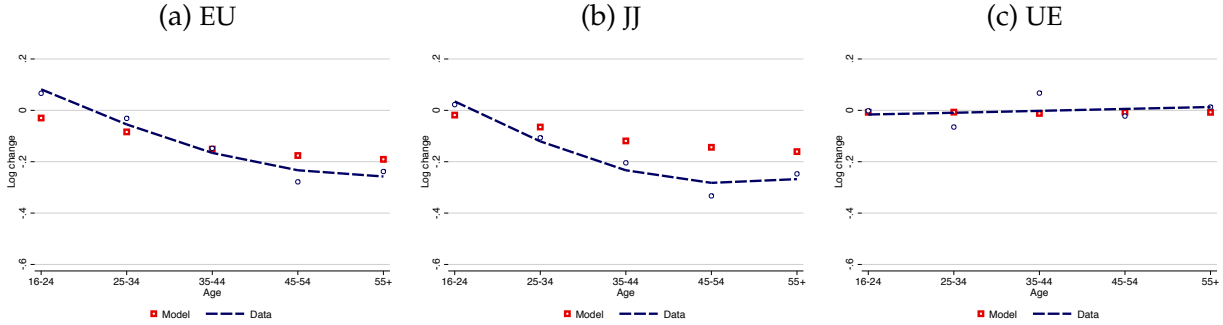
$$\widehat{\text{Effect of aging}} = \sum_a \beta_a^{\text{late}} \left[\text{share of labor force}_a^{\text{early}} - \text{share of labor force}_a^{\text{late}}\right]$$

[51] Additionally, the JJ hazard falls with age while the UE hazard does not; hence, a composition effect accounts for some of the difference.

[52] In contrast, the raw CPS and SIPP data provide different results with respect to this. The SIPP suggests that in relative terms the EU hazard has fallen uniformly across age groups while the JJ hazard has declined the most among young individuals; the CPS indicates the largest relative declines in the EU hazard among young individuals and a roughly uniform relative decline in the JJ hazard with age. One interpretation of this is that other forces at work over this period have particularly reduced mobility of younger individuals. It is an interesting task for future research to understand these other forces better.

Table B.9 in Appendix B.5 shows that the predicted effect of aging based on this methodology in the model accounts for 60 percent of the predicted effect in the data using the same methodology.[53] More importantly, this approach leads to a substantially understated role of aging in the decline in worker dynamics. It suggests that aging only accounts for 35–50 percent of the overall decline in the EU and JJ hazards in the model, respectively. Effectively, this reduced form approach treats the age-conditional mobility rates, $\beta_a$, as structural parameters which remain fixed in response to changes in the age composition, which the model suggests is not a valid assumption.

Figure 2.6: Change in worker life cycle dynamics




*Note: Log difference in reallocation rate from early to late period. Data: estimated based on cross-state panel regressions within age groups controlling for state fixed effects, year effects and growth in state real GDP per individual. CPS 1978–2014 (starting in 1994 for JJ).*

### 2.6.3 A level and a growth effect

The model implies that aging has reduced annual economic growth by 0.27 percentage points. Over this period, trend growth in real GDP per labor force participant has fallen from 2.6 percent in 1984–1988 to 1.7 percent in 2012–2016. At the same time, fewer individuals are unemployed in the late period. The unemployment rate has declined from 6.2

[53] Two reasons are behind why the model understates the predicted effect of composition in the data. First, it is not possible to perfectly match the change in the age composition by changing only one parameter, $\kappa(3)$. As noted above, I chose a conservative approach which understates the direct effect of aging. Second, the model understates somewhat the declines in these hazards over the life cycle.

percent to 5.2 percent in the model versus 6.9 percent to 5.8 percent in the data.[54] Table 2.5 summarizes these predictions.

Table 2.5: Impact of aging on aggregate economic outcomes

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Early | | Late | | Change | |
| | Data | Model | Data | Model | Data | Model |
| Growth | 2.6 | 1.42 | 1.7 | 1.15 | -0.9 | -0.27 |
| Unemployment rate | 0.069 | 0.062 | 0.058 | 0.052 | - 0.011 | - 0.010 |

*Note: Annual growth in real GDP per labor force participant 16 years of age and older in 1984–1988 and 2012–2016, as well as the unemployment rate in 1986 and 2015. Annual data from the BEA and BLS HP-filtered with smoothing parameter 6.25.*

In contrast to the negative growth effect, the model implies that aging has had a positive level effect on output, as summarized in Table 2.6. Output has increased by 1.4 log points due to a composition effect (older individuals are always better matched). It has risen further by 4.4 log points due to the shift of employment up the job ladder within age groups, while the shift in match productivity has had only a modest effect. Net output has increased by less than the sum of these effects because more resources are spent on vacancy creation—even though firms create fewer vacancies conditional on productivity, the underlying distribution of firms has shifted to higher productivity firms which have a higher marginal cost of vacancy creation since they create more vacancies.[55] Discounted net output has fallen by four log points due to the lower growth rate.

[54] Targeting hazard rates leads me to understate the unemployment rate. Instead recalibrating the model to match the unemployment rate, I find essentially identical results.

[55] Resources spent on entry has fallen, but not by enough to offset the change in the resource cost of vacancies.

Table 2.6: Impact of aging on level of output, model

| (1) Age composition | (2) Firm productivity | (3) Match productivity | (4) Net output | (5) Discounted net output |
|---|---|---|---|---|
| 0.014 | 0.044 | 0.004 | 0.055 | -0.040 |

*Note: Log change in output going from the young to the old economy due to composition effect, shift in firm productivity, change in share of high productive matches, change in net output after subtracting cost of vacancies and entry, and discounted change in net output.*

### 2.6.4 Quantifying the channels

To highlight the channels through which aging reduces the JJ and entry hazard, I decompose the changes based on equations (2.18)–(2.19). I start from the model calibrated to the old economy and gradually turn on each channel.[56] The direct effect of the shift, $m(a)$, generates a seven percent increase in JJ mobility. The effect of changes in firm vacancy creation, $\lambda(1 - F(\underline{z}^e(z, x, a))$, accounts for a 17 percent *decrease* in the JJ hazard. For the reasons mentioned above, the job finding rate, $\lambda$, is only modestly higher in the younger economy. The vacancy-weighted distribution of firms, $F(z)$, however, shifts to firms further down the ladder, with a lower probability that the individual will accept the offer holding everything else constant.[57] The shift in $F$ is the result of less productive firms disproportionately benefitting from the easier recruiting environment in the younger economy as well as a shift in the underlying distribution of firms. Finally, the faster turnover rate of firms leads to greater labor market mismatch conditional on age, i.e., it shifts $\hat{G}(z, x|a)$ towards lower productivity firms and a higher share of matches with unknown match productivity. This reduces the opportunity cost of a JJ move and accounts for a 23 percent increase in JJ mobility, of which 20 percentage points are due to the shift in the firm productivity dimension.

The shift in the age composition, $m(a)$, generates a 10 percent increase in entry. The shift in the entrepreneurship entry decision rules, $\bar{c}^e(z, x, a)$ ($\bar{c}^u$), in response to the easier

[56] Although this decomposition is not invariant to the order in which effects are included, changing the order has no meaningful effect on the conclusions.

[57] The shift in the acceptance policy, $\underline{z}^e(z, x, a)$, has a negligible effect.

recruiting environment accounts for a one percent increase in the entry rate. Although a higher turnover rate of firms increases the value of entry by shifting employment down the firm ladder, it also reduces the value since a potential entrant expects to be replaced faster.[58] Finally, the shift in $\hat{G}(z, x|a)$ accounts for a further 10 percent increase in the entry rate, of which less than one percentage point is due to the shift in match productivity. Table 2.7 summarizes these results.

Table 2.7: Decomposing the change in the JJ and entry hazard, model

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Entry hazard | | JJ hazard | |
| | % change | % of total | % change | % of total |
| Direct effect | 10.5 | 47.5 | 7.0 | 53.6 |
| Policies: $\bar{c}^e(z, x, a)/\lambda \left[1 - F\left(\underline{z}^e(z, x, a)\right)\right]$ | 1.2 | 5.4 | -17.3 | -133 |
| Mismatch: $\hat{G}(z, x|a)$ | 10.4 | 47.2 | 23.3 | 179 |
| Total effect | 22.2 | 100 | 13.1 | 100 |

*Note: Unweighted entry and JJ mobility in the young economy as a percent of that in the old economy. Channels are turned on sequentially starting from the top.*

I note that the above decomposition is for the unweighted entry rate. The weighted entry rate is an additional 30 percentage points higher in the young economy as entrant firms post more vacancies and hire more individuals per posted vacancy in response to the easier recruiting environment. A similar pattern holds in the data over this period: the weighted entry rate is an additional 30 percentage points higher than the unweighted entry rate in 1986 compared to 2014.

The decomposition highlights some of the key parameters governing the strength of the equilibrium effects of aging and what moments of the data inform them. The tenure profile of JJ mobility informs to what extent individuals become harder to recruit as they climb the ladder and learn their match productivity. If this is flat, JJ mobility will not

[58] Furthermore, the market effect on entry is linked to the incremental value created by an entrant over the least productive incumbent, and both incumbents and entrants are affected by the shift in labor market mismatch.

increase much in response to the worse-matched labor market, and hence, the recruiting environment for firms will not be significantly affected. Similarly, the tenure profile of entry informs the elasticity of entry with respect to changes in the value of entry. If this profile is flat, entry will not respond much to the potential entrant being further up the ladder, having learned her match productivity, or facing a different hiring market. Figure 2.1 in the previous section showed that the model matches these empirical counterparts well. This discussion highlights that the large estimated equilibrium effects of aging are not hardwired into the model but implied by key moments of the data.[59]

### 2.6.5 Summary

The model implies that aging has reduced business dynamism, labor market fluidity and economic growth in line with key secular trends over this period. On the firm side, turnover has declined both because entry and exit have fallen, job reallocation has declined also because incumbent firms have become less dynamic, and the latter is due to firms' weaker employment response to shocks. On the worker side, the EU and JJ hazards have declined substantially, but not the UE hazard, and a shift-share analysis indicates a large role for equilibrium effects. Finally, the model implies that aging has reduced annual economic growth by 0.27 percentage points.[60] The next section provides additional empirical support for the predictions of the model using variation across US states in the incidence of aging over this period.

[59] Appendix B.5 verifies that the model matches well the tenure distribution over this period using CPS tenure supplements. Of course, the fact that the model matches changes in the stock—tenure—may not be surprising given that it matches well changes in flows over this period. Nevertheless, it serves as a potentially useful robustness exercise in light of the above discussion.

[60] Appendix B.5 shows that aging in the model also captures well changes in a range of additional dimensions over this period, including a modest shift of employment towards larger firms, a decline in the variance of annual income innovations, and an increasing negative skewness of annual income shocks.

## 2.7 Additional Empirical Support of the Hypothesis

To provide additional empirical support to the hypothesis that aging has had important effects on dynamism, I exploit variation in the incidence of aging across US states from 1978–2014 in a panel regression framework. The implicit assumption underlying this approach is that the effects of aging work at the level of the state, so that variation in the timing and magnitude of aging across states can be used to shed light on its effects on dynamism.

The demographic data come primarily from the Annual Social and Economic Supplements of the CPS (March CPS), which I complement with data on the lagged age composition from the US Census Bureau's Intercensal Censi projections.[61] Data on establishment and firm dynamics are from the BDS. I use merged CPS monthly files for worker mobility rates, since the SIPP is not large enough to compute mobility rates at the state-year-age group level. Finally, I construct state real GDP per worker using estimates of state private sector GDP from BEA, regional CPIs from the BLS, and private sector employment from the BDS. Appendix B.1 contains further details on the construction of the data.

### 2.7.1 Methodology

I start by regressing various measures of establishment or firm dynamism, $y_{s,t}$, on the share of the labor force or population aged 19–64 that is aged 40–64 in state $s$ in year $t$, a full set of state fixed effects, $\xi_s$, $T-1$ year effects, $\xi_t$, and time-varying controls, $\mathbf{X}_{s,t}$,

$$y_{s,t} = \text{older}_{s,t} + \xi_s + \xi_t + \mathbf{X}_{s,t}\beta + \varepsilon_{s,t} \tag{2.20}$$

[61] The correlation between the share of older individuals in the Intercensal Censi and the March CPS is not one. As using the Census estimates typically provides even more pronounced results, I use the CPS as a baseline to be conservative (this also allows me to separately look at the age composition of the labor force, which is not available from the Census).

I have considered specifications with reallocation rates and the share of older in both logs and levels. As aging predicts somewhat less of the declines based on the specification in logs, I use that as the benchmark to be conservative (results in levels are available in Appendix B.6). All state-years are equally weighted and standard errors are clustered by state and year.[62] Two-way clustering of standard errors in this way accounts for errors being correlated both within a state over time as well as between states at a given point in time (Cameron et al., 2011; Thompson, 2011). Foote (2007) argues that accounting for this is important when using US state-level data.[63]

In a world where people move in and out of the labor force, it is not a priori clear whether the age composition of the labor force as opposed to the working age population provides the more relevant measure for understanding the effects of aging on the labor market. In light of this, I consider both specifications and find similar results.[64]

All my specifications control for growth in state real GDP per worker. I potentially control also for the share of females, the share of non-white, the share with a college degree (in the benchmark all in logs), the share of the labor force in nine aggregate sectors (again in the benchmark in logs), and a measure of the total state tax rate—accounting for income taxes, corporate taxes, sales taxes, et cetera—constructed by the Tax Foundation for each state for 1978–2012, and the state minimum wage.

To investigate the correlation between aging and worker mobility, I consider a slightly augmented version of the specification (2.20). Specifically, I let $y^a_{s,t}$ denote the EU, JJ and

[62] I have verified that my results hold when weighing states by population. I have also verified that my results are robust to excluding Alaska, which saw particularly rapid aging and declines in dynamism over this period.

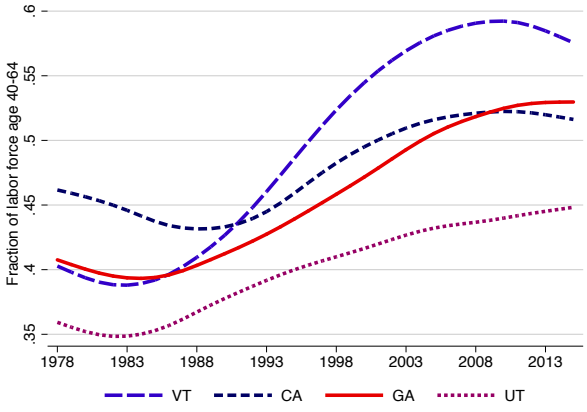
[63] I have also experimented with adjusting standard errors based on methods developed by Driscoll and Kraay (1998) and Thompson (2011) to account for an even more complex error structure, but this does not meaningfully change my conclusions. These results are available on request. With respect to Foote (2007), I also note that my sample contains 10–18 more years of data than Shimer (2001), which alleviates small-$T$ concerns.

[64] I have also considered a specification with the share in four age groups: 19–24, 25–34, 35–44 and 45–54. Although including the share of the labor force in several age groups potentially affords a more detailed understanding of the correlation between the age structure and labor market dynamism, having only one group helps interpretation and simplifies the IV-strategy by avoiding multiple endogenous regressors. This specification delivers similar results in terms of the overall predicted effect of aging over this period, and is available on request.

UE hazard of worker age group $a$ in state $s$ in year $t$, where $a$ is one group of 19–24, 25–34, 35–44, 45–54 and 55–64. I use this as my left-hand side variable and include also a set of dummies for each of the age groups on the right-hand side. All state-year-age bins are equally weighted. Finally, I study the relationship between aging and economic growth by letting the annual growth rate in state real GDP per worker be the left-hand side variable in specification (2.20).

**Identification.** Identification of the specification (2.20) comes from differential changes in the age composition of a state over time across states. To illustrate that there are indeed important differences across states in both the timing and magnitude of aging, Figure 2.7 plots the share of the working age population that is older in four selected states (one in the Northeast, one in the South, one in the Mountain region, and one in the West). Although all states (in fact all 50 states) experienced increases in the share of people in this age group since the 1980s, both the magnitude and timing of these changes differ importantly across states. The empirical framework exploits this variation to study to what extent it correlates with within-state changes in dynamism.

Figure 2.7: Share of working age population that is older in four selected states




*Note: US Intercensal Population estimates 1978–2015. Share of population aged 19–64 that is 40–64.*

Identification in the OLS framework relies on the assumption that aging is exogenous to dynamism. This would be violated if workers move across states in response to variation in dynamism. As noted by Shimer (2001), however, the worry is not as simple as for instance older people always moving to Florida, since that would be accounted for by the state effects. The concern is if one particular age group disproportionately moves in response to *temporary* variation in dynamism, such as if for instance a boom in firm entry in Florida induces disproportionately many young people to move into Florida in the years of the boom.[65] Notice also that the specification (2.20) includes controls for growth in state GDP per worker, so such temporary differential mobility trends by age would have to be in response to a component of dynamism that is orthogonal to GDP growth to potentially pose a problem.

To partly address such concerns, I instrument for the current age distribution using the 10-year lagged age distribution.[66] The exclusion restriction is that the 10-year lagged age composition only affects current dynamism through its effect on the current age distribution. I caution that although this specification may provide an improvement to the baseline OLS specification, concerns about reverse causality remain. That is, it may be that those aged 9–29 move differentially across state borders than those aged 30–54 in response to dynamism 10 year later. Once again, however, such mobility would have to be in response to a component of 10-years later dynamism that is orthogonal to growth in state real GDP per worker in order to be a problem.[67] Appendix B.6 presents first-stage

[65]When using the age composition of the labor force, a similar concern arises if, say, older people disproportionately drop out of the labor force in response to a decline in firm entry. The fact that results are similar using the age composition of the working age population suggests that this is not a first-order issue for the question at hand.

[66]Specifically, the share of the population of 6–55-year olds 10 years earlier that is 30 years or older. 10 years is chosen since annual Intercensal population estimates from the Census Bureau are only available starting in 1969.

[67]I have also considered a specification that instruments for the current share of older individuals in state $s$ by the total number of people age 40–65 born in state $s$, regardless of where they currently reside. I construct this based on Decennial Censi 1970–2000 and annual American Community Survey data from 2001 onwards, interpolating linearly between Census years. Although even more pronounced results hold under this specification, there are concerns about a weak first-stage once one takes into account the fact that the i.i.d. assumption is likely violated. Hence, it is not clear how much to make out of these results. These results are available in Appendix B.6. In ongoing work, I am further exploring other instruments.

regressions, showing that the lagged age composition has a high explanatory power on the current age composition.

### 2.7.2 Results

Table 2.8 presents point estimates and their standard error on the share of older individuals based on the specification (2.20). Columns 1–2 show baseline results with the age composition of the labor force and columns 3–4 with the age composition of the working age population. Across all specifications, the estimated coefficient on the share of older individuals does not appear to be driven by the participation margin. Similar results hold adding covariate controls, sector controls, and the limited measures of policy, suggesting that the correlation between aging and dynamism does not arise through a change in sectoral policy, state taxation or the state minimum wage.[68] These results are available in Appendix B.6.

Panel A shows that across all specifications, a greater share of older individuals is negatively correlated with establishment turnover. Job reallocation is also lower, and by more than what can be explained by establishment turnover alone (indicating lower incumbent dynamics). A similar pattern holds for firm dynamics in Panel B, with even more pronounced results. The point estimates are larger in the IV specification. Taken at face value, this appears at odds with the hypothesis that part of the negative correlation between the share of older individuals and dynamism is driven by endogenous cross-state mobility.[69]

[68] A related hypothesis is that differences in the age composition is associated with differences in demand, as would be the case if younger people consumed very differently from older people. I note with respect to this that all my regressions control for growth in state real GDP per worker, which to some extent should capture such a demand-driven boom. I also note that non-durable consumption displays an almost symmetric inverse u-shape over the life-cycle with a peak at aged 45–50 such that it has not fallen back to the level at age 22 until age 70 (Fernández-Villaverde and Krueger, 2007). This speaks against this hypothesis, although more research is needed on this. If data had been available at the state-sector level, this hypothesis could have been further tested by restricting attention to sectors producing tradable goods. Unfortunately, such data are not made available by the BDS.

[69] I have also conducted tests developed by Davidson and MacKinnon (1993) to test for the exogeneity of the current age distribution. I cannot reject that it is exogenous to dynamism.

Table 2.8: Estimated coefficient on the share of older individuals

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Labor force | | Working age pop. | |
| | OLS | IV | OLS | IV |
| *Panel A: Establishment dynamics* | | | | |
| Job reallocation | -0.448*** | -0.527*** | -0.518*** | -0.539*** |
| | (0.127) | (0.191) | (0.124) | (0.186) |
| Turnover | -0.630*** | -0.961*** | -0.774*** | -0.984*** |
| | (0.203) | (0.268) | (0.202) | (0.256) |
| Entry | -0.668*** | -0.999*** | -0.753*** | -1.022*** |
| | (0.189) | (0.247) | (0.188) | (0.245) |
| Exit | -0.600** | -0.940*** | -0.809*** | -0.962*** |
| | (0.243) | (0.322) | (0.239) | (0.304) |
| *Panel B: Firm dynamics* | | | | |
| Turnover | -0.764*** | -1.266*** | -0.923*** | -1.296*** |
| | (0.230) | (0.302) | (0.223) | (0.299) |
| Entry | -0.827*** | -1.361*** | -0.932*** | -1.393*** |
| | (0.199) | (0.278) | (0.195) | (0.291) |
| Exit | -0.712** | -1.203*** | -0.921*** | -1.231*** |
| | (0.298) | (0.355) | (0.283) | (0.339) |
| *Panel C: Worker dynamics* | | | | |
| EU hazard | -0.441*** | -0.926** | -0.495*** | -0.941** |
| | (0.146) | (0.375) | (0.160) | (0.406) |
| JJ hazard | -0.501** | -0.112 | -0.642*** | -0.127 |
| | (0.226) | (0.728) | (0.215) | (0.824) |
| UE hazard | -0.091 | -0.223 | -0.024 | -0.227 |
| | (0.126) | (0.273) | (0.123) | (0.280) |
| *Panel D: Growth* | | | | |
| GDP per worker growth | -0.066 | -0.090** | -0.063 | -0.092** |
| | (0.047) | (0.040) | (0.043) | (0.039) |

*Note: BDS, BEA, CPS and Intercensal Censi 1978–2014, HP-filtered annual data with smoothing parameter 6.25. Point estimates on the share of the labor force/population aged 19–64 that is aged 40 and older based on model* (2.20)*. Panel A–B control for state, year and annual growth in state real GDP per worker; Panel C controls for state, year, age and annual growth in state real GDP per worker; Panel D controls for state and year. All shares and reallocation rates are in logs. Standard errors clustered at state and year. *statistically significant at 10%; **statistically significant at 5%; ***statistically significant at 1%.*

Panel C shows that an older workforce is negatively correlated with the EU hazard, controlling for the individual's own age. The IV estimate is again larger than the OLS estimate. A larger share of older is also associated with a lower JJ hazard, but the IV estimate is smaller and not statistically significant. The JJ regressions are based on a substantially reduced sample since the measure is only available starting in 1994, which may account

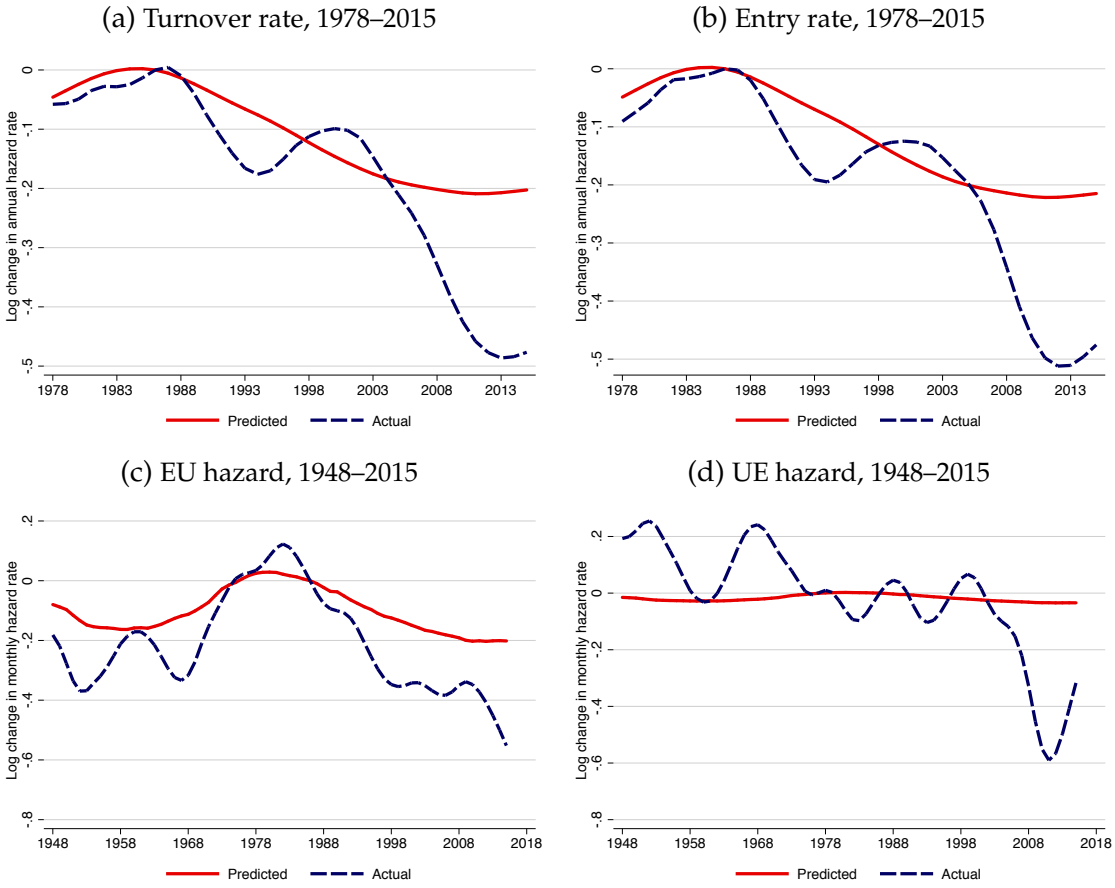
for the lack of statistical significance. There is no evidence of a correlation between aging and the UE hazard. Finally, Panel D shows that an older workforce is negatively correlated with economic growth, but only the IV estimates are statistically significant.

To illustrate the magnitude of the point estimates, I use the estimated coefficients from the panel regressions to predict dynamism at the national level over this period. I emphasize that this exercise is only meaningful under several strong assumptions. First, the estimates must obviously reflect a causal relationship. Although the IV specification gets somewhat closer to causality, there remains a concern that also the 10-year lagged age composition is endogenous to current dynamism (conditional on state fixed effects, year effects, and state GDP per worker growth). Second, it assumes that the cross-state estimates are informative about the time trend at the national level. To the extent that there are effects of aging that work at the national level but not the state level, these predictions may understate or overstate the true impact of aging on dynamism in the US over this period. It is difficult to address these concerns without more structure, which serves as a key motivation for interpreting the data through the lens of a structural model. Nevertheless, it remains of interest to compare the magnitude of the cross-state estimates to the changes in dynamism over this period.

Figure 2.8 plots the predicted impact of aging on establishment turnover, establishment entry, the EU hazard and the UE hazard at the national level based on the OLS panel estimates, normalized to zero in 1986 (the IV estimates provide an even more pronounced picture). I use data on EU mobility, UE mobility and the age composition of the labor force from the BLS to extend the series for the EU and UE hazard back to 1948. If the cross-state panel estimates reflect a causal relationship and they are informative about the effects of aging at the national level, they would imply that aging explains over 40 percent of the declines in establishment turnover, entry and the EU hazard, while accounting for little of the recent decline in the UE hazard. The direct effect of aging accounts for only a third of the predicted variation in the EU hazard. Appendix B.6 summarizes these pre-

dictions, showing that even more pronounced conclusions hold using measures of firm dynamics or unweighted establishment or firm turnover rates, that aging also predicts 30–60 percent of the decline in the JJ hazard, and that similar results hold regardless of whether the labor force or working age population is used. Aging predicts a substantial, one percentage point decline in GDP per worker growth, but the error bound is wide.

Figure 2.8: Predicted impact of aging on select measures of dynamism




*Note: BDS, BLS, CPS and Intercensal Censi 1948–2015. Predicted change in establishment turnover, establishment entry, the EU hazard and the UE hazard due to aging at the national level based estimates in column 1 in Table 2.8 in solid red, raw data in dashed blue.*

### 2.7.3 Other important changes

Aging is only one of several important changes to the US labor force over the last decades. I briefly discuss four other prominent changes (see Appendix B.2 for further details). First and second, the US labor force has become increasingly gender and racially diverse over

this period. Including the share female and non-white in regression (2.20), however, neither coefficient is typically statistically significant. Furthermore, predicting the change in dynamism due to these factors, the predicted effect is small (typically a net increase). Hence, although the US labor force has become more diverse along these dimensions, the changes have been relatively small, statistically not associated with changes in dynamism and if anything predict a small increase in dynamism.

Third, the share of the labor force with a college degree or more has risen substantially over this period. Across most specifications, the share with a college degree is associated with higher dynamism such that the predicted effect of changes in education goes the "wrong" way.[70] Although I interpret these results very cautiously in light of the fact that educational choices are endogenous, at least as a first pass it does not appear as though changes in educational attainment explain the large decline in dynamism over this period.

Fourth and related to the changing age composition of the labor force, labor supply growth has slowed over this period. The decline was particularly pronounced in the late 1970s and early 1980s, as the baby boomers entered the labor market. As noted earlier, in recent, related work Karahan et al. (2016) argue that the decline in labor supply growth may explain up to a quarter of the fall in firm entry over this period. I verify their conclusion that labor supply growth is positively correlated with entry by including it in regression (2.20). This, however, has no significant effect on the estimated coefficient on the share of older individuals, which remains statistically significant and economically large.[71] Appendix B.6 presents a full range of results controlling for labor supply growth. I conclude that although falling labor supply growth over this period is relevant for understanding the entry margin, changes in the age composition remain of first-order importance.

[70] This should not be confused with the *direct* effect of education on worker reallocation, which is typically negative.

[71] The decline in labor supply growth also predicts *increases* in the exit rate, the EU hazard and the JJ hazard.

## 2.8 Conclusion

The US has aged substantially over the past 30 years, while business dynamism, labor market fluidity and economic growth have declined. This paper embeds endogenous growth through creative destruction in an equilibrium job ladder model, and finds that aging explains 40–50 percent of the declines in business dynamism and labor market fluidity, and a 0.27 percentage point decline in annual economic growth. Cross-state variation supports these predictions.

Several questions remain. Although important, aging typically accounts for half or less of the large declines in dynamism over this period. In light of this, an important outstanding question is what other factors contributed to the declines. Lower labor supply growth may have contributed to reduced firm entry (Karahan et al., 2016) while occupational licensing (Kleiner and Krueger, 2013), higher training requirements (Cairo, 2013) and more stringent employment protection (Autor et al., 2007) may be factors behind lower worker reallocation. More research is needed to better understand the large declines in dynamism in the US over this period.

Anecdotal evidence suggests that population aging has contributed to a sclerotic labor market and poor economic growth in other countries, for example Japan. Yet a rigorous cross-country analysis is currently missing. Although such a study is complicated by the lack of long-time series of comparable data across countries, the increasing availability of administrative data may make it feasible. In light of rapidly aging populations in many developed countries, more research is needed to understand its effects on labor market performance.

# Chapter 3

# The Recruiting Process and Employment Fluctuations

## 3.1 Introduction

The decisions of whether to advertise a job opening, what applicant to hire and which positions to apply for are key decisions of firms and workers in the labor market. Yet despite the central role played by the hiring process in driving unemployment fluctuations, many theories of the labor market model it in reduced form as the single decision of when to post a vacancy. Although this approach has proven hugely successful in explaining a range of phenomena in labor markets and understanding the impact of different policies, it is at odds with increasing empirical evidence that hiring is an involved process.[1] In this paper, I develop a general equilibrium model that matches recent microevidence on the hiring process, and use it to reassess the impact of aggregate shocks on the labor market when hiring is a complex process.

[1]For instance, Davis and Samaniego de la Parra (2017) show that the posting phase constitutes only a fifth of the overall time it takes to fill a vacancy, indicating a prominent role for the screening phase of the hiring process, while Faberman et al. (2017) document large differences in application rates, success rates and starting wages between unemployed and employed workers, potentially suggesting that workers make an active decision of what jobs to apply for.

The environment I consider consists of single-worker firms and workers who search for better jobs on and off the job. Firms pay a cost to post advertisements for open positions. Informational frictions imply that searching workers only learn about some of these open positions at any point in time. When workers learn about an open position, they observe a noisy signal of how good the match would be and decide whether to apply for the job. Employers receive applications and spend resources screening applicants. Screening reveals how good a match the applicant would be for the job, and hiring commences if the fit is sufficiently good.

In line with recent microevidence in Faberman et al. (2017), the model predicts that the unemployed submit more applications than the employed but are less likely to convert an application into a job and are paid lower starting wages conditional on landing a job. This results from unemployed workers having a low opportunity cost of moving to a new job, inducing them to also apply for jobs that they in expectation are worse fits for. Consequently, a labor market with many unemployed workers is an environment in which employers receive many applications from workers who are not particularly well suited for the job. By lowering the average quality of applications, the cost of hiring a successful applicant increases. This counters firms' inclination to hire more when unemployment is high since they can strike a great bargain with unemployed workers. Depending on the relative strength of these two opposing forces, the economy may display a multiplicity of stationary equilibria.

To assess the model's ability to match large differences in application, interview and mobility rates as well as starting wages between unemployed and employed workers, I calibrate the model to recently available data on worker application behavior. The model fits well the empirical patterns. The unemployed submit 10 times as many applications as the employed, but have a lower success rate per application and receive lower starting wages, also conditional on observables and prior wages. The model matches such large differences in application behavior and job search outcomes without resorting to

exogenous differences in search efficiency and offer distributions between unemployed and employed workers.

In order to quantify the implication of these differences in application behavior for aggregate labor market outcomes, I use data on hiring costs to document that the cost of screening applicants constitutes as much as 80 percent of the overall cost of hiring. This is consistent with evidence in Davis and Samaniego de la Parra (2017) that the mean posting duration is only one-fifth of the average time it takes to fill a vacancy, suggesting a large role played by the screening phase of the hiring process. I find that screening costs of this magnitude are not sufficiently large to push the economy into multiple stationary equilibria, but they imply substantially larger propagation of aggregate productivity shocks to labor market flows. Incorporating aggregate shocks into the model and feeding in shocks of the same magnitude as in the data, unemployment is three times as volatile as in a model without applications and screening, matching well the volatility of the unemployment rate in the data. All of this is driven by a substantially more volatile job finding rate, in line with findings in Shimer (2012). I conclude that a better understanding of the hiring process significantly affects conclusions regarding the importance of aggregate productivity shocks for business cycle fluctuations in the unemployment rate.

My project is particularly related to three strands of the literature. The first documents differences in search behavior between unemployed and employed workers. Prior to Faberman et al. (2017) recent contribution, little was known about these differences.[2] To interpret their findings, they construct a parsimonious partial equilibrium model which suggests that employed workers must be much more efficient at converting applications to offers and sample from an exogenously better wage offer distribution. As they note, however, their study leaves open the important question of why wage offers are so much better for the employed. This paper proposes a micro-founded theory of why unemployed workers submit more applications but are less successful per application and

[2]Blau and Robins (1990) and Holzer (1987) are two early contributions.

receive lower starting wages. I also assess the implication of such micro behavior for aggregate economic outcomes in a general equilibrium framework.

The second strand of the literature studies the hiring process from the perspective of firms. Davis and Samaniego de la Parra (2017) document important facts about the hiring process, including that the advertising phase constitutes only a fifth of the overall time it takes to fill a vacancy. Wolthoff (2018) is one of the few theoretical models with an application decision of workers and a screening process of firms. To simplify, his directed search framework abstracts from on-the-job search and by nature of search being directed, his equilibria are constrained efficient. Hence, his analysis does not focus on the application externality at the core of this paper. Motivated by the evidence in Davis et al. (2013) that fast-growing firms fill vacancies faster, Kaas and Kircher (2015) and Gavazza et al. (2017) study firms' hiring behavior over the business cycle, specifically their choice of recruiting intensity per vacancy. Relative to these papers, I focus also on workers' decision of whether to apply for a job, and how this interacts with firms' hiring process.

The third strand of the literature studies the possibility that the labor market may display multiplicity of equilibria and relatedly the extent to which it propagates aggregate shocks. It is well known that multiplicity may arise if matching displays increasing returns (Diamond, 1982; Diamond and Fudenberg, 1989), but there is little empirical support for this notion. Eeckhout and Lindenlaub (2017) show that the search behavior of employed workers may give rise to multiplicity of equilibria, such that large fluctuations in labor market outcomes are possible absent fundamental shocks. Relative to them, I focus on the decision of both unemployed and employed workers of whether to apply for a job as distinct from whether to search actively.

As noted by Shimer (2005), the benchmark Mortensen and Pissarides (1994) model struggles to generate sufficient amplification of productivity shocks to labor market stocks and flows. A large subsequent literature attempts to resolve this apparent "puzzle." Hagedorn and Manovskii (2008) do so by estimating a very high value of unemployment. Re-

cent evidence in Mas and Pallais (2017), however, suggests that the flow value of unemployment is 60–70 percent of the average wage—substantially below the 95 percent value in Hagedorn and Manovskii (2008). Another approach is to make starting wages sticky as in Hall (2005a), but as noted by Mortensen and Nagypal (2007) inflexible wages are not a panacea in the sense that it still requires the difference between match output and the flow value of unemployment to be small. Pries (2008) introduces ex ante worker heterogeneity into the standard model to argue that the pool of unemployed shifts towards workers with a higher value of leisure during downturns, dampening firms' incentives to create jobs in a recession. He abstracts from on-the-job search, which is at the core of the current paper, and he requires exogenously given, time-varying differences in the separation rate by worker type to generate this result. The current model proposes a microfoundation for differences in the composition of applicants over the business cycle. Furthermore, it may be harder for firms to figure out whether a worker is a poor match for the specific position, as in the current paper, versus whether the worker is in general a poor worker.

Perhaps the paper most related to the current is Hall (2005b), who studies the impact of self-selection among applicants prior to sending an application. Specifically, he argues that unemployed workers are pickier in booms, because the opportunity cost of moving into a bad match increases when jobs are easy to find. In contrast, the current model introduces on-the-job search and studies changes in the composition of the pool of applicants along the unemployed-employed margin. This is motivated by recent microevidence indicating large differences in search behavior between the unemployed and employed.

This paper is organized as follows. Section 3.2 outlines a stationary version of the model and characterizes stationary equilibria. Section 3.3 estimates a partial equilibrium version of the model using data on application, interview and worker mobility rates as well as starting wages. Section 3.4 estimates the firm side of the model to assess the general equilibrium propagation of shocks on the labor market. Section 3.5 concludes.

## 3.2 A Stationary Model

This section develops a continuous time model of a labor market in which workers are selective in terms of what jobs they apply for and firms pay to advertise jobs and screen applicants. I start with a stationary environment and introduce aggregate shocks in Section 3.4.

### 3.2.1 Environment

The economy consists of a unit mass of infinitely-lived workers and some positive mass of one-worker firms who all discount the future at rate $\rho > 0$. I describe each agent in sequence.

**Firms.** Production takes place at the level of a match between a firm and a worker. The match is characterized by its productivity $p$, which may be unviable, bad or good. Bad matches produce flow output $p_b$ and good matches $p_g > p_b$ of a unique multipurpose good. Unviable matches risk destroying so much value that it is not worth forming them.[3] The productivity is realized at the time of formation and remains fixed for the duration of the match, with the exception that independently of current productivity it becomes unviable at Poisson rate $\delta$. Denote by $\pi_i$ the probability that a newly formed match is of productivity $p_i$.

In order to hire workers, firms pay a flow cost $c_v$ to spread information about open positions. For instance, many job boards charge a fee. For any application it receives, the firm has to pay a screening cost $c_s$ associated with reading through applicants' material. If a match is unviable, it is revealed at this stage with probability $\eta \in [0, 1]$. Furthermore, the pre-screening phase informs the firm of the applicant's employment status. If the firm so desires, it may discard an applicant with a particular employment background. For any

[3]For instance, online recruiting site CareerBuilder reports that 41 percent of companies say that a bad hire in the last year has cost them at least $25k while 25 percent say it has cost them at least $50k.

remaining applicant, the firm has to pay a cost $c_i$ to interview her. Having interviewed the worker, the productivity of the potential match becomes public information. I assume that the risk associated with forming an unviable match is so great that it is never optimal to hire without screening and interviewing applicants.

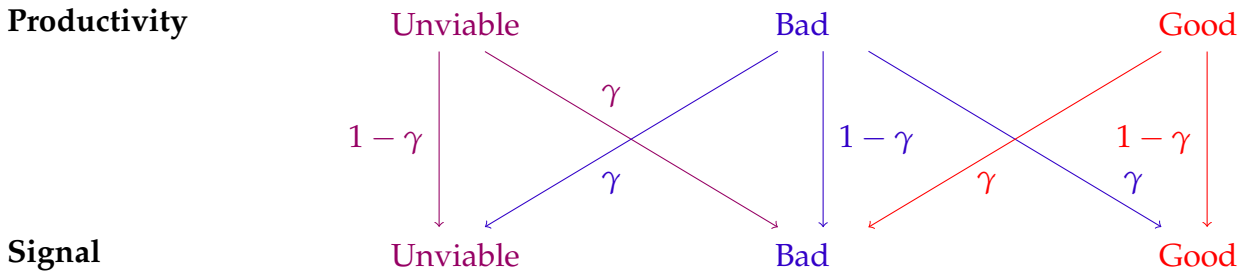
**Workers.** Workers can be unemployed or employed. An unemployed worker enjoys flow value $b$ while an employed worker earns endogenous wage $w$. I discuss how wages are determined momentarily. Both unemployed and employed workers search for jobs. Specifically, workers in bad matches (henceforth mismatched workers) search with relative efficiency $\phi$, while those in good matches (henceforth well-matched workers) do not search actively. As will become clear, the return to searching is zero for well-matched workers.

Due to informational frictions, workers do not immediately learn about all open positions. Denote by $\lambda$ unemployed workers' endogenous Poisson arrival rate of information about open positions—$\phi\lambda$ is hence mismatched workers' Poisson arrival rate of information about open positions. When a worker contacts an open position, she does not know with certainty how good a fit she would be with the position. Instead, she observes a signal $s$ of the productivity of the potential match. Denote by $S(s|p)$ the conditional probability of observing signal $s$ given underlying productivity $p$. I assume that:

$$S(s_j|p_i) = \begin{cases} \gamma & \text{if } j = b \\ 1-\gamma & \text{if } j = i \\ 0 & \text{o.w.} \end{cases}, \quad i \in \{u, g\}, \qquad \text{and} \qquad S(s_j|p_b) = \begin{cases} \gamma & \text{if } j \in \{u, g\} \\ 1-2\gamma & \text{if } j = b \end{cases}$$

Based on the signal, the worker decides whether to apply for the job, which comes at cost $c_a$. Figure 3.1 further illustrates the assumed structure of signals relative to underlying productivity.

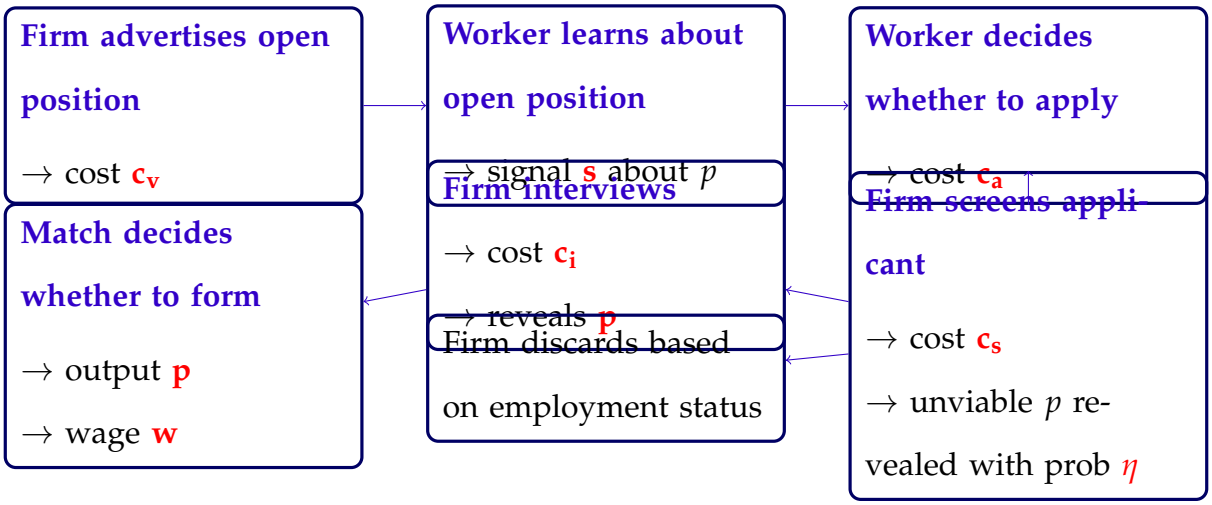
Figure 3.1: Structure of signals




**Timing.** Figure 3.2 illustrates the timing of the model. First, firms advertise open positions at cost $c_v$. Second, workers learn about open positions and observe a signal of the productivity of the potential match. Third, workers decide whether to apply for the position by paying cost $c_a$. Fourth, firms pay a cost $c_s$ to screen applications they receive, which reveals a fraction $\eta$ of unviable matches. It also learns the applicant's employment status and decides whether to proceed with the applicant. Fifth, it interviews applicants at cost $c_i$, which reveals the productivity of the match. Sixth, hiring takes place if the match is sufficiently good, production commences and wages are paid.

**Matching.** Denote by $u$ the endogenous unemployed rate, by $e_b$ the endogenous mass of mismatched workers, by $e_g$ the endogenous mass of well-matched workers, by $e = u + \phi e_b$ aggregate search intensity, by $v$ the endogenous mass of open positions, and by $\theta = v/e$ labor market tightness. The flow of meetings $m$ can be represented by a constant returns to scale matching function, $m(v, e)$, which is increasing and strictly concave in both arguments. Because of constant returns, the rate at which unemployed workers learn about open positions, $m(v, u)/u = m(v/u, 1) \equiv \lambda$, and the rate at which an open position contacts a potential applicant, $m(v, u)/v = \lambda/\theta$, are only functions of labor market tightness, $\theta = v/e$,

Figure 3.2: Timing of hiring events




**Wage setting.** Workers and firms bargain over the surplus of the match following Cahuc, Postel-Vinay and Robin (2006), with worker bargaining power $\beta$. I will later restrict attention to a positive but small worker bargaining power, $\beta \to 0$.

### 3.2.2 Workers' value functions

Denote by $V_u$ the value of an unemployed worker, by $V_b$ the joint value of a bad match, and by $V_g$ the joint value of good match. To save on notation, I suppress for now the dependence of the value functions on the aggregate state $\{v, u, e_b\}$. Because the bargaining protocol ensures that all decisions are bilaterally optimal, to solve for the allocation I do not need to consider separately the value of a matched worker and a matched firm.[4]

**Value of unemployment.** An unemployed worker enjoys flow value $b$ and contacts open positions at rate $\lambda$. The match draws a productivity and the worker observes a signal of the productivity. Based on the signal, she decides whether to submit an application. That is, the value of unemployment solves

[4]As this is a standard insight in these type of bargaining models, I do not prove it here (see, for instance, Jarosch, 2015).

$$
\begin{aligned}
\rho V_u &= b + \lambda \Bigg[ \underbrace{\left(\pi_g(1-\gamma) + \pi_b\gamma\right)}_{\text{Good signal}} \max\left\{ \frac{\pi_g(1-\gamma)\beta\left(V_g - V_u\right)}{\pi_g(1-\gamma)+\pi_b\gamma} + \frac{\pi_b\gamma\beta\left(V_b - V_u\right)}{\pi_g(1-\gamma)+\pi_b\gamma} - c_a, 0 \right\} \\
&+ \underbrace{\left(\pi_g\gamma + \pi_b(1-2\gamma) + \pi_u\gamma\right)}_{\text{Bad signal}} \max\left\{ \frac{\pi_g\gamma\beta\left(V_g - V_u\right)}{\pi_g\gamma+\pi_b(1-2\gamma)+\pi_u\gamma} + \frac{\pi_b(1-2\gamma)\beta\left(V_b - V_u\right)}{\pi_g\gamma+\pi_b(1-2\gamma)+\pi_u\gamma} - c_a, 0 \right\} \\
&+ + \underbrace{\left(\pi_b\gamma + \pi_u(1-\gamma)\right)}_{\text{Useless signal}} \max\left\{ \frac{\pi_b\gamma\beta\left(V_b - V_u\right)}{\pi_b\gamma+\pi_u(1-\gamma)} - c_a, 0 \right\} \Bigg]
\end{aligned} \tag{3.1}
$$

An unemployed worker applies for a position that sends a good signal if

$$
\frac{\pi_g(1-\gamma)\beta\left(V_g - V_u\right)}{\pi_g(1-\gamma)+\pi_b\gamma} + \frac{\pi_b\gamma\beta\left(V_b - V_u\right)}{\pi_g(1-\gamma)+\pi_b\gamma} \geq c_a
$$

She applies for a position that sends a bad signal if

$$
\frac{\pi_g\gamma\beta\left(V_g - V_u\right)}{\pi_g\gamma+\pi_b(1-2\gamma)+\pi_u\gamma} + \frac{\pi_b(1-2\gamma)\beta\left(V_b - V_u\right)}{\pi_g\gamma+\pi_b(1-2\gamma)+\pi_u\gamma} \geq c_a
$$

Finally, she applies for a position that sends an unviable signal if

$$
\frac{\pi_b\gamma\beta\left(V_b - V_u\right)}{\pi_b\gamma+\pi_u(1-\gamma)} \geq c_a
$$

Denote by $a_u(s_i) = \{0, 1\}$ the application decision of the unemployed conditional on signal $s_i$.

**Value of a bad match.** The value of a bad match solves

$$\begin{aligned}\rho V_b &= p_b + \delta\left(V_u - V_b\right) + \lambda\left[\underbrace{\left(\pi_g(1-\gamma)+\pi_b\gamma\right)}_{\text{Good signal}}\max\left\{\frac{\pi_g(1-\gamma)\beta\left(V_g-V_b\right)}{\pi_g(1-\gamma)+\pi_b\gamma}-c_a,0\right\}\right.\\ &+ \left.\underbrace{\left(\pi_g\gamma+\pi_b(1-2\gamma)+\pi_u\gamma\right)}_{\text{Bad signal}}\max\left\{\frac{\pi_g\gamma\beta\left(V_g-V_b\right)}{\pi_g\gamma+\pi_b(1-2\gamma)+\pi_u\gamma}-c_a,0\right\}\right] \qquad (3.2)\end{aligned}$$

A bad match produces $p_b$ and contacts open positions at rate $\phi\lambda$. It applies for a position that sends a good signal if

$$\frac{\pi_g(1-\gamma)\beta\left(V_g-V_b\right)}{\pi_g(1-\gamma)+\pi_b\gamma} \geq c_a$$

It applies for a position that sends a bad signal if

$$\frac{\pi_g\gamma\beta\left(V_g-V_b\right)}{\pi_g\gamma+\pi_b(1-2\gamma)+\pi_u\gamma} \geq c_a$$

Finally, it is never optimal for a bad match to apply for an open position that sends an unviable signal.[5] I denote by $a_b(s_i)$ the optimal application decision of bad matches conditional on receiving signal $s_i$.

**Value of a good match.** Finally, the value of a good match solves

$$\rho V_g = p_g + \delta\left(V_u - V_g\right) \qquad (3.3)$$

Good matches cannot gain anything from applying to new positions and are hence assumed to not search actively.

[5]Notice the assumption that the worker can exploit the prospect of potentially applying for a job to bargain up her wage with her current employer. This arguably strong assumption greatly improves tractability by ensuring that all decisions are made to maximize bilateral surplus of the match.

**Simplifying assumption.** To simplify the analysis, I assume that application costs are small, $c_a \to 0$, which from personal experience seems reasonable: the marginal cost of submitting one more application via EconJobMarket is close to zero. Second, I follow Lise and Robin (2017) in assuming that workers' bargaining power is low, $\beta \to 0$, which substantially simplifies the dynamic analysis. I require, however, that these limits go to zero in such a way that workers apply for any positions that offers a positive expected gain.

**Proposition 5.** *The value functions* (3.1)–(3.3) *equal*

$$V_u = \frac{b}{\rho}, \qquad \textit{and} \qquad V_i = \frac{1}{\rho+\delta}\left[p_i + \frac{\delta}{\rho}b\right], \quad i = \{b, g\} \tag{3.4}$$

*and application behavior is characterized by*

$$a_u(s_i) = 1, \quad \forall i \qquad \textit{and} \qquad a_b(s_i) = \begin{cases} 0 & \textit{if } i = u \\ 1 & \textit{o.w.} \end{cases} \tag{3.5}$$

That is, both the value of unemployment and of a match are independent of labor market tightness, $\theta$. In the equilibrium considered here, unemployed workers apply for all positions regardless of the signal, while mismatched workers apply for positions that send bad or good signals.

### 3.2.3 Equilibrium

In an equilibrium with positive job creation, firms enter until the gains from doing so are exhausted. Denote by $J$ the expected value an open position to a firm, by $X(u)$ the expected value of interviewing an applicant who is unemployed, and by $X(e)$ the expected

value of interviewing an applicant who is employed. The value of an open job, $J$, solves

$$\begin{aligned} J &= q\frac{u}{e}\left[\left((1-\eta)\pi_u+\pi_b+\pi_g\right)\max\left\{X(u),0\right\}-c_s\right] \\ &+ q\frac{\phi e_b}{e}\left(\gamma\pi_u+(1-\gamma)\pi_b+\pi_g\right)\left[\frac{(1-\eta)\gamma\pi_u+(1-\gamma)\pi_b+\pi_g}{\gamma\pi_u+(1-\gamma)\pi_b+\pi_g}\max\left\{X(e),0\right\}-c_s\right] \end{aligned}$$

An open job contacts a potential applicant at endogenous Poisson rate $q$. The worker is unemployed with probability $u/e$, in which case she always applies for the job. The firm screens the worker, which reveals an unviable match with probability $\eta$. Since there are no gains from proceeding with an applicant who is known to be unviable, she is discarded. The firm also learns the employment status of the applicant, and decides whether it is worthwhile to bring her in for an interview. Denote by $i(u) = \{0,1\}$ the decision to interview an unemployed worker.

With probability $\phi e_b/e$ the potential applicant is mismatched. The worker applies for the position if the signal is bad or good. The firm pays the cost of screening, which reveals an unviable match with probability $\eta$. The firm also learns the employment status of the applicant and decides whether to proceed to interview her. Denote by $i(e) = \{0,1\}$ the decision to interview an employed worker. Notice that it is never optimal for a firm to post a vacancy not intending to screen applicants, since no new information has been revealed between these two decisions.

The value of interviewing an unemployed worker equals

$$\begin{aligned} X(u) &= \frac{1}{(1-\eta)\pi_u+\pi_b+\pi_g}\left[(1-\eta)\pi_u(-c_i)+\pi_b\left(V_b-V_u-c_i\right)+\pi_g\left(V_g-V_u-c_i\right)\right] \\ &= \frac{\pi_b\left(V_b-V_u\right)+\pi_g\left(V_g-V_u\right)}{1-\eta\pi_u}-c_i \end{aligned}$$

while the value of interviewing an employed worker equals

$$\begin{aligned} X(e) &= \frac{1}{(1-\eta)\gamma\pi_u + (1-\gamma)\pi_b + \pi_g}\left[(1-\eta)\gamma\pi_u(-c_i) + (1-\gamma)\pi_b(-c_i) + \pi_g\left(V_g - V_b - c_i\right)\right] \\ &= \frac{\pi_g\left(V_g - V_b\right)}{(1-\eta)\gamma\pi_u + (1-\gamma)\pi_b + \pi_g} - c_i \end{aligned}$$

If an unemployed applicant passes the screening phase, the firm proceeds to interview her if

$$X(u) \geq c_i \iff \frac{\pi_b\left(p_b - b\right) + \pi_g\left(p_g - b\right)}{1 - \eta\pi_u} \geq (\rho + \delta)c_i \tag{3.6}$$

where I substituted for the value functions using (3.4). It interviews an employed person if

$$X(e) \geq c_i \iff \frac{\pi_g\left(p_g - p_b\right)}{(1-\eta)\gamma\pi_u + (1-\gamma)\pi_b + \pi_g} \geq (\rho + \delta)\, c_i \tag{3.7}$$

To simplify the exposition, I henceforth impose conditions (3.6)–(3.7). Section 3.3 estimates this to be the empirically relevant case. Under (3.6)–(3.7), the free entry condition becomes

$$\begin{aligned} J &= q\frac{u}{e}\left[\pi_b\left(V_b - V_u\right) + \pi_g\left(V_g - V_u\right) - (c_s + c_i) + c_i\eta\pi_u\right] \\ &+ q\frac{\phi e_b}{e}\left[\pi_g\left(V_g - V_b\right) - (c_s + c_i)\left((1-\eta)\gamma\pi_u + (1-\gamma)\pi_b + \pi_g\right) + c_i\eta\gamma\pi_u\right] \end{aligned} \tag{3.8}$$

A standard law of motion implies that the stationary distribution of workers equals

$$u = \frac{\delta}{\delta + \lambda(\pi_b + \pi_g)}, \qquad e_b = \frac{\lambda\pi_b\delta}{(\delta + \phi\lambda\pi_g)(\delta + \lambda(\pi_b + \pi_g))} \tag{3.9}$$

**Definition 4** (Stationary equilibrium)**.** *A stationary equilibrium with positive vacancy creation consists of value functions* $\left\{V_u, V_b, V_g\right\}$*, a mass of vacancies* $v$*, and a distribution of workers* $\left\{u, e_b, e_g\right\}$ *such that (a) the value functions solve the problem of unemployed workers and matches; (b) the free entry condition holds with equality; and (c) the distribution of workers is consistent with the law of motion and is stationary.*

### 3.2.4 Characterization of stationary equilibrium

Using the distribution of workers (3.9), the ratio of unemployed searchers to total searchers equals,

$$\frac{u}{e}\Big(\theta\Big) = \frac{\delta + \pi_g \phi \lambda(\theta)}{\delta + (\pi_b + \pi_g)\phi\lambda(\theta)} \tag{3.10}$$

This is the first key equilibrium condition, an augmented Beveridge Curve that relates the share of actively searching workers who is unemployed to labor market tightness $\theta$. It falls in tightness since $\lambda'(\theta) > 0$—a tighter labor market implies that workers find jobs quicker, which in the stationary economy translates into a smaller share of searching workers being unemployed.

Substituting the value functions into the free entry condition (3.8) and simplifying, I get the second key equilibrium condition, a Job Creation condition,

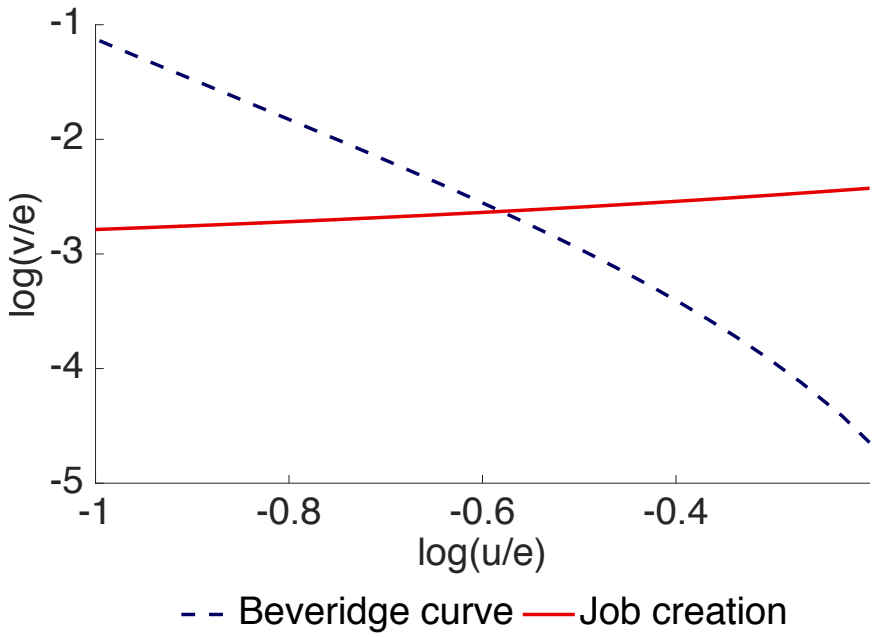
$$\begin{aligned} \frac{c_v \theta\left(\frac{u}{e}\right)}{\lambda\left(\theta\left(\frac{u}{e}\right)\right)} &= \pi_g \frac{p_g - p_b}{\rho + \delta} - (c_s + c_i)\left(\gamma\pi_u + (1-\gamma)\pi_b + \pi_g\right) + c_i \eta \gamma \pi_u \\ &+ \frac{u}{e}\left[(1-\pi_u)\frac{p_b - b}{\rho+\delta} - (c_s + c_i)\left((1-\gamma)\pi_u + \gamma\pi_b\right) + c_i\eta(1-\gamma)\pi_u\right] \end{aligned} \tag{3.11}$$

The left hand side of equilibrium condition (3.11) reflects the expected cost of contacting one potential applicant. It is increasing in labor market tightness $\theta$ since $\lambda$ is strictly concave: when the labor market is tight, firms have to spend more to meet one potential applicant. The right hand side reflects the expected return to contacting a potential applicant. If the costs of screening and interviewing are zero, $c_s = c_i = 0$, it is increasing in the share of actively searching workers who are unemployed, $u/e$, as illustrated by Figure 3.3. This reflects that fact that absent such costs, a firm would like as many applicants as possible to be unemployed since they are likely to accept a job offer and conditional on accepting it they can be bargained hard with. It is straightforward to show that:

**Proposition 6.** *The economy without screening and interviewing costs admits a unique stationary equilibrium.*

*Proof.* See Appendix. □

Figure 3.3: Equilibrium determination without screening and interviewing costs




Given the assumption that workers' bargaining power is zero, $\beta = 0$, starting wages do not respond to tightness conditional on the employment status of the applicant. That is, the equilibrium mechanism in this environment is not that wages out of unemployment rise when the labor market becomes tighter. On the job search, however, implies that a greater tightness is associated with a larger share of applicants coming from employment. Since these applicants are less likely to accept a job offer and have to be paid more conditional on accepting the offer, the value of opening a job falls in tightness.

More generally, the following propositions characterize equilibria in this economy,

**Proposition 7.** *If* $\pi_g \left(\frac{p_g - b}{\rho+\delta}\right) + \pi_b \left(\frac{p_b - b}{\rho+\delta}\right) > c_s$, *there exists at least one stationary equilibrium with positive vacancy creation.*

*Proof.* See Appendix. □

**Proposition 8.** *If* $\pi_g \left(\frac{p_g - b}{\rho+\delta}\right) + \pi_b \left(\frac{p_b - b}{\rho+\delta}\right) > c_s$ *and* $\frac{p_b - b}{\rho+\delta} > c_s \frac{\pi_b \gamma + \pi_u (1-\gamma)}{\pi_g + \pi_b}$*, there exists a unique stationary equilibrium with positive vacancy creation.*

*Proof.* See Appendix. □

As the costs of screening and interviewing increase, it becomes less and less attractive to meet unemployed workers. Although they are unlikely to reject a job offer and they get paid little, the unemployed apply for many positions that they are unlikely to be well suited for. By flooding employers with applications that are unlikely to be good, it drives up the cost of hiring. That is, as screening and interviewing costs become more important, the right hand side of equilibrium condition (3.11) increases by less and less in the share of actively searching workers that is unemployed $u/e$, until at some point it starts to fall in $u/e$. As we will see, this force may be so strong that the economy displays multiplicity of stationary equilibria.

### 3.2.5 Wages.

To identify all parameters of the model, I also require using wage data. To this end, denote by $W_b(w)$ the value to a worker of being employed in a poor match when paid wage $w$ and by $W_g(w)$ the value to a worker of being employed in a good match when paid wage $w$. The two value functions solve

$$\begin{aligned}
\rho W_b(w) =& w + \phi\lambda \left(\pi_b(1-\gamma) + \pi_g\right)\left(V_b - W_b(w)\right) + \delta\left(V_u - W_b(w)\right) \\
\rho W_g(w) =& w + \delta\left(V_u - W_g(w)\right)
\end{aligned}$$

Denote by $w_i(j)$ the wage of a worker in a match with productivity $i$ who at the time of her last renegotiation had as outside option a match with productivity $j$.

**Proposition 9.** *The wage policies satisfy*

$$w_b(u) = b - \phi\lambda \left(\pi_b(1-\gamma) + \pi_g\right) \frac{p_b - b}{\rho + \delta} \tag{3.12}$$

$$w_b(b) = p_b \tag{3.13}$$

$$w_g(u) = b \tag{3.14}$$

$$w_g(b) = p_b \tag{3.15}$$

Average log starting wages out of unemployment equal

$$w_{ue} = \frac{\pi_b}{\pi_b + \pi_g} \log\left(b - \phi\lambda \left(\pi_b(1-\gamma) + \pi_g\right) \frac{p_b - b}{\rho + \delta}\right) + \frac{\pi_g}{\pi_b + \pi_g} \log(b) \tag{3.16}$$

and average log starting wages for job-to-job movers are

$$w_{jj} = \log(p_b) \tag{3.17}$$

Finally, the labor share equals

$$labshare = \frac{1}{1-u}\left[\frac{m_b(u)w_b(u) + m_b(b)w_b(b)}{p_b} + \frac{m_g(u)w_g(u) + m_g(b)w_g(b)}{p_g}\right] \tag{3.18}$$

where the share of workers in different productivity matches by renegotiation benchmark is

$$\begin{aligned}
m_b(u) &= \frac{\lambda\pi_b}{\delta + \phi\lambda((1-\gamma)\pi_b + \pi_g)} u \\
m_b(b) &= \frac{\phi\lambda(1-\gamma)\pi_b}{\delta + \lambda\phi\pi_g} m_b(u) \\
m_g(u) &= \frac{\lambda\pi_g}{\delta} u \\
m_g(b) &= \frac{\phi\lambda\pi_g}{\delta}(m_b(u) + m_b(b))
\end{aligned}$$

## 3.3 A Partial Equilibrium Analysis of Worker Behavior

This section assesses the ability of the model to quantitatively match differences in application, interview and worker mobility rates as well as starting wages between unemployed and employed workers. I pre-set a few parameters based on standard values in the literature and calibrate remaining parameter values internally. The next section considers the parameters governing firm behavior and quantifies the general equilibrium implications of a microfounded application and hiring process.

### 3.3.1 Data and sample

I use data on applications submitted, interviews attended, offers received, mobility rates and wages from the Survey of Consumer Expectations (SCE) from 2013 to 2015. The survey is conducted by the Federal Reserve Bank of New York and administered to roughly 1,300 people. See Faberman et al. (2017) for greater details about the survey.[6]

I focus on male workers aged 18–64 who are either employed or unemployed. Among the employed, I drop those who are currently self-employed or public servants. Among the unemployed, I drop those whose last job was self-employment or in the public sector. To limit the inference drawn from a few observations that submit a very large number of applications, I trim the number of applications submitted in a month at 20. This affects 13 observations in the sample. The final sample contains 824 observations, 775 of whom are employed and 49 who are unemployed.

I use residual wages after having taken out a quadratic in age, eduction, year and sector dummies. I subsequently normalize all residual wages by the starting residual wage of job-to-job movers. As robustness, I have similarly cleaned application, interview

[6]These authors show that the sample matches well the same target population in the Current Population Survey on a range of dimensions.

and offer arrival rates of observable characteristics, but as this makes little difference to my estimates I use the raw numbers as baseline.[7]

### 3.3.2 Pre-set parameter values

I set the subjective discount rate $\rho$ to equal a five percent annual real interest rate and the curvature of the matching function $\alpha$ to 0.7, which is the average value reported by Petrongolo and Pissarides (2001) in models with on the job search. One of $b$, $p_b$ and $p_g$ can be normalized without loss of generality, so I normalize by setting $p_b = 1$. Since the starting wage of JJ movers equals $w_{jj} = p_b$, I normalize empirical wage measures by the residual starting wage of JJ movers.

Table 3.1: Pre-set parameter values

| | Description | Value |
|---|---|---|
| $\rho$ | Discount rate | 0.0041 |
| $\alpha$ | Elasticity of matches w.r.t vacancies | 0.7 |
| $p_b$ | Low productive match | 1 |

### 3.3.3 Methodology

I jointly estimate the combination of structural and auxiliary parameters $\{\delta, \lambda, \pi_b, \pi_g, \phi, \gamma, \eta, b, p_g\}$ based on the combined information contained in application flows, interviews flows, worker flows and starting wages. That is, I treat the equilibrium job finding rate $\lambda$ as a parameter in this section, and estimate parameters governing firm behavior and general equilibrium in the next section using $\lambda$ as an auxiliary moment.

Given that exogenous separations take place at Poisson rate $\delta$, the fraction of employed workers at the beginning of the month who do not flow out to unemployment at any point

[7] This may at first seem surprising given known, large differences in worker mobility by for instance age. The reason is primarily that differences in search behavior by employment status are so large that they swamp the impact of other observables, and secondly that the incidence of unemployment does not differ sufficiently by worker observables.

during the subsequent month equals

$$Prob(\text{no transition to } U|E_t) = e^{-\delta} \tag{3.19}$$

**Application rates.** With for instance hourly data, it would be straightforward to estimate the rate at which unemployed workers apply for jobs as the fraction of unemployed workers that submit an application in the next hour. Unfortunately, only monthly data are available, raising concerns about time aggregation bias. Specifically, some unemployed workers in the beginning of the month find a job during the month, leading them to reduce the number of applications they send. Given relatively low monthly mobility rates, I abstract from such bias in my baseline specification to estimate the application rate of unemployed workers as the average number of applications submitted during a month by workers who are unemployed at the beginning of the month,

$$\#\text{ applications}_t|U_t = \lambda \tag{3.20}$$

Robustness exercises suggests that adjusting for time aggregation bias makes only a minor difference.[8]

The application rate of mismatched workers is $\lambda(\gamma\pi_u + (1-\gamma)\pi_b + \pi_g)$, but equating this with the average number of applications submitted during a month by workers who are employed at the beginning of the month is again subject to the same time aggregation concerns as above (some mismatched workers find a good job during the month and stop applying for jobs while others lose their job and start applying for more jobs). Since monthly employment to unemployment and job to job mobility rates are low, I again abstract from such time aggregation bias. In the data, I cannot condition on a worker

[8]It is complicated to derive a closed form expression for the expected number of applications submitted during a month by workers unemployed in the beginning of the month. I have instead approximated the application rates using a weekly model, which suggests little difference to my baseline estimates using a monthly model.

being mismatched and hence I use the stationary distribution of workers (3.9) to derive the overall application rate of employed workers as

$$\#\text{ applications}_t|E_t = \frac{e_b}{1-u}\phi\lambda\left(\pi_g + \pi_b(1-\gamma) + \pi_u\gamma\right) = \frac{\pi_b\delta\phi\lambda\left(\pi_g + \pi_b(1-\gamma) + \pi_u\gamma\right)}{\left(\pi_b + \pi_g\right)\left(\delta + \phi\lambda\pi_g\right)} \tag{3.21}$$

**Interview rates.** As a share $\eta$ of unviable applications get discovered in the screening phase, I approximate the average number of interviews obtained by unemployed workers in a month as

$$\#\text{ interviews}_t|U_t = \lambda\left((1-\eta)\pi_u + \pi_b + \pi_g\right) \tag{3.22}$$

Robustness exercises suggest that adjusting for time aggregation bias makes only a small difference to my estimates and hence I do not do so in my baseline specification.

The interview rate of mismatched workers is $\phi\lambda\left((1-\eta)\gamma\pi_u + (1-\gamma)\pi_b + \pi_g\right)$. Using the stationary distribution of workers (3.9) and again disregarding time aggregation bias, the average number of interviews obtained by employed workers in a month equals

$$\#\text{ interviews}_t|E_t = \frac{\pi_b\delta\phi\lambda\left((1-\eta)\gamma\pi_u + (1-\gamma)\pi_b + \pi_g\right)}{\left(\pi_b + \pi_g\right)\left(\delta + \phi\lambda\pi_g\right)} \tag{3.23}$$

**Mobility rates.** Since the unemployed apply for any position and accept bad and good matches, the probability that an unemployed worker at the beginning of the month remains unemployed throughout the month equals

$$Prob(\text{no transition}|U_t) = e^{-\lambda\left(\pi_b + \pi_g\right)} \tag{3.24}$$

A mismatched worker remains with the same employer for a month with probability $\exp(-\delta - \phi\lambda((1-\gamma)\pi_b/2 + \pi_g))$, where I assume she switches half of the time when she meets a bad match. A well-matched worker remains with the same employer with probability $\exp(-\delta)$. Hence the probability that an employed worker remains with the

same employer throughout a month is

$$\begin{aligned} Prob(\text{no transition}|E_t) &= \frac{e_b}{e_b - e_g} e^{-\delta - \phi\lambda\left(\frac{(1-\gamma)\pi_b}{2} + \pi_g\right)} + \frac{e_g}{e_b - e_g} e^{-\delta} \\ &= \left[ \frac{\pi_b \delta e^{-\phi\lambda\left(\frac{(1-\gamma)\pi_b}{2} + \pi_g\right)} + \pi_b \phi\lambda\pi_g + \pi_g(\delta + \phi\lambda\pi_g)}{\left(\pi_b + \pi_g\right)\left(\delta + \phi\lambda\pi_g\right)} \right] e^{-\delta} \end{aligned} \tag{3.25}$$

The system (3.19)–(3.25) together with starting wages for unemployed workers (3.16) constitute eight equations in eight unknowns, $\{\delta, \lambda, \pi_b, \pi_g, \phi, \gamma, \eta, b\}$, and is hence in general identified. None of the equations, however, contains the productivity of good matches, $p_g$. Having estimated the other parameters governing worker mobility, I subsequently adjust $p_g$ based on (3.18) to target an average labor share between 2013–2015 of 59.3 percent.[9]

### 3.3.4 Parameter estimates

Table 3.2 presents a combination of structural and auxiliary parameter estimates. The flow value of leisure equals 96 percent of output in low productivity matches. This is required to match a 20.6 log point lower residual starting wage of workers coming from unemployment relative to employment. As it is well-known that the replacement rate plays a crucial role in the degree of amplification of shocks in the standard model (Hagedorn and Manovskii, 2008), it is worth noting that the flow value of unemployment equals only 60 percent of average productivity. This is below the 71 percent value estimated by Hall and Milgrom (2008) but above the 49 percent estimated by Mas and Pallais (2017). The estimated replacement rate is high but not extremely high.

Only a small share of matches can be viable, given the high application rate relative to mobility rate, and there must be substantial uncertainty about match quality conditional on the signal. Mismatched workers must search with a high intensity in order to match

[9]Constructed as the average quarterly labor share in the non-farm business sector from 2014Q1 to 2015Q4 from `https://fred.stlouisfed.org/graph/?g=mfz`.

the difference in application rates between unemployed and employed workers. A large share of unviable matches must be discovered by the screening phase in order to match the differences in application and interview rates between unemployed and employed workers.

Table 3.2: Estimated parameter values

| | Description | Value |
|---|---|---|
| $\delta$ | Separation rate | 0.021 |
| $\lambda$ | Arrival rate | 7.211 |
| $\pi_b$ | Probability of bad match | 0.023 |
| $\pi_g$ | Probability of good match | 0.005 |
| $\phi$ | Relative search intensity | 0.815 |
| $\gamma$ | Noise in signal | 0.435 |
| $\eta$ | Screening efficiency | 0.946 |
| $b$ | Flow value of leisure | 0.957 |
| $p_g$ | Productivity of good match | 1.915 |

### 3.3.5 Model fit

Table 3.3 compares the model fit with the data. In the data, unemployed workers submit eight times as many applications, receive seven times as many interviews, but less than four times as many offers. They are, however, more likely to accept a job offer, resulting in an eight times as high mobility rate. The model matches perfectly the empirical differences in application, interview and mobility rates, as well as starting wages between the unemployed and employed.

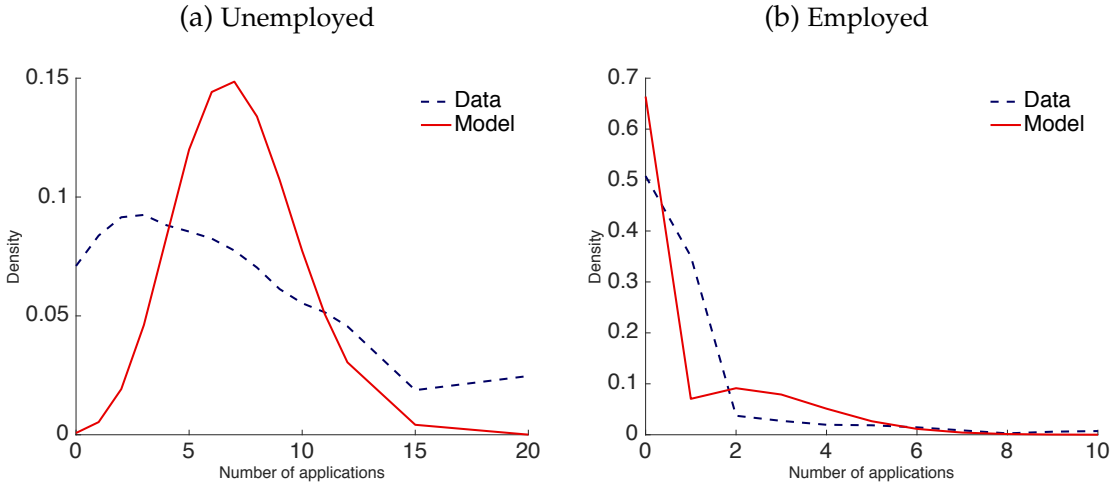
Table 3.3: Model fit

| | Data | | Model | |
|---|---|---|---|---|
| Moment | Unemp. | Empl. | Unemp. | Empl. |
| PANEL A: TARGETED MOMENTS | | | | |
| Application rate | 7.211 | 0.917 | 7.211 | 0.917 |
| Interview rate | 0.576 | 0.084 | 0.576 | 0.084 |
| Mobility rate | 0.179 | 0.022 | 0.179 | 0.022 |
| Starting wage | -0.209 | 0 | -0.209 | 0 |
| EU rate | 0.021 | | 0.021 | |
| Labor share | 0.593 | | 0.593 | |
| PANEL B: NON-TARGETED MOMENTS | | | | |
| Replacement rate | 0.488 | | 0.602 | |

*Note: Replacement rate relative to average productivity based on Mas and Pallais (2017).*

Figure 3.4 plots the distribution of submitted applications during a month by unemployed (left) and employed (right) workers in the model and data. The Poisson assumption captures reasonably well the distribution of applications in the data, more so for the employed. The mismatch between model and data for particularly the unemployed could be interpreted as evidence of unobserved heterogeneity in propensity to submit an application. Although interesting, I leave a better understanding of heterogeneity in job search behavior for future research.

Figure 3.4: Distribution of applications, model versus data




*Note: Distribution of submitted applications during a month by those unemployed in the beginning of the month (left) and employed in the beginning of the month (right). Data from SCE 2013–2015.*

## 3.4 A General Equilibrium Analysis of Firm Behavior

This section estimates parameters governing the firm side of the hiring process and assesses its implications for general equilibrium.

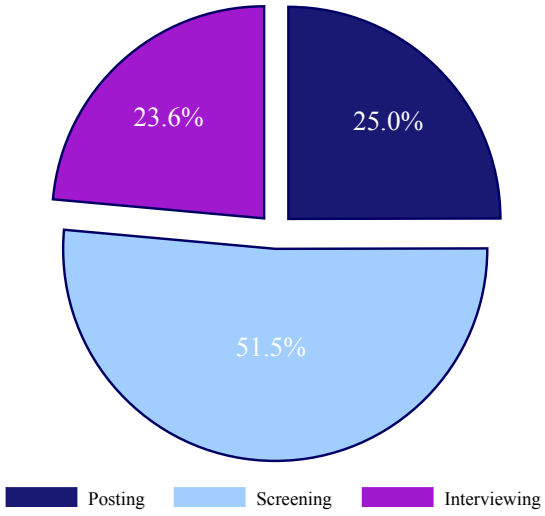
### 3.4.1 Data

To identify the cost of posting vacancies, $c_v$, screening workers, $c_s$, and interviewing, $c_i$, I use data on the costs of hiring collected by online hiring site GetHired.com.[10] Figure 3.5 breaks down the overall cost of the hiring process prior to extending an offer into the amount spent on advertising the position, reviewing applications and interviewing candidates. The cost of advertising positions constitutes 25 percent of the total cost of

[10]This company helps small and medium size businesses optimize hiring, and in the process collects data on the different steps involved in the hiring process.

hiring, while the review process accounts for 52 percent and the interviewing phase for 24 percent.[11]

Figure 3.5: Cost of advertising and screening




*Note: Posting includes "posting on job boards" and screening includes "reviewing and pre-screening applicants." Data from GetHired.com.*

### 3.4.2 Methodology

A vacancy contacts a potential applicant at rate $q = \chi^{1/\alpha}\lambda^{1-1/\alpha}$ while the probability that a randomly selected potential applicant submits an application is $\frac{u}{e} + \frac{\phi e_b}{e}\left(\gamma\pi_u + (1-\gamma)\pi_b + \pi_g\right)$. Given an estimated arrival rate of job opportunities, $\lambda$, from the previous section and an estimate of the number of applications per posted job, I estimate matching efficiency as

$$\chi = \lambda^{1-\alpha}\left[\frac{\text{\# applicants}}{\frac{u}{e} + \frac{\phi e_b}{e}\left(\gamma\pi_u + (1-\gamma)\pi_b + \pi_g\right)}\right]^{\alpha} \tag{3.26}$$

[11]To the extent that costs are roughly proportional to time, this breakdown is broadly consistent with evidence in Davis and Samaniego de la Parra (2017) that the mean time a vacancy is advertised online constitutes only one-fifth of the average time it takes to fill an open job.

I use Davis and Samaniego de la Parra (2017)'s estimate that on average, a vacancy attracts 13.28 applications, abstracting from vacancies posted by recruiting and staffing firms.[12]

The empirical decomposition of the cost of hiring is for a firm that successfully hires a worker. To construct the corresponding measure in the model, I first compute the number of flow vacancies a firm needs to post in order to in expectation hire a worker,

$$v^* = \left[ q \left( \frac{u}{e}(\pi_b + \pi_g) + \frac{\phi e_b}{e} \left( (1-\gamma)\pi_b/2 + \pi_g \right) \right) \right]^{-1}$$

Based on this, I compute the cost of advertising as the flow cost of a vacancy times the number of vacancies required to hire one worker,

$$Cost_v = c_v v^* \tag{3.27}$$

The cost of screening equals the cost of screening one application times the number of vacancies required to hire one worker times the number of applications received per vacancy,

$$Cost_s = c_s v^* q \left[ \frac{u}{e} + \frac{\phi e_b}{e} \left( \gamma \pi_u + (1-\gamma)\pi_b + \pi_g \right) \right] \tag{3.28}$$

Finally, the cost of interviewing equals the cost of interviewing one application times the number of vacancies required to hire one worker times the number of people interviewed per vacancy,

$$Cost_i = c_i v^* q \left[ \frac{u}{e} (1 - \eta \pi_u) + \frac{\phi e_b}{e} \left( (1-\eta)\gamma \pi_u + (1-\gamma)\pi_b + \pi_g \right) \right] \tag{3.29}$$

I subsequently compute the cost of advertising positions, screening applications and interviewing candidates as the ratio of these costs to the total cost of hiring. Given an

[12] Their data contain 7.7 million vacancies, of which 25.9 percent are by firms seeking to hire their own employees, and 65.9 million applications, of which 40.2 percent are to firms seeking to hire their own employees. See Davis and Samaniego de la Parra (2017) for further details.

estimate of matching efficiency from (3.26), I estimate the cost parameters based on the system (3.27)–.

### 3.4.3 Parameter estimates and model fit

Table 3.4 summarizes the estimated parameters governing matching and hiring. The total cost of hiring a worker is high at about seven months of flow output. Given a targeted labor share of 60 percent, firms make large profits on a hire, and consequently it must be expensive to hire in order to equilibrate the market. In line with this, several recent empirical papers document costs of hiring that are equivalent to several months of output (Dube, A., Freeman, E., Reich, 2010; Blatter et al., 2012). I also note that the estimated cost of hiring is such that conditions (3.6)–(3.7) hold, i.e. a firm wants to proceed to interview both unemployed and employed workers.

Table 3.4: Estimated parameter values

| | Description | Value |
|---|---|---|
| $\chi$ | Matching efficiency | 15.940 |
| $c_v$ | Cost of advertising position | 0.985 |
| $c_s$ | Cost of screening applicant | 0.162 |
| $c_i$ | Cost of interviewing applicant | 0.908 |

Table 3.5 shows that the model matches very well the data in the targeted dimensions. The implied average duration of a vacancy is 86 days, which compares well with the average duration reported by Davis et al. (2014) using German data.

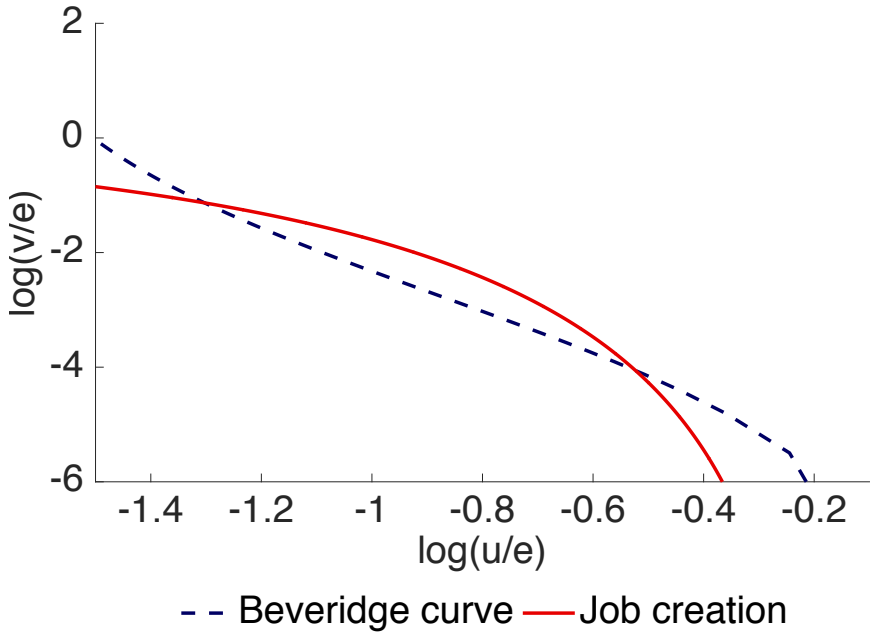
Table 3.5: Model fit

| Moment | Data | Model |
|---|---|---|
| PANEL A: TARGETED MOMENTS | | |
| Advertising share of cost | 0.236 | 0.236 |
| Screening share of cost | 0.515 | 0.515 |
| Interviewing share of cost | 0.249 | 0.249 |
| Applications per vacancy | 13.28 | 13.28 |
| PANEL B: NON-TARGETED MOMENTS | | |
| Duration of vacancy | 76 | 86.1 |

*Note: Costs of hiring from GetHired.com, duration of vacancies from Davis et al. (2014), applications per vacancy from Blatter et al. (2012).*

Figure 3.6 plots the two equilibrium conditions (3.10) and (3.11) under the estimated parameter values. The two curves intersect twice, indicating a multiplicity of equilibria. In one, firms hire a lot, resulting in few unemployed applicants. This in turn lowers the cost of hiring, rationalizing high job creation. In the other, firms hire little, resulting in many unemployed applicants and a high cost of hiring.

Figure 3.6: Equilibrium determination with estimated screening and interviewing costs




### 3.4.4 Impulse responses

As a first step towards understanding the amplification of productivity shocks under a realistic model of the hiring process, I introduce aggregate shocks. I assume that shocks to aggregate productivity, $z(t)$, multiply the productivity of bad and good matches, $\tilde{p}_i(t) = e^{z(t)}p_i$, while it neither affects the costs of hiring nor the flow value of leisure. I furthermore assume that the underlying process governing these shocks is a Brownian motion without drift, in which case it is easy to show that the surplus equals $V_i - V_u = e^{z(t)}(p_i - b)/(\rho + \delta)$ and $V_g - V_b = e^{z(t)}(p_g - p_b)/(\rho + \delta)$. Thus, the dynamic economy is characterized by the system

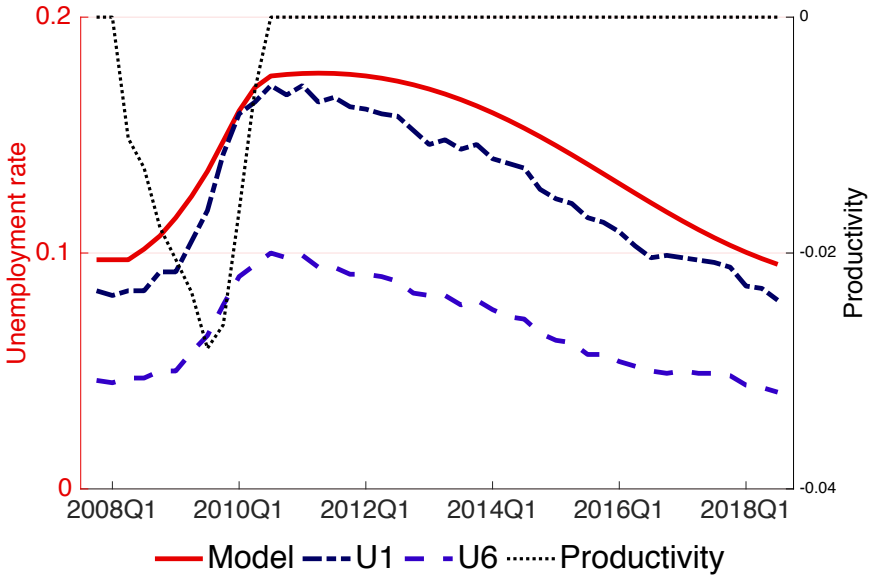
$$du(t) = \left[\delta(1-u(t)) - \lambda(\theta(t))\left(\pi_g + \pi_b\right)u(t)\right]dt \tag{3.30}$$

$$de_b(t) = \left[-\left(\phi\lambda(\theta(t))\pi_g + \delta\right)e_b(t) + \lambda(\theta(t))\pi_b u(t)\right]dt \tag{3.31}$$

$$\begin{aligned}\frac{c_v\lambda(\theta(t))}{\theta(t)} &= \pi_g e^{z(t)}\frac{p_g - p_b}{\rho+\delta} - (c_s + c_i)\left(\gamma\pi_u + (1-\gamma)\pi_b + \pi_g\right) + c_i\eta\gamma\pi_u \\ &+ \frac{u(t)}{u(t)+\phi e_b(t)}\left[\left(\pi_b + \pi_g\right)\frac{e^{z(t)}p_b - b}{\rho+\delta} - (c_s+c_i)\left((1-\gamma)\pi_u + \gamma\pi_b\right) + c_i\eta(1-\gamma)\pi_u\right]\end{aligned} \tag{3.32}$$

To simulate the effect of the Great Recession, I draw a sequence of productivity shocks that mimic the decline in labor productivity observed in the US from 2007Q3 to 2009Q4, and trace out the evolution of the unemployment rate assuming that productivity returns to trend 10 quarters after the onset of the decline. Figure 3.7 compares the effect of the productivity shocks on the unemployment rate in the model with the behavior of two measures of unemployment over this period, a broad measure of unemployment (U6) and the standard measure (U1). The model matches well the increase in unemployment seen over this period as well as the slow recovery, even though productivity returned to trend relatively quickly.

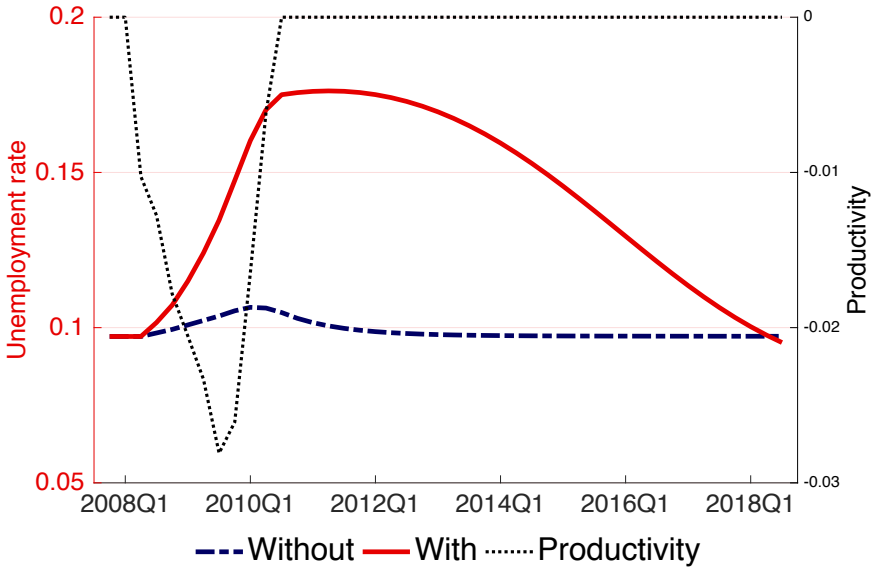
Figure 3.7: Unemployment rate during the Great Recession, model versus data




For comparison, Figure 3.8 plots the response of the unemployment rate to the same sequence of productivity shocks in the model without screening and interviewing costs. The difference is striking: without costs of screening and interviewing, the increase in unemployment is an order of magnitude lower than with such costs. Furthermore, the unemployment rate peaks five quarters later in the model with screening and interviewing costs and it takes 17 quarters for it to fall to half of its peak value versus only four quarters in the model without screening and interviewing costs. That is, the model with screening

and hiring costs generates substantial internal propagation of shocks. Evidently, a more realistic model of the hiring process has important consequences for our understanding of the impact of shocks on the labor market.

Figure 3.8: Unemployment rate during the Great Recession, with and without costs of screening and interviewing




*Note: HP filtered labor productivity series from FRED, unemployment rates from the BLS.*

## 3.5 Conclusion

This paper is motivated by large differences in application, interview and worker mobility rates as well as starting wages between the unemployed and employed together with evidence that a large fraction of firms' recruitment efforts are associated with screening and interviewing workers, as distinct from advertising open positions. A standard search model extended to incorporate an application and screening process matches these patterns, without resorting to exogenously different efficiency parameters or wage offer distributions. Furthermore, microfounding the hiring process significantly changes how aggregate productivity shocks are propagated to the labor market: relative to a model with-

out screening costs, labor market outcomes are an order of magnitude as volatile over the business cycle.

My findings have potentially important implications for the design of optimal policy. For instance, conditioning unemployment benefits on applying for a sufficient number of jobs may come at a cost if additional applications are achieved by applying for positions which are a worse expected match.

# Appendix A

# Worker Flows and Wage Growth over the Life-Cycle: A Cross-Country Analysis

## A.1 Details on data

The following appendix provides additional details on data sources, how I standardize them, and variable definitions.

### A.1.1 Details on data sources

**PSID** The PSID is a longitudinal survey directed by the University of Michigan. It started in 1968 with approximately 5,000 households, who together with their descendants have been followed annually up until 1997, when the survey became biannual. The PSID is arguably the most reliable source of representative, longitudinal micro data in the U.S. Moreover, the ECHP, BHPS and GSOEP were all inspired by the design of the PSID, substantially simplifying the task of making the data sets comparable and to some extent relieving concerns about heterogeneity in data collection driving the results.

The original PSID core sample consists of the Survey Research Center (SRC) sample, which was constructed to be representative of the U.S. population at the time, and an

oversample of the poor, the Survey of Economic Opportunity sample. In addition, additional households have been added over time. I restrict attention to the original core SRC sample, following among others Huggett et al. (2006). Although the SRC sample was constructed to be representative of the U.S. population, subsequent attrition and non-response necessitate the need to use the longitudinal individual weights provided by the survey.

The primary unit of analysis in the PSID is the household, and while the survey provides some individual level data, these are substantially less detailed. Within households, most of the questions refer to the "head" of the household and the "wife," with the former typically being defined as the male in the case a male is present in the family. For this reason, all my analysis is restricted to male heads of households.

I use data from the 1990–2013 family files of the PSID. The reason for the slightly different time period relative to the European countries is two-fold. First, the 2015 wave of the PSID is not released yet, forcing the upper cutoff. Second, including the 1990–1993 waves allows me to obtain an eight year panel of annual observations that mimics that for the ECHP. I use this shorter, annual data set to study the impact of worker mobility on wages.

Income variables are reported in nominal terms, and most of them refer to income during the previous year. I use the average annual Consumer Price Index (CPI) for all urban consumers to convert nominal values into 2011 real U.S. dollars.[1]

**ECHP** The ECHP is a longitudinal survey conducted between 1994–2001 by Eurostat, the statistical agency of the European Commission. The first wave contains 60,500 households and 130,000 individuals who are subsequently reinterviewed every year until 2001. The 15 countries covered by the ECHP are: Austria (from 1995), Belgium, Denmark, Germany (left in 1997), Greece, Finland (from 1996), France, Ireland, Italy, Luxembourg (left

[1]Available for download at the St Louis Fed webpage, `https://fred.stlouisfed.org/series/CPIAUCSL/downloaddata/`.

in 1997), the Netherlands, Portugal, Spain, and the U.K. (left in 1997). Starting in 1997, Germany, Luxembourg and the U.K. provide data to the ECHP from separate national longitudinal surveys—the GSOEP, the Living in Luxembourg (PSELL) survey, and the BHPS—while Sweden provides data from a national cross-sectional survey. For the other countries and years, the data are from a common questionnaire, which arguably is as good as it gets for a cross-country comparison.

I drop the ECHP data for Germany, Luxembourg, Sweden and the U.K. due to the limited number of years available (in addition the Swedish data are only cross-sectional). Instead, I include data on the U.K. and Germany directly from the GSOEP and BHPS (in addition the German statistical agency has not granted me access to its data from the ECHP). I am also forced to drop Portugal because that country has refused to grant me access to their ECHP data. Finally, I drop Greece because it only has a few years of data available from the EU-SILC, leaving me short of the requirement of at least 15 years of data by country. All my analysis uses the longitudinal weights provided by the ECHP.

Most of the income variables in the ECHP refer to the income reference year, which is typically the year prior to the interview. I first convert all nominal values in the respective national currencies to their 2001 real equivalents using the national annual CPI for all items available from the OECD.[2] Second, I convert real 2001 national currencies to 2001 real euros using the exchange rate in 2001, which is the official rate at which national currencies were exchanged for the euro. Third, I convert this to 2004 euros using the annual Harmonized Index of Consumer Prices (HICP) also available from the OECD.[3] Finally, I convert real 2004 euros to real 2004 U.S. dollars using the Purchasing Power Parity (PPP) adjusted exchange rate between each individual country in 2004 euros and 2004 U.S. dollars.[4]

[2]Available at `http://stats.oecd.org/viewhtml.aspx"datasetcode=MEI_PRICES&lang=en`.

[3]Available at `http://stats.oecd.org/viewhtml.aspx"datasetcode=MEI_PRICES&lang=en`.

[4]Specifically the series for actual individual consumption available from the OECD, `http://stats.oecd.org/Index.aspx"DataSetCode=SNA_Table4/`.

This method works well with the exception of Denmark, Finland, France and Ireland, which display a jump or fall in the level of wages between the ECHP and the EU-SILC. I adjust the level of wages in the ECHP for these countries with a factor such that the difference in average wages in the last year of the ECHP and the first year of the EU-SILC for that country equals the difference in average wages in those years reported by the OECD.

**EU-SILC** The EU-SILC launched in 2004 as the successor to the ECHP, and gradually expanded to include all current 28 EU members plus Iceland, Norway, Turkey, and Switzerland. For the set of countries also covered by the ECHP, I have data for 2004–2014 with the exception of Denmark (–2013), France (2005–), Ireland (missing 2009–2010), the Netherlands (2005–), and Italy (2007–). I exclude Greece from my analysis because it only has two years of available longitudinal data from the EU-SILC.

Instead of using a harmonized questionnaire as the ECHP, the EU-SILC is "output harmonized." Eurostat drafted a set of target variables that each survey has to answer, but left the actual design of the surveys up to the respective national statistical agency. The questionnaires hence differ across countries, and Eurostat has standardized responses ex post. This falls short of the gold standard of the ECHP. However, on key variables such as labor market flows, time trends across the ECHP-EU-SILC bridge show a high degree of consistency within countries. This is consistent with the stated objective of the EU-SILC to be the successor to the ECHP. Hence, I believe that the bridge between the two data sources is good.

The EU-SILC is a rotational panel similar to the Current Population Survey in the U.S. but with a lower frequency and a longer rotation. Typically, the EU-SILC follows individuals for up to four years, with the exception of France (nine years), Norway (eight years), and Luxembourg (pure panel). To verify that the life-cycle profiles documented in this paper are not driven by the shorter panel of the EU-SILC relative to the other data

sources, I assigned new, artificial person IDs to PSID/GSOEP/ECHP/BHPS respondents after every four years in the data and re-estimated the life-cycle profiles on this sample. It has very little impact on the estimated age coefficients; results are available on request.

Contrary to most longitudinal surveys, the EU-SILC provides two data sets: a longitudinal and a cross-sectional version. Although they are largely based on the same sample, the necessary variables to link two cross-sectional surveys or cross-sectional with longitudinal data have been removed from the cross-sectional data set, presumably for confidentiality reasons. Some variables are only available in the longitudinal data set and some only in the cross sectional, with generally more variables available in the latter. All my analysis uses the longitudinal version of the EU-SILC, and are weighted using the provided longitudinal individual weights.[5]

Eurostat provides the longitudinal data in overlapping waves, so that for instance the 2006 wave contains all previous years for everyone who participated in the 2006 wave (i.e. for instance years 2004–2006 for someone who entered the survey in 2004). As a result, a given individual-year is present in multiple waves—for instance the 2004 response of an individual who entered the survey in 2004 is included in the 2004–2007 waves. Hence, when combining multiple waves of the data one has to delete duplicate individual-years. This is complicated by the fact that some individual IDs appear to be reused in later waves.[6] Further complicating the process of merging multiple waves, key variables such as year of birth and income sometimes vary across waves for a given year for what appears to be the same individual. This makes it hard to know whether a given ID refers to the same person as in an earlier wave or a new person. I construct a procedure that avoids treating separate individuals as one, but with the drawback that it entirely drops some individuals when their IDs are being reused later. Given that this concerns relatively

[5]It is not clear whether the provided weights also account for non-response or only for survey design.

[6]This can be seen by computing the number of unique years by individual ID—for all of the core countries apart from Finland and Spain, the maximum number of observations is four (or nine in the case of France) which is in line with what we should expect given the four/nine year rotating panel. Finland and Spain, on the other hand, have IDs with five and eight observations, although they run four-year rotating panels.

few individuals, however, the loss in statistical precision resulting from this is arguably second order.[7]

I merge multiple waves by keeping the observation for an individual-year that is from the wave with the most observations on a given individual (using data from later waves in case of a tie). That is, if the 2006 wave contains four observations on individual i, the observations on individual i for years 2003–2006 are all taken from the 2006 wave. In a few cases, income or cohort varies within an individual-year across waves also in the countries that do not have contaminated IDs. In these cases, in order to reduce noise I assign an individual the mean income across waves that year, and I assign the cohort as the modal value across all waves. As noted above, this algorithm entirely drops an individual if his ID is being reused by a respondent with more available years (and appearing later in case of a tie).

The above procedure for removing duplicate individual-years does not work well for France, because France's nine-year panel is still reported in four-year-maximum segments in the EU-SILC. Hence an individual who entered in 2004 would appear with four observations in each of the 2007–2012 waves, and the above procedure would only keep the 2009–2012 responses from the 2012 wave. This drops an unsatisfactory amount of information. As the IDs are not contaminated for France, I merge all waves keeping in each individual-year the observation from the last available wave in the case of France.

Most of the income variables refer to the income reference year, which is typically the year prior to the survey. Exceptions to this are Ireland which collects data for the 12 months prior to the interview, and the U.K. which collects data for the period around the interview and annualizes this. Iacovou et al. (2012) argue that these differences in income reference period are unlikely to be a major source of non-comparability. I convert nominal values to 2004 real Euros (or national currency in the case of Denmark) using

[7]Computing the variation in a variable within individual-years gives a sense of how important the issue of contaminated IDs are. Less than one percent of observations in Finland and Spain has a positive variation within individual-years in both income and cohort, suggesting that the fraction of IDs representing multiple individuals is minor.

the national HICP available from the OECD. Subsequently, I convert this to 2004 real U.S. dollars using the PPP adjusted exchange rates discussed above.

**GSOEP** The GSOEP is a longitudinal study started in 1984 and collected by the Deutsches Institute for Wirtschaftsforschung (DIW). It was designed to closely mimic the PSID. Respondents are interviewed once a year about events that took place during the prior year. In contrast to the PSID, every adult in the household answers an individual questionnaire, and hence there is no need to restrict the analysis to heads of households.[8] I merge data from the personal files, person equivalent files, and person calendar files for 1990–2011.[9] Following Krebs and Yao (2016), I use all subsamples of the GSOEP apart from the rich oversample, sample G, for which only a few years of data are available. All results are weighted by the provided individual longitudinal weights.

Most of the income variables refer to the previous year, and are in nominal euros.[10] I convert this to real 2004 euros using the HICP for Germany, and then to real 2004 U.S. dollars following the same procedure as for the ECHP/EU-SILC.

**BHPS** The BHPS is a longitudinal study started in 1991 and collected by the Institute for Social and Economic Research at the University of Essex. The original survey included 5,500 households and 10,000 individuals in Great Britain with a stratified clustered design. The same individuals are interviewed annually, as well as split-off households from the original panel members. Additional households were added from Scotland and Wales in 1999 and Northern Ireland in 2001 in order to achieve sufficient sample size to analyze those countries independently. The initial seven waves of the BHPS also include the British ECHP sample, but provides no longitudinal weights to combine this with the BHPS sample. The BHPS was discontinued in 2008 to make way for a new survey, the

[8]Most prime age males are also heads of households, though, and restricting attention to heads produces very similar results.

[9]The GSOEP is currently available up to 2015 but I do not have access to it.

[10]The DIW has converted values recorded in German marks to euros using the official exchange rate at the time of German entry into the currency union.

Understanding Society survey. As the Scottish, Welsh and Northern Irish samples do not satisfy my requirement of 15 or more years of data, and the ECHP sample lacks the necessary weights, I only use the original BHPS sample. Because a few variables are missing the first year, I use the 1992–2008 waves. All results are weighted using individual longitudinal weights that adjust for both initial sampling probability and later attrition/nonresponse. In contrast to the PSID but similar to the other surveys used in this paper, all individuals 16 years and older answer an individual questionnaire.[11] I hence do not restrict attention to heads of households in order to maximize sample size.

I convert income variables to real 2004 pounds using the national CPI (from the OECD), and then to 2004 real U.S. dollars following the same procedure as for the other surveys.

### A.1.2 Detailed variable definitions

**Age** All surveys record either an individual's age or year of birth. I recode this using the longitudinal aspect of the data to the modal reported year of birth for an individual. Age is the income reference year plus one minus year of birth.

**Experience** The ECHP and the EU-SILC report at what age the respondent held his first job, which I use to define a measure of potential experience. I first recode the age at which the respondent first started working to the modal reported year across the waves of the survey. Subsequently, I define the respondent's potential experience as the year of the survey minus the age at which the respondent held his first job. In my main exercises, I prefer age rather than experience since the GSOEP, PSID and BHPS do not contain comparable data on experience, and arguably age has less measurement error. Finally, as shown in Appendix A.3 using age appears to be the conservative approach as results with experience are even more pronounced.

[11] Since 1994, children age 11–15 also answer a short questionnaire individually.

The EU-SILC additionally reports how many years the worker has been working since he first entered the labor market. Although I cannot use this in most of my analysis since it is available in too few years, its correlation with potential experience is 0.93. Hence, I believe that using actual instead of potential experience would yield similar results to those reported in the paper.

**Education** Education is coded in the ECHP into three broad groups based on the International Standard Classification of Education (ISCED) 1997: less than second stage of secondary education (ISCED 0–2), second stage of secondary education including post-secondary non-tertiary education (ISCED 3–4), and recognized third level education (ISCED 5–7). The EU-SILC provides a more detailed education classification based on the ISCED 1997 and later the ISCED 2011—I recode this to the broad groups available in the ECHP. I recode years of schooling in the GSOEP to less than secondary (0–10 years), secondary plus some post-secondary (10–15 years), and tertiary (16 and above). I recode reported years of education in the PSID into less than secondary (less than 12 years), secondary plus some post-secondary (12–15 years in school), and tertiary (16 or more years). In the BHPS, I classify those with comprehensive, elementary and secondary modern school as less than secondary; those with grammar school, sixth form college, and college of further education as secondary plus some post-secondary; and those with polytechnic or university as tertiary. All individuals are assigned their modal education group across waves.

**Occupation** The ECHP reports a relatively aggregated occupation measure, which I recode to 10 broad groups: managers, engineers and health professionals, teachers, other professionals, engineering and health associates, office administration and sales persons, personal and protective service workers, craftmen, machine operators, and laborers (including agricultural workers). I map the International Standard Classification of Occupation (ISCO) 1988 and 2008 classifications available in the EU-SILC, GSOEP and BHPS, and

the 3-digit occupation codes in the PSID from the 1970 and 2000 Census of Population, to the same broad occupations.

**Employment status** A worker is employed if he reports working full-time, part-time, being in vocational training, or being self-employed, and works at least 15 hours a week. As noted above, the hours criterion is primarily imposed to be consistent with the ECHP/EU-SILC, which do not record hours for someone working less than 15 hours a week. It also facilitates achieving a sample with a relatively strong connection to the labor force. A worker is unemployed if he reports being unemployed,[12] and self-employed if he reports being self-employed.

**Income** Income is broadly defined, including overtime pay, income from extra jobs, and bonus payments during the prior year. Each survey apart from the EU-SILC also reports current monthly gross income from labor at the time of the survey. I provide some further details on the income measures below.

In the PSID, total annual income from labor is the sum of total income from wages and salaries, bonus income, overtime pay, tips, commissions, miscellaneous labor income, and self-employment income consisting of the asset and labor part of business income, income from farming, and income from market gardening. The survey explicitly asks for total annual values for each of these categories during the prior year. All values are reported gross of taxes and social security contributions. I impute top-coded values in each year at the most disaggregated level as the conditional mean of a Pareto distribution fitted to the top decile of non-topcoded observations. It should be noted that the fraction of top-coded observations in the PSID is substantially smaller than in for instance the Current Population Survey. The survey also asks for weekly, bi-weekly or monthly income

[12]This is based on what the respondent considers his main current activity, and not the stringent classifications of the International Labor Organization (which for instance requires someone to have actively searched for a job recently and be available to start immediately in order to classify as unemployed).

from the current main job as well as current extra jobs. I use this to define a measure of contemporaneous gross monthly income from labor.

In the GSOEP, total annual income from labor includes wages and salaries as employee (including while in training and sick pay), income from extra-jobs, income from self-employment, and bonus payments (bonuses, 13th and 14th month pay, Christmas bonus). The first three of these categories are constructed from monthly averages in the prior year (the average is taken only over the months during which that type of income was received) times the number of months that source was received. Bonus payments are reported as total annual amounts. All values are gross and none is top-coded. Contemporaneous income is gross wages and salaries received in the month prior to the survey.

In the ECHP, total annual income from labor includes regular wage and salary earnings, lump sum wage and salary earnings, and self-employment income. No measure is top-coded. For all countries apart from France these measures are reported net of taxes and social security contributions. The ECHP also reports both net and gross current monthly wage and salary earnings, which I use to estimate a conversion factor between net and gross income for each individual in each year. I adjust all net values using this conversion factor to obtain gross numbers. Contemporaneous income includes all wage and salary income in the month of the survey.

In the EU-SILC, total annual income from labor includes all wage and salary income from main and extra jobs, holiday payments, overtime pay, commissions, tips, profit sharing and bonuses, as well as self-employment income. All values are gross and none is top-coded.

The BHPS constructs a measure of annual gross income from labor based on the survey responses to a series of questions on the gross monthly rate of wage, salary or self-employment income in each job held and weeks worked in that job. If income is reported net of taxes and social security contributions, the BHPS imputes a gross figure

using available information on sex, marital status, the spouse's employment status and pension membership.

Although the income measure is broad, it does not include non-cash benefits such as a company car or subsidized meals, as well as unemployment insurance premia, health insurance or social security contributions that are paid by the employer. Starting in 2007, the EU-SILC provides information these types of payments which allow me to investigate their importance. Such payments constitute a relatively small share of total income and as a share of total income they vary very little over the life-cycle or with income, consistent with such payments primarily being levied as flat rate taxes. Hence, I believe that inclusion of such payments would not materially affect the slope of life-cycle profiles.

**Hours** Each survey contains either usual or actual weekly hours at the time of the survey, as well as number of months worked in the reference year. As mentioned above, the ECHP/EU-SILC only contain weekly hours for employed workers working more than 15 hours a week, and hence I require that employed workers satisfy this criterion in order to qualify as employed across all surveys. Weekly hours include overtime and hours worked in extra jobs, with the exception of the EU-SILC which does not include hours worked in extra jobs.[13] Using the cross-sectional version of the EU-SILC, which does include hours in extra jobs, I find that hours in extra jobs as a fraction of total weekly hours worked for prime age males is small and varies little over the life-cycle. Hence, I believe that including hours in extra jobs also in the EU-SILC would not materially affect my estimated life-cycle profiles. Total annual hours is the product of total weekly hours at the time of the survey times four times number of months worked in the reference year (computed from the monthly calendar of events available in each survey).[14]

[13] In the GSOEP, I compute hours on extra jobs as hours per day worked in second jobs times days per month worked in second jobs divided by four.

[14] The PSID also asks for total weeks worked during the year, but to be as consistent as possible across surveys I use the above definition of hours worked.

The monthly calendar of events is missing for the Netherlands in the ECHP. In this case, I compute employment status in each month during the reference year of those currently employed using the information on start and end dates of employment spells for the Netherlands. As discussed in further detail below, these date strings do not allow me to infer whether a worker was employed or non-employed in a month prior to the last labor market transition during the prior year. For all other ECHP countries—for which I also have the monthly calendar of events—I find that this proceedure produces an average number of months worked that is 99.9 percent of that obtained using the monthly calendar of events, and hence I believe that imputing months worked in this way for the Netherlands is inconsequential.

**Wages** Based on the income and hours measures discussed above, I construct two measures of the hourly wage: an average annual hourly wage and a current hourly wage. The average annual wage is annual income divided by annual hours worked, while the current wage is current monthly income divided by four times current weekly hours. The advantage of the former is that it is based on a broader measure of income. However, since the annual income measures typically refer to the year prior to the survey, while the mobility questions refer to events between the current survey date and the previous survey date, the annual measures are not well suited for studying the impact of mobility or on-the-job training on wages. The latter wage measure is better for this purpose since it aligns with the measures of mobility and training.

**Labor market flows** Each survey records whether the respondent is currently employed, his employment status in each month during the reference year (generally the year prior to the year in which the survey is administered), and the month and year the survey was administered.[15] The EU-SILC in addition records whether the respondent

[15]For confidentiality reasons, the EU-SILC only reports the quarter and year of the survey. I impute the month of the survey as the middle month of the quarter.

changed employer since the last interview (or in the past 12 months for the first interview) and the reason behind this change. It also records any change in labor market status since the last interview including what type of change this was (EU, UE, etc). In case of multiple changes in labor market status since the last interview (past 12 months), the survey records the last change. Based on this, I define the variable $LT_{it}$ to take value zero if the worker changed neither labor market status nor employer in the past year, and value one otherwise.

I record the PSID, GSOEP, ECHP, and BHPS to the same format as the EU-SILC. Each of these surveys records in what year and month the current job started (if any is active), in what year and month the last job ended, and the reason the last job ended. The variable $LT_{it}$ takes value zero if the worker is employed and started his current job prior to the last survey (past 12 months), or if he is unemployed and his last job ended prior to the last survey, and value one otherwise. Notice that because each survey in general only records information on a maximum of two jobs,[16] we do not know what happened prior to the last transition. For instance, a worker could have first made an EU transition, and then a JtJ transition, but we would only be able to observe the last JtJ transition. I device below a methodology that delivers an estimate of average monthly hazard rates taking this into account.

A non-trivial fraction of currently non-employed workers are missing data on when their last job ended (of the nature of their last transition in case of the EU-SILC). To increase the precision of my estimates, I attempt to infer whether an employment spell ended in the past 12 months using the monthly calendar of events in these cases. Since each survey asks for the calendar of events in the past year and not the last 12 months, this is only possible in cases where I have subsequent waves of data.[17] Specifically, for

[16]The BHPS records up to nine employment spells (including employment and non-employment), while the PSID prior to 2003 records a maximum of two main jobs and two extra-jobs. Starting with the 2003 wave, the PSID stopped making the distinction between main and extra-jobs and since then records information on up to four jobs.

[17]Between 1997 and 2003, this is not possible in the PSID since the survey is bi-annual while the monthly calendar of events is only recorded for the past year. Starting in 2003, the survey asks for monthly employ-

a worker who is currently non-employed but with missing end dates of the last employment (or missing data on the type of last transition in the case of the EU-SILC), I set $LT_{it} = 0$ if he is non-employed in each month during the past 12 months (since the last interview), and $LT_{it} = 1$ if he is employed in some month during the past 12 months (/since the last interview). I find that this imputation improves precision but does not change point estimates.

For Denmark in the EU-SILC, unemployed workers who did not make a transition are coded together with missing values on the question on whether they made a labor market transition during the past year. As a result, the estimates of the UE hazard for Denmark are based exclusively on the ECHP survey. The same is true for this variable for employed workers over the 2003–2008 period—missing values are coded the same as a non-transition—and hence the estimates of the EU and the JtJ hazard are based on only the ECHP and the last five years of the EU-SILC for Denmark.

In the EU-SILC, a change of contract from a temporary to a permanent contract or reverse is coded as a change of employer even if the worker remains with the same employer. This only involves those who formally change contract between temporary and permanent (or vice versa), and not those who for instance only change duties with the current employer. Using data on the type of contract a worker currently works under (temporary or permanent), I investigated what fraction of reported changes of employer also involves a change of employment contract. In particular, I focus on the fraction of workers who change contract from temporary to permanent, since this is likely the most common change of contract not involving a change of employer.[18] The fraction of reported JtJ transitions that involves a transition from a temporary to a permanent contract varies between close to zero in Denmark to 14 percent in Spain, which has a significantly

ment status in the past two years, and hence it is again possible to do this imputation (although we may worry about higher measurement error due to recollection issues in this case).

[18]The reverse change in contract—from a permanent to a temporary contract—is arguably most likely involving an employer change. In fact, given that many European countries typically grant the employer an initial, probationary period for a new hire, it would not be surprising to find that many changes of employer involves a change in contract from permanent to temporary.

higher fraction of temporary contracts than any other of the countries in the sample. Assuming that all such transitions are spurious JtJ changes provides a lower bound on the true fraction of JtJ transitions, while assuming that all of them are true JtJ transitions provides an upper bound. I use the unadjusted number in my analysis, which might somewhat overstate true JtJ mobility.

Finally, the EU-SILC does not allow a differentiation between a scenario in which the respondent only made an UE transition in the past year from one in which he first made an UE transition and then a JtJ transition. I assign all such transitions as UE. Using the monthly calendar of events in the ECHP, the fraction of UE transitions followed by a JtJ transition within the same year is very low, as may be expected given the fairly low estimated monthly transition hazards. Hence, I believe that any bias arising from this assignment in the EU-SILC is minor.[19]

**Reason for separation** In case an employment relationship ended, each survey asks for the reason for the separation. I recode this to whether the worker voluntarily quit the job or involuntarily left. In the ECHP, a quit is voluntary if one of following reasons was reported: "obtained a better or more suitable job," "study, national service," or "wanted to retire or live off private means." An involuntary separation is for one of the following reasons: "obliged to stop by the employer," "end of contract/temporary job," "sale/closure of own or family business," "marriage," "child birth/need to look after children," "looking after old, sick, disabled person," "partner's job required move to another place," "own illness or disability," or "other."

In the EU-SILC, voluntary quits are "to take up or seek better job." Involuntary quits are for one of the following reasons: "end of temporary contract," "obliged to stop by employer (business closure, redundancy, early retirement, dismissal, etc.)," "sale or closure of

[19]The opposite assumption—that all instances of an UE transition together with a change of employer are JtJ mobility—is not a good one given that many people that make an UE transition likely also change employers.

own/family business," "child care and care for other dependent," "partner's job required us to move to another area or marriage," or "other reasons."

In the PSID, voluntary quits include if the worker reported the reason to be "quit, resigned, retired, pregnant, needed more money, just wanted a change." Is is involuntary if he reports that it ended due to "strike, lockout," "layoff, fire," "others, transfer, any mention of armed services," or "job was completed, seasonal work, was a temporary job."

In the GSOEP, voluntary quits are include "own resignation," "mutual agreement," or "leave of absence, sabbatical." An involuntary separation is for one of the following reasons: "place of work closed," "dismissal," "temporary contract expired," or "reached retirement age, pension."

In the BHPS, voluntary quits are if the worker "left for better job," while involuntary separations are for one of the following reasons "made redundant," "dismissed or sacked," "temporary job ended," "took retirement," "stopped for health reasons," "left to have a baby," "children/home care," "moved area," "started college/university," or "other reason."

**Fluidity** Fluidity is the fraction of employed workers who voluntarily switched from one employer to another at some point since the last survey date (last 12 months). It is constructed as the average across all workers age 25–50 giving each age and year equal weight. Although this measure only captures JtJ mobility, it is highly correlated with the UE hazard across countries.

**Weights** All my analysis is weighted using the provided longitudinal weights for each survey, adjusted such that each country receives a unit weight. I combine data for a country from the ECHP and EU-SILC such that each survey-country receives an aggregate weight commensurate with the number of years the country is present in the respective

survey, and such that the total weight of a country equals one.[20] For the PSID, GSOEP and BHPS I adjust the provided weights such that the sum of weights equals one for each country.

**Aggregate measures** I use measures of GDP per capita and GDP per hour for 1996–2014 available from the OECD.[21] I convert this first to real 2004 national currency and then to real 2004 U.S. dollars following the same procedure as for wages discussed above.

I clean each of the three aggregate measures of economic performance—output per capita, labor productivity and the employment rate—for observable factors that are not in the model. Specifically, I regress each of them on fluidity, age of the labor force, the fraction college, and year effects,

$$aggregate_{ct} = \beta_0 + \beta_1 fluidity_c + \beta_2 age_{ct} + \beta_3 college_{ct} + t + \varepsilon_{ct}$$

where $t$ is a set of year effects common to all countries and restricted to sum to zero. The measure I use is

$$\widehat{aggregate}_{ct} = \hat{\beta}_0 + \hat{\beta}_1 fluidity_c + e_{ct}$$

[20] For instance, Belgium is present in the ECHP for eight years and the EU-SILC for 11 years. Hence, the weights for Belgium from the ECHP are adjusted such that the sum of weights from the ECHP for Belgium equals 8/19, and the sum of weights from the EU-SILC equals 11/19.

[21] 1996 is the earliest year for which all 12 countries in my sample provide data.

## A.2 Monthly hazard rates

This appendix derives a set of flow-balance equations that I use to estimate monthly hazard rates based on the available data and presents results from this estimation.

### A.2.1 Methodology

As discussed in greater detail in Appendix B.1, I only observe the last labor market transition in the past year. Hence, I cannot trivially compute monthly hazard rates. I am, however, able to classify a transition at the monthly level, which allows me to avoid potentially serious time aggregation bias associated with only knowing a respondent's labor market status at the time of the survey and at the time of the previous survey, typically 12 months earlier.[22] The following section spells out a set of flow-balance equations that allow me to estimate monthly transition hazards using the data at hand.

Denote by $\delta$ the monthly separation hazard to non-employment, by $\lambda_{UE}$ the monthly re-employment hazard from non-employment, by $\lambda_{JTJ}$ the monthly JtJ hazard rate, and by $\tau_{it}$ the number of months since the last interview (or 12 if no last interview). The probability that a worker is currently employed and has made no transition since the last interview (in the past 12 months) equals the probability that he was employed at the time of the last survey and neither transited between employers nor lost his job at some point since the last interview

$$P(e_{it} = 1, LT_{it} = 0) = (1 - \lambda_{JTJ} - \delta)^{\tau_{it}} P(e_{it-\tau_{it}} = 1) \tag{A.1}$$

The probability that a worker is unemployed and has made no transition since the last interview (past 12 months) equals the probability that he was unemployed at the last

[22] Some time aggregation bias is still present since I only observe the month of transition. To the extent that such time aggregation issues bias the level of the hazard rates uniformly across countries, they do not affect the relative comparison of mobility across countries.

interview and did not transition to employment in any month since then,

$$P(e_{it} = 0, LT_{it} = 0) = (1 - \lambda_{UE})^{\tau_{it}} P(e_{it-\tau_{it}} = 0) \tag{A.2}$$

Finally, the probability that a worker is employed in the month of the survey equals the probability that he was employed in the month prior to the survey and did not lose his job, plus the probability that he was unemployed and found a job,

$$\begin{aligned} P(e_{it} = 1) &= P(e_{it-1} = 1)(1 - \delta) + P(e_{it-1} = 0)\lambda_{UE} \\ &= \lambda_{UE} + [1 - \delta - \lambda_{UE}]\, P(e_{it-1} = 1) \end{aligned}$$

Iterating this backwards, we have that

$$\begin{aligned} P(e_{it} = 1) &= \lambda_{UE} \sum_{i=1}^{\tau_{it}} (1 - \delta - \lambda_{UE})^{i-1} + (1 - \delta - \lambda_{UE})^{\tau_{it}} P(e_{it-\tau_{it}} = 1) \\ &= \frac{\lambda_{UE}}{\lambda_{UE} + \delta} \left[1 - (1 - \delta - \lambda_{UE})^{\tau_{it}}\right] + (1 - \delta - \lambda_{UE})^{\tau_{it}} P(e_{it-\tau_{it}} = 1) \end{aligned} \tag{A.3}$$

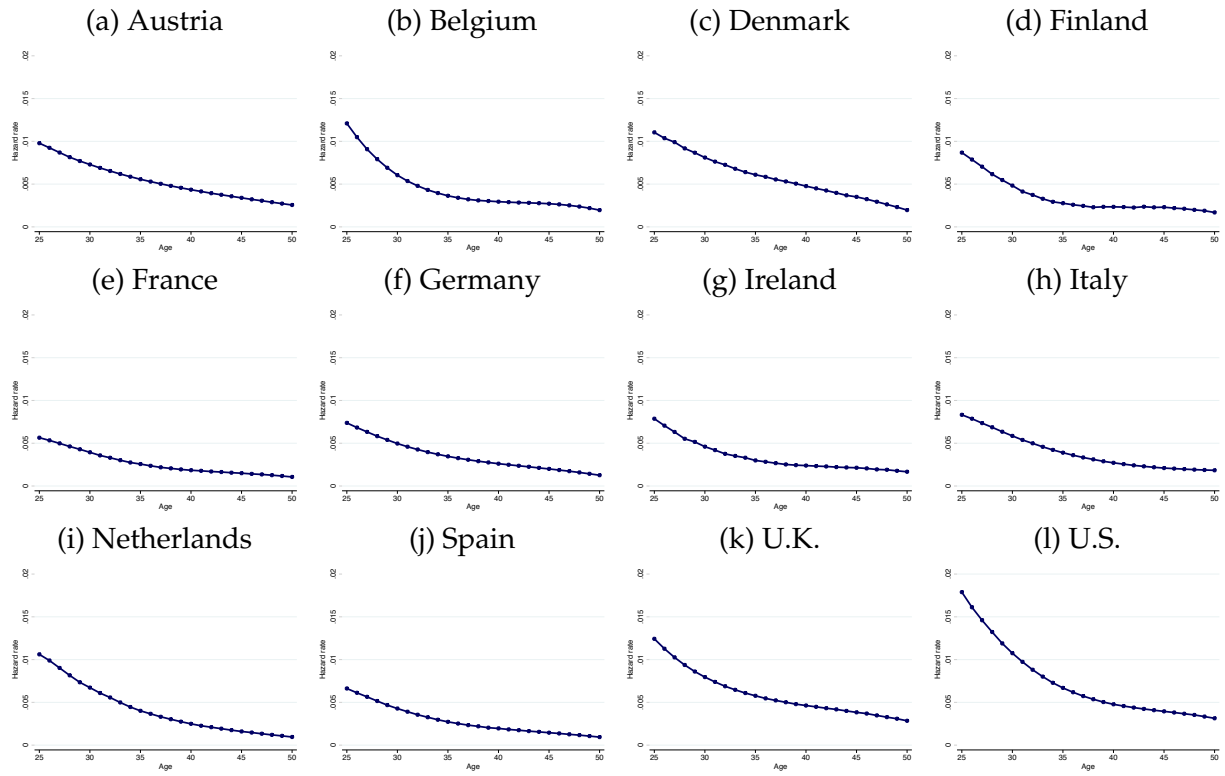
### A.2.2 Estimates

**JtJ mobility** Figure A.1 plots the estimated life-cycle profile of the monthly JtJ hazard by country. In all countries, it displays a distinct life-cycle pattern: it starts high at young ages and falls rapidly over the next 10 years, after which it flattens out. There are substantial differences across countries in the levels of voluntary mobility. For instance, American and Danish men are twice as likely to make a voluntary JtJ switch compared to their French and Italian peers in any month throughout their careers.

The estimated JtJ hazard is lower data sets such as the Survey of Income and Program Participation (Menzio et al., 2016). The raw data underlying my estimates are based on reported start and end dates of employment spells, not monthly employment status. In this sense, my data are closer to tenure-based data. Farber (2008) reports that the average

tenure of private-sector males age 40 in the U.S. is about eight years, which is roughly consistent with my estimates. This could, at least partly, be explained by recall, which is filtered out by my measures.

Figure A.1: Monthly voluntary JtJ hazard across 12 OECD countries



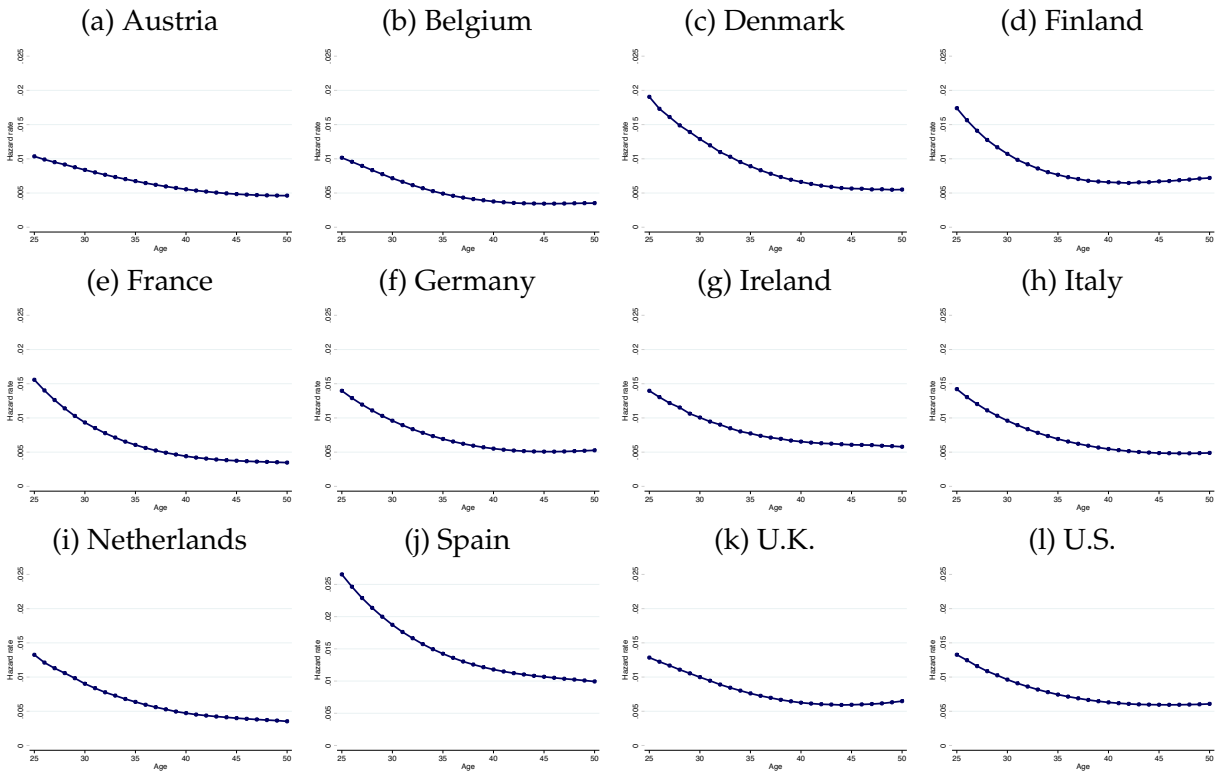

**EU mobility** Figure A.2 plots the estimated EU hazard across countries. Also this has a life-cycle pattern, with mobility being high initially and gradually falling with age.[23] The levels vary less across countries than the voluntary JtJ mobility hazard, with the exception of Spain. The much higher rate of involuntary mobility in Spain may be related to a high share of temporary work in Spain,[24] and possibly to the data issues surrounding transitions between such contracts and permanent contracts as discussed above. Excluding Spain, the separation rate varies by a factor of less than two moving from the lowest

[23]The estimated involuntary separation hazard for the U.S. is higher than what is suggested by tabulations from the monthly CPS, but in line with estimates in Menzio et al. (2016) using the 1996 SIPP and Krolikowski (2016) using the 1988–1997 waves of the PSID.

[24]Over 20 percent of 25–55 year male Spaniards work on a temporary contract, while the average across all other continental European countries is less than 10 percent.

to the highest separation country. If separations are interpreted as roughly corresponding to job reallocation, these results are consistent with a literature documenting large cross-country differences in worker flows, but smaller differences in job flows.

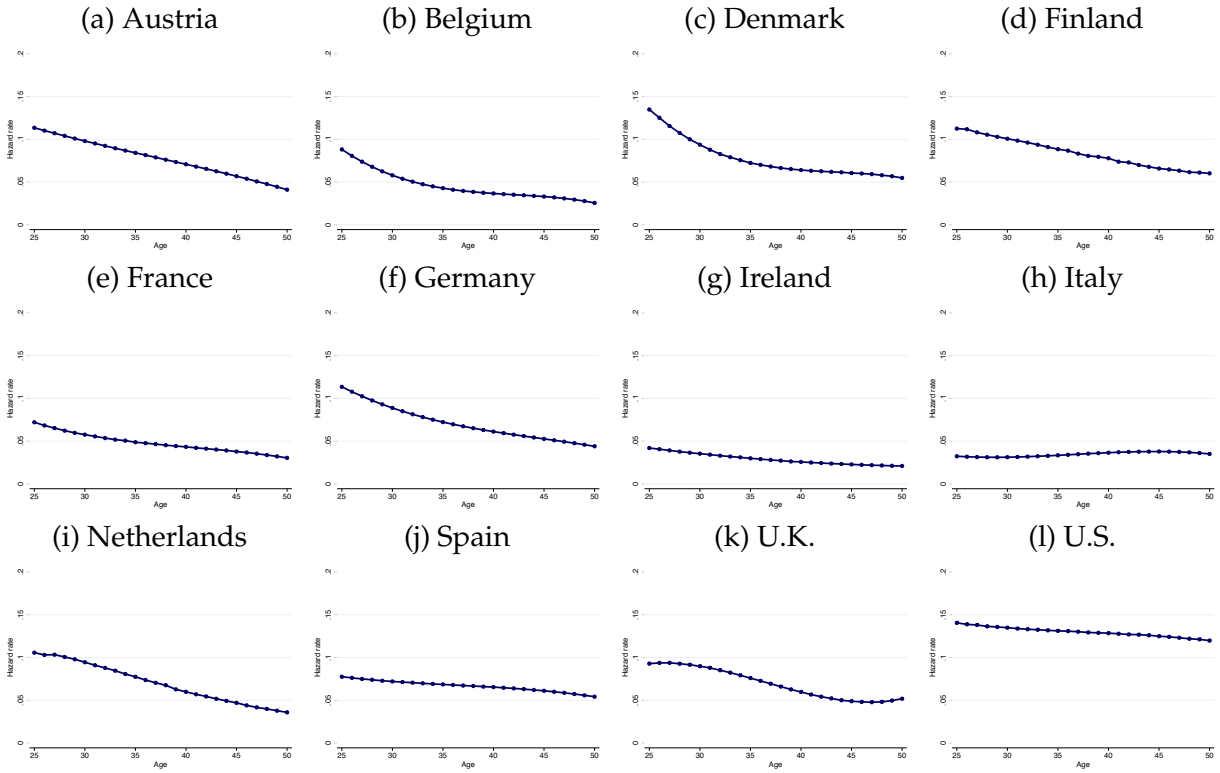
Figure A.2: Monthly EU hazard across 12 OECD countries




**UE mobility** Figure A.3 graphs the estimated UE hazard across countries. It declines as workers age, although the magnitude of the fall differs across countries.[25] The levels differ substantially across countries. For instance, 25 year olds in the U.S., Denmark and the Netherlands are at least twice as likely to return from unemployment in a given month compared to their French or Italian peers. The UE hazard is strongly positively correlated with the JtJ mobility hazard and positively correlated with the EU hazard across countries.

[25]The estimated re-entry hazard from unemployment for the U.S. is lower than tabulations from the CPS, and somewhat lower than that estimated by Menzio et al. (2016) and Krolikowski (2016).

Figure A.3: Monthly UE hazard across 12 OECD countries




**Correlation** Table A.1 correlates each of the estimated hazard rates with each other as well as with fluidity across countries. Each hazard is the unweighted average over the life-cycle. The monthly JtJ hazard is strongly positively correlated with the measure of fluidity, while the correlation between the UE hazard and fluidity is 0.55. The EU hazard is weakly negatively correlated with fluidity, but the relationship is not statistically significant at any meaningful level. The lack of a strong positive correlation between JtJ and UE mobility, on the one hand, and EU mobility, on the other, corroborates findings in Jolivet et al. (2006).

Table A.1: Cross-country correlation between hazard rates and fluidity

| | Fluidity | JtJ | EU | UE |
|---|---|---|---|---|
| Fluidity | 1.000 | | | |
| JtJ | 0.869 | 1.000 | | |
| EU | -0.200 | -0.297 | 1.000 | |
| UE | 0.552 | 0.382 | 0.267 | 1.000 |

Note: ECHP (1994–2001), EU-SILC (2004–2014), PSID (1990–2013), GSOEP (1991–2011), and BHPS (1992–2008); see text for further detail.

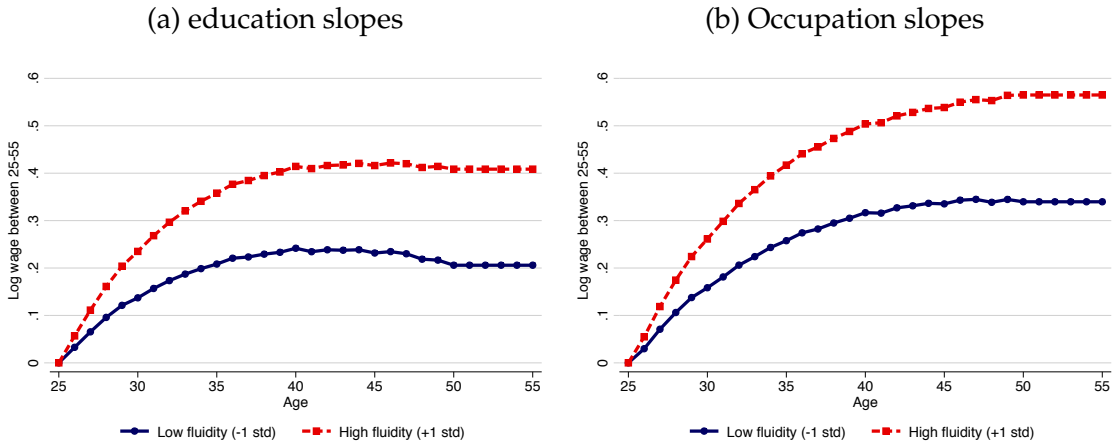
## A.3 Additional life-cycle wage profiles

This appendix presents additional results on life-cycle wage profiles across countries.

### A.3.1 Education or occupation controls

The left pane of Figure A.4 plots the predicted wage profile with a separate linear age slope for high-school graduates and a separate slope for college graduates. Plotted results are for the lowest education group. Although wage growth falls, the predicted cross country difference remains of similar magnitude. The right pane of Figure A.4 plots the predicted wage profile with occupation controls. Regression results underlying these graphs are available on request.

Figure A.4: Life-cycle wage growth with occupation or education slopes, low and high fluidity country

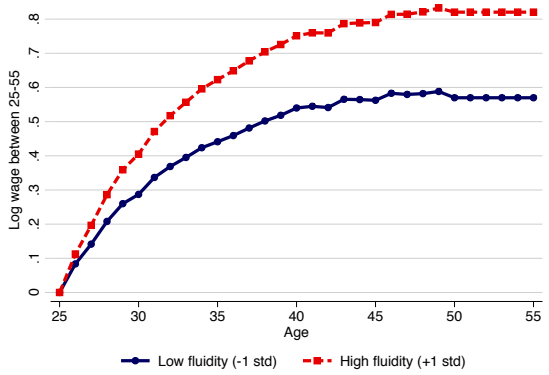



Note: ECHP (1994–2001), EU-SILC (2004–2014), PSID (1990–2013), GSOEP (1991–2011), and BHPS (1992–2008). See text for further details.

### A.3.2 College graduates only

Figure A.5 plots estimated wage profiles for a low and high fluidity country for college graduates. College graduates have much steeper wage growth. The difference associated with fluidity is as large as in the baseline specification with all education groups.

Figure A.5: Life-cycle wage growth for college graduates, low and high fluidity country

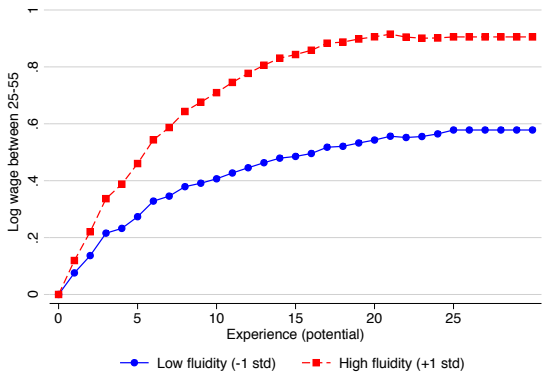



Note: ECHP (1994–2001), EU-SILC (2004–2014), PSID (1990–2013), GSOEP (1991–2011), and BHPS (1992–2008). See text for further details.

### A.3.3 By experience

Figure A.6 plots estimated life-cycle wage profiles for a low and high fluidity country using potential experience instead of age. Since potential experience only is available in the ECHP/EU-SILC, the analysis is restricted for those countries. Overall wage growth is steeper when using potential experience instead of age, and more fluid labor markets have substantially greater wage growth. Regression results underlying these graphs are available on request.

Figure A.6: Life-cycle wage growth by experience, low and high fluidity country

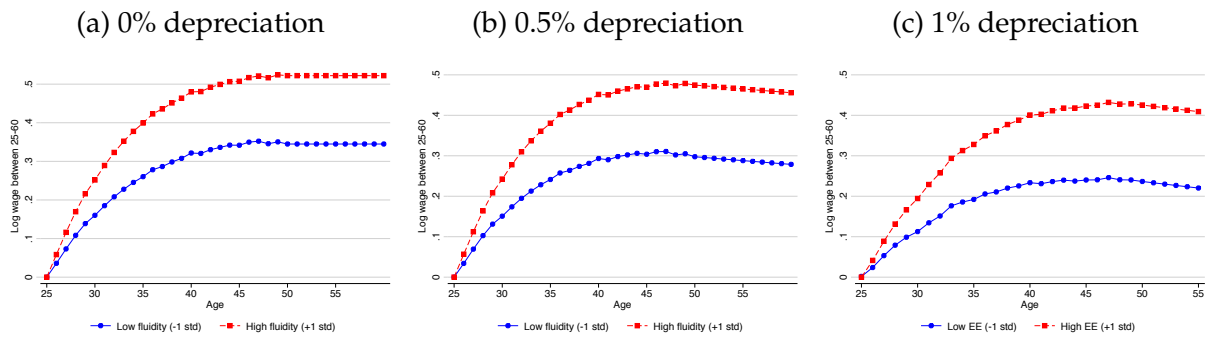



Note: ECHP (1994–2001), EU-SILC (2004–2014), PSID (1990–2013), GSOEP (1991–2011), and BHPS (1992–2008). See text for further details.

### A.3.4 Allowing for depreciation

Figure A.7 plots results under different assumptions for the depreciation rate late in life. The right pane shows results assuming a zero percent depreciation rate between age 50–60, the middle pane assuming a 0.5 percent annual depreciation rate between age 50–60, and the right graph assuming a one percent annual depreciation rate between age 50–60. The results suggest an important feature of the impact of assuming different depreciation rates: while the level of wages changes, the cross-country difference remains close to identical. Regression results underlying these graphs are available on request.

Figure A.7: Life-cycle wage growth under alternative assumptions on depreciation, low and high fluidity country



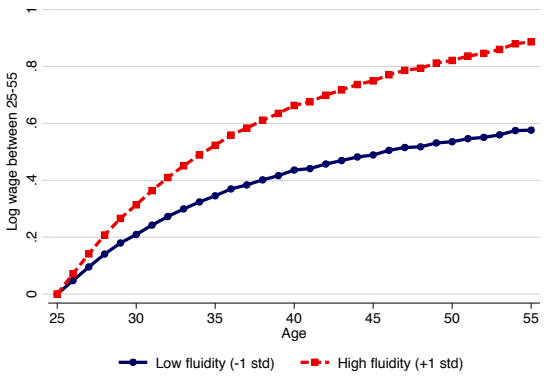

Note: ECHP (1994–2001), EU-SILC (2004–2014), PSID (1990–2013), GSOEP (1991–2011), and BHPS (1992–2008). See text for further details.

### A.3.5 Deaton (1997)–Hall (1968) or GDP controls

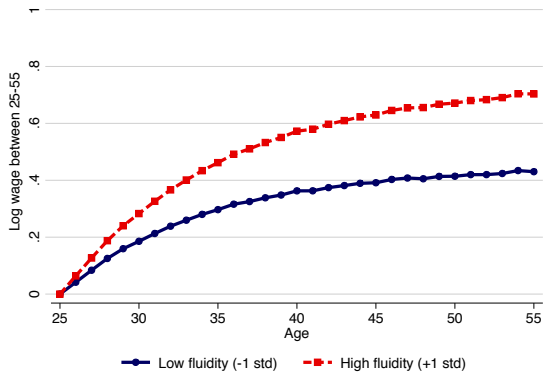
Figure A.8 plots results under alternative methods to deal with the collinearity of age, time and individual effects. The left pane graphs results imposing the normalization advocated by Deaton (1997), namely that secular changes are due to age and cohort effects, while time effects capture business cycles. The right pane shows results including a quadratic in GDP per hour (in constant PPP-adjusted 2004 U.S. dollars) to control for time trends. To the extent that wages grow faster in faster growing economies, this would be picked up the GDP control. Estimates of total life-cycle wage growth in the average fluidity country are greater, yet the cross-country difference predicted by differences in fluidity remains large. Regression results underlying these graphs are available on request.

Figure A.8: Life-cycle wage growth under alternative methods, low and high fluidity country

(a) Deaton (1997) method




(b) GDP controls




Note: ECHP (1994–2001), EU-SILC (2004–2014), PSID (1990–2013), GSOEP (1991–2011), and BHPS (1992–2008). See text for further details.

## A.4 Return to mobility

Table A.2 presents estimated returns to mobility. All estimates control for individual fixed effects and weigh countries equally. The coefficient $JtJ_{t+2}$ captures the wage impact of a JtJ transition two years in the future, $JtJ_t$ the impact of a JtJ transition in the past year, etc. The coefficient on $\overline{JtJ}$ captures the impact of a JtJ transition in any of the prior seven years. The 5–7 year lags on mobility are estimated off a very small set of individuals in the eight year panel, and hence should be interpreted with caution.[26]

Column 1 shows results from model 1.3 controlling for country-year effects (in addition to the individual fixed effects). Wages are somewhat depressed prior to a JtJ transition, while they begin to fall two years prior to an EU transition. Wages jump by six log points in the year of a JtJ transition, while wages are eight log points lower in the year a worker returns to work after an EU transition. Wages continue to grow relative to counter-factual over the next few years after a JtJ transition, but at a declining pace.[27]

Column 2 adds an age-specific country-year effect, specifically by imposing a separate linear term in age in each country-year. The predicted effect of a voluntary transition declines somewhat, in particular due to lower subsequent growth in wages post transition. This could be a result of the fact that young workers are more likely to transition and have higher unconditional wage growth. Nevertheless, the predicted wage growth due to mobility remains substantial at around seven log points two years after the transition.

Column 3 allows the return to mobility to vary with age, which suggests that the gains from JtJ mobility falls with age while the losses from displacement increase. Column 4

[26]Furthermore, given that the regressions include individual fixed effects and up to two years of future mobility, the coefficients on 5–7 years of lagged mobility are identified off individuals who have no years of data in the eight year panel without any indicator switched on. Their individual fixed effects are hence estimated off the difference between their wages in years 1–2 prior to mobility and 0–4 after mobility, and that predicted based on the 1–2 future and 0–4 lagged indicators estimated off individuals who do have years without a single indicator switched on. The 5–7 year lagged indicators are estimated off the difference in these individuals' wages in years 5–7 after mobility and their imputed fixed effects.

[27]In the event that JtJ mobility is not exogenous (conditional on individual, country-year and age effects), the group of non-moving workers does not provide an ideal control group for understanding trend in wages absent mobility. The lack of a strong pre-trend in wages lends some support to this assumption, but "counter-factual" should be interpreted with this caveat in mind.

finds no support for the hypothesis that the return to JtJ mobility varies with fluidity, while the loss from displacement increases in fluidity.[28]

[28]I have also allowed the post-transition return to vary freely by country. The f-tests that the return to JtJ mobility is the same across countries at all post-transition lags cannot be rejected at any reasonable confidence level (p-value 0.186), while the loss from displacement differs statistically across countries (p-value 0.00).

Table A.2: Estimated return to mobility

| | (1) Baseline | (2) Age | (3) Age slope | (4) Fluidity |
|---|---|---|---|---|
| $JtJ_{t+2}$ | -0.00367 | -0.01507** | -0.01427** | -0.01501** |
| | (0.00713) | (0.00707) | (0.00705) | (0.00706) |
| $JtJ_{t+1}$ | -0.01815*** | -0.03204*** | -0.03066*** | -0.03203*** |
| | (0.00665) | (0.00665) | (0.00666) | (0.00665) |
| $JtJ_t$ | 0.04442*** | 0.02856*** | 0.04938*** | 0.02869*** |
| | (0.00678) | (0.00685) | (0.00863) | (0.00697) |
| $JtJ_{t-1}$ | 0.05652*** | 0.03400*** | 0.05542*** | 0.03408*** |
| | (0.00744) | (0.00753) | (0.00910) | (0.00758) |
| $JtJ_{t-2}$ | 0.07434*** | 0.04847*** | 0.07061*** | 0.04868*** |
| | (0.00776) | (0.00792) | (0.00958) | (0.00799) |
| $JtJ_{t-3}$ | 0.07833*** | 0.05019*** | 0.07302*** | 0.05052*** |
| | (0.00888) | (0.00903) | (0.01065) | (0.00906) |
| $JtJ_{t-4}$ | 0.07730*** | 0.04741*** | 0.07100*** | 0.04770*** |
| | (0.00950) | (0.00964) | (0.01123) | (0.00966) |
| $JtJ_{t-5}$ | 0.08987*** | 0.05998*** | 0.08449*** | 0.06037*** |
| | (0.01164) | (0.01193) | (0.01343) | (0.01190) |
| $JtJ_{t-6}$ | 0.09883*** | 0.06960*** | 0.09573*** | 0.06993*** |
| | (0.01327) | (0.01325) | (0.01463) | (0.01322) |
| $JtJ_{t-7}$ | 0.03833** | 0.01320 | 0.04126** | 0.01395 |
| | (0.01929) | (0.01922) | (0.02028) | (0.01921) |
| $EU_{t+2}$ | 0.00467 | 0.00065 | -0.00057 | 0.00059 |
| | (0.00702) | (0.00697) | (0.00695) | (0.00696) |
| $EU_{t+1}$ | -0.02658*** | -0.02948*** | -0.02769*** | -0.02952*** |
| | (0.00728) | (0.00722) | (0.00720) | (0.00721) |
| $EU_t$ | -0.07631*** | -0.07943*** | -0.04822*** | -0.07832*** |
| | (0.00771) | (0.00765) | (0.00883) | (0.00759) |
| $EU_{t-1}$ | -0.03664*** | -0.04436*** | -0.01459* | -0.04329*** |
| | (0.00752) | (0.00745) | (0.00854) | (0.00740) |
| $EU_{t-2}$ | -0.01086 | -0.02149*** | 0.00840 | -0.02057*** |
| | (0.00773) | (0.00767) | (0.00875) | (0.00764) |
| $EU_{t-3}$ | -0.00164 | -0.01313* | 0.01778* | -0.01224 |
| | (0.00797) | (0.00792) | (0.00910) | (0.00789) |
| $EU_{t-4}$ | -0.00038 | -0.01171 | 0.02008** | -0.01089 |
| | (0.00923) | (0.00914) | (0.01013) | (0.00911) |
| $EU_{t-5}$ | -0.00452 | -0.01431 | 0.01939* | -0.01355 |
| | (0.00943) | (0.00934) | (0.01062) | (0.00932) |
| $EU_{t-6}$ | 0.00311 | -0.00681 | 0.02723** | -0.00624 |
| | (0.01164) | (0.01153) | (0.01264) | (0.01151) |
| $EU_{t-7}$ | -0.02739 | -0.03868* | -0.00226 | -0.03835* |
| | (0.02272) | (0.02260) | (0.02359) | (0.02261) |
| $\overline{JtJ} \times Fluidity$ | | | | -0.04556 |
| | | | | (0.31321) |
| $\overline{EU} \times Fluidity$ | | | | -0.86006** |
| | | | | (0.40872) |
| $\overline{JtJ} \times Age$ | | | -0.00242*** | |
| | | | (0.00060) | |
| $\overline{EU} \times Age$ | | | -0.00413*** | |
| | | | (0.00061) | |
| N | 142,711 | 142,711 | 142,711 | 142,711 |
| R2 | 0.83181 | 0.83279 | 0.83304 | 0.83281 |



Note: ECHP (1994–2001), GSOEP (1994–2001), BHPS (1994–2001), and PSID (1990–1997); *10%; **5%; ***1%; see text for further details.

## A.5 Proofs

### A.5.1 Proof of proposition 1

*Proof.* Note first that

$$\lim_{v\to 0} i^W(v) = \left(\frac{p_1}{c_h}\right)^{\frac{1}{\gamma-1}} > 0, \quad \lim_{v\to 0} i^E(v) = -h < 0$$

Hence, if $\lim_{v\to\infty} \frac{i^E(v)}{i^W(v)} > 1$ there is at least one equilibrum

$$\lim_{v\to\infty} \frac{\frac{4c_v v^{1-\alpha}}{(1-\beta)(p_2-p_1)} - h}{\left[\frac{1}{c_h}\left(p_1 + v^\alpha \beta \frac{1}{2}(p_2-p_1)\right)\right]^{\frac{1}{\gamma-1}}} = \lim_{v\to\infty} v^{1-\alpha-\frac{\alpha}{\eta-1}} \frac{\frac{4c_v}{(1-\beta)(p_2-p_1)} - \frac{h}{v^{1-\alpha}}}{\left[\frac{1}{c_h}\left(\frac{p_1}{v^\alpha} + \beta \frac{1}{2}(p_2-p_1)\right)\right]^{\frac{1}{\gamma-1}}}$$

The second term is strictly positive. Hence, if and only if

$$1 - \alpha - \frac{\alpha}{\gamma-1} > 0 \iff \gamma(1-\alpha) > 1$$

the limit tends to infinity and there is at least one solution. If $\gamma(1-\alpha) = 1$, the limit tends to

$$\lim_{v\to\infty} \frac{i^E(v)}{i^W(v)} = \frac{\frac{4c_v}{(1-\beta)(p_2-p_1)}}{\left[\frac{1}{c_h}\beta\frac{1}{2}(p_2-p_1)\right]^{\frac{1}{\gamma-1}}}$$

which is greater than one if and only if

$$2c_h(4c_v)^{\gamma-1} > \beta(1-\beta)^{\gamma-1}(p_2-p_1)^\gamma$$

To see that the solution is unique, consider the derivatives

$$\begin{aligned}
\frac{\partial i^W(v)}{\partial v} &= \frac{1}{\eta-1} i^W(v) \left[\frac{1}{c_h}\left(p_1 + v^\alpha \beta \frac{1}{2}(p_2-p_1)\right)\right]^{-1} \frac{1}{c_h}\beta\frac{1}{2}(p_2-p_1)\alpha v^{\alpha-1} \\
\frac{\partial i^E(v)}{\partial v} &= \left[i^E(v) + \frac{4c_v}{(1-\beta)(p_2-p_1)}h\right]\frac{1-\alpha}{v}
\end{aligned}$$

If $\frac{i^E(v)}{i^W(v)} \geq 1 \Rightarrow \frac{\frac{\partial i^E(v)}{\partial v}}{\frac{\partial i^W(v)}{\partial v}} > 1$ then the solution is unique. Suppose $\frac{i^E(v)}{i^W(v)} \geq 1$, then we need to show that

$$\begin{aligned}
\frac{\frac{1-\alpha}{v}\left(p_1 + v^\alpha \beta \frac{1}{2}(p_2 - p_1)\right)}{\frac{1}{\eta-1}\beta\frac{1}{2}(p_2-p_1)\alpha v^{\alpha-1}} &\geq 1 \\
p_1 + v^\alpha \beta \frac{1}{2}(p_2 - p_1) &\geq \frac{1}{(\eta-1)(1-\alpha)}\beta\frac{1}{2}(p_2-p_1)\alpha v^\alpha \\
\frac{2p_1}{\beta(p_2-p_1)} &\geq \left[\frac{\alpha}{(\eta-1)(1-\alpha)} - 1\right] v^\alpha
\end{aligned}$$

To ensure uniqueness, we need this to hold $\forall v \geq 0$, and hence we need

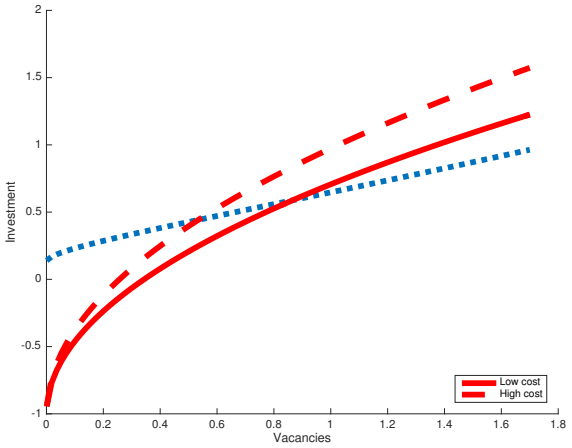
$$\begin{aligned}
\frac{\alpha}{(\eta-1)(1-\alpha)} - 1 &\leq 0 \\
1 &\leq \eta(1-\alpha)
\end{aligned}$$

□

### A.5.2 Proof of proposition 2

*Proof.* In the unique equilibrium, $\frac{di^E(v^*)}{dv} > \frac{di^W(v^*)}{dv}$ must hold since both curves are upward sloping and $\lim_{v\to 0} i^E(v) < \lim_{v\to 0} i^W(v)$. Since $\frac{\partial i^E(v)}{\partial c_v} > 0$ while $\frac{\partial i^W(v)}{\partial c_v} = 0$, an increase in the cost of creating jobs rotates $i^E(v)$ upwards, which implies that in equilibrium investment and vacancies fall. Figure A.9 illustrates this intuition.

Figure A.9: Policy function




□

### A.5.3 Proof of proposition 3

*Proof.* As noted above, an increase in the cost of creating jobs rotates $i^E(v)$ upwards. The magnitude of this shift is independent of $\gamma$. To understand the equilibrium impact of this on investment and vacancies, note that

$$\frac{di^W(v)}{dv} \Big/ \frac{i^W(v)}{v} = \frac{1}{\gamma - 1} \frac{\beta \frac{1}{2}(p_2 - p_1)\alpha v^\alpha}{p_1 + \beta \frac{1}{2}(p_2 - p_1)v^\alpha}$$

Hence, a given change in $c_v$ results in a larger equilibrium fall in investment and vacancies the smaller is $\gamma$. □

### A.5.4 Proof of proposition 4

*Proof.* In the unique competitive equilibrium,

$$i^{CE} = \frac{8c_v p_1 + (1-\beta)\beta(p_2 - p_1)^2 h}{8c_v c_h - (1-\beta)\beta(p_2 - p_1)^2}$$
$$v^{CE} = \left[\frac{(1-\beta)(p_2 - p_1)(c_h h + p_1)}{8c_h c_v - (1-\beta)\beta(p_2 - p_1)^2}\right]^2$$

The planning problem is

$$V^{SP} = \max_{v,\lambda,i,h'} \left\{ p_1 h - \frac{c_h}{2} i^2 + \left[ p_1 + \sqrt{v} \frac{1}{2} (p_2 - p_1) \right] (h + i) - 2 c_v v \right\}$$

Taking first-order conditions and rearranging,

$$\begin{aligned} i^{SP} &= \frac{8 c_v p_1 + (p_2 - p_1)^2 h}{8 c_v c_h - (p_2 - p_1)^2} \\ v^{SP} &= \left[ \frac{2 (p_2 - p_1) c_h h + p_1}{8 c_h c_v - (p_2 - p_1)^2} \right]^2 \end{aligned}$$

Consider the ratio of investment in the competitive economy to the social planner: we need to show that $\frac{i^{CE}}{i^{SP}} < 1$. After some algebra, we have that this is true if and only if

$$\left[ 1 - (1 - \beta)\beta \right] c_h h + p_1 \left[ 1 - (1 - \beta)\beta \right] > 0$$

Since $\beta \in [0, 1]$, it must hold that $\beta(1 - \beta) \in [0, 0.25]$ and hence the left hand side is always positive. □

## A.6 Numerical solution

The following section contains details on the endogenous grid point method that I use to solve the model numerically.

The first-order condition for optimal search of unemployed workers is

$$s_a^u(h) = \left[ \frac{1}{c_u h} \lambda\beta \int_{\underline{p}}^{\bar{p}} J_{a+1}(h,p) - W_{a+1}(h) dF(p) \right]^{\frac{1}{\eta-1}}$$

Substituting in the solution gives the value function $W_a$ at each grid point. The derivative at the grid point is given by

$$\frac{dW_a(h)}{dh} = \rho \left[ -\frac{c_u}{\eta} \left(s_a^u(h)\right)^\eta + \frac{dW_{a+1}(h)}{dh} + s_a^u(h)\lambda\beta \int_{\underline{p}}^{\bar{p}} \frac{dJ_{a+1}(h,p)}{dh} - \frac{dW_{a+1}(h)}{dh} dF(p) \right]$$

The first-order condition for optimal search of the employed is

$$s_a^e\left[h(h',p),p\right] = \left[ \frac{1}{c_e h'} \lambda\beta \int_{\underline{p}}^{\bar{p}} \int_{\tilde{p}}^{\bar{p}} \left[ J_{a+1}(h',p') - J_{a+1}(h',\tilde{p}) \right] dF(p') dG(\tilde{p}|p) \right]^{\frac{1}{\eta-1}}$$

This defines an optimal search policy over some endogenous grid for $h$ as a function of $h'$ and $p$.

The first-order condition for optimal investment can be written as,

$$\begin{aligned} i\left[h(h',p),p\right] \;=\; & \left\{ \frac{\rho}{c_h} \left[ \int_{\underline{p}}^{\bar{p}} \left( \frac{\partial J_{a+1}(h',\tilde{p})}{\partial h'} + \delta \left[ \frac{dW_{a+1}(h')}{dh'} - \frac{\partial J_{a+1}(h',\tilde{p})}{\partial h'} \right] + \right. \right. \\ & + s_a^e\left[h(h',p),p\right] \lambda\beta \int_{\tilde{p}}^{\bar{p}} \left[ \frac{\partial J_{a+1}(h',p')}{\partial h'} - \frac{\partial J_{a+1}(h',\tilde{p})}{\partial h'} \right] dF(p') \Bigg) dG(\tilde{p}|p) - \\ & \left. - \frac{c_e s_a^e\left[h(h',p),p\right]^\eta}{\eta} \right] \Bigg\}^{\frac{1}{\gamma-1}} \end{aligned}$$

This provides an optimal investment policy at the endogenous grid point. The derivative at the endogenous grid point is given by the envelope condition,

$$\begin{aligned}\frac{\partial J_a\left[h(h',p),p\right]}{\partial h} &= p+\rho\left\{\int_{\underline{p}}^{\bar{p}}\left(\frac{\partial J_{a+1}(h',\tilde{p})}{\partial h'}+\delta\left[\frac{dW_{a+1}(h')}{dh'}-\frac{\partial J_{a+1}(h',\tilde{p})}{\partial h'}\right]+\right.\right.\\ &\quad \left.+s_a^e\left[h(h',p),p\right]\lambda\beta\int_{\tilde{p}}^{\bar{p}}\left[\frac{\partial J_{a+1}(h',p')}{\partial h'}-\frac{\partial J_{a+1}(h',\tilde{p})}{\partial h'}\right]dF(p')\right)dG(\tilde{p}|p)-\\ &\quad \left.-\frac{c_e\left(s_a^e\left[h(h',p),p\right]\right)^{\eta}}{\eta}\right\}\end{aligned}$$

Finally, I obtain the value functions at the endogenous grip points by substituting in the optimal policies. I interpolate the optimal policy functions, value functions and derivatives over the endogenous grid to obtain them at the exogenous grid point for $h$.

## A.7 Additional model predictions

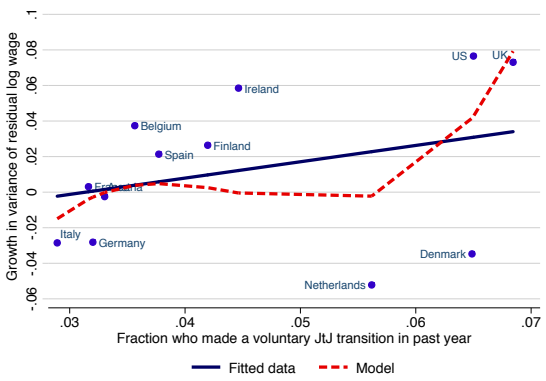
The following section compares additional moments from the model with the data.

### A.7.1 Inequality

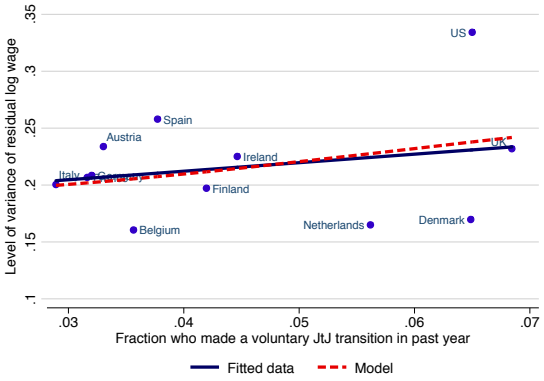
Figure A.10 plots inequality in the model and data as a function of fluidity. Data moments are residual inequality controlling for separate education-age and education-year trends. The left graph plots the increase in inequality over the life-cycle in the model and the data, while the right graph plots the steady-state level of inequality. There is only a weak covariance between age measure and fluidity in both the model and data.

Figure A.10: Inequality, model versus data

(a) Growth over the life-cycle




(b) Steady-state level

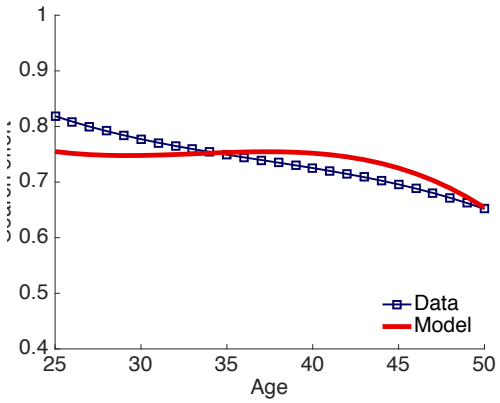



### A.7.2 Search from unemployment

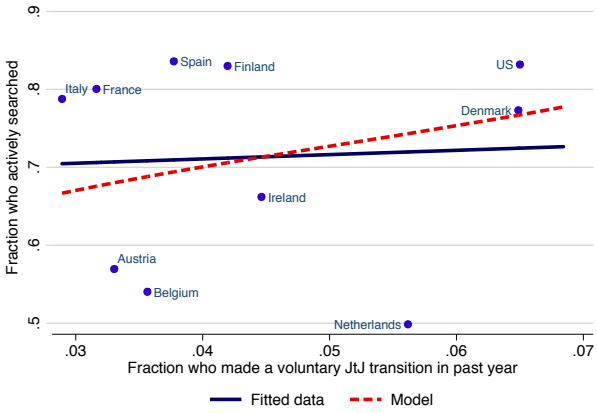
Figure A.11 compares the model's predictions for job search from unemployment with the data. The left pane plots the life-cycle profile, while the right pane plots the cross-country relationship between unemployed search and fluidity. In both cases, the model does a reasonable job at matching the lack of a strong pattern in the data.

Figure A.11: Unemployed search, model versus data

(a) Life-cycle profile




(b) Search and fluidity



## A.8 Additional details on on-the-job training

The following section provides additional robustness results with respect to the empirical measures of on-the-job training.

### A.8.1 Training and fluidity: Regression results

Let $train_{it}$ either indicate the number of weeks someone trained since January last year, or be an indicator for whether someone trained during the prior year. I regress by OLS this measure of training on the fluidity of the labor market while controlling for worker observables,

$$train_{it} = \alpha fluidity_{c(i)} + \mathbb{X}_{it}\beta + \varepsilon_{it}$$

Weights are adjusted such that each country receives the same aggregate weight, and standard errors are clustered at the country level. I include as controls a cubic in age, a college control, and occupation controls.

Alternatively, I relate the extent to which college graduates train more than those with less than a college degree within countries to the fluidity of college graduates relative to those with less than a college degree within countries. Specifically, I regress training on a cubic in age, country-fixed effects, a college effect, and an education-country specific fluidity,

$$train_{it} = \alpha fluidity_{c(i),col(i)} + \phi(age_{it}) + College_{it} + \Phi_{c(i)} + \varepsilon_{it}$$

Weights are adjusted such that each country receives the same aggregate weight, and standard errors are clustered at the country level. By controlling for both country and college fixed effects, the coefficient of interest $\alpha$ captures the extent to which a relatively higher fluidity of college graduates in a country is associated with a relatively higher incidence of training of college graduates in that country.

Table A.3 presents regression results on the relationship between on-the-job training and labor market fluidity. Column 1–3 uses as dependent variable the number of weeks in training since January last year, while columns 4–6 uses an indicator for whether someone trained at all since January last year. The former is advantageous since it provides a more complete measure of the intensity of training, while the advantage of the latter is mainly that the former is not available for the U.K. and the Netherlands.

The ECHP only contains information on the number of days spent on the last training course during the previous year. If workers trained on multiple occasions since January last year, I only observe the time spent in the last session. Hence, the measured number of weeks trained is a lower bound on the total number of weeks in training. To the extent that workers in more fluid labor markets are more likely to train on multiple occasions during a year, the measured cross-country difference also provides a lower bound on the true cross-country difference. Reversely, if workers are *more* likely to train on multiple occasions conditional on training at least once in low fluidity countries, the observed difference in weeks trained overstates the true difference. I view this as less likely given that the frequency of training at least once is lower in a low fluidity country.

As can be seen in column 1–2, more fluid labor markets have a greater number of weeks trained. A two standard deviation difference in fluidity is associated with three more weeks of training on average. Given that the average number of weeks of training of a 25 year old is just under five, this is a large difference. The indicators for training reveal an equally strong positive correlation between training and fluidity across countries, see column 4–5. Both measures of training fall with age, and college graduates train more. The ranking of occupations is largely a mirror image of life-cycle wage growth of occupations: engineers and managers have the highest levels of training, whereas laborers have the lowest incidence of training.

Column 3 presents results within countries on the relationship between the relative number of weeks of training of college graduates and that group's relative fluidity within

the country. The estimated effect is positive, suggesting that in countries where college graduates are relatively more mobile compared to non-college graduates, they have a relatively higher number of weeks trained. Column 6 contradicts this conclusion using the indicator of training. The point estimate is negative, but this is highly statistically insignificant (p-value 0.74).

Table A.3: Fluidity and on-the-job training

| | Weeks | | | Whether | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Educ. | Occup. | Within | Educ. | Occup. | Within |
| Fluidity | 101.514*** | 107.535*** | 48.392* | 6.037** | 5.608* | -1.028 |
| | (7.855) | (9.382) | (23.234) | (2.483) | (2.862) | (2.988) |
| Age | -0.537* | -0.536* | -0.550** | -0.007** | -0.008** | -0.008** |
| | (0.270) | (0.276) | (0.210) | (0.003) | (0.003) | (0.003) |
| $Age^2$ | 0.027 | 0.027 | 0.028** | 0.000 | 0.000 | 0.000 |
| | (0.016) | (0.016) | (0.013) | (0.000) | (0.000) | (0.000) |
| $Age^3$ | -0.000 | -0.000 | -0.001* | -0.000 | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| College | 1.943*** | | 1.451*** | 0.233*** | | 0.223*** |
| | (0.390) | | (0.228) | (0.037) | | (0.021) |
| Manager | | -0.909 | | | -0.012 | |
| | | (1.066) | | | (0.039) | |
| Engineer/Doctor | | -1.408 | | | 0.069* | |
| | | (1.287) | | | (0.037) | |
| Professional | | -0.018 | | | 0.035 | |
| | | (1.728) | | | (0.023) | |
| Health Associate | | -0.053 | | | 0.002 | |
| | | (0.934) | | | (0.019) | |
| Salesman | | -1.863** | | | -0.116*** | |
| | | (0.708) | | | (0.032) | |
| Service worker | | -2.097* | | | -0.154*** | |
| | | (0.922) | | | (0.036) | |
| Craftman | | -2.421** | | | -0.221*** | |
| | | (0.966) | | | (0.039) | |
| Operative | | -2.652** | | | -0.226*** | |
| | | (0.987) | | | (0.042) | |
| Laborer | | -2.858** | | | -0.283*** | |
| | | (1.092) | | | (0.047) | |
| Constant | 4.699*** | 7.060** | 2.795** | 0.284*** | 0.480*** | 0.342** |
| | (1.302) | (2.121) | (1.019) | (0.040) | (0.065) | (0.142) |
| N | 90,464 | 87,494 | 90,180 | 115,562 | 111,968 | 115,188 |

### A.8.2 Impact of training on mobility

This section presents some support in favor of the assumption in the model that human capital is general using the behavior of mobility around training. Let $mob_{it}$ either indicate whether individual $i$ makes a JtJ or an EU transition in year $t$. I regress this on indicators for whether the individual trained up to two years into the future and three years in the past, plus worker controls

$$mob_{it} = \sum_{\tau=-2}^{3} \xi_\tau train_{it-\tau} + \mathbb{X}_{it}\beta + \varepsilon_{it}$$

I alternatively include in $\mathbb{X}_{it}$ age, education, occupation and country-year controls, or individual fixed effects together with country-year or country-year-age controls. Weights are adjusted such that each country receives the same aggregate weight, and standard errors are clustered at the individual level.

Table A.4 presents results. Column 1 shows result for the JtJ hazard with age, education, occupation and country-year controls, but no individual fixed effects. Column 2 shows estimates with individual fixed effects and country-year controls, and column 3 with individual fixed effects and a country-year-specific age slope. No specification provides evidence of an impact of training on JtJ mobility. Thus, it does not appear as though training "locks" the worker to the training employer. Furthermore, the fact that mobility is not higher in the years before training takes place suggests that the cross-country correlation between fluidity and training is not driven mechanically by a high need to train early in a match.

Column 3–6 shows the same result for the probability of an involuntary separation. This falls significantly after training, and stays lower for the subsequent three years. This could potentially support the notion that investment is in firm-specific human capital. However, if this were the case it is not clear why we do not observe a similar fall in the hazard of leaving the firm voluntarily for another employer.

Another hypothesis would be if it takes time for the worker and firm to learn about the quality of their match, or alternatively if this quality fluctuates over time. Suppose that the perceived value of their match increases (either because they gain new information or because the match is subject to a positive shock)—this could lead to both increased training and a lower probability of separation, regardless of whether such investment is in firm-specific human capital or not. However, also under this hypothesis it is unclear why not a similar trend is observed for the JtJ hazard—if investment takes place after the worker and firm have realized that their match is more valuable than previously thought, we should observe a fall also in the separation rate to other employers after investment.

An explanation that is in line with the behavior of both hazard rates is that investment raises the value of any match relative to unemployment, hence reducing the separation rate to non-employment while leaving the separation rate to other employers unchanged.

Table A.4: Training and mobility

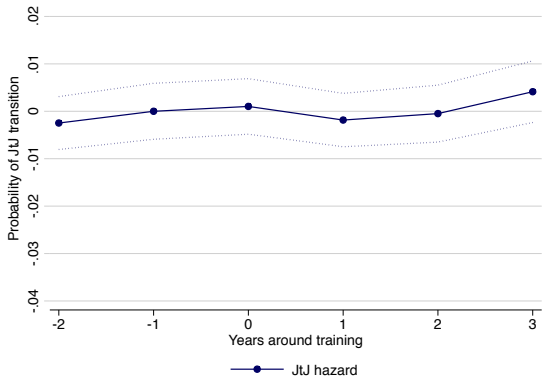
| | JtJ | | | EU | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Base | FE | FE+Age | Base | FE | FE+Age |
| $training_{t+2}$ | -0.00413 | -0.00322 | -0.00257 | -0.01614*** | -0.00740* | -0.00472 |
| | (0.00258) | (0.00286) | (0.00285) | (0.00377) | (0.00416) | (0.00411) |
| $training_{t+1}$ | 0.00069 | 0.00029 | -0.00009 | -0.00408 | 0.00337 | 0.00602 |
| | (0.00263) | (0.00301) | (0.00301) | (0.00355) | (0.00389) | (0.00384) |
| $training_t$ | 0.00298 | 0.00083 | 0.00093 | 0.02309*** | 0.00694* | 0.00824** |
| | (0.00247) | (0.00300) | (0.00299) | (0.00358) | (0.00405) | (0.00393) |
| $training_{t-1}$ | -0.00188 | -0.00280 | -0.00194 | -0.03018*** | -0.02533*** | -0.02165*** |
| | (0.00280) | (0.00296) | (0.00287) | (0.00348) | (0.00413) | (0.00406) |
| $training_{t-2}$ | -0.00245 | -0.00130 | -0.00058 | -0.02106*** | -0.01553*** | -0.01099** |
| | (0.00296) | (0.00316) | (0.00306) | (0.00359) | (0.00433) | (0.00435) |
| $training_{t-3}$ | 0.00078 | 0.00589* | 0.00403 | -0.02562*** | -0.01491*** | -0.01100** |
| | (0.00323) | (0.00345) | (0.00331) | (0.00388) | (0.00445) | (0.00453) |
| N | 102,445 | 111,257 | 111,257 | 102,445 | 111,257 | 111,257 |
| R2 | 0.03076 | 0.26637 | 0.26566 | 0.05580 | 0.46168 | 0.46298 |

Note: ECHP (1994–2001); *10%; **5%; ***1%; see text for further details.

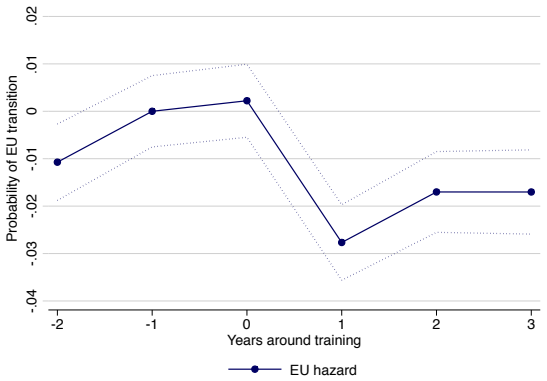
Figure A.12 graphs these results: the left pane for the JtJ hazard and the right pane for the EU hazard around the time of training at time zero.

Figure A.12: Estimated impact of on-the-job training on mobility

(a) JtJ hazard




(b) EU hazard




Note: ECHP (1994–2001); see text for further details.

### A.8.3 Impact of training on wages

In the same spirit as the study of the impact of mobility on wages, I employ the following fixed effects framework to evaluate the effect of training on wages. Wages are regressed on a set of indicators for whether the individual trained in up to two years into the future and seven years in the past, controlling for individual and country-year effects,

$$wage_{it} = \sum_{\tau=-2}^{7} \xi_\tau train_{it-\tau} + \mathbb{X}_{it}\beta + \varepsilon_{it}$$

Weights are adjusted such that each country receives the same aggregate weight, and standard errors are clustered at the individual level. I alternatively substitute separate country-year-specific age interactions for the country-year effects to control for life-cycle factors or age specific country-year trends.

I subsequently allow the return to training to vary with age by including an interaction between age and an indicator for whether the worker trained at any point in the last seven years,

$$wage_{it} = \sum_{\tau=-2}^{7} \xi_\tau train_{it-\tau} + \zeta age_{it} \times \overline{train}_{it} + \mathbb{X}_{it}\beta + \varepsilon_{it}$$

Notice that age is assumed to only impact the return post training. $\mathbb{X}_{it}$ includes a full set of individual effects and a linear in age fully interacted with country-year.

Finally, I investigate whether returns vary with fluidity by including an interaction between fluidity and an indicator for whether the worker trained at any point in the last seven years,

$$wage_{it} = \sum_{\tau=-2}^{7} \xi_\tau train_{it-\tau} + \zeta fluidity_{it} \times \overline{train}_{it} + \mathbb{X}_{it}\beta + \varepsilon_{it}$$

where $\mathbb{X}_{it}$ includes a full set of individual and country-year effects.

Table A.5 presents results. Column 1 shows results with controls for country-year and individual fixed effects. Wages increase post training by a little over two log points, and this increase gradually builds up over the next two years after training. There is no statistically significant trend in wages prior to training, hence lending little support to there for instance being an "Ashenfelter" dip in wages prior to training (Ashenfelter, 1978). Column 2 controls for country-year-age trends by substituting a country-year specific linear age term for the country-year effects. The return to training is 1.7 log points three years after. Column 3 adds allows the return to vary by age. The return to training is increasing with training. Finally, Column 4 adds an interaction between labor market fluidity and having received training at any point in the past seven years. The estimated return to training is increasing in fluidity.

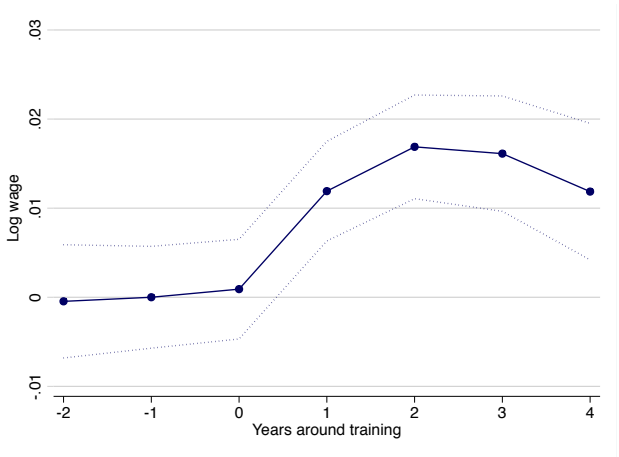
Table A.5: Return to on-the-job training

| | (1) Baseline | (2) Age | (3) Age slope | (4) Fluidity |
|---|---|---|---|---|
| $train_{t+2}$ | 0.004 | 0.000 | 0.001 | 0.005 |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| $train_{t+1}$ | 0.003 | -0.000 | -0.000 | 0.004 |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| $train_t$ | 0.002 | -0.001 | -0.005 | -0.001 |
| | (0.003) | (0.003) | (0.003) | (0.004) |
| $train_{t-1}$ | 0.018*** | 0.011*** | 0.009*** | 0.017*** |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| $train_{t-2}$ | 0.026*** | 0.020*** | 0.018*** | 0.025*** |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| $train_{t-3}$ | 0.017*** | 0.011*** | 0.010** | 0.016*** |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| $train_{t-4}$ | 0.022*** | 0.020*** | 0.019*** | 0.022*** |
| | (0.005) | (0.004) | (0.004) | (0.005) |
| $\overline{train} \times Age$ | | | 0.001*** | |
| | | | (0.000) | |
| $\overline{train} \times Fluidity$ | | | | 0.205* |
| | | | | (0.114) |
| N | 104,129 | 104,129 | 104,129 | 104,129 |
| R2 | 0.841 | 0.843 | 0.843 | 0.841 |

Note: ECHP (1994–2001); *10%; **5%; ***1%; see text for further details.

Figure A.13 illustrates the wage impact of training based on the estimates in column 2.

Figure A.13: Estimated wage impact of on the job training in year zero




Note: ECHP (1994–2001); see text for further details.

## A.9 Additional details on search

The following section presents additional results on the measure of active search. As noted above, this part of the analysis is based on the ECHP and the 1990–1997 PSID. The ECHP asks employed workers whether they are looking for a new job, and if so whether they have taken any active steps to find a new job in the past four weeks. The PSID asks whether an employed worker has looked for a new job in the past four weeks.

### A.9.1 Search and fluidity: Regression results

I estimate by a linear probability model whether an employed worker searched actively for a new job within the past four weeks on the measure of labor market fluidity and worker observable controls,

$$search_{it} = \alpha fluidity_{c(i)} + \mathbb{X}_{it}\beta + \varepsilon_{it}$$

where I include in $\mathbb{X}_{it}$ age controls or age and college controls. Results are weighted with the provided survey weights adjusted such that each country receives the same weight, and standard errors are clustered at the country level. I implement an identical analysis for unemployed job search.

Table A.6 presents results from this regression model. Column 1 shows results for the probability of employed job search versus labor market fluidity with year and age controls, while column 2 also includes education controls. On average, 11 percent of employed 25 year olds searched for a new job in the past four weeks. This falls with age to be close to zero at age 55. College educated search with a higher intensity than non-college graduates. Under both specifications, there is a statistically strong positive correlation between fluidity and the probability that someone searches on the job.

Columns 3–4 contain the same specifications but for unemployed workers. Recall that unemployment in my sample is defined based on self-perceived status, and hence a

worker does not have to actively search to be unemployed. Nevertheless, we may suspect that a person's self-perceived status is influenced by the formal definition of unemployment. Close to 80 percent of self-described unemployed workers searched for a job in the past four weeks. As for employed search, this falls with age, but not at all a strongly. Again college graduates search with higher intensity. The point estimate of the correlation between job search of the unemployed and fluidity is negative, but it is far from statistically significant (p-value of 0.77). Given that such a high fraction of unemployed workers search actively for a job, there might be better measures of the search intensity of the unemployed than what I have available, and it is possible that such measures would reveal a positive cross-country correlation between job search of the unemployed and the likelihood of returning to work.

Table A.6: Fluidity and job search

| | Employed | | Unemployed | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | No educ. | Educ. | No educ. | Educ. |
| Fluidity | 1.07836*** | 1.00252*** | -0.65925 | -0.76280 |
| | (0.24843) | (0.25321) | (2.17610) | (2.11217) |
| Age | -0.00425** | -0.00436** | -0.01008* | -0.00977* |
| | (0.00140) | (0.00140) | (0.00468) | (0.00460) |
| $Age^2$ | 0.00006 | 0.00007 | 0.00045 | 0.00047 |
| | (0.00008) | (0.00008) | (0.00045) | (0.00044) |
| $Age^3$ | -0.00000 | -0.00000 | -0.00001 | -0.00001 |
| | (0.00000) | (0.00000) | (0.00001) | (0.00001) |
| College | | 0.02027** | | 0.07565* |
| | | (0.00682) | | (0.03591) |
| Constant | 0.11209*** | 0.10630*** | 0.81710*** | 0.80079*** |
| | (0.00978) | (0.00973) | (0.02915) | (0.02985) |
| N | 119,002 | 118,617 | 11,696 | 11,629 |
| R2 | 0.01577 | 0.01718 | 0.02049 | 0.02458 |

Note: ECHP (1994–2001) and PSID (1990–1997); *10%; **5%; ***1%; see text for further details.

### A.9.2 Impact of search on mobility

To evaluate whether active search appears to predict future mobility, I estimate the probability of making a JtJ or EU transition on whether the worker searched for a new job while employed in up to two years in the future and two years in the past,

$$mob_{it} = \sum_{\tau=-2}^{2} \xi_\tau search_{it-\tau} + \mathbb{X}_{it}\beta + \varepsilon_{it}$$

I alternatively include in $\mathbb{X}_{it}$ age, education, occupation and country-year controls, or individual fixed effects together with country-year or country-year-age controls. Weights are adjusted such that each country receives the same aggregate weight, and standard errors are clustered at the individual level.

Table A.7 presents results. Column 1 shows the estimated relationship between searching on the job and the probability of JtJ transition controlling for education, age, occupation and country-year, but not individual fixed effects. Column 2 controls for individual fixed effects and country-year effects, while column 3 controls for individual fixed effects and country-year-specific age effects (specifically a linear in age in each country-year). Under all specifications, the hazard rate of making a JtJ transition is depressed in the year the worker reports searching for a job, increases by 12 percentage points in the year after employed job search, and remains somewhat elevated two years after. Given that the average JtJ hazard is four percent, this is triple the average hazard rate in the year after job search, indicating that employed search strongly predicts future mobility.

Columns 4–6 repeat the same analysis using instead the fraction who experienced an EU transition. The probability of this jumps by 18 percentage points in the year after search, or a 50 percent increase over its average value. A plausible interpretation is that workers correctly perceive that their job has a high likelihood of ending prior to the event (possibly due to mandatory advance notice requirements), inducing them to search for a new job prior to the formal termination of their old job.

Table A.7: Search on-the-job and mobility

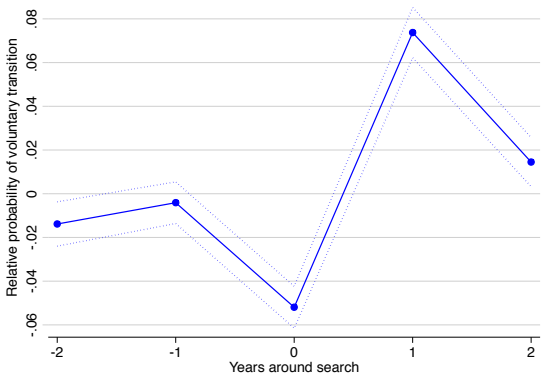
| | JtJ | | | EU | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Base | FE | FE+Age | Base | FE | Fe+Age |
| $search_{t+2}$ | -0.00312 | -0.01435*** | -0.01385*** | 0.06451*** | -0.01131 | -0.01416* |
| | (0.00415) | (0.00516) | (0.00517) | (0.00742) | (0.00798) | (0.00797) |
| $search_{t+1}$ | 0.00532 | -0.00384 | -0.00409 | 0.07079*** | -0.02500*** | -0.02684*** |
| | (0.00400) | (0.00486) | (0.00486) | (0.00662) | (0.00686) | (0.00684) |
| $search_t$ | -0.03238*** | -0.05223*** | -0.05192*** | 0.02745*** | 0.00504 | 0.00485 |
| | (0.00368) | (0.00493) | (0.00489) | (0.00641) | (0.00653) | (0.00651) |
| $search_{t-1}$ | 0.07609*** | 0.07374*** | 0.07373*** | 0.27215*** | 0.18281*** | 0.18495*** |
| | (0.00545) | (0.00587) | (0.00586) | (0.00765) | (0.00726) | (0.00722) |
| $search_{t-2}$ | 0.01948*** | 0.01476** | 0.01449** | 0.07620*** | -0.01916** | -0.01365* |
| | (0.00484) | (0.00574) | (0.00573) | (0.00696) | (0.00746) | (0.00743) |
| N | 112,377 | 110,623 | 110,623 | 112,864 | 121,847 | 121,847 |
| R2 | 0.04008 | 0.27717 | 0.27652 | 0.12413 | 0.46163 | 0.46353 |

Note: ECHP (1994–2001) and PSID (1990–1997); *10%; **5%; ***1%; see text for further details.

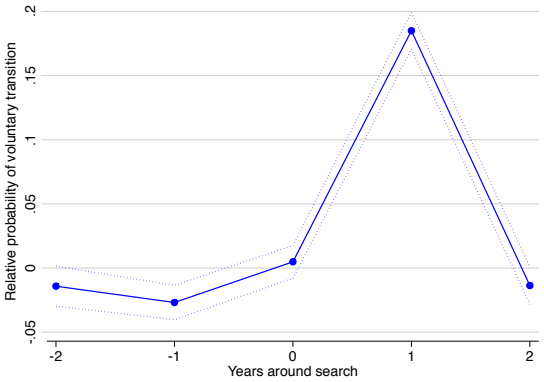
The left pane of Figure A.14 plots the estimated change in the JtJ hazard around the time of search on the job based on the estimates in column 3. The right pane of Figure A.14 plots the estimated change in the involuntary separation hazard around the time of employed job search, based on the estimates in column 6.

Figure A.14: Mobility around the year of on-the-job search

(a) JtJ




(b) EU




Note: ECHP (1994–2001) and PSID (1990–1997); see text for further details.

# Appendix B

# Firm and Worker Dynamics in an Aging Labor Market

## B.1 Additional Details on Data

### B.1.1 Sources

**BDS.** The BDS is based on micro data on firms and establishments collected in the Longitudinal Business Database by the Census Bureau. The data are publicly available at `https://www.census.gov/ces/dataproducts/bds/`. It provides aggregate measures on business dynamism at the establishment and firm level for the U.S. private-sector economy.[1] It excludes self-employed individuals, employees of private households, railroad employees, agricultural production employees, and most government employees. Annual data are currently available at the state level for 1977–2015. It also provides more disaggregated data by sector, size and age of the firm (but not separately by state). The BDS measures employment as the number of full- and part-time employees on March 12 every year. This includes employees on paid sick leave, holidays, and vacations. The

[1] Alternative measures of firm dynamics are provided by the Business Employment Dynamics (BED) dataset starting in 1991. I use the BDS since it provides a preferable definition of a firm and a longer time series, but also the BED displays a sharp decline in firm dynamics over the period it covers.

measure is at the establishment level, defined as a fixed physical location where economic activity occurs. The BDS also contains data aggregated up to the firm level, where a firm is defined as the highest level of operational control.

**BEA.** State private sector GDP is available from the Bureau of Economic Analysis (BEA), `https://www.bea.gov/regional`. I also use total real GDP and real GDP per hour available from the BEA.

**BLS.** The BLS publishes data on the total number of employed, unemployed and short-term unemployed workers back to 1948, as well as the number of employed and unemployed by age groups. Data on unemployment by duration is not available broken down by age. These data are available at `https://www.bls.gov/cps/cpsatabs.htm`. I use seasonally adjusted series.

The BLS also publishes regional CPIs which I use to construct real GDP per worker. These are available to download at `https://www.bls.gov/regions/`.

**CPS.** The CPS is conducted by the United States Census Bureau for the Bureau of Labor Statistics. The survey interviews about 60,000 households at a monthly frequency on a short rotating basis and is designed to be representative of the U.S. civilian non-institutionalized population. In March every year the CPS fields the Annual Social and Economic supplement—commonly known as the March CPS—which collects demographic characteristics on household residents. The CPS micro data are available at the state level starting in 1977, with earlier surveys aggregating states into groups.[2] Since two of the explanatory variables of interest are annual growth rates of labor supply and state GDP per worker, I start my analysis in 1978.

I use two sources of data from the CPS. First, I obtain data on the characteristic of a state's labor force by year from the March CPS downloaded from `https://cps.ipums.`

[2]Specifically, the available March CPS micro data identifies states from 1962–1967, then aggregates states from 1968–1976, and then again identifies states from 1977 onwards.

org/cps/. Specifically, I compute the fraction of the labor force or working age population that is female, non-white, college-educated (including more than college), and in five age bins (19–24, 25–34, 35–44, 45–54 and 55–64), as well as the growth in private sector employment, the labor force and working age population. An individual is in the labor force if she is employed or unemployed. I recode race to non-Hispanic white or not, and education to less than college or college or more. I also compute the share of employment in each of nine aggregate sectors in each state-year. All computations use the provided March CPS individual weights.

Second, in addition to the March CPS, I merge monthly basic CPS data to create a short panel. Specifically, I use the code kindly made available for public use by Robert Shimer,[3] combined with basic monthly files downloaded from http://www.nber.org/data/cps_basic.html. See Shimer (2012) for a further discussion of the issues involved in linking individuals across months in the basic CPS files. The short panel allows me to estimate flows from employment to unemployment (EU) and from unemployment to employment (UE) by state and year for 1978–2015. I also use the fact that since the introduction of dependent interviewing techniques with the 1994 redesign of the CPS, the survey asks whether an employed worker works for the same employer as last month. All computations use the provided basic monthly CPS weight. I use merged CPS monthly files for worker mobility rates, since the SIPP is not large enough to compute worker mobility rates at the state-year-age group level.[4]

**Global Entrepreneurship Monitor (GEM).** The GEM was designed with an explicit attempt to try to capture early entrepreneurial activity. I use this to construct life cycle profiles of entry into entrepreneurship. See Liang et al. (2016) for further details.

[3] https://sites.google.com/site/robertshimer/research/flows

[4] A literature going back at least to Abowd and Zellner (1985) notes that the merged CPS data suffer from classification error as well as non-random missing values, which tend to inflate measured worker flows. In my calibration exercise, I hence prefer to rely on SIPP data.

**Intercensal Censi.** I complement the March CPS demographic data with data on the lagged age composition from U.S. Census Bureau's Intercensal Censi projections to construct the 10 year lagged age composition. The Intercensal Censi estimates are available from `https://seer.cancer.gov/popdata/download.html` at an annual frequency back to 1969.[5]

**The Kauffman Firm Survey (KFS).** I use the KFS from 2004–2010 to study post-entry performance of start-ups by age of the founder. This data source provides a panel of newly started businesses that are followed during the first years after inception.

**The Panel Study of Entrepreneurial Dynamics (PSED).** I use the PSED from 2005–2010 to study post-entry performance of start-ups by age of the founder. As the KFS, this data source provides a panel of start-ups that are followed during the first years after inception.

**SIPP.** The SIPP is conducted by the Census Bureau in several separate panels from 1984 to 2013. Each panel lasts 2.5–4 years and follows between 14,000–52,000 households, interviewing respondents once every four months (a so called *wave*). The explicit longitudinal design of the SIPP alleviates concerns in the merged CPS data of classification error (Nagypál, 2008).

The SIPP asks for a respondent's employment status in each month during the prior four months. It also collects details on up to two employment spells and two self-employment spells, including the start and possible end dates of the spells. I define a worker as employed in a month if she is working at least one week during the month, as unemployed if she is not working the entire month but looking for a job, and otherwise as not in the labor force. I note that these definitions will imply some time aggregation bias

[5]To obtain the age composition in 1968, which is the earliest year I use, I linearly interpolate the 1960 Census and the 1969 Intercensal Censi estimates.

when computing worker flows. I also assign a main employer to an employed worker in a month as the spell the worker worked for most hours in the month.

A well-known issue with the SIPP is so called seam bias: an outsized share of transitions are reported between waves rather than within waves. To the extent that a transition is eventually reported, properly aggregating data should avoid the bias. To this end, I drop the last wave of any individual and compute the mean of monthly worker flows at the panel-wave level. I assign the date of that panel-wave as the third month in that panel-wave, and subsequently aggregate the panel-wave data to the annual level. All measures are weighted by the provided person-level weights, adjusted such that each panel receives the same aggregate weight (this is only relevant for the pre-1996 panels since they overlap). Finally, there was a significant redesign of the SIPP in 1996, which caused a break in the series for JJ mobility (Mazumder, 2007; Nagypál, 2008). I discuss in further detail below how I potentially adjust for this.

**State economic policy.** I use a measure of total state taxation per capita by year from the Tax Foundation for 1977–2012,[6], and state minimum wages from the Washington Center for Equitable Growth for 1974–2016.[7] The state minimum wage is the maximum of the average state minimum wage in that year and the average federal minimum wage in that year. The tax rate as computed by the Tax Foundation is a measure of the total applicable tax rate for a state resident in that year, including sales taxes, corporate taxes, income taxes, local property taxes, etc.

**QWI.** The QWI provides aggregate data based on state unemployment insurance records provided to the Census Bureau as part of the Longitudinal Employer-Household Dynamics (LEHD) micro data collection. It excludes federal employees (but covers local

[6] `https://taxfoundation.org/state-and-local-tax-burdens-historic-data/` (downloaded on March 27, 2017).

[7] `http://equitablegrowth.org/working-papers/historical-state-and-sub-state-minimum-wage-data/` (downloaded on June 15, 2017).

and state employees in addition to private sector employment). The underlying micro data in the LEHD is at the job-worker-quarter level. The concept of an employer is that of an Employer Identification Number (EIN). Based on this, the QWI constructs aggregate statistics on employment, hires, separations, job creation and job destruction by state and quarter. It also provides data broken down by firm characteristics (geography, industry, age, size) and worker demographics information (sex, age, education, race, ethnicity). Data are available for an increasing number of states over time, with 32 states going back to 1998.

### B.1.2 Variable definitions

**Entrepreneurship entry.** Following Liang et al. (2016), I define entry in the GEM as being actively involved in the management of a business that has paid owners' salaries and wages for at most 42 months and owning all or part of the enterprise. I alternatively consider several more stringent definitions of entry. In one, I additionally condition on entering because the individual saw a business opportunity in contrast to not having a better choice for work.[8] In another, I condition on either having hired at least one, five or 10 people at the time of the survey or expecting to hire one, five or 10 people over the next five years. The latter addresses facts uncovered by Hurst and Pugsley (2011) that a non-trivial share of entrants do not expect to grow, which may be different from the concept of entrepreneurship in the model.

**Firm dynamics.** Denote by $E_{it}$ employment of establishment $i$ in year $t$.[9] Job creation is the sum of net employment gains of expanding establishments and job destruction the

[8]This is the literal phrasing of the question. One would typically think that an individual only takes an action when she has no other better choice, which makes this phrasing somewhat confusing.

[9]Specifically, the BDS measures employment as those who were on the payroll in the pay period ending March 12.

sum of net employment losses of contracting establishments between two years,

$$JC_t = \frac{\sum_i \max\{E_{it} - E_{it-1}, 0\}}{0.5\sum_i (E_{it} + E_{it-1})}, \qquad JD_t = \frac{\sum_i \max\{E_{it-1} - E_{it}, 0\}}{0.5\sum_i (E_{it} + E_{it-1})}$$

Job reallocation is the sum of job creation and destruction, which can be decomposed into job creation and destruction of establishments that continue to be active and that due to establishment exit and entry,

$$\underbrace{JC_t + JD_t}_{\text{Job reallocation}_t} = \underbrace{JC_t^{incumbent} + JD_t^{incumbent}}_{\text{Incumbent job reallocation}_t} + \underbrace{JC_t^{entry} + JD_t^{exit}}_{\text{Establishment turnover}_t}$$

I alternatively construct unweighted measures of entry and exit as the count of entering and exiting establishments over the total count of establishments. I also compute firm entry as the share of employment at age zero firms and firm exit as the share of employment of exiting firms,[10] as well as unweighted measures of firm entry and exit.

**GDP.** To construct growth in state real GDP per worker, I convert nominal GDP to real GDP using regional CPIs from the BLS. Subsequently, I divide real GDP by the average of private sector employment in March in the current year and March in the subsequent year based on the BDS. Finally, I take the log difference of this to construct growth in state real GDP per worker. To construct growth in real GDP per labor force participant, I divided total real GDP by total labor force participants aged 16 and older from the CPS.

**Worker dynamics.** In the CPS and the SIPP, I define a worker as making an EU transition if she is employed in month $t$ and unemployed in month $t+1$, and an UE transition if she is unemployed in month $t$ and employed in month $t+1$. She makes a JJ transition if she is employed in month $t$ and $t+1$ but with a different employer. I note that these

[10]The BDS defines firm exit as an event when all establishments owned by a firm close down. It does not include exit due to a pure change of ownership.

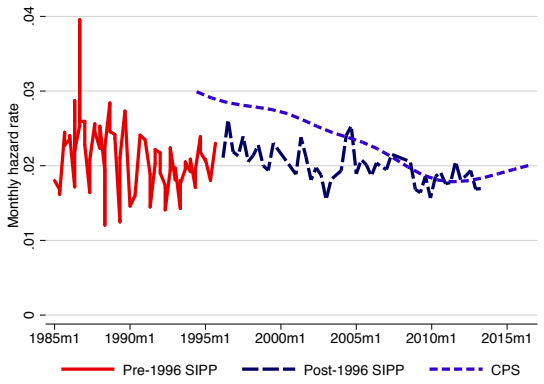
definitions will lead to some time aggregation bias.[11] Based on this, I estimate the EU, UE and JJ hazard rates at time $t$ as the fraction of employed or unemployed that undertakes one of these transitions between month $t$ and $t+1$. All rates condition on the individual remaining in the labor force in month $t+1$. I focus my main analysis on workers who remain in the labor force to align with the theoretical analysis later. I show below that there has also been a decline in the hazard rate of exiting and entering the labor force over this period.

As noted above, the SIPP was redesigned in 1996, and as discussed by earlier authors this leads to an inconsistency in the JJ series in the 1995–1996 break (Nagypál, 2008; Mazumder, 2007).[12] In my baseline results, I do not make any adjustment for this. I have alternatively adjusted the pre-1996 series by first collapsing the JJ mobility rate by panel and wave (to avoid the issues with seam-bias discussed above) and then by year. I HP-filter the pre-1996 and post-1996 series individually using a smoothing parameter of 6.25, and compute an adjustment factor as the ratio of trend JJ in 1996 over trend JJ in 1995, $adj = JJ_{1996}/JJ_{1995}$. Finally, I adjust the pre-1996 series by this factor. Figure B.1 plots the raw SIPP and CPS monthly JJ mobility series. The data are collapsed to the panel-wave frequency in the SIPP and the year level in the CPS.

[11] Recall may drive part of the measured EU and UE hazards (Fujita and Moscarini, 2017). Based on the limited evidence presented by these authors, there does not appear to be a strong time trend in the recall rate (see in particular their Tables A3–A4). I proceed under the assumption that accounting for recall would shift the hazard rates down but not bias the time trends.

[12] This does not appear to be an issue for the EU and UE hazard rates, because the question about monthly employment status is asked in a similar fashion pre and post the redesign.

Figure B.1: Monthly unadjusted JJ hazard in the SIPP, 1985–2013




*Note: SIPP 1984–2013 and CPS 1994–2016. JJ: share of employed in month t who are employed with a different employer in $t+1$ (conditional on remaining in the labor force). Collapsed to panel-wave level in SIPP; year-level in CPS.*

I also consider a third estimate of the EU and UE hazards based on the aggregate stock of employed, unemployed and short-term unemployed published by the BLS and the methodology of Shimer (2012),[13] which I sometimes refer to as the duration approach. Shimer (2012) outlines a flow-balance approach that allows him to estimate monthly EU and UE hazard rates based on the stock of employed, unemployed and short-term unemployed published by the BLS.[14] Specifically, denote by $E_t$, $U_t$ and $S_t$ the stock of employed, unemployed and short-term unemployed (less than four weeks), respectively. Suppose workers find and loose jobs at a monthly frequency, then the following flow balance equations relates the job finding rate, $\lambda$, and the separation rate, $\delta$,

$$E_t = \lambda_t U_{t-1} + (1-\delta_t)E_{t-1}, \qquad S_t = \delta_t E_{t-1}$$

The second equation identifies $\delta_t$, which implies that the first equation pins down $\lambda_t$. Shimer (2012) writes down a continuous-time system that allows him to adjust for time-

[13] With the exception that I do not employ Shimer (2012)'s continuous time methodology to address time aggregation bias. Doing so complicates the analysis without changing the conclusions regarding the secular decline (the adjusted series is available on request and also in Shimer, 2012).

[14] These data are based on underlying CPS micro data, but the original micro data prior to 1967 has sadly been lost.

aggregation. This, however, matters little for the secular trends and hence for simplicity I abstract from this.

Based on the establishment level data in the QWI, I define worker reallocation as the sum of hires and separations across all firms between two quarters. Churn as the difference between worker and job reallocation,

$$\text{Worker reallocation}_t \equiv \text{Job reallocation}_t + \text{Churn}_t \tag{B.1}$$

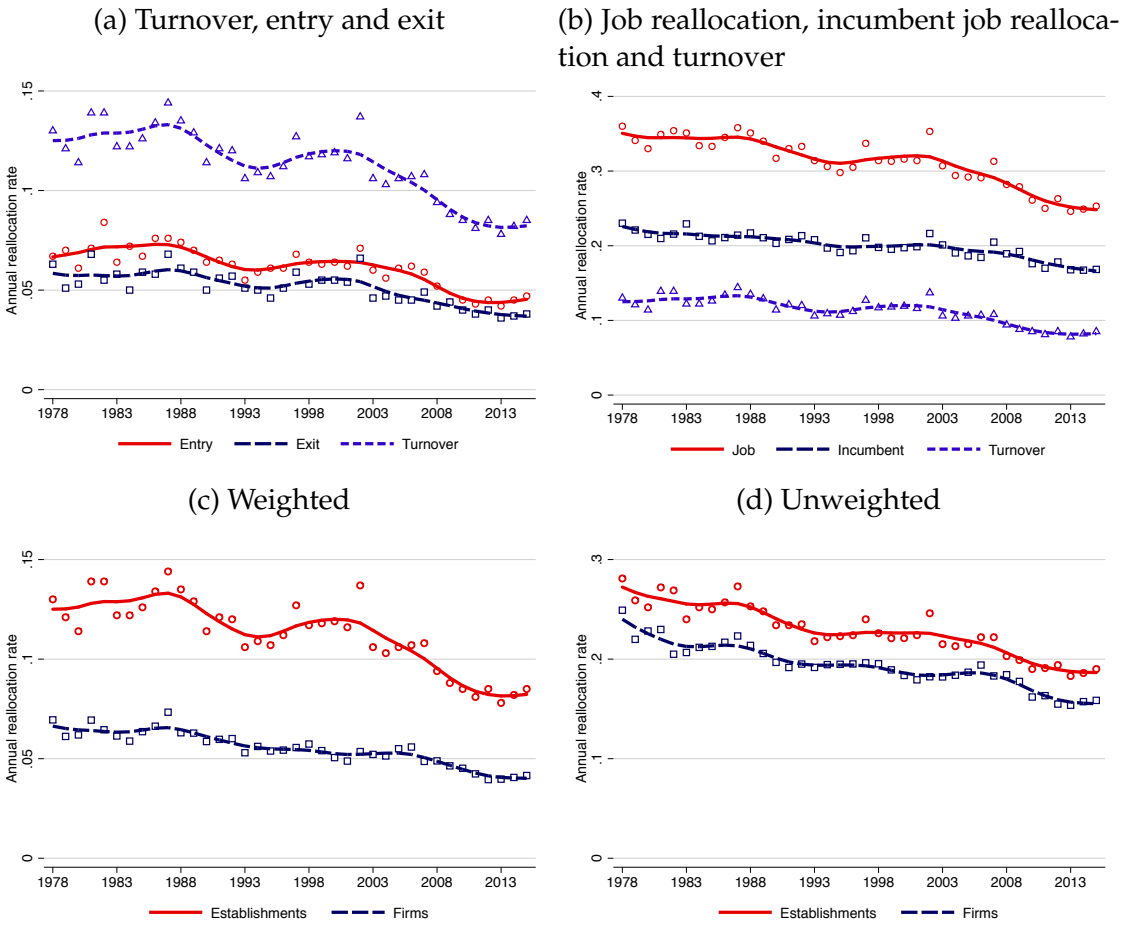
Churn may hence be thought of as replacement hiring—a worker left the firm but was replaced by a new worker so that the job stayed with the firm. The QWI only provides quarterly data. I aggregate these to the annual level as the unweighted quarterly average, and HP-filter the annual series with a smoothing parameter of 6.25.

## B.2 Additional Details on Facts

### B.2.1 Business dynamism

The top left panel of Figure B.2 illustrates that turnover of establishments has declined both because entry and exit have fallen. The top right panel shows that also a decline in job reallocation of incumbent firms has contributed importantly to the overall decline in job reallocation. The bottom left panel compares changes in firm turnover with establishment turnover, while the bottom right panel plots unweighted firm and establishment turnover. As is evident, dynamism has fallen across the board.

Figure B.2: Annual establishment dynamics, 1978–2015




*Note: BDS 1978–2015. Private, non-agricultural employment. Weighted establishment turnover: job creation and destruction of entering and exiting establishments/firms divided by half the sum of employment in the prior and current year. Weighted firm turnover: sum of jobs created by age zero firms and jobs destroyed due to firm exit divided by total employment. Unweighted: count of exiting and entering establishments/firms divided by total count of establishments/firms. All measures are annual and HP-filtered with smoothing parameter of 6.25.*

Table B.1 summarizes the declines in firm dynamics. Job reallocation has fallen by 28 percent since 1986, and establishment entry and turnover by 38 percent. Instead focusing on firms leads to a similar conclusion: firm turnover has fallen by 39 percent and firm entry by 47 percent. The employment-weighted establishment and firm entry rate has declined by more than the unweighted rate, indicating that entering firms/establishments enter somewhat smaller now than 30 years ago. Yet also unweighted entry and turnover rates show notable declines.

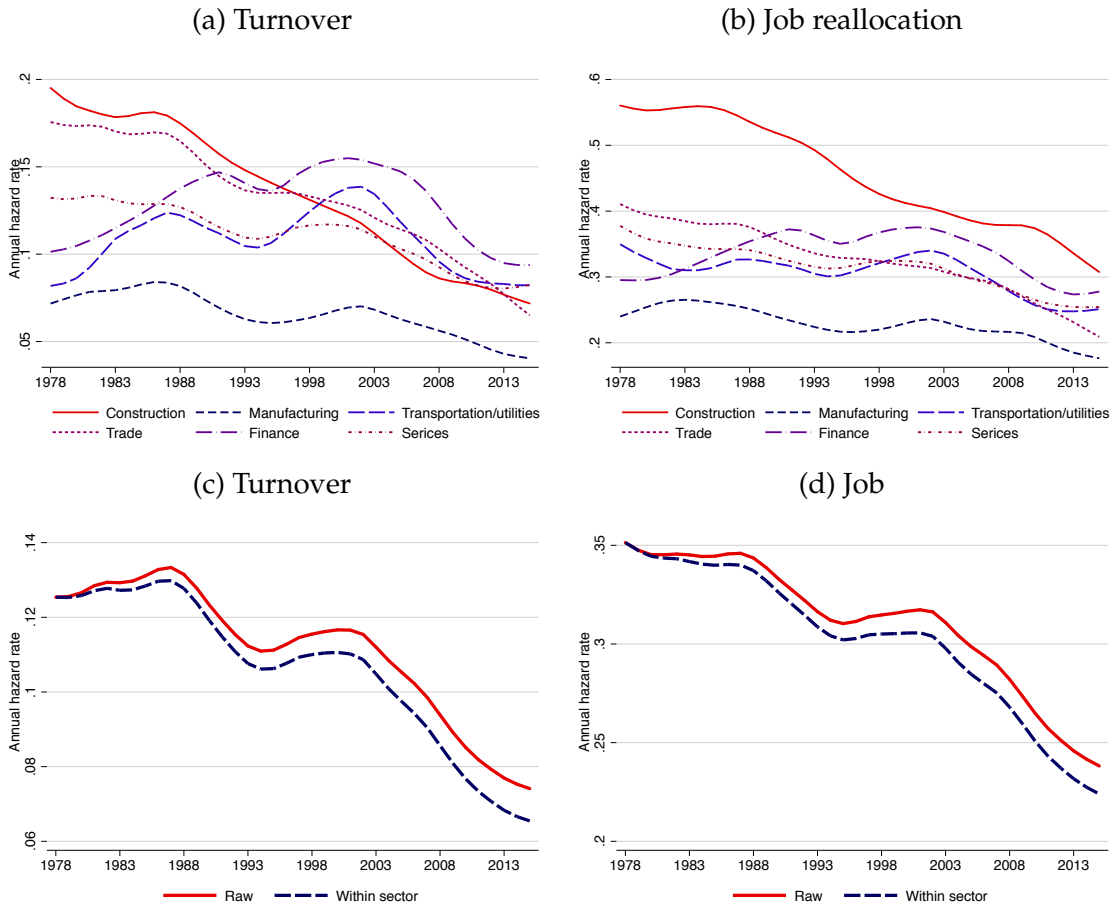
Table B.1: Establishment and firm dynamics, 1986–2015

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | Job reallocation | | | Turnover | | | Entry | | |
| | 1986 | 2015 | % fall | 1986 | 2015 | % fall | 1986 | 2015 | % fall |
| *Panel A: Establishments* | | | | | | | | | |
| Weighted | 0.345 | 0.248 | -28.1 | 0.133 | 0.082 | -37.9 | 0.073 | 0.045 | -37.8 |
| Unweighted | | | | 0.256 | 0.187 | -27.2 | 0.142 | 0.101 | -29.2 |
| *Panel B: Firms* | | | | | | | | | |
| Weighted | | | | 0.065 | 0.040 | -38.5 | 0.037 | 0.020 | -46.6 |
| Unweighted | | | | 0.214 | 0.155 | -27.5 | 0.125 | 0.080 | -36.1 |

*Note: BDS 1978–2015. Private, non-agricultural employment. Job reallocation: sum of employment gains of expanding establishments and employment losses of contracting establishments; turnover: job creation and destruction of entering and exiting establishments/firms; entry: job creation of entrants. All measures are annual, expressed as rates by dividing by half the sum of employment in the prior and current year, and HP-filtered with smoothing parameter of 6.25.*

**Firm dynamics by industry.** The top left panel of Figure B.3 plots establishment turnover by six aggregate sectors, while the top right panel does the same for overall job reallocation. Finance and to a lesser extent transportation and utilities displays a somewhat different trend, increasing for the first 20 years of the sample and then falling sharply in the last 15 years. Clearly there are important differences across sectors which future research may want to explore further. The bottom left panel plots the year effects from a regression of establishment turnover on year and sector dummies, while the bottom right panel does the same with job reallocation. Employment has if anything reallocated to sectors with *higher* reallocation rates, making the puzzle of the decline even larger.

Figure B.3: Reallocation rates by industry and controlling for industry, 1978–2015




*Note: BDS 1978–2015. Private, non-agricultural employment. Job reallocation: sum of employment gains of expanding establishments and employment losses of contracting establishments; turnover: job creation and destruction of entering and exiting establishments/firms. All measures are annual, expressed as rates by dividing by half the sum of employment in the prior and current year, and HP-filtered with smoothing parameter of 6.25. Residual is the year effects from a regression of the reallocation rate on year and sector dummies.*

## B.2.2 Labor market fluidity

Figure B.4 plots the EU, JJ and UE hazard across the different data sources. The different data sources differ importantly in levels, which is the source of an existing literature. Shimer (2012) suggests that the duration approach may overestimate the UE hazard rate due to the implicit assumption that all unemployment spells end with a transition to employment. Furthermore, to the extent that some workers report being unemployed

for less than four weeks when they enter unemployment from out of the labor force, this may explain the higher estimated EU hazard using the duration data. With respect to the difference between the SIPP and the CPS, Abowd and Zellner (1985) and Poterba and Summers (1986) argue that substantial classification error in respondents' employment status in the CPS as well as non-random sample attrition bias estimates of worker flows upwards.[15]

The more important take-away for my purposes is that the different data sources largely agree on the secular time trends. In particular, the EU hazard shows a large, secular decline over this period,[16] with the different data sources primarily disagreeing on the spike in the Great Recession,[17] Similarly, the JJ hazard displays a large decline over this period, which is larger in the CPS than the SIPP in the overlapping years.[18]

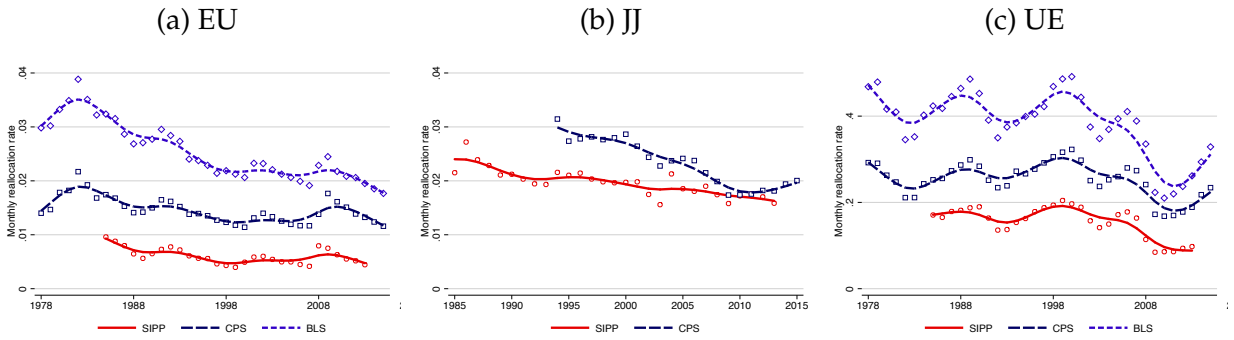
[15]These authors also develop methods to adjust the raw data. I do not pursue such an adjustment further, noting that the CPS displays both similar time trends and life cycle profiles (see the next section) as the SIPP. For the level of hazard rates, I rely on the SIPP.

[16]See also Davis (2008) for similar evidence of a large decline in job loss using initial unemployment insurance claims data.

[17]As noted by Shimer (2012), the greater increase in the micro data relative to the aggregate BLS data in the Great Recession may be due to particularly pronounced flows out of the labor force during that period.

[18]As I discuss in Appendix B.1, this measure is only available from the SIPP and CPS. Furthermore, the latter is only available from 1994, while the former is adjusted for a break in the series with the redesign of the SIPP in 1996. As such an adjustment involves a good amount of uncertainty, the resulting series should be interpreted cautiously.

Figure B.4: Monthly EU, JJ and UE mobility, 1978–2015




*Note: SIPP 1984–2013, BLS 1978–2015, CPS 1978–2015. Labor force age 16 and older. SIPP and CPS: EU hazard is the share of employed in month t who are unemployed in $t+1$; UE hazard is the share of unemployed in t who are employed in $t+1$; JJ hazard is the share of employed in month t who are employed at a different employer in $t+1$; all condition on remaining in the labor force. BLS: estimated from aggregate employment, unemployment and short-term unemployment following the method of Shimer (2012). The SIPP JJ series is adjusted for a break in 1996, see Appendix B.1 for details. Average monthly rate during the year HP-filtered with smoothing parameter of 6.25.*

Table B.2 summarizes the declines in the various measures of worker mobility across the different data sources.

Table B.2: Worker dynamics, 1986–2015

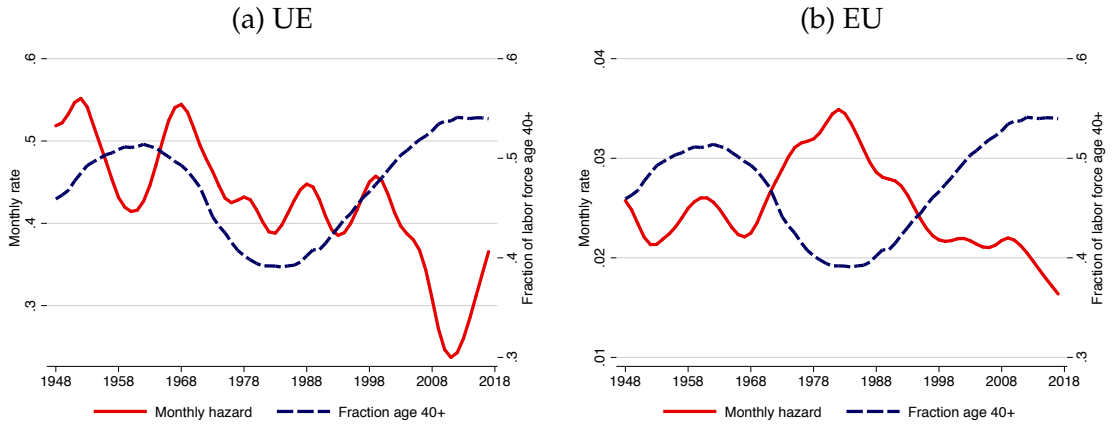
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | EU | | | UE | | | JJ | | |
| | 1986 | 2015 | % fall | 1986 | 2015 | % fall | 1986 | 2015 | % fall |
| BLS | 0.031 | 0.018 | -42.5 | 0.427 | 0.311 | -27.0 | | | |
| CPS | 0.016 | 0.012 | -29.0 | 0.259 | 0.224 | -13.5 | 0.030 | 0.020 | -34.2 |
| SIPP | 0.008 | 0.005 | -44.2 | 0.174 | 0.088 | -49.4 | 0.024 | 0.016 | -32.0 |

*Note: SIPP 1984–2013, BLS 1978–2015, CPS 1978–2015. 1986 refers to 1994 for JJ in CPS and 2015 refers to 2013 in SIPP due to lack of data. Labor force age 16 and older. SIPP and CPS: EU hazard is the share of employed in month t who are unemployed in $t+1$; UE hazard is the share of unemployed in t who are employed in $t+1$; both condition on remaining in the labor force. BLS: estimated from aggregate employment, unemployment and short-term unemployment following the method of Shimer (2012). Average monthly rate during the year HP-filtered with smoothing parameter of 6.25.*

**A longer time series.** Few nationally representative measures of dynamism are available prior to the late 1970s, but one can construct measures of EU and UE mobility back

to 1948 following Shimer (2012).[19] Figure B.5 plots the HP-filtered annualized monthly UE hazard (left) and EU hazard (right) in solid red and the share of the labor force 16 and older that is 40 years and older in dashed blue. The UE hazard possibly displays a secular decline, but it is hard to tell with the substantial business cycle volatility in this series. The EU hazard shows a strong negative time series correlation with the share of older ($\rho = 0.8$). Only a fraction of the covariation can be accounted for by the direct effect.

Figure B.5: EU and UE hazard and the share of older, 1948–2017



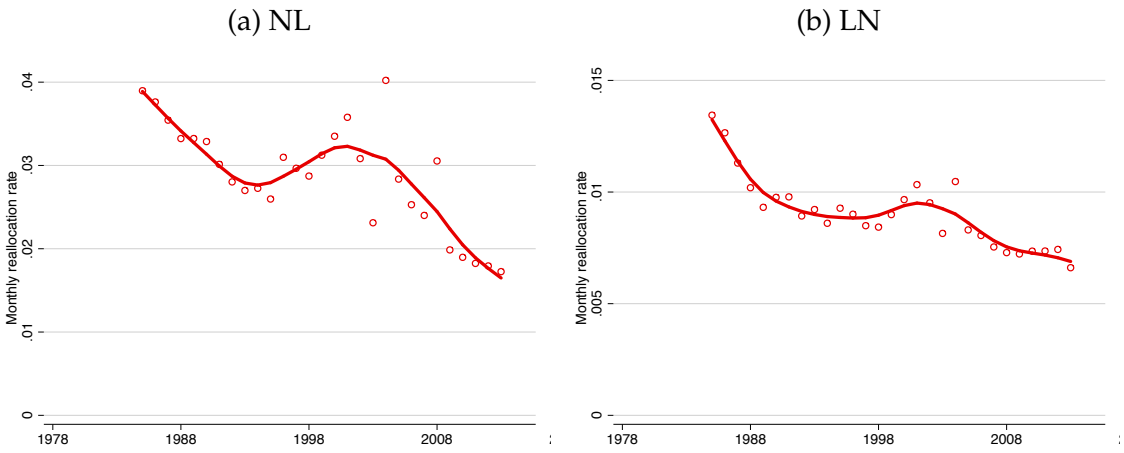

*Note: BLS 1948–2017. Labor force age 16 and older. Monthly EU and UE hazards estimated based on the stock of employed, unemployed and short-term unemployed following the methodology of Shimer (2012). Share of labor force that is 40 years and older constructed as half of those age 35–45 plus everyone 45 and older. All series are seasonally adjusted, annualized and HP-filtered with smoothing parameter 6.25.*

**Flows in and out of the labor force** Figure B.6 plots monthly hazard rates of moving in and out of the labor force based on the SIPP. I do not compute these measures in the merged CPS micro data since earlier research has concluded that classification error leads to a particularly large bias in estimates of flows into and out of the labor force in the monthly CPS data (Nagypál, 2008). The NL hazard is substantially below the UE hazard,

[19] These are clearly limited measures of dynamism. Yet Davis et al. (2010) find that long run changes in job loss of workers are positively correlated with changes in job destruction of firms using cross-industry data (I verify a similar positive correlation across states).

while the LN hazard is larger than the EU hazard. Both series display secular declines over this period.

Figure B.6: Monthly flows in and out of the labor force, 1985–2013




*Note: SIPP 1984–2013. NL: share of workers not in the labor force in month $t$ who are in the labor force in month $t+1$; LN: share of individuals who are in the labor force in month $t$ who are not in the labor force in month $t+1$. Average monthly rate during the year. HP-filtered with smoothing parameter of 6.25. See text for further details.*

**Linking worker reallocation to job reallocation** Overall worker reallocation in period $t$ equals the sum of workers flowing in and out of unemployment, in and out of the labor force, and directly between employers,

$$worker_t = eu_t + ue_t + nl_t + ln_t + 2 * jj_t$$

where lower letters represent the number of workers (as distinct from the hazard rate). From an accounting perspective, overall worker reallocation consists of job reallocation and *churn*, i.e. worker reallocation over an above what is necessary to account for job flows,

$$worker_t = job_t + churn_t$$

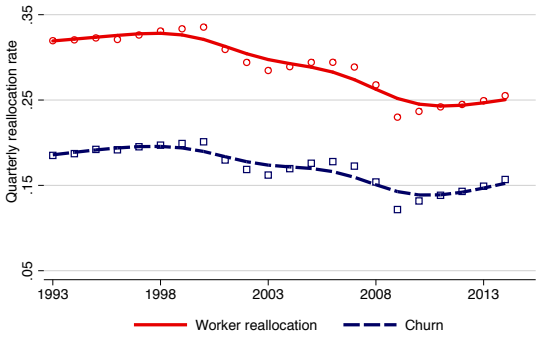
The left panel of Figure B.7 plots the secular trend in quarterly job reallocation and churn based on the QWI for 1993–2014. As noted above, the data are only available back

to 1993 and only a limited number of states provide data that far back. Furthermore, the data are at the EIN level, which differs in subtle ways from establishments or firms. Nevertheless, taken at face value the figure suggests that the decline in job reallocation only accounts for about half of the decline in worker reallocation over this period, with a large fall also in churn.

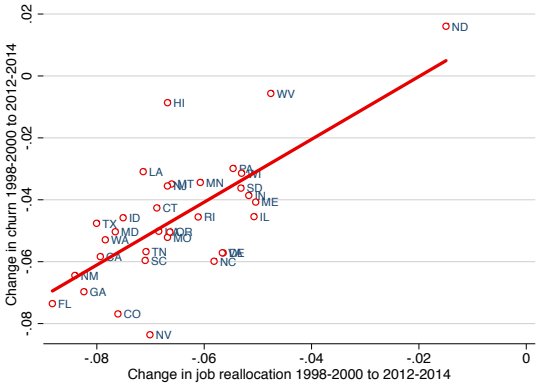
To what extent is the decline in worker reallocation that cannot directly be traced back to firm dynamics driven by factors distinct from those that have led to declining job reallocation? The right panel of Figure B.7 plots the within-state change in job reallocation between 1998–2000 and 2012–2014 on the x-axis against the within-state change in churn over the same period on the y-axis across U.S. states. Only 32 states provide data back to 1998 and I cannot meaningfully go back earlier than that due to a lack of data. The strong correlation between secular changes in job reallocation and churn across U.S. states may be interpreted as a common factor leading to declines in both rates.

Figure B.7: Worker reallocation and churn, 1993–2014

(a) Job reallocation and churn




(b) Linking declines across states

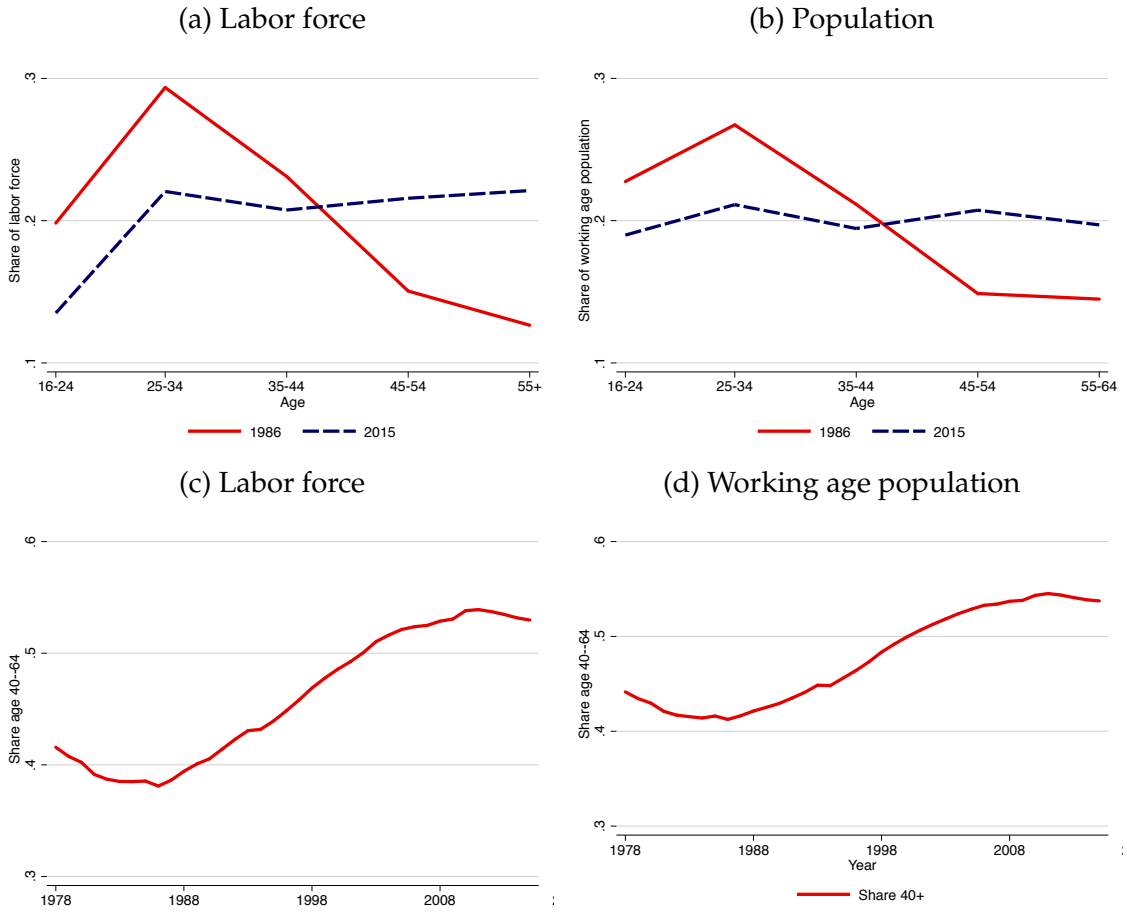



*Note: QWI 1993–2014 and BDS 1998–2014. Private, state and local employment (QWI), private employment (BDS). Job reallocation: sum of employment gains of expanding establishments (EINs) and employment losses of contracting establishments (EINs); worker reallocation: sum of hires and separations; churn: difference between worker reallocation and churn.*

### B.2.3 Aging

The top left panel of Figure B.8 plots the age composition of the the labor force age 16 and older, and the top right panel the age composition of the population age 16–64. Although labor force participation differs systematically by age so that the levels are somewhat different, the change over time is similar. The bottom two panels illustrate this by plotting the share of the labor force (left) or population (right) age 19–64 that is 40–64 from 1978–2015. The majority of the increase in the share of older over this period is due to population aging, not differential trends in labor force participation by age.

Figure B.8: Age composition of the U.S. labor force/population 1978–2015




*Note: BLS, Intercensal Censi and CPS 1978–2015. Top left: total number of labor force participants of the given age group relative to the total labor force age 16 and older; Top right: total number of individuals of the given age group relative to the total population 16–64; Bottom left: share of labor force participants age 19–64 that is 40–64; Bottom right: share of population age 19–64 that is 40–64.*

### B.2.4 Growth

Figure B.9 plots the HP-filtered annual growth rate in real GDP per worker and per hour since 1971. Growth was notably high in the late 1990s driven by rapid advanced in IT technology. As noted by other authors (Fernald, 2014), the growth rate appears to show a decline starting in the early 2000s.

Figure B.9: Growth in real GDP




*Note: OECD. Annual data HP-filtered with smoothing parameter of 6.25.*

### B.2.5 Life cycle mobility and the direct effect of aging

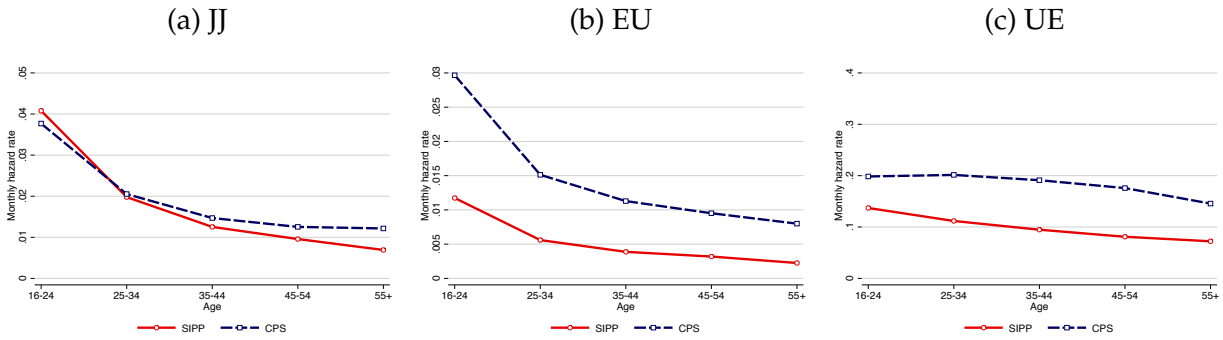
This section provides additional empirical facts on life cycle individual mobility.

**Worker mobility.** Figure B.10 compares estimated life cycle profiles of worker mobility in the CPS and the SIPP.[20] The data sources largely agree on both the level and the shape of the JJ hazard in the left panel. The probability of a JJ move falls from around four percent per month for young workers to around one percent for older workers, with a slightly more pronounced fall in the SIPP. The level of the EU hazard is substantially larger in the CPS than the SIPP, as can be seen in the middle panel. As discussed in the

[20] I consistently present results aggregated to these five age groups to be consistent with the subsequent analysis of the indirect effects of aging in Section 2.7. Results by more disaggregated age groups are similar and available on request. Given the high number of observations, the means are tightly estimated and I do not include confidence intervals in the graphs to avoid clutter.

previous section, this is likely at least part due to well-documented issues with classification error inflating gross worker flows in and out of unemployment in the CPS. Both data sources agree on the life cycle shape: young workers are roughly three times as likely to experience an EU transition relative to older workers. The right panel shows that the UE hazard displays a less pronounced life cycle profile.

Figure B.10: Worker mobility over the life cycle




*Note: SIPP 1984–2013, CPS 1978–2015. Labor force age 16 and older. EU hazard: share of employed in month $t$ who are unemployed in $t+1$; UE hazard: share of employed in month $t$ who are unemployed in $t+1$; JJ hazard: share of employed in $t$ who are employed in $t+1$ but with a different employer; both condition on remaining in the labor force. Weighted using the provided survey weights. Pooled data across all years adjusted such that the average matches that in 2012–2013.*

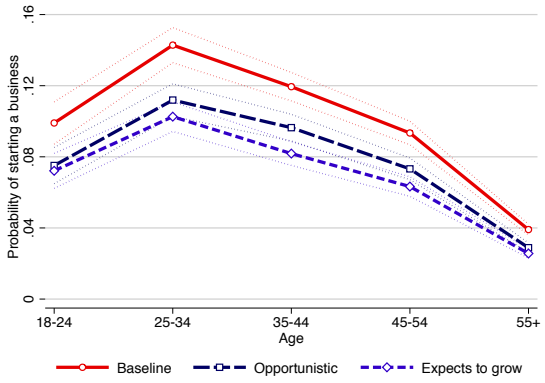
**Entry to entrepreneurship.** To study the life cycle profile of entry into entrepreneurship, I follow Liang et al. (2016) to use data from the GEM. Figure B.11 plots the entry rate into entrepreneurship by age. In solid red with circles is the baseline, while the long-dashed navy blue series with squares additionally conditions on those that report that they started the business to take advantage of a business opportunity. Finally the short-dashed royal blue series with diamonds additionally conditions on those that expect to hire at least one person over the next five years.

In all cases, entrepreneurship rises at young ages to peak at around age 30, and subsequently falls monotonically with age.[21] In line with findings in Hurst and Pugsley (2011),

[21]This should not be confused with the *level* of entrepreneurship, which displays a monotonically increasing, concave profile with age. I will argue later that entry to entrepreneurship plays a special role in

a non-trivial share of those that enter do not expect to grow their enterprise, but focusing on those that expect to add workers provides a similar conclusion with respect to the life cycle pattern of entry (instead conditioning on expecting to add five or 10 employees provides a similar conclusion).

Figure B.11: Entrepreneurship over the life cycle




*Note: GEM 2001–2010. Share of population who are active in the management of a startup that has paid owners' salaries and wages for at most 42 months and who own all or part of the enterprise. Opportunistic: additionally conditions on having entered to take advantage of a business opportunity (in contrast to not having a better choice for work). Expects to grow: additionally conditions on expecting to employ at least one person (plus the owner) in five years. The GEM does not provide data on individuals younger than 18. Weighted by the provided survey weights. Dotted lines are 95% confidence intervals.*

**The direct effect of aging.** To estimate the importance of the direct effect over this period, I first compute age-conditional JJ, EU and UE mobility rates as well as entrepreneurship entry rates in a late period.[22] Denote these coefficients on the respective age groups in the late period by $\beta^a_{\text{late}}$. Subsequently, I compute the reallocation rate that would result from only changes in the age composition as $\widehat{rate}_{\text{period}} = \sum_a \beta^a_{\text{late}} share^a_{\text{period}}$, where $share^a_{\text{period}}$ is the share of the labor force that is in age group $a$ in that period. The direct

driving firm dynamics and economic growth, which motivates the focus on entry as distinct from the level of entrepreneurship.

[22]Specifically, I use the SIPP in 2011–2013, the CPS in 2015, and the GEM in 2001–2010. I pool all years in the GEM due to the relatively small sample size and normalize the entry rate to match the level in 2010.

effect of aging equals $\widehat{rate}_{\text{late}} - \widehat{rate}_{\text{early}}$. Throughout this paper, I use as base period a late period due to better data availability at the end of my sample period and in this sense run all exercises "backwards."

The mechanical effect of aging accounts for 23–27 percent of the change in JJ and EU mobility, less of the recent fall in UE mobility (but as noted above this decline is likely at least partly a business cycle phenomenon), and 18–19 percent of the change in entry over this period.[23] Table B.3 summarizes the estimated direct effect of aging on JJ, EU and UE mobility as well as firm start-up rates.

[23]For comparison, Hyatt and Spletzer (2013) find that the direct effect of aging accounts for 9–23 percent of changes in worker mobility in the LEHD and CPS between 1998–2010. The reason I attribute a somewhat larger direct effect is likely due to the sample period. These authors start in 1998, after the baby boomers have mostly moved out of the young age groups characterized by very high mobility, and stop in the midst of the Great Recession, when the raw series is likely depressed below trend.

Table B.3: Direct effect of aging on dynamism, 1986–2015

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Early | | Late | | % change | | |
| | Raw | Direct | Raw | Direct | Raw | Direct | Share |
| *Panel A: JJ mobility* | | | | | | | |
| SIPP | 0.024 | 0.019 | 0.017 | 0.017 | 45.4 | 12.3 | 27.1 |
| *Panel B: EU mobility* | | | | | | | |
| SIPP | 0.009 | 0.006 | 0.005 | 0.005 | 61.3 | 14.0 | 22.9 |
| CPS | 0.017 | 0.015 | 0.012 | 0.014 | 42.0 | 10.7 | 25.6 |
| *Panel C: UE mobility* | | | | | | | |
| SIPP | 0.175 | 0.101 | 0.090 | 0.093 | 94.5 | 8.6 | 9.1 |
| CPS | 0.251 | 0.199 | 0.221 | 0.196 | 13.7 | 1.9 | 13.9 |
| *Panel D: Entry to entrepreneurship* | | | | | | | |
| Baseline | 156.5 | 109.9 | 100 | 100 | 56.5 | 9.9 | 17.5 |
| Opportunistic | 156.5 | 110.0 | 100 | 100 | 56.5 | 10.0 | 17.7 |
| Expect to grow | 156.5 | 110.8 | 100 | 100 | 56.5 | 10.8 | 19.2 |

*Note: SIPP 1984–2013, CPS 1978–2015, GEM 2001–2010, BDS 1978–2015. Labor force age 16 and older. Early refers to 1986, late to 2013 in the SIPP and 2015 in the CPS and for the entrepreneurship rates. % change is* $100 * (early/late - 1)$. *EU: share of employed in month* $t$ *who are unemployed in* $t+1$*; UE: share of unemployed in month* $t$ *who are employed at* $t+1$*; JJ: share of employed in* $t$ *who are employed in* $t+1$ *but with a different employer; all condition on remaining in the labor force. Baseline: share who started a firm in the past 42 months; opportunistic: additionally conditions on having started the firm to take advantage of a perceived business opportunity; growth: additionally conditions on expecting to add at least one worker over the next five years; raw entry rate is the unweighted firm entry rate in the BDS; all entry rates are normalized to 100 in the late period. Direct effect estimated based on a shift-share methodology, raw data is annual and HP-filtered with smoothing parameter of 6.25. See text for further details.*

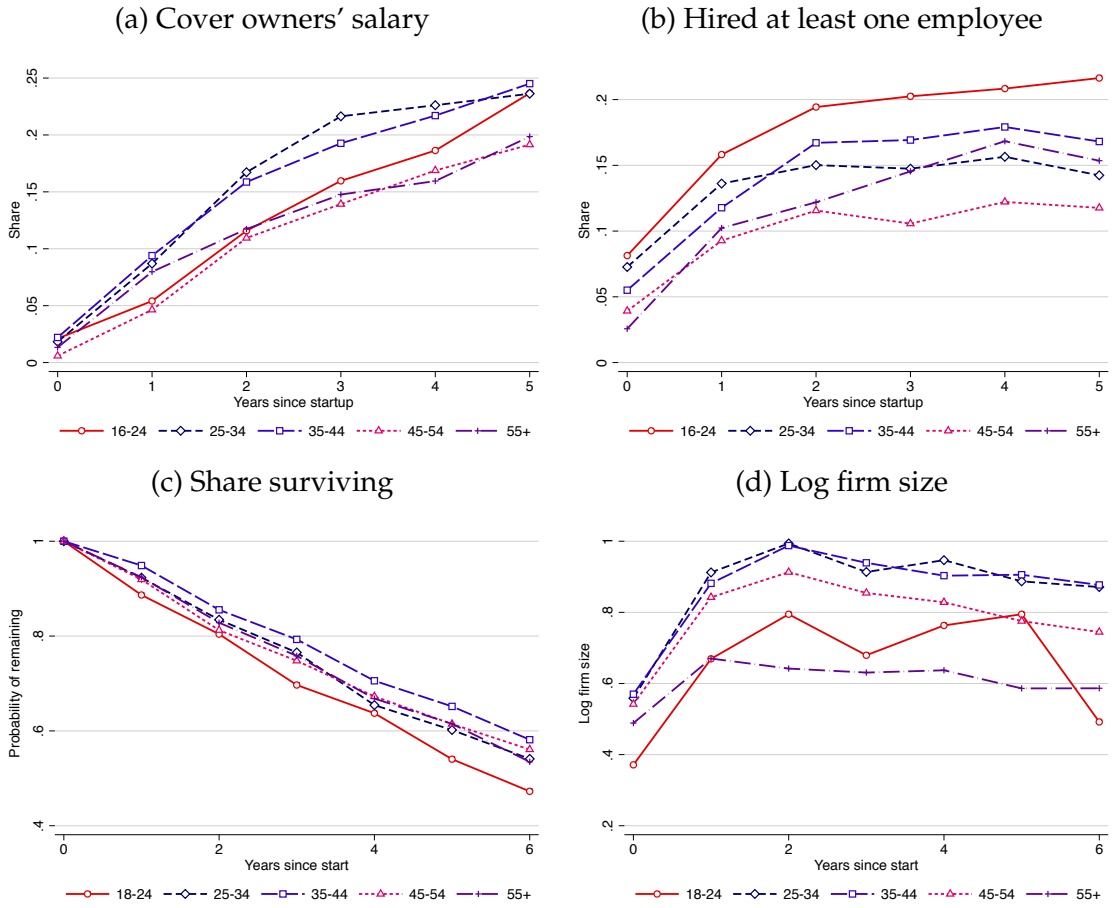
**Post-entry performance by age of founder.** To understand the importance of aging for aggregate economic outcomes through the entrepreneurship channel, more than the life cycle profile of entry arguably matters. Figure B.12 investigates the relationship between the age of the founder of a firm at the time of its inception and its subsequent performance based on the KFS and PSED. The top left panel plots the share of startups that have evolved to cover the founders' salaries for up to five years after entry based on the PSED.[24] The top right panel plots the share of active startups in year $t$ that have hired at

[24]To avoid clutter, I exclude confidence intervals from the graphs, but differences across age groups are in most cases not statistically significant.

least one employee based on the PSED (the survey does not ask a more detailed firm size question). The bottom left panel plots the share of start-ups in year 0 that remain active up to seven years after entry based on the KFS.[25] Finally, the bottom right panel plots average log firm size (plus one) of active start-ups in year $t$. These graphs generally provide little evidence of any pronounced, systematic differences in post-entry performance by age of the founder.

[25]The exit rate is lower than in the BDS and it shows no evidence of declining with the age of the firm, in contrast to the BDS. These discrepancies may be due to contemporaneous time effects given that the first few years cover the pre-Great Recession boom and the last few years the subsequent large bust. It is not clear to what extent this may differentially affect firms depending on the age of its founder and the results should be interpreted with this caveat in mind.

Figure B.12: Startup dynamics by age of founder

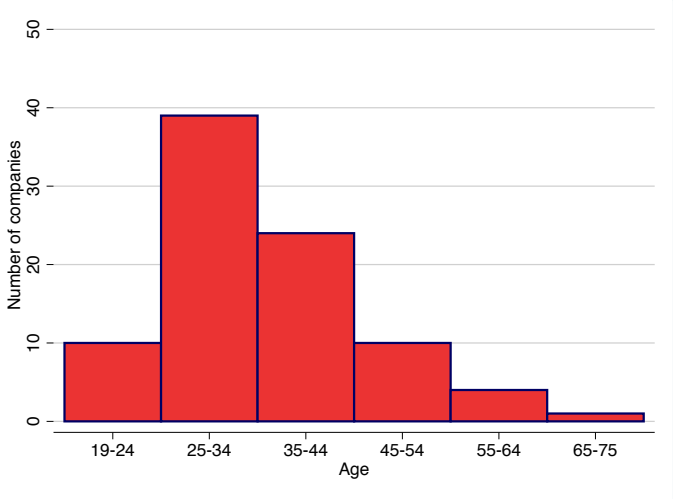



*Note: Top graphs use the PSED 2005–2010, bottom graphs the KFS 2004–2010. Top left: share of all start-ups in year 0 that have evolved to cover owners' salaries; top right: share of all start-ups that remain active in year t that has hired at least one worker; bottom left: share of all start-ups in year 0 that remains active; bottom right: average log number of employees plus one of start-ups that remain in year t. All measures broken down by the age of the founder(s) at the time of inception of the firm in year 0 (average age in case of multiple founders). The KFS starts at age 18. Weighted by the provided survey weights.*

**Founders of S&P100 companies.** If young entrepreneurs engage in a lengthy period of trial and error before they come up with a viable business idea, one may expect this to be reflected in the age distribution of the founders of current, successful companies. Figure B.13 investigates this by plotting the companies in the S&P100 index by the age of their founder at time of inception. These are some of the largest and most established

companies in the U.S., representing over half of market capitalization in the U.S. Although it does not account for the underlying age distribution of the population at the time of inception, Figure B.13 appears at odds with the hypothesis that a prolonged period of unsuccessful entrepreneurship is required before founding a highly successful company.

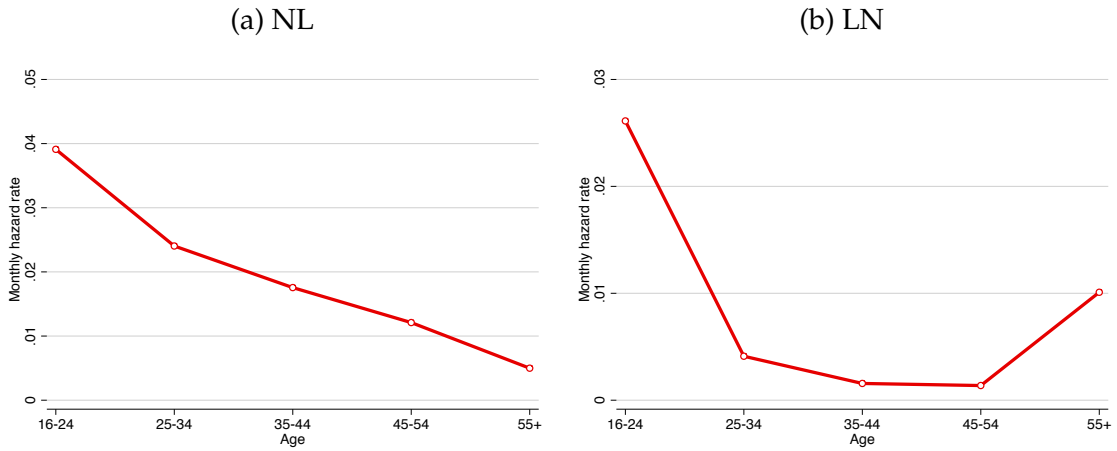
Figure B.13: Number of S&P100 companies by age of founder at time of inception




*Note: Author's calculations. S&P100 companies with an identified founder binned by the age of the founder at the time of inception. In case of multiple founders, a company is represented by the average age of the founders. In case the traded company was created through a merger or acquisition, it is the average age of the original, purchasing company (or the average age of the constituent companies in case of a merger). The final data contains 88 companies with identified founders.*

**NL and LN flows over the life cycle.** The left panel of Figure B.14 plots the hazard rate of entering the labor force from not in the labor force and the right panel the hazard rate of exiting the labor force. Given that an earlier literature has documented that flows in and out of the labor force suffer particularly from the classification error in the CPS, I only compute the latter two series in the SIPP (Nagypál, 2008).

Figure B.14: NL and LN mobility over the life cycle




*Note: SIPP 1984–2013. Labor force age 16 and older. NL: share of NILF in month $t$ who are in the labor force in $t+1$; LN: share of the labor force in month $t$ who are NILF in $t+1$. Weighted using the provided survey weights. Pooled data across all years adjusted such that the average matches that in 2012–2013.*

### B.2.6 Direct effect of firm aging

Table B.4 summarizes the direct effect of firm aging on the exit rate and incumbent job reallocation. The shift towards older firms accounts for a substantial share of the declines in dynamism, including 25 percent of the fall in incumbent job reallocation, 42 percent of the decline in establishment exit and a full 78 percent of the decline in firm exit. Of course, this is in a pure accounting sense: there is no reason to not expect a change in age-conditional behavior of firms over this period.

Table B.4: Direct effect of firm aging on dynamism, 1989–2015

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Early | | Late | | % change | | |
| | Raw | Direct | Raw | Direct | Raw | Direct | Share |
| *Panel A: Establishment dynamics* | | | | | | | |
| Incumbent | 0.213 | 0.181 | 0.168 | 0.170 | 27.0 | 6.8 | 25.1 |
| Exit | 0.058 | 0.047 | 0.037 | 0.038 | 54.9 | 22.9 | 41.7 |
| Exit (unweighted) | 0.103 | 0.088 | 0.074 | 0.076 | 39.8 | 15.2 | 38.2 |
| *Panel B: Firm dynamics* | | | | | | | |
| Exit (firms) | 0.031 | 0.030 | 0.021 | 0.022 | 48.8 | 38.1 | 78.1 |
| Exit (unweighted, firms) | 0.079 | 0.073 | 0.063 | 0.065 | 25.4 | 12.9 | 50.6 |

*Note: BDS 1988–2014. Labor force age 16 and older. Early refers to 1986, late to 2013 in the SIPP and 2015 in the CPS and for the entrepreneurship rates. % change is* $100 * (early/late - 1)$*. EU: share of employed in month t who are unemployed in* $t + 1$*; UE: share of unemployed in month t who are employed at* $t + 1$*; JJ: share of employed in t who are employed in* $t + 1$ *but with a different employer; all condition on remaining in the labor force. Baseline: share who started a firm in the past 42 months; opportunistic: additionally conditions on having started the firm to take advantage of a perceived business opportunity; growth: additionally conditions on expecting to add at least one worker over the next five years; raw entry rate is the unweighted firm entry rate in the BDS; all entry rates are normalized to 100 in the late period. Direct effect estimated based on a shift-share methodology, raw data is annual and HP-filtered with smoothing parameter of 6.25. See text for further details.*

## B.3 Additional Details on Model

### B.3.1 Stylized example

This section considers a simple example that illustrates a key implication of combining creative destruction with on-the-job search in a frictional labor market. For that purpose, I abstract for now from life-cycle considerations and assume that a unit mass of infinitely lived workers may be employed by low or high productivity firms. Entrepreneurs enter as high productive and attempt to hire workers (I assume for simplicity that only entrants may hire). High-productive firms become low-productive at rate $\pi$, and workers find new jobs at rate $\lambda$. I treat $\pi$ and $\lambda$ as exogenous for now and will endogenize them later.

Denote by $V_1$ and $V_2$ the value of a match between a worker and a firm with low and high productivity, respectively. Bargaining takes place as in Cahuc et al. (2006) with worker bargaining power $\beta$ (this is explained in greater detail in the next section), so that the value functions solve

$$\rho V_1 = p_1 + \lambda\beta\left(V_2 - V_1\right), \qquad \text{and} \qquad \rho V_2 = p_2 + \pi\left(V_1 - V_2\right)$$

At rate $\lambda$ a worker employed in a low-productive job finds a high-productive job, in which case he gets the full value of his current match plus a slice $\beta$ of the differential surplus. At rate $\pi$ a high-productive job becomes low-productive.

Let $F_1$ denote the fraction of workers in low productivity jobs. It is characterized by a simple flow-balance equation whose solution is $F_1 = \frac{\pi}{\pi+\lambda}$. Based on this and a solution to the Bellman equations, the value of a job can be written as

$$J = qF_1(1-\beta)(V_2 - V_1) = q(1-\beta)\frac{\pi}{\pi+\lambda}\frac{1}{\rho+\lambda\beta+\pi}(p_2 - p_1) \tag{B.2}$$

At for now exogenous rate $q$ the job contacts a worker, who is employed in a low-productive job with probability $F_1$. In this case, the entrant firm successfully recruits a

worker and gets a slice $1-\beta$ of the differential surplus, while in all other cases the payoff is zero.

Three things are worth noting: First, a higher turnover rate of firms increases labor market mismatch, $\partial F_1/\partial\pi > 0$. Second, a higher turnover rate increases job-to-job mobility, since less well-matched workers are more likely to accept a new job offer, $\partial JtJ/\partial\pi = \partial(\lambda F_1)/\partial\pi > 0$. Finally, the impact of higher turnover on the value of a job—and hence job creation—is ambiguous due to two offsetting effects. On the one hand, the match falls behind in productivity faster, which lowers the value of entering—a *duration effect*. On the other hand, it makes the labor market more mismatched, which increases the value of entering—a *mismatch effect*. In this simplified example, the following inequality characterizes the tradeoff,

$$\frac{\partial J}{\partial \pi} > 0 \iff \lambda\rho + \lambda^2\beta > \pi^2 \tag{B.3}$$

In the full-fledged model developed below, the drift in firm productivity, $\pi$, equals the growth rate of the economy. $\rho > \pi$ is necessary to ensure that the problem is meaningful.[26] The on-the-job job finding rate is typically estimated to be greater than the growth rate of the economy, $\lambda > \pi$, while $\beta \in [0,1]$. This suggests that the inequality (B.3) may be satisfied and the value of entering increasing in the turnover rate. Regardless of whether parameter values are such that (B.3) holds, however, the more general insight from this stylized example is that in an environment with creative destruction and on-the-job search, the duration effect of higher growth on the value of entering is moderated by a labor market mismatch effect.[27] The quantitative general equilibrium model I develop below embeds this intuition into a life-cycle model of firm and worker dynamics.

[26]Strictly speaking, $\pi$ is the growth rate due to selection. To the extent that also incumbent firms contribute to growth, an even stricter requirement is necessary to ensure that the problem does not explode.

[27]In contrast, the models in Aghion and Howitt (1994) and Mortensen and Pissarides (1998) feature job creation/entry that may be increasing in the growth rate as a result of a capitalization effect and the option to upgrade technology, respectively, with neither of them studying the effect of on-the-job search.

### B.3.2 Value of match with known productivity

$$\rho V(z,x,a) = e^z x - \underbrace{\mu \frac{\partial V(z,x,a)}{\partial z}}_{\text{Drift in } z} + \underbrace{\frac{\sigma^2}{2}\frac{\partial^2 V(z,x,a)}{\partial z^2}}_{\text{Shocks to } z} + \underbrace{\kappa(a)\left[\max\left\{V(z,x,a+1), U(a+1)\right\} - V(z,x,a)\right]}_{\text{Worker ages}} +$$
$$\underbrace{+ \lambda\beta \int_0^{\infty} \max\left\{V\left(z', x_u, a\right) - V(z,x,a), 0\right\} dF(z')}_{\text{New job offer}} +$$
$$\underbrace{+ \nu(a) \int_{\underline{c}}^{\bar{c}} \max\left\{E - c - V(z,x,a) + U(a), 0\right\} d\Omega(c)}_{\text{Entrepreneurship opportunity}}$$

### B.3.3 Individual's value function and wage policies

Denote by $W^w(z,x,a,w)$ the value to a worker with productivity $x$ and age $a$ working for a firm with productivity $z$ while being paid wage $w$, again with the convention that $W^w(z,x_u,a,w)$ denotes the expected value for a worker with unknown productivity. It solves the recursion

$$
\begin{aligned}
\rho W^w(z,x_u,a,w) =& w - \underbrace{\mu \frac{\partial W^w(z,x_u,a,w)}{\partial z}}_{\text{Drift in } z} + \underbrace{\frac{\sigma^2}{2}\frac{\partial^2 W^w(z,x_u,a,w)}{\partial z^2}}_{\text{Shocks to } z} + \\
&+ \underbrace{\kappa(a)\left[\max\left\{\min\left\{W^w(z,x_u,a+1,w), V(z,x_u,a+1)\right\}, U(a+1)\right\} - W^w(z,x_u,a,w)\right]}_{\text{Worker ages}} + \\
&+ \underbrace{\lambda \int_0^z \max\left\{V\left(z',x_u,a\right) + \beta\left[V\left(z,x_u,a\right) - V\left(z',x_u,a\right)\right] - W^w(z,x_u,a,w), 0\right\} dF(z')}_{\text{Worse job offer}} + \\
&+ \underbrace{\lambda \int_z^\infty \left\{V\left(z,x_u,a\right) + \beta\left[V\left(z',x_u,a\right) - V\left(z,x_u,a\right)\right] - W^w(z,x_u,a,w)\right\} dF(z')}_{\text{Better job offer}} + \\
&+ \underbrace{\psi \sum_{i\in\{b,g\}} \pi(x_i) \max\left\{\min\left\{W^w(z,x_i,a,w), V(z,x_i,a)\right\}, U(a)\right\} - W^w(z,x_u,a,w)}_{\text{Worker's productivity is revealed}} + \\
&+ \underbrace{\nu(a) \int_{\underline{c}}^{\bar{c}} \max\left\{E - c - W^w(z,x_u,a,w) + U(a), 0\right\} d\Omega(c)}_{\text{Entrepreneurship opportunity}}
\end{aligned}
$$

When a worker meets a new potential employer, I impose the bargaining protocol. For the other continuation values, the assumption is that if one party has a credible threat to abandon the renegotiation takes place to avoid a bilaterally inefficient separation. The outcome of such renegotiation is assumed to leave the party who initiated the renegotiation with zero surplus from the match. For instance, if the worker ages and would prefer to be unemployed at a given wage $w$ when in fact there are positive gains from trade, renegotiation takes place such that the worker gets exactly her outside option and is willing to remain in the match. Similarly, if in this case the firm would have preferred to fire the worker rather than pay wage $w$, renegotiation takes place such that the firm is indifferent between firing the worker and remaining in the match. Allowing for such

renegotiation is necessary to ensure that the value of the match does not depend on the way the value is split.

$$
\begin{aligned}
\rho W^w(z,x,a,w) = w &- \underbrace{\mu \frac{\partial W^w(z,x,a,w)}{\partial z}}_{\text{Drift in } z} + \underbrace{\frac{\sigma^2}{2}\frac{\partial^2 W^w(z,x,a,w)}{\partial z^2}}_{\text{Shocks to } z} + \\
&+ \underbrace{\kappa(a)\left[\max\left\{\min\left\{W^w(z,x,a+1,w), V(z,x,a+1)\right\}, U(a+1)\right\} - W^w(z,x,a,w)\right]}_{\text{Worker ages}} + \\
&+ \underbrace{\lambda \int_0^{\underline{z}^e(x,a)} \max\left\{V(z',x_u,a) + \beta\left[V(z,x,a) - V(z',x_u,a)\right] - W^w(z,x,a,w), 0\right\} dF(z')}_{\text{Worse job offer}} + \\
&+ \underbrace{\lambda \int_{\underline{z}^e(x,a)}^{\infty} \left\{V(z,x,a) + \beta\left[V(z',x_u,a) - V(z,x,a)\right] - W^w(z,x,a,w)\right\} dF(z')}_{\text{Better job offer}} + \\
&+ \underbrace{\nu(a) \int_{\underline{c}}^{\bar{c}} \max\left\{E - c - W^w(z,x,a,w) + U(a), 0\right\} d\Omega(c)}_{\text{Entrepreneurship opportunity}}
\end{aligned}
$$

Based on this, I can define the wage an unemployed receives when starting at a firm $z$, $w_u(z,a)$, as

$$W^w(z,x,a,w_u(z,a)) = U(a) + \beta\left[V(z,x_u,a) - U(a)\right]$$

The wage of a worker employed at $z$ with productivity $x$ who receives a competing offer $z'$ that is not better than the current match receives updated wage $w_s(z,x,a,z')$ with the old firm, where

$$W^w(z,x,a,w_s(z,x,a,z')) = V(z',x_u,a) + \beta\left[V(z,x,a) - V(z',x_u,a)\right]$$

subject to the natural constraint that the worker cannot be worse off with his current firm from receiving a new offer. That is, his updated wage is $\max\{w, w_s(z,x,a,z')\}$. A worker

who receives a better offer $z'$ receives wage $w_m(z, z', x, a)$ with the new firm, where

$$W^w(z', x_u, a, w_m(z, x, a, z')) = V(z, x, a) + \beta \left[ V(z', x_u, a) - V(z, x, a) \right]$$

Finally, I need to specify adjustments to wages that ensures that all separations are bilaterally optimal. In cases where either the firm's or worker's participation constraint becomes binding, I assume that wages adjust such that the party with a binding constraint is indifferent between remaining in the match and quitting it. Hence, a worker who receives an entrepreneurship opportunity that is not worth pursuing potentially receives an updated wage $w_e(z, x, a, c)$ to ensure that he only enters entrepreneurship when it is bilaterally efficient, where $W^w(z, x, a, w_e(z, x, a, c)) = E - c + U(a)$. When a worker would rather quit to unemployment, he receives updated wage $w_r(z, x, a)$, where $W^w(z, x, a, w_r(z, x, a)) = U(a)$. Finally when a firm would rather lay off a worker at the given wage (but such a layoff would not be bilaterally optimal), the worker receives adjusted wage $w_f(z, x, a)$ such that $W^w(z, x, a, w_f(z, x, a)) = V(z, x, a)$.

### B.3.4 Firm's value function and value of match

Denote by $W^f(z, x, a, w)$ the value to a firm with productivity $z$ of a match with productivity $x$ with a worker of age $a$ when the worker is paid $w$, again with the convention that $W^f(z, x_u, a, w)$ denotes the value when match productivity is unknown. The value when

match productivity is unknown solves the recursion,

$$\rho W^f(z,x_u,a,w) = e^z - w - \underbrace{\mu\frac{\partial W^f(z,x_u,a,w)}{\partial z}}_{\text{Drift in } z} + \underbrace{\frac{\sigma^2}{2}\frac{\partial^2 W^f(z,x_u,a,w)}{\partial z^2}}_{\text{Shocks to } z} +$$

$$+\underbrace{\kappa(a)\left[\max\left\{\min\left\{W^f(z,x_u,a+1,w), V(z,x_u,a+1) - U(a+1)\right\},0\right\} - W^f(z,x_u,a,w)\right]}_{\text{Worker ages}} +$$

$$+\underbrace{\lambda\int_0^z \left[V(z,x_u,a) - \max\left\{V(z',x_u,a) + \beta\left[V(z,x_u,a) - V(z',x_u,a)\right], W^w(z,x_u,a,w)\right\} - W^f(z,x_u,a,w)\right] dF(z')}_{\text{Worker gets worse job offer}} +$$

$$-\underbrace{\lambda(1-F(z))W^f(z,x_u,a,w)}_{\text{Worker gets better job offer}} + \underbrace{\psi\sum_{i\in\{b,g\}}\pi(x_i)\max\left\{\min\left\{W^f(z,x_i,a,w), V(z,x_i,a) - U(a)\right\},0\right\} - W^f(z,x_u,a,w)}_{\text{Worker's productivity is revealed}} +$$

$$+\underbrace{\nu(a)\int_{\bar{c}^e(z,x_u,a)}^{\bar{c}} V(z,x_u,a) - \max\left\{E - c + U(a), W^w(z,x_u,a,w)\right\} - W^f(z,x_u,a,w)d\Omega(c)}_{\text{Worker gets bad entrepreneurship opportunity}} - \underbrace{\nu(a)\Omega\left(\bar{c}^e(z,x_u,a)\right)W^f(z,x_u,a,w}_{\text{Worker gets good entrepreneurship opportu}}$$

Adding the value of a match to the firm and to the individual and cancelling terms reveals that the value of the match is independent of $w$.

## B.4 Additional Calibration Details

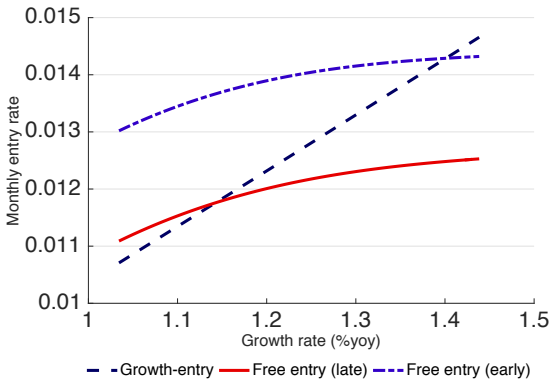
### B.4.1 Solving the model

The model is solved at the monthly frequency. I discretize the grid for productivity using 80 grid points, and I simulate the model for 1,000,000 workers for 1,200 months, discarding the initial 240 months. The high number of workers is necessary to obtain a sufficient number of firms while matching average firm size. A higher number of workers has no meaningful impact on results.

I approximate labor market events assuming that at most one of them can happen in any month, I note that all the finding rates in the model are calibrated to be low (the highest is the monthly job finding rate which is 0.17). In the simulation, I assign workers to firms based on weights corresponding to the number of vacancies it creates relative to the average number of vacancies.

To solve the model, I construct a grid for the growth rate of the economy. For each point on the grid, I guess an allocation, solve individuals' and firms' problem, update the allocation, etc., until the problem has converged for that given growth rate. By aggregating all individuals' entry decisions over the distribution of individuals, I obtain the aggregate entry rate that results from individual optimization for that given growth rate. Subsequently I look for a fixed point such that the given aggregate entry rate is consistent with the guessed growth rate. Figure B.15 illustrates the optimal aggregate entry rate as a function of the growth rate, as well as the growth rate that results for a given entry rate. An equilibrium is where the two lines cross.

Figure B.15: Entry rate and growth rate

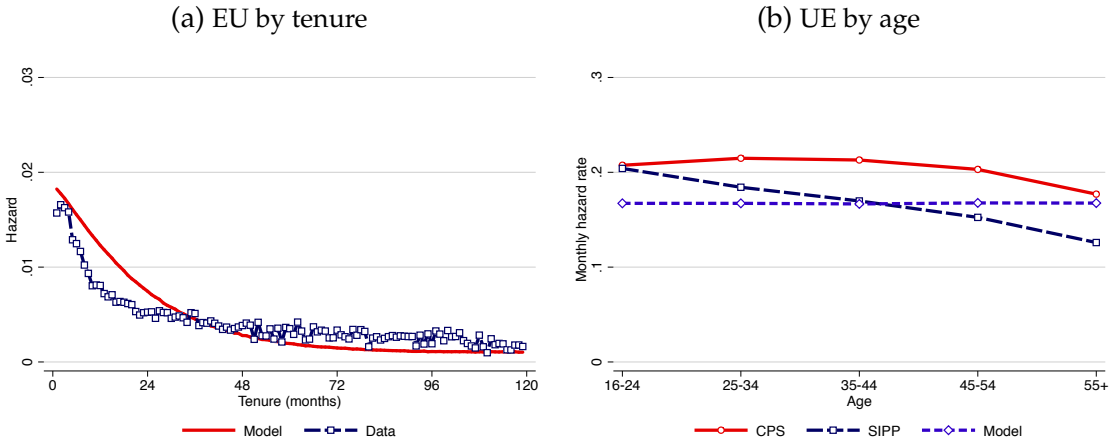



Under the uniform cost function that I assume, the two lines may cross twice. The lower intersection would be an unstable equilibrium, in the sense that a small deviation would either cause the firm productivity distribution to explode or lead to convergence to the stable equilibrium that I focus on. A different functional form for the cost function that guarantees that the entry rate is sufficiently inelastic at low growth rates may guarantee a unique equilibrium. I do not consider this further, but instead restrict attention to the stable equilibrium.

### B.4.2 Worker mobility

The left panel of Figure B.16 plots the EU hazard with tenure. The model matches the data well given that neither the magnitude nor the timing of the decline is a target in the calibration. The right panel shows that the model cannot match the modest decline in the UE hazard with age in the data.

Figure B.16: Validation: EU tenure profile and UE life cycle profile

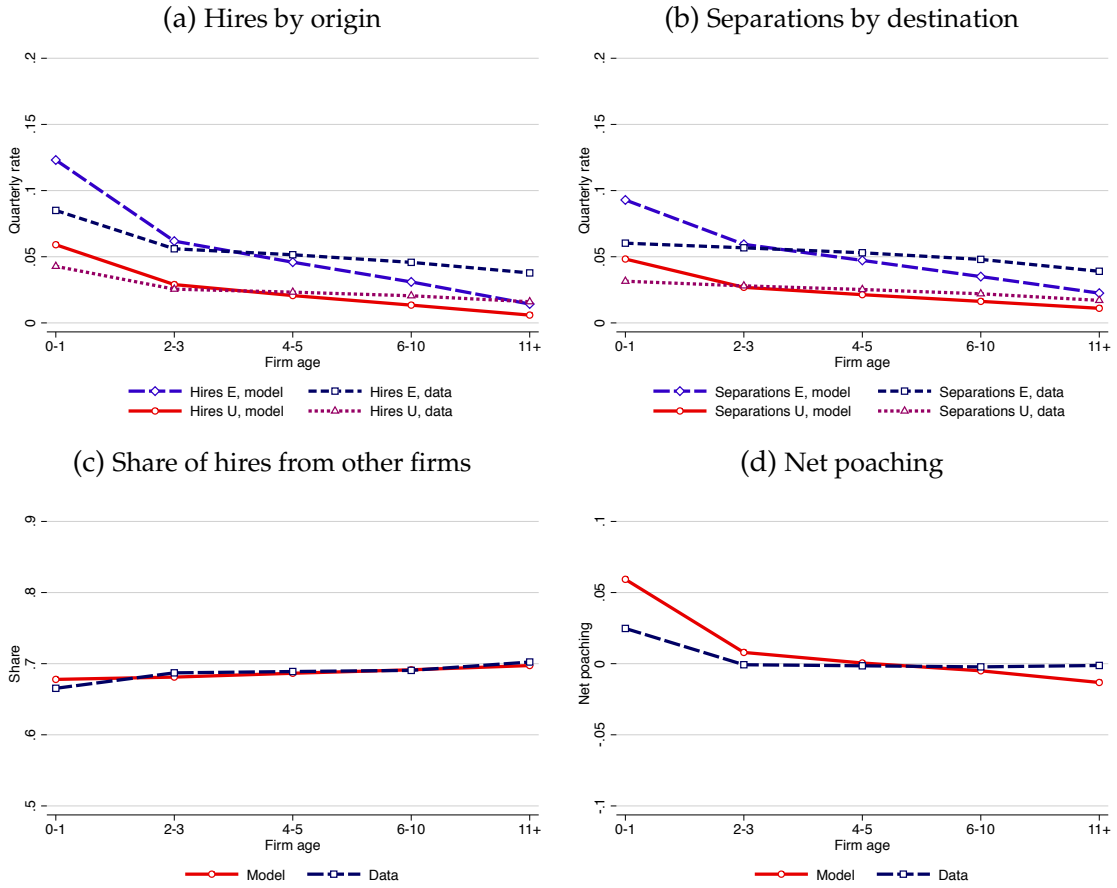



*Note: Left: SIPP in 1996–2013; Right: SIPP 2012–2013 adjusted to fit 1985–2007 average and CPS in 2014. Labor force age 16 and older. EU: share of employed in month $t$ who are unemployed in $t+1$; UE: share of unemployed in $t$ who are employed in $t+1$. All are conditional on remaining in the labor force.*

### B.4.3 Firm reallocation rates

The top two panels of Figure B.17 illustrate that the model captures well empirical hiring and separation patterns with firm age. In particular, young firms have high "churn rates" and in both the model and the data there is a modest increase in the share of hires coming from other firms with firm age. To help visual interpretation, I normalize the level of hires and separation in the model to match the empirical level, but the model also matches well the levels given that worker reallocation in the model is calibrated to match an entirely different data source.

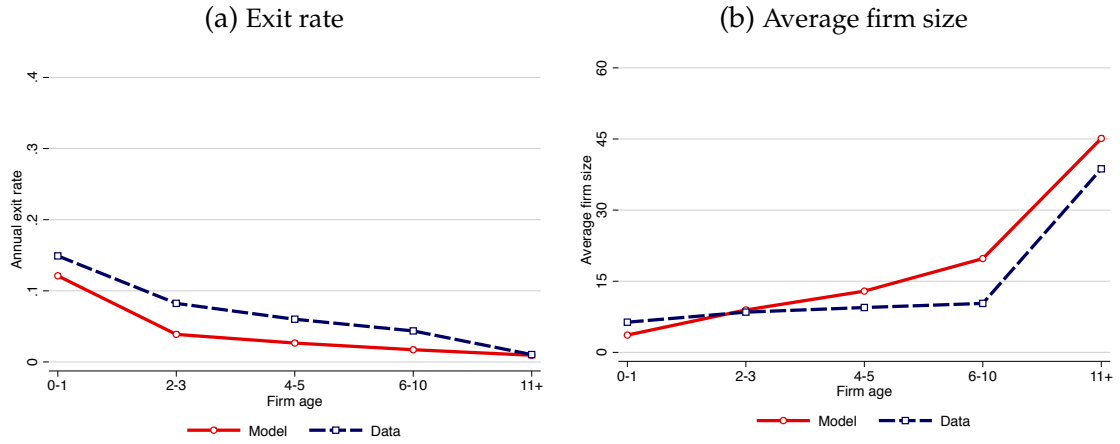
Figure B.17: Validation: Hires and separations by firm age




*Note: J2J Beta Release in 2014 after HP-filtering the data. Share hires from other firms is the sum of quarterly hires that were employed in the previous quarter divided by the total sum of hires in that firm age group; net poaching is the difference between the sum of hires who were employed in the previous quarter and the sum of separations who are employed in the subsequent quarter in that firm age group divided by the total sum of employment in that firm age group. Hiring and separation rates are normalized to match the corresponding empirical mean.*

Figure B.18 plots unadjusted exit and firm size by firm age.

Figure B.18: Unadjusted firm exit and firm size



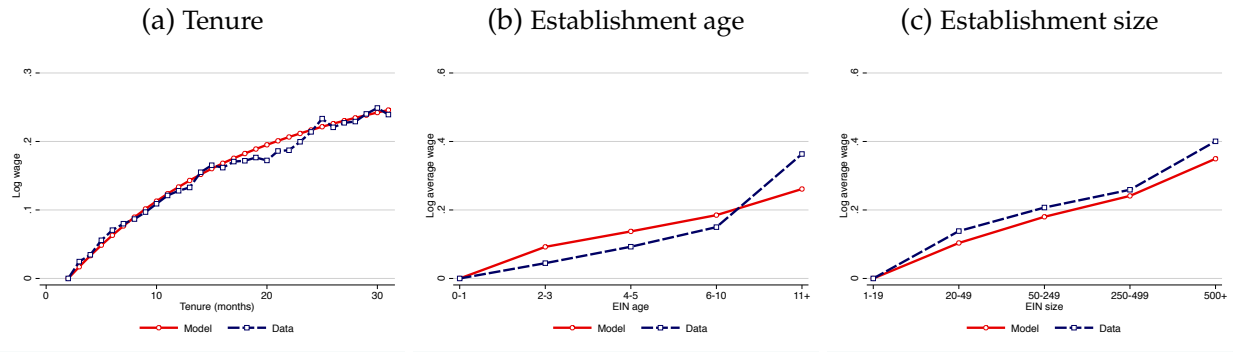

*Note: BDS in 2014 after HP-filtering the data. Exit rate: sum of employment of firms whose employment in the subsequent year is zero; Firm age: years lapsed since first year with positive employment. All within firm age groups and divided by total employment in that age group.*

### B.4.4 Wages

Figure B.19 shows that the model matches well wages by tenure, firm age and firm size in the data, which serves as a further validation of the structure of the model given that none is targeted.[28] As wage growth with tenure partly results from re-bargaining, the fact that the model fits so well the tenure profile of wages in the left panel supports the pre-set value for workers' bargaining power, $\beta$. I show below that the model also matches well empirical gains from JJ mobility, which is also informative about $\beta$. Interpreted through the structure of the model, the fact that the model matches well the firm age-pay and firm size-pay gradients indicates that the amount of underlying productivity dispersion in the model is in line with the data.

[28]The model also captures a little over half of life cycle wage growth, with most of the increase taking place early in careers. This is broadly in line with estimates of the contribution of search to life cycle wage growth (Engbom, 2017).

Figure B.19: Validation: Average pay by tenure and establishment age

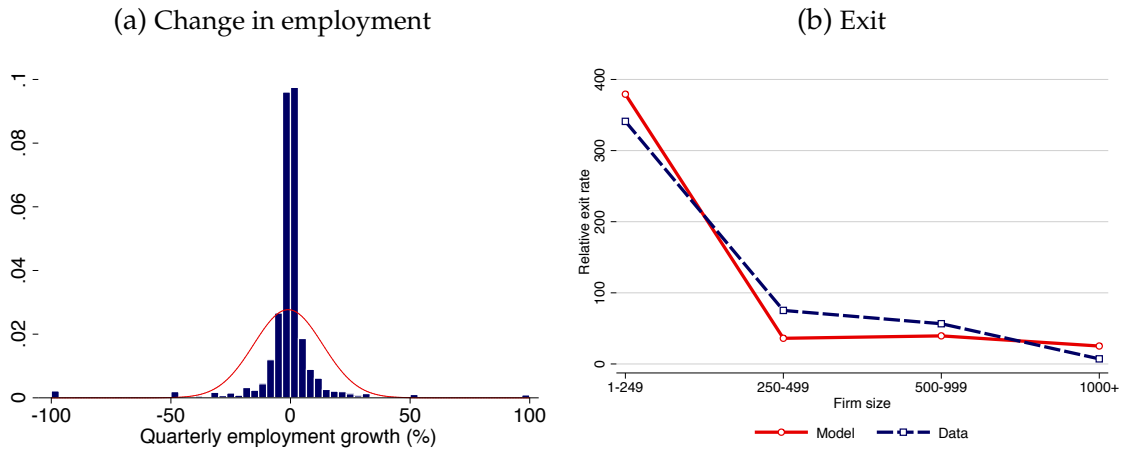



*Note: SIPP 1996–2013 (left) and QWI 1993–2014 (middle and right). Left panel: Log real hourly wage at main employer, constructed as total monthly labor income from that employer divided by weeks worked at that employer in the month times average hours per week at that employer. Main employer is the employment spell with the greatest number of hours in the month (splitting on income in case of a tie). Tenure is continuous time since employment spell first started. Right panel: Log average monthly income of workers at Employer Identification Number (EIN).*

### B.4.5 Higher order moments and exit by size

Job reallocation can be viewed as the second moment of employment changes at the establishment level. The left panel of Figure B.20 shows that the model also replicates well higher order moments of employment changes, specifically the fact that such changes have a large spike at zero and fat tails (Elsby and Michaels, 2013). The right panel of Figure B.20 shows that the model matches well the exit rate of firms by firm size in the data.

Figure B.20: Quarterly employment changes at firm level and exit rate by size




*Note: Right: change in employment between $t$ and $t+1$ over employment at $t$ multiplied by 100. Weighted by employment. Right: BDS in 2015 after HP-filtering annual data with smoothing parameter 6.25. Sum of jobs destroyed due to exit of firms from that size group divided by sum of employment in that size group.*

### B.4.6 Income inequality and dynamics

Table B.10 presents summary statistics on wages in the model and data. As can be seen in the first row, the level of wage inequality is substantially lower than in the data. Several things should be noted with respect to this, though. First, wages are measured without noise in the model, while wage rates in survey data are notoriously noisy. Second, the model features no ex ante heterogeneity in individual ability. A more comparable empirical measure may hence be between-firm dispersion in pay (or AKM firm effects), which typically is estimated to be substantially lower. For instance, Abowd et al. (2002) report a standard deviation of AKM firm effects of 0.231 using hourly wages in the state of Washington based on administrative data for 1984–1993, which is close to the dispersion in wages in the model. As can be seen in the second row, the model matches the dispersion in log average firm pay in the data, constructed as the average annual income of all workers at an establishment. To the extent that this averages out some individual hetero-

geneity and reduces measurement error by not dividing by hours, this may better align with the model-based moments.

Table B.5: Summary statistics on wages and income in model

| Moment | Data source | (1) Data | (2) Model |
|---|---|---|---|
| Standard deviation of wages | AKM firm effect (Abowd et al., 2002) | 0.23 | 0.22 |
| Variance of log average firm pay | Barth et al. (2016) | 0.48 | 0.46 |
| Standard deviation of income innovations | Guvenen et al. (2014) | 0.51 | 0.52 |
| Skewness of income innovations | Guvenen et al. (2014) | -0.31 | -0.32 |
| Kurtosis of income innovations | | | 8.71 |
| Pass-through from productivity to wage | Van Reenen (1996) | 0.29 | 0.27 |
| Wage gain from JJ mobility | Topel and Ward (1992) | 7% | 7% |

*Note: AKM firm effects based on hourly wages in Washington state 1984–1993; variance of log average firm pay is the variance of log average annual income of an establishment's workers across establishments in 2009; income innovations use total annual log labor income; pass-through coefficient is estimated based on a regression of log wage innovation from December to December on log firm productivity innovation from December to December of workers who remain with the firm between the two years; gain from JJ mobility is monthly wage gain from a JJ move.*

The third to fifth row show that the model matches closely the second and third moment of annual income innovations in the data reported by Guvenen et al. (2014) in 2010 based on social security data. The model also displays substantial excess kurtosis, which is in line with other recent findings using social security data from the U.S.[29] The sixth row provides some insight into why the model is able to match income innovations well. The estimated pass-through from annual TFP innovations of the firm to annual wage innovations of workers who remain with the firm between the two years is low, in line with the seminal "rent-sharing" estimate by Van Reenen (1996).[30] Despite random nor-

[29]Hubmer (2017) develops a one worker-one firm matching model without shocks to firm productivity but with human capital that is subject to a random walk, and reaches a similar conclusion with respect to the ability of a job ladder to match higher order moments of income innovations.

[30]Card et al. (2016) survey the empirical rent-sharing literature and report estimates between 0.05–0.15, i.e. smaller than Van Reenen (1996)'s estimate. Measurement error in the data would give rise to a downward bias of the estimated coefficient.

mal shocks hitting firm productivity continuously, the assumption that wages can only be changed by mutual consent implies that only a fraction of productivity innovations is passed on to wages of workers who remain with the firm. Instead, income volatility of workers is much lumpier, driven by labor market shocks including job loss, JJ mobility, and rebargaining of wages in response to more preferable outside offers.[31] This produces a dynamic wage and income process that shares key features with the data, including a spike in annual income changes at zero, negative skewness and excess kurtosis. The final two rows show that the model matches well gains from JJ mobility and the fact that a high share of JJ movers experience wage losses.[32] None of these moments was targeted in the calibration.

[31] A similar argument is made in Postel-Vinay and Turon (2010) in a one worker-one firm matching model.

[32] The latter is the result of multiple forces. First, in the discretized model I assume that those who learn that their match productivity is bad may find a new job within the same month. Since these individuals have a bad bargaining position, a relatively high fraction of them experience wage losses when they move. Second, since firm productivity drifts down over time, many workers move to leave a "sinking ship." Since wages are assumed to be fixed until either party may force a renegotiation, many of these workers experience only small wage gains from such mobility.

## B.5 Additional Quantitative Results

### B.5.1 Shift in age distribution

Table B.6 compares the shift in the age distribution in the model and in the data. As noted in the main text, I target the change in the share of older individuals, which implies that I understate the decline in the share young and overstate the decline in the share middle aged somewhat. Since the young are more mobile than the middle aged and have about the same entrepreneurship entry rates, this will understate the direct impact of aging and presumably also the indirect effect.

Table B.6: Share of individuals in each age group by period, model versus data

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Early | | Late | | Change | |
| | Data | Model | Data | Model | Data | Model |
| Young | 0.492 | 0.434 | 0.356 | 0.339 | - 0.136 | - 0.095 |
| Middle aged | 0.231 | 0.289 | 0.208 | 0.226 | - 0.023 | - 0.063 |
| Older | 0.277 | 0.277 | 0.436 | 0.436 | 0.159 | 0.158 |

*Note: Empirical moments corresponds to the share of the labor force age 16–34 (young), 35–44 (middle aged) and 45+ (older) in 1986 and 2015 from the BLS.*

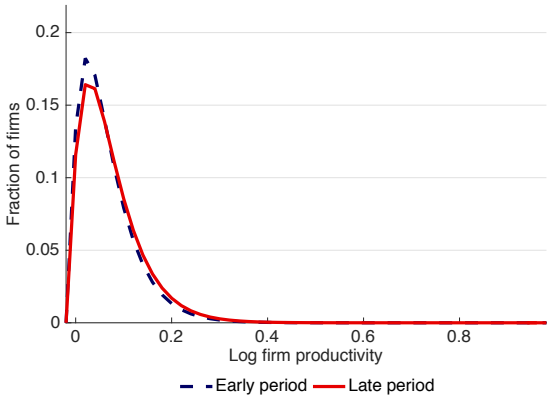
### B.5.2 Shifts in firms' job posting decisions

The left panel of Figure B.21 plots the underlying distribution of firms in the two periods. I note that the unweighted distribution of firms is substantially to the left of the weighted distribution, as there are many small, unproductive firms in the model. I also note that part of the shift in the employment distribution is driven by a shift in the underlying

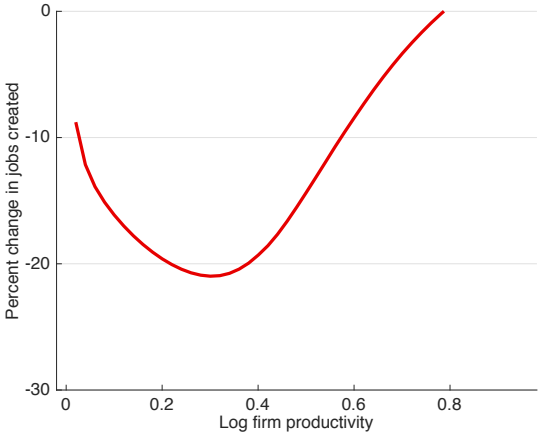
distribution of firms.[33] The right panel plots the change in vacancies posted by firm productivity between the older and younger economy. As can be seen, firms post more jobs conditional on productivity in the younger economy.

Figure B.21: Change in firm productivity distribution and job creation by productivity of the firm

(a) Firm productivity distribution




(b) Vacancy creation




### B.5.3 Declining variance of shocks versus a fall in the pass-through

Table B.7 shows that the model replicates the empirical fact documented by Decker et al. (2017a) that the decline in job reallocation is driven by a weaker pass-through from underlying TFP shocks to employment adjustment.

Table B.7: Pass-through from productivity to employment innovations, model

| | (1) All firms | (2) Young firms | (3) Mature firms |
|---|---|---|---|
| $\Delta$ TFP | 3.504*** | 5.604*** | 2.394*** |
| Late period $\times \Delta$ TFP | -0.566*** | -0.212*** | -0.177*** |

*Note: Young firms are <5 years, mature firms $\geq$ 5 years. Outcome variable is annual change in log firm size. Independent variable is annual change in log firm productivity. Weighted by employment.*

[33] This only explains part of the shift, however, with also a shift of employment across firm ranks.

### B.5.4 Firm aging and the decline in firm dynamics

I compute firm age conditional reallocation rates in a late period, $\beta_a^{\text{late}}$, and change the employment distribution over firm age assuming that firm age-conditional reallocation rates remain constant,

$$\widehat{\text{Effect of aging}} = \sum_a \beta_a^{\text{late}} \left[ \text{share of employment}_a^{\text{early}} - \text{share of employment}_a^{\text{late}} \right] \quad \text{(B.4)}$$

Table B.8 shows that the effects of aging in the model match well the reduced-form patterns in the data.[34] As in the data, the shift towards older firms accounts for all (or even more than that) of the decline in exit and a substantial share of the decline in incumbent job reallocation. Firm aging accounts for a relatively larger share in the model due to the more pronounced life cycle profiles of exit and incumbent job reallocation with firm age relative to the data. As noted in the previous section, however, if there is any measurement error in firm age, that would tend to flatten the life cycle profiles and bias the empirical figures towards zero. The model captures the pattern that firm aging accounts for more of the decline in exit than incumbent dynamics.

[34] For all statistics broken down by firm age, the early period corresponds to 1988 since data on the oldest age group of firms is not available prior to that.

Table B.8: Firm aging and firm dynamics

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Early | | Late | | Change | |
| | Data | Model | Data | Model | Data | Model |
| Exit | 0.029 | 0.021 | 0.020 | 0.018 | - 0.008 | - 0.003 |
| *Direct effect* | 0.029 | 0.023 | 0.020 | 0.018 | - 0.008 | - 0.004 |
| *% of total* | | | | | 96.8 | 142.4 |
| Incumbent | 0.211 | 0.176 | 0.166 | 0.152 | - 0.045 | - 0.024 |
| *Direct effect* | 0.176 | 0.170 | 0.166 | 0.152 | - 0.010 | - 0.018 |
| *% of total* | | | | | 22.7 | 74.4 |

*Note: Annual firm reallocation rates. Data moments from the BDS in 1988 and 2014 after HP-filtering the data with smoothing parameter 6.25. Direct effect is based on a shift-share methodology assuming that firm age conditional reallocation rates remain fixed at their late values and only shifting the distribution of firm age. Weighted by employment.*

### B.5.5 Direct and indirect effect of aging

Table B.9 shows results from a standard shift-share analysis.

Table B.9: Composition versus equilibrium effect of aging on worker dynamics

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Early | | Late | | Change | | |
| | Data | Model | Data | Model | Data | Model | Share |
| EU | 0.009 | 0.006 | 0.005 | 0.005 | - 0.003 | - 0.001 | 35.7 |
| *Direct effect* | 0.006 | 0.005 | 0.005 | 0.005 | - 0.001 | - 0.000 | 59.2 |
| *% of total* | | | | | 20.7 | 34.4 | |
| JJ | 0.023 | 0.020 | 0.018 | 0.017 | - 0.005 | - 0.002 | 47.6 |
| *Direct effect* | 0.020 | 0.018 | 0.018 | 0.017 | - 0.002 | - 0.001 | 60.2 |
| *% of total* | | | | | 40.8 | 51.7 | |

*Note: Monthly worker reallocation rates from the SIPP in 1986 and 2012–2013. Converted to annual averages and HP-filtered with smoothing parameter 6.25. Direct effect estimated based on a shift-share methodology holding age-conditional mobility rates fixed at the values in the late period and shifting only the age distribution.*

### B.5.6 Understanding the decline in dynamism

Figure B.22 illustrates the equilibrium shifts in the distribution of employment over firm productivity and match productivity from the old to the young economy. The left panel plots the distribution of young and old individuals over firm productivity in the early and late period,[35] while the right panel plots the share of individuals of each age who have learned that they are high-productive in the two periods. The aggregate labor market is shifted to more productive firms in the older economy both because older individuals are on average employed higher up the firm ladder, and because the slower turnover rate of firms endogenously shift the distribution of employment up the firm ladder. Similarly, the share who know that they are in a high productive match is higher in the older economy

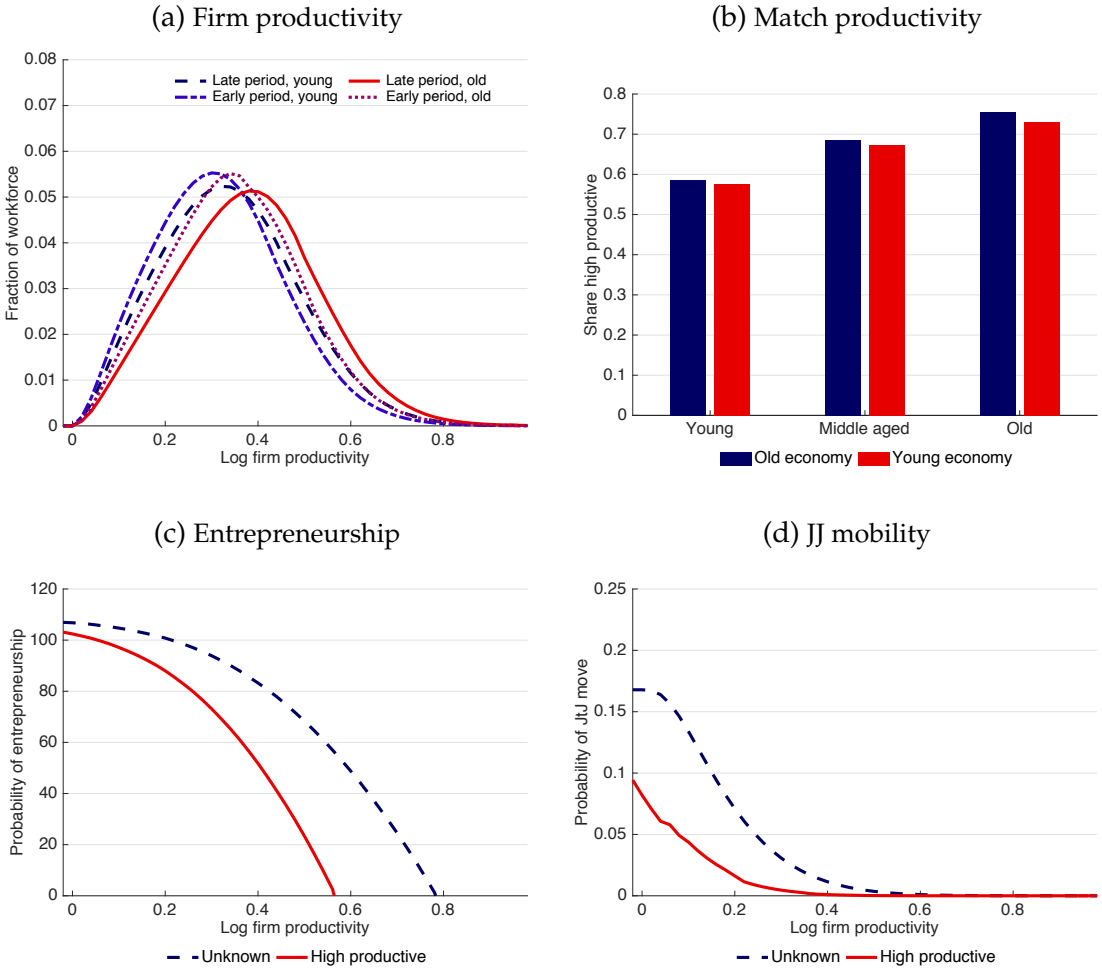
[35]Specifically it plots those who have not yet learned their match productivity. To avoid clogging up the graph I do not plot middle aged individuals, but naturally it is in between young and older individuals.

both because it is higher among older individuals and because the longer employment spells implies that more matches have learned their productivity.

To understand the impact of shifts in the distribution of workers over firm productivity and worker productivity on the probability of entry and making a JJ move, Figure B.22 plots the probability of entering entrepreneurship and of accepting an outside job offer as a function of current place in the job ladder and whether the worker knows that he is high-skilled or does not know his skill level.[36] As a worker climbs the job ladder and learns his skill level, he is less likely to enter entrepreneurship and switch employer since it increases his opportunity cost.

[36]Specifically for middle aged workers in the late period, but the other period and age groups look similar.

Figure B.22: Firm and match productivity and entry and JJ mobility decision rules in early and late period



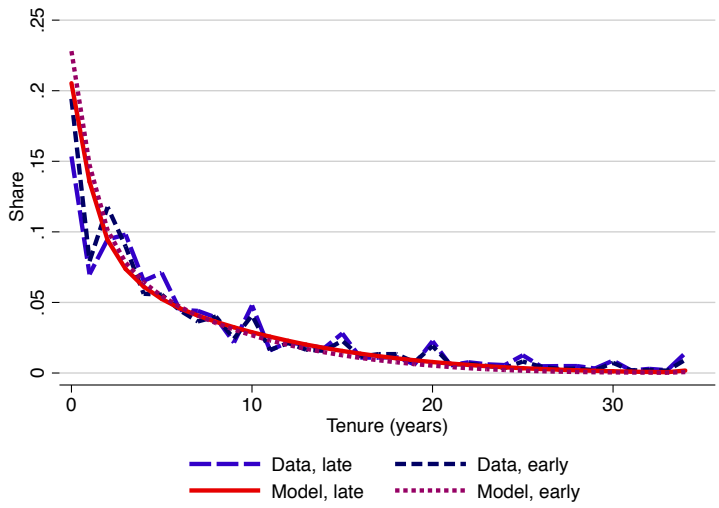

*Note: Top left: distribution of young and older individuals over firm productivity (specifically those that have not yet learned their match productivity); Top right: share of individuals who know that they are in a high-productive match, aggregating across all firm productivities; Bottom left: Probability of entering entrepreneurship normalized to 100 for young workers with unknown skill in the late period; Bottom right: Probability of JJ move.*

### B.5.7 Tenure distribution in model and data

Figure B.23 plots the tenure distribution in the model and the data in the early and late period. The empirical moments are based on the CPS tenure supplements in 1987 and 2014 for workers age 20–64 and was kindly provided to me by Henry Farber. The model

matches well the tenure distribution in the CPS in levels, somewhat overpredicting the share of workers at very low tenures. This tentatively supports the lower SIPP based reallocation rates relative to the higher rates in the matched CPS data. Furthermore, the model matches well the change in the tenure distribution over time.

Figure B.23: Tenure distribution in model and data, early and late period

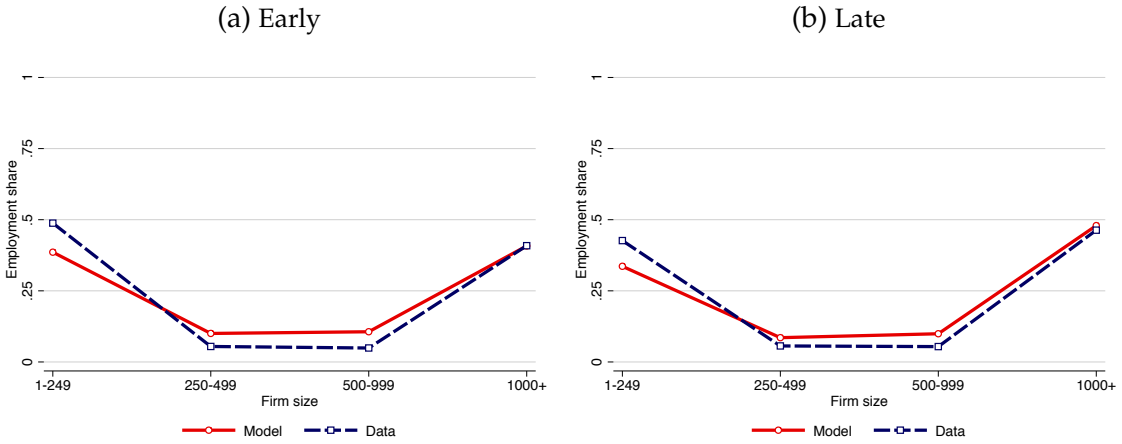



*Note: CPS tenure supplements in 1987 and 2014. Workers age 20–64, weighted with provided survey weights. I thank Henry Farber for providing me with these data.*

### B.5.8 Shift in employment size distribution

Figure B.24 shows that the model captures well changes in the share of employment by firm size over this period, specifically the fact that large firms have seen a modest expansion in their employment share at the expense of small firms.

Figure B.24: Employment shares by firm size in early and late period, model and data




*Note: Data from the BDS in 1986 and 2015 after HP-filtering the annual data with smoothing parameter 6.25.*

### B.5.9 Income dynamics

This section evaluates of the effect of aging on income inequality and income dynamics.[37] Panel A offers two main insights on between-firm dispersion in productivity and pay. First, the model matches well the level of between-firm dispersion in pay, despite not targeting this in the calibration. Second, aging increases dispersion in productivity and pay across firms. This is qualitatively in line with the data over this period, although quantitatively it accounts for only a modest share of the increase. Panel B shows the impact of aging on income dynamics, providing three take-aways. First, despite not targeting these moments, the model matches very well the level of both the variance and skewness of annual income innovations in the data.[38] Second, the less dynamic labor market in the older economy is associated with a lower variance of income innovations. The change matches well the trend over this period documented by Guvenen et al. (2014). Third, skewness has

[37]The model predicts a slight decrease in the labor share from the early to the late period. This highlights that the relevant object for other firms' incentives to create jobs is not the split of payments among existing matches but the productivity of such matches relative to the potential hiring firm. The labor market has become better matched in the sense that individuals are in relatively more productive matches, not in the sense that they are paid more conditional on output.

[38]The model also produces a kurtosis of annual income changes of over 8, in line with recent findings of substantial excess kurtosis in the data. Hubmer (2017) reaches a similar finding in a one worker-firm matching model.

become increasingly negative, again in line with empirical trends (Guvenen et al., 2014).[39] Workers are on average further up the ladder in the older economy, with the potential for a greater fall in case of a perverse labor market shock.

Table B.10: Inequality and income dynamics

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Early | | Late | | Change | | |
| | Data | Model | Data | Model | Data | Model | Share |
| *Panel A: Inequality* | | | | | | | |
| Standard deviation of productivity | 0.35 | 0.127 | 0.42 | 0.138 | 0.07 | 0.011 | 13.9 |
| Variance of firm pay | 0.40 | 0.446 | 0.48 | 0.463 | 0.08 | 0.017 | 21.3 |
| *Panel B: Annual income innovations* | | | | | | | |
| Standard deviation | 0.545 | 0.539 | 0.506 | 0.515 | - | - | 61.5 |
| | | | | | 0.039 | 0.024 | |
| Skewness | - | - | - | - | - | -0.07 | 70.7 |
| | 0.213 | 0.253 | 0.312 | 0.323 | 0.099 | | |

*Note: Empirical counterparts are the following: Standard deviation of firm productivity is the standard deviation of within-detailed industry TFP of manufacturing firms from Decker et al. (2017a)'s Figure A1 in HP-filtered data in 1986 and 2011; Standard deviation of wages is the standard deviation of residual log weekly earnings and the variance of firm pay is the variance of log average annual income of all individuals at the firm, both from Barth et al. (2016)'s Figure 1 in 1986 and 2009; Moments of income innovation distribution from Guvenen et al. (2014) in HP-filtered data in 1986 and 2010.*

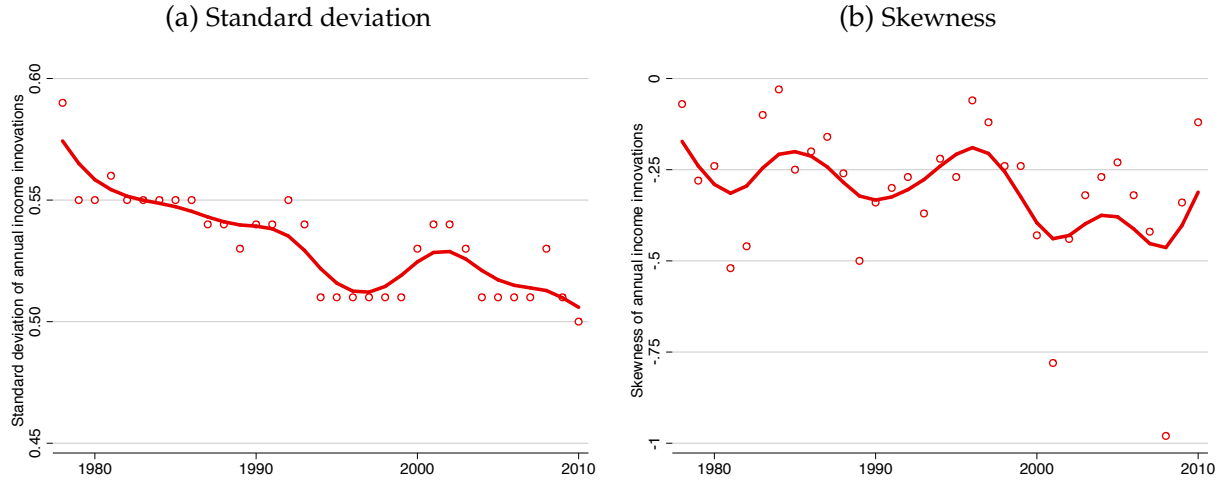
### B.5.10 Empirical trends in income innovations

Figure B.25 plots the empirical trend in the standard deviation and skewness of annual income innovations based on the administrative social security data in Guvenen et al. (2014). There is a clear downward trend in income volatility as measured by the standard deviation. Skewness has also declined, although as emphasized by these authors it dis-

[39]Skewness, however, displays substantial business cycle variation and it is difficult to separate trend from cycle in the data. HP-filtering Guvenen et al. (2014)'s published data from 1978–2010, detrended skewness has declined from -0.213 in 1986 to -0.312 in 2010, while if I instead fit a linear time trend to their raw data skewness is predicted to have fallen secularly from -0.259 in 1986 to -0.404 in 2010. See Appendix B.5 for details.

plays important business cycle variation and hence it is less clear how much to make out of the decline at this point.

Figure B.25: Empirical trend in standard deviation and skewness of annual log income innovations




*Note: Data from Guvenen et al. (2014). Annual innovations of log income HP-filtered with annual smoothing parameter of 6.25. See their paper for further details.*

## B.6 Additional Details on Cross-state Regressions

### B.6.1 Construction of data set

Data sources and variable definitions are described in Appendix B.1. All measures are aggregated to the annual level and HP-filtered with smoothing parameter of 6.25. The BDS covers private sector employment while in the CPS I focus on workers age 19–64. Given that I need one lagged year and one future year of employment to construct growth in GDP per worker at the state level, I focus my regression analysis on the 1978–2014 period.

Although the data identify Washington D.C., I drop D.C. due to the high share of its labor force does not live in the "state." Based on Decennial Census/American Community Survey data from 1980–2015, on average 70 percent of the people that work in D.C. do not live in D.C. (the second highest share is in Delaware with 14 percent). Thus the age composition of people living in D.C. is a poor proxy for the age composition that is important for determining dynamism in the state (results are modestly weaker including D.C.).

### B.6.2 First stage regressions

Table B.11 presents first stage regression of the current share of older in the labor force (column 1) or working age population (column 2) on the 10-year lagged share of older workers (with state fixed effects, year effects and growth in state real GDP per worker). Together with state and year effects, the lagged age composition explains 94–95 percent of the overall variation in the current age composition. It explains 27 percent of the residual variation after having taken out state and year effects. The Kleibergen-Paap rk Wald statistic is just over 16.

Table B.11: First stage regressions

| | (1) | (2) |
|---|---|---|
| | LF | WP |
| 10-year lagged share | 0.880*** | 0.860*** |
| | (0.214) | (0.238) |
| N | 1,850 | 1,850 |
| R2 | 0.952 | 0.939 |
| R2 (within) | 0.273 | 0.272 |

*Note: BDS and CPS 1978–2014. All columns contain state fixed effects, year effects and growth in state real GDP per worker. Dependent variable is share of labor force (column 1) or working age population (column 2) age 19–64 that is age 40–64. Two-way clustered standard errors by state and year. *statistically significant at 10%; **statistically significant at 5%; ***statistically significant at 1%. See text for further details.*

### B.6.3 Additional establishment level dynamics

**Logs.** Table B.12 shows the full range of point estimates and their standard errors based on regression (2.20) with establishment dynamics. All reallocation rates and population shares are in logs.

Table B.12: Estimated coefficient on share of labor force/population that is age 40 and older, employment-weighted establishment level outcomes in logs

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (9) |
|---|---|---|---|---|---|---|---|---|
| | Baseline | | Covar | | Sector | | Policy | |
| | OLS | IV | OLS | IV | OLS | IV | OLS | IV |
| *Panel A: Labor force* | | | | | | | | |
| Job reallocation | -0.448*** | -0.527*** | -0.386*** | -0.476** | -0.354*** | -0.440** | -0.430*** | -0.527** |
| | (0.127) | (0.191) | (0.104) | (0.181) | (0.111) | (0.186) | (0.125) | (0.204) |
| Turnover | -0.630*** | -0.961*** | -0.558*** | -0.919*** | -0.503*** | -0.861*** | -0.593*** | -0.945*** |
| | (0.203) | (0.268) | (0.170) | (0.244) | (0.180) | (0.264) | (0.195) | (0.276) |
| Entry | -0.668*** | -0.999*** | -0.597*** | -0.933*** | -0.526*** | -0.903*** | -0.645*** | -1.006*** |
| | (0.189) | (0.247) | (0.158) | (0.236) | (0.159) | (0.247) | (0.193) | (0.263) |
| Exit | -0.600** | -0.940*** | -0.532** | -0.928*** | -0.485** | -0.825** | -0.550** | -0.898*** |
| | (0.243) | (0.322) | (0.216) | (0.283) | (0.224) | (0.318) | (0.226) | (0.324) |
| *Panel B: Working age population* | | | | | | | | |
| Job reallocation | -0.518*** | -0.539*** | -0.447*** | -0.467** | -0.410*** | -0.458** | -0.496*** | -0.538** |
| | (0.124) | (0.186) | (0.105) | (0.195) | (0.114) | (0.186) | (0.123) | (0.197) |
| Turnover | -0.774*** | -0.984*** | -0.683*** | -0.933*** | -0.629*** | -0.898*** | -0.734*** | -0.966*** |
| | (0.202) | (0.256) | (0.163) | (0.256) | (0.184) | (0.263) | (0.194) | (0.259) |
| Entry | -0.753*** | -1.022*** | -0.661*** | -0.962*** | -0.588*** | -0.941*** | -0.724*** | -1.029*** |
| | (0.188) | (0.245) | (0.161) | (0.263) | (0.164) | (0.254) | (0.193) | (0.256) |
| Exit | -0.809*** | -0.962*** | -0.729*** | -0.934*** | -0.682*** | -0.860*** | -0.759*** | -0.918*** |
| | (0.239) | (0.304) | (0.194) | (0.286) | (0.225) | (0.313) | (0.221) | (0.300) |

*Note: BDS, CPS and Intercensal Censi 1978–2014, HP-filtered annual data with smoothing parameter 6.25. Point estimates on the share of the labor force/population age 19–64 that is age 40 and older on employment-weighted establishment dynamics. All columns control for state, year, share female, share college or more, share non-white and annual growth in state real GDP per worker. All shares and reallocation rates are in logs. Covariates: controls for the share female, non-white, and with a college degree or more; Sector: controls for share of the labor force in nine aggregate sectors; Policy: controls for state minimum wage and total state tax rate per capita. Standard errors clustered at state and year. *statistically significant at 10%; **statistically significant at 5%; ***statistically significant at 1%.*

Table B.13 summarizes the predicted power of aging on aggregate dynamism across measures from 1986 to 2015. Across all measures and regardless of whether I use the labor force or working age population aging predicts substantial declines.

Table B.13: Predicted cumulative effect of aging on establishment reallocation rates 1986–2015

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|---|
| | | Baseline | | Covariates | | Sector | | Policy | |
| | Raw | OLS | IV | OLS | IV | OLS | IV | OLS | IV |
| *Panel A: Labor force* | | | | | | | | | |
| Job | -0.329 | -0.144 | -0.169 | -0.124 | -0.153 | -0.114 | -0.141 | -0.138 | -0.169 |
| % of raw | 100 | 43.7 | 51.4 | 37.7 | 46.5 | 34.5 | 42.9 | 41.9 | 51.4 |
| Turnover | -0.477 | -0.203 | -0.309 | -0.179 | -0.295 | -0.162 | -0.277 | -0.191 | -0.304 |
| % of raw | 100 | 42.5 | 64.8 | 37.6 | 61.9 | 33.9 | 58.1 | 40.0 | 63.7 |
| Entry | -0.475 | -0.215 | -0.321 | -0.192 | -0.300 | -0.169 | -0.290 | -0.207 | -0.324 |
| % of raw | 100 | 45.2 | 67.5 | 40.4 | 63.1 | 35.5 | 61.0 | 43.6 | 68.1 |
| Exit | -0.478 | -0.193 | -0.302 | -0.171 | -0.298 | -0.156 | -0.265 | -0.177 | -0.289 |
| % of raw | 100 | 40.3 | 63.2 | 35.8 | 62.4 | 32.6 | 55.5 | 36.9 | 60.4 |
| *Panel B: Working age population* | | | | | | | | | |
| Job | -0.329 | -0.135 | -0.140 | -0.116 | -0.122 | -0.107 | -0.119 | -0.129 | -0.140 |
| % of raw | 100 | 40.9 | 42.6 | 35.3 | 36.9 | 32.3 | 36.2 | 39.2 | 42.5 |
| Turnover | -0.477 | -0.201 | -0.256 | -0.178 | -0.243 | -0.164 | -0.233 | -0.191 | -0.251 |
| % of raw | 100 | 42.2 | 53.7 | 37.2 | 50.9 | 34.3 | 49.0 | 40.1 | 52.7 |
| Entry | -0.475 | -0.196 | -0.266 | -0.172 | -0.25 | -0.153 | -0.245 | -0.188 | -0.268 |
| % of raw | 100 | 41.2 | 55.9 | 36.1 | 52.6 | 32.2 | 51.5 | 39.6 | 56.3 |
| Exit | -0.478 | -0.211 | -0.250 | -0.190 | -0.243 | -0.177 | -0.224 | -0.197 | -0.239 |
| % of raw | 100 | 44.0 | 52.3 | 39.7 | 50.8 | 37.1 | 46.8 | 41.3 | 49.9 |

*Note: BDS, CPS and Intercensal Censi 1978–2015. Predicted cumulative effect of aging from 1986 to 2015 based on cross-state panel estimates applied to the national time trend in aging.*

**Levels.** Table B.14 shows regression results of establishment dynamics on the share of older workers in levels, while Table B.15 summarizes the cumulative predicted impact of aging. The results are more pronounced than in the specification in logs.

Table B.14: Estimated coefficient on share of labor force/population that is age 40 and older, employment-weighted establishment level outcomes in levels

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (9) |
|---|---|---|---|---|---|---|---|---|
| | Baseline | | Covar | | Sector | | Policy | |
| | OLS | IV | OLS | IV | OLS | IV | OLS | IV |
| *Panel A: Labor force* | | | | | | | | |
| Job reallocation | -0.364** | -0.371 | -0.386*** | -0.415** | -0.283** | -0.288 | -0.357** | -0.394* |
| | (0.141) | (0.229) | (0.108) | (0.181) | (0.110) | (0.174) | (0.136) | (0.231) |
| Turnover | -0.181** | -0.235* | -0.192*** | -0.255** | -0.147** | -0.202** | -0.176** | -0.252* |
| | (0.080) | (0.131) | (0.063) | (0.100) | (0.063) | (0.097) | (0.076) | (0.130) |
| Entry | -0.106** | -0.128* | -0.114*** | -0.138** | -0.084*** | -0.108** | -0.106** | -0.143* |
| | (0.043) | (0.070) | (0.032) | (0.052) | (0.031) | (0.051) | (0.043) | (0.072) |
| Exit | -0.075* | -0.106 | -0.079** | -0.117** | -0.063* | -0.094* | -0.070* | -0.110* |
| | (0.040) | (0.064) | (0.035) | (0.052) | (0.034) | (0.050) | (0.037) | (0.062) |
| *Panel B: Working age population* | | | | | | | | |
| Job reallocation | -0.409** | -0.379 | -0.402*** | -0.423** | -0.301** | -0.298 | -0.398*** | -0.401* |
| | (0.151) | (0.230) | (0.109) | (0.194) | (0.121) | (0.180) | (0.144) | (0.231) |
| Turnover | -0.215** | -0.240* | -0.205*** | -0.265** | -0.167** | -0.209** | -0.208** | -0.257* |
| | (0.086) | (0.131) | (0.062) | (0.109) | (0.068) | (0.101) | (0.080) | (0.129) |
| Entry | -0.116** | -0.131* | -0.110*** | -0.145** | -0.085** | -0.112** | -0.115** | -0.145* |
| | (0.046) | (0.070) | (0.034) | (0.059) | (0.034) | (0.054) | (0.046) | (0.072) |
| Exit | -0.099** | -0.109* | -0.095*** | -0.120** | -0.082** | -0.097* | -0.093** | -0.112* |
| | (0.042) | (0.064) | (0.032) | (0.054) | (0.036) | (0.052) | (0.038) | (0.061) |

*Note: BDS, CPS and Intercensal Censi 1978–2014, HP-filtered annual data with smoothing parameter 6.25. Point estimates on the share of the labor force/population age 19–64 that is age 40 and older on employment-weighted establishment dynamics. All columns control for state, year, share female, share college or more, share non-white and annual growth in state real GDP per worker. All shares and reallocation rates are in levels. Covariates: controls for the share female, non-white, and with a college degree or more; Sector: controls for share of the labor force in nine aggregate sectors; Policy: controls for state minimum wage and total state tax rate per capita. Standard errors clustered at state and year. *statistically significant at 10%; **statistically significant at 5%; ***statistically significant at 1%.*

Table B.15: Predicted cumulative effect of aging on establishment reallocation rates 1986–2015 based on specification in levels

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|---|
| | | Baseline | | Covariates | | Sector | | Policy | |
| | Raw | OLS | IV | OLS | IV | OLS | IV | OLS | IV |
| *Panel A: Labor force* | | | | | | | | | |
| Job | -0.097 | -0.053 | -0.054 | -0.056 | -0.061 | -0.041 | -0.042 | -0.052 | -0.057 |
| % of raw | 100 | 54.9 | 56 | 58.2 | 62.5 | 42.7 | 43.4 | 53.8 | 59.3 |
| Turnover | -0.05 | -0.026 | -0.034 | -0.028 | -0.037 | -0.021 | -0.03 | -0.026 | -0.037 |
| % of raw | 100 | 52.7 | 68.2 | 55.9 | 74.1 | 42.8 | 58.7 | 51.3 | 73.3 |
| Entry | -0.028 | -0.015 | -0.019 | -0.017 | -0.02 | -0.012 | -0.016 | -0.016 | -0.021 |
| % of raw | 100 | 56.1 | 67.9 | 60.2 | 72.9 | 44.4 | 57.3 | 56.2 | 75.4 |
| Exit | -0.023 | -0.011 | -0.016 | -0.011 | -0.017 | -0.009 | -0.014 | -0.01 | -0.016 |
| % of raw | 100 | 48.5 | 68.6 | 50.7 | 75.6 | 40.7 | 60.5 | 45.2 | 70.7 |
| *Panel B: Working age population* | | | | | | | | | |
| Job | -0.097 | -0.05 | -0.047 | -0.05 | -0.052 | -0.037 | -0.037 | -0.049 | -0.049 |
| % of raw | 100 | 52.1 | 48.3 | 51.2 | 53.8 | 38.3 | 38 | 50.7 | 51.1 |
| Turnover | -0.05 | -0.026 | -0.03 | -0.025 | -0.033 | -0.021 | -0.026 | -0.026 | -0.032 |
| % of raw | 100 | 52.7 | 58.9 | 50.4 | 65 | 40.9 | 51.4 | 51.1 | 63.1 |
| Entry | -0.028 | -0.014 | -0.016 | -0.014 | -0.018 | -0.01 | -0.014 | -0.014 | -0.018 |
| % of raw | 100 | 51.8 | 58.6 | 49.2 | 64.5 | 37.8 | 50.1 | 51.3 | 64.9 |
| Exit | -0.023 | -0.012 | -0.013 | -0.012 | -0.015 | -0.01 | -0.012 | -0.012 | -0.014 |
| % of raw | 100 | 53.8 | 59.3 | 51.7 | 65.5 | 44.6 | 52.9 | 50.9 | 60.8 |

*Note: BDS, CPS and Intercensal Censi 1978–2015. Predicted cumulative effect of aging from 1986 to 2015 based on cross-state panel estimates applied to the national time trend in aging.*

**Instrumenting with the total number of people age 40–64.** Table B.16 compares point estimates and their standard errors in the baseline OLS specification in column 1 and IV specification in column 2 with an IV specification that instruments for the current share of older workers using the (log) total number of people age 40–64 in year $t$ who were born state $s$, regardless of where they currently reside. I construct this based on information in Decennial Censi in 1970, 1980, 1990 and 2000 as well as the American Community Survey in 2001–2014 on where a person was born (I linearly interpolate between Census years in the early years). The idea is that to the extent that mobility is imperfect, if relatively more people were born in state $s$ 40–64 years ago (conditional on state and year effects)

this should be reflected in a higher share of older people currently.[40] Although Table B.16 indicates that even larger estimates obtain when I use this instrument, standard errors are substantially larger. Furthermore, the i.i.d. assumption on errors is inapplicable and the Kleibergen-Paap Wald statistic suggest that the instrument is weak with a value just over four. Hence I do not read much into these results, but focus on my 10-year lagged instrument.

Table B.16: Estimated coefficient on share of labor force/population that is age 40 and older, employment-weighted establishment dynamics with alternative instrument

| | (1) OLS | (2) Lagged share | (3) Number born |
|---|---|---|---|
| *Panel A: Labor force* | | | |
| Job reallocation | -0.448*** | -0.527*** | -1.127** |
| | (0.126) | (0.191) | (0.466) |
| Establishment turnover | -0.630*** | -0.961*** | -1.645** |
| | (0.199) | (0.268) | (0.737) |
| Entry rate | -0.668*** | -0.999*** | -1.721*** |
| | (0.200) | (0.247) | (0.594) |
| Exit rate | -0.600** | -0.940*** | -1.484 |
| | (0.227) | (0.322) | (1.043) |
| *Panel B: Working age population* | | | |
| Job reallocation | -0.518*** | -0.539*** | -0.988*** |
| | (0.119) | (0.186) | (0.333) |
| Establishment turnover | -0.774*** | -0.984*** | -1.442*** |
| | (0.196) | (0.256) | (0.526) |
| Entry rate | -0.753*** | -1.022*** | -1.508*** |
| | (0.196) | (0.245) | (0.459) |
| Exit rate | -0.809*** | -0.962*** | -1.300 |
| | (0.220) | (0.304) | (0.781) |

*Note: BDS, CPS, Intercensal Censi, Decennial Censi and ACS 1970–2014, HP-filtered annual data with smoothing parameter 6.25. Point estimates on the share of the labor force/population age 19–64 that is age 40 and older on employment-weighted establishment dynamics. All columns control for state, year and annual growth in state real GDP per worker. All shares and reallocation rates are in logs. Lagged share: instrumenting for current share of older using 10-year lagged share in that age group; Number born: instrumenting for current share of older using log number of people born in state 40–64 years earlier (who are currently alive). Standard errors clustered at state and year. *statistically significant at 10%; **statistically significant at 5%; ***statistically significant at 1%.*

[40]Note that this is not equivalent to the number of people born in the state. It is possible that mortality rates covary with business dynamics. I have not been able to acquire birth rates by state back to 1914.

### B.6.4 Firm dynamics

**Logs.** Table B.17 shows point estimates and their standard errors based on regression (2.20) with firm level outcomes in logs. Table B.18 shows the cumulative predicted impact of aging between 1986 and 2015 based on these specifications. The predicted impact of aging is if anything even larger when using firm-level outcomes.

Table B.17: Estimated coefficient on share of labor force/population that is age 40 and older, employment-weighted firm level outcomes

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Baseline | | Covariates | | Sector | | Policy | |
| | OLS | IV | OLS | IV | OLS | IV | OLS | IV |
| *Panel A: Labor force* | | | | | | | | |
| Turnover | -0.764*** | -1.266*** | -0.685*** | -1.237*** | -0.608*** | -1.142*** | -0.743*** | -1.321*** |
| | (0.230) | (0.302) | (0.199) | (0.293) | (0.201) | (0.285) | (0.224) | (0.301) |
| Entry | -0.827*** | -1.361*** | -0.748*** | -1.316*** | -0.647*** | -1.249*** | -0.814*** | -1.425*** |
| | (0.199) | (0.278) | (0.174) | (0.287) | (0.173) | (0.264) | (0.201) | (0.283) |
| Exit | -0.712** | -1.203*** | -0.636** | -1.191*** | -0.567** | -1.044*** | -0.659** | -1.222*** |
| | (0.298) | (0.355) | (0.285) | (0.333) | (0.274) | (0.348) | (0.294) | (0.349) |
| *Panel B: Working age population* | | | | | | | | |
| Turnover | -0.923*** | -1.296*** | -0.814*** | -1.254*** | -0.744*** | -1.190*** | -0.895*** | -1.350*** |
| | (0.223) | (0.299) | (0.179) | (0.312) | (0.203) | (0.291) | (0.212) | (0.290) |
| Entry | -0.932*** | -1.393*** | -0.831*** | -1.353*** | -0.730*** | -1.302*** | -0.907*** | -1.456*** |
| | (0.195) | (0.291) | (0.165) | (0.316) | (0.177) | (0.282) | (0.194) | (0.285) |
| Exit | -0.921*** | -1.231*** | -0.825*** | -1.202*** | -0.753*** | -1.088*** | -0.869*** | -1.249*** |
| | (0.283) | (0.339) | (0.249) | (0.344) | (0.270) | (0.343) | (0.273) | (0.326) |

*Note: BDS, CPS and Intercensal Censi 1978–2014, HP-filtered annual data with smoothing parameter 6.25. Point estimates on the share of the labor force/population age 19–64 that is age 40 and older on employment-weighted firm dynamics. All columns control for state, year and annual growth in state real GDP per worker. All shares and reallocation rates are in logs. Covariates: additionally controls for the share female, share college or more, share non-white (in logs); Sector: additionally controls for covariates and the share of the labor force in nine aggregate sectors; Policy: additionally controls for covariates and state minimum wage and total state tax rate per capita. Standard errors clustered at state and year. *statistically significant at 10%; **statistically significant at 5%; ***statistically significant at 1%.*

Table B.18: Predicted cumulative effect of aging on firm reallocation rates 1986–2015

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|---|
| | | Baseline | | Covariates | | Sector | | Policy | |
| | Raw | OLS | IV | OLS | IV | OLS | IV | OLS | IV |
| *Panel A: Labor force* | | | | | | | | | |
| Turnover | -0.486 | -0.246 | -0.407 | -0.220 | -0.398 | -0.195 | -0.367 | -0.239 | -0.425 |
| % of total | 100 | 50.5 | 83.7 | 45.3 | 81.7 | 40.2 | 75.5 | 49.1 | 87.3 |
| Entry | -0.627 | -0.266 | -0.437 | -0.241 | -0.423 | -0.208 | -0.402 | -0.262 | -0.458 |
| % of total | 100 | 42.4 | 69.8 | 38.4 | 67.5 | 33.2 | 64.1 | 41.7 | 73 |
| Exit | -0.325 | -0.229 | -0.387 | -0.205 | -0.383 | -0.182 | -0.336 | -0.212 | -0.393 |
| % of total | 100 | 70.4 | 118.9 | 62.9 | 117.8 | 56.0 | 103.2 | 65.2 | 120.8 |
| *Panel B: Working age population* | | | | | | | | | |
| Turnover | -0.486 | -0.24 | -0.337 | -0.212 | -0.326 | -0.194 | -0.309 | -0.233 | -0.351 |
| % of total | 100 | 49.4 | 69.3 | 43.5 | 67.0 | 39.8 | 63.6 | 47.9 | 72.2 |
| Entry | -0.627 | -0.242 | -0.362 | -0.216 | -0.352 | -0.19 | -0.339 | -0.236 | -0.379 |
| % of total | 100 | 38.7 | 57.8 | 34.5 | 56.1 | 30.3 | 54 | 37.6 | 60.4 |
| Exit | -0.325 | -0.239 | -0.32 | -0.215 | -0.313 | -0.196 | -0.283 | -0.226 | -0.325 |
| % of total | 100 | 73.6 | 98.5 | 66.0 | 96.1 | 60.3 | 87.1 | 69.5 | 99.9 |

*Note: BDS, CPS and Intercensal Censi 1978–2015. Predicted cumulative effect of aging from 1986 to 2015 based on cross-state panel estimates applied to the national time trend.*

**Levels.** Table B.19 shows estimated point estimates and their standard errors from regressions with firm-level measures of dynamics in levels. Table B.20 shows the predicted cumulative effect of aging on firm dynamics based on the specification in levels.

Table B.19: Estimated coefficient on share of labor force/population that is age 40 and older, employment-weighted firm level outcomes in levels

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Baseline | | Covariates | | Sector | | Policy | |
| | OLS | IV | OLS | IV | OLS | IV | OLS | IV |
| *Panel A: Labor force* | | | | | | | | |
| Turnover | -0.120** | -0.169** | -0.122*** | -0.179*** | -0.097*** | -0.151*** | -0.122*** | -0.188** |
| | (0.045) | (0.072) | (0.035) | (0.054) | (0.035) | (0.052) | (0.043) | (0.071) |
| Entry | -0.079*** | -0.104** | -0.080*** | -0.108*** | -0.061*** | -0.091*** | -0.082*** | -0.117** |
| | (0.026) | (0.043) | (0.018) | (0.030) | (0.019) | (0.030) | (0.026) | (0.044) |
| Exit | -0.042* | -0.067** | -0.043** | -0.072*** | -0.037* | -0.061** | -0.040* | -0.070** |
| | (0.022) | (0.032) | (0.020) | (0.026) | (0.019) | (0.025) | (0.022) | (0.030) |
| *Panel B: Working age population* | | | | | | | | |
| Turnover | -0.140*** | -0.173** | -0.128*** | -0.184*** | -0.107*** | -0.156*** | -0.140*** | -0.191** |
| | (0.048) | (0.072) | (0.032) | (0.059) | (0.038) | (0.054) | (0.044) | (0.070) |
| Entry | -0.087*** | -0.106** | -0.078*** | -0.112*** | -0.063*** | -0.094*** | -0.089*** | -0.120** |
| | (0.027) | (0.043) | (0.018) | (0.035) | (0.020) | (0.032) | (0.027) | (0.044) |
| Exit | -0.054** | -0.068** | -0.050*** | -0.073*** | -0.045** | -0.063** | -0.051** | -0.072** |
| | (0.022) | (0.032) | (0.017) | (0.027) | (0.019) | (0.026) | (0.021) | (0.030) |

*Note: BDS, CPS and Intercensal Censi 1978–2014, HP-filtered annual data with smoothing parameter 6.25. Point estimates on the share of the labor force/population age 19–64 that is age 40 and older on employment-weighted firm dynamics. All columns control for state, year and annual growth in state real GDP per worker. All shares and reallocation rates are in levels. Covariates: additionally controls for the share female, share college or more, share non-white (in logs); Sector: additionally controls for covariates and the share of the labor force in nine aggregate sectors; Policy: additionally controls for covariates and state minimum wage and total state tax rate per capita. Standard errors clustered at state and year. *statistically significant at 10%; **statistically significant at 5%; ***statistically significant at 1%.*

Table B.20: Predicted cumulative effect of aging on firm reallocation rates in levels 1986–2015

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|---|
| | | Baseline | | Covariates | | Sector | | Policy | |
| | Raw | OLS | IV | OLS | IV | OLS | IV | OLS | IV |
| *Panel A: Labor force* | | | | | | | | | |
| Turnover | -0.025 | -0.018 | -0.025 | -0.018 | -0.026 | -0.014 | -0.022 | -0.018 | -0.027 |
| % of raw | 100 | 69.8 | 98.2 | 70.6 | 103.8 | 56.5 | 87.4 | 70.6 | 108.8 |
| Entry | -0.017 | -0.011 | -0.015 | -0.012 | -0.016 | -0.009 | -0.013 | -0.012 | -0.017 |
| % of raw | 100 | 66.1 | 87 | 67.1 | 90.4 | 51.2 | 76.4 | 68.6 | 98.4 |
| Exit | -0.008 | -0.006 | -0.01 | -0.006 | -0.011 | -0.005 | -0.009 | -0.006 | -0.01 |
| % of raw | 100 | 79.7 | 125 | 80 | 135.6 | 69.4 | 114.1 | 74.7 | 131.8 |
| *Panel B: Working age population* | | | | | | | | | |
| Turnover | -0.025 | -0.017 | -0.021 | -0.016 | -0.023 | -0.013 | -0.019 | -0.017 | -0.024 |
| % of raw | 100 | 68.8 | 84.8 | 62.7 | 90.3 | 52.7 | 76.5 | 68.7 | 93.7 |
| Entry | -0.017 | -0.011 | -0.013 | -0.01 | -0.014 | -0.008 | -0.012 | -0.011 | -0.015 |
| % of raw | 100 | 61.7 | 75.1 | 55.6 | 79.6 | 44.5 | 66.8 | 63 | 84.7 |
| Exit | -0.008 | -0.007 | -0.008 | -0.006 | -0.009 | -0.006 | -0.008 | -0.006 | -0.009 |
| % of raw | 100 | 85.8 | 107.9 | 79.5 | 115.6 | 71.8 | 99.8 | 81.3 | 113.5 |

*Note: BDS, CPS and Intercensal Censi 1978–2015. Predicted cumulative effect of aging from 1986 to 2015 based on cross-state panel estimates applied to the national time trend in aging.*

### B.6.5 Labor supply growth

Table B.21 presents point estimates and standard errors from a joint regression framework with establishment and firm level reallocation rates on the share of older workers and growth in labor supply. Labor supply growth is positively related to establishment and firm entry, in line with findings in Karahan et al. (2016). The point estimate is strongly statistically significant. The relationship with establishment and firm turnover is economically and statistically weaker, due to a negative correlation with the exit rate. Across the board, controlling for labor supply growth has very little impact on the estimated coefficient on the share of older in the labor force/working age population.

Table B.22 summarizes the cumulative predicted power of changes in the age composition and labor supply growth on establishment and firm dynamics from 1986 to 2015. In all fairness, it should be noted that a big share of the decline in labor supply growth

happened in the late 1970s and early 1980s, which this calculation misses. Going back to 1978 raises the predicted decline due to weaker labor supply growth by a couple of percentage points.

Table B.21: Estimated coefficient on share of labor force/population that is age 40 and older, employment-weighted establishment level outcomes in levels

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|---|
| | | Labor force | | | | Working age population | | | |
| | | OLS | | IV | | OLS | | IV | |
| | | Base | LF | Base | LF | Base | LF | Base | LF |
| *Panel A: Establishment dynamics* | | | | | | | | | |
| JR | Age | -0.448*** | -0.439*** | -0.527*** | -0.534*** | -0.518*** | -0.503*** | -0.539*** | -0.553*** |
| | | (0.127) | (0.123) | (0.191) | (0.186) | (0.124) | (0.118) | (0.186) | (0.176) |
| | Δ | | 0.435** | | 0.411** | | 0.668*** | | 0.649*** |
| | | | (0.162) | | (0.154) | | (0.203) | | (0.191) |
| Turnover | Age | -0.630*** | -0.622*** | -0.961*** | -0.966*** | -0.774*** | -0.760*** | -0.984*** | -0.995*** |
| | | (0.203) | (0.200) | (0.268) | (0.264) | (0.202) | (0.197) | (0.256) | (0.246) |
| | Δ | | 0.387 | | 0.302 | | 0.630** | | 0.543* |
| | | | (0.230) | | (0.226) | | (0.290) | | (0.276) |
| Entry | Age | -0.668*** | -0.641*** | -0.999*** | -1.018*** | -0.753*** | -0.716*** | -1.022*** | -1.053*** |
| | | (0.189) | (0.180) | (0.247) | (0.228) | (0.188) | (0.177) | (0.245) | (0.220) |
| | Δ | | 1.278*** | | 1.185*** | | 1.590*** | | 1.467*** |
| | | | (0.406) | | (0.381) | | (0.545) | | (0.503) |
| Exit | Age | -0.600** | -0.615** | -0.940*** | -0.927*** | -0.809*** | -0.823*** | -0.962*** | -0.948*** |
| | | (0.243) | (0.245) | (0.322) | (0.329) | (0.239) | (0.243) | (0.304) | (0.312) |
| | Δ | | -0.699* | | -0.776* | | -0.583 | | -0.629 |
| | | | (0.378) | | (0.402) | | (0.389) | | (0.404) |
| *Panel B: Firm dynamics* | | | | | | | | | |
| Turnover | Age | -0.764*** | -0.760*** | -1.266*** | -1.268*** | -0.923*** | -0.908*** | -1.296*** | -1.307*** |
| | | (0.230) | (0.227) | (0.302) | (0.301) | (0.223) | (0.216) | (0.299) | (0.291) |
| | Δ | | 0.209 | | 0.084 | | 0.656** | | 0.510* |
| | | | (0.250) | | (0.248) | | (0.296) | | (0.296) |
| Entry | Age | -0.827*** | -0.801*** | -1.361*** | -1.379*** | -0.932*** | -0.896*** | -1.393*** | -1.423*** |
| | | (0.199) | (0.188) | (0.278) | (0.264) | (0.195) | (0.179) | (0.291) | (0.275) |
| | Δ | | 1.219*** | | 1.078*** | | 1.617*** | | 1.424*** |
| | | | (0.414) | | (0.384) | | (0.559) | | (0.519) |
| Exit | Age | -0.712** | -0.732** | -1.203*** | -1.184*** | -0.921*** | -0.932*** | -1.231*** | -1.218*** |
| | | (0.298) | (0.301) | (0.355) | (0.365) | (0.283) | (0.288) | (0.339) | (0.344) |
| | Δ | | -0.984* | | -1.095* | | -0.499 | | -0.604 |
| | | | (0.509) | | (0.542) | | (0.521) | | (0.555) |

*Note: BDS, CPS and Intercensal Censi 1978–2014, HP-filtered annual data with smoothing parameter 6.25. Point estimates on the share of the labor force/population age 19–64 that is age 40 and older ("Age"), and annual log difference in labor force participants/working age population age 19–64 ("Δ") on employment-weighted establishment dynamics. All columns control for state fixed effects, year effects, and annual growth in state real GDP per worker. All shares and reallocation rates are in logs. Standard errors clustered at state and year. *statistically significant at 10%; **statistically significant at 5%; ***statistically significant at 1%.*

Table B.22: Predicted cumulative effect of aging on establishment and firm reallocation rates due to aging and labor supply growth, 1986–2015

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | | OLS | | | IV | | |
| | Raw | Base | Age | Δ | Base | Age | Δ |
| *Panel A: Establishment dynamics with labor force* | | | | | | | |
| Job reallocation | -0.329 | -0.144 | -0.141 | -0.007 | -0.169 | -0.172 | -0.006 |
| % of raw | 100 | 44 | 43 | 2 | 51 | 52 | 2 |
| Turnover | -0.477 | -0.203 | -0.2 | -0.006 | -0.309 | -0.311 | -0.005 |
| % of raw | 100 | 43 | 42 | 1 | 65 | 65 | 1 |
| Entry | -0.475 | -0.215 | -0.206 | -0.02 | -0.321 | -0.327 | -0.018 |
| % of raw | 100 | 45 | 43 | 4 | 68 | 69 | 4 |
| Exit | -0.478 | -0.193 | -0.198 | 0.011 | -0.302 | -0.298 | 0.012 |
| % of raw | 100 | 40 | 41 | -2 | 63 | 62 | -2 |
| *Panel B: Firm dynamics with labor force* | | | | | | | |
| Turnover | -0.486 | -0.246 | -0.244 | -0.003 | -0.407 | -0.408 | -0.001 |
| % of raw | 100 | 51 | 50 | 1 | 84 | 84 | 0 |
| Entry | -0.627 | -0.266 | -0.258 | -0.019 | -0.437 | -0.443 | -0.016 |
| % of raw | 100 | 42 | 41 | 3 | 70 | 71 | 3 |
| Exit | -0.325 | -0.229 | -0.235 | 0.015 | -0.387 | -0.381 | 0.017 |
| % of raw | 100 | 70 | 72 | -5 | 119 | 117 | -5 |
| *Panel C: Establishment dynamics with working age population* | | | | | | | |
| Job reallocation | -0.329 | -0.135 | -0.131 | -0.004 | -0.14 | -0.144 | -0.004 |
| % of raw | 100 | 41 | 40 | 1 | 43 | 44 | 1 |
| Turnover | -0.477 | -0.201 | -0.198 | -0.004 | -0.256 | -0.259 | -0.003 |
| % of raw | 100 | 42 | 41 | 1 | 54 | 54 | 1 |
| Entry | -0.475 | -0.196 | -0.186 | -0.009 | -0.266 | -0.274 | -0.008 |
| % of raw | 100 | 41 | 39 | 2 | 56 | 58 | 2 |
| Exit | -0.478 | -0.211 | -0.214 | 0.003 | -0.25 | -0.247 | 0.004 |
| % of raw | 100 | 44 | 45 | -1 | 52 | 52 | -1 |
| *Panel D: Firm dynamics with working age population* | | | | | | | |
| Turnover | -0.486 | -0.24 | -0.236 | -0.004 | -0.337 | -0.34 | -0.003 |
| % of raw | 100 | 49 | 49 | 1 | 69 | 70 | 1 |
| Entry | -0.627 | -0.242 | -0.233 | -0.009 | -0.362 | -0.37 | -0.008 |
| % of raw | 100 | 39 | 37 | 1 | 58 | 59 | 1 |
| Exit | -0.325 | -0.239 | -0.242 | 0.003 | -0.32 | -0.317 | 0.003 |
| % of raw | 100 | 74 | 75 | -1 | 98 | 97 | -1 |

*Note: BDS, CPS and Intercensal Censi 1978–2015. Predicted cumulative effect of aging from 1986 to 2015 based on cross-state panel estimates applied to the national time trend.*

### B.6.6 Unweighted dynamics

Table B.23 shows the estimated impact of aging on unweighted establishment and firm dynamics. Table B.24 summarizes the predicted cumulative declines based on these regressions. Aging predicts an even larger share of the declines than in the employment-weighted measures.

Table B.23: Estimated coefficient on share of labor force/population that is age 40 and older, unweighted establishment and firm level outcomes in logs

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Baseline | | Covariates | | Sector | | Policy | |
| | OLS | IV | OLS | IV | OLS | IV | OLS | IV |
| *Panel A: Establishment dynamics with labor force* | | | | | | | | |
| Turnover | -0.111*** | -0.204*** | -0.108*** | -0.213*** | -0.089*** | -0.189*** | -0.114*** | -0.217*** |
| | (0.038) | (0.051) | (0.033) | (0.045) | (0.033) | (0.043) | (0.038) | (0.052) |
| Entry | -0.069*** | -0.122*** | -0.068*** | -0.126*** | -0.059*** | -0.121*** | -0.073*** | -0.135*** |
| | (0.023) | (0.030) | (0.022) | (0.028) | (0.019) | (0.024) | (0.025) | (0.032) |
| Exit | -0.043** | -0.082*** | -0.041*** | -0.087*** | -0.030* | -0.068*** | -0.041*** | -0.082*** |
| | (0.017) | (0.026) | (0.013) | (0.021) | (0.015) | (0.024) | (0.015) | (0.025) |
| *Panel B: Firm dynamics with labor force* | | | | | | | | |
| Turnover | -0.113*** | -0.202*** | -0.110*** | -0.207*** | -0.094*** | -0.192*** | -0.115*** | -0.216*** |
| | (0.032) | (0.037) | (0.029) | (0.036) | (0.030) | (0.033) | (0.032) | (0.038) |
| Entry | -0.074*** | -0.127*** | -0.073*** | -0.130*** | -0.064*** | -0.126*** | -0.079*** | -0.142*** |
| | (0.020) | (0.027) | (0.018) | (0.027) | (0.017) | (0.022) | (0.022) | (0.028) |
| Exit | -0.039*** | -0.075*** | -0.036*** | -0.077*** | -0.030** | -0.066*** | -0.035*** | -0.074*** |
| | (0.013) | (0.016) | (0.013) | (0.016) | (0.014) | (0.018) | (0.012) | (0.017) |
| *Panel C: Establishment dynamics with working age population* | | | | | | | | |
| Turnover | -0.130*** | -0.208*** | -0.115*** | -0.214*** | -0.105*** | -0.197*** | -0.132*** | -0.222*** |
| | (0.040) | (0.048) | (0.032) | (0.046) | (0.034) | (0.042) | (0.039) | (0.047) |
| Entry | -0.074*** | -0.125*** | -0.064*** | -0.126*** | -0.064*** | -0.126*** | -0.077*** | -0.138*** |
| | (0.025) | (0.029) | (0.022) | (0.030) | (0.020) | (0.025) | (0.027) | (0.030) |
| Exit | -0.056*** | -0.084*** | -0.050*** | -0.088*** | -0.041*** | -0.071*** | -0.055*** | -0.084*** |
| | (0.016) | (0.024) | (0.012) | (0.021) | (0.015) | (0.024) | (0.014) | (0.024) |
| *Panel D: Firm dynamics with working age population* | | | | | | | | |
| Turnover | -0.127*** | -0.206*** | -0.112*** | -0.208*** | -0.107*** | -0.200*** | -0.129*** | -0.221*** |
| | (0.033) | (0.035) | (0.028) | (0.038) | (0.031) | (0.032) | (0.033) | (0.034) |
| Entry | -0.078*** | -0.130*** | -0.069*** | -0.131*** | -0.068*** | -0.131*** | -0.084*** | -0.145*** |
| | (0.022) | (0.027) | (0.018) | (0.029) | (0.018) | (0.024) | (0.023) | (0.027) |
| Exit | -0.048*** | -0.077*** | -0.043*** | -0.078*** | -0.039*** | -0.069*** | -0.045*** | -0.076*** |
| | (0.012) | (0.015) | (0.010) | (0.017) | (0.013) | (0.017) | (0.011) | (0.015) |

*Note: BDS, CPS and Intercensal Censi 1978–2014, HP-filtered annual data with smoothing parameter 6.25. Point estimates on the share of the labor force/population age 19–64 that is age 40 and older on unweighted establishment and firm dynamics. All columns control for state, year and annual growth in state real GDP per worker. All shares and reallocation rates are in logs. Covariates: additionally controls for the share female, share college or more, share non-white (in logs); Sector: additionally controls for covariates and the share of the labor force in nine aggregate sectors; Policy: additionally controls for covariates and state minimum wage and total state tax rate per capita. Standard errors clustered at state and year. *statistically significant at 10%; **statistically significant at 5%; ***statistically significant at 1%.*

Table B.24: Predicted cumulative effect of aging on establishment and firm unweighted reallocation rates in logs 1986–2015

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|---|
| | | Baseline | | Covariates | | Sector | | Policy | |
| | Raw | OLS | IV | OLS | IV | OLS | IV | OLS | IV |
| *Panel A: Establishment dynamics with labor force* | | | | | | | | | |
| Turnover | -0.07 | -0.036 | -0.065 | -0.035 | -0.068 | -0.029 | -0.061 | -0.037 | -0.07 |
| % of raw | 100 | 51.4 | 93.9 | 50 | 98.2 | 40.9 | 87 | 52.4 | 99.9 |
| Entry | -0.042 | -0.022 | -0.039 | -0.022 | -0.04 | -0.019 | -0.039 | -0.023 | -0.043 |
| % of raw | 100 | 53.1 | 94.3 | 52.5 | 97.4 | 45.8 | 93.2 | 56.1 | 104.1 |
| Exit | -0.028 | -0.014 | -0.026 | -0.013 | -0.028 | -0.009 | -0.022 | -0.013 | -0.026 |
| % of raw | 100 | 48.8 | 93.3 | 46.4 | 99.4 | 33.7 | 77.8 | 47 | 93.8 |
| *Panel B: Firm dynamics with labor force* | | | | | | | | | |
| Turnover | -0.059 | -0.036 | -0.065 | -0.035 | -0.067 | -0.03 | -0.062 | -0.037 | -0.07 |
| % of raw | 100 | 62 | 110.2 | 59.9 | 113.2 | 51.6 | 104.7 | 62.8 | 118.1 |
| Entry | -0.045 | -0.024 | -0.041 | -0.024 | -0.042 | -0.021 | -0.04 | -0.026 | -0.046 |
| % of raw | 100 | 52.9 | 90.2 | 52 | 92.5 | 45.5 | 89.4 | 56.5 | 101.1 |
| Exit | -0.014 | -0.013 | -0.024 | -0.012 | -0.025 | -0.01 | -0.021 | -0.011 | -0.024 |
| % of raw | 100 | 91.7 | 177 | 85.5 | 182.2 | 71.4 | 155.8 | 83.3 | 174.4 |
| *Panel C: Establishment dynamics with working age population* | | | | | | | | | |
| Turnover | -0.07 | -0.034 | -0.054 | -0.03 | -0.056 | -0.027 | -0.051 | -0.034 | -0.058 |
| % of raw | 100 | 48.4 | 77.7 | 42.7 | 80 | 39.1 | 73.4 | 49.1 | 82.6 |
| Entry | -0.042 | -0.019 | -0.032 | -0.017 | -0.033 | -0.017 | -0.033 | -0.02 | -0.036 |
| % of raw | 100 | 46 | 78.1 | 40.2 | 79.1 | 39.8 | 78.6 | 48.1 | 86.1 |
| Exit | -0.028 | -0.015 | -0.022 | -0.013 | -0.023 | -0.011 | -0.018 | -0.014 | -0.022 |
| % of raw | 100 | 51.8 | 77.2 | 46.5 | 81.5 | 38 | 65.6 | 50.6 | 77.5 |
| *Panel D: Firm dynamics with working age population* | | | | | | | | | |
| Turnover (firms) | -0.059 | -0.033 | -0.054 | -0.029 | -0.054 | -0.028 | -0.052 | -0.033 | -0.057 |
| % of raw | 100 | 56 | 91.2 | 49.6 | 92 | 47.5 | 88.3 | 56.9 | 97.7 |
| Entry (firms) | -0.045 | -0.02 | -0.034 | -0.018 | -0.034 | -0.018 | -0.034 | -0.022 | -0.038 |
| % of raw | 100 | 45.1 | 74.7 | 39.8 | 75.3 | 39.3 | 75.4 | 48.3 | 83.6 |
| Exit (firms) | -0.014 | -0.013 | -0.02 | -0.011 | -0.02 | -0.01 | -0.018 | -0.012 | -0.02 |
| % of raw | 100 | 92.1 | 146.5 | 81.9 | 148.1 | 74.5 | 131.4 | 85.3 | 144.2 |

*Note: BDS, CPS and Intercensal Censi 1978–2015. Predicted cumulative effect of aging from 1986 to 2015 based on cross-state panel estimates applied to the national time trend in aging.*

### B.6.7 Additional worker dynamics

Table B.25 shows the estimated coefficient and standard error on the share older in the state as well as the estimated age coefficients and their standard errors based on the specification with worker reallocation rates.

Table B.25: Worker dynamics

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | EU | | JJ | | UE | |
| | OLS | IV | OLS | IV | OLS | IV |
| *Panel A: Labor force* | | | | | | |
| Share of older in state | -0.445*** | -0.915** | -0.501** | -0.112 | -0.084 | -0.228 |
| | (0.142) | (0.373) | (0.226) | (0.728) | (0.124) | (0.271) |
| Direct effects | | | | | | |
| 19–24 | 0.742*** | 0.742*** | 0.801*** | 0.801*** | 0.071*** | 0.071*** |
| | (0.029) | (0.029) | (0.024) | (0.024) | (0.017) | (0.017) |
| 25–34 | 0.087** | 0.088** | 0.213*** | 0.213*** | 0.013 | 0.013 |
| | (0.034) | (0.034) | (0.020) | (0.020) | (0.016) | (0.016) |
| 35–44 | -0.135*** | -0.135*** | -0.035 | -0.035 | -0.003 | -0.003 |
| | (0.034) | (0.034) | (0.027) | (0.027) | (0.013) | (0.013) |
| 45–54 | -0.168*** | -0.168*** | -0.129*** | -0.128*** | -0.012 | -0.012 |
| | (0.023) | (0.023) | (0.022) | (0.022) | (0.012) | (0.012) |
| *Panel B: Working age population* | | | | | | |
| Share of older in state | -0.491*** | -0.931** | -0.642*** | -0.127 | -0.015 | -0.232 |
| | (0.158) | (0.404) | (0.215) | (0.824) | (0.122) | (0.278) |
| Direct effects | | | | | | |
| 19–24 | 0.742*** | 0.742*** | 0.801*** | 0.801*** | 0.071*** | 0.071*** |
| | (0.029) | (0.029) | (0.024) | (0.024) | (0.017) | (0.017) |
| 25–34 | 0.087** | 0.088** | 0.213*** | 0.213*** | 0.013 | 0.013 |
| | (0.034) | (0.034) | (0.020) | (0.020) | (0.016) | (0.016) |
| 35–44 | -0.135*** | -0.135*** | -0.035 | -0.035 | -0.003 | -0.003 |
| | (0.034) | (0.034) | (0.027) | (0.027) | (0.013) | (0.013) |
| 45–54 | -0.168*** | -0.168*** | -0.129*** | -0.128*** | -0.012 | -0.012 |
| | (0.023) | (0.023) | (0.022) | (0.022) | (0.012) | (0.012) |

*Note: CPS 1994–2014 (JJ) and 1978–2014 (EU/UE). All columns control for state fixed effects, age fixed effects, year effects and annual growth in state real GDP per worker. Share of older is the log share of the labor force/population age 19–64 that is age 40–64. The dependent variables are the log of HP-filtered annualized monthly worker reallocation rates. Two-way clustered standard errors at state and year level.*

Table B.26 compares the predicted direct and indirect effect of aging on worker dynamics over this period with the raw log declines in the SIPP and the CPS over this period.[41] A conservative reading of the evidence suggests that aging may account for 30 percent of the decline in JJ mobility, 40 percent of the fall in EU mobility and not much of the recent decline in UE mobility.

[41] The predicted direct effect of aging on JJ and EU mobility is somewhat smaller than the decomposition in Section 2.2 due to a less pronounced life-cycle of these hazard rates in the CPS relative to the SIPP.

Table B.26: Cumulative predicted effect of aging on worker mobility, 1986–2015

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | | | | Indirect effect | | | |
| | Raw data | | | Labor force | | Working age pop. | |
| | SIPP | CPS | Direct effect | OLS | IV | OLS | IV |
| JJ | -0.365 | -0.401 | -0.069 | -0.161 | -0.036 | -0.166 | -0.033 |
| % of SIPP | 100 | 109.7 | 18.8 | 44.0 | 9.8 | 45.5 | 9.0 |
| EU | -0.472 | -0.290 | -0.055 | -0.143 | -0.293 | -0.127 | -0.241 |
| % of SIPP | 100 | 61.5 | 11.7 | 30.2 | 62.1 | 26.9 | 51.1 |
| UE | -0.675 | -0.120 | -0.006 | -0.027 | -0.073 | -0.004 | -0.06 |
| % of SIPP | 100 | 17.8 | 0.80 | 4.0 | 10.8 | 0.6 | 8.9 |

*Note: CPS 1978–2014, SIPP 1985–2013 and Intercensal Censi 1969–2014. Cumulative predicted effect of aging from 1986 to 2015 in logs (starting in 1994 for JJ in the CPS).*

**Labor supply.** Table B.27 shows estimates of different worker reallocation rates on the age composition controlling for labor supply growth.

Table B.27: Worker dynamics with labor supply growth

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | EU | | JJ | | UE | |
| | OLS | IV | OLS | IV | OLS | IV |
| *Panel A: Labor force* | | | | | | |
| Share of older in state | -0.484*** | -0.898** | -0.502** | 0.095 | -0.059 | -0.248 |
| | (0.153) | (0.365) | (0.229) | (0.689) | (0.126) | (0.271) |
| Annual growth in supply | -1.954*** | -2.058*** | -0.983 | -0.982 | 1.545*** | 1.501*** |
| | (0.595) | (0.624) | (0.739) | (0.791) | (0.479) | (0.463) |
| Direct effects | | | | | | |
| 19–24 | 0.742*** | 0.742*** | 0.801*** | 0.801*** | 0.070*** | 0.070*** |
| | (0.029) | (0.029) | (0.024) | (0.024) | (0.017) | (0.017) |
| 25–34 | 0.088** | 0.088** | 0.213*** | 0.213*** | 0.013 | 0.012 |
| | (0.034) | (0.034) | (0.020) | (0.020) | (0.016) | (0.016) |
| 35–44 | -0.135*** | -0.135*** | -0.035 | -0.035 | -0.004 | -0.004 |
| | (0.034) | (0.034) | (0.027) | (0.027) | (0.013) | (0.013) |
| 45–54 | -0.168*** | -0.168*** | -0.129*** | -0.128*** | -0.013 | -0.013 |
| | (0.023) | (0.023) | (0.022) | (0.022) | (0.012) | (0.012) |
| *Panel B: Working age population* | | | | | | |
| Share of older in state | -0.547*** | -0.907** | -0.670*** | 0.042 | 0.023 | -0.259 |
| | (0.164) | (0.393) | (0.224) | (0.749) | (0.121) | (0.277) |
| Annual growth in supply | -2.076*** | -2.221*** | -1.009 | -0.819 | 1.898*** | 1.788*** |
| | (0.706) | (0.745) | (0.806) | (0.892) | (0.496) | (0.476) |
| Direct effects | | | | | | |
| 19–24 | 0.742*** | 0.742*** | 0.801*** | 0.801*** | 0.070*** | 0.070*** |
| | (0.029) | (0.029) | (0.024) | (0.024) | (0.017) | (0.017) |
| 25–34 | 0.088** | 0.088** | 0.213*** | 0.213*** | 0.013 | 0.013 |
| | (0.034) | (0.034) | (0.020) | (0.020) | (0.016) | (0.016) |
| 35–44 | -0.135*** | -0.135*** | -0.036 | -0.035 | -0.003 | -0.004 |
| | (0.034) | (0.034) | (0.027) | (0.027) | (0.013) | (0.013) |
| 45–54 | -0.168*** | -0.168*** | -0.129*** | -0.128*** | -0.012 | -0.012 |
| | (0.023) | (0.023) | (0.022) | (0.022) | (0.012) | (0.012) |

*Note: CPS 1994–2014 (JJ) and 1978–2014 (EU/UE). All columns control for state fixed effects, age fixed effects, year effects and annual growth in state real GDP per worker. Share of older is the log share of the labor force/population age 19–64 that is age 40–64. The dependent variables are the log of HP-filtered annualized monthly worker reallocation rates. Two-way clustered standard errors at state and year level.*

**Worker dynamics by age.** Table B.28 shows estimates of worker reallocation rates within age groups. The estimates are only statistically significant for the older age groups.

Table B.28: Aging and worker mobility by age of worker

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | 19–24 | | 25–34 | | 35–44 | | 45–54 | | 55–64 | |
| | OLS | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV |
| *Panel A: EU mobility* | | | | | | | | | | |
| LF | 0.246 | 0.303 | -0.095 | -0.172 | -0.540** | -0.810 | -0.994*** | -1.676** | -0.825*** | -2.144*** |
| | (0.154) | (0.280) | (0.188) | (0.314) | (0.237) | (0.506) | (0.279) | (0.630) | (0.222) | (0.729) |
| WP | 0.255 | 0.308 | -0.121 | -0.175 | -0.569** | -0.825 | -1.070*** | -1.706** | -0.915*** | -2.171** |
| | (0.163) | (0.286) | (0.187) | (0.320) | (0.245) | (0.541) | (0.347) | (0.687) | (0.222) | (0.802) |
| *Panel B: UE mobility* | | | | | | | | | | |
| LF | -0.094 | 0.153 | -0.323* | -0.455 | 0.192 | -0.000 | -0.179 | -0.374 | -0.092 | -0.448 |
| | (0.161) | (0.344) | (0.172) | (0.326) | (0.228) | (0.404) | (0.170) | (0.360) | (0.268) | (0.422) |
| WP | -0.007 | 0.155 | -0.250 | -0.464 | 0.259 | -0.000 | -0.086 | -0.383 | 0.049 | -0.456 |
| | (0.183) | (0.350) | (0.198) | (0.340) | (0.232) | (0.410) | (0.172) | (0.367) | (0.259) | (0.430) |
| *Panel C: JJ mobility* | | | | | | | | | | |
| LF | 0.056 | 0.499 | -0.367 | 1.041 | -0.668** | -0.858 | -1.318*** | -0.422 | -0.389 | 0.037 |
| | (0.400) | (1.272) | (0.300) | (0.891) | (0.276) | (0.651) | (0.328) | (0.972) | (0.507) | (1.323) |
| WP | 0.086 | 0.565 | -0.411 | 1.184 | -0.786** | -0.976 | -1.281*** | -0.481 | -0.951* | 0.042 |
| | (0.412) | (1.446) | (0.341) | (1.060) | (0.309) | (0.691) | (0.294) | (1.100) | (0.466) | (1.524) |

*Note: CPS 1994–2014 (JJ) and 1978–2014 (EU/UE). All columns control for state fixed effects, year effects and annual growth in state real GDP per worker. Share of older is the log share of the labor force/population age 19–64 that is age 40–64. The dependent variables are the log of HP-filtered annualized monthly worker reallocation rates. Two-way clustered standard errors at state and year level.*

## B.6.8 Additional details on growth

Table B.29: Aging and economic growth, 1978–2014

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Labor force | | Working age | |
| | OLS | IV | OLS | IV |
| 40–64 | -0.066 | -0.090** | -0.063 | -0.092** |
| | (0.047) | (0.040) | (0.043) | (0.039) |
| N | 1,850 | 1,850 | 1,850 | 1,850 |
| R2 | 0.256 | 0.254 | 0.253 | 0.250 |
| R2 (within) | 0.024 | 0.021 | 0.020 | 0.016 |

*Note: BEA, CPS and Intercensal Censi 1978–2014. All columns control for state and year effects. Dependent variable is growth in state real GDP per worker. Share 40–64 is the share of the labor force/population age 19–64 that is age 40–64. Instrument is share of population age 9–54 that is age 30–54 10 years earlier. Standard errors are clustered at the state and year level. *statistically significant at 10%; **statistically significant at 5%; ***statistically significant at 1%.*

# Appendix C

# The Recruiting Process and Employment Fluctuations

## C.1 Appendix: Proofs

*Proof.* We have $\lim_{\theta\to\infty}$ LHS of (3.11) $= \infty$ and $\lim_{\theta\to 0}$ LHS of (3.11) $= 0$, while $\lim_{\theta\to\infty}$ RHS of (3.11) $= C < \infty$ and

$$\lim_{\theta\to 0} \text{ RHS of (3.11)} = \pi_g \left(\frac{p_g - b}{\rho + \delta}\right) + \pi_b \left(\frac{p_b - b}{\rho + \delta}\right) - c_s$$

Hence, if $\pi_g \left(\frac{p_g - b}{\rho+\delta}\right) + \pi_b \left(\frac{p_b - b}{\rho+\delta}\right) > c_s$ there exists at least one equilibrium. □

*Proof.* By proposition 7, under the first condition there exists a stationary equilibrium. The left-hand side of (3.11) is increasing in tightness $\theta$. Hence, the equilibrium is unique if the right-hand side of (3.11) decreases in $\theta$. Since

$$\partial \left(\frac{\delta + \phi\chi\theta^{1-\alpha}\pi_g}{\delta + \phi\chi\theta^{1-\alpha}(\pi_b + \pi_g)}\right) / \partial\theta < 0$$

this is true if the last term in brackets in equation (3.11) is positive

$$\frac{p_b - b}{\rho + \delta} > c_s \frac{\pi_b \gamma + \pi_u (1 - \gamma)}{\pi_b + \pi_g} \tag{C.1}$$

□

*Proof.* Solving workers' value functions

$$\begin{aligned} W_b(w) =& \frac{w + \phi\lambda \left(\pi_b(1-\gamma) + \pi_g\right) V_b + \delta V_u}{\rho + \delta + \phi\lambda \left(\pi_b(1-\gamma) + \pi_g\right)} \\ W_g(w) =& \frac{w}{\rho + \delta} + \frac{\delta}{\rho + \delta} V_u \end{aligned}$$

The wage paid to a worker in a bad match when her renegotiation benchmark is unemployment, $w_b(u)$, satisfies $W_b(w_b(u)) = V_u$, i.e.

$$\frac{w_b(u)}{\rho + \delta + \phi\lambda \left(\pi_b(1-\gamma) + \pi_g\right)} + \frac{\phi\lambda \left(\pi_b(1-\gamma) + \pi_g\right) V_b}{\rho + \delta + \phi\lambda \left(\pi_b(1-\gamma) + \pi_g\right)} + \frac{\delta V_u}{\rho + \delta + \phi\lambda \left(\pi_b(1-\gamma) + \pi_g\right)} = V_u$$

Substituting for the value functions and rearranging, we arrive at the proposed expression. The worker is paid less than the flow value of unemployment since she anticipates the opportunity to use the job to bargain up her wage with future employers.

The wage paid to a worker in a bad match when her renegotiation benchmark is a bad match, $w_b(b)$, equals the full flow output of the bad match. The wage paid to a worker in a good match when her renegotiation benchmark is unemployment, $w_g(u)$, equals her flow value of unemployment, since she has no future opportunity to bargain up her wage. Finally, the wage paid to a worker in a good match when her renegotiation benchmark is a bad match, $w_g(b)$, equals the flow value of the bad match, since there is no future option to bargain up the wage. □

*Proof.* Denote by $m_b(u)$ the mass of workers in bad matches with unemployment as renegotiation benchmark. In the stationary economy, it satisfies

$$\begin{aligned} 0 &= -\left[\delta + \phi\lambda\left(\pi_b\gamma_b + \pi_g\right)\right] m_b(u) + \lambda\pi_b u \\ m_b(u) &= \frac{\lambda\pi_b}{\delta + \phi\lambda\left(\pi_b\gamma_b + \pi_g\right)} u \end{aligned} \tag{C.2}$$

Denote by $m_b(b)$ the mass of workers in bad matches with a bad match as renegotiation benchmark,

$$\begin{aligned} 0 &= -\left[\delta + \phi\lambda\pi_g\right] m_b(b) + \phi\lambda\pi_b\gamma_b m_b(u) \\ m_b(b) &= \frac{\phi\lambda\pi_b\gamma_b}{\delta + \phi\lambda\pi_g} \frac{\lambda\pi_b}{\delta + \phi\lambda\left(\pi_b\gamma_b + \pi_g\right)} u \end{aligned} \tag{C.3}$$

Denote by $m_g(u)$ the mass of workers in good matches with unemployment as renegotiation benchmark,

$$\begin{aligned} 0 &= -\delta m_g(u) + \lambda\pi_b u \\ m_g(u) &= \frac{\lambda\pi_g}{\delta} u \end{aligned} \tag{C.4}$$

Denote by $m_g(b)$ the mass of workers in good matches with a bad match as renegotiation benchmark,

$$\begin{aligned} 0 &= -\delta m_g(b) + \phi\lambda\pi_g\left[m_b(u) + m_b(b)\right] \\ m_g(b) &= \frac{\phi\lambda\pi_g}{\delta} \frac{\lambda\pi_b}{\delta + \phi\lambda\pi_g} u \end{aligned} \tag{C.5}$$

The average wage in the economy equals

$$\bar{w} = \frac{m_b(u)}{1-u} w_b(u) + \frac{m_b(b)}{1-u} w_b(b) + \frac{m_g(u)}{1-u} m_g(u) + \frac{m_g(b)}{1-u} m_g(b)$$

Substituting the above expressions and simplifying we arrive at the proposed expression for the average wage. □

# Bibliography


**Abowd, John M. and Arnold Zellner**, "Estimating gross labor-force flows," *Journal of Business & Economic Statistics*, 1985, *3* (3), 254–283.

**Abowd, John M, Robert H Creecy, and Francis Kramarz**, "Computing Person and Firm Effects Using Linked Longitudinal Employer-Employee Data," *Longitudinal employer-household dynamics technical paper*, 2002, (6).

**Acemoglu, Daron**, "Training and Innovation in an Imperfect Labour Market," *The Review of Economic Studies*, 1997, *64* (3), 445–464.

_ , *Introduction to Modern Economic Growth*, 1 ed., Princeton: Princeton University Press, 2011.

_ **and Jorn-Steffen Pischke**, "Why Do Firms Train? Theory and Evidence," *The Quarterly Journal of Economics*, 1998, *113* (1), 79–119.

_ **and** _ , "The Structure of Wages and Investment in General Training," *Journal of Political Economy*, 1999, *107* (3), 539–572.

_ **, U Akcigit, and Ma Celik**, "Young, Restless and Creative: Openness to Disruption and Creative Innovations," 2017.

**Aghion, Philippe and Peter Howitt**, "A Model of Growth Through Creative Destruction," *Econometrica*, 1992, *60* (2), 323–351.

_ **and** _ , "Oxford University Press," *The Review of Economic Studies*, 1994, *61* (3), 477–494.

**Ashenfelter, Orley**, "Estimating the Effect of Training Programs on Earnings," *The Review of Economics and Statistics*, 1978, *60* (1), 47–57.

**Autor, David H, William R Kerr, and Adriana D Kugler**, "Do Employment Protections Reduce Productivity? Evidence from U.S. States," *The Economic Journal*, 2007, *117*, 189–217.

**Bagger, By Jesper, François Fontaine, Fabien Postel-vinay, and Jean marc Robin**, "Tenure, Experience, Human Capital, and Wages," *American Economic Review*, 2014, *104* (6), 1551–1596.

**Barlevy, Gadi**, "Identification of Search Models using Record Statistics," *The Review of Economic Studies*, 2008, *75* (1), 29–64.

**Barth, Erling, Alex Bryson, James C Davis, and Richard Freeman**, "It's Where You Work: Increases in Earnings Dispersion across Establishments and Individuals in the U.S.," *Journal of Labor Economics*, 2016, *34* (S2), S67–S97.

**Bassanini, Andrea, Alison Booth, Giorgio Brunello, Maria De Paola, and Edwin Leuven**, "Workplace Training in Europe," 2005.

**Becker, Gary S.**, *Human Capital*, Chicago: University of Chicago Press, 1964.

**Ben-Porath, Yoram**, "The Production of Human Capital and the Life Cycle of Earnings," *Journal of Political Economy*, 1967, *75* (4), 352–365.

**Blatter, Marc, Samuel Muehlemann, and Samuel Schenker**, "The costs of hiring skilled workers," *European Economic Review*, 2012, *56* (1), 20–35.

**Blau, David M and Philip K Robins**, "Job Search Outcomes for the Employed and Unemployed," *Journal of Political Economy*, 1990, *98* (3), 637–655.

**Bollard, Albert, Peter Klenow, and Huiyu Li**, "Entry Costs Rise with Development," 2016.

**Borovickova, Katarina**, "Job flows, worker flows and labor market policies," 2016.

**Bosler, Canyon and Nicolas Petrosky-Nadeau**, "Job-to-Job Transitions in an Evolving Labor Market," *FRBSF Economic Letter*, 2016, *34* (November).

**Bowlus, Audra J and Huju Liu**, "The contributions of search and human capital to earnings growth over the life cycle," *European Economic Review*, 2013, *64*, 305–331.

**Burda, Michael C and Antje Mertens**, "Estimating wage losses of displaced workers in Germany," *Labour Economics*, 2001, *8*, 15–41.

**Burdett, Kenneth and Dale T Mortensen**, "Wage Differentials, Employer Size, and Unemployment," *International Economic Review*, 1998, *39* (2), 257–273.

**Cahuc, Pierre, Fabien Postel-Vinay, and Jean-Marc Robin**, "Wage Bargaining with On-the-Job Search: Theory and Evidence," *Econometrica*, 2006, *74* (2), 323–364.

**Cairo, Isabel**, "The slowdown in business employment dynamics: the role of changing skill demands," 2013.

**Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller**, "Robust Inference With Multiway Clustering," *Journal of Business & Economic Statistics*, 2011, *29* (2), 238–249.

**Card, David, Ana Rute Cardoso, Jörg Heining, and Patrick Kline**, "Firms and Labor Market Inequality: Evidence and Some Theory," 2016.

**Caves, Richard E.**, "Industrial organization and new findings on the turnover and mobility of firms," *Journal of Economic Literature*, 1998, *36* (4), 1947–1982.

**Davidson, Russell and James MacKinnon**, *Estimation and Inference in Econometrics*, New York: Oxford University Press, 1993.

**Davis, Steven J**, "The Decline of Job Loss and Why It Matters," *American Economic Review Papers & Proceedings*, 2008, *98* (2), 263–267.

_ **and Brenda Samaniego de la Parra**, "Application Flows," 2017.

_ **and John Haltiwanger**, "Labor Market Fluidity and Economic Performance," *National Bureau of Economic Research Working Paper Series*, 2014, *No. 20479* (November), 98.

_ **, Christof Röttger, Anja Warning, and Enzo Weber**, "Job Recruitment and Vacancy Durations in Germany," 2014.

_ **, R Jason Faberman, and John C Haltiwanger**, "The Establishment-Level Behavior of Vacancies and Hiring," *Quarterly Journal of Economics*, 2013, (1997), 581–622.

**Davis, Steven J., R. Jason Faberman, John Haltiwanger, Ron Jarmin, and Javier Miranda**, "Business Volatility, Job Destruction, and Unemployment," *American Economic Journal: Macroeconomics*, 2010, *2* (2), 259–287.

**Davis, Steven, John Haltiwanger, Ron Jarmin, and Javier Miranda**, "Volatility and Dispersion in Business Growth Rates: Publicly Traded versus Privately Held Firms," in Daron Acemoglu, Kenneth Rogoff, and Michael Woodford, eds., *NBER Macroeconomics Annual*, Vol. 21, MIT Press, 2006, pp. 107–180.

**Deaton, Angus**, *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy* 1997.

**Decker, Ryan A., John Haltiwanger, Ron S. Jarmin, and Javier Miranda**, "Declining Business Dynamism: What We Know and the Way Forward," *American Economic Review*, 2016, *106* (5), 203–207.

**Decker, Ryan A, John Haltiwanger, Ron S Jarmin, and Javier Miranda**, "Changing Business Dynamism and Productivity: Shocks vs. Responsiveness," 2017.

_ **,** _ **,** _ **, and** _ , "Declining Dynamism, Allocative Efficiency, and the Productivity Slowdown," 2017.

**Diamond, Peter A.**, "Aggregate Demand Management in Search Equilibrium," *Journal of Political Economy*, 1982, *90* (5), 881–894.

**Diamond, Peter and Drew Fudenberg**, "Rational Expectations Business Cycles in Search Equilibrium," *Journal of Political Economy*, 1989, *97* (3), 606–619.

**Driscoll, John C and Aart C Kraay**, "Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data," *The Review of Economics and Statistics*, 1998, *10* (4), 307–324.

**Dube, A., Freeman, E., Reich, M.**, "Employee Replacement Costs," 2010.

**Dustmann, Christian and Sonia C Pereira**, "Wage Growth and Job Mobility in the United Kingdom and Germany," *Industrial and Labor Relations Review*, 2008, *61* (3).

**Eeckhout, Jan and Ilse Lindenlaub**, "Unemployment Cycles," 2017.

**Elsby, Michael W L and Ryan Michaels**, "Marginal jobs, heterogeneous firms, and unemployment flows," *American Economic Journal: Macroeconomics*, 2013, *5* (1), 1–48.

**Engbom, Niklas**, "Worker Flows and Wage Growth over the Life-Cycle : A Cross-Country Analysis," 2017.

**Faberman, R. Jason, Andreas Mueller, Aysegul Sahin, and Giorgio Topa**, "Job Search Behavior among the Employed and Non-Employed," 2017.

**Farber, Henry**, "Employment Insecurity: The Decline in Worker-Firm Attachment in the United States," 2008.

**Fernald, John G**, "Productivity and Potential Output Before, During, and After the Great Recession," 2014.

**Fernández-Villaverde, Jesús and Dirk Krueger**, "Consumption over the Life Cycle: Facts from Consumer Expenditure Survey Data," *Review of Economics and Statistics*, 2007, *89* (3), 552–565.

**Foote, Christopher L**, "Space and Time in Macroeconomic Panel Data: Young Workers and State-Level Unemployment Revisited," 2007.

**Fujita, Shigeru and Giuseppe Moscarini**, "Recall and Unemployment," *American Economic Review*, 2017, *102* (7), 3875–3916.

**Gavazza, Alessandro, Simon Mongey, and Giovanni L Violante**, "Aggregate Recruiting Intensity," 2017.

**Griliches, Zvi**, "Capital-Skill Complementarity," *The Review of Economics and Statistics*, 1969, *51* (4), 465–468.

**Grossman, Gene M and Elhanan Helpman**, "Quality Ladders in the Theory of Growth," *The Review of Economic Studies*, 1991, *58* (1), 43–61.

**Guvenen, Fatih, Burhanettin Kuruscu, and Serdar Ozkan**, "Taxation of human capital and wage inequality: A cross-country analysis," *Review of Economic Studies*, 2013, *81* (2), 818–850.

**_ , Serdar Ozkan, and Jae Song**, "The Nature of Countercyclical Income Risk," *Journal of Political Economy*, 2014, *122* (3), 621–660.

**Hagedorn, Marcus and Iourii Manovskii**, "The Cyclical Behavior of Equilibrium Unemployment and Vacancies Revisited," *American Economic Review*, 2008, *98* (4), 1692–1706.

**Hall, Robert E.**, "Technical Change and Capital from the Point of View of the Dual," *The Review of Economic Studies*, 1968, *35* (1), 35–46.

_ , "Employment fluctuations with equilibrium wage stickiness," *American Economic Review*, 2005, *95* (1), 50–65.

**Hall, Robert E**, "The Amplification of Unemployment Fluctuations through Self-Selection," 2005.

**Hall, Robert E. and Paul R. Milgrom**, "The limited influence of unemployment on the wage bargain," *American Economic Review*, 2008, *98* (4), 1653–1674.

**Heckman, James J, Lance Lochner, and Christopher Taber**, "Explaining Rising Wage Inequality: Explorations with a Dynamic General Equilibrium Model of Labor Earnings with Heterogeneous Agents," *Review of Economic Dynamics*, 1998, *1* (1), 1–58.

**Hobijn, Bart and Aysegul Sahin**, "Job-finding and separation rates in the OECD," *Economics Letters*, 2009, *104* (3), 107–111.

**Holzer, Harry J.**, "Informal Job Search and Black Youth Unemployment," *The American Economic Review*, 1987, *77* (3), 446–452.

**Hopenhayn, Hugo**, "Entry , Exit , and firm Dynamics in Long Run," *Econometrica*, 1992, *60* (5), 1127–1150.

**Hornstein, Andreas, Per Krusell, and Giovanni L. Violante**, "Technology-Policy Interaction in Frictional Labour-Markets," *The Review of Economic Studies*, 2007, *74* (4), 1089–1124.

**_ , _ , and Giovanni L Violante**, "Frictional wage dispersion in search models: A quantitative assessment," *American Economic Review*, 2011, *101* (7), 2873–2898.

**Hubmer, Joachim**, "The Job Ladder and its Implications for Earnings Risk," 2017.

**Huggett, Mark, Gustavo Ventura, and Amir Yaron**, "Human capital and earnings distribution dynamics," *Journal of Monetary Economics*, 2006, *53* (2), 265–290.

**_ , _ , and** _ , "Sources of lifetime inequality," *American Economic Review*, 2011, *101* (7), 2923–2954.

**Hurst, Erik and Benjamin Pugsley**, "What Do Small Businesses Do?," *Bookings Papers on Economic Activity*, 2011, (Fall), 70.

**Hyatt, H R and J R Spletzer**, "The recent decline in employment dynamics," *IZA Journal of Labor Economics*, 2013, *2:5.*

**Hyatt, Henry**, "The decline in job-to-job flows," *IZA World of Labor*, 2015, *175.*

**Iacovou, Maria, Olena Kaminska, and Horacio Levy**, "Using EU-SILC data for cross-national analysis: strengths , problems and recommendations," 2012.

**Jacobson, Louis S, Robert J Lalonde, and Daniel G Sullivan**, "Earnings Losses of Displaced Workers," *American Economic Review*, 1993, *83* (4), 685–709.

**Jaimovich, Nir and Henry E. Siu**, "The young, the old, and the restless: Demographics and business cycle volatility," *American Economic Review*, 2009, *99* (3), 804–826.

**Jarosch, Gregor**, "Searching for Job Security and the Consequences of Job Loss," 2015.

**Jeong, Hyeok, Yong Kim, and Iourii Manovskii**, "The price of experience," *American Economic Review*, 2015, *105* (2), 784–815.

**Jolivet, Grégory, Fabien Postel-Vinay, and Jean Marc Robin**, "The empirical content of the job search model: Labor mobility and wage distributions in Europe and the US," *European Economic Review*, 2006, *50* (4), 877–907.

**Jones, Benjamin F.**, "Age and Great Invention," *The Review of Economics and Statistics*, 2010, *92* (1), 1–14.

**Josef, Anika, David Richter, Gregory R. Samanez-Larkin, Gert G. Wagner, Ralph Hertwig, and Rui Mata**, "Stability and Change in Risk-Taking Propensity Across the Adult Lifespan," *Journal of Personality and Social Psychology*, 2016, *111* (3), 430–450.

**Kaas, Leo and Philipp Kircher**, "Efficient Firm Dynamics in a Frictional Labor Market," *American Economic Review*, 2015, *105* (10), 3030–3060.

**Kambourov, Gueorgui and Iourii Manovskii**, "Occupational specificity of human capital," *International Economic Review*, 2009, *50* (1), 63–115.

**Kaplan, Greg and Sam Schulhofer-Wohl**, "Understanding the Long-Run Decline in Interstate Migration," *International Economic Review*, 2017, *58* (1), 57–94.

**Karahan, Fatih, Benjamin Pugsley, and Aysegul Sahin**, "Demographic Origins of the Startup Deficit," 2016.

**Kleiner, Morris M. and Alan B. Krueger**, "Analyzing the Extent and Influence of Occupational Licensing on the Labor Market," *Journal of Labor Economics*, 2013, *31* (S1), S173–S202.

**Klette, Tor Jakob and Samuel Kortum**, "Innovating Firms and Aggregate Innovation," *Journal of Political Economy*, 2004, *112* (5), 986–1018.

**Kortum, Samuel**, "Research, Patenting, and Technological Change," *Econometrica*, 1997, *65* (6), 1389–1419.

**Krebs, Tom and Yao Yao**, "Labor Market Risk in Germany," 2016.

**Krolikowski, Pawel**, "Job Ladders and Earnings of Displaced Workers," *American Economic Journal: Macroeconomics*, 2016.

**Lagakos, David, Benjamin Moll, Tommaso Porzio, Nancy Qian, and Todd Schoellman**, "Life-Cycle Wage Growth Across Countries," 2016.

**Laing, Derek, Theodore Palivos, and Ping Wang**, "Learning, Matching and Growth," *Review of Economic Studies*, 1995, *62* (1), 115–129.

**Liang, James, Hui Wang, and Edward P. Lazear**, "Demographics and Entrepreneurship," 2016.

**Lise, Jeremy and Jean Marc Robin**, "The macrodynamics of sorting between workers and firms," *American Economic Review*, 2017, *107* (4), 1104–1135.

**Lucas, Robert E. and Benjamin Moll**, "Knowledge Growth and the Allocation of Time," *Journal of Political Economy*, 2014, *122* (1), 1–51.

**Luttmer, Erzo G. J.**, "Selection, Growth, and the Size Distribution of Firms," *Quarterly Journal of Economics*, 2007, *122* (3), 1103–1144.

**Luttmer, Erzo G J**, "Technology diffusion and growth," *Journal of Economic Theory*, 2012, *147* (2), 602–622.

**Maestas, Nicole, Kathleen J Mullen, and David Powell**, "The Effect of population aging on economic growth, the labor force and productivity," 2016.

**Mas, Alexandre and Amanda Pallais**, "Labor Supply and the Value of Non-Work Time: Experimental Estimates from the Field," 2017.

**Mazumder, Bhashkar**, "New evidence on labor market dynamics over the business cycle," *Economic Perspectives*, 2007, *31* (1), 36.

**Mcgrattan, Ellen R and Edward C Prescott**, "On financing retirement with an aging population," *Quantitative Economics*, 2017, *8*, 75–115.

**Menzio, Guido, Irina A Telyukova, and Ludo Visschers**, "Directed search over the life cycle," *Review of Economic Dynamics*, 2016, *19*, 38–62.

**Michau, Jean Baptiste**, "Creative destruction with on-the-job search," *Review of Economic Dynamics*, 2013, *16* (4), 691–707.

**Michelacci, Claudio and David Lopez-Salido**, "Technology Shocks and Job Flows," *The Review of Economic Studies*, 2007, *74*, 1195–1227.

**Miyamoto, Hiroaki and Yuya Takahashi**, "Productivity growth, on-the-job search, and unemployment," *Journal of Monetary Economics*, 2011, *58* (6-8), 666–680.

**Molloy, R, C L Smith, R Trezzi, and A Wozniak**, "Understanding Declining Fluidity in the US Labor Market," *Brookings Papers on Economic Activity*, 2016, (Spring), 183–259.

**Mortensen, D. T. and C. A. Pissarides**, "Job Creation and Job Destruction in the Theory of Unemployment," *The Review of Economic Studies*, 1994, *61* (3), 397–415.

**Mortensen, Dale and Christopher Pissarides**, "Technological Progress, Job Creation, and Job Destruction," *Review of Economic Dynamics*, 1998, *1*, 733–753.

**Mortensen, Dale T. and Eva Nagypal**, "More on unemployment and vacancy fluctuations," *Review of Economic Dynamics*, 2007, *10* (3), 327–347.

**Moscarini, Giuseppe and Fabien Postel-Vinay**, "Stochastic Search Equilibrium," *Review of Economic Studies*, 2013, *80* (4), 1545–1581.

_ **and** _ , "Wage posting and business cycles: A quantitative exploration," *Review of Economic Dynamics*, 2016, *19*, 135–160.

**Nagypál, Eva**, "Learning by Doing vs Learning about Match Quality: Can We Tell Them Apart?," *The Review of Economic Studies*, 2007, *74* (2), 537–566.

_ , "Worker Reallocation over the Business Cycle," 2008.

**Perla, Jesse and Christopher Tonetti**, "Equilibrium Imitation and Growth," *Journal of Political Economy*, 2014, *122* (1), 1–21.

**Petrongolo, Barbara and Christopher A. Pissarides**, "Looking into the Black Box : A Survey of the Matching Function," *Journal of Economic Literature,*, 2001, *39* (2), 390–431.

**Pigou, Arthur C.**, *Wealth and Welfare*, London: Macmillan, 1912.

**Pissarides, Christopher A. and Giovanna Vallanti**, "The impact of TFP growth on steady-state unemployment," *International Economic Review*, 2007, *48* (2), 607–640.

**Postel-Vinay, Fabien**, "The Dynamics of Technological Unemployment," *International Economic Review*, 2002, *43* (3), 737–760.

_ **and Hélène Turon**, "On-the-job search, productivity shocks, and the individual earnings process," *International Economic Review*, 2010, *51* (3), 599–629.

**Poterba, James M and Lawrence H Summers**, "Reporting Errors and Labor Market Dynamics," *Econometrica*, 1986, *54* (6), 1319–1338.

**Prat, Julien**, "The impact of disembodied technological progress on unemployment," *Review of Economic Dynamics*, 2007, *10* (1), 106–125.

**Pries, Michael and Richard Rogerson**, "Hiring Policies, Labor Market Institutions, and Labor Market Flows," *Journal of Political Economy*, 2005, *113* (4), 811–839.

**Pries, Michael J.**, "Persistence of employment fluctuations: A model of recurring job loss," *Review of Economic Studies*, 2004, *71* (1), 193–215.

_ , "Worker heterogeneity and labor market volatility in matching models," *Review of Economic Dynamics*, 2008, *11* (3), 664–678.

**Pugsley, Benjamin W and Aysegul Sahin**, "Grown-Up Business Cycles," 2015.

**Romer, Paul M.**, "Endogenous Technological Change," *Journal of Political Economy*, 1990, *98* (5, Part 2), S71–S102.

**Rubinstein, Ariel**, "Perfect Equilibrium in a Bargaining Model," *Econometrica*, 1982, *50* (1), 97–109.

**Rubinstein, Yona and Yoram Weiss**, "Post Schooling Wage Growth: Investment, Search and Learning," in "Handbook of the Economics of Education," Vol. 1 2006, pp. 1–67.

**Ruth, Jan-Erik and James E. Birren**, "Creativity in Adulthood and Old Age: Relations to Intelligence, Sex and Mode of Testing," *International Journal of Behavioral Development*, 1985, *8* (1), 99–109.

**Ryan, Joseph J., Jerome M. Sattler, and Shane J. Lopez**, "Age effects on Wechsler Adult Intelligence Scale-III subtests," *Archives of Clinical Neuropsychology*, 2000, *15* (4), 311–317.

**Sampson, Thomas**, "Dynamic Selection: An Idea Flows Theory of Entry, Trade, Growth," *Quarterly Journal of Economics*, 2016, *131* (1), 315–380.

**Schaal, Edouard**, "Uncertainty and Unemployment," 2016.

**Schönberg, Uta**, "Wage Growth Due to Human Capital Accumulation and Job Search: A Comparison between the United States and Germany," *Industrial and Labor Relations Review*, 2007, *60* (4), 562–586.

**Shimer, Robert**, "The Impact of Young Workers on the Aggregate Labor Market," *The Quarterly Journal of Economics*, 2001, *116* (3), 969–1007.

_ , "The Cyclical Behavior of Equilibrium and Vacancies Unemployment," *American Economic Review*, 2005, *95* (1), 25–49.

_ , "Reassessing the ins and outs of unemployment," *Review of Economic Dynamics*, 2012, *15* (2), 127–148.

**Sutton, John**, "Gibrat ' s Legacy," *Journal of Economic Literature*, 1997, *XXXV* (March), 40–59.

**Thompson, Samuel B.**, "Simple formulas for standard errors that cluster by both firm and time," *Journal of Financial Economics*, 2011, *99* (1), 1–10.

**Topel, Robert H and Michael P Ward**, "Job Mobility and the Careers of Young Men," *Quarterly Journal of Economics*, 1992, *107* (2), 439–479.

**Van Reenen, John**, "The creation and capture of rents: Wages and innovation in a panel of UK companies," *Quarterly Journal of Economics*, 1996, *111* (1), 195–226.

**Wasmer, Etienne**, "General versus Specific Skills in Labor Markets with Search Frictions and Firing Costs," *The American Economic Review*, 2006, *96* (3), 811–831.

**Wolthoff, Ronald**, "Applications and Interviews: Firms' Recruiting Decisions in a Frictional Labour Market," *The Review of Economic Studies*, 2018, *85* (2), 1314–1351.

**Wong, Arlene**, "Transmission of Monetary Policy to Consumption and Population Aging *," 2016.

**Yamaguchi, Shintaro**, "Job Search , Bargaining , and Wage Dynamics," *Journal of Labor Economics*, 2010, *28* (3), 595–631.