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

Niklas Engbom

October 21, 2017

Abstract

Using panel data for 1990–2014 from 12 OECD countries, I document three facts about cross-country labor market outcomes. 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. Third, the direct effect of job shopping accounts for only a quarter of this covariation. I build an equilibrium life-cycle model of the labor market that features search and human capital accumulation on the job, showing that a faster rate of climbing the job ladder increases incentives to accumulate human capital. A calibrated version of the model suggests that differences in the cost to firms of hiring may account for the empirical covariation between fluidity and wage growth, the empirical covariation between fluidity and output per capita, and 43–45 percent of the overall variation in these measures.

JEL Codes: J24, J48, J64

Keywords: Human Capital, Labor Productivity, Labor Market Policy, Job Search

*Department of Economics, Princeton University, 001 Fisher Hall, Princeton, NJ 08544 (e-mail: nengbom@princeton.edu). I am grateful for the generous support and advice of Greg Kaplan and Richard Rogerson. I thank Mark Aguiar, Jorge Alvarez, Martin Beraja, Henry Farber, Oleg Itskhoki, Gregor Jarosch, Nobu Kiyotaki, Guido Menzio, Ben Moll, Chris Moser, Ezra Oberfield, Gianluca Violante, and seminar participants at Princeton University, and financial support from the Gregory C. and Paula K. Chow Macroeconomic Research Program, the Industrial Relations Section, and the Fellowship of Woodrow Wilson Scholars. I also thank Eurostat for granting me access to the ECHP and EU-SILC data sets. The results and conclusions in this paper are mine and do not represent Eurostat, the European Commission or any of the national statistical agencies whose data are used. All errors are my own.
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 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 re-entry 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. 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. 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 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 2 outlines the data sources, variable definitions and sample restrictions that I use to derive my empirical results. Section 3 presents three stylized facts on life-cycle mobility and wage dynamics across countries. Section 4 develops a structural search model with endogenous training on the job, which Section 5 brings to the data. Section 6 presents quantitative results on the impact of policies that affect vacancy creation on life-cycle outcomes of

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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.
workers and aggregate outcomes for the economy, and Section 7 concludes.

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.

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, and the United States. I combine this with aggregate economic outcomes from the Organization of Economic Co-operation and Development (OECD). Appendix A 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 4 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.

3 Strictly speaking Great Britain since the BHPS only contains respondents living in Great Britain during the 1991–1998 period.
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 is broadly defined, including bonuses and other forms of compensation. Appendix A 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 B 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.

### 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, \( \Psi_{c(i)t} \),

\[
\text{wage}_{it} = \phi(a_{it}) \times \text{fluidity}_{c(i)} + \Xi_{a(i,t)} + \Phi_i + \Psi_{c(i)t} + \epsilon_{it}
\]  

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

\[
\Xi_{a} = (1 - \eta)^a - \bar{a} \Xi_{\bar{a}} \quad \forall a > \bar{a}
\]

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. This assumption is motivated by the predictions of the theory developed in Section 4, which suggests that average wage growth late in life should be small. 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 compute 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.

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

5Another 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.
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). 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:

\[ \text{wage}_{it} = \sum_{\tau = -2}^{7} \{ \xi J_{jt-\tau} + \upsilon E_{jt-\tau} \} + a \text{ge}_{it} \{ \zeta \overline{J}_{jt} + \kappa \overline{EU}_{jt} \} + X_{it} \beta + \epsilon_{it} \]  

where \( J_{jt-\tau} \) takes value one if individual \( i \) made a voluntary JtJ transition in year \( t - \tau \), \( \overline{J}_{jt} \) takes value one if individual \( i \) made a voluntary JtJ transition at some point in year \( t - 7 \) to \( t \), and \( X \) 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 \( \upsilon \) 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.

Weights are adjusted such that 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 \( a \), \( \text{gain}_{a} = \hat{\xi} \times \hat{\xi} - \hat{\xi} + \hat{\zeta} \times a \). Subsequently, I compute the job shopping component of wages at age \( a \) as the cumulative sum of wage gains up to age \( a \)

\[ \text{wage}_{Search}^{c,a} = \sum_{s=26}^{a} \text{gain}_{s} \times \text{fluidity}_{c,s} \]

where \( \text{fluidity}_{c,s} \) is the fraction of employed \( s \) year olds in country \( c \) who made a voluntary JtJ

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6This 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.

7I 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.

8The 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.
transition in the past year.

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.

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

Figure 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 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 B presents estimated life-cycle profiles of monthly JtJ, EU and UE transition rates based on these data.

Figure 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.

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

Figure 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.

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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.
Fraction who made a voluntary JtJ transition in past year

Figure 1. Fraction of employed who made a voluntary JtJ move in past year

(a) Austria  (b) Belgium  (c) Denmark  (d) Finland

(e) France  (f) Germany  (g) Ireland  (h) Italy

(i) Netherlands  (j) Spain  (k) U.K.  (l) U.S.

Figure 2. Estimated life-cycle wage profiles

(a) Austria  (b) Belgium  (c) Denmark  (d) Finland

(e) France  (f) Germany  (g) Ireland  (h) Italy

(i) Netherlands  (j) Spain  (k) U.K.  (l) U.S.

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 presents regression results based on equation (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 behind 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. FLUIDITY AND LIFE-CYCLE WAGE GROWTH

<table>
<thead>
<tr>
<th></th>
<th>(1) Fluidity × Age</th>
<th>(2) Fluidity × Age²</th>
<th>(3) Fluidity × Age³</th>
<th>(4) College × Age</th>
<th>(5) Baseline Education slopes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fluidity × Age</td>
<td>0.817***</td>
<td>0.771***</td>
<td>0.801***</td>
<td>0.923*</td>
<td>0.988**</td>
</tr>
<tr>
<td></td>
<td>(0.171)</td>
<td>(0.176)</td>
<td>(0.172)</td>
<td>(0.438)</td>
<td>(0.452)</td>
</tr>
<tr>
<td>Fluidity × Age²</td>
<td>-0.039***</td>
<td>-0.039***</td>
<td>-0.039***</td>
<td>-0.045**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.008)</td>
<td>(0.020)</td>
<td></td>
</tr>
<tr>
<td>Fluidity × Age³</td>
<td>0.001***</td>
<td>0.001***</td>
<td>0.001***</td>
<td>0.001*</td>
<td></td>
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<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
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</tr>
<tr>
<td>High-school × Age</td>
<td></td>
<td>-0.001</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>(0.003)</td>
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</tr>
<tr>
<td>College × Age</td>
<td></td>
<td>0.017**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.006)</td>
<td></td>
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<tr>
<td>N</td>
<td>401,945</td>
<td>400,364</td>
<td>379,350</td>
<td>120,384</td>
<td>400,364</td>
</tr>
<tr>
<td>R²</td>
<td>0.812</td>
<td>0.812</td>
<td>0.816</td>
<td>0.804</td>
<td>0.815</td>
</tr>
</tbody>
</table>


To illustrate the magnitude of these differences, Figure 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 24 in Appendix C 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 25 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 C 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 C 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 4. PREDICTED LIFE-CYCLE WAGE GROWTH, HIGH AND LOW FLUIDITY COUNTRY

![Predicted Life-Cycle Wage Growth](image)


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

Figure 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.\(^\text{10}\) The gains continue to accrue for up to three years after the transition. As discussed in further detail in Appendix D, 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.\(^\text{11}\) Appendix D provides additional results and regression tables.

\(^{10}\)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 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. 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.

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

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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.
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.

Figure 6. Wage growth due to job shopping, high and low fluidity country


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.

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.
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 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 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

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

I assume that human capital does not depreciate.

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

\(^{14}\)An earlier version of this paper considered a Ben-Porath (1967) specification with similar results.
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 I presents empirical evidence on the behavior of mobility around on-the-job training that is consistent with human capital being general.

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 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,

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

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 chooses 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. 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, $w \times \left( y - \frac{c}{\gamma} t \right)$ (Barlevy 2008; Bagger et al. 2014). As I show in Section 6, this assumption generates a process.

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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.
for wages that fits the data well\textsuperscript{17}

\section*{4.5 Analysis}

\textbf{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 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\textsuperscript{18}

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

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

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

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.

An optimal investment rule satisfies,

\[ i^N(v) = \left[ \frac{1}{c_h} \left( p_1 + v^\alpha \beta \frac{1}{2} (p_2 - p_1) \right) \right]^{1 - \gamma} \]  \hfill (4)

\textsuperscript{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.

\textsuperscript{18}High productive matches in period one are unaffected by changes in job creation in period two.
which is increasing in vacancies. We can rewrite the free entry condition as,

\[ v(i) = \left[ \frac{(1 - \beta)(p_2 - p_1) (h + i)}{4c_v} \right]^{\frac{1}{1-\alpha}} \iff i^E(v) = \frac{4c_v v^{1-\alpha}}{(1 - \beta)(p_2 - p_1) - h} \tag{5} \]

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 7 plots the \( v-i \) combinations that are consistent with optimal behavior as characterized by (4)–(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.

\[ \text{Figure 7. BEST RESPONSE FUNCTIONS} \]

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 E.

The next proposition shows that, although as in Acemoglu and Pischke (1998) a higher prob-
ability 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 E.*

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 E.*

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 E.

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.

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.  

**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 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.

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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 I presents evidence supporting this assumption.
Third, with exogenous search the model cannot match the magnitude of the fall with age in the JtJ and UE hazards.

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

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

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 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,

\[
\lambda(s, \theta) = s \theta^a, \quad q_0(S_e, S_u, \theta) = \frac{S_u}{S_u + S_e} \theta^{a-1}, \quad q(S_e, S_u, \theta) = \frac{S_e}{S_u + S_e} \theta^{a-1}
\]

4.7 Value functions

Let \( W_u(h) \) 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

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

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.
subject to $h' = h + i$ and $i \in [0, I]$, where $I$ is an upper bound on investment that ensures that flow output is always positive \footnote{In the quantitative exercises, this upper bound never binds in optimum for the estimated parameter values.} and

$$J_a(h, p) = \max \{ \bar{J}_a(h, p), W_a(h) \}$$

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 $s_a(h, p)$ the optimal search policy, and by $\bar{p}_a(h)$ a reservation productivity such that

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

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

$$W_a(h) = \max_s \left\{ b + \rho \left[ -\frac{c_u h}{\eta_u} s_{I_a} + W_{a+1}(h) + s \lambda \beta \int P_{a+1} \left( J_{a+1}(h, p) - W_{a+1}(h) dF(p) \right) \right] \right\} \quad (6)$$

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

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

$$V_a(h, p, w) = w \left[ ph - \frac{c_u}{\eta_u} i_a(h, p) \right] + \rho \left[ -\frac{c_u h'}{\eta_u} s_{I_a} + \int \left\{ (1 - s^u_{I_a}(h, p) \lambda) W_{a+1}(h', \bar{p}, w) + (1 - s^u_{I_a}(h, p) \lambda) W_{a+1}(h', \bar{p}, w) dF(p') \right\} + \int \left\{ (1 - s^u_{I_a}(h, p) \lambda) V_{a+1}(h', \bar{p}, w) - W_{a+1}(h) dF(p) \right\} \right]$$

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

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

$$V_a(h, p, w) = \min \left\{ \max \left\{ V_a(h, p, w), W_a(h) \right\}, J_a(h, p) \right\}$$
**Wage policies** Define $\bar{w}(h, p)$ as the lowest wage a worker age $a$ with human capital $h$ working for firm $p$ may be paid,

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

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

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

and

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

### 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

$$\frac{c_v}{1 - \beta} = q_0 \sum_A \int_{\underline{h}}^{\bar{h}} \int_{\underline{p}}^{\bar{p}} s_a^u(h) \frac{s_a^u(h)}{S_u} \{J_a(h, p) - W_a(h)\} dF(p) dN_a(h) +

q \sum_A \int_{\underline{h}}^{\bar{h}} \int_{\underline{p'}}^{\bar{p}} s_a^e(h, p') \frac{s_a^e(h, p')}{S_e} \{J_a(h, p) - J_a(h, p')\} dF(p) dE_a(h, p')$$

An open job meets an unemployed worker at rate $q_0$, who at rate $s_a^u(h) n_a(h)$ 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 $s_a^e(h, p') e_a(h, p')$
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 $f_a$; an investment policy $i_a(h, p)$, search policies $s_a^u(h)$ and $s_a^e(h, p)$, and a reservation rule $p_a(h)$; 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.

## 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.\footnote{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.} 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 F contains further details.

### 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)](https://www.jstor.org/stable/1167397). 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 \( \sigma \). 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 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, \( J_t \), EU and UE mobility, and the dynamics of gains from \( J_t \) mobility. The return to \( J_t \) 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 \( J_t \) 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 \( J_t \) hazard is informative about the employed search cost parameters, \( c_e \) and \( \eta_{ce} \), while the average and curvature of the UE hazard is informative about the unemployed search cost parameters, \( c_u \) and \( \eta_{cu} \). 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.

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23The 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.
distribution and unemployment.

5.2 Parameter values

Table 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 2. Parameter values

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Target</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \rho )</td>
<td>4% interest rate</td>
<td>0.9967</td>
</tr>
<tr>
<td>( A )</td>
<td>35 years in market</td>
<td>420</td>
</tr>
<tr>
<td>( \chi )</td>
<td>Normalization</td>
<td>1</td>
</tr>
<tr>
<td>( a )</td>
<td>Petrongolo and Pissarides (2001)</td>
<td>0.6</td>
</tr>
</tbody>
</table>

| \( \zeta \) | 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 |

5.3 Model fit

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

Figure 8. WAGES IN AVERAGE FLUIDITY COUNTRY, MODEL VS DATA

Figure 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 9. MOBILITY HAZARDS IN AVERAGE FLUIDITY COUNTRY, MODEL VS DATA

(a) JTJ
(b) EU
(c) UE

Figure 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 10. RETURNS TO MOBILITY IN AVERAGE FLUIDITY COUNTRY, MODEL VS DATA

(a) Mobility gain
(b) Displacement loss

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 depreciation of human capital, the fact that workers cannot invest when unemployed reduces wage growth relative to counter-factual. Second, displacement brings the worker down the job ladder, which makes it more

24Based on this, one may suspect that the model predicts the largest losses early in careers. Countering this effect,
likely that a shock will cause subsequent displacement (Krolikowski, 2016).

5.4 Sources of life-cycle wage growth

Figure 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 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).

Figure 11. DECOMPOSITION OF LIFE-CYCLE WAGE GROWTH, MODEL

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.
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.

6.1 Micro-level predictions

Table 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 3. Micro-level outcomes in model versus data

<table>
<thead>
<tr>
<th></th>
<th>Low fluidity</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Data</td>
<td>Model</td>
<td>Data</td>
<td>Model</td>
<td>Data</td>
</tr>
<tr>
<td>JtJ hazard (% of average)</td>
<td>0.0034</td>
<td>0.0034</td>
<td>0.0043</td>
<td>0.0044</td>
<td>0.0054</td>
</tr>
<tr>
<td>EU hazard (% of average)</td>
<td>0.0078</td>
<td>0.0084</td>
<td>0.0080</td>
<td>0.0079</td>
<td>0.0082</td>
</tr>
<tr>
<td>UE hazard (% of average)</td>
<td>0.053</td>
<td>0.058</td>
<td>0.068</td>
<td>0.067</td>
<td>0.082</td>
</tr>
<tr>
<td>Gain from JtJ (Log points)</td>
<td>0.072</td>
<td>0.081</td>
<td>0.073</td>
<td>0.077</td>
<td>0.074</td>
</tr>
<tr>
<td>Loss from EU (Log points)</td>
<td>-0.025</td>
<td>-0.052</td>
<td>-0.035</td>
<td>-0.063</td>
<td>-0.045</td>
</tr>
</tbody>
</table>
The last four rows in Table 3 evaluate the wage impact of mobility. In line with the data, the model predicts essentially no difference in the return to JfJ 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 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 12. PREDICTED WAGE PROFILES IN MODEL VERSUS DATA

(a) LOW FLUIDITY

(b) HIGH FLUIDITY

Figure 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 G 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.
6.2 Macro-level predictions

Figure 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.

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

Table 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 4. FRACTION OF COVARIANCE AND TOTAL VARIATION EXPLAINED BY MODEL

<table>
<thead>
<tr>
<th>Moment</th>
<th>% of covariance</th>
<th>% of total</th>
<th>(\rho(\text{model, data}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output per capita</td>
<td>98.7%</td>
<td>44.8%</td>
<td>0.673</td>
</tr>
<tr>
<td>Labor productivity</td>
<td>99.3%</td>
<td>27.7%</td>
<td>0.528</td>
</tr>
<tr>
<td>Employment rate</td>
<td>98.9%</td>
<td>73.6%</td>
<td>0.859</td>
</tr>
<tr>
<td>Life-cycle wage growth</td>
<td>98.4%</td>
<td>43.2%</td>
<td>0.660</td>
</tr>
</tbody>
</table>
6.3 The role of human capital

Figure 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 16. LABOR PRODUCTIVITY, HUMAN CAPITAL AND MATCH PRODUCTIVITY, MODEL](image)

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 a target in the estimation), and in Appendix H that training is associated with subsequent wage growth conditional on individual and year ef-

\(^{25}\)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.
ffects, 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 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 H 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 4: 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 17. ON-THE-JOB TRAINING ACROSS COUNTRIES

(a) EMPLOYER PROVIDES FREE OR SUBSIDIZED TRAINING

(b) WEEKS IN TRAINING SINCE JANUARY LAST YEAR

Figure 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. 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 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.

Figure 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 fluidity, I use questions on employed job search from the ECHP and the 1990–1997 PSID. Appendix I shows that the measure of on-the-job search strongly predicts future mobility, lending credibility to interpreting these measures of search. Figure 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.

27Model 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 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 20 plots the life-cycle profile of job search in the model and data for the average fluidity country. 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 20. On-the-job search, model versus data

Appendix G 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.

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


A Details on data

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

A.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 fol-
lowed 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.  

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

29Available for download at the St Louis Fed webpage, https://fred.stlouisfed.org/series/CPIAUCSL/downloaddata/
(from 1996), France, Ireland, Italy, Luxembourg (left 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. 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. 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.

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.

32 Specifically the series for actual individual consumption available from the OECD, http://stats.oecd.org/
**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.

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.\footnote{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.} 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 few individuals, however, the loss in statistical precision resulting from this is arguably second order.\footnote{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.}

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
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. [Jacovou 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 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 Institut für 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. I merge data from the personal files, person equivalent files, and person calendar files for 1990–2011. 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. 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

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

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

38 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.
this with the BHPS sample. The BHPS was discontinued in 2008 to make way for a new survey, the 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/non-response. 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. 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.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 C using age appears to be the conservative approach as results with experience are even more pronounced.

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.

39Since 1994, children age 11–15 also answer a short questionnaire individually.
**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 re-code 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 and self-employed if he reports being self-employed.

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40This 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).
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 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[^41]. 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)[^42].

The monthly calendar of events is missing for the Netherlands in the ECHP. In this case, I

[^41]: 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.
[^42]: 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.
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 procedure 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. The EU-SILC in addition records whether the respondent 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 $LT_t$ 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

\footnote{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.}
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, 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. Specifically, for 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

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44 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.

45 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 employment 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).
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.\footnote{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.}

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 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.\footnote{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.}

**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 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.\(^48\) For the PSID, GSOEP and BHPS I adjust the provided weights such that the sum of weights equals one for each country.

\(^{48}\)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.
Aggregate measures  I use measures of GDP per capita and GDP per hour for 1996–2014 available from the OECD. 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,

$$aggregate_{ct} = \beta_0 + \beta_1 fluidity_{c} + \beta_2 age_{ct} + \beta_3 college_{ct} + \tau + \epsilon_{ct}$$

where $\tau$ is a set of year effects common to all countries and restricted to sum to zero. The measure I use is

$$\hat{aggregate}_{ct} = \hat{\beta}_0 + \hat{\beta}_1 fluidity_{c} + \epsilon_{ct}$$

B  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.

B.1  Methodology

As discussed in greater detail in Appendix A, 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. 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 $\tau_{lt}$ the number of months since the last interview (or 12 if no last interview). The probability that a

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491996 is the earliest year for which all 12 countries in my sample provide data.
50Some 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.
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

\[ P(e_{it} = 1, LT_{it} = 0) = (1 - \lambda_{JTJ} - \delta)^{\tau_{it}} P(e_{it-\tau_{it}} = 1) \]  

(7)

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 interview and did not transition to employment in any month since then,

\[ P(e_{it} = 0, LT_{it} = 0) = (1 - \lambda_{UE})^{\tau_{it}} P(e_{it-\tau_{it}} = 0) \]  

(8)

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,

\[ P(e_{it} = 1) = P(e_{it-1} = 1)(1 - \delta) + P(e_{it-1} = 0)\lambda_{UE} \]

\[ = \lambda_{UE} + [1 - \delta - \lambda_{UE}] P(e_{it-1} = 1) \]

Iterating this backwards, we have that

\[ P(e_{it} = 1) = \lambda_{UE} \sum_{i=1}^{\tau_{it}} (1 - \delta - \lambda_{UE})^{i-1} + (1 - \delta - \lambda_{UE})^{\tau_{it}} P(e_{it-\tau_{it}} = 1) \]

\[ = \frac{\lambda_{UE}}{\lambda_{UE} + \delta} [1 - (1 - \delta - \lambda_{UE})^{\tau_{it}}] + (1 - \delta - \lambda_{UE})^{\tau_{it}} P(e_{it-\tau_{it}} = 1) \]  

(9)

B.2 Estimates

JtJ mobility  Figure [21] 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 21. MONTHLY VOLUNTARY JTJ HAZARD ACROSS 12 OECD COUNTRIES

EU mobility Figure 22 plots the estimated EU hazard across countries. Also this has a life-cycle pattern, with mobility being high initially and gradually falling with age.\textsuperscript{51} 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,\textsuperscript{52} and possibly to the data issues surrounding transitions between such contracts.

\textsuperscript{51}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.

\textsuperscript{52}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.
and permanent contracts as discussed above. Excluding Spain, the separation rate varies by a factor of less than two moving from the lowest 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 22. MONTHLY EU HAZARD ACROSS 12 OECD COUNTRIES

![Graphs showing the estimated UE hazard across countries.](image)

**UE mobility**  Figure 23 graphs the estimated UE hazard across countries. It declines as workers age, although the magnitude of the fall differs across countries. 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.

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53 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).
Correlation Table 5 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 5. CROSS-COUNTRY CORRELATION BETWEEN HAZARD RATES AND FLUIDITY

<table>
<thead>
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<th>Fluidity</th>
<th>JTJ</th>
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<th>UE</th>
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C Additional life-cycle wage profiles

This appendix presents additional results on life-cycle wage profiles across countries.

C.1 Education or occupation controls

The left pane of Figure 24 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 24 plots the predicted wage profile with occupation controls. Regression results underlying these graphs are available on request.

Figure 24. LIFE-CYCLE WAGE GROWTH WITH OCCUPATION OR EDUCATION SLOPES, LOW AND HIGH FLUIDITY COUNTRY

(a) EDUCATION SLOPES

(b) OCCUPATION SLOPES


C.2 College graduates only

Figure 25 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 25. **LIFE-CYCLE WAGE GROWTH FOR COLLEGE GRADUATES, LOW AND HIGH FLUIDITY COUNTRY**

![Graph showing life-cycle wage growth for college graduates, low and high fluidity country.](image)


C.3 **By experience**

Figure 26 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 26. **LIFE-CYCLE WAGE GROWTH BY EXPERIENCE, LOW AND HIGH FLUIDITY COUNTRY**

![Graph showing life-cycle wage growth by experience, low and high fluidity country.](image)

C.4 Allowing for depreciation

Figure 27 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.


C.5 Deaton (1997)–? or GDP controls

Figure 28 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 28. LIFE-CYCLE WAGE GROWTH UNDER ALTERNATIVE METHODS, LOW AND HIGH FLUIDITY COUNTRY

(a) DEATON (1997) METHOD

(b) GDP CONTROLS


D Return to mobility

Table 6 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 $JtJ$ 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.\(^{54}\)

Column 1 shows results from model 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

\(^{54}\)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.
JTJ transition, but at a declining pace. 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 finds no support for the hypothesis that the return to JTJ mobility varies with fluidity, while the loss from displacement increases in fluidity.

E Proofs

E.1 Proof of proposition

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 equilibrium
\[
\lim_{v \to \infty} \frac{\frac{4c_v p_1^\alpha}{(1-\beta)(p_2-p_1)} - h}{\left[ \frac{1}{c_h} \left( p_1 + v^\alpha \beta^2 \frac{1}{2} (p_2 - p_1) \right) \right]^{\frac{1}{\gamma-1}}} = \lim_{v \to \infty} v^{1-\alpha - \frac{\alpha}{\gamma-1}} - \frac{\frac{4c_v}{(1-\beta)(p_2-p_1)} - h}{v^{1-\alpha}} \left[ \frac{1}{c_h} \left( p_1 + \beta \frac{1}{2} (p_2 - p_1) \right) \right]^{\frac{1}{\gamma-1}}
\]

The second term is strictly positive. Hence, if and only if
\[
1 - \alpha - \frac{\alpha}{\gamma-1} > 0 \iff \gamma(1 - \alpha) > 1
\]

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.

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 6. ESTIMATED RETURN TO MOBILITY

<table>
<thead>
<tr>
<th></th>
<th>(1) Baseline</th>
<th>(2) Age</th>
<th>(3) Age slope</th>
<th>(4) Fluidity</th>
</tr>
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<tr>
<td>$J_{t+2}$</td>
<td>-0.00367</td>
<td>-0.01507**</td>
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<td>(0.00705)</td>
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<td>-0.03203***</td>
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<td>(0.00665)</td>
<td>(0.00666)</td>
<td>(0.00665)</td>
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<tr>
<td>$J_t$</td>
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<td>0.02856***</td>
<td>0.04938***</td>
<td>0.02869***</td>
</tr>
<tr>
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<td>(0.00863)</td>
<td>(0.00697)</td>
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<tr>
<td>$J_{t-1}$</td>
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<tr>
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<td>(0.00753)</td>
<td>(0.00910)</td>
<td>(0.00758)</td>
</tr>
<tr>
<td>$J_{t-2}$</td>
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<td>0.04847***</td>
<td>0.07061***</td>
<td>0.04868***</td>
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<tr>
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<td>(0.00909)</td>
<td>(0.01065)</td>
<td>(0.00906)</td>
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<td>0.07100***</td>
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<td>(0.01123)</td>
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<td>0.06299***</td>
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<td>0.06037***</td>
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<td>(0.01164)</td>
<td>(0.01193)</td>
<td>(0.01343)</td>
<td>(0.01190)</td>
</tr>
<tr>
<td>$J_{t-6}$</td>
<td>0.14137***</td>
<td>0.06960***</td>
<td>0.09573***</td>
<td>0.06963***</td>
</tr>
<tr>
<td></td>
<td>(0.01327)</td>
<td>(0.01325)</td>
<td>(0.01463)</td>
<td>(0.01322)</td>
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<tr>
<td>$J_{t-7}$</td>
<td>0.16333**</td>
<td>0.07220***</td>
<td>0.09826***</td>
<td>0.07832***</td>
</tr>
<tr>
<td></td>
<td>(0.01929)</td>
<td>(0.01922)</td>
<td>(0.02028)</td>
<td>(0.01921)</td>
</tr>
<tr>
<td>$EU_{t+2}$</td>
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<td>0.00065</td>
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<td>0.00059</td>
</tr>
<tr>
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<td>(0.00696)</td>
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<tr>
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<tr>
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<td>(0.00720)</td>
<td>(0.00721)</td>
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<tr>
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<td>-0.07943***</td>
<td>-0.04822***</td>
<td>-0.07832***</td>
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<td>(0.00765)</td>
<td>(0.00883)</td>
<td>(0.00759)</td>
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<tr>
<td>$EU_{t-1}$</td>
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<td>-0.0434**</td>
<td>-0.01459*</td>
<td>-0.04329**</td>
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<td>(0.00752)</td>
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<td>(0.00854)</td>
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<tr>
<td>$EU_{t-2}$</td>
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<td>-0.02149***</td>
<td>0.00840</td>
<td>-0.02057***</td>
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<td>(0.00773)</td>
<td>(0.00767)</td>
<td>(0.00875)</td>
<td>(0.00764)</td>
</tr>
<tr>
<td>$EU_{t-3}$</td>
<td>-0.00164</td>
<td>-0.01313*</td>
<td>0.01778*</td>
<td>-0.01224</td>
</tr>
<tr>
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<td>(0.00797)</td>
<td>(0.00792)</td>
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<td>(0.00789)</td>
</tr>
<tr>
<td>$EU_{t-4}$</td>
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<td>-0.01171</td>
<td>0.02088**</td>
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<tr>
<td></td>
<td>(0.00923)</td>
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<td>(0.00911)</td>
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<tr>
<td>$EU_{t-5}$</td>
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<td>-0.01431</td>
<td>0.01939*</td>
<td>-0.01355</td>
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<tr>
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<td>(0.00943)</td>
<td>(0.00934)</td>
<td>(0.01062)</td>
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<tr>
<td>$EU_{t-6}$</td>
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<td>0.02723**</td>
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<tr>
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<td>(0.00116)</td>
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<tr>
<td>$EU_{t-7}$</td>
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<td>-0.03868*</td>
<td>-0.00226</td>
<td>-0.03835*</td>
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<tr>
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<td>(0.02272)</td>
<td>(0.02260)</td>
<td>(0.02359)</td>
<td>(0.02261)</td>
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</table>

$\bar{J} J \times Fluidity$     -0.04556
                               (0.31321)

$\bar{E} U \times Fluidity$   -0.86006**
                               (0.40872)

$\bar{J} J \times Age$         -0.00242***
                               (0.00066)

$\bar{E} U \times Age$        -0.00413***
                               (0.00061)

N 142,711 142,711 142,711 142,711
R2 0.83181 0.83279 0.83304 0.83281

the limit tends to infinity and there is at least one solution. If \( \gamma(1-\alpha) = 1 \), the limit tends to

\[
\lim_{v \to \infty} \frac{i^E(v)}{i^W(v)} = \frac{4c_v}{(1-\beta)(p_2-p_1)} \left[ \frac{1}{c_h} \frac{\beta}{2}(p_2 - p_1) \right]^{1/\gamma}
\]

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

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

\[
\frac{\partial i^E(v)}{\partial v} = \left[ \frac{\partial i^W(v)}{\partial v} \cdot \frac{4c_v}{(1-\beta)(p_2-p_1)} \right] \frac{1-\alpha}{v}
\]

If \( \frac{i^E(v)}{i^W(v)} \geq 1 \Rightarrow \frac{\partial i^E(v)}{\partial v} > 1 \) then the solution is unique. Suppose \( \frac{i^E(v)}{i^W(v)} \geq 1 \), then we need to show that

\[
\frac{1-\alpha}{\eta-1} \frac{p_1 + v^\alpha \beta \frac{1}{2}(p_2 - p_1)}{\beta \frac{1}{2}(p_2 - p_1) \alpha v^{\alpha-1}} \geq 1
\]

\[
p_1 + v^\alpha \beta \frac{1}{2}(p_2 - p_1) \geq \frac{1}{(\eta-1)(1-\alpha)} \beta \frac{1}{2}(p_2 - p_1) \alpha v^{\alpha}
\]

\[
\frac{2p_1}{\beta(p_2-p_1)} \geq \left[ \frac{\alpha}{(\eta-1)(1-\alpha)} - 1 \right] v^{\alpha}
\]

To ensure uniqueness, we need this to hold \( \forall v \geq 0 \), and hence we need

\[
\frac{\alpha}{(\eta-1)(1-\alpha)} - 1 \leq 0
\]

\[
1 \leq \eta(1-\alpha)
\]

\[\square\]

### E.2 Proof of proposition 2

**Proof.** In the unique equilibrium, \( \frac{dE(v^*)}{dv} > \frac{dW(v^*)}{dv} \) must hold since both curves are upward sloping and \( \lim_{v \to 0} i^E(v) < \lim_{v \to 0} i^W(v) \). Since \( \frac{\partial E(v)}{\partial c_v} > 0 \) while \( \frac{\partial W(v)}{\partial c_v} = 0 \), an increase in the cost of
creating jobs rotates $i^E(v)$ upwards, which implies that in equilibrium investment and vacancies fall. Figure 29 illustrates this intuition.

**Figure 29. POLICY FUNCTION**

![Diagram showing the policy function with two lines representing low and high cost scenarios.](image)

E.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

$$\frac{d i^W(v)}{d v} = \frac{i^W(v)}{v} = \frac{1}{\gamma - 1} \frac{\beta \frac{1}{2} (p_2 - p_1) \alpha v^\alpha}{p_1 + \beta \frac{1}{2} (p_2 - p_1) v^\alpha}$$

Hence, a given change in $c_v$ results in a larger equilibrium fall in investment and vacancies the smaller is $\gamma$. □

E.4 Proof of proposition 4

**Proof.** In the unique competitive equilibrium,

$$i^{CE} = \frac{8 c_v p_1 + (1 - \beta) \beta (p_2 - p_1)^2 h}{8 c_v c_h - (1 - \beta) \beta (p_2 - p_1)^2}$$

$$v^{CE} = \left[ \frac{(1 - \beta) (p_2 - p_1) (c_h h + p_1)}{8 c_h c_v - (1 - \beta) \beta (p_2 - p_1)^2} \right]^2$$

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The planning problem is

\[ V^{SP} = \max_{v, \lambda, i, h} \left\{ p_1h - \frac{c_v h^2}{2} + \left[ p_1 + \sqrt{\frac{1}{2}(p_2 - p_1)} \right] (h + i) - 2c_v v \right\} \]

Taking first-order conditions and rearranging,

\[ i^{SP} = \frac{8c_v p_1 + (p_2 - p_1)^2 h}{8c_v c_h - (p_2 - p_1)^2} \]

\[ v^{SP} = \left[ \frac{2(p_2 - p_1)c_h h + p_1}{8c_v c_h - (p_2 - p_1)^2} \right] \]

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

\[ [1 - (1 - \beta) \beta] c_h h + p_1 [1 - (1 - \beta) \beta] > 0 \]

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.

\[ \square \]

F 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

\[ s_a^u(h) = \left[ \frac{1}{c_{uh}} \lambda \beta \int_p^\rho J_{a+1}(h, p) - W_{a+1}(h) dF(p) \right]^{\frac{1}{\eta - 1}} \]

Substituting in the solution gives the value function \( W_a \) at each grid point. The derivative at the grid point is given by

\[ \frac{dW_a(h)}{dh} = \rho \left[ -\frac{c_a}{\eta} (s_a^u(h))^{\eta - 1} + \frac{dW_{a+1}(h)}{dh} s_a^u(h) \lambda + s_a^u(h) \lambda \beta \int_p^\rho \frac{dJ_{a+1}(h, p)}{dh} - \frac{dW_{a+1}(h)}{dh} dF(p) \right] \]

71
The first-order condition for optimal search of the employed is

\[ s^e_a[h(h', p), p] = \left[ \frac{1}{c_e h'} \lambda \beta \int_p^p \int_p^p [J_{a+1}(h', p') - J_{a+1}(h', \bar{p})] \, dF(p') \, dG(\bar{p} | p) \right]^{\frac{1}{1 - \gamma}} \]

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,

\[ i[h(h', p), p] = \left\{ \rho + \frac{\rho}{c_h} \left[ \int_p^p \left( \frac{\partial J_{a+1}(h', \bar{p})}{\partial h'} + \delta \left[ \frac{\partial W_{a+1}(h')}{\partial h'} - \frac{\partial J_{a+1}(h', \bar{p})}{\partial h'} \right] \right) \, dF(p') \right\} \frac{1}{\eta} \]

This provides an optimal investment policy at the endogenous grid point. The derivative at the endogenous grid point is given by the envelope condition,

\[ \frac{\partial J_a[h(h', p), p]}{\partial h} = p + \rho \left\{ \int_p^p \left( \frac{\partial J_{a+1}(h', \bar{p})}{\partial h'} + \delta \left[ \frac{\partial W_{a+1}(h')}{\partial h'} - \frac{\partial J_{a+1}(h', \bar{p})}{\partial h'} \right] \right) \, dF(p') \right\} \frac{1}{\eta} \]

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 \( h \).

G Additional model predictions

The following section compares additional moments from the model with the data.

G.1 Inequality

Figure 30 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 30. **INEQUALITY, MODEL VERSUS DATA**

(a) GROWTH OVER THE LIFE-CYCLE

(b) STEADY-STATE LEVEL

G.2 Search from unemployment

Figure 31 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 31. **UNEMPLOYED SEARCH, MODEL VERSUS DATA**

(a) LIFE-CYCLE PROFILE

(b) SEARCH AND FLUIDITY
H 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.

H.1 Training and fluidity: Regression results

Let $\text{train}_{it}$ 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,

$$\text{train}_{it} = \alpha \text{fluidity}_{c(i)} + X_{it} \beta + \epsilon_{it}$$

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,

$$\text{train}_{it} = \alpha \text{fluidity}_{c(i),col(i)} + \phi(\text{age}_{it}) + \text{College}_{it} + \Phi_{c(i)} + \epsilon_{it}$$

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 7 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 7. Fluidity and on-the-job training

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<th>Weeks</th>
<th>Whether</th>
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<td>107.535***</td>
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<tr>
<td></td>
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<td>(9.382)</td>
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<td>Age</td>
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<td>-0.536*</td>
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<tr>
<td></td>
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<td>(0.276)</td>
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<td>Age²</td>
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<td>0.027</td>
</tr>
<tr>
<td></td>
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<td>(0.016)</td>
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<tr>
<td>Age³</td>
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<td>-0.000</td>
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<tr>
<td></td>
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<td>(0.000)</td>
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<tr>
<td>College</td>
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<td>1.451***</td>
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<td></td>
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<td>(0.228)</td>
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<td>-0.012</td>
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<tr>
<td></td>
<td>(1.066)</td>
<td>(0.039)</td>
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<tr>
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<td>0.069*</td>
</tr>
<tr>
<td></td>
<td>(1.287)</td>
<td>(0.037)</td>
</tr>
<tr>
<td>Professional</td>
<td>-0.018</td>
<td>0.035</td>
</tr>
<tr>
<td></td>
<td>(1.728)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Health Associate</td>
<td>-0.053</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>(0.934)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>Salesman</td>
<td>-1.863**</td>
<td>-0.116***</td>
</tr>
<tr>
<td></td>
<td>(0.708)</td>
<td>(0.032)</td>
</tr>
<tr>
<td>Service worker</td>
<td>-2.097*</td>
<td>-0.154***</td>
</tr>
<tr>
<td></td>
<td>(0.922)</td>
<td>(0.036)</td>
</tr>
<tr>
<td>Craftman</td>
<td>-2.421**</td>
<td>-0.221***</td>
</tr>
<tr>
<td></td>
<td>(0.966)</td>
<td>(0.039)</td>
</tr>
<tr>
<td>Operative</td>
<td>-2.652**</td>
<td>-0.226***</td>
</tr>
<tr>
<td></td>
<td>(0.987)</td>
<td>(0.042)</td>
</tr>
<tr>
<td>Laborer</td>
<td>-2.858**</td>
<td>-0.283***</td>
</tr>
<tr>
<td></td>
<td>(1.092)</td>
<td>(0.047)</td>
</tr>
<tr>
<td>Constant</td>
<td>4.699***</td>
<td>7.060**</td>
</tr>
<tr>
<td></td>
<td>(1.302)</td>
<td>(2.121)</td>
</tr>
<tr>
<td>N</td>
<td>90,464</td>
<td>87,494</td>
</tr>
<tr>
<td>R²</td>
<td>0.019</td>
<td>0.020</td>
</tr>
</tbody>
</table>

Note: ECHP (1994–2001) and BHPS (1994–2001); *10%; **5%; ***1%; see text for further details.

### H.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 \( \text{mob}_{it} \) 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

\[
\text{mob}_{it} = \sum_{\tau=-2}^{3} \xi_{\tau} \text{train}_{it-\tau} + X_{it} \beta + \epsilon_{it}
\]
I alternatively include in $X_{it}$ 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 8 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.
Figure 32 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.

### Table 8. TRAINING AND MOBILITY

<table>
<thead>
<tr>
<th></th>
<th>JtJ</th>
<th>EU</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) Base</td>
<td>(2) FE</td>
</tr>
<tr>
<td>training_t+2</td>
<td>-0.00413</td>
<td>-0.00322</td>
</tr>
<tr>
<td></td>
<td>(0.00258)</td>
<td>(0.00286)</td>
</tr>
<tr>
<td>training_t+1</td>
<td>0.00069</td>
<td>0.00029</td>
</tr>
<tr>
<td></td>
<td>(0.00263)</td>
<td>(0.00301)</td>
</tr>
<tr>
<td>training_t</td>
<td>0.00298</td>
<td>0.00083</td>
</tr>
<tr>
<td></td>
<td>(0.00247)</td>
<td>(0.00300)</td>
</tr>
<tr>
<td>training_t-1</td>
<td>-0.00188</td>
<td>-0.00280</td>
</tr>
<tr>
<td></td>
<td>(0.00280)</td>
<td>(0.00296)</td>
</tr>
<tr>
<td>training_t-2</td>
<td>-0.00245</td>
<td>-0.00130</td>
</tr>
<tr>
<td></td>
<td>(0.00296)</td>
<td>(0.00316)</td>
</tr>
<tr>
<td>training_t-3</td>
<td>0.00078</td>
<td>0.00589*</td>
</tr>
<tr>
<td></td>
<td>(0.00323)</td>
<td>(0.00345)</td>
</tr>
<tr>
<td>N</td>
<td>102,445</td>
<td>111,257</td>
</tr>
<tr>
<td>R2</td>
<td>0.03076</td>
<td>0.26637</td>
</tr>
</tbody>
</table>

Note: ECHP (1994–2001); *10%; **5%; ***1%; see text for further details.

H.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,

\[ \text{wage}_{it} = \sum_{\tau=-2}^{7} \xi_{\tau} \text{train}_{it-\tau} + \chi_{it} \beta + \epsilon_{it} \]

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,

\[ \text{wage}_{it} = \sum_{\tau=-2}^{7} \tilde{\xi}_{\tau} \text{train}_{it-\tau} + \tilde{\zeta} \text{age}_{it} \times \text{train}_{it} + \chi_{it} \beta + \epsilon_{it} \]

Notice that age is assumed to only impact the return post training. \( \chi_{it} \) 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,

\[ \text{wage}_{it} = \sum_{\tau=-2}^{7} \tilde{\xi}_{\tau} \text{train}_{it-\tau} + \tilde{\zeta} \text{fluidity}_{it} \times \text{train}_{it} + \chi_{it} \beta + \epsilon_{it} \]

where \( \chi_{it} \) includes a full set of individual and country-year effects.

Table 9 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 9. RETURN TO ON-THE-JOB TRAINING

<table>
<thead>
<tr>
<th></th>
<th>(1) Baseline</th>
<th>(2) Age</th>
<th>(3) Age slope</th>
<th>(4) Fluidity</th>
</tr>
</thead>
<tbody>
<tr>
<td>( train_{t+2} )</td>
<td>0.004</td>
<td>0.000</td>
<td>0.001</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>( train_{t+1} )</td>
<td>0.003</td>
<td>-0.000</td>
<td>-0.000</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>( train_{t} )</td>
<td>0.002</td>
<td>-0.001</td>
<td>0.005</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>( train_{t-1} )</td>
<td>0.018***</td>
<td>0.011***</td>
<td>0.009***</td>
<td>0.017***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>( train_{t-2} )</td>
<td>0.026***</td>
<td>0.020***</td>
<td>0.018***</td>
<td>0.025***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>( train_{t-3} )</td>
<td>0.017***</td>
<td>0.011***</td>
<td>0.010***</td>
<td>0.016***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>( train_{t-4} )</td>
<td>0.022***</td>
<td>0.020***</td>
<td>0.019***</td>
<td>0.022***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>( train \times Age )</td>
<td></td>
<td>0.001***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.000)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( train \times Fluidity )</td>
<td></td>
<td></td>
<td>0.205*</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.114)</td>
<td></td>
</tr>
</tbody>
</table>

R2 0.841 0.843 0.843 0.841

Note: ECHP (1994–2001); *10%; **5%; ***1%; see text for further details.

Figure 33 illustrates the wage impact of training based on the estimates in column 2.

Figure 33. ESTIMATED WAGE IMPACT OF ON THE JOB TRAINING IN YEAR ZERO

Note: ECHP (1994–2001); see text for further details.
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.

I.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,

$$ \text{search}_{it} = \alpha \text{fluidity}_{c(i)} + X_{it}\beta + \varepsilon_{it} $$

where I include in $X_{it}$ 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 10 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 fluid-
ity 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 10. **Fluidity and Job Search**

<table>
<thead>
<tr>
<th></th>
<th>Employed</th>
<th>Unemployed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) No educ.</td>
<td>(2) Educ.</td>
</tr>
<tr>
<td>Fluidity</td>
<td>1.07836***</td>
<td>1.00252***</td>
</tr>
<tr>
<td></td>
<td>(0.24843)</td>
<td>(0.25321)</td>
</tr>
<tr>
<td>Age</td>
<td>-0.00425**</td>
<td>-0.00436**</td>
</tr>
<tr>
<td></td>
<td>(0.00140)</td>
<td>(0.00140)</td>
</tr>
<tr>
<td>Age²</td>
<td>0.00006</td>
<td>0.00007</td>
</tr>
<tr>
<td></td>
<td>(0.00008)</td>
<td>(0.00008)</td>
</tr>
<tr>
<td>Age³</td>
<td>-0.00000</td>
<td>-0.00000</td>
</tr>
<tr>
<td></td>
<td>(0.00000)</td>
<td>(0.00000)</td>
</tr>
<tr>
<td>College</td>
<td>0.02027**</td>
<td>0.07565*</td>
</tr>
<tr>
<td></td>
<td>(0.00682)</td>
<td>(0.03591)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.11209***</td>
<td>0.10630***</td>
</tr>
<tr>
<td></td>
<td>(0.00978)</td>
<td>(0.00973)</td>
</tr>
<tr>
<td>N</td>
<td>119,002</td>
<td>118,617</td>
</tr>
<tr>
<td>R²</td>
<td>0.01577</td>
<td>0.01718</td>
</tr>
</tbody>
</table>

Note: ECHP (1994–2001) and PSID (1990–1997); *10%; **5%; ***1%; see text for further details.

I.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,

\[ \text{mob}_{it} = \sum_{\tau = -2}^{2} \xi_{\tau} \text{search}_{it-\tau} + X_{it} \beta + \epsilon_{it} \]

I alternatively include in \( X_{it} \) 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 II 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>
<thead>
<tr>
<th>JtJ</th>
<th>EU</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Base FE FE+Age</td>
</tr>
<tr>
<td>search (_{t+2})</td>
<td>-0.00312 -0.01435*** -0.01385***</td>
</tr>
<tr>
<td></td>
<td>(0.00415) (0.00516) (0.00517)</td>
</tr>
<tr>
<td>search (_{t+1})</td>
<td>0.00532 -0.00384 -0.00409</td>
</tr>
<tr>
<td></td>
<td>(0.00400) (0.00486) (0.00486)</td>
</tr>
<tr>
<td>search (_{t})</td>
<td>-0.03238*** -0.05223*** -0.05192***</td>
</tr>
<tr>
<td></td>
<td>(0.00368) (0.00493) (0.00489)</td>
</tr>
<tr>
<td>search (_{t-1})</td>
<td>0.07609*** 0.07374*** 0.07373***</td>
</tr>
<tr>
<td></td>
<td>(0.00545) (0.00587) (0.00586)</td>
</tr>
<tr>
<td>search (_{t-2})</td>
<td>0.01948*** 0.01476** 0.01449**</td>
</tr>
<tr>
<td></td>
<td>(0.00484) (0.00574) (0.00573)</td>
</tr>
<tr>
<td>N</td>
<td>112,377 110,623 110,623</td>
</tr>
<tr>
<td>R2</td>
<td>0.04008 0.27717 0.27652</td>
</tr>
</tbody>
</table>

Note: ECHP (1994–2001) and PSID (1990–1997); *10%; **5%; ***1%; see text for further details.

The left pane of Figure 34 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 34 plots the estimated change in the involuntary separation hazard around the time of employed job search, based on the estimates in column 6.
Figure 34. 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.