Labor Market Fluidity and Human Capital Accumulation

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November, 2020

Abstract

I document in rich micro panel data across 23 OECD countries that life-cycle wage growth is greater in countries where job-to-job mobility is more common, but only a quarter of this is accounted for by wage gains upon job-to-job moves. A life-cycle theory of training and job shopping predicts that a faster rate of climbing the job ladder incentivizes training by raising the return to human capital. Policies that lower labor market fluidity reduce labor productivity by 15 percent across the OECD relative to the US. I provide direct, reduced-form evidence that training is higher in more fluid labor markets.

*niklas.engbom@gmail.com. This is the first chapter of my PhD dissertation at Princeton University. It previously circulated under the title "Worker Flows and Wage Growth over the Life-Cycle: A Cross-Country Analysis." I am grateful for the generous support and advice of Richard Rogerson. I thank Mark Aguiar, Jorge Alvarez, Adrien Bilal, Victoria Gregory, Veronica Guerrieri, Gregor Jarosch, Greg Kaplan, Burhan Kuruscu, Guido Menzio, Claudio Michelacci, Ben Moll, Chris Moser, Diego Restuccia, Todd Schoellman, Gianluca Violante, three anonymous referees, and seminar participants at various places. 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 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.[1] The literature, however, has tended to focus on the effect 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 workers' responses to such large differences in the functioning of the labor market may have a first-order effect on aggregate economic outcomes.

My main contribution is to quantify the impact of differences in the fluidity of the labor market on workers' careers, where by *labor market fluidity* I henceforth mean the frequency at which workers make job-to-job (JJ) transitions. To that end, I proceed in five steps. I start by building an internationally comparable worker-level panel data set covering almost one million observations for over 20 years. These data offer a unique cross-country perspective on life-cycle labor market dynamics, and suggest wide dispersion across countries in labor market flows and worker career dynamics. For instance, labor market fluidity differs by a factor of 2.5 across countries, while workers experience substantially greater life-cycle wage growth in some countries, mirroring findings in Lagakos et al. (2018).

My main empirical finding is that wages grow more over the life-cycle in more fluid labor markets. The panel dimension of my data allows me to rule out that this is driven by differential selection patterns over the life-cycle across countries by controlling for individual-fixed effects. Moreover, by standardizing education and occupation classifications across countries, I conclude that differences in workforce composition along such dimensions across countries do not drive the patterns.

Yet it is not entirely surprising that wages grow more over the life-cycle in countries where JJ mobility is more common, as such transitions are typically associated with wage gains. Indeed, I document that wages, in a residual sense, rise by 5–6 percent more in years when a worker makes a JJ move, and that the magnitude of these gains is uncorrelated with labor market fluidity. Nevertheless, in an accounting sense, accumulating such wage gains over the life-cycle, they cumulatively account for only about a quarter of the steeper life-cycle wage growth in more fluid labor markets. That is, most of the steeper life-cycle wage growth in more fluid labor markets arises within jobs, as opposed to between jobs.

To understand these patterns, the second part of the paper develops an equilibrium search model in the Diamond (1982)–Mortensen and Pissarides (1994) tradition with on-the-job training. The marginal product of a worker's human capital differs across firms, but frictions in the labor market prevent work-

[1] See, e.g. Bentolila and Bertola (1990), Hopenhayn and Rogerson (1993), Ljungqvist and Sargent (1998, 2008), Alvarez and Veracierto (1999), Blanchard and Portugal (2001) and Pries and Rogerson (2005).

ers from immediately reallocating to their most productive use. I make one key modification to an earlier literature on training in frictional labor markets (Acemoglu, 1997; Acemoglu and Pischke, 1998, 1999): I allow workers to move directly from one employer to another without an intervening spell of unemployment, motivated by empirical evidence that such job-to-job (JJ) mobility is a pervasive feature of workers' careers (Topel and Ward, 1992).[2] A young worker enters the labor market with few skills and in a job that does not utilize her skills particularly well. Through on-the-job training, she gradually builds her skills. Other firms try to poach her, such that over time she reallocates toward jobs that use her skills efficiently—she *climbs the job ladder* (Burdett and Mortensen, 1998). As a result, life-cycle growth in both the quantity and price of human capital are endogenous equilibrium objects.

I use the model to examine the impact on worker careers of wedges to firms' cost of creating jobs, motivated by a large literature that argues that policies such as, for instance, employment protection legislation, business regulations, and labor taxes serve to raise the cost to firms of hiring (Fonseca et al., 2001; Pries and Rogerson, 2005). Such wedges reduce labor market fluidity. As workers have a harder time finding a job that uses their skills efficiently, the expected value of human capital declines. Workers respond by accumulating less human capital, such that the stock of human capital falls.

In the third part of the paper, I bring the model to the data, targeting the US as a high fluidity country. JJ mobility declines over the life-cycle, as workers gradually find a good job. Wages grow rapidly early in careers, as young workers have significant scope to climb the job ladder and face high returns to training. My estimates imply that human capital is the most important source of life-cycle wage and productivity growth, with growth in match productivity a close second.

The fourth part of the paper uses the estimated framework to quantify the impact of labor market fluidity on workers' careers. Holding all other parameters fixed at their estimated values, I consider the impact of wedges to firms' cost of creating jobs such that the model matches the cross-country variation in labor market fluidity. Differences in labor market fluidity account for 50 percent of the steeper life-cycle wage growth in more fluid labor markets across my sample of OECD countries. Across the OECD, labor productivity is 15 log points lower relative to the US. In summary, my findings highlight that policies and regulations that reduce labor market fluidity in turn have large negative consequences on both workers' life-cycle wage growth and aggregate economic outcomes.

I proceed to conduct a series of counterfactual exercises that isolate the role of various forces. Match productivity grows less over the life-cycle in less fluid labor markets as workers climb the job ladder slower, accounting for 40 percent of the lower life-cycle wage growth. Of the eight log point lower

[2] Acemoglu and Pischke (1998) briefly discuss the effect of allowing for poaching—what they refer to as *raids*—noting that "whether raids are possible or not, may have important consequences for training." They do not pursue this further, though.

accumulation of human capital in the least fluid labor market relative to the US, 41 percent is due to the fact that workers spend more time in unemployment, where they do not accumulate skills. 35 percent is accounted for by workers increasingly being stuck at the bottom of the job ladder, where they have less incentive to accumulate skills since those are less useful. The remainder is due to the fact that conditional on a worker's current labor market state, she is discouraged from accumulating skills by the higher expected incidence of unemployment and slower rate of climbing the job ladder.

In the last part of the paper, I return to the micro data to document three patterns consistent with the theory. To that end, I standardize data on vocational training for nine countries based on an identical survey fielded by the European Union's statistical agency, Eurostat. First, workers spend more time on vocational training in more fluid labor markets. This pattern is not accounted for by cross-country differences in age, education or occupation. Second, conditional on worker-fixed effects and time-varying covariates, within countries workers train more when employed at larger, higher paying employers. This pattern is consistent with the predictions of the theory that, *ceteris paribus*, workers train more in more productive, higher paying matches, as such matches afford them greater use of their skills. Third, workers in less fluid labor markets train disproportionately less at small, low paying employers. According to the theory, this is because in less fluid labor markets workers currently in low productive matches have a harder time moving to jobs where they can better use their skills. Expecting this, they train less.

The premise of this paper is to take differences in labor market fluidity as given to assess their consequences for worker behavior. I hence purposefully avoid taking a strong stand on the exact policies that result in lower labor market fluidity, which has been the focus of a large literature. My reading of that literature is that several polices likely combine to discourage firms from creating jobs in some countries. Consistent with this view, I end my analysis by showing that policies such as employment protection legislation, regulations that raise the cost on firms of doing business, and labor taxes on firms are all negatively correlated with labor market fluidity. That being said, I offer no new insights on this front. Rather, the novelty of this paper should be viewed as taking such policies and the static misallocation they give rise to as given to assess their dynamic consequences, in the spirit of Restuccia and Rogerson (2017, p.170)'s argument that "whereas much of the literature has focused on static misallocation, we think the dynamic effects of misallocation deserve much more attention going forward."

Previous literature. This paper contributes to three strands of the literature. First, a literature documents cross-country differences in labor market outcomes. Whereas much work has focused on hours worked or unemployment (see Nickell, 1997, for an overview), less work assesses differences in life-cycle wage growth or labor market flows, particularly JJ mobility. Based on aggregate data, Hobijn and Sahin

(2009) document flows in and out of unemployment across 27 OECD countries, while Jolivet et al. (2006) find JJ mobility patterns consistent with this paper across 11 countries for 1994–1997. Blanchard and Portugal (2001), Schönberg (2007), and Dustmann and Pereira (2008) provide two-country comparisons. Lagakos et al. (2018) show that richer countries have steeper life-cycle wage growth across 18 countries at different stages of development, while Donovan et al. (2020) study differences in labor market flows across rich and poor countries.[3]

Second, a literature studies on-the-job training in frictional labor markets (Pigou, 1912; Becker, 1964). Stevens (1994) and Acemoglu (1997) show that training is generally inefficient as future employers appropriate part of the returns; Moen and Rosén (2004) overturn this conclusion in a directed search framework. Acemoglu and Pischke (1998, 1999) argue that training may decrease with mobility. Wasmer (2006) notes that high turnover increases incentives to accumulate general rather than specific skills—a distinction which I abstract from. A related literature quantifies the role of human capital and search in life-cycle outcomes (Yamaguchi, 2010; Bagger et al., 2014; Karahan et al., 2020). Bowlus and Liu (2013) are closest to this paper in that they allow for endogenous training, but in a partial equilibrium setting. Gregory (2019) shows that workers grow their human capital more at some firms, which is consistent with the argument in this paper (but here it arises through optimizing training decisions rather than exogenous differences in firms' learning environment). Engbom (2020) proposes a theory of search and entrepreneurship to study the impact of demographic change within countries, whereas the current paper assesses how search and training interacts in a model of endogenous human capital accumulation with a focus on cross-country patterns.

Third, a vast literature assesses the sources of cross-country income differences. Seminal work by Klenow and Rodríguez-Clare (1997), Prescott (1998) and Hall and Jones (1999) find that differences in total factor productivity (TFP) play a key role behind income differences. Erosa et al. (2010) and Manuelli and Seshadri (2014) challenge this conclusion, arguing that human capital accounts for a significant share of cross-country differences. The latter is closest to this paper in that they also allow for on-the-job accumulation of skills, but abstract from labor market frictions.

Section 2 documents how wage growth and labor market fluidity covary across countries. Section 3 develops the theory and Section 4 estimates it. Section 5 quantifies the impact of labor market fluidity in the estimated model. Finally, Section 6 provides reduced-form support for the predictions of the theory.

[3] The latter confirm my findings among the set of developed countries for which our data overlap, but find that poor countries are characterized by *higher* labor market flows. See, for instance, Panel B of their Table 2, which "provides the regression estimates from a sample that includes only EU countries, Switzerland, the U.K., and the United States. For this sample, we also find a positive relationship between labor market flows and development" (Donovan et al., 2020, p.14). This finding is reassuring given that they rely on different data.

2 Motivating correlations

I start by documenting how life-cycle wage growth and labor market fluidity covary across countries. To that end, I build an internationally comparable worker-level panel data set covering 23 OECD countries. Specifically, I rely on data from the following sources and time periods: the US Panel Study of Income Dynamics (PSID) 1994–2015; the German Socio-Economic Panel (GSOEP) 1991–2011; the British Household Panel Survey (BHPS) 1991–2008; the European Community Household Panel (ECHP) 1994–2001; and the European Union Statistics on Income and Living Conditions (EUSILC) 2003–2014. While a cross-country comparison inevitably is subject to issues of comparability, an important advantage of these data sets is that they are modeled on the PSID, facilitating the international comparison.[4] In the interest of space, Appendix A.1 provides a more detailed discussion of the data sources.

2.1 Variable definitions

I construct two samples. The first is an annual sample used in my wage analysis. The wage is total gross labor income in the prior calendar year divided by annual hours worked,[5] constructed as the product of weeks worked times usual weekly hours. I top-code weekly hours at 98 hours to be consistent with the PSID. I include in labor income also income from self-employment to be consistent with the BHPS, which does not distinguish sources of labor income. I do, however, focus on those who are wage employed at the time of the survey—henceforth employees.[6] I convert nominal values to real 2004 local currency using the national CPI, then to real US dollars using the PPP-adjusted exchange rate in 2004.

The second sample is a monthly data set, which I use to estimate labor market flows. The surveys ask for labor market status in each month during the prior *calendar year*. By linking subsequent years, I obtain labor force status in each month during the 12 months prior to the *survey month*. In particular, a worker is said to make an EU transition if she is employed in the current month but unemployed in the subsequent month. She makes an UE transition if she is unemployed in the current month but employed in the subsequent month.[7] The available data sets do not allow for the construction of a satisfactory monthly

[4] For this reason, I prefer to use the PSID in my main analysis of worker flows. Appendix A.2 shows that the resulting flows are broadly consistent with those in the US Survey of Income and Program Participation (SIPP).

[5] In the PSID, each subcomponent of total income is top-coded at separate thresholds that vary across years. I use a Pareto imputation to top-coded subcomponents in each year before I sum each component to get total income (Heathcote et al., 2010). The BHPS records income and hours from September to September instead of by calendar year.

[6] Robustness exercises suggest that differences in self-employment income among wage employees are third-order with respect to the patterns documented here (available for all countries but the UK).

[7] The PSID does not allow a distinction between wage and self-employment in the monthly calendar of events, and hence to be consistent all monthly flows include the self-employed as employed. In the other data sets as well as in the US SIPP, though, flows from employment to (and from) self-employment are an order of magnitude smaller than those to (and from) unemployment, so I believe that this issue is second-order.

measure of JJ mobility, because the surveys in general ask for information on only (up to) two employment spells in the prior year. As a consequence, at most one JJ move can be observed during the past 12 months, even though the worker might have made multiple transitions. For young, highly mobile workers in particular, this restriction is not innocuous. Hence, I instead construct a consistent measure of JJ mobility across countries as the fraction of employees who started working for their current employer at some point in the past 11 months while having had employment as the main employment status in every of the past 12 months. Subject to one caveat, this measure accounts for intervening months of non-employment between job switches—it is *not* equivalent to the fraction of employed workers who were at a different employer 12 months earlier. The one caveat is that it does not rule out short intervening spells of unemployment, as I only observe main employment status in a month. Because flows in and out of unemployment are so low, however, I doubt time aggregation majorly biases my results.[8]

I standardize year of birth to the modal value across panel years, education into two groups—less than college or college or more—based on an individual's highest reported degree across panel years, and occupation into 10 internationally comparable, aggregate occupation groups based on ISCO-88.

2.2 Sample selection and variable definitions

I focus on men, as female labor force participation likely varies across countries for reasons that the theory in the next section abstracts from.[9] To limit the impact of issues associated with labor force entry and retirement, I primarily focus on ages 25–54, but present additional samples as robustness. As I discuss in Appendix A.3, male labor force participation rates are consistently high across countries between ages 25–54. Moreover, there is no statistically significant correlation between labor force participation rates and labor market fluidity, either at the aggregate level, at age 25 or at age 54. Additionally, I drop observations with missing year of birth or employment status, as well as individuals whose reported year of birth deviates by more than five years across panel years. This excludes very few observations.

I focus on employees and flows in and out of unemployment, as the theory also abstracts from self-employment and non-participation. Flows in and out of non-participation are small, however, and do not vary systematically with labor market fluidity among prime aged men. I include all wage employees, regardless of full-time status, but similar results hold among those working 30+ hours a week. In my

[8] As part of the estimation in Section 4, I simulate a monthly approximation to the underlying continuous time model. I have alternatively simulated a weekly model and aggregated that up to the monthly level. It has a second-order impact on my measure of JJ mobility, precisely because flows in and out of unemployment are so low. The fact that flows in and out of unemployment are estimated to be much lower in panel data relative to primarily cross-sectional data such as the US Current Population Survey has been long recognized in the literature, driven by employment status classification error (Abowd and Zellner, 1985; Poterba and Summers, 1986). See Appendix A.2 for more details and a comparison with the US SIPP.

[9] In a separate, ongoing project I study cross-country gender differences in careers.

main analysis, I do not condition on being in the private sector, partly because the EUSILC does not make available sector to researchers. Appendix A.4 argues that the public-private distinction is unlikely to be a main force driving the cross-country patterns documented here (among primate aged men).

My analysis focuses primarily on 13 developed Western European countries and the US for which I have 15 or more years of data. I report robustness results including an additional 10 OECD countries for which I have fewer years of data.[10] The core annual sample includes over six hundred thousand observations, with another two hundred thousand observations for the other OECD countries.

Figure 1 plots the share of employees who made a JJ move at some point in the previous year—my measure of labor market fluidity—over the life-cycle across the core countries. JJ mobility has a common shape: it is high early in careers, and subsequently declines substantially as individuals age. There are significant differences in the level of labor market fluidity across countries, with some countries displaying higher fluidity at all ages. These high fluidity countries include the Anglo-Saxon countries (UK and US), as well as Denmark and the Netherlands. On the other end of the spectrum, Belgium, Austria and Greece have JJ mobility rates that are less than half those in the US at all ages.

I next construct life-cycle wage profiles by regressing separately by country the log hourly real wage of individual i in year t, w_{it}, on age effects, A_{it}, year effects, Y_t, and individual fixed effects, I_i,

$$w_{it} \;=\; A_{it} + Y_t + I_i + \varepsilon_{it} \tag{1}$$

The inclusion of individual fixed effects in regression (1) addresses important concerns about differences in sample attrition across countries biasing the cross-country comparison of life-cycle wage growth. In my benchmark, I compute wage growth by age. But I also report results below controlling for education—isomorphic to wage growth by potential experience—with similar results.

Whenever an individual gets one year older, time also increases by one year, and vice versa. That is, age, time and individual fixed effects are collinear. Hence, a restriction is needed to identify regression (1). I follow Heckman et al. (1998) and Lagakos et al. (2018) in imposing that wages depreciate at some rate d after some age $\bar{A}$. This restriction is sufficient to separate individual, time and age effects. Effectively, fluctuations in wages among individuals older than $\bar{A}$ identify the year effects. The age effects can then be recovered from within-individual fluctuations in wages among those aged less than $\bar{A}$.

Figure 1 plots wage growth between ages 25–50 across countries, assuming that wages do not grow

[10] The EUSILC also contains a few years of data from five non-OECD countries: Bulgaria, Cyprus, Malta, Romania and Serbia. I have confirmed that my empirical facts hold also including these non-OECD countries, but I prefer to focus in this paper on the set of relatively comparable OECD countries. This has the added convenience that the OECD provides easily accessible, internally consistent measures of GDP per hour, price levels, PPP-adjusted exchange rates, etc., online for its member countries.

after age 50. Across all countries, life-cycle wage profiles share a common shape, with wages growing rapidly early in careers. In contrast to the common shape, there is a remarkable degree of heterogeneity across countries in the overall wage growth over the life-cycle, as emphasized by Lagakos et al. (2018).[11]

Appendix A.5 plots the EU and UE rates over the life-cycle across countries. The EU rate shares a common shape across countries, with high rates of job loss early in careers and subsequent declines. Aggregate cross-country differences are less pronounced than for JJ mobility, with Spain as an exception. The UE rate is roughly flat between ages 25–54 in most countries, although its shape is somewhat more heterogeneous across countries than the EU and JJ rates. Labor market fluidity is negatively correlated with the aggregate EU rate and positively correlated with the aggregate UE rate.

2.3 Wages grow more over the life-cycle in more fluid labor markets

The left panel of Figure 2 plots life-cycle wage growth against labor market fluidity across the core set of 13 countries. Wages grow substantially more in more fluid labor markets. For instance, wages grow by 75 log points in the US between age 25–54, but only by 30 log points in Italy. The right panel shows that similar results hold when including the additional 10 countries with fewer years of data, with a correlation coefficient between life-cycle wage growth and labor market fluidity of around 0.8.

One possible factor behind these patterns is differences in workforce composition. To assess this, I consider an augmented version of regression (1) that instead pools all countries and years,

$$w_{it} \quad = \quad \alpha \times \text{fluidity}_c \times a_{it} \; + \; X_{it}\beta \; + \; I_i \; + \; Y_t \; + \; A_{it} \; + \; \varepsilon_{it} \tag{2}$$

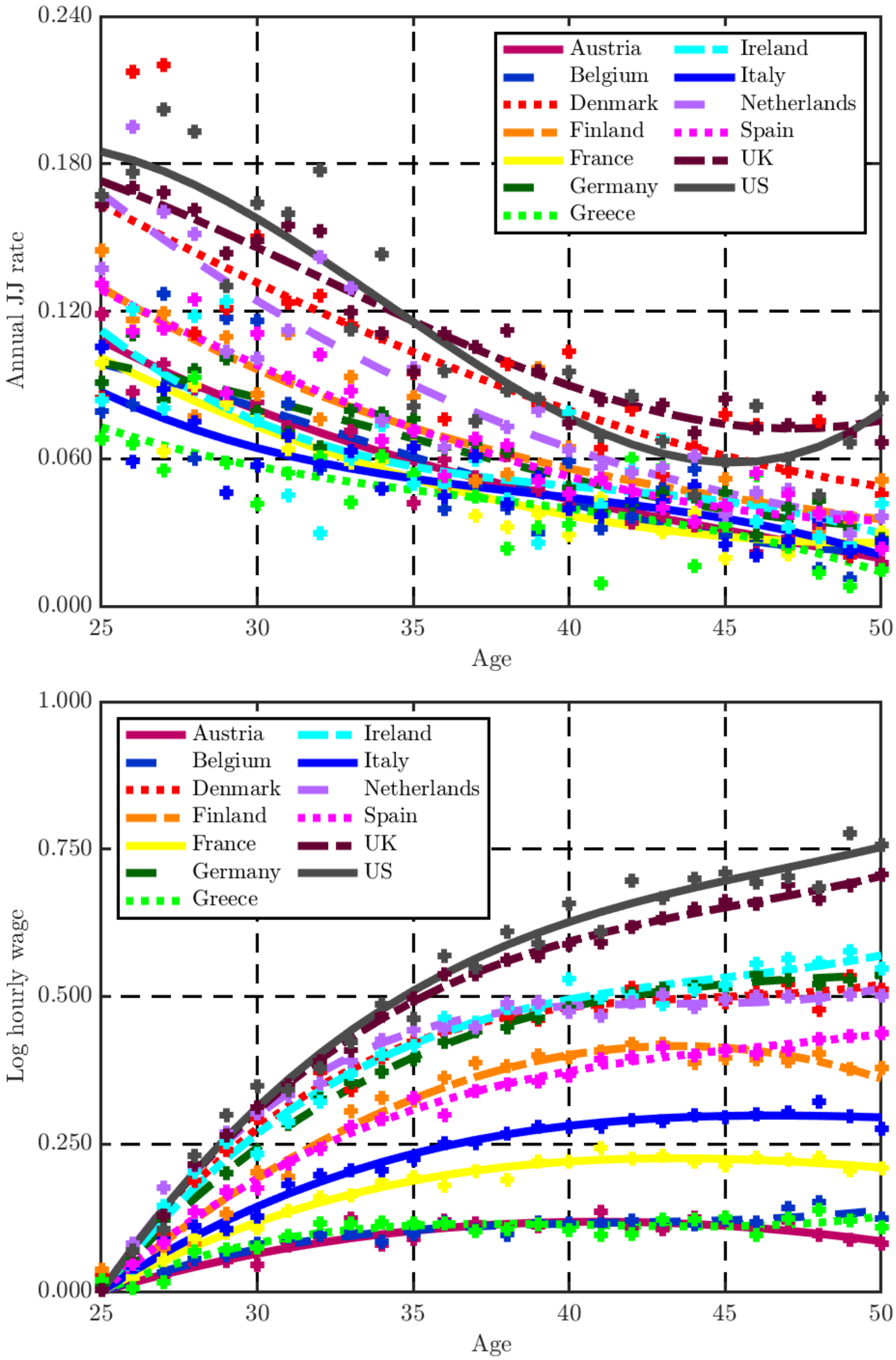
As above, w_{it} is the log real hourly wage, I_i are individual fixed effects, Y_t are year effects, and A_{it} are restricted age effects. The coefficient α captures the covariance between life-cycle wage growth and labor market fluidity, while X_{it} controls for separate age slopes for two education groups or 10 occupation groups (minus one due to collinearity). I renormalize the provided survey weights such that each country in the aggregate receives a total weight of one,[12] and cluster standard errors by country.

Table 1 presents regression results from several specifications, including allowing for wages to fall late in life and extending the sample to include all workers aged 22–59. Confirming the pattern in Figure

[11] Broadly, where our studies overlap, the wage profiles I document align well with Lagakos et al. (2018). The main exception is Germany, which they find has the highest wage growth (steeper than the US). I confirm this finding in a specification that includes workers aged 22–59, which may be closer to their specifications that include all workers with 0–40 years of experience. My patterns remain robust to such alternative specifications. Nevertheless, I prefer to focus on ages 25–54 due to higher non-participation rates prior to 25 and after age 54 (see Appendix A.3), which the theory abstracts from. Another difference is that my panel data allow me to control for selection on unobservables using worker fixed effects.

[12] For countries with observations in the ECHP and EUSILC, I adjust the weights such that each country-survey receives a relative weight equal to the number of years of data for that country in that survey, and the total weight for the country is one.

FIGURE 1. LABOR MARKET FLUIDITY (TOP) AND WAGE PROFILES (BOTTOM)

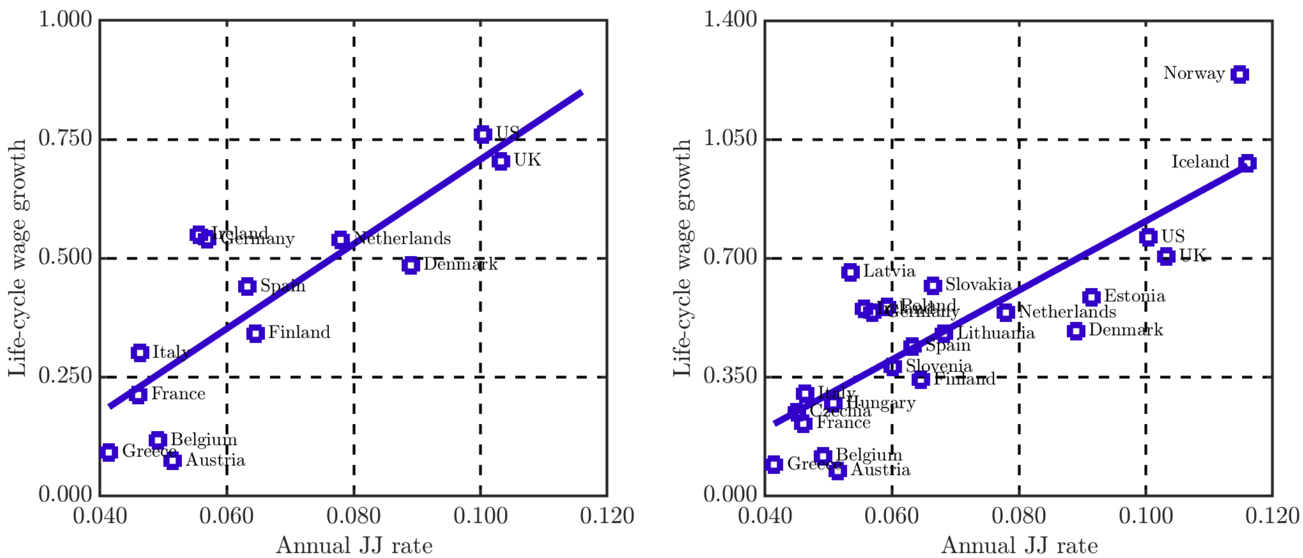


Note: Male employees aged 25–54. JJ mobility: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Employment in the past 12 months includes self-employment due to data limitations. Constructed by first collapsing the data to the country-age-year level using the provided survey weights, then to the country-age-level. Log hourly real wage profile based on (1) with worker fixed effects, time effects and age effects restricted to not grow past age 50. *Source:* BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

2, there is a strong, statistically significant positive correlation between labor market fluidity and life-cycle wage growth in the baseline specification. While college graduates, for instance, experience greater life-cycle wage growth, differences in educational or occupational composition across these developed countries are much too small to change this conclusion. Allowing for a different depreciation rate late in careers makes virtually no difference to the point estimate. Moreover, extending the sample to start at age 22 and/or include those up to age 59 does not change the conclusion. In additional results I reach the same conclusion including workers up to age 64, including instead setting $\bar{A} = 55$.

FIGURE 2. LIFE-CYCLE WAGE GROWTH AND LABOR MARKET FLUIDITY

(A) CORE COUNTRIES (B) ALL COUNTRIES



Note: Male employees aged 25–54. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Employment in the past 12 months includes self-employment due to data limitations. Constructed by first collapsing the data to the country-age-year level using the provided survey weights, then to the country-level. Life-cycle wage growth: Log hourly real wage profile based on regression (1) with worker fixed effects, time effects and age effects restricted to zero growth after age 50. *Source:* BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

It is, perhaps, not surprising that wages grow more in countries where workers on average make more JJ transitions, as such transitions typically involve a wage gain. Indeed, the left panel of Figure 3 shows that across all countries, the average worker tends to experience greater growth in wages in years when she made a JJ move. It projects the difference in median annual wage growth between those who made a JJ move in the year and those who did not on labor market fluidity, computed within age-year bins and subsequently aggregated to the country-level giving equal weight to each year-age. I use the median to limit the impact of a few outliers.[13] A JJ mover experiences 5.5 percent greater residual

[13]Because the PSID turned biannual in 1997, the estimate of wage gains for the US relies only on years 1994–1997. As I show in Section 4, however, the wage gain upon a JJ move is similar in the SIPP for more recent years and I reach very similar

wage growth in a year relative to a stayer with the same age in the same year. There is no systematic relationship between the wage gain upon a JJ move and labor market fluidity.

TABLE 1. LIFE-CYCLE WAGE GROWTH AND LABOR MARKET FLUIDITY

	Ages 25–54			1% depreciation			Ages 22–59		
	Panel A. Core 13 countries								
	Baseline	Educ	Occup	Baseline	Educ	Occup	Baseline	Educ	Occup
α	0.244***	0.217**	0.224***	0.244***	0.217**	0.224***	0.261***	0.230***	0.238***
	(0.074)	(0.076)	(0.069)	(0.074)	(0.076)	(0.069)	(0.069)	(0.069)	(0.065)
N	336,349	334,415	323,888	336,349	334,415	323,888	393,910	391,042	379,094
	Panel B. All 23 countries								
α	0.242***	0.217**	0.219**	0.242***	0.217**	0.219**	0.257***	0.228***	0.231***
	(0.081)	(0.083)	(0.078)	(0.081)	(0.083)	(0.078)	(0.078)	(0.078)	(0.076)
N	474,919	472,836	449,644	474,919	472,836	449,644	562,239	559,214	531,729

Note: Male employees. Ages 25–54: Wages restricted to not grow after age 50. 1% depreciation: Ages 25–54 with wages restricted to depreciate 1% annually after age 50. Ages 22–59: Wages restricted to not grow after age 50. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Employment in the past 12 months includes self-employment due to data limitations. Constructed by first collapsing the data to the country-age-year level using the provided survey weights, then to the country level. α: Fluidity-age interaction in regression (2) with worker fixed effects, time effects and restricted age effects. Standard error below are clustered at the country-level. ** statistically significant at 5%; *** statistically significant at 1%. *Source:* BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

The right panel uses these gains upon a JJ move to estimate the contribution of a higher rate of job shopping in more fluid labor markets toward life-cycle wage growth. In particular, the *between-job* series multiplies the wage gain from a JJ move with the average number of JJ moves an individual makes between age 25–54 to get the total predicted wage gain associated with JJ moves over the life-cycle.[14] I compute the *within-job* series as the difference between total wage growth and between-job wage growth. I stress that no structural interpretation should be assigned to the components—it is simply an accounting decomposition. Less than a quarter of the steeper life-cycle wage growth in more fluid labor markets is accounted for by between-job wage growth. Because the average wage gain is not correlated with fluidity, the steeper between-job wage growth in more fluid labor markets is entirely driven by the higher frequency of moves. Hence, while the between-job component is non-trivial, the majority of the steeper life-cycle wage growth in more fluid labor markets takes place within-jobs.

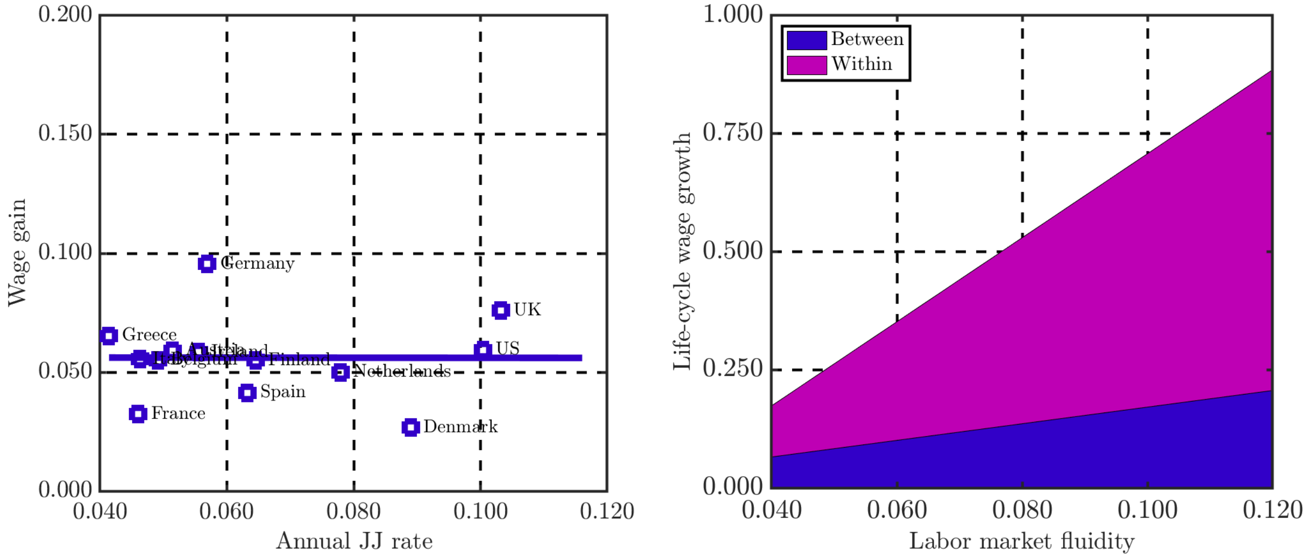
conclusions if I approximate the annual wage gain after 1997 in the PSID with the bi-annual wage gain.

[14]While there is a life-cycle profile to the wage gains upon a JJ move, this computation relies only on life-cycle averages. That is, it makes no difference to the total to use the age-specific wage gains (although it does matter for the timing of the gains).

FIGURE 3. THE ROLE OF BETWEEN-JOB WAGE GROWTH

(A) WAGE GAIN IN YEAR OF JJ MOVE

(B) BETWEEN VS WITHIN JOB



Note: Male employees aged 25–54. Panel A. Median annual wage growth of workers who made a JJ move in the past year relative to those who did not, computed within country-year-age groups and then collapsed to the country-level giving equal weight to each year-age. Panel B. Between-job: Product of the median wage gain from a JJ move and the average total number of JJ moves between age 25–54. Within-job: Difference between total wage growth between age 25–54 and the between-job component. Total wage growth based on (1) with worker fixed effects, time effects and age effects restricted to be zero past age 50. All panels. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Employment in the past 12 months includes self-employment due to data limitations. Constructed by first collapsing the data to the country-age-year level using the provided survey weights, then to the country level. *Source:* BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

2.4 Discussion

Before I go to the model, I establish some additional empirical patterns that help guide the analysis.

Entry wages. Table 2 regresses wages of labor market entrants—those aged 21–24—on labor market fluidity. Because this specification assesses level differences across countries, I cannot control for individual fixed effects. Wages of labor market entrants are in fact *lower* in more fluid labor markets, although the pattern is not statistically significant. Quantitatively, the estimates imply that entry wages are 2–6 percent higher in the least fluid labor market relative to the US. Controlling for differences in education or occupation composition does not change the broad takeaway. Controlling for real GDP per hour in 2004 PPP-adjusted US dollars makes the pattern more pronounced.[15]

[15] I am not convinced, however, that doing so makes sense. To the extent that the labor share does not covary systematically with fluidity (which it does not), controlling for labor productivity is isomorphic to controlling for the average wage. Given steeper life-cycle wage profiles in more fluid labor markets, controlling for the average wage will by construction result in entry wages appearing lower in more fluid labor markets.

TABLE 2. ENTRY WAGES AND LABOR MARKET FLUIDITY

$$w_{it} = \alpha fluidity_c + X_{it}\beta + \varepsilon_{it}$$

	Raw	Educ	Occup	GDP
α	-0.891	-0.358	-0.637	-3.105*
	(2.795)	(2.921)	(2.722)	(1.721)
N	21,266	20,342	20,200	21,266

Note: Male employees 21–24. Raw: Year controls only. Educ: Year and education controls. Occup: Year and occupation controls. GDP: Year and real GDP per hour controls (in 2004 PPP-adjusted USD). Wages: Log hourly real wage in 2004 US PPP-adjusted dollars. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Employment in the past 12 months includes self-employment due to data limitations. Constructed by first collapsing the data to the country-age-year level using the provided survey weights, then to the country-level. Standard errors are clustered at the country-level. * significant at 10%. *Source:* BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

What workers grow their wage more? Assessing what workers grow their wages more in more fluid labor markets may shed further light on potential driving forces behind the patterns. The left panel of Figure 4 re-estimates life-cycle wage growth based on (1) separately by education group, and projects it on labor market fluidity, also computed separately by education group. College educated workers grow their wage more over the life-cycle in all countries. Moreover, the gradient with labor market fluidity is steeper among college graduates (although Italy is a peculiar outlier).

The right panel considers an augmented version of the pooled regression (2) that includes a linear in an occupation's wage rank, as well as its interaction with age, fluidity and age times fluidity. I rank occupations within each country-year, and then assign the occupation its (unweighted) average across country-years.[16] Higher wage occupations experience steeper life-cycle wage growth. Moreover, they experience disproportionately steeper wage growth in more fluid labor markets relative to lower wage occupations, although the pattern is not statistically significant (p-value of 0.25). I conclude from these two exercises that the cross-country correlation between life-cycle wage growth and labor market fluidity is not driven by low skilled, low wage workers. At face value, this speaks against factors such as the minimum wage or unions, which typically impact lower skilled workers the most.

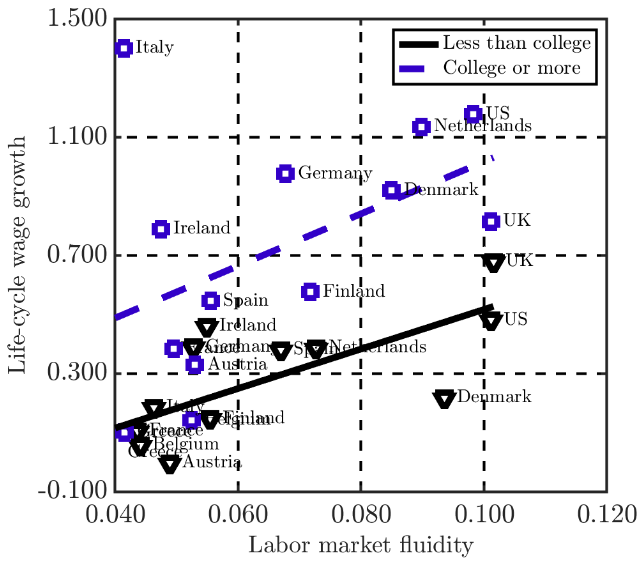
Inequality. Patterns for inequality may provide useful guidance on what drives the positive correlation between life-cycle wage growth and fluidity. For instance, Guvenen et al. (2014) emphasize that progressive taxation reduces life-cycle wage growth and inequality, which may be correlated with labor market fluidity. The top left panel of Figure 5 relates labor market fluidity to the standard deviation of log residual wages. I focus here on residual inequality, because that is what the theory in the next section is about. As I believe that this finding is somewhat novel to the literature, I provide a further discussion and robustness in Appendix A.6.

The top right panel graphs life-cycle growth in inequality against fluidity, where the former is the

[16] The resulting ranking makes intuitive sense, with engineers and doctors ranked the highest and laborers ranked the lowest.

difference in standard deviation of residual log wages at age 50–54 relative to at age 25–29. Neither the level of inequality nor its change over the life-cycle is systematically related to labor market fluidity. While inequality in general rises over the life-cycle across these countries, it is primarily accounted for by increasing dispersion across education and occupation groups. Within groups, there is not much of an increase in inequality, even in the US. See Appendix A.6 for more details.

FIGURE 4. WAGE GROWTH AND LABOR MARKET FLUIDITY BY EDUCATION AND OCCUPATION



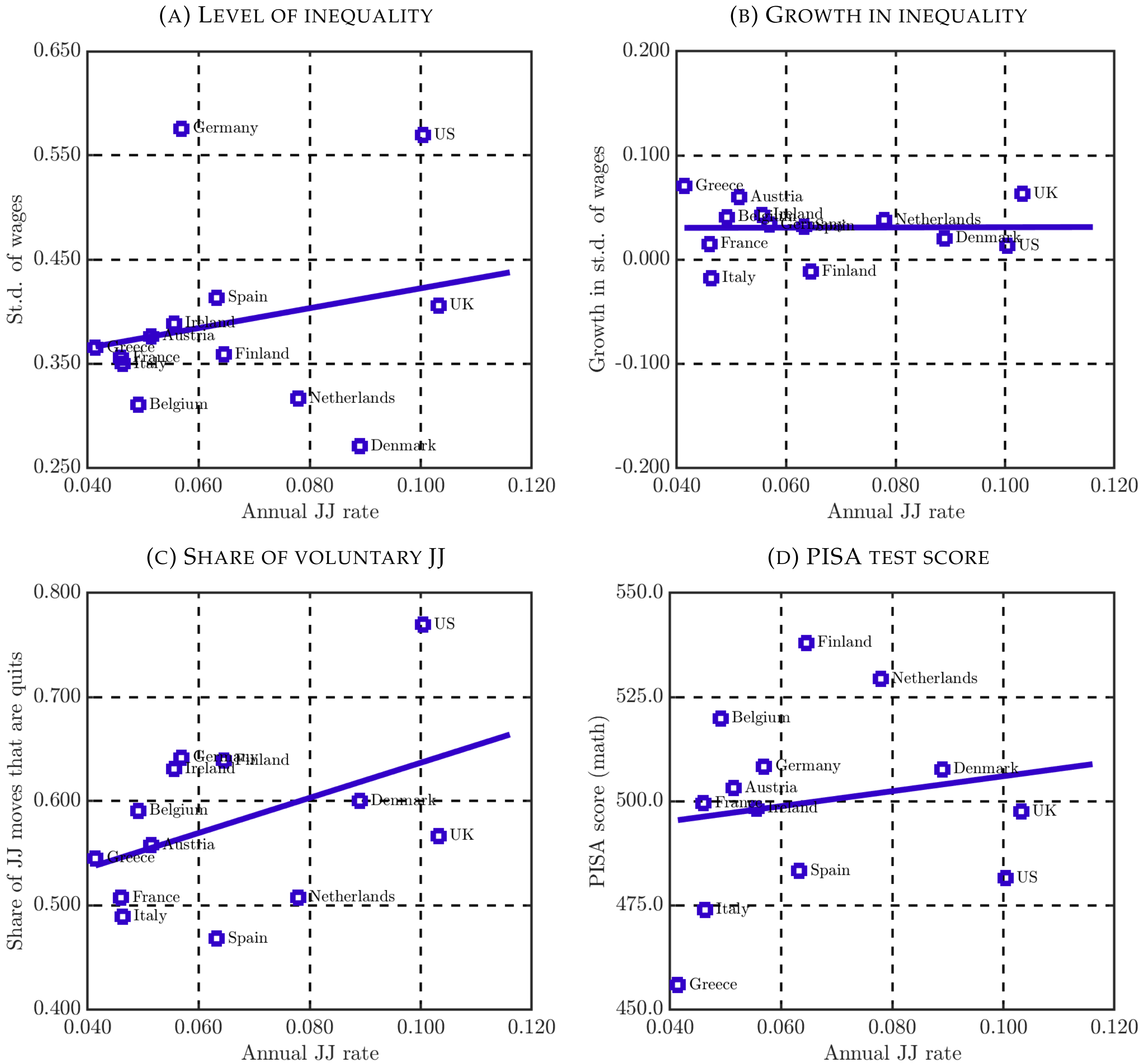
Interaction with occupation's wage rank

fluidity × age	0.222***
	(0.070)
occupation wage rank	-0.021***
	(0.006)
occupation wage rank × fluidity	-0.122
	(0.163)
occupation wage rank × age	0.002***
	(0.001)
occupation wage rank × fluidity × age	0.017
	(0.014)
N	359,394

Note: Male employees aged 25–54. Left panel. Life-cycle wage growth based on regression (1) separately by country and education groups with age effects restricted to not grow past age 50. Right panel. Pooled regression based on (2) with a linear in an occupation's wage rank (10 occupations), as well as its linear interaction with age, fluidity and fluidity times age. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Employment in the past 12 months includes self-employment due to data limitations. Constructed by first collapsing the data to the country-age-year level using the provided survey weights, then to the country-level (in the left panel separately by education groups). *Source:* BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

Voluntary versus involuntary. The data sets also include information on the reason for separation, which I standardize into those who quit the job versus the firm initiated the separation, which I somewhat loosely refer to as an involuntary separation. The bottom left panel shows that only about 60 percent of JJ movers report that they quit their job, with the remainder saying that the firm initiated the separation. If anything, the share of quits among JJ movers is higher in more fluid labor markets. Hence, the higher JJ rate is not driven by more involuntary movers. The distinction between an employer initiated separation and a quit, however, is murky. Indeed, the model in the next section predicts that separations are bilaterally optimal, with no theoretical distinction between a quit and the employer letting the worker go. For this reason, I prefer to use the overall measure of JJ mobility as my benchmark.

FIGURE 5. LABOR MARKET FLUIDITY AND POTENTIAL CONFOUNDING FACTORS



Note: Male employees aged 25–54. Panel A. St.d. of residual log hourly wages, controlling for year-education-age and year-occupation effects separately by country. Panel B. Growth in st.d. of residual log hourly wage between ages 25–29 and 50–54. Panel C. Share of JJ transitions in which the worker quit. Panel D. PISA math test score. Panels A–C. Constructed by first collapsing the data to the country-year-age level using the provided survey weights, then to the country-level. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Employment in the past 12 months includes self-employment due to data limitations. Constructed by first collapsing the data to the country-age-year level using the provided survey weights, then to the country-level. *Source:* BHPS, ECHP, EUSILC, GSOEP, OECD, and PSID 1991–2015.

Workforce quality. As alluded to above, one possibility is that the covariance between wage growth and fluidity is driven by workforce composition. Several reasons lead me to discount this hypothesis. First, the panel dimension of my data allows me to control for differential patterns of selection (in levels) via worker-fixed effects. Second, the estimates remain essentially unchanged when controlling for different education or occupational slopes. Third, as illustrated by the bottom right panel of Figure 5, labor market fluidity is not correlated with observable measures of the "quality" of the workforce, such as various PISA test score outcomes.[17] Fourth, my core sample includes only highly developed OECD countries, which arguably somewhat limits the potential scope for such differences to drive results.

3 Model

To interpret the patterns in the previous section and assess their aggregate implications, this section develops an equilibrium search model in the Diamond (1982)–Mortensen and Pissarides (1994) tradition with on-the-job search and training. In essence, the framework introduces endogenous skill accumulation following Ben-Porath (1967) into an otherwise standard equilibrium search model.

3.1 Environment

Time is continuous and infinite, there are no aggregate shocks and I focus on the long-run steady-state. The economy consists of a unit mass of finitely-lived workers and some positive mass of firms.

Preferences. All agents have linear preferences over a single output good discounted at rate ρ. Workers may allocate a unit of time indivisibly toward working or not working. As unemployed, a worker enjoys flow value of leisure $b(a,h)$, which may depend on her age a and current human capital h.

Demographics. Workers are ex ante heterogeneous in initial skills $h_0 \sim \Lambda$ and enter the labor market as unemployed. They exit the labor market at age A and are replaced with an equal mass of young workers. Upon retirement, workers enjoy a continuation value $\mathscr{A}$ that is independent of their labor market history. Under linear utility, I may, without loss of generality, normalize the continuation value to zero, $\mathscr{A} = 0$. I neither model the distribution of initial skills Λ, the retirement age A, nor the continuation value $\mathscr{A}$, and I later take these to be identical across countries. The lack of a systematic relationship between labor market fluidity, on the one hand, and the overall labor force participation rate as well as that at age 25 and 54, on the other hand (see Appendix A.3), leads me to focus my analysis elsewhere.

Technology. The single good of the economy is produced by one worker-one firm matches, and serves as the numeraire. A large number of potential firms may pay flow cost c in return for the opportunity to

[17]In the interest of space, I only show the math test score here, but similar results hold for reading and science.

meet with a worker. All costs are in terms of the final good. If a firm contacts a worker, the two draw an idiosyncratic productivity z from exogenous offer distribution Γ. Match output is,

$$y = zh$$

As in Acemoglu and Pischke (1998) and Bagger et al. (2014), human capital and technology are complements. That is, a worker may use her skills more effectively in some jobs. As discussed further by Acemoglu (1997), a large empirical literature going back to Griliches (1969) has found evidence of complementarities between physical and human capital. I hence also abstract from purely firm-specific human capital, consistent with the evidence in Kambourov and Manovskii (2009) and Lazear (2009).

Workers may accumulate skills on-the-job. Only the employed may invest and the technology for accumulating skills is independent of worker age a. Following Ben-Porath (1967), if a worker sets aside some fraction of her work time i toward building her skills, her human capital grows by

$$\dot{h} = \frac{\mu}{\eta}\left(izh\right)^{\eta}, \qquad \mu > 0,\ \eta \in (0,1)$$

The opportunity cost of training is foregone production, izh. Human capital does not depreciate.[18] In Ben-Porath (1967), there is no employer heterogeneity, z, such that if a worker sets aside ih, she grows her human capital by $\mu(ih)^{\eta}/\eta$. The current specification provides an extension to the case of employer heterogeneity. I show below that it is consistent with micro patterns of training across employers.

Search. The labor market is characterized by informational frictions that prevent the immediate reallocation of workers to the jobs that use their skills the most efficiently. Search is random. Both the unemployed and employed search for jobs, in the latter case with exogenous relative efficiency ϕ.

Employed workers separate to unemployment at rate $\delta(z)$. The dependence on match productivity z captures in reduced-form the view that less productive matches are more likely to separate in response to idiosyncratic shocks. It allows the model to match the decline in EU mobility with age.

Market structure. If firms create vacancies V and workers search with efficiency S, total meetings are,

$$m = \chi V^{\alpha} S^{1-\alpha}, \qquad \alpha \in (0,1)$$

The job finding rate is hence $p = \chi(V/S)^{\alpha}$, while the worker finding rate of firms is $q = \chi(V/S)^{\alpha-1}$.

[18] An earlier version of this paper allowed for depreciation. As results were insensitive to (reasonable) variation in the extent of depreciation and the rate of depreciation was hard to identify from the available data, I opt to abstract from it.

Following Bagger et al. (2014), I adopt the bargaining protocol of Dey and Flinn (2005) and Cahuc et al. (2006), which has become a benchmark in the literature for its tractability and empirical relevance. A worker without a job who meets a firm with productivity z gets a share β of the difference between the value of the match and the value of unemployment, henceforth the surplus. If a worker employed at a firm with productivity z meets a potential new employer with productivity z', a second price auction starts between the two firms for the worker. This is won by the bidder with the higher valuation of the worker's services, and it leaves the worker with the full value of working for the least productive firm as her outside option. The worker and winning firm bargain over the differential surplus such that the worker receives a slice β of the differential surplus.[19] Finally, I assume following Barlevy (2002) and Bagger et al. (2014) that wages are paid as a piece-rate r of net output, $w = r(1-i)zh$.

I assume that the worker makes the decision of how much to train, but that the amount of training can be contracted on between the worker and firm. That is, the firm can condition pay on the amount of training done by the worker. Without this assumption, the bargaining set may be non-convex, potentially rendering the bargaining protocol above invalid (Shimer, 2006). As I discuss further below, this assumption implies that it does not matter who pays for training—the match will agree on the bilaterally optimal level and share the cost. The latter is consistent with lower entry wages in more fluid labor markets. More directly, Appendix B.2 shows that workers—conditional on worker fixed effects and time-varying covariates—earn lower hourly wages in years when they spend more hours on training.

3.2 Value functions

Let $U(a,h)$ be the value of unemployment to a worker of age a with human capital h, $W(a,z,h,r)$ the value of employment of an age a worker with human capital h in a match with productivity z when paid piece rate r, and $J(a,z,h)$ the value of a match between a worker of age a with human capital h and a firm with productivity z. As I discuss in further detail below, the allocation is independent of how value is split between the worker and incumbent firm, and can hence be determined without alluding to the value of the worker. This appealing feature of the bargaining protocol serves to speed up estimation.

Value of unemployment. The value of unemployment $U(a,h)$ solves the differential equation

$$\rho U(a,h) \quad = \quad b(a,h) + p\beta \int_0^\infty \max\left\{J(a,z,h) - U(a,h), 0\right\} d\Gamma(z) + \frac{\partial U(a,h)}{\partial a}$$

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

subject to the terminal condition $U(A,h) = 0$. The unemployed worker enjoys flow value of leisure $b(a,h)$. She meets potential employers at rate p, who are sampled from the offer distribution Γ. She accepts the job if it provides a positive surplus and she gets a slice β of the surplus.

Value of a match. The value of a match $J(a,z,h)$ solves

$$
\begin{aligned}
\rho J(a,z,h) &= \max_{i\in[0,1]} \left\{ (1-i)zh + \mu\Big(izh\Big)^{\eta} \frac{\partial J(a,z,h)}{\partial h} \right\} + \frac{\partial J(a,z,h)}{\partial a} \\
&+ \phi p \beta \int_{z}^{\infty} J(a,z',h) - J(a,z,h) d\Gamma(z') \\
&+ \delta(z)\Big(U(a,h) - J(a,z,h)\Big)
\end{aligned} \tag{3}
$$

subject to the boundary conditions $J(A,z,h) = 0$ and $J(a,z,h) \geq U(a,h)$. The match optimally invests in training and produces net output $(1-i)zh$. The worker finds a new potential job at rate ϕp, drawn from the offer distribution Γ. If the new job is better than the current, she switches employer and gets a slice β of the differential surplus. The match breaks up exogenously at rate $\delta(z)$, in which case the worker becomes unemployed and the firm gets continuation value zero.

Value of a worker. Given an training rule $i(a,z,h)$ and reservation threshold $\underline{z}(a,h)$ that solve the problem of the match (3), the value of a worker, $W(a,z,h,r)$, is for $z \geq \underline{z}(a,h)$,

$$
\begin{aligned}
\rho W(a,z,h,r) &= r(1-i(a,z,h))zh + \frac{\mu}{\eta}\Big(i(a,z,h)zh\Big)^{\eta} \frac{\partial W(a,z,h,r)}{\partial h} + \frac{\partial W(a,z,h,r)}{\partial a} \\
&+ \phi p \int_{0}^{z} \max\Big\{ J(a,z',h) + \beta\Big(J(a,z,h) - J(a,z',h)\Big) - W(a,z,h,r), 0 \Big\} d\Gamma(z') \\
&+ \phi p \int_{z}^{\infty} \Big(J(a,z,h) + \beta\Big(J(a,z',h) - J(a,z,h)\Big) - W(a,z,h,r)\Big) d\Gamma(z') \\
&+ \delta(z)\Big(U(a,h) - W(a,z,h,r)\Big)
\end{aligned}
$$

subject to the boundary conditions $W(A,z,h,r) = 0$, $W(a,z,h) \geq U(a,h)$ and $W(a,z,h) \leq J(a,z,h)$. The worker receives a share r of net output and grows her human capital at rate $\mu(i(a,z,h)zh)^{\eta}$. At rate ϕp, she receives outside job offers from offer distribution Γ. If the new productivity is lower than the current, she remains with her current firm, but potentially with an updated piece rate. If the new match is better than the current, she switches jobs. Finally, she is subject to separation shocks.

Wage policies. Four wage policies determine wages. First, the wage $w^u(a,z,h)$ characterizes a worker's wage out of unemployment. Second, the wage $w^e(a,z,z',h)$ gives the worker's wage when simultaneously in contact with two employers z and $z' < z$. Third, the wage $w^r(a,z,h)$ ensures that a worker always prefers working in a viable match relative to unemployment. Fourth, the wage $w^f(a,z,h)$ ensures that the firm always prefers to employ a worker in a viable match. These are defined by the conditions

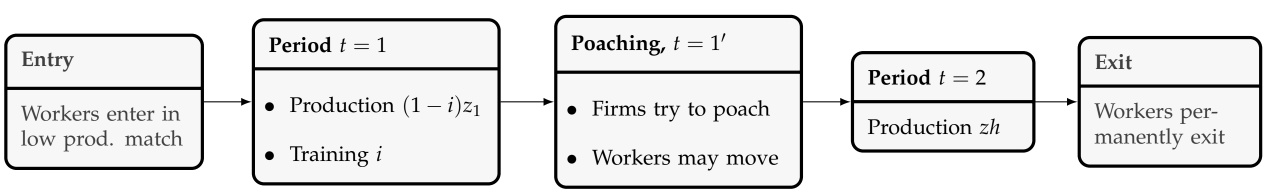
$$\begin{aligned}
W\Big(a,z,h,w^u(a,z,h)\Big) &= U(a,h) + \beta\Big(J(a,z,h) - U(a,h)\Big) \\
W\Big(a,z,h,w^e(a,z,z',h)\Big) &= J(a,z',h) + \beta\Big(J(a,z,h) - J(a,z',h)\Big) \\
W\Big(a,z,h,w^r(a,z,h)\Big) &= U(a,h) \\
W\Big(a,z,h,w^f(a,z,h)) &= J(a,z,h)
\end{aligned}$$

Free entry. Appendix B.1 characterizes further how the evolution of the distribution $G(a,z,h)$ of workers over age, productivity and human capital evolves as well as the distribution of unemployed workers over age and human capital, $u(a,h)$. Given these objects, free entry requires

$$\begin{aligned}
c &= (1-\beta)q\frac{u}{S}\int_0^\infty \int \max\Big\{J(a,z,h),0\Big\}du(a,h)d\Gamma(z) \\
&+ (1-\beta)q\frac{\phi(1-u)}{S}\int_0^\infty \int_0^z J(a,z,h) - J(a,z',h)dG(a,z',h)d\Gamma(z)
\end{aligned}$$

where u is the aggregate unemployment rate. In return for flow cost of a vacancy c, the firm contacts a potential hire at rate q. The first term is the return from meeting an unemployed potential hire and the second term the payoff from contacting an employed potential hire. In both cases, the new potential match draws a productivity from $\Gamma(z)$ and the firm gets a slice $1-\beta$ of any match that is formed.

FIGURE 6. TIMING OF EVENTS



3.3 Qualitative insights

Before turning to a quantitative analysis, I provide some qualitative insights in a simplified version of the model. To that end, suppose instead that time is discrete and has two periods, there is no discounting, and productivity can take a low, $z = z_1$, or a high value, $z = z_2 > z_1$, with equal probability. Moreover, I abstract from unemployment to focus on how training and poaching interact. Specifically, I assume that young workers enter in low productive matches, workers do not separate exogenously, employed workers search with $\phi = 1$ intensity, and recruiting firms compete for young workers going into the second period. Figure 6 illustrates the timing of the simplified two-period model.

Denote by $W(r,i)$ the value to a young worker of being in a low productive match under some amount of training i and piece rate r. Without loss of generality, I normalize initial human capital, $h_0 = 1$, and abstract from it as an argument to simplify the notation. The value $W(r,i)$ solves,

$$W(r,i) \quad = \quad (1-i)z_1 r + \left((1-p)z_1 r + \frac{p}{2}z_1 + \frac{p}{2}(z_1 + \beta(z_2 - z_1))\right)\left(1 + \frac{\mu}{\eta}(z_1 i)^{\eta}\right) \tag{4}$$

The worker is paid piece rate r on net output $(1-i)z_1$ (the level of training need not be optimal at this point). The worker's human capital rises to $1 + \mu(z_1 i)^{\eta}/\eta$ in the second period. The worker receives no new job offer with probability $1-p$, in which case she continues to be paid piece rate r. With probability $p/2$, the worker receives a job offer from another low productive firm. I impose the tie-breaking rule that an indifferent worker switches employer (this only impacts the measured JJ mobility, though). The worker extracts the full surplus of the current match, i.e. she gets an updated piece rate equal to the productivity of the match, z_1. Finally, with probability $p/2$, the worker receives a job offer from a high-productive match, in which case she switches employer and gets a piece rate that reflects the full value of the least productive match, z_1, plus a share β of the differential value, $z_2 - z_1$.

Denote by $F(r,i)$ the value to a low productive firm of employing a young worker under some piece rate r and training policy i (again, not necessarily the optimal one). It satisfies,

$$F(r,i) \quad = \quad (1-i)z_1(1-r) + (1-p)z_1(1-r)\left(1 + \frac{\mu}{\eta}(z_1 i)^{\eta}\right) \tag{5}$$

The firm makes profits $1-r$ per net output, $(1-i)z_1$. With probability $1-p$, the worker receives no outside offer and the firm makes profits $1-r$ per net output in the second period. If the worker receives an outside offer, the firm makes no profit in the second period.[20]

Proposition 1. *For any level of training i, the joint value of a match between a young worker and a low-productive firm, $J(i) = W(r,i) + F(r,i)$, is independent of how it is split between the worker and firm, r,*

$$J(i) \quad = \quad (1-i)z_1 + \left(z_1 + \frac{p}{2}\beta(z_2 - z_1)\right)\left(1 + \frac{\mu}{\eta}(z_1 i)^{\eta}\right) \tag{6}$$

Proof. All proofs are in Appendix B.3. □

[20] Even if the worker had remained, the firm would have had to pay the worker her full marginal product to keep her.

Differentiating the joint value (6) with respect to the job finding rate, p, holding training fixed, $\frac{\partial J(i)}{\partial p}\Big|_i = \frac{1}{2}\beta(z_2 - z_1)(1 + \mu(z_1 i)^\eta/\eta) > 0$. Hence, *ceteris paribus*, the joint value increases in the rate at which the worker switches employer (assuming $\beta > 0$). Although the incumbent employer ex post loses value when the worker leaves, the worker is compensated by the poaching firm with the full value of the incumbent match plus a share β of the differential surplus. From the joint perspective of the incumbent match, the gain to the worker more than offsets the loss to the firm. Ex ante, an incumbent firm benefits from the opportunity of the worker leaving by having to pay the worker less.

Proposition 2. *Optimal investment choosen by the worker maximizes the bilateral surplus,*

$$i = \frac{1}{z_1}\left(\mu\left(z_1 + p\beta\frac{z_2 - z_1}{2}\right)\right)^{\frac{1}{1-\eta}} \tag{7}$$

The optimal training policy (7) increases in the job finding rate, p. Although as in Acemoglu and Pischke (1998) a higher probability that the worker meets a new employer lowers the value of human capital to the firm, it increases the value of human capital to the worker. When workers' bargaining power, β, is positive, the latter effect outweighs the former. The reason is that a higher arrival rate of outside offers allows the worker to use her skills at an employer that values them higher. Because the incumbent match gets (partly) compensated for this, it raises the value of human capital to the incumbent match. As a result, the match invests more in response to a higher arrival rate of outside offers. Allowing for JJ 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.

This conclusion clearly depends on the stipulated bargaining protocol, which ensures that a JJ mover obtains a share of the additional value of human capital in a new match. Nonetheless, I believe that the insight is more general. For instance, in a partial equilibrium version of the model in the spirit of McCall (1970) in which workers sample exogenously given piece rates per human capital, if workers sample outside offers more frequently and hence expect to grow their piece rate faster, it would encourage human capital accumulation. The current framework may be viewed as a general equilibrium version of that model, in which the piece rate is determined in equilibrium via bargaining.

That being said, there exists alternative models of equilibrium wage setting—most prominently those of wage posting—in which cases could arise where the incumbent firm loses more value than the worker gains when she moves to a new employer. In such cases, I hypothesize that training may fall in the poaching rate (over parts of the domain for productivity, the gain to the worker may still outweigh the loss to the firm, though). Such a model, however, would likely be significantly more difficult to solve, as the firm would have to internalize how its wage offer affects workers' incentives to train. Hence, this remains only a hypothesis. In any case, such cases are arguably the least appealing feature of wage posting models, as the worker and incumbent firm would have a very strong incentive to renegotiate the contract since they could both benefit from doing so. But for some (unmodeled) reason, such renegotiation is ruled out. For this reason, I prefer my framework for the particular question at hand. Still, the model allows for the possibility that the incumbent match does not benefit from poaching (i.e. $\beta = 0$).

Equilibrium. Firms create jobs up to the point where the cost of doing so, c, equals the expected return,

$$c \quad = \quad q\frac{1}{2}(1-\beta)(z_2 - z_1)\left(1 + \frac{\mu}{\eta}(z_1 i)^\eta\right) \tag{8}$$

A recruiting firm contacts a worker at rate q and with probability 0.5 the potential match draws a high productivity. Only in this case is the firm successful and it gets slice $1-\beta$ of the surplus. If the worker invested amount i in training in the first period, human capital in the second period is $1 + \mu(z_1 i)^\eta/\eta$.

Definition 1 (Stationary search equilibrium)**.** *A stationary search equilibrium with positive vacancy creation consists of a value function, J; a training policy, i; and a mass of vacancies, v, such that*

1. *The value function and training policy maximizes* (6) *given a mass of vacancies;*
2. *The mass of vacancies is consistent with free entry* (8)*;*
3. *And the economy is time invariant.*

The equilibrium is characterized by two curves. The first is a *training curve*, which can be derived from the first-order condition (7) by substituting for the job finding rate using the matching function,

$$i(v) \quad = \quad \frac{1}{z_1}\left(\mu\left(z_1 + v^\alpha \beta \frac{z_2 - z_1}{2}\right)\right)^{\frac{1}{1-\eta}} \tag{9}$$

The second curve is a *job creation curve*, derived by substituting the worker finding rate in the free entry condition (8) (I normalize the scalar in the matching technology, $\chi = 1$, to minimize notation),

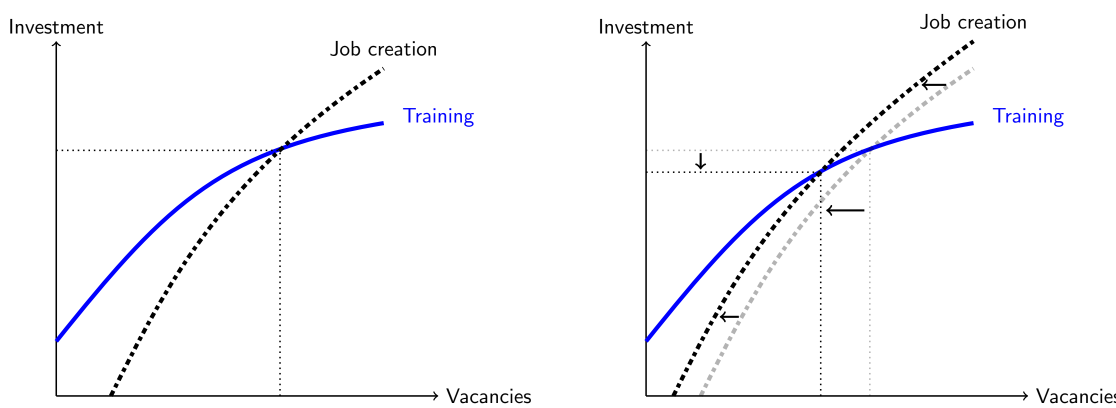
$$v(i) \quad = \quad \left((1-\beta)\frac{(z_2 - z_1)}{2c}\left(1 + \frac{\mu}{\eta}(z_1 i)^\eta\right)\right)^{\frac{1}{1-\alpha}} \tag{10}$$

Figure 7 graphs the training and job creation curves (9)–(10) in v-i space. At zero vacancies, $v = 0$, the training curve (9) is positive. It subsequently rises in vacancies. A higher job finding rate raises the return to human capital since workers expect to use it more efficiently, encouraging training. At zero training, $i = 0$, the job creation curve (10) is positive. Optimal job creation subsequently increases in the training rate of workers. If workers invest more, matches produce more output, and recruiting firms get a share of this. The training and job creation curves may in fact cross multiple times.

FIGURE 7. COMPARATIVE-STATIC IMPACT OF A HIGHER COST OF HIRING

(A) LOW COST

(B) HIGH COST



Note: The comparative-static equilibrium impact of a higher cost of creating jobs, c. Training: Equation (9). Job creation: Equation (10).

Proposition 3. *If $(1-\eta)/\eta > \alpha/(1-\alpha)$, the economy admits a unique stationary equilibrium.*

The key parameters governing whether the economy may display multiple stationary equilibria are the curvatures of the matching technology, α, and the human capital accumulation technology, η. If it is easier to scale up training (i.e. η is higher), a given increase in job creation leads to a stronger optimal increase in training. If the worker finding rate declines less with an increase in vacancies (i.e. α is higher), a given increase in training leads to a stronger optimal increase in job creation.

Proposition 4. *Suppose $(1-\eta)/\eta > \alpha/(1-\alpha)$ and that workers' bargaining power is positive, $\beta > 0$. A higher cost of creating jobs, c, is associated with lower average match productivity and human capital.*

In response to a higher cost of vacancy creation, firms create fewer vacancies for any given level of training of workers. That is, the job creation curve in Figure 7 shifts to the left. The lower job finding rate, in turn, reduces the expected value of human capital to workers, lowering training.

The planning problem. Before I go to the data, I briefly turn to the question of the efficiency of the decentralized equilibrium. The planning problem is to maximize life-time output minus costs,

$$\max_{v,i} \left\{ (1-i)z_1 + \left(z_1 + v^{\alpha} \frac{1}{2}(z_2 - z_1) \right) \left(1 + \frac{\mu}{\eta}(z_1 i)^{\eta} \right) - cv \right\} \tag{11}$$

with first order conditions,

$$i_{sp}(v) = \frac{1}{z_1}\left(\mu\left(z_1 + v^{\alpha}\frac{z_2 - z_1}{2}\right)\right)^{\frac{1}{1-\eta}}, \qquad v_{sp}(i) = \left(\alpha\frac{z_2 - z_1}{2c}\left(1 + \frac{\mu}{\eta}(z_1 i)^{\eta}\right)\right)^{\frac{1}{1-\alpha}}$$

Lemma 1. *Suppose $(1-\eta)/\eta > \alpha/(1-\alpha)$ and that training in the decentralized economy equaled the constrained first best, $i(v) = i_{sp}(v)$. Then the decentralized equilibrium attains the constrained first best number of vacancies iff the elasticity of matches w.r.t. vacancies equals firms' bargaining power, $\alpha = 1 - \beta$.*

Abstracting from the training decision, the model reproduces a well-known property of this class of models going back to Hosios (1990). Firms face two externalities in their vacancy creation decision. On the one hand, they do not internalize the fact that part of the gain from job creation accrues to workers. On the other hand, they do not internalize the fact that when they create jobs, they lower the worker finding rate of other firms. It turns out that when firms' bargaining power equals the elasticity of the matching function with respect to vacancies, these two forces exactly offset.

Lemma 2. *Suppose $(1-\eta)/\eta > \alpha/(1-\alpha)$ and that job creation in the decentralized economy equaled the constrained first best, $v(i) = v_{sp}(i)$. Then the decentralized equilibrium attains the constrained first best amount of training iff workers' bargaining power is one, $\beta = 1$.*

Due to a positive externality of training on future employers, for a given number of vacancies the decentralized economy in general features less training in human capital relative to the social optimum, as in Stevens (1994) and Acemoglu (1997). Only if incumbent matches enjoy the full marginal benefit from additional training upon a JJ move would they undertake the socially optimal level of training.

Proposition 5. *Suppose $(1-\eta)/\eta > \alpha/(1-\alpha)$. There exists no bargaining power of workers $\beta \in [0,1]$ such that the decentralized search equilibrium coincides with the constrained optimal allocation.*

Only if workers' bargaining power β is one would training in the decentralized and planned economy coincide, given vacancies. For vacancy creation in the decentralized equilibrium to coincide with the constrained first best under such a high β, the elasticity of matches with respect to vacancies α would have to be zero, violating the assumption that $\alpha \in (0,1)$. Moreover, by leaving nothing for the recruiting firm, such a high bargaining power of workers is inconsistent with positive job creation in equilibrium.

4 Estimation

This section estimates the model targeting the US as a high-fluidity country. The next section introduces *wedges* to firms' cost of creating jobs to match cross-country differences in labor market fluidity, and assesses their impact on workers' optimal behavior in the estimated model.

4.1 Methodology

I externally calibrate the discount rate, ρ, to a four percent annual real interest rate. The available data do not allow identification of the curvature of the matching function, so I set $\alpha = 1 - \beta$ consistent with a Hosios (1990) condition. The resulting value is within the range of typical estimates (Petrongolo and Pissarides, 2001). I estimate nine parameters using SMM (Gourieroux et al., 1993) to minimize the sum of weighted squared percentage deviations between a set of moments in the model and the data,

$$\mathbf{p}^* = \underset{\mathbf{p}\in\mathscr{P}}{\arg\min} \sum_i w_i \left(\frac{m_i^{\text{model}}(\mathbf{p}) - m_i^{\text{data}}}{m_i^{\text{data}}} \right)^2$$

As discussed further below, some moments particularly inform some parameters. I set the weights w_i such that each set of moments particularly informing one parameter receives the same total weight (that is, if n moments particularly inform parameter p, each of these moments receives a weight $1/n$). The two exceptions are total life-cycle wage growth and aggregate labor market fluidity, which I assign five times this weight given their key role in the analysis.

I solve the model and compute moments in continuous time, which allows me to correctly time-aggregate to any desired frequency.[21] It is difficult, however, to derive a law of motion for labor market fluidity. Hence, I compute it based on a simulated discrete-time, monthly approximation for 13 months for 800,000 individuals uniformly distributed between ages 25–54, where each age group is initialized from its age-conditional distribution over employment state, human capital and match productivity. This corresponds to my empirical measure, which assigns equal weight to each age 25–54.

I assume that initial match productivity, z, is Pareto distributed with tail index $1/\zeta$. I assume that initial human capital, h_0, is drawn from a Pareto distribution with tail index $1/\sigma$. I parameterize the separation rate, $\delta(z) = \delta_0 e^{-\delta_1 (\ln z - \ln \underline{z})/(\ln \bar{z} - \ln \underline{z})}$, where $\bar{z}$ ($\underline{z}$) is the maximum (minimum) productivity on the discretized grid for productivity. The flow value of leisure $b(a, h)$ is recovered such that workers of each age and human capital level are indifferent between unemployment and working at the second lowest grid point for productivity. The nine parameters to estimate internally are,

$$\mathbf{p} = \left\{ \mu, \eta, \sigma, \zeta, p, \phi, \delta_0, \delta_1, \beta \right\}$$

[21] I solve the model on a discretized grid for productivity, human capital, piece rates and age with 25, 10, 8 and 6 grid points, respectively. The age grid points are set to reflect real life ages of 24–29, 30–34, 35–39, 40–44, 45–49, 50–64. I approximate between these age bins to obtain more disaggregated age outcomes.

While the estimation is joint, it is nevertheless useful to provide a heuristic discussion of what moments particularly inform what parameter. The scalar in the human capital accumulation technology, μ, and its curvature, η, are jointly informed by the life-cycle wage profile. If μ is higher, wages in general grow more over the life-cycle. If η is higher, the marginal return to investment falls less with investment such that investment is more front loaded and the wage profile more concave.

Dispersion in initial human capital, σ, as well as the shape of the offer distribution, ζ, are informed by the life-cycle profile of the standard deviation of wages. If σ is larger, inequality is greater. If ζ is larger—the tail of the productivity distribution is fatter—inequality grows more with age. The job finding rate p targets the aggregate UE rate. While p is an endogenous outcome, the cost of a vacancy, c, is a free parameter. I set it ex post to rationalize the job finding rate. The relative search efficiency of employed workers, ϕ, is set to target the aggregate JJ mobility rate. If ϕ is higher, JJ is greater. The intercept, δ_0, and slope, δ_1, of the separation rate are jointly informed by the life-cycle EU rate. If δ_0 is higher, the EU rate is generally higher, while if δ_1 is higher, the separation rate falls more with productivity and hence also with age as workers move up the job ladder with age. Finally, workers' bargaining power, β, is informed by wage gains upon a JJ move, because if it is larger, wage gains from moving are more front loaded. To compute the empirical counterpart, I additionally rely on data from the US SIPP.[22]

4.2 Estimates and model fit

Table 3 summarizes the parameter estimates, expressed at a monthly frequency.[23] While it is not known whether the condition for uniqueness in Proposition 3 extends to the richer model, the high estimated curvature of the human capital accumulation technology, η, suggests that the equilibrium may be unique. Moreover, I have not uncovered any evidence of multiplicity. I estimate a relatively high concavity of the Ben-Porath (1967) technology because job shopping serves to increase the concavity of the wage profile,

[22]I use the SIPP for this particular moment because the PSID became biannual in 1997, leaving me with only a few years of annual wage growth observations. An additional advantage of the SIPP is that I can compute the measure of wage gains upon a JJ move at a monthly frequency, which avoids the need to simulate this moment in estimation (it is difficult to derive analytically a KFE for the annual wage growth of JJ movers). The annual measure in the PSID for 1994–1997 lines up well with the monthly measure in the SIPP for 1996–2013, however, and the model replicates the former when targeting the latter. The SIPP has been conducted in separate panels since the mid-1980s, but a break in the survey in 1996 implies that data on job-to-job mobility in the earlier panels are not directly comparable to that in the later panels. To align with the time period covered by the other data sets used by this paper, I focus on SIPP data from 1996–2012 (i.e. the 1996, 2001, 2004 and 2008 panels). Each panel of the SIPP follows a group of individuals over time. Data are collected in "waves", with the respondent in each wave being asked to recall labor market events during the prior four months. The survey asks for information regarding up to four employment spells during the past four months (two as employee and two as self-employed), including start dates and end dates (if applicable), income, hours, occupation, sector, etc. It also contains standard demographic characteristics. I use the provided survey weights throughout my analysis to make results representative of the overall US population.

[23]I normalize the flow value of leisure such that workers are indifferent between unemployment and employment at the second grid point on the discretized grid for human capital to avoid any potential numerical issues associated with the boundary of the grid. Hence, the estimated job finding rate p is higher than the actual UE rate, since some job offers are not accepted.

requiring a less elastic human capital margin. The employed search by roughly 40 percent of the intensity of the unemployed. Workers' bargaining power β is 0.32, with an implied labor share of 82 percent (for comparison, Bagger et al., 2014, estimate $\beta \approx 0.3$ with an implied labor share of 81–85 percent).

TABLE 3. PARAMETER ESTIMATES

	Parameter	Estimate	Targeted moment	Model	Data
	Panel A. Externally set				
ρ	Discount rate	0.003	4% annual real interest rate		
α	Elasticity of matches w.r.t. vacancies	0.679	Hosios (1990) condition		
	Panel B. Internally estimated				
μ	Drift of human capital	0.001	Life-cycle wage growth	0.761	0.760
η	Curvature of human capital production function	0.497	Life-cycle wage profile	See Figure 8	
σ	Initial human capital dispersion	0.491	Life-cycle inequality profile	See Figure 8	
ζ	Shape of productivity distribution	0.154	Life-cycle inequality profile	See Figure 8	
p	Job finding rate	0.472	Aggregate UE rate (monthly)	0.226	0.230
ϕ	Relative search efficiency of employed	0.394	Aggregate JJ rate (annual)	0.100	0.100
δ_0	Separation rate, intercept	0.016	Life-cycle EU rate	See Figure 8	
δ_1	Separation rate, slope in z	3.131	Life-cycle EU rate	See Figure 8	
β	Worker bargaining power	0.321	Wage gain upon a JJ move	0.079	0.082

Note: Men aged 25–54. When applicable, parameter estimates are expressed at a monthly frequency. *Source:* Model, PSID and SIPP 1994–2015.

Figure 8 illustrates the model fit to life-cycle dynamics. Wages grow rapidly early in careers, as workers have much scope to move up the job ladder and bargain up their wage, and face high returns to training.[24] As noted above and discussed further in Appendix A, the standard deviation of residual wages is essentially flat in the data. The model matches this reasonably well. It understates somewhat the decline in the EU rate. The EU rate falls as workers move away from low productive matches with a high likelihood of breaking up. To a first order, the UE rate is flat over the life-cycle in both the model and data. Finally, the model matches well the fall in JJ mobility, as workers gradually find a good job.

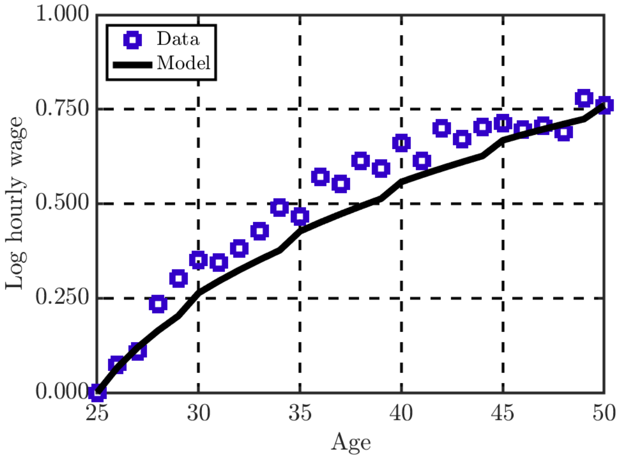
4.3 The workings of the model

Before I turn to the cross-country analysis, I pause to illustrate the workings of the model in the cross-section. Figure 9 plots in the left panel the distribution of young workers over log match productivity and human capital. The right panel illustrates the optimally chosen growth rate of human capital, $\dot{h}(a, z, h)/h$. Assuming that the solution for optimal investment is away from the corner, $i \in (0, 1)$, taking

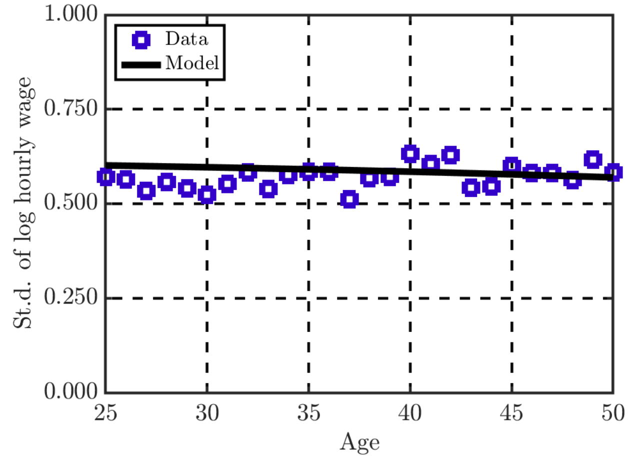
[24] The slight "jumpiness" of the model wage profile is due to the approximation to six underlying age groups. The model does not fully match the curvature of the wage profile in the data, potentially raising concern about the empirical restriction to zero wage growth after age 50. While in my benchmark results I do not impose this restriction in the model, I show in Appendix C.1 that the cross-country patterns for life-cycle wage growth are virtually identical if I impose it.

FIGURE 8. MODEL FIT

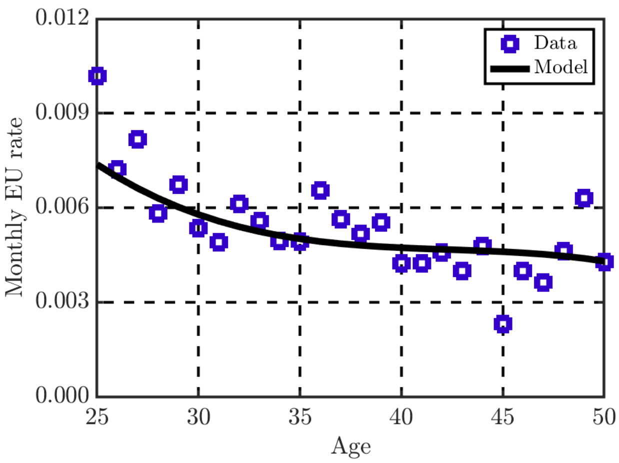
(A) MEAN LOG WAGE



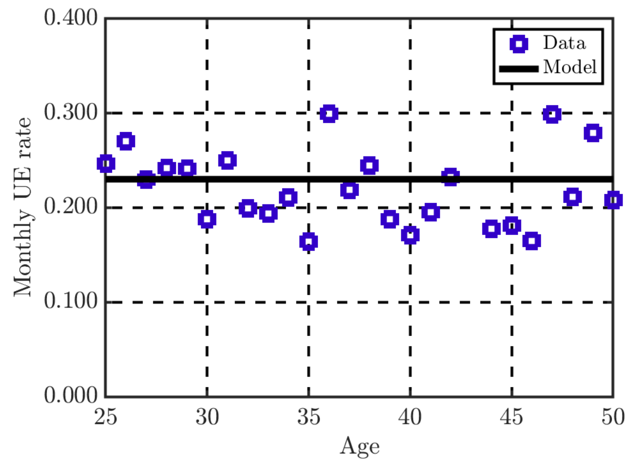
(B) ST.D. OF LOG WAGES



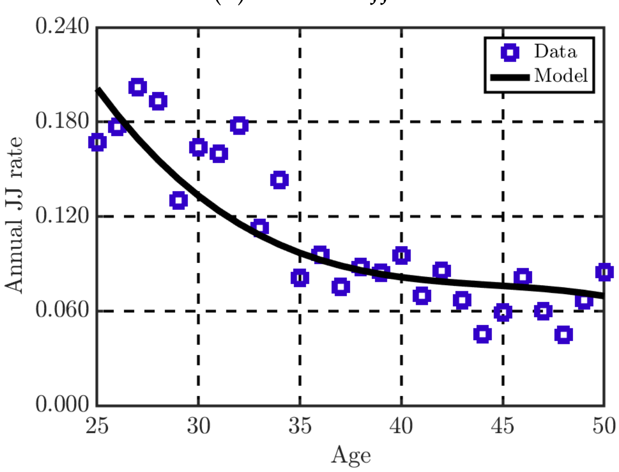
(C) MONTHLY EU RATE



(D) MONTHLY UE RATE



(E) ANNUAL JJ RATE



Note: Men aged 25–54. Panel A. Average log real hourly wage. Data: Based on regression (1) controlling for worker fixed effects, year effects and age effects restricted to not grow after age 50. Panel B. Standard deviation of residual log hourly wages. Data: Residual wages controlling for year-education-age and year-occupation effects and dropping the bottom 1% of wages. Panel C. Share of employed workers who are unemployed in the subsequent month. Data: Employment includes self-employment due to data limitations. Panel D. Share of unemployed workers who are employed in the subsequent month. Data: Employment includes self-employment due to data limitations. Panel E. Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Data: Employment in the past 12 months includes self-employment due to data limitations. All panels. Empirical moments constructed by first collapsing to the age-year level using the provided survey weights, then to the age level. *Source:* Model and PSID 1994–2015.

first-order conditions of the problem of the match (3), and rearranging, it is given by

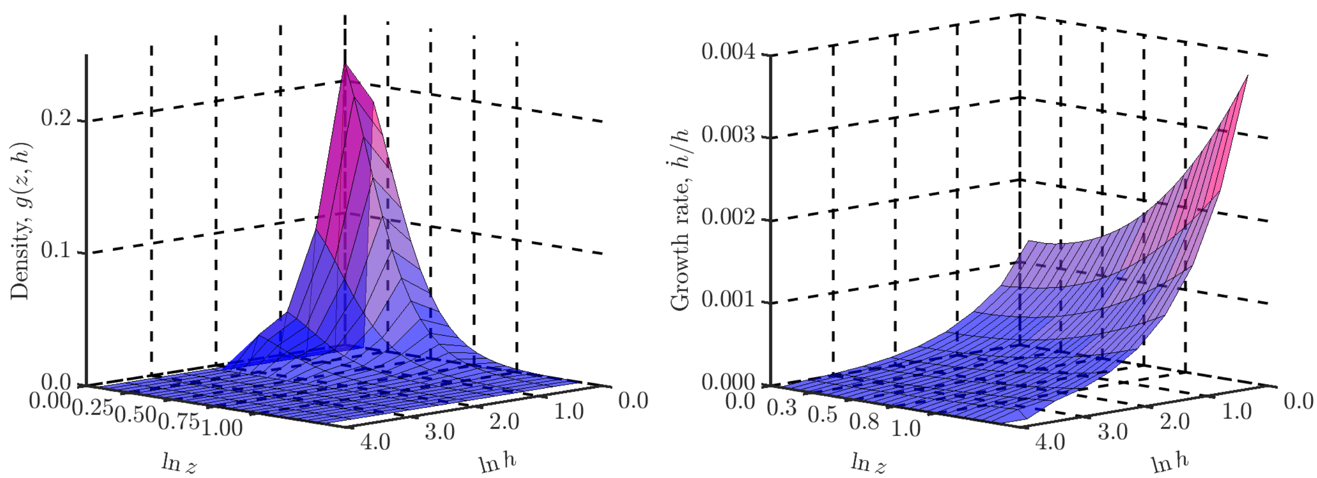
$$\frac{\dot{h}(a,z,h)}{h} = \frac{\mu}{\eta}\left(\mu\frac{\partial J(a,z,h)}{\partial h}\right)^{\frac{\eta}{1-\eta}} \times \frac{1}{h}$$

The value function is close to affine in human capital, so growth in human capital is close to independent of h. The growth *rate* hence falls in human capital. The marginal value of human capital rises in match productivity, $\partial^2 J(a,z,h)/\partial h \partial z > 0$, due to the complementarity in production. Hence, the growth rate of human capital increases in match productivity. That is, workers who find a high productive job respond by growing their human capital more, propagating the impact of luck in the labor market.

FIGURE 9. THE OPTIMAL GROWTH RATE OF HUMAN CAPITAL

(A) DISTRIBUTION OF WORKERS

(B) GROWTH RATE OF HUMAN CAPITAL



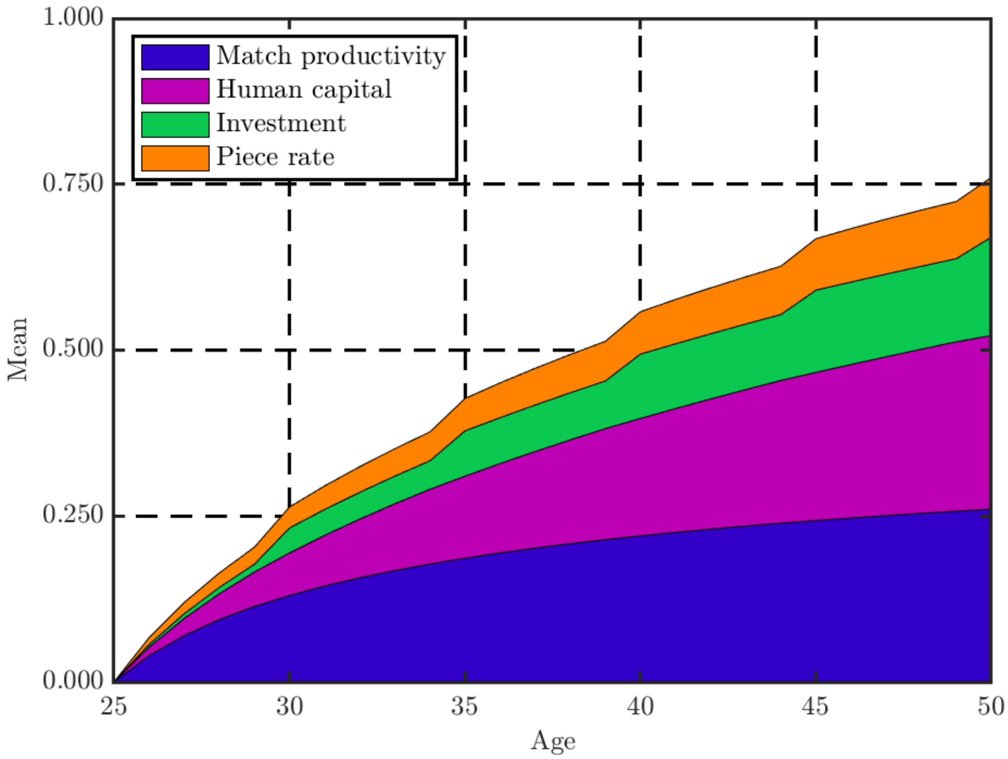
Note: Panel A. Distribution of first age group, $a = 1$, over the match productivity, $\ln z$, and human capital, $\ln h$. Panel B. Optimally chosen growth rate of human capital, $\dot{h}/h$, of first age group as a function of match productivity and human capital. *Source:* Model.

Figure 10 decomposes life-cycle wage growth in the estimated model based on the identity,

$$\underbrace{\ln\ w}_{\text{Wage}} = \underbrace{\ln\ z}_{\text{Match productivity}} + \underbrace{\ln\ h}_{\text{Human capital}} + \underbrace{\ln(1-i)}_{\text{Investment}} + \underbrace{\ln\ r}_{\text{Piece rate}} \tag{12}$$

Growth in human capital, h, is the most important source of life-cycle wage growth, with growth in match productivity a close second. Human capital accumulation, however, does not come for free. Indeed, a fall in the amount of time spent on training is also an important source of growth in life-cycle wages, with young workers earning lower wages partly to offset the cost of training. Finally, the piece rate grows as workers gradually bargain up their wage through counteroffers.

FIGURE 10. DECOMPOSING LIFE-CYCLE WAGES, MODEL



Note: Decomposition of average life-cycle wage growth based on the accounting identity (12). *Source:* Model.

5 Labor market fluidity and human capital accumulation

I now turn to the effect of differences in labor market fluidity on worker careers. Specifically, I pursue a *wedge*-like approach in the spirit of Hsieh and Klenow (2009), adjusting the cost of creating vacancies, c, to match cross-country differences in labor market fluidity.[25] This approach purposefully avoids taking a strong stand on the specific policies that lead to differences in labor market fluidity, as this has already been extensively studied in the literature (see, e.g., Pries and Rogerson, 2005, and references therein). In Section 6, I return to the question of what drives differences in fluidity to document that, consistent with the literature, fluidity correlates negatively with measures of employment protection legislation, the cost of doing business and labor taxes. In this section, however, I focus on the key novelty of this paper, which is to take such differences as given to quantify their impact on worker behavior.

[25] I allow the flow value of leisure to adjust such that each human capital group is indifferent between unemployment and employment at the least productive firm on the grid for productivity. Not doing this, however, only marginally affect results.

5.1 The effect of labor market fluidity

I start by contrasting the predictions of the model with the cross-country data. My discussion focuses primarily on the core set of 13 Western European countries and the US for which I have 15 or more years of data. Appendix C.2 considers the full set of 23 OECD countries with similar conclusions.

The top left panel of Figure 11 shows that life-cycle wage growth is significantly greater in more fluid labor markets, although the mechanism emphasized here only accounts for some of the empirical patterns. The top right panel plots the unemployment rate in the model and the data. Note that the model understates the unemployment rate in the US, because the targeted EU and UE rates are inconsistent with the implied unemployment rate from a flow-balance equation. A plausible reason is flows in and out of non-employment, which the model abstracts from. In light of this, I prefer to get the flows right, as opposed to the stock of unemployed. I have, however, re-estimated the model targeting instead the EU rate and the unemployment rate (hence missing the UE rate), with similar results. The bottom panel plots labor productivity. In the data, this is real GDP per hour in PPP-adjusted US dollars. In the model, it is total net output, $(1-i)zh$, divided by total employment. As the data and model objects are non-comparable in levels, I normalize the model moment to the data moment in the US. An important caveat is that the model is estimated for men, while productivity is only available at the economy level. Note also that this measure of output is net of training costs, but *not* net of costs of job creation and forgone value of leisure. Adjusting for the costs of job creation, however, leaves the cross-country patterns virtually the same. The reason is that while vacancy creation is lower in less fluid labor markets, each vacancy is more expensive due to the wedge. The two effects close to offset.[26]

Table 4 summarizes these predictions for life-cycle wage growth (see Appendix C.4 for the same tables for other outcomes). It shows for each country the difference in life-cycle wage growth to the US in the model and the data. The mechanism emphasized here accounts for 50 percent of the empirical covariance between life-cycle wage growth and labor market fluidity (60 percent in the full sample of 23 countries). Moreover, while the correlation between life-cycle wage growth and fluidity is high, there is also a significant amount of orthogonal variation. Hence, while non-trivial, the forces emphasized here are far from the sole driver of cross-country dispersion in life-cycle wage growth—see, for instance, Guvenen et al. (2014) for a complementary mechanism.

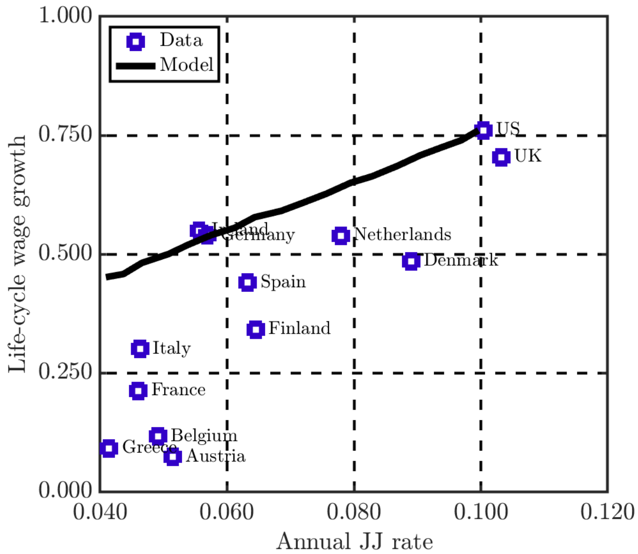
Appendix C.5 shows that the mechanism matches well the lack of a pronounced relationship between cross-sectional inequality as well as life-cycle growth in inequality. The one aspect of the data the mech-

[26] Alternatively, I have added back the wedge times total vacancy creation to net output, reflecting the view that these wedges are something agents value, such as taxes that provide valuable government services as opposed to red tape. It does not much impact the pattern, because the total amount of resources spent on vacancy creation is relatively low.

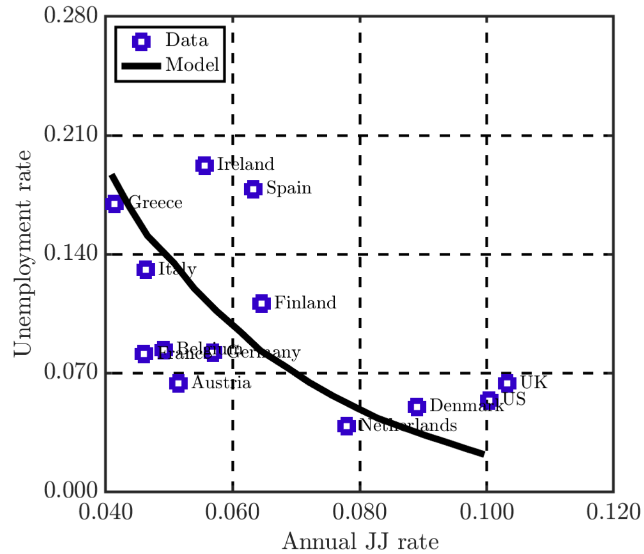
anism fails to fully capture is the lack of correlation between the wage gain upon a JJ move and labor market fluidity. The model predicts that this should decline with fluidity, as workers in more fluid labor markets are higher up the job ladder and hence have less scope to further climb it. I discuss in Appendix C.5 an extension to the model that allows also for so called *godfather* shocks (Jolivet et al., 2006), which resolves this tension without changing any of my main conclusions. Appendix C.3 conducts a sensitivity analysis of the estimated effects of labor market fluidity.

FIGURE 11. THE IMPACT OF LABOR MARKET FLUIDITY, MODEL VERSUS DATA

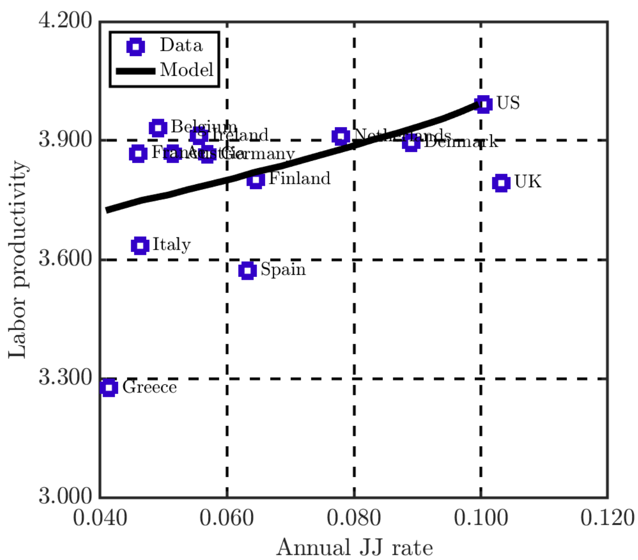
(A) LIFE-CYCLE WAGE GROWTH



(B) UNEMPLOYMENT RATE



(C) LABOR PRODUCTIVITY



Note: Men aged 25–54. Panel A. Wage growth between age 25–50. Data: Based on regression (1) with worker fixed effects, year effects and age effects restricted to not grow after age 50. Panel B. Share of unemployed workers. Data: Constructed by first collapsing the data to the country-year-age level using the provided survey weights, then to the country-level. Model: Constructed by first collapsing the data to the country-age level, then to the country-level. Panel C. Log real output per hour. Data: 2014 real GDP per hour in 2004 PPP-adjusted US dollars. Model: Total net output, $\int(1-i(a,z,h))zh dG(a,z,h)$, divided by total employment, in logs, and normalized to equal the data for the US. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Data: Employment in the past 12 months includes self-employment due to data limitations. Constructed by first collapsing the data to the country-age-year level using the provided survey weights, then to the country-level. Model: Constructed by first collapsing the data to the country-age level, then the country-level. *Source:* Model, BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

TABLE 4. LIFE-CYCLE WAGE GROWTH AND LABOR MARKET FLUIDITY, MODEL VERSUS DATA

		AT	BE	DK	FI	FR	DE	EL	IE	IT	NL	ES	UK	US	**Core**	**All**
Data	Level	0.07	0.12	0.48	0.34	0.21	0.54	0.09	0.55	0.30	0.54	0.44	0.70	0.76	0.37	0.47
	ΔUS_d	-0.69	-0.64	-0.28	-0.42	-0.55	-0.22	-0.67	-0.21	-0.46	-0.22	-0.32	-0.06	0.00	-0.39	-0.29
Model	Level	0.51	0.49	0.70	0.57	0.48	0.53	0.45	0.53	0.48	0.64	0.57	0.77	0.76	0.56	0.58
	ΔUS_d	-0.25	-0.27	-0.06	-0.19	-0.28	-0.23	-0.30	-0.23	-0.28	-0.12	-0.19	0.01	0.00	-0.20	-0.17
$\Delta US_m / \Delta US_d$		0.37	0.41	0.22	0.45	0.51	1.02	0.45	1.10	0.61	0.53	0.60	-0.26	- -	**0.50**	**0.60**

Note: Men aged 25–54. ΔUS: Difference in life-cycle wage growth relative to the US. $\Delta US_m / \Delta US_d$: Difference in life-cycle wage growth relative to the US in the model relative to the data. Core: Average difference relative to the US across the 12 core countries. All: Average difference relative to the US across the 22 countries in the full sample. Data moments are based on regression (1) with worker fixed effects, year effects and age effects restricted to not grow after age 50. *Source:* Model, BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

5.2 Understanding the effects

I now turn to understanding the channels through which labor market fluidity impacts worker careers via a series of decomposition and counterfactual experiments in the model.

The importance of human capital. The left panel of Figure 12 decomposes life-cycle wage growth into the components in accounting identity (12). Specifically, I take the difference in log wages and each of its components between ages 50 and 25. Match productivity grows by 13 log points more in the US relative to the least fluid labor market, while human capital grows by eight log points more. Because the cost of training is shared with workers through a lower wage and young workers train more in more fluid labor markets, the investment component contributes four log points to steeper wage growth in the US relative to the least fluid labor market market. Finally, the piece rate grows by six log points more, as workers receive more outside offers allowing them to bargain up the wage.

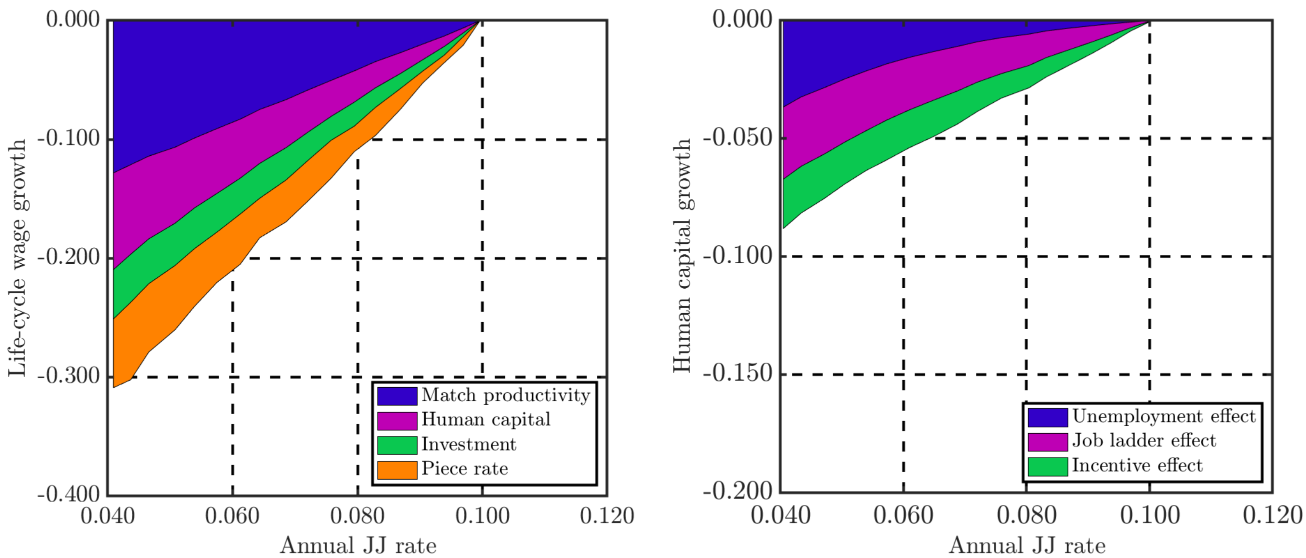
Unemployment, job ladder and incentive effects. Labor market fluidity impacts accumulation of skills through three channels. First, workers spend more time in unemployment in less fluid labor markets, since the job finding rate is lower. Although skills do not depreciate when unused, workers cannot accumulate skills in unemployment. Consequently, *ceteris paribus*, a higher incidence of unemployment reduces skill accumulation. I refer to this as the *unemployment effect*. I isolate its role by holding all decision rules as well as the job finding rate from employment fixed at their estimated US values but adjust the job finding rate from unemployment as in the benchmark cross-country experiment.

Second, workers move up the job ladder faster in more fluid labor markets. Workers higher up the job ladder grow their human capital more, because they expect to have greater use for it (recall Figure 9). Hence, holding decision rules fixed, workers accumulate more skills in more fluid labor markets, since they move faster to matches were they train a lot. I refer to this as the *job ladder effect*. Starting from the *unemployment effect* counterfactual, I compute it as the incremental effect of also letting the job finding rate from employment adjust as in the benchmark. Decision rules are still kept fixed at their US values.

Finally, a worker trains more in more fluid labor markets conditional on her current state, (a, z, h), as she expects to use her skills more efficiently in the future, i.e. the policy $i(a, z, h)$ changes. This is the force highlighted in the qualitative analysis in Section 3. I refer to this as the *incentive effect* and compute it as the residual between the total effect and the sum of the *unemployment effect* and *job ladder effect*.

FIGURE 12. DECOMPOSING THE EFFECT, MODEL

(A) WAGE GROWTH (B) HUMAN CAPITAL ACCUMULATION



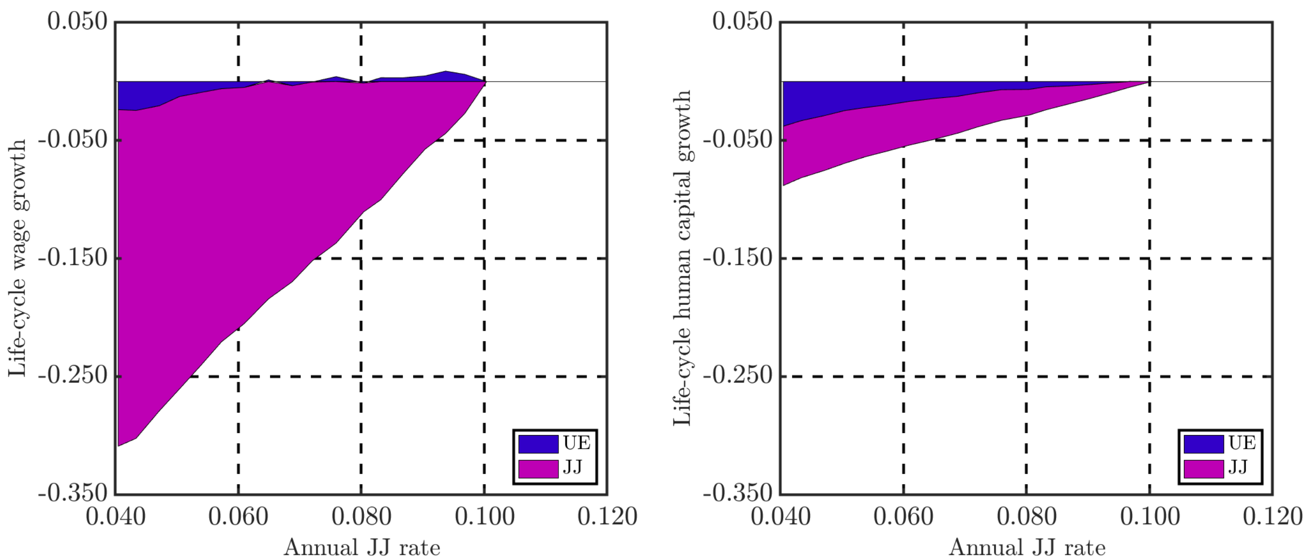
Note: Panel A. Decomposition of the effect of labor market fluidity on life-cycle wage growth based on (12). Panel B. Unemployment effect: Counterfactual impact of labor market fluidity holding decision rules and all flows fixed at their US values apart from the job finding rate from unemployment, which evolves as in the benchmark cross-country experiment. Job ladder effect: Incremental counterfactual impact of labor market fluidity of also letting the JJ mobility rate evolve as in the benchmark cross-country experiment, but still under decision rules fixed at their US values. Incentive effect: Incremental effect of also letting decision rules adjust as in the benchmark cross-country experiment, computed as the difference between the total effect and the combined unemployment and job ladder effects. *Source:* Model.

The right panel of Figure 12 plots the results from these counterfactual exercises for life-cycle human capital accumulation. Going from the US to the least fluid labor market, life-cycle human capital accumulation falls by eight percent. Initially, the *job ladder effect* is the most important channel, accounting for half of the fall in human capital accumulation, with the *unemployment effect* accounting for less than 15 percent and the *incentive effect* for the remaining 36 percent. The relative importance of the *unemployment effect*, however, rises as labor market fluidity falls further relative to the US, rising to 41 percent in the least fluid labor market. Correspondingly, the relative importance of the *job ladder effect* falls to 35 percent and the *incentive effect* to 24 percent for the least fluid labor market.

One interpretation of this finding is that the most important channel through which labor market fluidity impacts human capital accumulation is *backward* looking, as opposed to *forward* looking. Greater labor market fluidity allows workers to faster locate jobs where they have greater use for their skills and where they consequently optimally accumulate more skills. This includes moving out of unemployment faster. In contrast, the expectation of future mobility to more productive matches plays a non-trivial yet quantitatively less important role. For this reason, my estimated impact of labor market fluidity on human capital accumulation is not very sensitive to workers' bargaining power, as I discuss further in Appendix C.3. Workers' bargaining power primarily impacts training through the *incentive effect*, and this effect only accounts for a quarter to a third of the overall impact of fluidity on human capital accumulation. Nevertheless, I stress that it remains critical to model training as endogenous in order to reach this conclusion, since otherwise training would not differ over the job ladder.

FIGURE 13. THE ROLE OF A HIGHER RATE OF CLIMBING THE JOB LADDER, MODEL

(A) WAGE GROWTH — (B) HUMAN CAPITAL ACCUMULATION



Note: JJ: Counterfactual effect of only letting the job finding rate from employment adjust as in the benchmark cross-country experiment, holding fixed the job finding rate from unemployment, p, at its US value, computed by varying relative search efficiency of the employed, ϕ, to match the cross-country variation in labor market fluidity. UE: Counterfactual effect of only letting the job finding rate from unemployment adjust as in the benchmark cross-country experiment, holding fixed the job finding rate from employment, computed as the difference between the total effect and the JJ effect. *Source:* Model.

The role of labor market fluidity. The incentive effect in Figure 12 is in turn a response to both a slower rate of leaving unemployment and a slower rate of climbing the job ladder in less fluid labor markets. To decompose the importance of each, I resolve workers' problem holding the job finding rate from unemployment, p, fixed at the estimated value for the US, instead adjusting the relative search efficiency from employment, ϕ, so as to match observed cross-country variation in labor market fluidity.[27]

The left panel of Figure 13 shows that a slower rate of climbing the job ladder accounts for 92 percent of the slower life-cycle growth in wages in less fluid labor markets. This finding is, per se, not surprising given that less growth in match productivity plays an important role behind weaker life-cycle wage growth in less fluid labor markets (Figure 12). When only the UE rate varies, life-cycle growth in match productivity remains equally large as in the US by construction.[28] The right panel shows that 40 percent of the lower human capital accumulation in less fluid labor markets is accounted for by the lower UE rate. The remaining 60 percent is accounted for by a slower rate of climbing the job ladder, which reduces human capital accumulation both by slowing down workers' reallocation up the job ladder to jobs where they train a lot and by discouraging training conditional on place in the job ladder.

6 Supporting correlations

In this last section of the paper, I turn to direct evidence on how training covaries with labor market fluidity. To that end, I exploit the fact that the ECHP asks about vocational training since January last year, including whether the worker undertook any training, the type of training, on how many occasions she trained, how many total days she spent in training, when the training started, how many hours per week during the weeks she trained, who paid for the training, etc. Based on this, I compute the fraction of work days and work hours a worker spent in training during the prior 12 months, expressed as a fraction of potential work days (5*52) or work hours (40*52).[29] An key advantage of the ECHP for this analysis is that it was conducted by the EuroStat, the European Union's statistical agency, using a common questionnaire and identical data processing routines. This facilitates the cross-country comparison.

I regress various measures of training on labor market fluidity and controls in Table 5. Panel A considers as the outcome measure of training an indicator for whether the individual trained since January

[27]Because workers still move away from low productive jobs with a higher chance of breaking up at a slower rate when the search intensity from employment, ϕ, is lower, the incidence of unemployment remains higher in low-ϕ countries. Nevertheless, over 90 percent of unemployment differences disappear once differences in the job finding rate from unemployment are shut down, such that remaining differences in the incidence of unemployment play a second-order role in driving results.

[28]With only the UE rate varying, wage growth initially *rises* as labor market fluidity falls, because workers are less willing to remain unemployed. Consequently, they start at a lower piece rate. Greater growth in the piece rate more than offsets lower growth due to human capital and investment for small changes in fluidity when the JJ rate is held fixed.

[29]The reported time in training is since January in the year prior to the survey. If the worker reports that her training started more than 12 months prior to the survey date, I use the reported start date of training to adjust the amount of training to a per-past-12-months basis (i.e. if the worker reports 20 training days since January last year, her survey was conducted in April and she reports starting training in February last year, my measure of training days is $12/14 * 20$). I top-code the training measures at 13 weeks of full time training per year. This concerns roughly 1.5 percent of observations and results are more pronounced without top-coding—see Appendix D.2. In the initial years, the training questions were only asked for private sector workers. To be consistent, I restrict the entire sample to the private sector.

last year. The first column shows the point estimate from a projection on aggregate labor market fluidity with year effects. The second column adds controls for worker observable characteristics, including a linear in age, a college dummy and 10 occupation dummies. The third column adds also a control for whether the worker made a JJ move in the past year. Panels B–C repeat the same analysis for number of days and hours on training in the past 12 months, respectively, expressed as a fraction of total work days/hours. Standard errors are clustered at the country level.

TABLE 5. TRAINING AND LABOR MARKET FLUIDITY

	Panel A. Whether trained			*Panel B. Days (fraction of year)*			*Panel C. Hours (fraction of year)*		
	Raw	Controls	Direct	Raw	Controls	Direct	Raw	Controls	Direct
Fluidity	9.123***	8.317***	8.432***	0.403***	0.373***	0.336***	0.338***	0.324***	0.304***
	(1.105)	(1.144)	(1.121)	(0.105)	(0.105)	(0.068)	(0.061)	(0.060)	(0.033)
JJ			-0.015			0.000			0.000
			(0.012)			(0.001)			(0.001)
Age		-0.006***	-0.004***		-0.000***	-0.000**		-0.000***	-0.000**
		(0.001)	(0.001)		(0.000)	(0.000)		(0.000)	(0.000)
College		0.166***	0.113***		0.007***	0.008***		0.004**	0.004***
		(0.025)	(0.028)		(0.002)	(0.002)		(0.001)	(0.001)
N	108,209	107,777	44,020	107,917	107,488	43,895	107,756	107,331	43,818

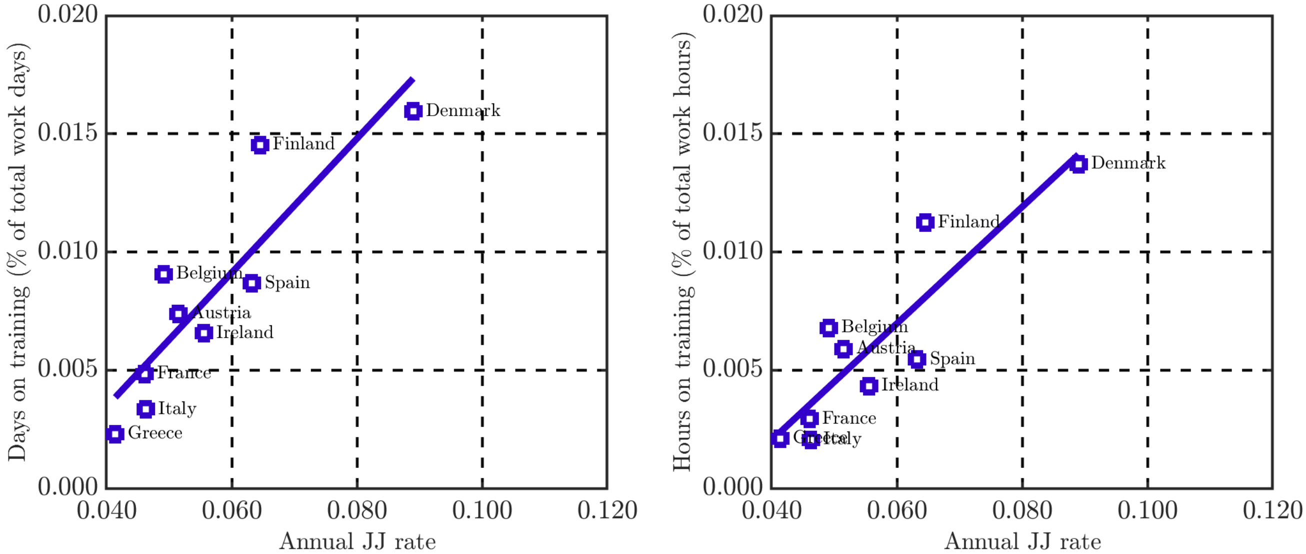
Note: Male private sector employees 25–54. Projection of training outcome on labor market fluidity without or with controls. Panel A. Whether worker undertook any vocational training since January last year. Panel B. Days on vocational training in the past 12 months, expressed as a fraction of potential work days (5*52). Panel C. Hours on vocational training in the past 12 months, expressed as a fraction of potential work hours (40*52). Hours and days on training are top-coded at 13 weeks of full time training per year. All panels. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Employment in the past 12 months includes self-employment. Constructed by first collapsing the data to the country-age-year level using the provided survey weights, then to the country level. Standard errors are clustered at the country-level. * statistically significant at 10%; ** statistically significant at 5%; *** statistically significant at 1%. *Source:* ECHP 1995–2001.

Workers train more in more fluid labor markets. While older workers train less and college graduates train more, controlling for compositional differences does not change the main takeaway of a positive correlation between aggregate fluidity and incidence of training. Moreover, there is no statistical correlation between training and JJ mobility in the past year. Hence, the positive correlation between labor market fluidity and training does not appear to be due to a somewhat mechanical effect of new hires being trained to perform the required tasks of the new job. Figure 14 illustrates the variation.

Appendix D shows that a large share of workers report that their employer paid for their vocational training (although the evidence on wages in Appendix B.2 somewhat contradicts this view). If anything, the share rises with labor market fluidity, but the pattern is not statistically significant. I also report in Appendix D that there is no statistically significant correlation between vocational training in the previous year and current JJ mobility. That is, workers who train more are not more likely to remain with their current employer, in contrast to what one may have hypothesized if skills were *firm-specific*.

FIGURE 14. ON-THE-JOB TRAINING AND LABOR MARKET FLUIDITY

(A) DAYS ON TRAINING (B) HOURS ON TRAINING



Note: Male private sector employees aged 25–54. Panel A. Days on vocational training in the past 12 months, expressed as a fraction of potential work days (5*52). Panel B. Hours on vocational training in the past 12 months, expressed as a fraction of potential work hours (40*52). Hours and days on training are top-coded at 13 weeks of full time training per year. All training measures: Constructed by first collapsing the data to the country-age-year level using the provided survey weights, then to the country level. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Employment in the past 12 months includes self-employment. Constructed by first collapsing the data to the country-age-year level using the provided survey weights, then to the country level. *Source:* ECHP 1995–2001.

The theory also makes rich predictions for how training varies in the cross-section across countries. As highlighted by Figure 9, workers grow their human capital less when employed in less productive matches, as they expect to have less use for it. In more fluid labor markets, however, workers currently in low productive matches expect to be able to move away from such matches faster. Consequently, workers train more in more fluid labor markets, and particularly so when in low productive matches. In contrast, absent separation shocks, training at the very top of the job ladder would be unaffected by labor market fluidity. Separation shocks moderate this prediction, but the intuition remains: training should be particularly low in less productive matches in less fluid labor markets.

Assessing this prediction empirically requires two steps. First, I assume that larger firms are more productive, consistent with theoretical predictions and empirical observations in earlier work (Engbom, 2020). This assumption allows me to impute a productivity rank of firms based on size.[30] Only the latter is available in the data, coded into six roughly equally large bins (in an employment-weighted sense). Second, I follow the search literature to equate firms with a set of matches with the same productivity (Bagger et al., 2014), and group firms into employment-weighted sextiles based on productivity.

[30]Consistent with this, larger firms in my data pay better, conditional on worker-fixed effects and time-varying controls.

I regress hours on training in the past 12 months on the rank of the worker's employer in terms of size/productivity, $rank_{it}$, and its interaction with fluidity, controlling for worker-fixed effects and age,

$$training_{it} \quad = \quad \alpha_0 rank_{it} + \alpha_1 rank_{it} + I_i + X_{it}\beta + \varepsilon_{it} \tag{13}$$

where $rank_{it} \in \{1, 2, 3, 4, 5, 6\}$ is an (increasing) ranking of firm size (data)/productivity (model).

Table 12 provides results, offering two main takeaways. First, workers train more when employed at larger, higher paying firms, consistent with findings in Arellano-Bover (2020). The reason is that they have greater use for their skills in more productive matches, and as a consequence invest more. Second, workers in low fluidity countries particularly train less when employed at small, low paying firms. The reason is that workers currently in a low productive match are particularly stuck with its current employer in low fluidity countries, and respond by training less.

TABLE 6. TRAINING AND LABOR MARKET FLUIDITY IN THE CROSS-SECTION

$training_{it} = \alpha_0 rank_{it} + \alpha_1 rank_{it} fluidity_c$

Panel A. Data		*Panel B. Model*	
$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\alpha}_0$	$\hat{\alpha}_1$
0.003**	-0.046***	0.004***	-0.033***
(0.001)	(0.014)	(0.000)	(0.002)

Note: Male private sector employees 25–54. Training: Hours on vocational training in the past 12 months as a fraction of potential work hours (40*52). Rank: Ordering of firms into 6 roughly equally large (in terms of employment) bins of size (data) / productivity (model). Regression controls for worker fixed effects and age. Hours on training are top-coded at 13 weeks of full time training per year. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Employment in the past 12 months includes self-employment. Constructed by first collapsing the data to the country-age-year level using the provided survey weights, then to the country level. Standard errors are clustered at the country-level. ** statistically significant at 5%; *** statistically significant at 1%. *Source:* ECHP 1995–2001.

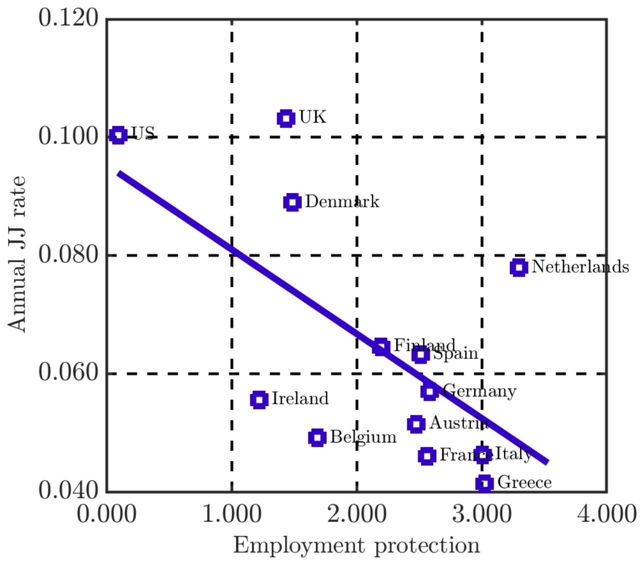
7 Conclusion

I argue that lower labor market fluidity reduces life-cycle wage growth of workers and the stock of human capital in the economy. The reason is that makes it harder for workers to find jobs that fully utilize their skills, discouraging human capital accumulation. Differences in labor market fluidity account for half of lower life-cycle wage growth in less fluid labor markets across OECD countries and result in 15 percent lower labor productivity relative to the US.

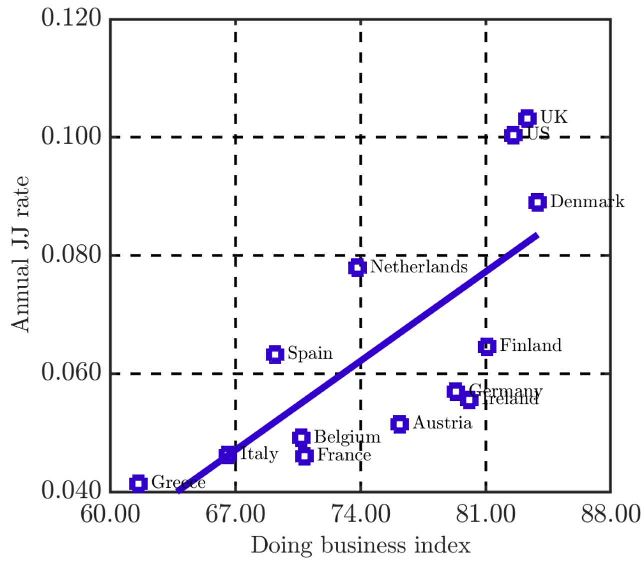
I end with a brief review of potential factors behind fluidity. Figure 15 correlates labor market fluidity with a few factors that the previous literature has emphasized as important drivers of firms' incentives to create jobs. Labor market fluidity is negatively correlated with measures of employment protection, the cost of doing business, and labor tax rates on firms. The latter two findings are consistent with Fonseca et al. (2001), who argue that differences in the cost of starting businesses are more important in driving cross-country variation in aggregate labor market outcomes than labor market policies. I conclude that, consistent with a large existing literature, policies that serve to effectively raise the cost on firms of hiring are associated with lower labor market fluidity.

FIGURE 15. DETERMINANTS OF LABOR MARKET FLUIDITY

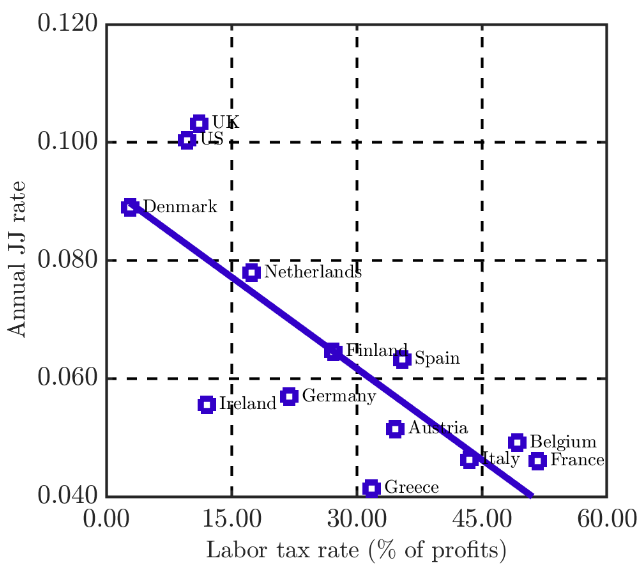
(A) EMPLOYMENT PROTECTION LEGISLATION



(B) DOING BUSINESS INDEX



(C) LABOR TAX RATE



Note: Male employees aged 25–54. Panel A. Employment protection legislation index compiled by the OECD. Panel B. Doing business score compiled by the World Bank (downloaded https://www.doingbusiness.org). Panel C. Average tax rate on labor on firms as reported by the World Bank. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Employment in the past 12 months includes self-employment. Constructed by first collapsing the data to the country-age-year level using the provided survey weights, then to the country level. *Source:* BHPS, ECHP, EUSILC, GSOEP, OECD, PSID and World Bank 1991–2015.

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A Data — FOR ONLINE PUBLICATION

This section describes the data sources in some more detail and provides additional empirical results.

A.1 Data sources

Table 7 summarizes the annual data set and Table 8 the monthly data set. In total, the annual sample contains roughly nine hundred thousand individual-years and the monthly sample roughly 11 million individual-months. I describe the data sources in some more detail below.

PSID. The PSID has been collected annually since 1968 (biannually since 1997) based on an initially representative sample of households and their offspring. Over time, additional households have been added, but I focus on the original core sample and their descendants (the so called Survey Research Center sample). Initially, no weights were provided for this sample, since it was representative of the US population. Subsequent attrition and non-response, however, necessitate the use of survey weights, which I employ throughout my analysis. As a large share of the questions in the PSID center around the "head" of the household, I restrict attention to heads of households. Starting in 1988, the PSID asks respondents for a monthly calendar of labor market events during the prior calendar year (during the prior two calendar years starting with the 2003 survey). It also asks for information on up to two employment spells (in some years more), including start and end dates, earnings, hours, occupation, etc.

GSOEP. The GSOEP was modeled on the PSID and has followed the same individuals annually since 1984. Additional samples have been added over time, but I restrict attention to the original, representative samples for West and East Germany. I start the analysis with German reunification in 1991, which also corresponds well with the sample period available from the other data sources. I end the analysis in 2011 because it was the last year available when I applied for the data several years ago.[31] The GSOEP asks a rich set of questions about demographics, income and hours worked, as well as labor force status in each month during the past calendar year and the start date of the current employment spell. I use survey weights throughout my analysis to adjust for nonrandom attrition and non-response.

BHPS. The BHPS began in 1991 and was discontinued in 2008. It is similar to the PSID. The sample has expanded over time, but I focus on the original core sample. As the PSID/GSOEP, the BHPS contains demographic characteristics on the respondent, as well as annual information on gross income and hours

[31] I am awaiting an extension of my project to add the last few years from the GSOEP as well as the EUSILC.

worked. The BHPS also contains information on start and end dates on all labor market spells since the last survey, which I use to construct a monthly calendar of labor market events as in the PSID/GSOEP. I use survey weights throughout my analysis to adjust for nonrandom attrition and non-response.

TABLE 7. OVERVIEW OF ANNUAL DATA SET

	Source	Years	T	NT	N
	Panel A. Core Western European countries plus the US				
Austria	ECHP/EUSILC	1995–2014	18	39,700	13,276
Belgium	ECHP/EUSILC	1994–2014	19	36,070	12,849
Denmark	ECHP/EUSILC	1994–2013	18	25,883	8,901
Finland	ECHP/EUSILC	1996–2014	16	48,432	17,867
France	ECHP/EUSILC	1994–2014	16	58,981	15,951
Germany	GSOEP	1991–2011	21	60,346	6,640
Greece	ECHP/EUSILC	1994–2014	15	36,341	12,425
Ireland	ECHP/EUSILC	1994–2014	17	25,018	8,935
Italy	ECHP/EUSILC	1994–2014	15	85,926	33,668
Netherlands	ECHP/EUSILC	1994–2014	18	61,312	21,073
Spain	ECHP/EUSILC	1994–2014	19	92,355	32,976
UK	BHPS	1991–2008	18	32,910	4,119
US	PSID	1994–2015	13	19,047	2,914
Total			**223**	**622,321**	**191,594**
	Panel B. Other OECD countries				
Czech Republic	EUSILC	2005–2014	9	27,761	10,805
Estonia	EUSILC	2004–2014	10	19,682	8,113
Hungary	EUSILC	2005–2014	10	37,406	16,059
Iceland	EUSILC	2004–2014	10	10,407	4,522
Latvia	EUSILC	2007–2014	7	12,684	6,207
Lithuania	EUSILC	2005–2014	9	13,495	5,414
Norway	EUSILC	2004–2014	10	22,994	8,241
Poland	EUSILC	2005–2014	9	46,972	19,850
Slovak Republic	EUSILC	2005–2013	8	15,404	6,166
Slovenia	EUSILC	2005–2014	9	47,708	23,487
Total			**71**	**221,112**	**96,101**

Note: Men aged 25–54. T: Number of years; NT: Number of individual-years; N: Number of individuals.

ECHP. The ECHP was run 1994–2001 across the original set of European Union countries. Because of confidentiality restrictions, however, data from Germany and Portugal are not released to researchers. The data from Sweden are only available for a few years and miss several key variables, forcing me to exclude Sweden. Luxembourg switched to collecting data via a separate, national survey after three years in the ECHP, dropping several key variables in the process. As the Luxembourg sample for the first three years in the ECHP is small, I drop also Luxembourg from my analysis (similar results hold including the few available years, though). While data from the UK are available in the ECHP, several years are missing so I opt to use the larger and consistently collected BHPS instead. The ECHP follows the same individuals annually for up to eight years. The survey is similar to the PSID, including a similar set of variables. In particular, it asks for a monthly calendar of events in the prior calendar year and the start date of the current employment spell. I weigh all results using the provided survey weights.

TABLE 8. OVERVIEW OF MONTHLY DATA SET

	Source	Years	T	NT	N
	Panel A. Core Western European countries plus the US				
Austria	ECHP/EUSILC	1995–2014	214	544,535	15,029
Belgium	ECHP/EUSILC	1994–2014	225	482,697	14,548
Denmark	ECHP/EUSILC	1994–2014	213	243,673	6,163
Finland	ECHP/EUSILC	1996–2014	189	430,234	11,935
France	ECHP/EUSILC	1994–2014	201	833,033	18,442
Germany	GSOEP	1991–2011	239	756,609	6,758
Greece	ECHP/EUSILC	1994–2014	177	491,048	14,198
Ireland	ECHP/EUSILC	1994–2014	201	342,759	10,175
Italy	ECHP/EUSILC	1994–2014	177	1,162,774	38,537
Netherlands	ECHP/EUSILC	1994–2014	213	550,911	14,440
Spain	ECHP/EUSILC	1994–2014	225	1,247,297	37,304
UK	BHPS	1991–2014	228	466,563	4,412
US	PSID	1994–2015	225	374,570	2,978
Total			**2,727**	**7,926,703**	**194,919**
	Panel B. Other OECD countries				
Czech Republic	EUSILC	2005–2014	106	387,008	12,714
Estonia	EUSILC	2004–2014	118	267,939	9,227
Hungary	EUSILC	2005–2014	118	523,418	18,824
Iceland	EUSILC	2004–2014	82	95,374	4,198
Latvia	EUSILC	2007–2014	82	172,982	7,164
Lithuania	EUSILC	2005–2014	106	191,482	6,337
Norway	EUSILC	2004–2014	118	225,178	7,227
Poland	EUSILC	2005–2014	106	651,946	22,992
Slovak Republic	EUSILC	2005–2013	94	204,716	6,849
Slovenia	EUSILC	2005–2014	106	646,751	26,696
Total			**1,036**	**3,366,794**	**122,228**

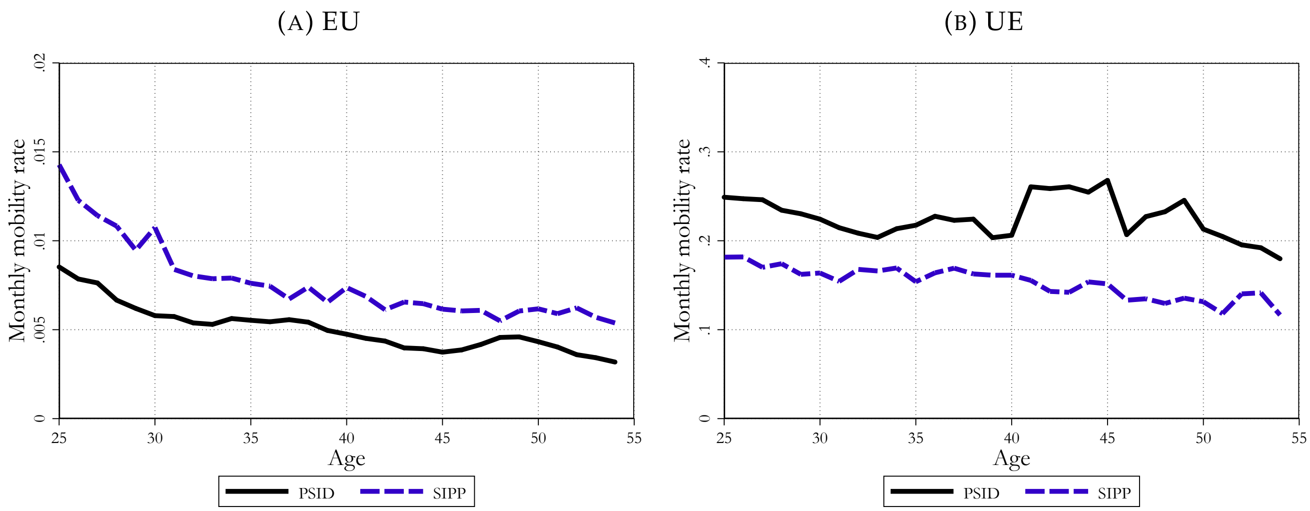
Note: Men aged 25–54. T: Number of months; NT: Number of individual-months; N: Number of individuals.

EUSILC. The EUSILC is the successor to the ECHP starting in 2003. It gradually expanded the set of countries covered to eventually include all EU members plus a set of affiliated countries. The survey is annual and uses a rotating panel design, which differs somewhat in length across countries. Most countries follow the same individuals for up to four years, but France follows individuals for eight years and Norway for six. As the other surveys, it contains the standard demographic and income variables, including gross annual labor income and hours worked during the previous calendar year. It also contains a monthly calendar of labor market events for the prior calendar year. It differs slightly from the other surveys in that it does not contain the start date of the current employment spell, instead recording whether the individual switched employer in the past 12 months. All results use survey weights.

A.2 Benchmarking the PSID with the SIPP

The EU rate in the PSID is lower than what researchers typically find in the CPS, but more in line with what other research has found in the SIPP (Engbom, 2020). Figure 16 compares the monthly EU and UE rates in the PSID against the SIPP. Broadly, the series compare reasonably well. In particular, both the PSID and SIPP show significantly lower mobility than, for instance, the CPS. This is consistent with well-known issues with classification error leading to substantially overstated gross worker flows in the CPS (Abowd and Zellner, 1985; Poterba and Summers, 1986).

FIGURE 16. MONTHLY EU AND UE RATES, PSID VERSUS SIPP

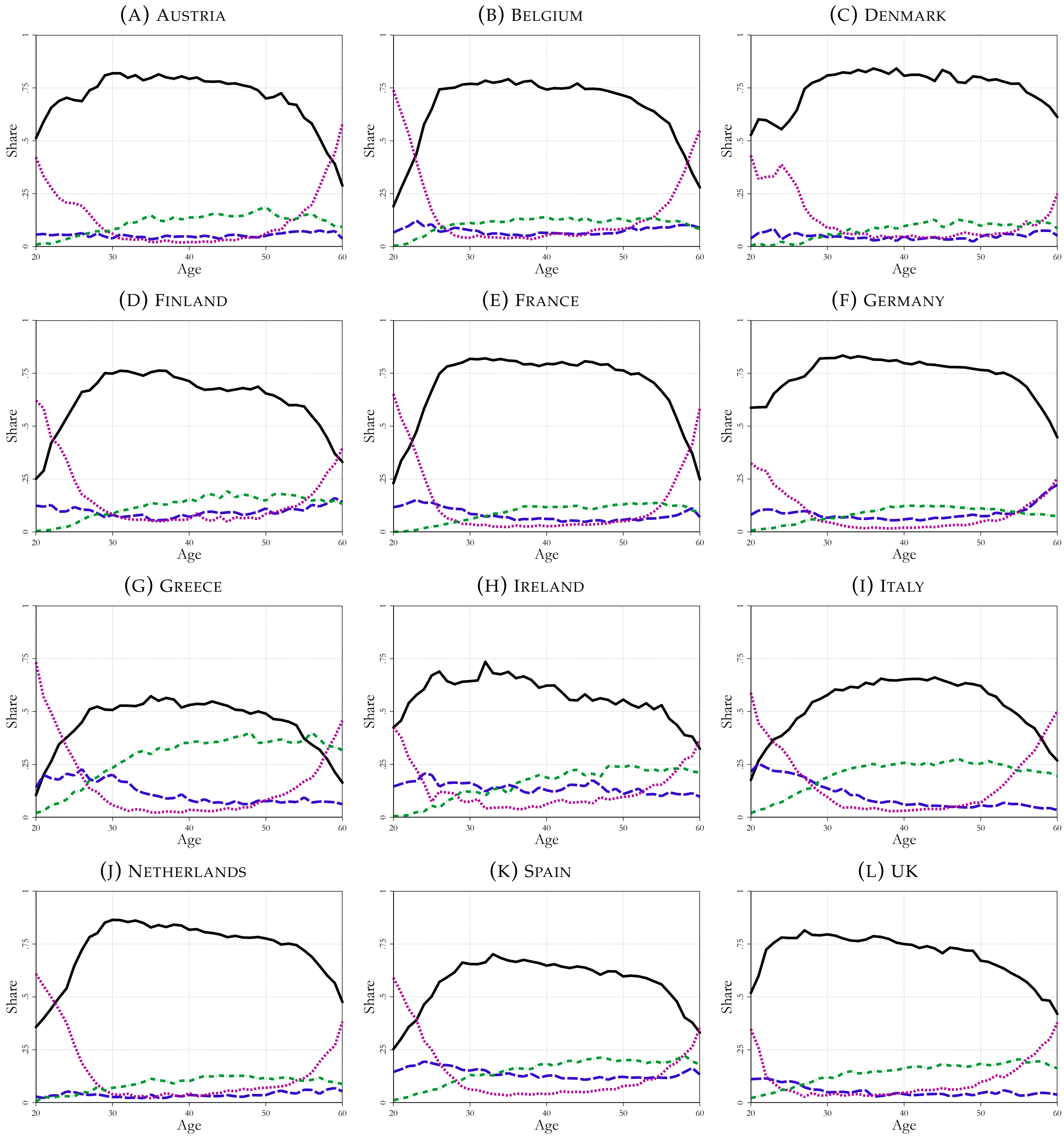


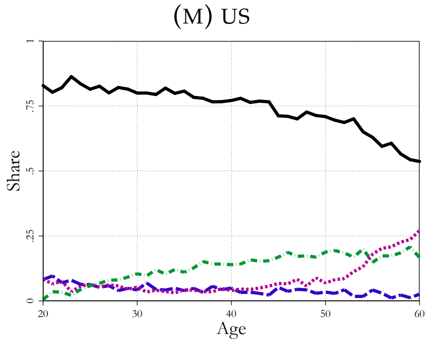
Note: Men 25–54. Panel A. Share of employed workers who are unemployed in the subsequent month. Panel B. Share of unemployed workers who are employed in the subsequent month. All panels. Employment includes self-employment due to data limitations. Definitions follow ILO standard. Constructed by first collapsing the data to the country-year-age level using the provided survey weights, then to the country-level. *Source:* PSID and SIPP 1994–2015.

A.3 Life-cycle labor market states

Figure 17 plots the distribution of men across four labor market states—wage employment, self employment, unemployment and non-participation—over the life-cycle, offering three main takeaways. First, workers enter the labor market at a declining pace up to age 30. There is no pronounced covariation between age of entry and labor market fluidity, although the US (and somewhat less the UK) appears to be an outlier. The way the PSID is collected, however, may bias participation rates at young ages if those who participate in the labor market are also more likely to have formed their own households (the SIPP, in contrast, shows an increase in male labor force participation rates between age 20–25). By not focusing on the head of household like the PSID, the other surveys may be less prone to this.

FIGURE 17. LIFE-CYCLE LABOR MARKET STATES



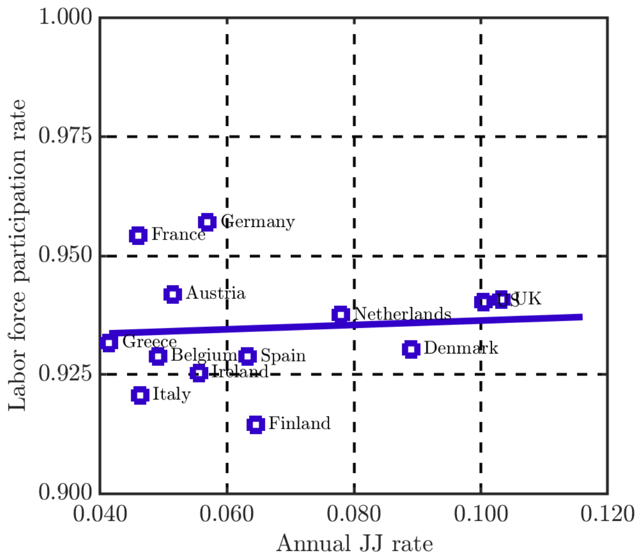


Note: Share of men aged 20–60 by labor market status. Solid black: wage employed. Dash-dotted green: self-employed. Dashed blue: unemployed. Dotted purple: not-in-the labor force. Labor market states follow ILO standard. All moments: Constructed by first collapsing the data to the country-year-age level using the provided survey weights, then to the country-level. *Source:* BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

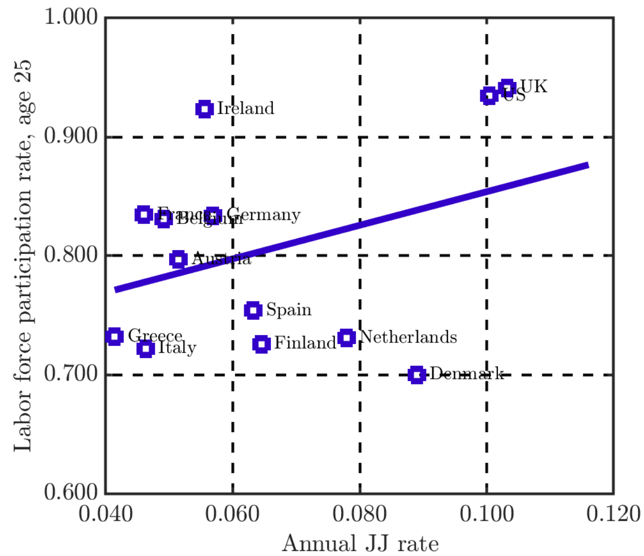
Second, participation rates remain high and roughly constant until age 50, after which they start to decline. The decline becomes pronounced after around age 55. Third, the share of wage employed falls gradually after age 30, while the share of self-employed rises. There is also some evidence of a higher self-employment rate in less fluid labor markets. As I show in Appendix C.6, the model is consistent with this pattern if self-employment is interpreted as out of necessity, i.e. akin to unemployment. While the share of self-employment remains modest across all countries, it would be interesting to develop a deeper theory of this than necessity entrepreneurs in future research (see, for instance, Engbom, 2020, for a joint model of labor market search and entrepreneurship).

FIGURE 18. LABOR FORCE PARTICIPATION RATES AND LABOR MARKET FLUIDITY

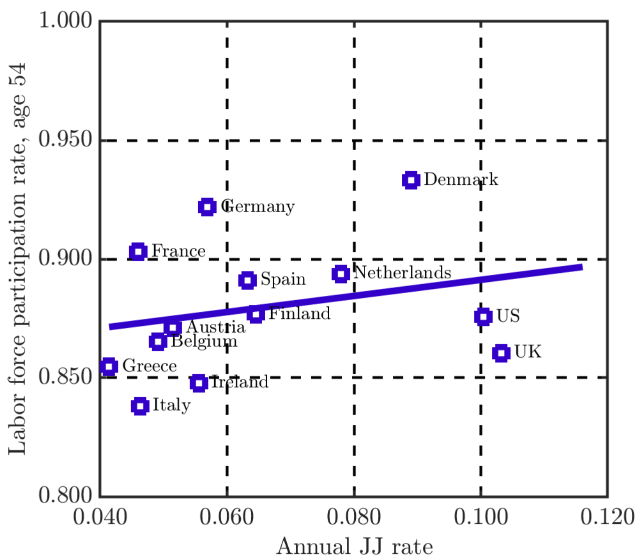
(A) ALL



(B) AGE 25



(C) AGE 54



Note: Men aged 25–54. Panel A. Share of all men aged 25–54 that is in the labor force. Panel B. Share of men aged 25 that is in the labor force. Panel C. Share of men aged 54 that is in the labor force. All panels. Labor force includes the wage employed, self-employed and unemployed. Employment status based on ILO standard. Constructed by first collapsing the data to the country-year-age level using the provided survey weights, then to the country level. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Employment in the past 12 months includes self-employment due to data limitations. Constructed by first collapsing the data to the country-age-year level using the provided survey weights, then to the country-level. *Source:* BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

Figure 18 plots labor force participation rates for all men 25–54, men aged 25 and men aged 54 against labor market fluidity. While there is dispersion across countries in labor force participation rates, it is only weakly correlated with labor market fluidity.

Figure 19 plots the share of men who are in the labor force in year t but not in the labor force in year $t+2$. I focus on two-year later outcomes to be able to use also the biannual PSID years after 1997. The share remains low up to around age 50, when it starts to gradually rise.

A.4 The public sector

The left panel of Figure 20 shows that the share of prime aged male employees that work in the public sector is about 25 percent and that it declines with labor market fluidity, although the relationship is driven by the US. The right panel plots the estimated life-cycle wage profile of private and public employees based on a regression of log hourly real wages, w_{it}, of individual i in year t on separate age effects for the private, A_{it}, and public sector, PA_{it}, country-year effects, Y_{ct}, and worker fixed effects, I_i,

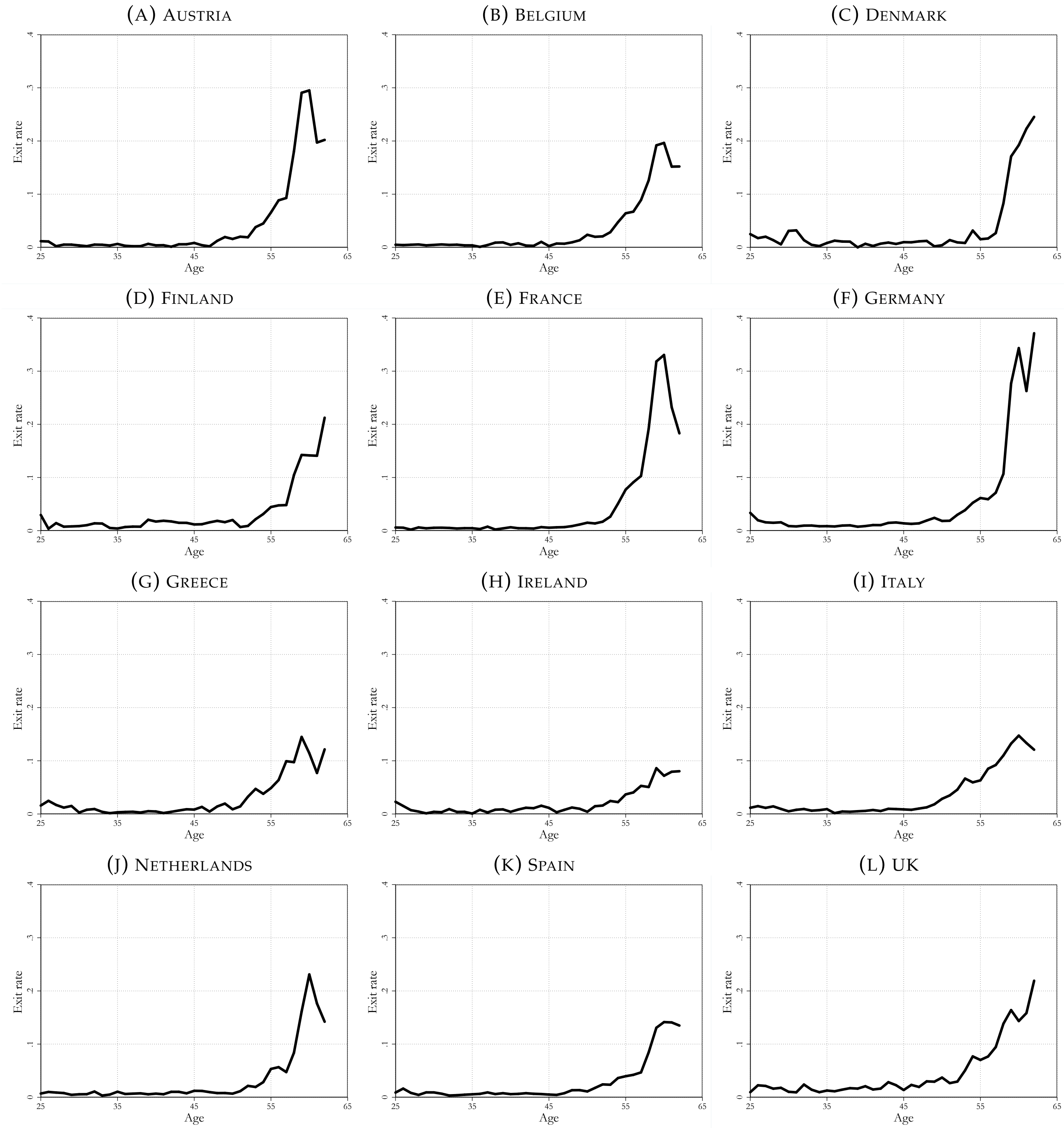
$$w_{it} = A_{it} + PA_{it} + Y_{c(i)t} + I_i + \varepsilon_{it} \tag{14}$$

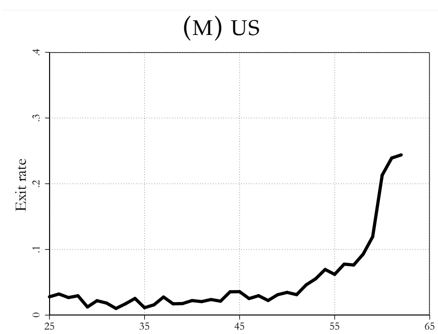
I focus on the sample of 25–54 year olds and restrict wages to not grow after age 50. While in principle this restriction is only required for one of the two sectors, to treat both identically I impose it in both. Inclusion of worker fixed effects in (14) controls for differences in worker composition across sectors, i.e. identification of the level wage difference is based on workers switching between sectors. Note also that the required data for this exercise are only available from the ECHP, GSOEP and PSID. Young workers earn less when employed in the public sector, but the public sector is associated with *steeper* within-worker residual life-cycle growth in wages. Hence, the fact that the share of public sector employees declines with labor market fluidity tends to, *ceteris paribus*, *flatten* the relationship between life-cycle wage growth and labor market fluidity. The differences in life-cycle wage growth, however, are modest, so it is unlikely that this would have a major impact on the patterns documented in this paper.

A.5 Flows in and out of unemployment

The top panel of Figure 21 plots the monthly EU rate over the life-cycle across countries. The EU rate shares a common shape across countries, with high rates of job loss early in careers and subsequent declines. Aggregate cross-country differences are less pronounced than for JJ mobility, with Spain as an exception. Moreover, there is no evidence that high-fluidity countries also have higher EU mobility rates. In fact, the correlation between the aggregate EU rate and labor market fluidity is negative.

FIGURE 19. LABOR FORCE EXIT RATES

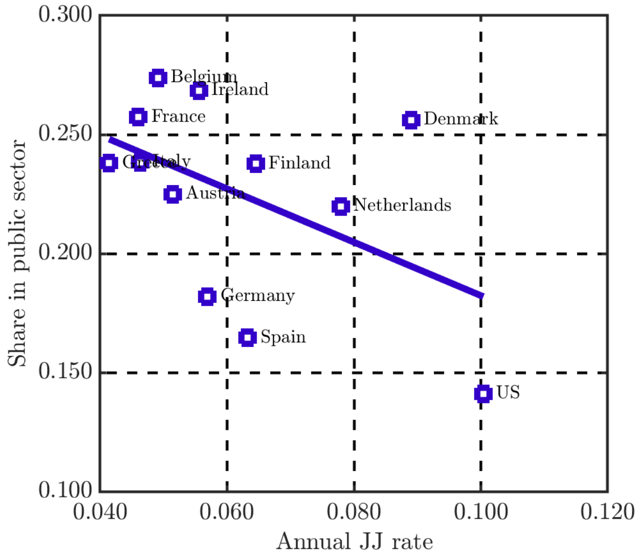




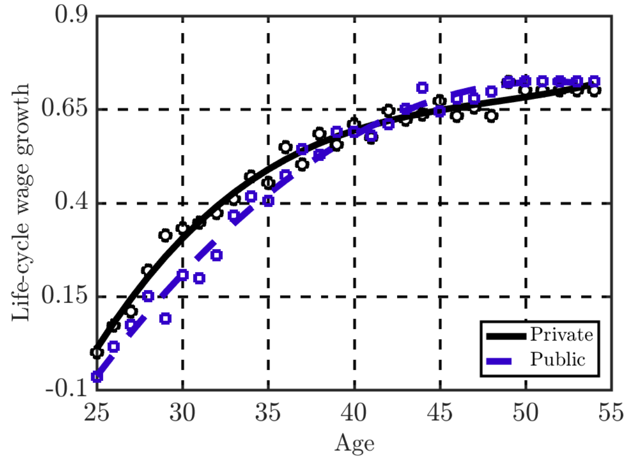
Note: Male employees aged 25–63. Share of labor force participants in year t who are not in the labor force at year $t+2$. Employment status is based on ILO standards. Computed by first collapsing the data to the age-year-country level using the provided survey weights, then to the country-age-level. *Source:* BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

FIGURE 20. PUBLIC SECTOR

(A) SHARE PUBLIC



(B) LIFE-CYCLE WAGE



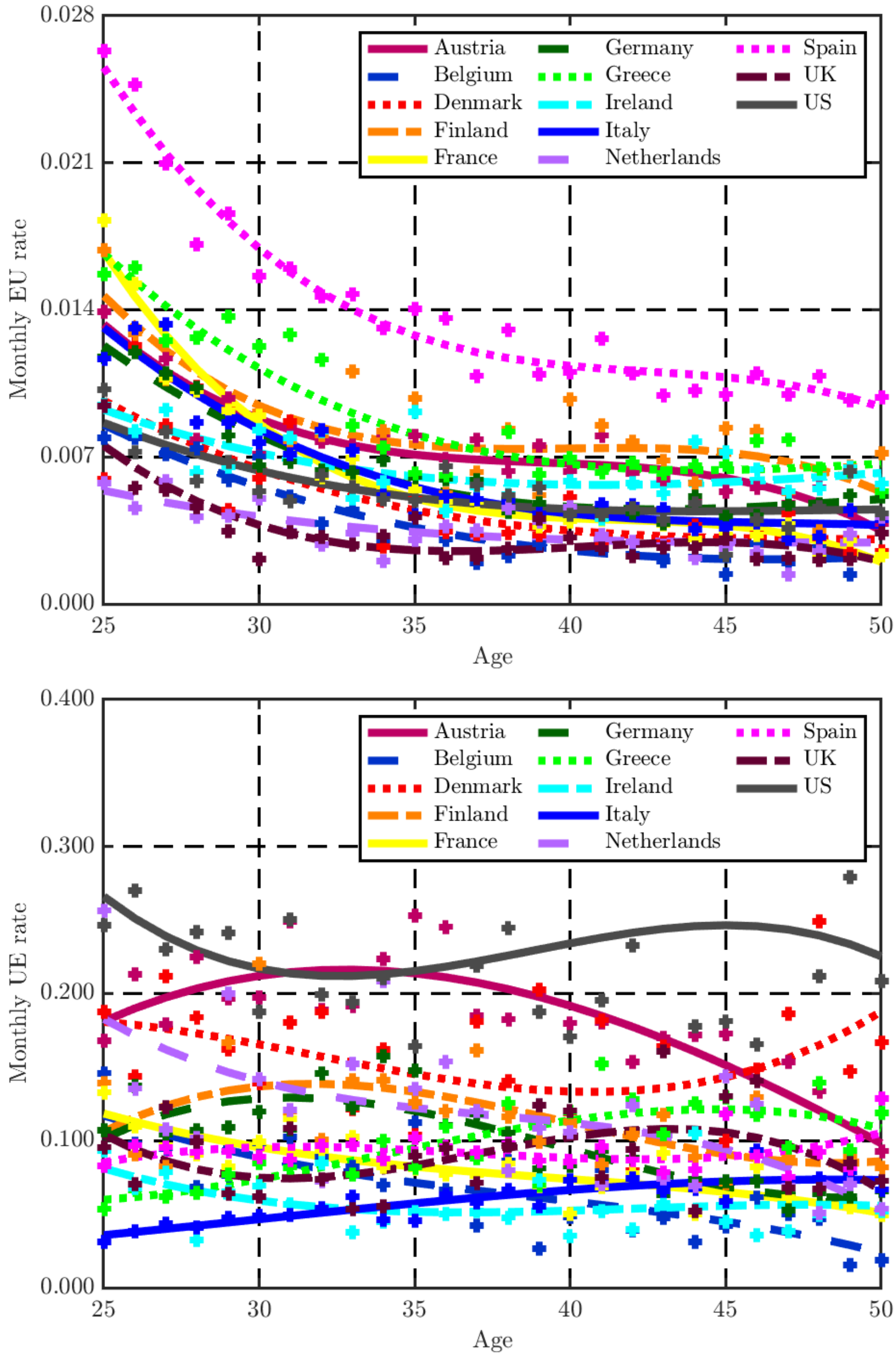
Note: Male employees aged 25–54. Panel A. Share of employees that work in public sector, computed by first collapsing the data to the age-year-country level using the provided survey weights, then to the country-age-level. Panel B. Wage profile for ages 25–54 with wages restricted to not grow past age 50 based on regression (14). Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Employment in the past 12 months includes self-employment due to data limitations. Constructed by first collapsing the data to the country-age-year level using the provided survey weights, then to the country-level. *Source:* ECHP, GSOEP and PSID 1991–2015.

The bottom panel plots the monthly UE rate over the life-cycle across countries. The profiles are noisier than the other mobility rates, because the sample of unemployed is much smaller than the sample of employed. The life-cycle pattern of UE mobility is somewhat more heterogeneous across countries. Most countries display modest declines in the UE rate over the life-cycle, but a few countries have more pronounced declines, while others see increases. There are also significant differences also in the UE rate across countries, and the aggregate UE rate is positively correlated with labor market fluidity.

A.6 Raw and residual life-cycle inequality

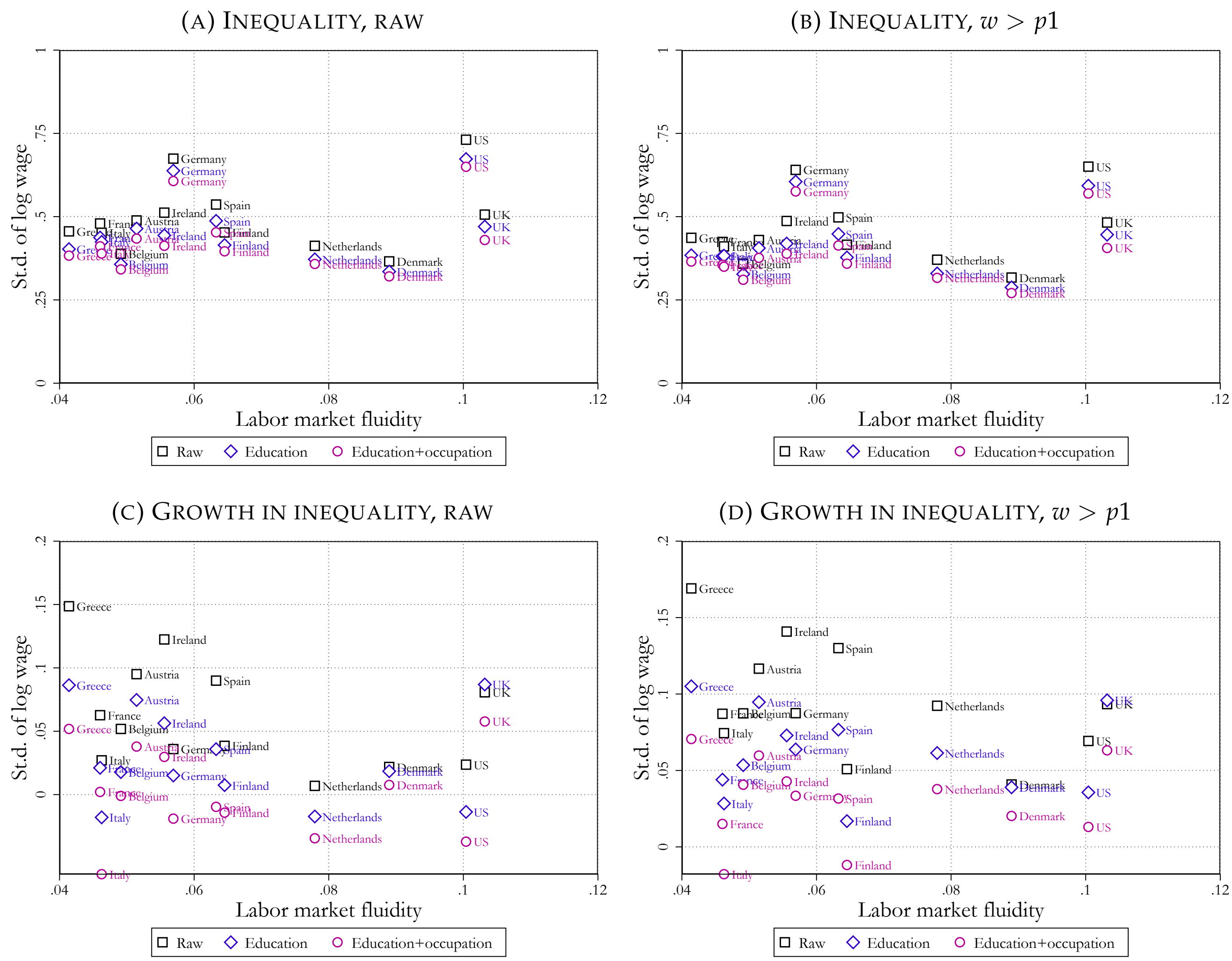
Figure 22 correlates various measures of inequality and life-cycle growth in inequality with labor market fluidity. There is possibly some evidence that inequality is higher in more fluid labor markets, while growth in inequality is lower. As it turns out, these patterns are consistent with the predictions of the model. The patterns, however, are not pronounced (which is also consistent with the theory).

FIGURE 21. EU (TOP) AND UE RATE (BOTTOM)



Note: Men aged 25–54. EU: Share of employed who are unemployed in the subsequent month. UE: Share of unemployed who are employed in the subsequent month. Employment includes self-employed due to data limitations. Constructed by first collapsing to the country-age-year level using the provided survey weights, then to the country-age level. *Source:* BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

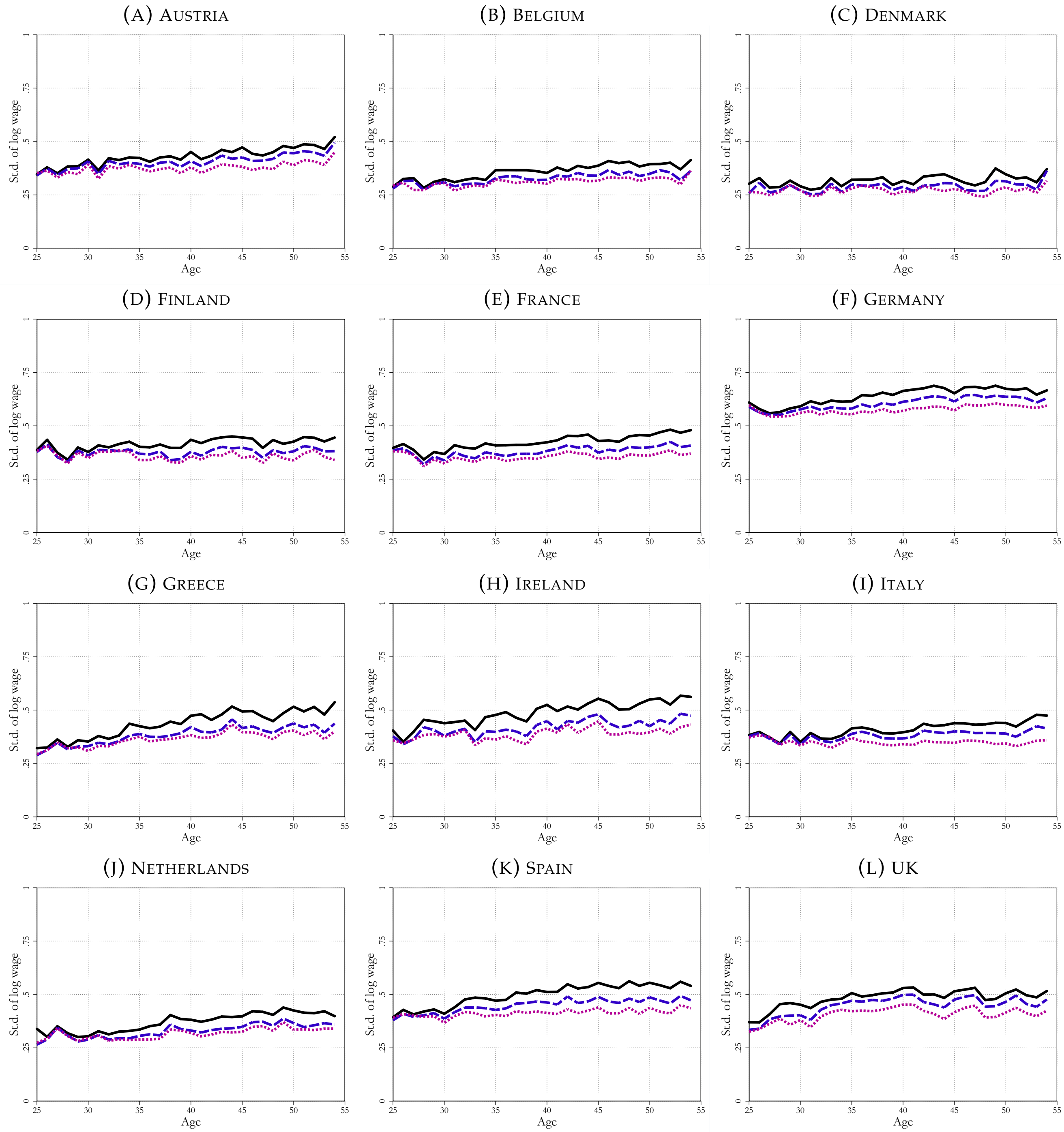
FIGURE 22. INEQUALITY AND LABOR MARKET FLUIDITY, ALTERNATIVE MEASURES

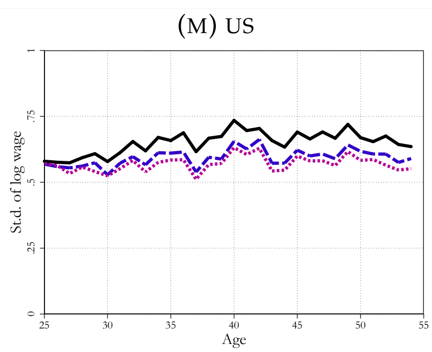


Note: Male employees aged 25–54. Panel A. Cross-sectional standard deviation of residual log hourly real wages. Panel B. Cross-sectional standard deviation of residual log hourly real wages dropping the bottom 1% of residual wages in each country. Panel C. Growth in standard deviation of residual log hourly real wages between age 25–29 and age 50–54. Panel D. Growth in standard deviation of residual log hourly real wages between age 25–29 and age 50–54 after first dropping the bottom 1% of residual wages in each country. All panels. Raw: Only country-year controls. Education: Country-year-education-age controls. Education+occupation: Country-year-education-age and country-occupation-year controls. All moments: Constructed by first collapsing the data to the country-age-year level using the provided survey weights, then to the country level. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Employment in the past 12 months includes self-employment due to data limitations. Constructed by first collapsing the data to the country-age-year level using the provided survey weights, then to the country-level. *Source:* BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

Figure 23 plots the standard deviation of log hourly wages over the life-cycle for various measures. I drop the bottom one percent of wages to reduce the impact of a few outliers, but this primarily impacts the level of inequality and not the life-cycle patterns. Inequality rises over the life-cycle. This, however, is largely accounted for by increasing dispersion *across* education and occupation groups. I believe that this finding is novel to the literature. At least, it has received little attention as far as I am aware.

FIGURE 23. LIFE-CYCLE INEQUALITY





Note: Male employees aged 25–54. Solid black: Standard deviation of log hourly wages controlling for country-year effects. Dashed blue: Standard deviation of residual log hourly wages controlling for country-year-education-age effects. Dotted purple: Standard deviation of residual log hourly wages controlling for country-year-education-age effects and country-year-occupation effects (10 occupations). All moments first drop the bottom 1% of wages in each country and are computed by first collapsing the data to the age-year-country level using the provided survey weights, then to the country-age-level. *Source:* BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

B Model — FOR ONLINE PUBLICATION

This appendix contains additional model details, including proofs of propositions.

B.1 Evolution of states

The quantitative analysis sets the flow value of leisure, $b(a,h)$, such that workers of all ages and human capital share the same match productivity reservation threshold, $\underline{z}$. That is, $b(a,h) : J(a,\underline{z},h) = U(a,h)$, $\forall a,h$. Given this, the distribution of workers over age, match productivity and human capital, $g(a,z,h)$, solves for $z \geq \underline{z}$ and $a \in (0,A)$ the Kolmogorov Forward Equation (KFE)

$$\begin{aligned} \frac{\partial g(a,z,h)}{\partial a} &= -\Big(\delta(z) + \phi p(1-\Gamma(z))\Big) g(a,z,h) - \frac{\mu}{\eta}(i(a,z,h)zh)^{\eta} \frac{\partial g(a,z,h)}{\partial h} \\ &+ \gamma(z)\left(p\frac{u(a,h)}{e} + \phi p \int_{\underline{z}}^{z} g(a,z',h)dz'\right) \end{aligned}$$

subject to the boundary conditions $g(0,z,h) = 0$, $g(A,z,h) = 0$ and $g(a,\underline{z},h)$ for all a, z, and h, where the number of unemployed of age a with human capital h, $u(a,h)$, is given by

$$\frac{\partial u(a,h)}{\partial a} = -pu(a,h) + \int_{\underline{z}}^{\infty} \delta(z) g(a,z,h)dz$$

subject to $u(A,h) = 0$ for all h and $u(0,h) = \lambda(h)/A$. and $e = 1 - \int u(a,h)dadh$ is the total number of employed. Workers flow out due to exogenous separations at rate $\delta(z)$ and up the job ladder at rate $\phi p(1-\Gamma(z))$. With probability $\gamma(z)$, workers who receive an offer contact a match with productivity z, which they accept if they are either unemployed or employed lower down the job ladder. Finally, the density changes due to accumulation of human capital and aging.

B.2 Wages and training

This subsection provides support for the assumption that workers share the cost of training with firms through a lower wage using the ECHP training data (see Section 6 for a description of the data). Table 9 regresses wages in the past calendar year on days or hours on training in the past 12 months (expressed as a fraction of total work days/hours), controlling for worker fixed effects and year effects. In years when a worker spends more time on training, she is paid less per hour. Quantitatively, when a worker spends one percent more of her work time on training, she is paid 0.28 percent less per hour.

TABLE 9. WAGES AND TRAINING

	Days (fraction of year)	Hours (fraction of year)
β	-0.165***	-0.278***
	(0.056)	(0.095)
N	55,057	54,952

Note: Male private sector employees 25–54. Log hourly real wage on days/hours on training in the past 12 months (as a fraction of total work days/hours), year effects and worker fixed effects. Hours and days on training are top-coded to 13 weeks of full time training per year. Standard errors are clustered at the individual-level. *** statistically significant at 1%. *Source:* ECHP 1995–2001.

B.3 Proofs

Proof of proposition 1. Adding the value of the worker (4) and the value of the firm (5) and cancelling terms, it is immediate that the piece rate r drops out.

Proof of proposition 2. The problem of the worker is to chose investment to maximize her value,

$$W(r,i) = \max_i \left\{(1-i)r(i)z_1 + \left((1-p)z_1 r(i) + \frac{p}{2}z_1 + \frac{p}{2}(z_1+\beta(z_2-z_1))\right)\left(1+\frac{\mu}{\eta}(z_1 i)^\eta\right)\right\} \quad (15)$$

Because the bargaining protocol ensures that the worker is delivered a share of the surplus, the piece rate a worker gets paid is implicitly a function of the training she undertakes. In particular, when a young worker is hired, the bargaining protocol ensures that she gets paid a piece rate such that

$$\begin{aligned} W(r,i) &= U + \beta(J(i)-U) \\ (1-i)r(i)z_1 &= U + \beta(J(i)-U) - \left((1-p)z_1 r(i) + \frac{p}{2}z_1 + \frac{p}{2}(z_1+\beta(z_2-z_1))\right)\left(1+\frac{\mu}{\eta}(z_1 i)^\eta\right) \end{aligned} \quad (16)$$

where U is the value of unemployment. Substituting for $(1-i)r(i)z_1$ in (15) using (16) and simplifying

$$W(r,i) = \max_i \{U + \beta(J(i)-U)\}$$

Hence, the optimal choice of training by the worker satisfies $J'(i) = 0$, i.e. it coincides with that which maximizes the joint value.

Proof of proposition 3. Define $i_w(v)$ and $i_e(v)$ based on (9)–(10) to be

$$\begin{aligned} i_w(v) &= \left(\mu\left(z_1 + v^\alpha \beta \frac{z_2-z_1}{2}\right)\right)^{\frac{\eta}{1-\eta}} \\ i_e(v) &= \frac{\eta}{\mu}\left(\frac{2cv^{1-\alpha}}{(1-\beta)(z_2-z_1)} - 1\right) \end{aligned}$$

Then,

$$\lim_{v\to 0} i_w(v) = \mu^{\frac{\eta}{1-\eta}} > 0, \qquad \lim_{v\to 0} i_e(v) = -\frac{\eta}{\mu} < 0$$

Hence, if $\lim_{v\to\infty} \frac{i_e(v)}{i_w(v)} > 1$, there is at least one equilibrium. Consider the limit $\lim_{v\to\infty} \left(\frac{i_e(v)}{i_w(v)}\right)^{\frac{1-\eta}{\eta}}$,

$$\lim_{v\to\infty} \frac{\left(\frac{\eta}{\mu}\left(\frac{2cv^{1-\alpha}}{(1-\beta)(z_2-z_1)} - 1\right)\right)^{\frac{1-\eta}{\eta}}}{\left(z_1 + v^\alpha \beta \frac{z_2-z_1}{2}\right)\mu} = \lim_{v\to\infty} v^{(1-\alpha)\frac{1-\eta}{\eta}-\alpha} \frac{\left(\frac{\eta}{\mu}\left(\frac{2c}{(1-\beta)(z_2-z_1)} - \frac{1}{v^{1-\alpha}}\right)\right)^{\frac{1-\eta}{\eta}}}{\left(\frac{1}{v^\alpha} + \beta\frac{z_2-z_1}{2}\right)\mu} \tag{17}$$

In the limit $v \to \infty$, the second term in (17) is strictly positive. Hence, $\lim_{v\to\infty} \frac{i_e(v)}{i_w(v)} > 1$ if and only if

$$(1-\alpha)\frac{1-\eta}{\eta} - \alpha \quad > \quad 0$$

Hence, under this condition, the limit tends to infinity and there is at least one solution.

To see that the solution is unique, take derivatives of the best-response functions,

$$\begin{aligned}
\frac{\partial i_w(v)}{\partial v} &= \frac{\eta}{1-\eta} i_w^{\frac{2\eta-1}{\eta}} \mu\alpha v^{\alpha-1}\beta\frac{z_2-z_1}{2} \\
\frac{\partial i_e(v)}{\partial v} &= \frac{1-\alpha}{v}\left(i_e + \frac{\eta}{\mu}\right)
\end{aligned}$$

Recall that $i_w(0) > i_e(0)$ and that, under the assumption that $\frac{1-\eta}{\eta} > \frac{\alpha}{1-\eta}$, there exists at least one v such that $i^W(v) = i^E(v)$. Consider any such equilibrium point. If it is the case that $\frac{\partial i_e(v)}{\partial v} > \frac{\partial i_w(v)}{\partial v}$, then it must be that the equilibrium is unique,

$$\begin{aligned}
\frac{\partial i_e(v)}{\partial v} &> \frac{\partial i_w(v)}{\partial v} \\
\frac{1-\alpha}{v}\left(i + \frac{\eta}{\mu}\right) &> \frac{\eta}{1-\eta} i^{\frac{2\eta-1}{\eta}} \mu\alpha v^{\alpha-1}\beta\frac{z_2-z_1}{2} \\
i + \frac{\eta}{\mu} &> \frac{\eta}{1-\eta} i^{\frac{2\eta-1}{\eta}} \mu \frac{\alpha}{1-\alpha} v^\alpha \beta\frac{z_2-z_1}{2}
\end{aligned}$$

Since $i + \frac{\eta}{\mu} > i$, surely the above inequality is true if

$$\begin{aligned}
i &> \frac{\eta}{1-\eta} i^{\frac{2\eta-1}{\eta}} \mu \frac{\alpha}{1-\alpha} v^{\alpha} \beta \frac{z_2 - z_1}{2} \\
i^{\frac{1-\eta}{\eta}} &> \frac{\eta}{1-\eta} \frac{\alpha}{1-\alpha} \mu v^{\alpha} \beta \frac{z_2 - z_1}{2} \\
\left(z_1 + v^{\alpha} \beta \frac{z_2 - z_1}{2} \right) \mu &> \frac{\eta}{1-\eta} \frac{\alpha}{1-\alpha} \mu v^{\alpha} \beta \frac{z_2 - z_1}{2} \\
z_1 + v^{\alpha} \beta \frac{z_2 - z_1}{2} &> \frac{\eta}{1-\eta} \frac{\alpha}{1-\alpha} \mu v^{\alpha} \beta \frac{z_2 - z_1}{2} \\
z_1 &> \left(\frac{\eta}{1-\eta} \frac{\alpha}{1-\alpha} - 1 \right) v^{\alpha} \beta \frac{z_2 - z_1}{2}
\end{aligned}$$

For this to be guaranteed to hold for any v, it is sufficient that

$$\begin{aligned}
\frac{\eta}{1-\eta} \frac{\alpha}{1-\alpha} - 1 &< 0 \\
\frac{\alpha}{1-\alpha} &< \frac{1-\eta}{\eta}
\end{aligned}$$

Proof of proposition 4. Holding investment fixed, an increase in the cost of job creation shifts the job creation curve to the left in Figure 7, $\frac{\partial v}{\partial c}|_i < 0$. Holding fixed vacancy creation, an increase in the cost of job creation has no impact on the training curve, $\frac{\partial i}{\partial c}|_v = 0$. As established above, the unique equilibrium is characterized by the job creation curve crossing the training curve from below. Hence, in equilibrium job creation falls by more and training declines. As the job finding rate of workers falls, average match quality declines. As training falls, average human capital declines.

Proof of lemmas 1–2 and proposition 5. Compare the first-order condition for optimal investment and the free entry condition in the decentralized equilibrium to those in the planned economy,

$$i(v) = \frac{1}{z_1} \left(\mu \left(z_1 + v^{\alpha} \beta \frac{z_2 - z_1}{2} \right) \right)^{\frac{1}{1-\eta}} \tag{18}$$

$$i_{sp}(v) = \frac{1}{z_1} \left(\mu \left(z_1 + v^{\alpha} \frac{z_2 - z_1}{2} \right) \right)^{\frac{1}{1-\eta}} \tag{19}$$

$$v(i) = \left((1-\beta) \frac{(z_2 - z_1)}{2c} \left(1 + \frac{\mu}{\eta} (z_1 i)^{\eta} \right) \right)^{\frac{1}{1-\alpha}} \tag{20}$$

$$v_{sp}(i) = \left(\alpha \frac{z_2 - z_1}{2c} \left(1 + \frac{\mu}{\eta} (z_1 i)^{\eta} \right) \right)^{\frac{1}{1-\alpha}} \tag{21}$$

Suppose that the decentralized economy created total vacancies equal to the constrained first best, $v_{sp} = v$. Then only for $\beta = 1$ would investment coincide with the first-best solution. To ensure that $v_s p = v$ would in turn require that $\alpha = 0$, which is inconsistent with the assumption that $\alpha \in (0, 1)$ (moreover, even if $\alpha = 0$ was allowed, it would imply that there was no vacancy creation in this equilibrium).

C Results — FOR ONLINE PUBLICATION

This section provides additional quantitative results.

C.1 Restricting wage growth

In the benchmark results reported in the paper, I do not impose the restriction of zero wage growth after age 50. To verify that this does not bias results, I estimate a version of the empirical specification (2) on model generated data with or without imposing the restriction of zero wage growth after age 50. To be precise, I simulate a monthly approximation to the continuous time model for 18 countries for 50,000 individuals in each country for the entire life-cycle starting at age 24 and ending at age 54. Individuals enter as unemployed at age 24 with human capital drawn from the initial skill distribution Λ.

I aggregate the data to the annual level and designated "May" as the survey month, and compute the wage during the prior "calendar" year. The wage is the sum of monthly income during the prior "calendar" year divided by the number of months worked. I construct labor market fluidity identically to the data in the simulated data, i.e. as the share of employed workers in "May" who were at a different main employer in "May" the previous year without any month of unemployment in between. I randomly select five consecutive years for each individual and drop the other years to mimic the amount of time an individual on average remains in the panel. Finally, as employment rates differ across these "countries," I design weights such that each of the 18 simulated countries receives the same weight in the aggregate.

Table 10 reports results from the benchmark model specification in the paper, which does not impose the empirical restriction of no wage growth after age 50, and an alternative specification that imposes no wage growth after age 50. Results are virtually identical.

TABLE 10. LIFE-CYCLE WAGE GROWTH AND LABOR MARKET FLUIDITY, MODEL

	Unrestricted	Restricted
α	0.156***	0.156***
	(0.008)	(0.008)
N	3,982,295	3,982,295

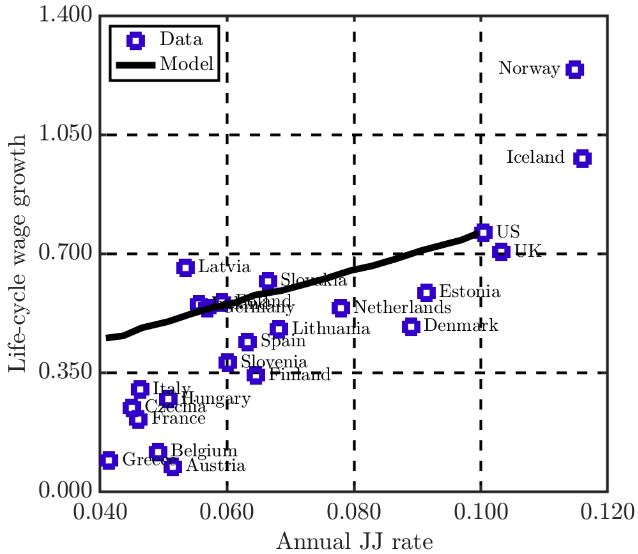
Note: Simulated monthly data for 18 countries for 50,000 individuals per country, aggregated to the annual level to replicate as closely as possible the real data. See text for more details. α: Fluidity-age interaction in regression (2) with worker fixed effects, time effects and restricted age effects. Standard error below are clustered at the country-level. Unrestricted: No restriction on wage effects. Restricted: No wage growth after age 50. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Constructed by first collapsing the simulated data to the country-age level, then to the country level. *** statistically significant at 1%. *Source:* Model.

C.2 Full sample results

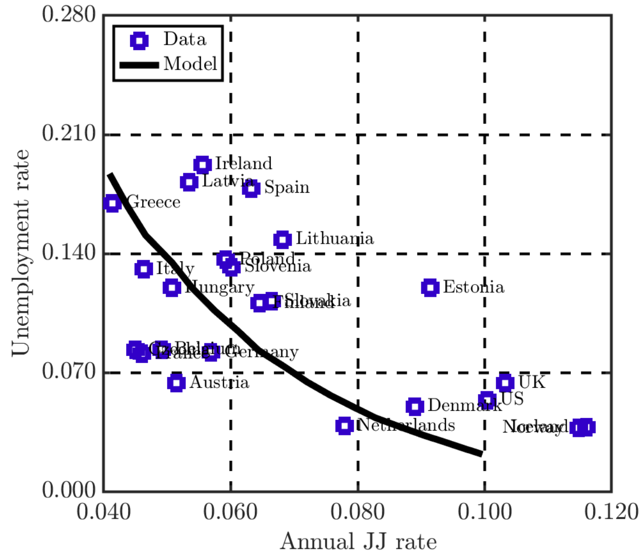
Figure 27 plots life-cycle wage growth, unemployment and labor productivity against labor market fluidity in the model and the data for the full sample of 23 OECD countries. Results are similar as for the core sample.

FIGURE 24. THE IMPACT OF LABOR MARKET FLUIDITY, MODEL VERSUS DATA

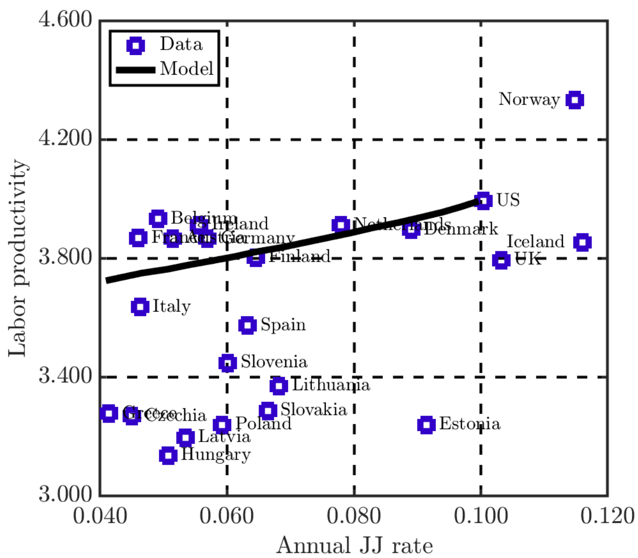
(A) LIFE-CYCLE WAGE GROWTH



(B) UNEMPLOYMENT RATE



(C) LABOR PRODUCTIVITY



Note: Men aged 25–54. Panel A. Wage growth between age 25–50. Data: Based on regression (1) with worker fixed effects, year effects and age effects restricted to not grow after age 50. Panel B. Share of unemployed workers. Data: Constructed by first collapsing the data to the country-year-age level using the provided survey weights, then to the country-level. Model: Constructed by first collapsing the data to the country-age level, then to the country-level. Panel C. Log real output per hour. Data: 2014 real GDP per hour in 2004 PPP-adjusted US dollars. Model: Total net output, $\int (1 - i(a, z, h)) zh dG(a, z, h)$, divided by total employment, in logs, and normalized to equal the data for the US. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Data: Employment in the past 12 months includes self-employment due to data limitations. Constructed by first collapsing the data to the country-age-year level using the provided survey weights, then to the country-level. Model: Constructed by first collapsing the data to the country-age level, then the country-level.
Source: Model, BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

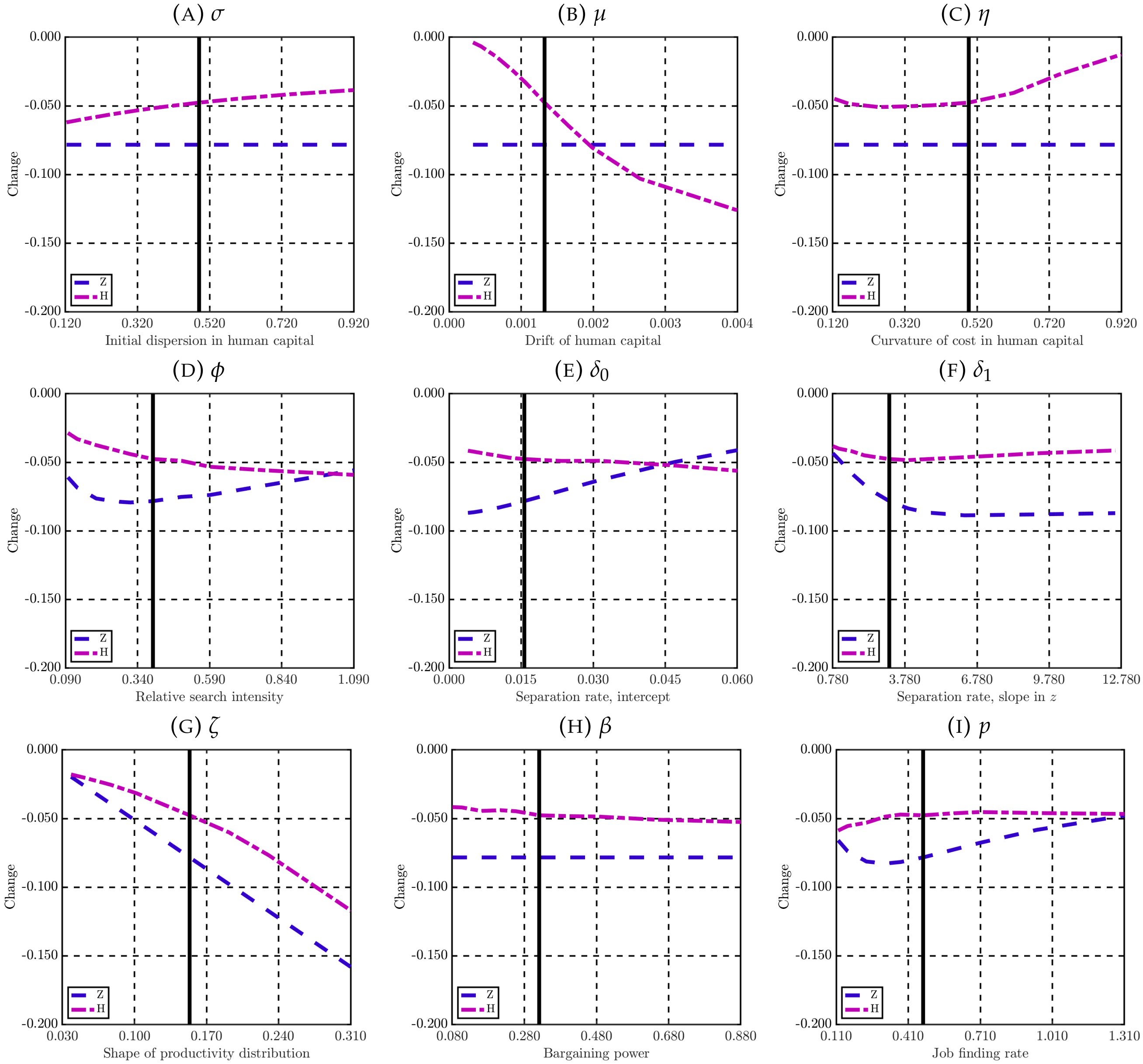
C.3 Sensitivity analysis

Figure 25 considers the impact of a 67 percent fall in the job finding rate, p, on life-cycle growth in human capital, H, and match productivity, Z, as each of the nine estimated parameters varies around its estimated value, holding the other parameters fixed at their estimated values. The predicted impact of changes in labor market fluidity on life-cycle growth in match productivity is sensitive in particular to the tail parameter of the match productivity distribution, ζ. This makes sense—a fatter tail (higher value of ζ) implies a greater scope for climbing the job ladder, and hence greater scope for labor market fluidity to influence productivity growth. This is also reflected in greater scope for human capital differences, since human capital accumulation responds to match productivity growth. Human capital accumulation is also sensitive to the scalar in the human capital technology, μ. This also makes sense—if μ is higher, it implies greater growth in general in human capital over the life-cycle. Because human capital becomes more important with a higher μ, it implies greater scope for labor market fluidity to reduce it.

Human capital is also somewhat sensitive to the curvature of the human capital technology, η, but this particular exercise confounds two forces. Because I scale the technology by μ/η, changing η impacts both the curvature and the scalar in the technology. I prefer to do it this way because it simplifies the first order conditions, but I have verified the following intuition by *only* changing the curvature of the technology, holding the scalar fixed. A higher η (holding fixed μ/η), makes the impact of fluidity on human capital accumulation more pronounced. This makes sense, as it effectively means investment is more elastic. The first order effect of a higher η, however, is through the change in the scale, μ/η, and hence an increase in η impacts the results the same way as a fall in μ.

Finally, notice that workers' bargaining power, β, impacts results in the expected way—a higher β increases the scope for labor market fluidity to affect human capital accumulation. The impact, however, is not particularly pronounced, as it only impacts human capital accumulation through the *incentive effect*, whereas the *unemployment effect* and *job ladder effect* remain unaffected.

FIGURE 25. CHANGE IN GROWTH IN MATCH PRODUCTIVITY AND HUMAN CAPITAL IN RESPONSE TO A 67% DECLINE IN THE JOB FINDING RATE AS A FUNCTION OF EACH PARAMETER



Note: Change in growth in match productivity Z (dash-dotted purple) and human capital H (dashed blue) between age 25–50 in response to an increase in the cost of job creation, c, such that the job finding rate falls by 67% as each of the parameters varies around its estimated value (solid black) holding all other parameters fixed. *Source:* Model.

C.4 Unemployment and labor productivity

Table 11 shows the explanatory power of the mechanism for unemployment, EU and UE flows, and labor productivity. The mechanism overstates the empirical covariance between unemployment and labor market fluidity, predicting 161 percent of the higher unemployment across the OECD relative to the US

(135 percent across the full sample). In an accounting sense, this is because the mechanism overstates the covariation between the EU rate and labor market fluidity in the data (138 and 126 percent across the core and full sample, respectively), whereas it gets the covariance between the UE rate and labor market fluidity about right (106 and 89 percent across the core and full sample, respectively). It matches 82 percent of the lower labor productivity across the OECD relative to the US (42 percent across the full sample). Figure 26 illustrates the EU and UE flows across countries in the model and data.

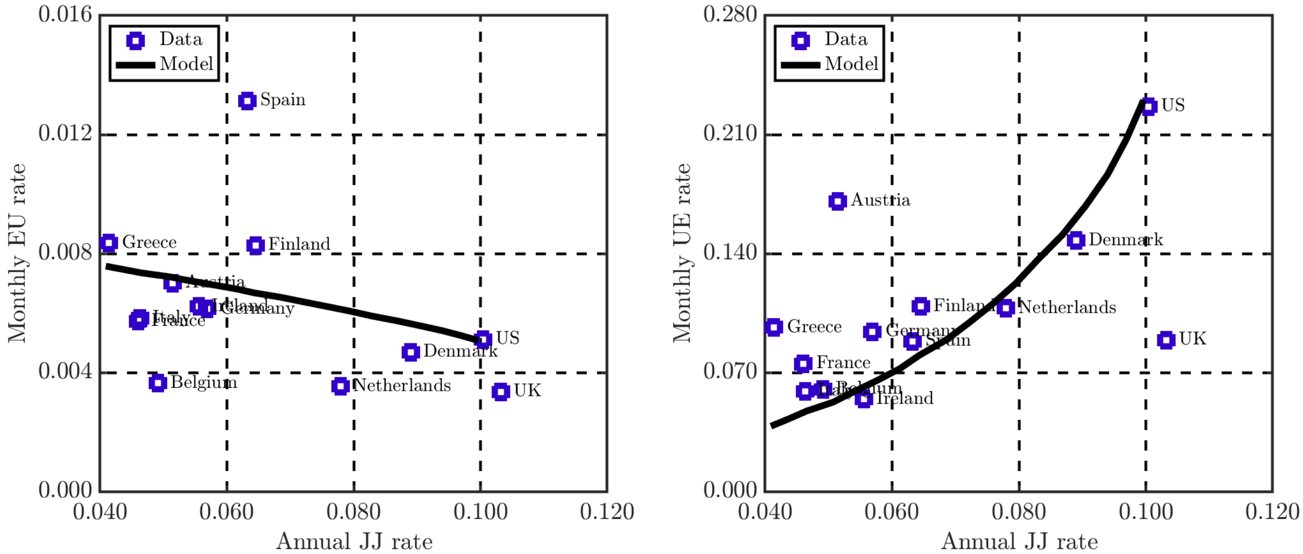
TABLE 11. THE IMPACT OF LABOR MARKET FLUIDITY, MODEL VERSUS DATA

		AT	BE	DK	FI	FR	DE	EL	IE	IT	NL	ES	UK	US	**Core**	**All**
								Panel A. Unemployment rate								
Data	Level	0.06	0.08	0.05	0.11	0.08	0.08	0.17	0.19	0.13	0.04	0.18	0.06	0.05	0.10	0.11
	ΔUS_d	0.01	0.03	-0.00	0.06	0.03	0.03	0.12	0.14	0.08	-0.02	0.12	0.01	0.00	0.05	0.05
Model	Level	0.13	0.14	0.03	0.08	0.16	0.11	0.18	0.12	0.15	0.05	0.09	0.03	0.03	0.11	0.10
	ΔUS_d	0.11	0.12	0.01	0.06	0.13	0.09	0.15	0.09	0.13	0.03	0.06	-0.00	0.00	0.08	0.07
$\Delta US_m / \Delta US_d$		10.72	3.90	-2.04	1.04	4.76	3.03	1.31	0.65	1.68	-1.65	0.51	-0.03	- -	**1.61**	**1.35**
								Panel B. Monthly EU rate								
Data	Level	0.01	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.00	0.01	0.01	0.01
	ΔUS_d	0.00	-0.00	-0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.00	0.01	-0.00	0.00	0.00	0.00
Model	Level	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.01
	ΔUS_d	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.00	0.00	0.00	0.00
$\Delta US_m / \Delta US_d$		1.12	-1.48	-1.27	0.51	3.80	1.87	0.76	1.77	3.24	-0.66	0.21	0.08	- -	**1.38**	**1.26**
								Panel C. Monthly UE rate								
Data	Level	0.17	0.06	0.15	0.11	0.08	0.09	0.10	0.05	0.06	0.11	0.09	0.09	0.23	0.10	0.09
	ΔUS_d	-0.06	-0.17	-0.08	-0.12	-0.15	-0.13	-0.13	-0.17	-0.17	-0.12	-0.14	-0.14	0.00	-0.13	-0.13
Model	Level	0.05	0.05	0.16	0.08	0.05	0.06	0.04	0.06	0.05	0.12	0.07	0.24	0.22	0.09	0.10
	ΔUS_d	-0.17	-0.17	-0.06	-0.15	-0.18	-0.16	-0.18	-0.17	-0.18	-0.11	-0.15	0.02	0.00	-0.14	-0.12
$\Delta US_m / \Delta US_d$		3.09	1.05	0.75	1.25	1.18	1.23	1.39	0.96	1.06	0.89	1.09	-0.12	- -	**1.06**	**0.89**
								Panel D. Labor productivity								
Data	Level	3.87	3.93	3.90	3.80	3.87	3.86	3.28	3.91	3.63	3.91	3.57	3.79	3.99	3.78	3.62
	ΔUS_d	-0.13	-0.06	-0.10	-0.19	-0.12	-0.13	-0.72	-0.08	-0.36	-0.08	-0.42	-0.20	0.00	-0.21	-0.37
Model	Level	1.23	1.22	1.40	1.28	1.21	1.25	1.19	1.25	1.21	1.34	1.28	1.47	1.45	1.28	1.30
	ΔUS_d	-0.22	-0.23	-0.06	-0.17	-0.24	-0.20	-0.26	-0.21	-0.24	-0.11	-0.18	0.02	0.00	-0.18	-0.15
$\Delta US_m / \Delta US_d$		1.79	3.87	0.61	0.90	1.96	1.60	0.36	2.59	0.68	1.38	0.42	-0.08	- -	**0.82**	**0.42**

Note: Men aged 25–54. Labor productivity is for the entire private economy due to data availability. Panel A. Share of unemployed workers. Panel B. Share of employed workers who are unemployed in the subsequent month. Panel C. Share of unemployed workers who are employed in the subsequent month. Panels A–C. Data: Constructed by first collapsing the data to the country-year-age level using the provided survey weights, then to the country-level. Model: Constructed by first collapsing the data to the country-age level, then to the country-level. Panel D. Log real output per hour. Data: 2014 real GDP per hour in 2004 PPP-adjusted US dollars. Model: Total net output, $\int(1-i(a,z,h))zhdG(a,z,h)$, divided by total employment, and in logs. ΔUS: Difference in the outcome variable relative to the US. $\Delta US_m / \Delta US_d$: Difference in the outcome variable relative to the US in the model relative to the data. Core: Average difference relative to the US across the 12 core countries. All: Average difference relative to the US across the 22 countries in the full sample. *Source:* Model, BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

FIGURE 26. THE IMPACT OF LABOR MARKET FLUIDITY, MODEL VERSUS DATA

(A) EU (B) UE

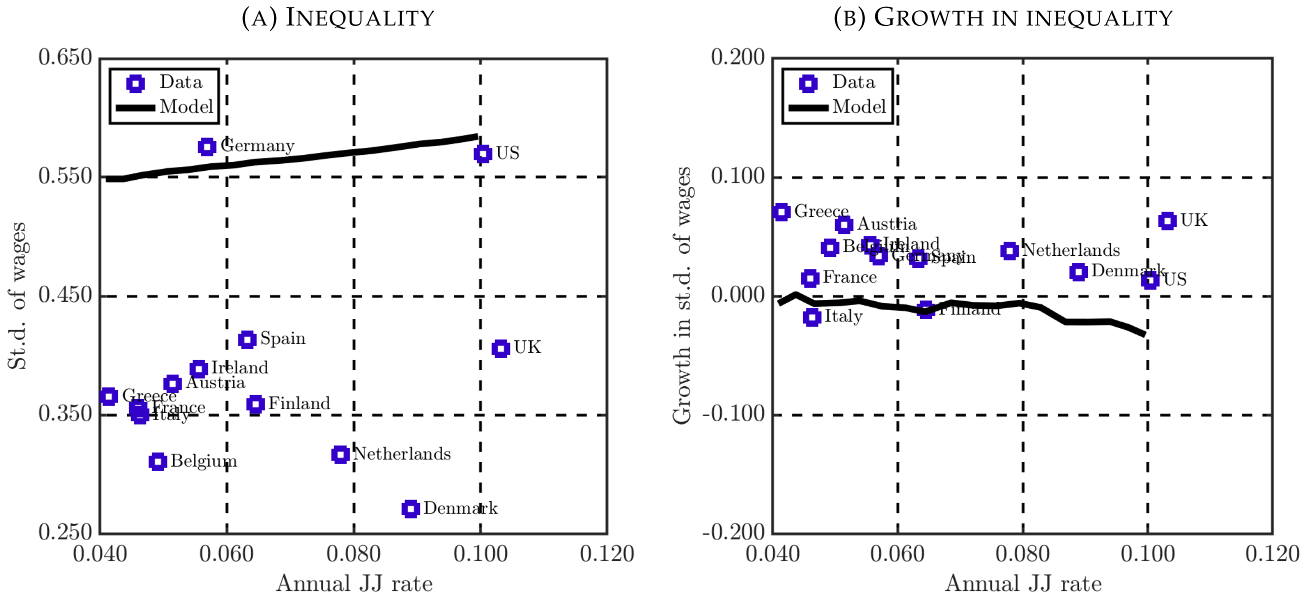


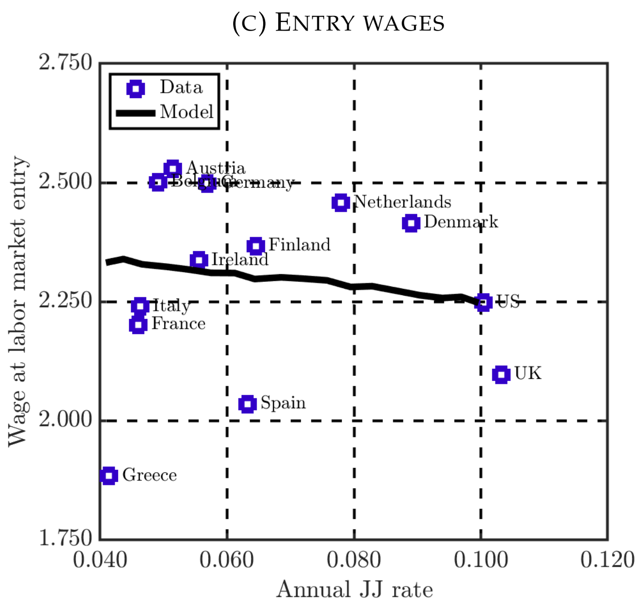
Note: Men aged 25–54. Panel A. Share of employed workers who are unemployed in the subsequent month. Panel B. Share of unemployed workers who are employed in the subsequent month. All panels. Data: Constructed by first collapsing the data to the country-age-year level using the provided survey-weights, then to the country-level. Model: Constructed by first collapsing the data to the country-age level, and then the country-level. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Data: Employment in the past 12 months includes self-employment due to data limitations. Constructed by first collapsing the data to the country-age-year level using the provided survey weights, then to the country-level. Model: Constructed by first collapsing the data to the country-age level, then the country-level. *Source:* Model, BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

C.5 Additional outcomes

This section compares additional model predictions with the cross-country variation. The top left panel of Figure 27 plots the level of inequality against labor market fluidity, illustrating only a minor increase in inequality with labor market fluidity in both the model and the data. As shown in the top right panel, the higher inequality in more fluid labor markets is not accounted for by greater life-cycle growth in inequality, in either the model or the data. As shown in the bottom left panel, wages of labor market entrants are somewhat lower in more fluid labor markets, by a similar amount in the model and the data. Note that entry wages have been normalized to match those in the data for the US, as the levels are non-comparable in the model and data.

FIGURE 27. THE IMPACT OF LABOR MARKET FLUIDITY, MODEL VERSUS DATA



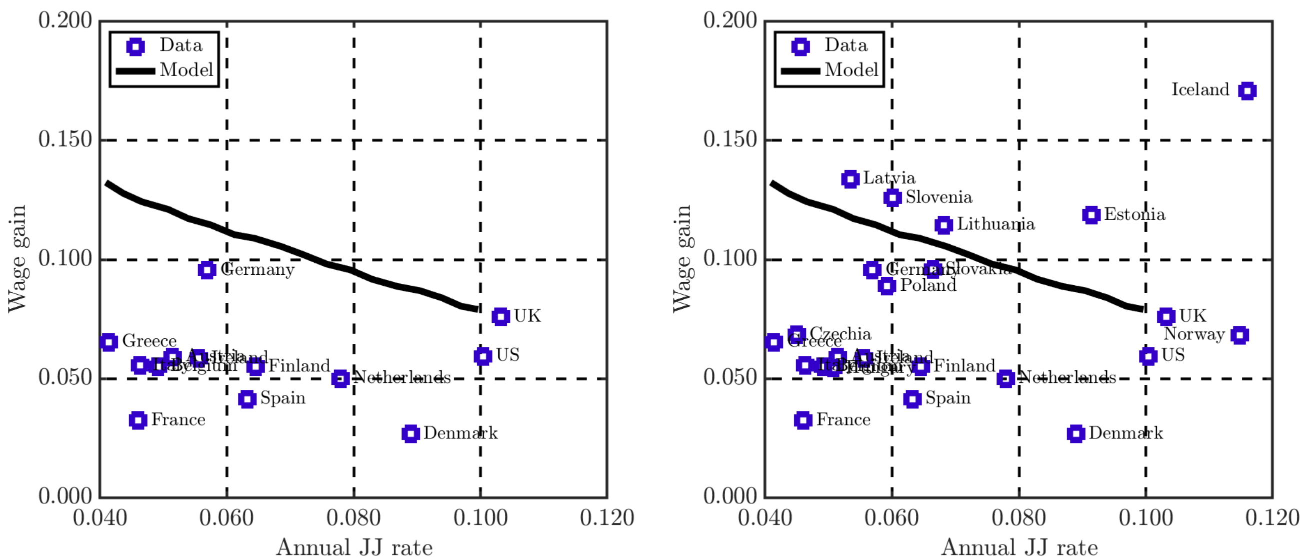


Note: Men aged 25–54. Panel A. St.d. of residual log hourly wages, controlling for year-education-age and year-occupation effects separately by country. Panel B. Growth in st.d. of residual log hourly wage between age 25–29 and age 50–54. Panel C. Log hourly real wages of workers aged 21–24 (data) / 24 (model). Model is normalized to equal the data for the US. All panels. Data: Constructed by first collapsing the data to the country-age-year level using the provided survey-weights, then to the country-level. Model: Constructed by first collapsing the data to the country-age level, and then the country-level. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Data: Employment in the past 12 months includes self-employment due to data limitations. Constructed by first collapsing the data to the country-age-year level using the provided survey weights, then to the country-level. Model: Constructed by first collapsing the data to the country-age level, then the country-level. *Source:* Model, BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

Figure 28 plots the wage gain associated with JJ mobility in the model and data. Note that the US moment is higher in the model than the data because I target the monthly gain in the SIPP, which deviates (modestly) from the annual gain in the PSID. It illustrates the biggest discrepancy between the predictions of the model and the data. The model implies that the wage gain associated with JJ mobility should decline with labor market fluidity, as workers in more fluid labor markets on average are higher up the job ladder and hence have less scope to move further up the job ladder. An earlier version of this paper also allowed for so called *godfather* shocks—involuntary JJ mobility shocks meant to capture, for instance, the need to move to accompany a spouse, with the worker bargaining with the employer as though she is coming from unemployment Jolivet et al. (2006). To the extent that such shocks are equally common across countries, they serve to flatten the relationship between the wage gain from JJ mobility and labor market fluidity. The reason is that a larger share of JJ moves in less fluid labor markets is involuntary in nature, reducing the average gain from JJ mobility in such countries.

FIGURE 28. WAGE GAIN FROM JJ MOVE, MODEL VERSUS DATA

(A) CORE COUNTRIES (B) ALL COUNTRIES



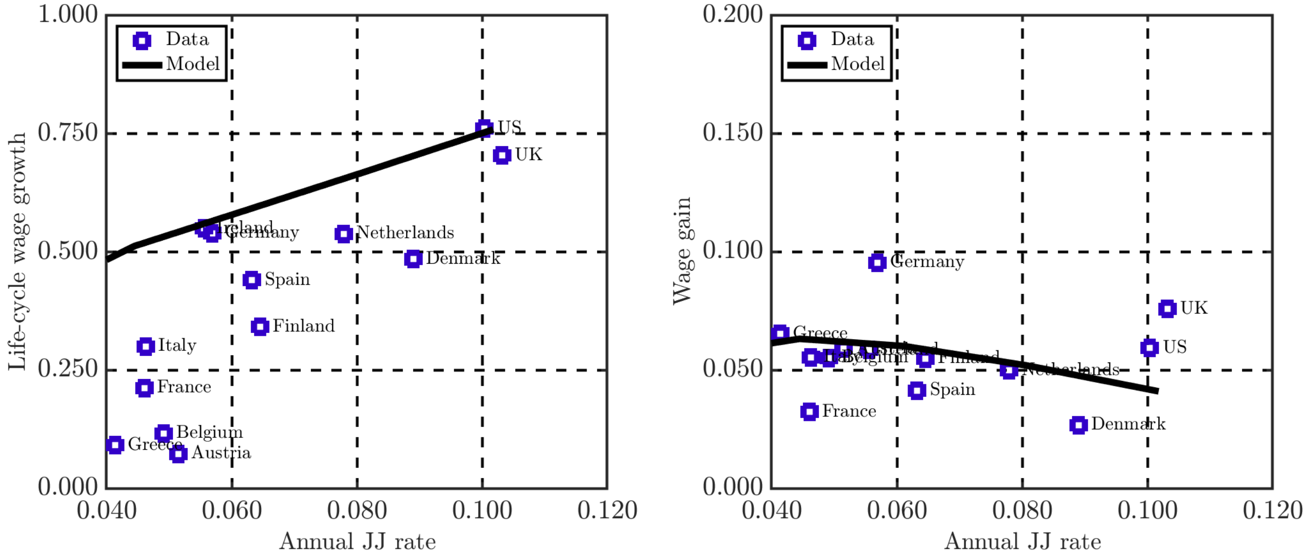
Note: Men aged 25–54. Difference in annual wage growth between those who made a JJ move in the year and those who did not. Data: Constructed by first collapsing the data to the country-age-year level taking the median using the provided survey-weights, then to the country-level. Model: Constructed by first collapsing the data to the country-age level, and then the country-level. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Data: Employment in the past 12 months includes self-employment due to data limitations. Constructed by first collapsing the data to the country-age-year level using the provided survey weights, then to the country-level. Model: Constructed by first collapsing the data to the country-age level, then the country-level. *Source:* Model, BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

To illustrate this point, Figure 29 provides the results from a rough calibration of this extended model, with the frequency of godfather shocks set arbitrarily to 0.15 percent monthly. I recalibrate the scalar in the human capital technology, μ, and the relative search efficiency from employment, ϕ, to hit the same life-cycle wage growth and aggregate labor market fluidity, but leave other parameters unchanged. Even a small frequency of such shocks is sufficient to significantly flatten the relationship between wage gains associated with a JJ move and labor market fluidity, as a larger share of JJ moves in low fluidity countries now is due to such involuntary moves. The main prediction for life-cycle wage growth (as well as other outcomes) remains essentially unchanged.

FIGURE 29. THE IMPACT OF LABOR MARKET FLUIDITY IN GODFATHER SHOCK MODEL

(A) LIFE-CYCLE WAGE GROWTH

(B) WAGE GAIN UPON JJ MOBILITY

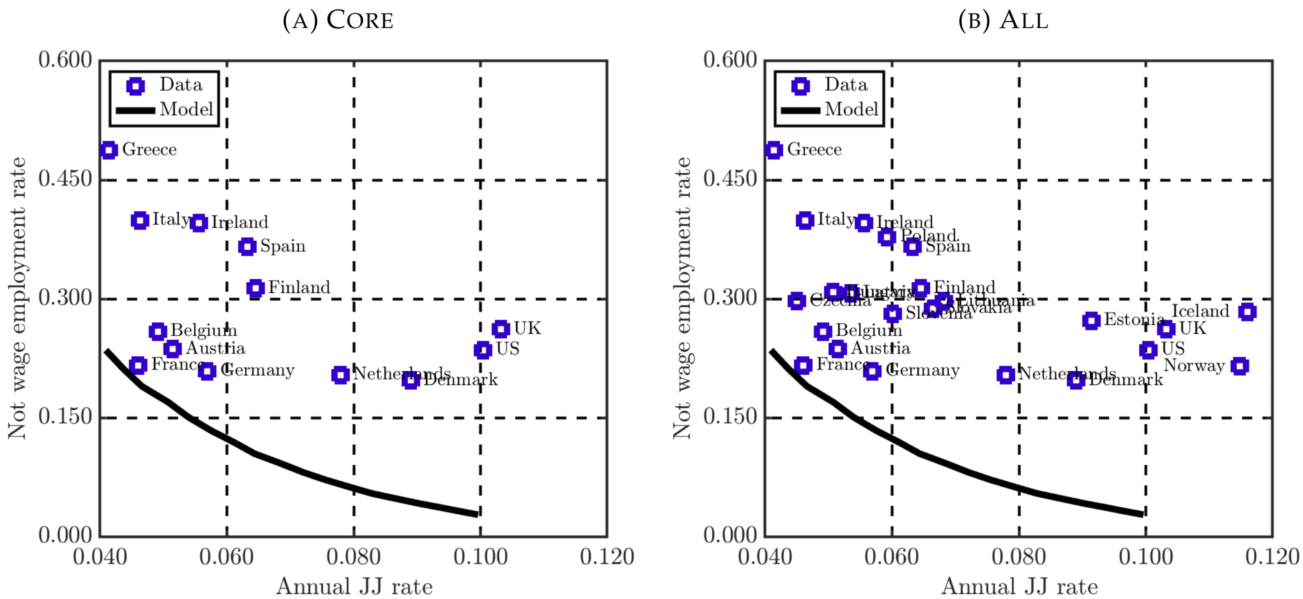


Note: Men aged 25–54. Panel A. Wage growth between age 25–50. Data: Based on regression (1) with worker fixed effects, year effects and age effects restricted to not grow after age 50. Panel B. Difference in annual wage growth between those who made a JJ move in the year and those who did not. Data: Constructed by first collapsing the data to the country-age-year level taking the median using the provided survey-weights, then to the country-level. Model: Constructed by first collapsing the data to the country-age level, and then the country-level. All panels. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Data: Employment in the past 12 months includes self-employment due to data limitations. Constructed by first collapsing the data to the country-age-year level using the provided survey weights, then to the country-level. Model: Constructed by first collapsing the data to the country-age level, then the country-level. *Source:* Model, BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

C.6 Wage employment

As noted in Appendix A.3, the share of self-employed workers is higher in less fluid labor markets. The model is consistent with this pattern under the assumption that self-employment is akin to unemployment—something workers do when they cannot find a wage employment job. Figure 30 illustrates this by plotting the share of not-wage-employed men aged 25–54 against labor market fluidity in the model and data. The share in the US in the model and data differs by construction, since the model is estimated to match the unemployment rate in the US excluding the self-employed. Although the view that a large share of self-employed are necessity entrepreneurs does receive support in the literature, it would be interesting to have a deeper theory of self-employment. That, however, is beyond this paper.

Figure 30. Not-wage-employment (unemployed, self-employed and non-participants) and labor market fluidity



Note: Men aged 25–54. Not wage employment rate: Share of men aged 25–54 that is *not* wage employed, i.e. unemployed, self-employed and non-participants. Data: Constructed by first collapsing the data to the country-year-age level using the provided survey weights, then to the country-level. Model: Constructed by first collapsing the data to the country-age level, then to the country-level. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Data: Employment in the past 12 months includes self-employment due to data limitations. Constructed by first collapsing the data to the country-age-year level using the provided survey weights, then to the country-level. Model: Constructed by first collapsing the data to the country-age level, then the country-level. *Source:* Model, BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

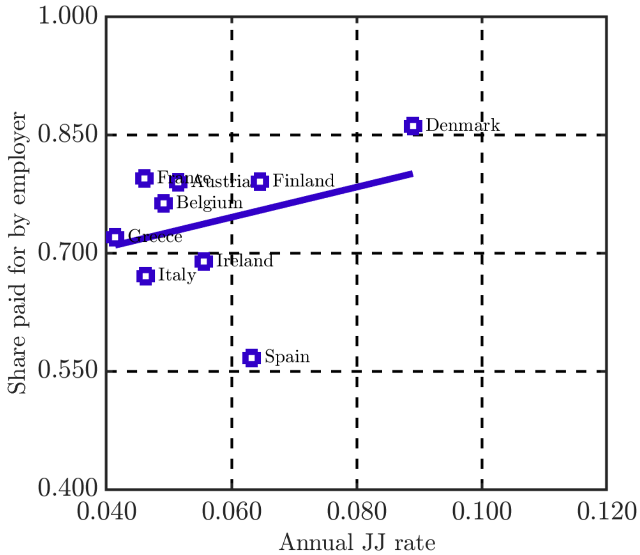
D Training — FOR ONLINE PUBLICATION

This appendix contains additional details on training.

D.1 Share of training paid for by employer

Figure 31 plots the share of workers who report that their employer paid for their vocational training since January in the year prior to the survey. If anything, the share rises with labor market fluidity, but the pattern is not statistically significant.

FIGURE 31. SHARE OF TRAINING PAID FOR BY EMPLOYER AND LABOR MARKET FLUIDITY



Note: Male private sector employees aged 25–54. Share of workers who report that their employer paid for their vocational training since January last year. Constructed by first collapsing the data to the country-age-year level using the provided survey weights, then to the country level. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Employment in the past 12 months includes self-employment due to data limitations. Constructed by first collapsing the data to the country-age-year level using the provided survey weights, then to the country-level. *Source:* ECHP 1995–2001.

D.2 Not top-coding training

My benchmark training results top-code days and hours on training at 13 weeks of full-time training during the past 12 months to limit the role of a few extreme observations. Table 12 reports results from a regression of various training measures on fluidity without top-coding. The point estimates grow in magnitude, but the takeaway remains the same.

TABLE 12. TRAINING AND LABOR MARKET FLUIDITY WITHOUT TOP-CODE

	Panel A. Whether trained			*Panel B. Days (fraction of year)*			*Panel C. Hours (fraction of year)*		
	Raw	Controls	Direct	Raw	Controls	Direct	Raw	Controls	Direct
Fluidity	9.123***	8.317***	8.432***	1.790***	1.745***	1.658***	1.392***	1.424***	1.242***
	(1.105)	(1.144)	(1.121)	(0.282)	(0.267)	(0.113)	(0.165)	(0.154)	(0.132)
JJ			-0.015			-0.011			-0.003
			(0.012)			(0.008)			(0.002)
Age		-0.006***	-0.004***		-0.003**	-0.003**		-0.002**	-0.002*
		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
College		0.166***	0.113***		0.012	0.027***		-0.007	0.003
		(0.025)	(0.028)		(0.012)	(0.005)		(0.011)	(0.003)
N	108,209	107,777	44,020	107,917	107,488	43,895	107,756	107,331	43,818

Note: Male private sector employees 25–54. Projection of training outcome on labor market fluidity without or with controls. Panel A. Whether worker undertook any vocational training since January last year. Panel B. Days on vocational training in the past 12 months, expressed as a fraction of potential work days (5*52). Panel C. Hours on vocational training in the past 12 months, expressed as a fraction of potential work hours (40*52). All panels. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Employment in the past 12 months includes self-employment. Constructed by first collapsing the data to the country-age-year level using the provided survey weights, then to the country level. Standard errors are clustered at the country-level. * statistically significant at 10%; ** statistically significant at 5%; *** statistically significant at 1%. *Source:* ECHP 1995–2001.

D.3 Training and subsequent mobility

Table 13 relates JJ in the past 12 months to training in the year prior to that (13–24 months ago). The first column shows the raw correlation with only country and year controls, the second adds age, education and occupation controls, and the third controls for worker fixed effects and year effects.[32] There is no evidence that workers who trained more in the past year are less likely to make a JJ move in the current year. In fact, the raw data suggest the opposite, although this appears to be driven by selection. In any case, if skills had been primarily *firm-specific*, one may have hypothesized that worker mobility would decline with training.

[32]Due to collinearity, I cannot simultaneously control for individual fixed effects, year and age. The same conclusion holds with age controls instead of year controls.

Table 13. JJ mobility and lagged training

	Panel A. Whether trained			Panel B. Days (fraction of year)			Panel C. Hours (fraction of year)		
	Raw	Controls	Within	Raw	Controls	Within	Raw	Controls	Within
Training	0.005	-0.000	-0.002	0.083*	0.043	0.037	0.134*	0.075	0.082
	(0.005)	(0.005)	(0.006)	(0.048)	(0.048)	(0.057)	(0.071)	(0.069)	(0.089)
N	32,690	32,646	30,223	32,595	32,551	30,124	32,541	32,497	30,063

Note: Male private sector employees 25–54. Projection of JJ in the past year on various measures of vocational training 13–24 months ago, without or with controls. Raw: Country and year controls; Controls: Country, year, age, education and occupation controls; Within: Individual fixed effects and year controls. Panel A. Whether worker undertook any vocational training since January last year. Panel B. Days on vocational training in the past 12 months, expressed as a fraction of potential work days (5*52). Panel C. Hours on vocational training in the past 12 months, expressed as a fraction of potential work hours (40*52). All panels. JJ mobility: Whether worker started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Employment in the past 12 months includes self-employment. Standard errors are clustered at the country-level. * statistically significant at 10%; ** statistically significant at 5%; *** statistically significant at 1%. *Source:* ECHP 1995–2001.