Labor Market Fluidity and Human Capital Accumulation

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Abstract

Using panel data from 23 OECD countries, I document that wages grow more over the life-cycle in countries where job-to-job mobility is more common. A life-cycle theory of job shopping and accumulation of skills on the job highlights that a more fluid labor market allows workers to faster relocate to jobs where they can better use their skills, incentivizing accumulation of skills. Lower labor market fluidity reduces life-cycle wage growth by 20 percent and aggregate labor productivity by nine percent across the OECD relative to the US. I derive a set of testable predictions for training and confront them with comparable cross-country training data, finding support for the theory.

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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 has, however, 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.

In this paper, I quantify the consequences of cross-country differences in labor market fluidity on workers' careers, where I measure labor market fluidity as how frequently workers make job-to-job (JJ) transitions. In particular, I argue that greater labor market fluidity encourages individuals to accumulate skills on-the-job. The reason is that it improves their ability to locate a job where their skills are more useful. Consequently, labor market fluidity facilitates life-cycle wage growth, both by allowing workers to move toward jobs that reward their skills better and by inducing them to grow their skills more.

I proceed in three steps. In the first part of the paper, I establish a series of new facts on cross-country differences in life-cycle careers. To that end, I build an internationally comparable worker-level panel data set covering close to a million observations for over 20 years across 23 OECD countries. The data suggest wide dispersion across countries in labor market flows and life-cycle wage growth. 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.

[1] See, e.g. Bentolila and Bertola (1990), Hopenhayn and Rogerson (1993), and Ljungqvist and Sargent (1998, 2008).

Although novel and intriguing, these correlations fall short of a quantitative assessment of the impact of differences in labor market fluidity on workers' careers. For this purpose, I propose in the second part of the paper a tractable life-cycle theory of accumulation of skills in a frictional labor market. The framework combines two benchmark models of worker career outcomes: endogenous accumulation of human capital on-the-job as in Ben-Porath (1967) and a job ladder model in the spirit of Diamond (1982)–Mortensen and Pissarides (1994). While on their own each framework is well understood, their combination offers a rich set of testable predictions for how human capital accumulation and job mobility interact. The marginal product of a worker's human capital differs across firms, but frictions in the labor market prevent workers from immediately relocating to their most productive use. A key difference to an earlier literature on training in frictional labor markets is that I allow workers to move directly from one employer to another without an intervening spell of unemployment (Acemoglu, 1997; Acemoglu and Pischke, 1998, 1999b).[2] By leaving a worker in a favorable bargaining position with a new employer, the nature of such JJ mobility differs from mobility through unemployment. 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.

I examine in the model the impact on workers' careers of wedges to firms' cost of creating jobs, motivated by a large literature that argues that policies such as, for instance, business regulations, labor taxes and employment protection legislation (EPL) serve to raise the cost to firms of hiring (Hopenhayn and Rogerson, 1993; 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 value of human capital declines. Workers respond by accumulating less human capital, such that the stock of human capital falls.

I calibrate the model to match key life-cycle outcomes in the US as a typical high-fluidity country. As in the data, JJ mobility declines with age, as workers gradually settle into jobs that use their skills efficiently. Wages grow rapidly early in careers, as young workers climb the job ladder and face high marginal returns to training. My estimates imply that human capital is the most important source of life-cycle wage and productivity growth, contributing 25 log points between age 25 and 50. Growth in match productivity is a close second. Wages also grow as the arrival of outside offers allows workers to bargain up their pay, and due to a declining share of time devoted to training over the life-cycle.

To quantify the impact of labor market fluidity on workers' careers, I introduce in the calibrated model wedges to firms' cost of creating jobs such that the model matches the cross-country variation in

[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.

labor market fluidity. By holding all other parameters fixed at their estimated US values, this approach isolates the impact of labor market fluidity on workers' careers. 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. Match productivity grows less over the life-cycle in less fluid labor markets as workers climb the job ladder slower, accounting for a third of the impact of labor market fluidity on wage growth. Less human capital accumulation accounts for another third, with the remainder due to slower growth in the share of match output appropriated by workers and less training early in careers. Across the OECD, aggregate labor productivity is nine 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.

The theory makes rich predictions for how training varies both across and within countries. In the third part of the paper, I confront key predictions of the model with cross-country panel data on on-the-job training and job mobility. Using these data, I uncover several patterns consistent with the theory. First, workers spend more time on training in countries with a more fluid labor market and in occupations and sectors with relatively higher labor market fluidity within countries. Second, conditional on worker-fixed effects, 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 firms, as such firms 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 firms have a harder time moving to jobs where they can better use their skills. Expecting this, they train less.

Most of this paper purposefully avoids taking a strong stand on the exact policies that result in differences in labor market fluidity, which as noted above has been extensively studied in the literature. Instead, I focus on the implication of such differences for worker behavior, 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." That being said, I provide reduced-form empirical evidence that labor market fluidity is negatively correlated with policies and regulations that raise the cost on firms of doing business, consistent with the literature (Lazear, 1990; Fonseca et al., 2001). Moreover, I find that the wedges required to match differences in labor market fluidity are also quantitatively consistent with cross-country differences in the cost of starting firms estimated by the World Bank. Finally, I exploit a significant reduction in EPL in Spain in 1994–1995 to show that the fall in EPL was associated with an increase in labor market fluidity, as well as a fall in wages of labor market entrants, a steepening of subsequent wage growth, and an increase in vocational training. These empirical patterns are quantitatively consistent with the predictions of the model.

Related literature. A vast literature documents cross-country differences in labor market outcomes.[3] Whereas much work has focused on hours worked or unemployment (Nickell, 1997; Bick et al., 2018; Feng et al., 2020), less work assesses differences in wage growth and labor market flows, particularly JJ flows. 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. 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) document differences in labor market flows across rich and poor countries.[4] Guner et al. (2018) document and propose a theory that accounts for steeper earnings growth for managers relative to non-managers in rich countries.

Recent work combines human capital and search in studies of workers' careers (Bagger et al., 2014), building on seminal work by Becker (1962), Ben-Porath (1967), Diamond (1982), Mortensen and Pissarides (1994), and Burdett and Mortensen (1998). This literature typically models human capital as exogenous via learning-by-doing (Yamaguchi, 2010; Burdett et al., 2011, 2020), although Rubinstein and Weiss (2006), Fu (2011) and Bowlus and Liu (2013) are important exceptions. I instead follow Ben-Porath (1967) to model training as a choice. This approach provides rich insights into how search and human capital accumulation interact. Herkenhoff et al. (2018) study learning through interactions with co-workers.[5] Wasmer (2006) provides a theory of on-the-job accumulation of skills and search, which highlights that high turnover increases incentives to accumulate general rather than firm-specific skills. Relative to him, I abstract from firm-specific skills, motivated by a recent literature that questions the importance of such skills (Kambourov and Manovskii, 2009; Lazear, 2009). Indeed, I provide novel evidence consistent with this recent view based on the joint dynamics of on-the-job training and worker mobility. While the theory in this paper is less general than Wasmer (2006), I offer a quantitative assessment of the impact of labor market fluidity on cross-country differences in career outcomes, including direct empirical support for the predictions of the model based on panel micro data on training.

In Michelacci and Pijoan-Mas (2012), workers accumulate skills by working longer hours. They show that an increase in wage inequality accounts for two-thirds of the increase in average hours worked in

[3] Another voluminous literature assesses the sources of cross-country income differences. Manuelli and Seshadri (2014) is closest to this paper in that they also allow for on-the-job accumulation of skills, but abstract from labor market frictions.

[4] Consistent with this paper, the latter find that richer countries have higher JJ flows among a set of developed countries—for instance, their Table 2 "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). In contrast, developing countries are characterized by *higher* labor market flows.

[5] In Engbom (2020), I propose a theory of search and entrepreneurship to study the impact of demographic change, whereas the current paper assesses how search and training interact with a focus on cross-country patterns.

the US since 1970. I abstract from an intensive margin of labor supply—motivated by a lack of correlation between labor market fluidity and average hours worked per week across countries—to instead model human capital accumulation following Ben-Porath (1967). Lentz and Roys (2016) incorporate risk aversion in a model of endogenous on-the-job accumulation of skills and labor market search. Although their focus is not on understanding cross-country patterns, they show that lower labor market frictions encourage training, mirroring findings in this paper. Flinn et al. (2017) use NLSY 1997 training data to discipline a rich theory of training and search. While I do not use training data in estimation, I use such data to validate the predictions of the model across countries. Other important differences include this paper's focus on cross-country patterns and the introduction of a proper notion of a life-cycle.

Doepke and Gaetani (2020) develop a quantitative life-cycle model of search and training to understand the different evolution of the college premium in the US and Germany over the past decades. Relative to them, I incorporate and put center stage JJ mobility, motivated by the large cross-country differences in such flows that I document. Gregory (2019) offers a rich framework in which firms differ in both their productivity and learning environment.[6] While the current paper also predicts that workers grow their skills more in some firms—consistent with her reduced-form patterns—such differential growth rates arise here through workers' and firms' optimizing behavior. In addition, I use data on training on-the-job to establish new facts on how training varies across jobs.

This paper is organized as follows. Section 2 establishes a series of novel facts on cross-country differences in life-cycle careers, while Section 3 proposes a theory of endogenous accumulation of skills in a frictional labor market to interpret the empirical patterns. Section 4 estimates the model targeting the US as a typical high-fluidity country, and uses it to quantify the impact of labor market fluidity on workers' careers as well as ultimately aggregate outcomes across countries. Section 5 derives and contronts key predictions of the theory with standardized training data across countries. Section 6 discusses factors behind cross-country differences in labor market fluidity, while Section 7 concludes.

2 Motivating facts

This section contributes to the literature by establishing a set of new facts on life-cycle labor market outcomes across countries. To that end, I build an internationally comparable worker-level panel data set covering 23 OECD countries based on the following sources: 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 Eu-

[6] Her work, this paper and much of the macro-labor literature share that there is no distinction between a firm and a match.

ropean 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 comparison.[7] See Appendix A.2 for details.

2.1 Sample selection

I focus on men, as female labor force participation likely varies across countries for reasons that the theory in the next section abstracts from. 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 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 prime 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.[8] The core annual sample includes over six hundred thousand observations, with another two hundred thousand observations for the other OECD countries.

2.2 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, constructed as the product of

[7] For this reason, I prefer to use the PSID in my main analysis of worker flows. Appendix A.1 shows that the resulting flows are broadly consistent with those in the US Survey of Income and Program Participation (SIPP).

[8] The EUSILC also contains a few years of data for Bulgaria, Cyprus, Malta, Romania and Serbia. I have confirmed that my findings hold also including these countries, but I prefer to focus on the set of relatively comparable OECD countries.

weeks worked times usual weekly hours.[9] 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.[10] 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.[11] The available data sets do not allow for the construction of a satisfactory monthly 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.[12]

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,

[9]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.

[10]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).

[11]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.

[12]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.1 for more details and a comparison with the US SIPP.

and occupation into 10 internationally comparable, aggregate occupation groups based on ISCO-88.

I 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,

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

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 $\bar{A}$.

Appendix A.5 plots JJ, EU and UE mobility as well as wages over the life-cycle across countries.

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

Panel A of Figure 1 plots life-cycle wage growth against labor market fluidity across the core set of 13 countries. Wages grow substantially more over the life-cycle in more fluid labor markets. For instance, wages rise by 75 log points in the US between ages 25–54, but only by 30 log points in Italy. Panel B 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.

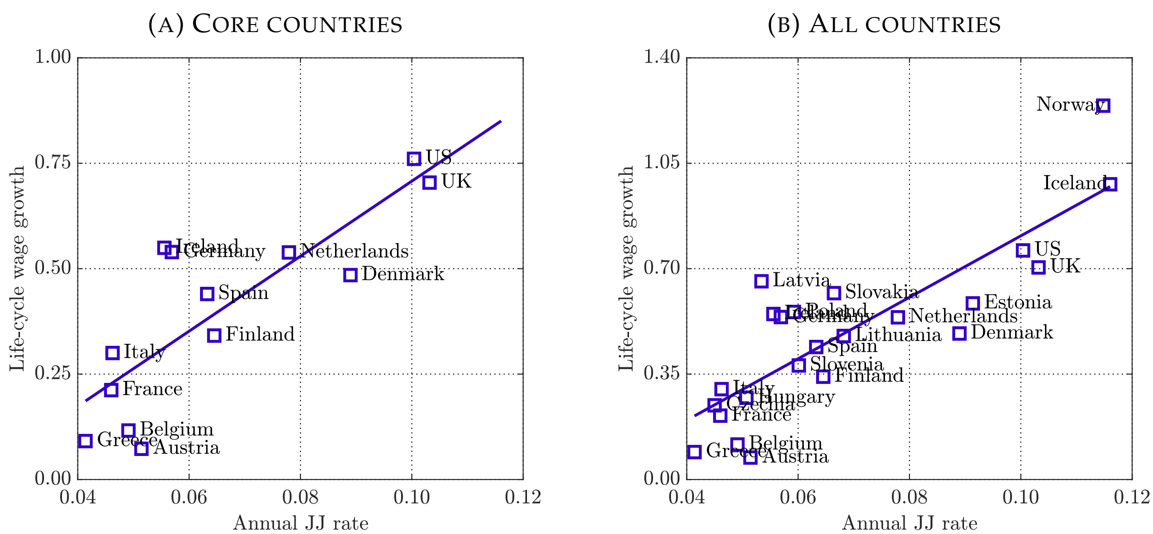
One possible factor behind these patterns is differences in workforce composition. To assess this, I consider an augmented version of regression (1) that instead pools all countries and years,

$$w_{it} \quad = \quad \alpha \text{ fluidity}_c \times a_{it} + \sum_e \beta^e e_{it} \times a_{it} + I_i + Y_t + A_{it} + \varepsilon_{it} \tag{2}$$

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, controlling 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,[13] 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. Appendix A.6 shows that similar results hold for the full sample of 23 countries. Confirming the pattern in Figure 1, 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 1. LIFE-CYCLE WAGE GROWTH AND LABOR MARKET FLUIDITY



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 (Topel and Ward, 1992). Indeed, Panel A of Figure 2 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,

[13] 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.

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.[14] A JJ mover experiences 5.5 percent greater residual 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.

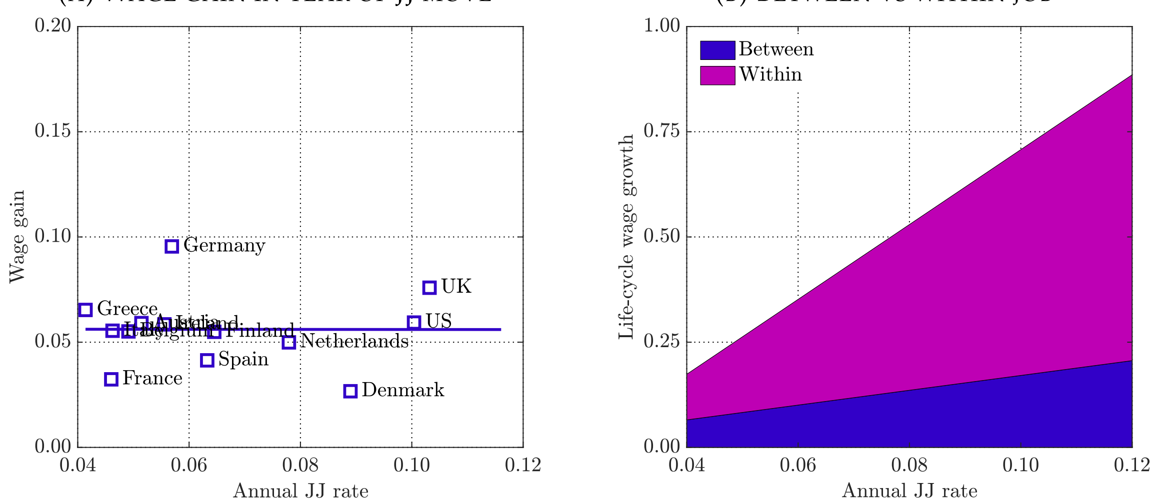
TABLE 1. LIFE-CYCLE WAGE GROWTH AND LABOR MARKET FLUIDITY

	Panel A. Ages 25–54			*Panel B. 1% depreciation*			*Panel C. Ages 22–59*		
	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

Note: Male employees. Panel A. Wages restricted to not grow after age 50. Panel B. Ages 25–54 with wages restricted to depreciate 1% annually after age 50. Panel C. 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.

FIGURE 2. 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.

Panel B uses the gain upon a JJ move to estimate the contribution of job shopping toward life-cycle

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

wage growth. I compute *between-job* life-cycle wage growth by multiplying the wage gain from a JJ move with the average number of JJ moves a worker makes between age 25–54.[15] I compute *within-job* life-cycle wage growth 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.

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 on labor market fluidity, with or without controls. Because this exercise assesses level differences, I cannot control for worker fixed effects. Entry wages are *lower* in more fluid labor markets, although not statistically significantly so. Quantitatively, entry wages are 2–6 percent higher in the least fluid labor market relative to the US. Controlling for real GDP per hour in 2004 PPP-adjusted US dollars makes the pattern more pronounced.[16]

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. Panel A of Figure 3 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).

Panel B 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.[17] Higher wage occupations experience steeper life-cycle wage growth. Moreover, they

[15] 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).

[16] I am not, however, convinced 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. Hence with such a control, the steepness of life-cycle wage profiles and entry wages are the flip side of the same coin.

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

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 explanations based on minimum wages or unions, which typically impact lower skilled workers the most.

TABLE 2. ENTRY WAGES AND LABOR MARKET FLUIDITY

	Year	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

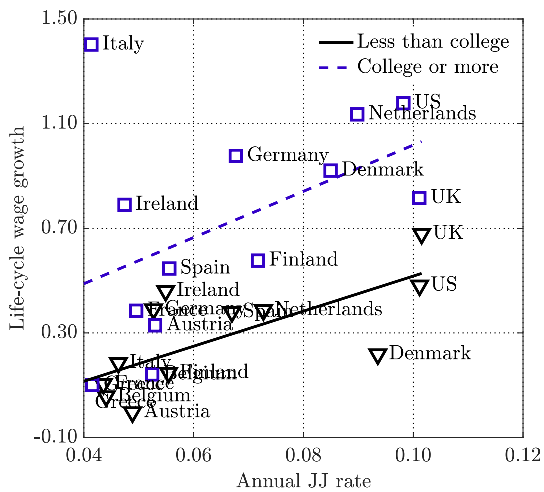
Note: Male employees 21–24. Log hourly real wage in 2004 PPP-adjusted USD. Year: Year controls. Educ: Year and education controls. Occup: Year and occupation controls. GDP: Year and GDP per hour controls (in 2004 PPP-adjusted USD). Labor market fluidity: Share of employees who started working for their 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.

Inequality. Patterns for inequality may provide additional guidance regarding the forces at work. For instance, Guvenen et al. (2013) emphasize that progressive taxation reduces life-cycle wage growth and inequality, which may be correlated with labor market fluidity. Panel A of Figure 4 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. Appendix A.7 contains additional results.

Panel B graphs life-cycle growth in inequality against fluidity, where the former is the 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, the increase in inequality is less pronounced, even in the US. I provide a further discussion and robustness in Appendix A.7.

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. Panel C shows that, 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 3. 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.

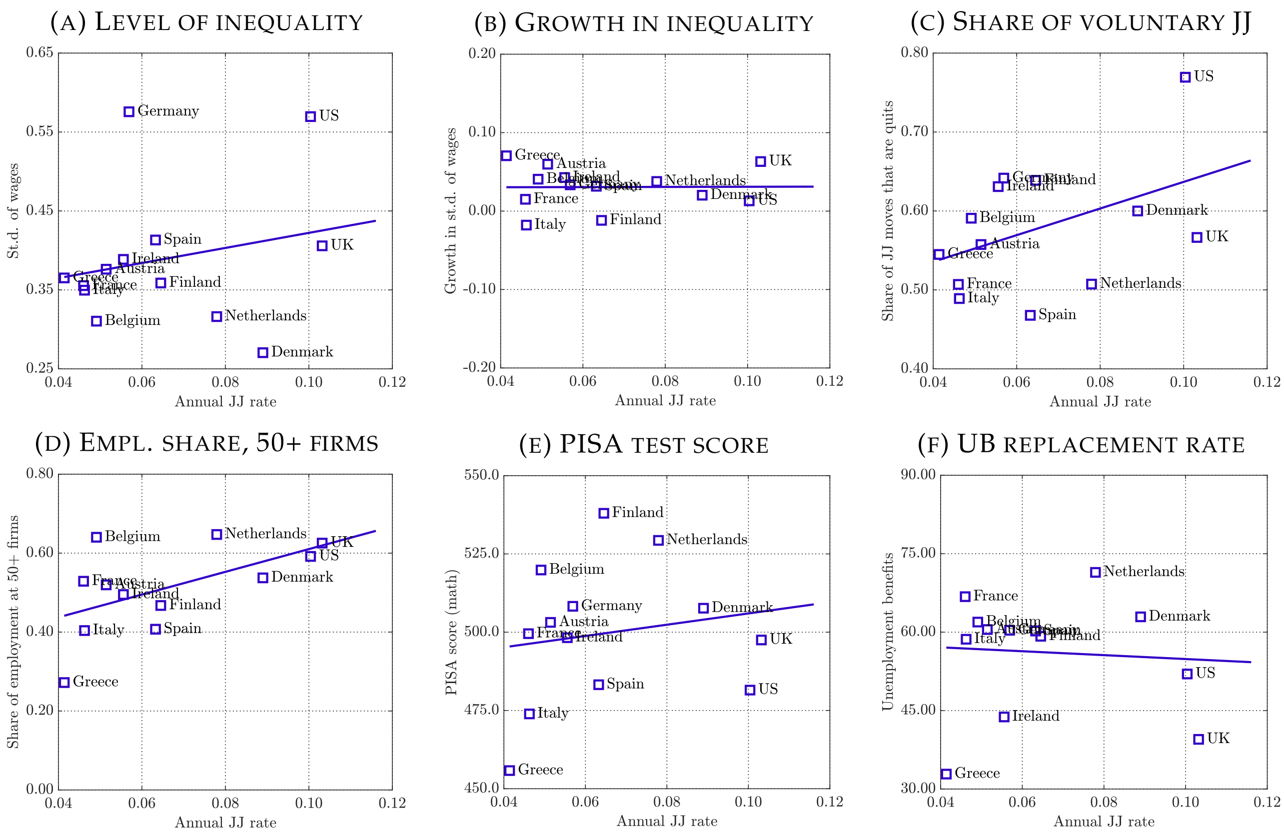
The boundary of the firm. My measure of fluidity captures only mobility between firms. Hence, less mobility across firms may be compensated for by higher mobility within firms. To the extent that large firms offer greater scope for within-firm mobility, this scenario may be particularly plausible if firms are smaller in more fluid labor markets. Panel D, however, shows that a larger share of workers work at large firms in more fluid labor markets.[18] At face value, this suggests that the higher mobility rates in some countries is not driven by greater fragmentation of firms in such countries.

Other factors. Panel E shows that labor market fluidity is not correlated with PISA test scores. Together with the facts that my results remain unchanged when controlling for education or occupation-specific age slopes and that my core sample includes only highly developed OECD countries, this observation leads me to discount the hypothesis that the steeper wage growth in more fluid labor markets is primarily accounted for by workforce composition. Panel F shows that there is important cross-country variation in the level of the unemployment benefit replacement rate, but it does not correlate strongly with labor

[18]My measure is the share of employment at firms with 50 employees or more. This is the only firm size measure consistently available across countries and years, and is not available for all countries (in particular, Germany is missing).

market fluidity. This pattern is consistent with the argument that other factors such as the cost of starting a firm are more important determinants of labor market fluidity (Fonseca et al., 2001).

FIGURE 4. ADDITIONAL OUTCOMES



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 between ages 25–29 and 50–54 in st.d. of residual log hourly wages, controlling for year-education-age and year-occupation effects separately by country. Panel C. Share of JJ transitions in which the worker quit as opposed to the firm initiated the separation (restricted to employees only). Panel D. Share of employees working at firms with 50 or more workers. Firm size is only available in the cross-sectional version of the EUSILC, missing from the BHPS (I use the ECHP/EUSILC), coded into non-comparable bins in the GSOEP, and only available in 1999 and 2003–2015 in the PSID. Panel E. PISA math test score. Panel F. Average short-term unemployment benefit replacement rate as reported by the OECD. Panels A–D. Constructed by first collapsing the outcome variable 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.

Taking stock. Using detailed panel micro data, the above analysis establishes a set of new facts on cross-country differences in career outcomes, the most prominent being that wages grow more over the life-cycle in more fluid labor markets. This pattern is not accounted for by observable worker characteristics, and the majority of it takes place within-jobs.

While novel and intriguing, however, these correlations do not settle the main question this paper aims to answer: the impact of labor market fluidity on workers' careers. To assess this, I now proceed to propose a structural model that I use as a laboratory to isolate the impact of labor market fluidity as well as explore its mechanisms. Section 5 returns to the data to test key predictions of the theory.

3 Model

At a conceptual level, a stylized job ladder model in the spirit of Burdett and Mortensen (1998) may suffice to account for steeper wage growth in more fluid labor markets, as workers move up the job ladder more. At the same time, a vast literature emphasizes the critical role played by human capital accumulation in driving life-cycle wage and productivity growth (Becker, 1962; Mincer, 1974), suggesting that it is important to understand how labor market fluidity impacts human capital accumulation. Hence, I propose in this section an equilibrium model of careers that merges endogenous skill accumulation as in Ben-Porath (1967) with a search model in the spirit of Bagger et al. (2014). The combination of search and endogenous human capital accumulation leads to a rich set of predictions for how mobility and training interact, which Section 5 finds empirical support for in both within-country and cross-country variation.

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. 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 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, leads me to focus my analysis elsewhere (see Appendix A.3 for details).

Production 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 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.

Output of a match between a firm with productivity z and a worker with human capital h is $y = zh$, i.e. human capital and technology are complements, as in Acemoglu and Pischke (1998) and Bagger et al. (2014). 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. The critical aspect of this assumption is the view that an individual may use her skills more efficiently in some jobs than others—if an individual's human capital is equally productive in all jobs, the predictions of this paper would not go through. I hence also abstract from purely firm-specific human capital, consistent with the evidence in Kambourov and Manovskii (2009) and Lazear (2009). Section 5 and Appendix E.4 document cross-sectional patterns consistent with these two key assumptions.

Human capital accumulation. Employed workers may accumulate skills on-the-job. The human capital accumulation technology is independent of worker age a. Building on Ben-Porath (1967), if a worker sets aside some fraction of her work time i toward building her skills, her human capital grows by

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

The opportunity cost of training is foregone production, izh. Human capital does not depreciate.[19]

In Ben-Porath (1967) there is no productivity dispersion, z, such that human capital grows by $\mu(ih)^{\eta}/\eta$ at cost ih. The current specification provides an extension to the case of employer heterogeneity. Note in particular that a given amount of time, i, is assumed to grow human capital by more in a more productive firm. Absent this assumption, training falls in productivity, which is inconsistent with the positive correlation between training, on the one hand, and firm size and firm pay, on the other, that I document in Section 5 (conditional on worker fixed effects and time varying controls). In contrast, under the current assumption, the model matches these empirical patterns well. The view that workers may learn more in some jobs goes back to Rosen (1972) and more recently Jovanovic and Nyarko (1996) and Gregory (2019).

Labor market. The labor market is characterized by informational frictions that prevent the immediate reallocation of a worker to the job that uses her skills the most efficiently. Both the unemployed and employed search for jobs at random in a common labor market, in the latter case with exogenous relative efficiency ϕ. Employed workers separate to unemployment at rate $\delta(z)$. The dependence on productivity

[19] 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.

z captures in reduced-form the view that less productive jobs are more likely to separate in response to idiosyncratic shocks. It allows the model to match the decline in EU mobility with age.

If firms create V vacancies and workers search with aggregate efficiency S, the number of meetings are, $m = \chi V^{\alpha} S^{1-\alpha}$, where $\alpha \in (0,1)$ is the elasticity of matches with respect to vacancies. The job finding rate is hence $p = \chi(V/S)^{\alpha}$, while the worker finding rate of firms is $q = \chi(V/S)^{\alpha-1}$.

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. Following Barlevy (2002) and Bagger et al. (2014), wages are paid as a piece-rate r of net output, $w = r(1-i)zh$. The worker and firm bargain over the piece rate, r, and a training policy, $i(a,h,z)$. The latter can be conditioned on the observable states a, h and z. Under generalized Nash bargaining, the parties adopt the training policy that maximizes their joint value, and split the proceeds.[20] The firm and the worker can commit to the contract $\{r, i(a,h,z)\}$, but commitment is limited in the sense that either party can force a renegotiation when they have a credible threat to abandon the match under the existing contract.

This contracting structure implies that workers share in the cost of training through lower pay, consistent with the fact that entry wages are lower in more fluid labor markets. More directly, Appendix B.1 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 Wages

Let $U(a,h)$ be the value of unemployment to a worker of age a with human capital h, $W(a,h,z,r,i)$ the value of the worker when employed in a firm with productivity z when paid piece rate r and under training policy i, $F(a,h,z,r,i)$ the corresponding value to the firm, and $J(a,h,z)$ the maximized joint value of the match. I show below that the maximized joint value does not depend on how it is split.

Consider a meeting between an unemployed worker and a firm. The worker and firm bargain over a training policy and a piece rate, leading them to adopt the training policy that maximizes their joint value and a piece rate $w^u(a,h,z,i)$ determined by,

$$W\Big(a,h,z,w^u(a,h,z,i),i\Big) \quad = \quad U(a,h) + \beta\Big(J(a,h,z) - U(a,h)\Big) \tag{3}$$

Consider next the case when an employed worker contacts a poaching firm. The new and the old firm Bertrand compete for the worker, such that the worker's outside option becomes the full value of

[20] Although the outcome is the same, Cahuc et al. (2006) microfound the bargaining protocol based on alternating offers Rubinstein (1982).

the least productive match, $J(a,h,z)$. Let $w^e(a,h,z',z,i)$ denote the pay of a worker who was employed in firm z but gets poached by a firm $z' > z$ under training policy i. It is given by

$$W\Big(a,h,z',w^e(a,h,z',z,i),i\Big) = J(a,h,z) + \beta\Big(J(a,h,z') - J(a,h,z)\Big) \tag{4}$$

If the poaching firm is less productive, $z' < z$, the worker remains with her current firm, but possibly with an updated piece rate given by the maximum of $w^e(a,h,z,z',i)$ and her previous wage, r. Let $r(a,h,z,r,i)$ be the lowest outside offer that leads to a renegotiation of the current contract, given by $J(a,h,r(a,h,z,r,i)) + \beta(J(a,h,z) - J(a,h,r(a,h,z,r,i))) = W(a,h,z,r,i)$.

Because age and human capital change over time, instances may arise when either the worker or the firm would want to quit the match under the existing contract, even though the match has positive surplus. In these instances, I assume that wages are rebargained according to (3).[21]

3.3 Value functions

Given an optimal training policy that maximizes the joint value as well as the splitting rules (3)–(4), the value of unemployment solves the differential equation

$$\rho U(a,h) = b(a,h) + \frac{\partial U(a,h)}{\partial a} + p\beta \int_0^\infty \Big(J(a,h,z) - U(a,h)\Big)^+ d\Gamma(z) \tag{5}$$

subject to the terminal condition $U(A,h) = 0$, where $x^+ = \max\{x,0\}$. 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. If she accepts the job, she gets a share β of the surplus of the new match.

The value of a worker, $W(a,h,z,r,i)$, evolves according to,

$$\begin{aligned}
\rho W(a,h,z,r,i) &= r(1-i(a,h,z))zh + \frac{\mu}{\eta}\Big(i(a,h,z)zh\Big)^\eta \frac{\partial W(a,h,z,r,i)}{\partial h} + \frac{\partial W(a,h,z,r,i)}{\partial a} \\
&+ \phi p \int_{r(a,h,z,r,i)}^{z} \Big(J(a,h,z') + \beta(J(a,h,z) - J(a,h,z')) - W(a,h,z,r,i)\Big) d\Gamma(z') \\
&+ \phi p \int_{z}^{\infty} \Big(J(a,h,z) + \beta(J(a,h,z') - J(a,h,z)) - W(a,h,z,r,i)\Big) d\Gamma(z') \\
&+ \delta(z)\Big(U(a,h) - W(a,h,z,r,i)\Big)
\end{aligned} \tag{6}$$

subject to $W(A,h,z,r,i) = 0$, $W(a,h,z,r,i) \geq U(a,h)$ and $W(a,h,z,r,i) \leq J(a,h,z)$. The worker receives

[21] In practice in the estimated model, these two cases are extremely rare, such that aggregate wage dynamics are essentially invariant to alternative assumptions regarding how wages get rebargained in these scenarios.

a share r of net output today, grows her human capital and ages. At rate ϕp, she receives outside offers from distribution Γ. If the new match is worse than her current, she remains with her current firm but possibly with updated pay, otherwise she switches firms. Finally, she is subject to separation shocks.

Let $F(a,h,z,r,i)$ be the value to a firm of productivity z when employing a worker of age a with human capital h under piece rate r and the training policy that maximizes worker and joint surplus,

$$\begin{aligned}
\rho F(a,h,z,r,i) &= (1-r)(1-i(a,h,z))zh + \frac{\mu}{\eta}\Big(i(a,h,z)zh\Big)^{\eta}\frac{\partial F(a,h,z,r,i)}{\partial h} + \frac{\partial F(a,h,z,r,i)}{\partial a} \\
&+ \phi p \int_{r(a,h,z,r,i)}^{z} \Big((1-\beta)(J(a,h,z)-J(a,h,z')) - F(a,h,z,r,i)\Big) d\Gamma(z') \\
&- \Big(\phi p(1-F(z)) + \delta(z)\Big) F(a,h,z,r,i)
\end{aligned} \tag{7}$$

subject to the boundary conditions $F(A,h,z,r,i) = 0$, $F(a,h,z,r,i) \geq 0$ and $F(a,h,z,r,i) \leq J(a,h,z)$.

Combining the value of a worker (6) and the value of a firm (7), imposing the fact that $J(a,h,z) = W(a,h,z,r,i) + F(a,h,z,r,i)$ and collecting terms,

$$\begin{aligned}
\rho J(a,h,z) &= (1-i(a,h,z))zh + \frac{\mu}{\eta}\Big(i(a,h,z)zh\Big)^{\eta}\frac{\partial J(a,h,z)}{\partial h} + \frac{\partial J(a,h,z)}{\partial a} \\
&+ \phi p \beta \int_{z}^{\infty} \Big(J(a,h,z') - J(a,h,z)\Big) d\Gamma(z') + \delta(z)\Big(U(a,h) - J(a,h,z)\Big)
\end{aligned} \tag{8}$$

subject to the boundary conditions $J(A,h,z) = 0$ and $J(a,h,z) \geq U(a,h)$. Since the piece rate r does not enter this expression, this verifies the conjecture that the joint value does not depend on how it is split. The optimal training policy is that which maximizes (8), i.e. it is given by the first-order condition

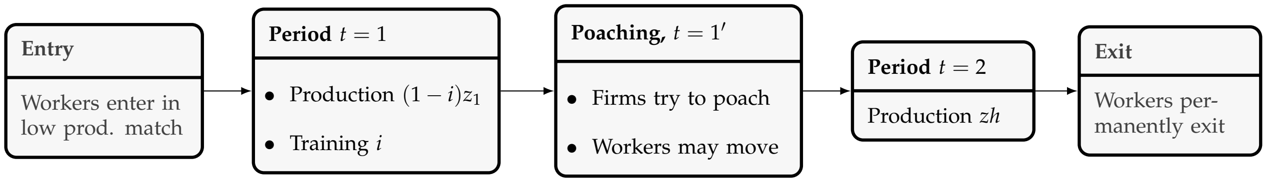
$$\Big(i(a,h,z)zh\Big)^{1-\eta} = \mu \frac{\partial J(a,h,z)}{\partial h} \tag{9}$$

3.4 Equilibrium

Let $G(a,h,z)$ be the distribution of workers over age, productivity and human capital, $u(a,h)$ the distribution of unemployed workers over age and human capital, $u(a,h)$, and u the aggregate unemployment rate. The free entry condition writes,

$$c = (1-\beta)q \int_{0}^{\infty} \left(\frac{u}{S} \int_{a,h} J(a,h,z)^{+} du(a,h) + \frac{\phi(1-u)}{S} \int_{a,h} \int_{0}^{z} J(a,h,z) - J(a,z',h) dG(a,z',h) \right) d\Gamma(z) \tag{10}$$

FIGURE 5. TIMING OF EVENTS



In return for flow cost of a vacancy c, the firm contacts a potential hire at rate q. The first term in the bracket 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.

The value of unemployment (5) and a match (8), optimal training (9), the law of motion for the evolution of the aggregate state $\{G(a,h,z), u(a,h)\}$ in Appendix B.2, and the free entry condition (10) fully characterize the allocation of the decentralized equilibrium. Given an allocation, wages are determined by the value of a worker (6) and the wage policies (3)–(4) under the optimal training policy.

3.5 Insights from a simple two-period economy

Before turning to a quantitative analysis, it is useful to provide some brief 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, $z = z_2 > z_1$. 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 high-productive, poaching firms compete for young workers going into the second period. Figure 5 illustrates the timing of the simplified two-period model and Appendix B.3 outlines the value functions. I also establish in Appendix B.3 that optimal training is given by,

$$i \quad = \quad \frac{1}{z_1}\left(\mu\Big(z_1 + p\beta(z_2 - z_1)\Big)\right)^{\frac{1}{1-\eta}} \tag{11}$$

The optimal training policy (11) 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 incumbent 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 renegotation 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. $\beta \to 0$).

Appendix B.3 defines the stationary equilibrium, which can be characterized by two curves. The first is a *training curve*, which can be derived from the first-order condition (11) by substituting for the job finding rate using the matching function,

$$i(v) \quad = \quad \frac{1}{z_1}\left(\mu\Big(z_1 + v^{\alpha}\beta(z_2 - z_1)\Big)\right)^{\frac{1}{1-\eta}} \tag{12}$$

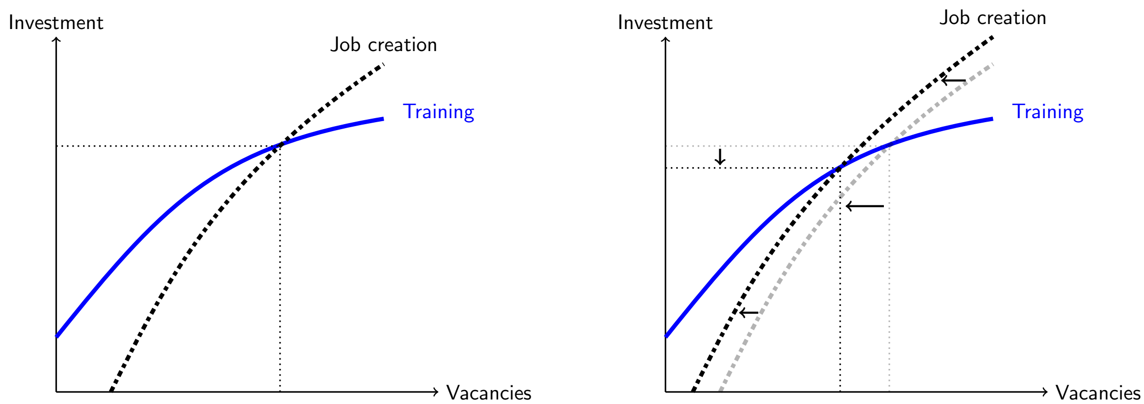
The second is a *job creation curve*, derived from a simplified version of the free entry condition (10) (I normalize the scalar in the matching technology, $\chi = 1$, to reduce notation; see Appendix B.3 for details),

$$v(i) \quad = \quad \left((1-\beta)\frac{(z_2 - z_1)}{c}\left(1 + \frac{\mu}{\eta}(z_1 i)^{\eta}\right)\right)^{\frac{1}{1-\alpha}} \tag{13}$$

FIGURE 6. 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 (12). Job creation: Equation (13).

Figure 6 graphs the training and job creation curves (12)–(13) in v-i space. At zero vacancies, $v = 0$, the training curve (12) 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 (13) is positive. Optimal job creation subsequently increases in the training rate of workers. If workers invest more, matches produce more output, and poaching firms get a share of this. I show in Appendix B.3 that the economy admits a unique stationary equilibrium if

$$\frac{1-\eta}{\eta} > \frac{\alpha}{1-\alpha}$$

In response to a higher cost of job creation, poaching firms create fewer vacancies for any given level of training of workers. That is, the job creation curve (13) shifts to the left. A higher cost of job creation does not directly impact the training curve (12). In equilibrium, however, the lower poaching rate reduces the expected value of human capital to workers, reducing training. Hence, a higher cost of creating jobs, c, is associated with lower life-cycle growth in both match productivity and human capital.

I highlight in Appendix B.4 that the decentralized equilibrium is generically inefficient.

4 Quantitative analysis

I now turn to a quantitative assessment of the impact of labor market fluidity on worker careers. To that end, I first estimate the model targeting the US as a high-fluidity country. Subsequently, I introduce wedges to firms' cost of creating jobs in the spirit of Hsieh and Klenow (2009) to quantify the impact of cross-country differences in labor market fluidity on workers' optimal behavior in the estimated model.

4.1 Fitting the model to the US

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 $\alpha = 0.5$ based on Petrongolo and Pissarides (2001). I assume that firm productivity, z, and initial human capital, h_0, are both Pareto distributed with tail indices $1/\zeta$ and $1/\sigma$, respectively. I parameterize the separation rate as $\delta(z) = \delta_0 e^{-\delta_1(\ln z - \ln \underline{z})/(\ln \overline{z} - \ln \underline{z})}$, where $\overline{z}$ ($\underline{z}$) 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 are indifferent between unemployment and working at the second lowest grid point for productivity. These assumptions leave nine parameters to estimate via SMM (Gourieroux et al., 1993),

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

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 grow more over the life-cycle. If η is higher, the return to training falls less with training such that training 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. 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. 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 in an employment spell. To compute the empirical counterpart, I additionally rely on data from the US SIPP.[22] Appendix C provides further details on the estimation routine.

[22] I use the SIPP for this particular moment because the PSID became biannual in 1997, leaving 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, though. I describe the SIPP in more detail in Appendix A.2.

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	0.500	Petrongolo and Pissarides (2001)		
	Panel B. Internally normalized				
$b(h, a)$	Flow value of leisure	See Figure 7	Indifference at 2nd grid point		
	Panel C. Internally estimated				
μ	Drift of human capital	0.001	Life-cycle wage growth	0.761	0.760
η	Curvature of human capital accumulation	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.

4.2 Estimates and model fit

Table 3 summarizes the parameters, expressed at a monthly frequency.[23] I estimate a relatively high concavity of the Ben-Porath (1967) technology, because job shopping serves to increase the concavity of the wage profile. Consequently, the model requires a less elastic human capital margin to match the concavity of the empirical life-cycle wage profile.[24] The employed search with 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).

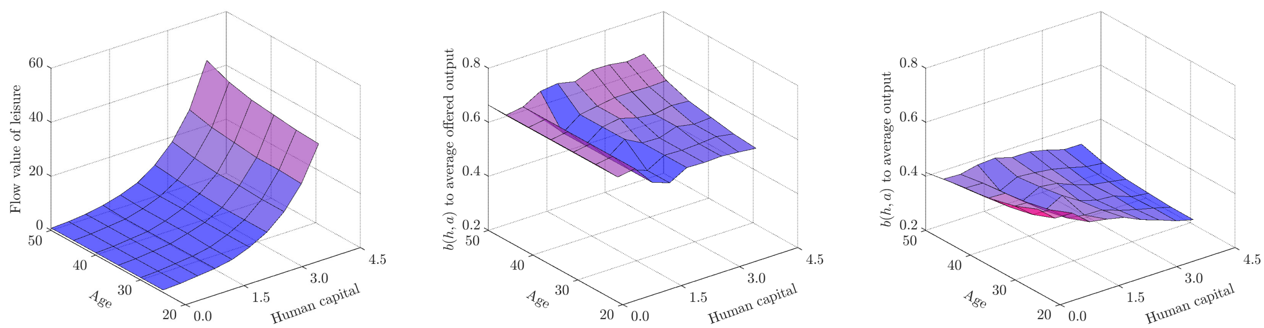
Panel A of Figure 7 illustrates the estimated flow value of leisure, $b(h, a)$. As noted above, it is normalized such that workers are indifferent between unemployment and employment at the second lowest grid point for productivity. Panel B relates it to the average offered productivity, conditional on human capital and age, while panel C instead plots it as a share of average productivity, conditional on human capital and age. The estimated flow value of leisure is high, at about 60 percent of the average offered productivity and 40 percent of the average productivity. Note that wages offered and earned are below productivity, so that relative to wages the flow value of leisure is even higher. Three reasons are behind the contrast with the findings in Hornstein et al. (2011). First, my estimate of relative search efficiency

[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.

[24] Although it is not known whether the equilibrium is unique, I have not uncovered any evidence of multiplicity.

FIGURE 7. ESTIMATED FLOW VALUE OF LEISURE

(A) LEVEL (B) OFFERED PRODUCTIVITY (C) PRODUCTIVITY



Note: Estimated flow value of leisure, $b(h,a)$. Panel A. Flow value of leisure by human capital and age. Panel B. Flow value of leisure by human capital and age relative to average offered flow output conditional on human capital and age. Panel C. Flow value of leisure by human capital and age relative to average flow output conditional on human capital and age. *Source:* Model.

in employment is reasonably high, $\phi \approx 0.4$, which limits the option value of continuing to search from unemployment. Second, when a match decides to form, it does not internalize the fact that part of the benefit from continued search accrues to future employers (unless $\beta = 1$). In particular, the relatively low bargaining power of workers ($\beta \approx 0.3$) implies that compared to a social planner, workers are too eager to accept employment (in a partial equilibrium sense). Third, the option of accumulating skills on-the-job is valuable. Consequently, individuals are willing to give up the option value of continued search from unemployment, since employment provides the opportunity to accumulate skills.

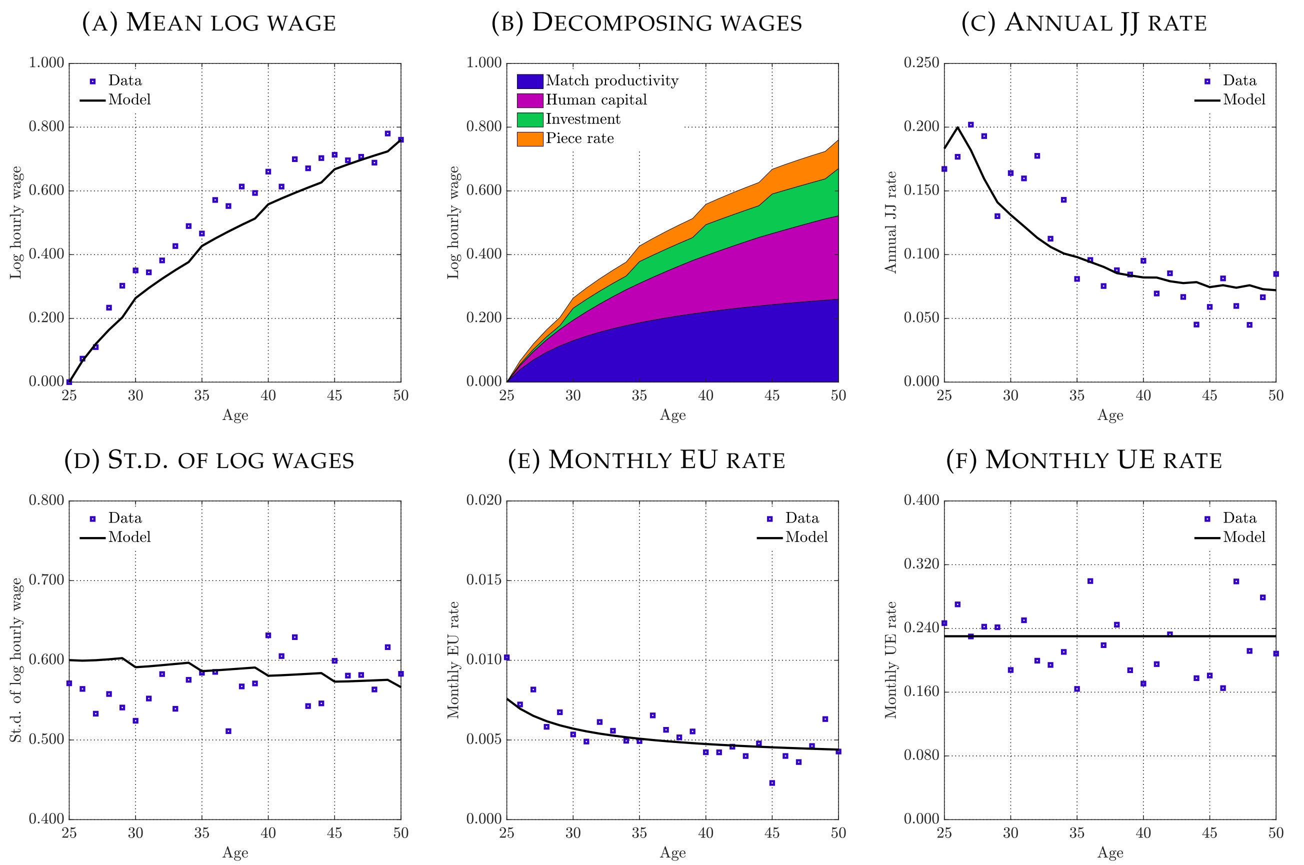
Figure 8 illustrates the model fit to life-cycle dynamics. Wages in panel A grow rapidly early in careers, as workers have much scope to move up the job ladder and bargain up their wage, and face high returns to training.[25] Panel B decomposes life-cycle wage growth in the model based on the identity,

$$\underbrace{\ln\ w}_{\text{Wage}} = \underbrace{\ln\ z}_{\text{Productivity}} + \underbrace{\ln\ h}_{\text{Human capital}} + \underbrace{\ln(1-i)}_{\text{Investment}} + \underbrace{\ln\ r}_{\text{Piece rate}} \tag{14}$$

Growth in human capital, h, is the most important source of life-cycle wage growth, with growth in 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. The model matches well the fall in JJ mobility in panel C as workers age, driven by the fact that workers gradually find a good job.

[25]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 D.1 that the cross-country patterns for life-cycle wage growth are virtually identical if I impose it.

FIGURE 8. MODEL FIT



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. Model-based decomposition of life-cycle wage growth based on (14). Panel C. 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. Panel D. 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 E. Share of employed workers who are unemployed in the subsequent month. Data: Employment includes self-employment due to data limitations. Panel F. Share of unemployed workers who are employed in the subsequent month. Data: Employment 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.

The standard deviation of residual wages rises over the life-cycle as shown in panel D, which the model fails to reflect. Yet as noted above and discussed further in Appendix A, the growth in the standard deviation of residual wages (controlling for year-education-age and year-occupation effects) is less pronounced than that of raw wages. I hypothesize that allowing for heterogeneity in learning ability along the lines of Huggett et al. (2011) and Guvenen et al. (2013) would allow the model to also match the growth in inequality over the life-cycle. It understates the decline in the EU rate (panel E), suggesting that other forces such as learning about occupational fit may be at work too (Gervais et al., 2016). 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 (panel F).

4.3 Quantifying the dynamic effects of misallocation

To assess the effect of labor market fluidity on worker careers, I introduce wedges to firms' optimal job creation condition (10) such that the model matches cross-country differences in labor market fluidity, in the spirit of Hsieh and Klenow (2009). In practice, I adjust directly the cost of a vacancy, c (this is isomorphic to changing matching efficiency, χ, i.e. identical results could be obtained by instead adjusting χ).[26] I make two observations with respect to this approach. First, by holding all other parameters fixed at their estimated US values, it isolates the importance of differences in labor market fluidity on worker careers. Moreover, no other cross-country outcome than differences in fluidity are targeted in this exercise, such that the model does not mechanically load any other outcomes on the proposed mechanism. Second, it purposefully avoids taking a strong stand on the specific policies that lead to differences in labor market fluidity, which has been extensively studied in the literature (see, e.g., Pries and Rogerson, 2005). 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 the cost to firms of doing business. Indeed, Figure 12 finds that the wedges required to match observed differences in labor market fluidity across countries are of the same order of magnitude as observed cross-country differences in the cost of starting a business, as estimated by the World Bank. In this section, however, I focus on the key novelty of this paper, which is quantify the impact of such differences on worker behavior.

Panel A of Figure 9 shows that life-cycle wage growth is greater in more fluid labor markets, while panel B illustrates that unemployment is lower (a similar pattern holds for wage employment rates in Appendix D.3).[27] As I show in Appendix D.4, this is the result of both a higher UE and a lower EU rate in more fluid labor markets. Panel C highlights that labor productivity is higher in more fluid labor markets, constructed as real PPP-adjusted GDP per hour in the data. An important caveat is that the model is estimated for men, while productivity is only available at the economy level. In the model, I construct labor productivity as total output net of training costs and the cost of job creation excluding the wedge: $((1-u)\int(1-i)zhdG(a,z,h) - cV)/(1-u)$. That is, I adopt the view that the wedge is tax revenue ultimately used productively. Across the core sample, labor productivity is 8.8 percent lower than in the US (7.9 percent across the full sample). For comparison, Hopenhayn and Rogerson (1993) find that differences in labor market policies across the OECD lead to static productivity losses of a little over two percent, while a typical finding in the literature is a static loss of 3-4 percent. Consequently,

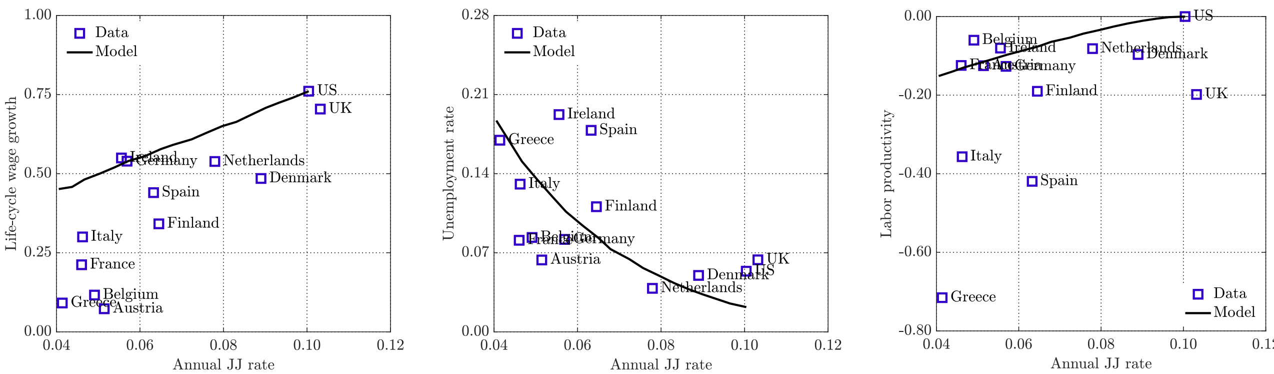
[26] I allow the flow value of leisure to adjust such that each human capital group is indifferent between unemployment and employment at the least productive firm on the grid for productivity. Not doing this, however, only marginally affect results.

[27] 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. I prefer to get the flows right, as opposed to the stocks, but I have re-estimated the model targeting instead the EU and unemployment rates (hence missing the UE rate), with similar results.

the dynamic losses are over twice as large, as workers climb the job ladder slower and accumulate less human capital. An alternative approach would be to assume that the wedges are a waste of resources (for instance due to unproductive bureaucracy). Under this less conservative view, labor productivity would be 16.0 percent lower (14.0 percent across the full sample).[28] I focus here on the core sample, but similar results hold for the full sample in Appendix D.2.

FIGURE 9. THE IMPACT OF LABOR MARKET FLUIDITY

(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 (1) with worker fixed effects, year effects and age effects restricted to not grow after age 50. Panel B. Data: Collapsed to the country-year-age level using the provided survey weights, then to the country-level. Model: Collapsed to the country-age level, then to the country-level. Panel C. Data: Real output per hour in 2014 in 2004 PPP-adjusted US dollars. Model: Output per worker net of training and job creation costs excluding the wedge per worker, $((1-u)\int(1-i(a,z,h))zhdG(a,z,h)-cV)/(1-u)$. Both data and model are in logs and relative to 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 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 summarizes these predictions for life-cycle wage growth (see Appendix D.6 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 systematic relationship between life-cycle wage growth and labor market fluidity in the data (60 percent in the full sample of 23 countries). Moreover, while the correlation between life-cycle wage growth and fluidity is high, additional orthogonal variation implies that differences in labor market fluidity account for 44 percent of the overall variation in life-cycle wage growth across the core set of countries (46 percent across the full sample). 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. (2013) for a complementary mechanism. In an accounting sense, the model matches the between-job component in Figure 2 by construction, since I target the average wage gain upon a JJ move in estimation and match differences in the frequency of JJ

[28] The levels are not comparable, so I normalize the model moment to the data moment in the US. None of the numbers presented above is isomorphic to welfare, since neither accounts for the forsaken value of leisure. Adjusting also for forgone leisure, welfare is 11 percent lower across the core countries relative to the US (10 percent across the full sample).

TABLE 4. LIFE-CYCLE WAGE GROWTH AND LABOR MARKET FLUIDITY

		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.

moves across countries. Consequently, the model understates the importance of the within-job component, which is the residual between overall wage growth and the between-job component.

Appendix D.4 shows that the mechanism matches well the lack of a pronounced relationship between labor market fluidity and various inequality outcomes. The one aspect of the data that it 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 D.4 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 D.5 conducts a sensitivity analysis.

4.4 The importance of endogenous human capital accumulation

This paper argues that by allowing workers to find a better use for their skills, a more fluid labor market encourages accumulation of skills. How important is this interaction for understanding the steeper life-cycle wage growth in more fluid labor markets? To assess this, panel A of Figure 10 starts by decomposing life-cycle wage growth into the components in accounting identity (14). Specifically, I take the difference in log wages and each of its components between ages 50 and 25. Match productivity grows by 12.8 log points more in the US relative to the least fluid labor market, while human capital grows by 8.2 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 4.2 log points to steeper wage growth in the US relative to the least fluid labor market market. Finally, the piece rate grows by 5.8 log points more, as workers receive more outside offers, allowing them to bargain up the wage. In an accounting sense, if cross-country differences in human capital accumulation had been shut down, only match productivity and the piece rate would have contributed to steeper wage growth in the US, accounting for 60 percent of the predicted effect and 30 percent of the empirical pattern.

To further understand the importance of endogenous accumulation of skills, let $e(a,h)$ be the number of employed workers of age a with human capital h, $\tilde{g}(z|a,h)$ the conditional distribution of employed workers of age a with human capital h over productivity z, and $\dot{h}(a,z,h)$ the optimally chosen growth of human capital of workers of age a with human capital h employed in a firm with productivity z. Since $\frac{1}{A}$ is the number of workers of age a, the average growth of human capital of workers of age a, $d\overline{h}(a)$, is

$$\underbrace{d\overline{h}(a)}_{\text{growth of human capital}} = \frac{1}{A}\int_{\underline{h}}^{\overline{h}}\int_{\underline{z}}^{\overline{z}} \underbrace{\dot{h}(a,z,h)}_{\text{incentive effect}} \underbrace{\tilde{g}(z|a,h)}_{\text{job ladder effect}} dz \underbrace{e(a,h)}_{\text{unemployment effect}} dh$$

Hence, labor market fluidity impacts human capital accumulation through three channels.

First, workers spend more time in unemployment in less fluid labor markets, since the job finding rate is lower—$e(a,h)$ changes. 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.[29]

Second, workers move up the job ladder faster in more fluid labor markets—$\tilde{g}(z|a,h)$ changes. Workers higher up the job ladder optimally grow their human capital more as illustrated by panel B, because they expect to have greater use for it. Hence, workers accumulate more skills in more fluid labor markets, since they move faster to matches where they train a lot. I refer to this as the *job ladder effect*. Starting from the unemployment effect, I compute it as the incremental effect of also letting the job finding rate from employment adjust as in the benchmark.[30] Decision rules are still kept fixed at their US values.

Finally, a worker grows her human capital more in more fluid labor markets conditional on her current state, as she expects to use her skills more efficiently in the future—$\dot{h}(a,z,h)$ 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 and job ladder effects.

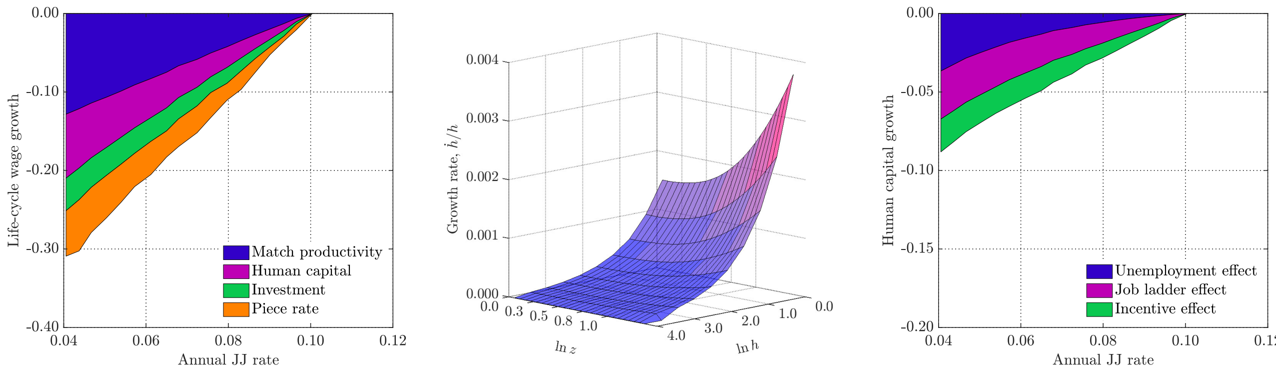
Panel C plots the results from these counterfactual exercises for life-cycle human capital accumulation. Going from the US to the least fluid labor market, life-cycle human capital accumulation falls by eight percent. Initially, the job ladder effect is the most important channel, accounting for half 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,

[29]I achieve this by adjusting the job finding rate p as in the cross-country experiment, while at the same time raising relative search efficiency from employment, ϕ, such that the job finding rate from employment, ϕp, remains fixed at its US value.

[30]Achieved by instead *not* letting relative search efficiency, ϕ, adjust to hold ϕp fixed as the job finding rate p changes.

FIGURE 10. UNDERSTANDING THE INTERACTION BETWEEN TRAINING AND FLUIDITY

(A) WAGE GROWTH (B) OPTIMAL GROWTH RATE (C) HUMAN CAPITAL



Note: Panel A. Decomposition of the effect of labor market fluidity on life-cycle wage growth based on (14). 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.

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 key 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 lets workers faster locate jobs where they have greater use for their skills and where they consequently optimally accumulate more skills. This includes leaving unemployment faster. In contrast, faster expected future growth in match productivity plays a non-trivial, yet quantitatively less important role.[31] To the extent that human capital accumulation is exogenous but workers cannot accumulate skills when unemployed, the unemployment effect would still be operative. In this scenario, human capital would grow by four percent more in the US relative to the least fluid labor market. Alternatively, suppose that human capital accumulation remained unaffected by changes in labor market fluidity, but still varied in the cross-section across the job ladder as in the estimated model. In this case, also the job ladder effect would be at work, such that human capital accumulation would be seven log points greater in the US relative to the least fluid labor market.

Instead of holding human capital accumulation fixed across countries, an alternative counter-factual would be to assume that it plays no role in life-cycle wage growth. Indeed, I find in a model recalibrated to load all life-cycle wage growth in the US on the job ladder that cross-country differences in labor

[31] For this reason, the impact of labor market fluidity on human capital accumulation is not very sensitive to workers' bargaining power, as I discuss further in Appendix D.5. 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.

market fluidity account for a similar share of differences in life-cycle wage growth and aggregate labor productivity as in the benchmark model. I stress, however, that the estimated model nests this possibility ($\mu \to 0$), but my estimates reject this scenario. Instead, the estimates imply that human capital accumulation does play an important role in life-cycle wage growth. For this reason, I view this alternative counter-factual as less relevant, and abstract from discussing it further in the interest of space.

4.5 An alternative policy experiment

The analysis above introduced wedges to firms' cost of job creation, targeted to match cross-country differences in labor market fluidity. This approach is motivated by a long literature that argues that various policies serve to raise the cost on firms of hiring (Hopenhayn and Rogerson, 1993), as well as observable differences in the cost to firms of doing business (see Section 6). That being said, an alternative approach to matching differences in labor market fluidity would be to introduce differences in the relative intensity of search on the job, ϕ. Figure 11 instead varies ϕ to match cross-country differences in labor market fluidity, while holding the job finding rate p fixed at its US level.[32] I label this alternative experiment the *JJ effect*, since it isolates the role of moving up the job ladder. I compute the importance of variation in p only—the *UE effect*—as the residual between the overall effect and the impact of varying ϕ only.

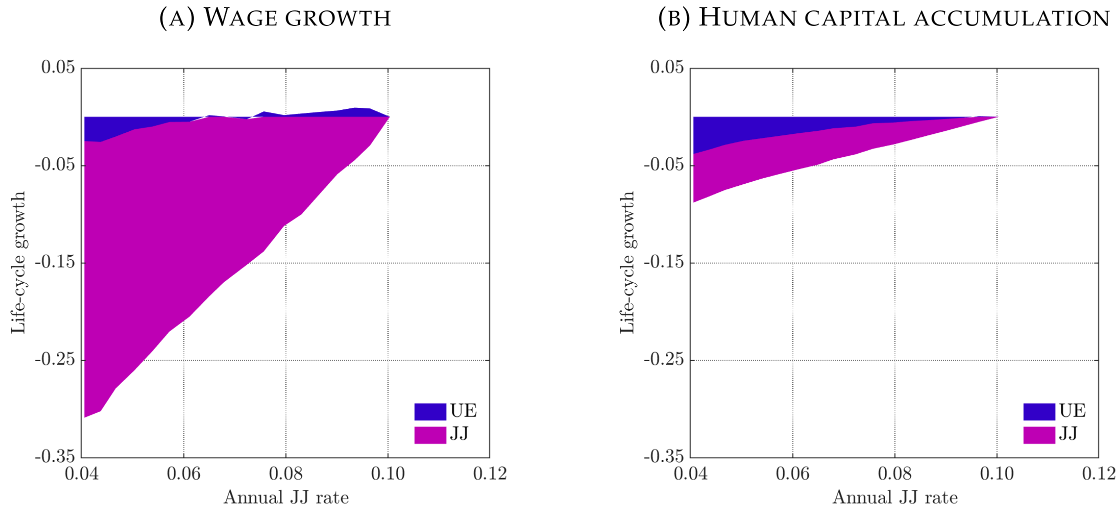
Panel A shows that a slower rate of climbing the job ladder accounts for 92 percent of the slower life-cycle growth in wages in less fluid labor markets, while Panel B finds that it accounts for 60 percent of the lower accumulation of human capital. It reduces human capital accumulation both by slowing 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, since workers expect to have less use for their skills in the future. While this alternative interpretation of cross-country differences in labor market fluidity does not allow the model to also match the higher UE rate in more fluid labor markets (see Appendix D), I conclude that the main predictions carry through (although they are somewhat moderated).

5 Confronting the theory with training data

The theory makes rich predictions for how training varies both across and within countries. In this section, I confront the predictions of the model with cross-country micro data on training. To that end, I

[32] Note that because the job finding rate p is an equilibrium object, this requires varying the cost of job creation c in the background. I prefer this approach of holding p fixed, since it isolates the importance of variation in ϕ only. 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.

FIGURE 11. THE ROLE OF A HIGHER RATE OF CLIMBING THE JOB LADDER



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.

exploit the ECHP, which records days and hours spent on on-the-job training, who paid for the training, etc. A key advantage of the ECHP is that it was conducted by the statistical agency of the EU using a common questionnaire and processing routines, facilitating the cross-country comparison. This limits concerns about comparability in cross-country studies of training (Acemoglu and Pischke, 1999a).

5.1 Aggregate patterns

Panel A of Table 5 regresses days or hours on training in the past 12 months, expressed as a fraction of total work days/hours (5*52 or 40*52, respectively), on labor market fluidity at the country-level.[33] The "Raw" column includes only year controls. Workers train more in more fluid labor markets. The "Controls" column adds controls for worker observable characteristics, including age, education, one-digit occupation and one-digit sector. 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 labor market fluidity and time on training. The "Direct" column also controls for whether the worker made a JJ move in the past year. There is no statistical correlation between training and JJ mobility in the past year. Hence, the positive correlation between labor market fluidity and training is not due to

[33] The reported time in training is since January in the year prior to the survey. If the training started more than 12 months prior to the survey date, I use reported start dates of training to adjust 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 1.5 percent of observations. Results without top-coding in Appendix E.1 are more pronounced.

a mechanical effect of new hires being trained to perform the required tasks of the new job.[34]

The "Model" column repeats the exercise in the model. I simulate a monthly approximation of the model and aggregate it to yearly data such that employer outcomes are recorded in "May" every year, while annual training is the sum of $i(a, z, h)$ over the 12 months prior to the "survey," and the wage is the average wage over the past "calendar year." I simulate several "countries" that span the relevant range for labor market fluidity, and implement the same regression as in the data on the pooled model-generated data. The mechanism emphasized in this paper accounts for a large share of the systematically higher level of training in more fluid labor markets, somewhat understating the empirical relationship.

Panel B instead exploits within-country variation across education groups (less than college and college or more), occupations (10 one-digit occupations), or sectors (12 one-digit sectors). I compute labor market fluidity in the same way as above, but separately by education groups/occupation/sector and country, and relate this to hours on training in the past 12 months, expressed as a fraction of total work hours (40*52). In order to reduce somewhat the wide standard errors, I expand the sample to include all men aged 18–64. The "Baseline" column shows results with country and year fixed effects. Workers spend more time on training in more fluid education groups/occupations/sectors, although the standard errors are much larger than in the cross-country specification such that not all point estimates are statistically significant. The "FE" column adds also education group/occupation/sector fixed effects, i.e. it exploits the fact that, for instance, college graduates may be particularly fluid and train disproportionately much in some country, relative to average fluidity and training in that country as well as average fluidity and training of college graduates across all countries. Workers spend more time on training when their education group/occupation/sector is more fluid relative to the rest of their country as well as the same education group/occupation/sector in other countries, although not all point estimates are statistically significant. I also repeat the model estimates from the cross-country simulated data, which is valid under the strong assumption that education group/occupation/sector is a permanent trait of workers and labor markets are perfectly segmented by such traits. I conclude that both the across and within-country variation is supportive of the hypothesis in this paper, also quantitatively.

Appendix E.3 shows that over 70 percent of workers report that their employer paid for their training (if anything, the share rises with labor market fluidity but the pattern is not statistically significant). At the same time, it is not clear whether a respondent correctly perceives who paid for the training. In fact, Appendix B.1 finds that workers earn lower wages during periods when they train more, conditional on

[34] The ECHP also records whether a reason for taking the course was to improve the respondent's skills or job prospects. On average across countries, 93 percent of respondents answer yes to this question and there is no meaningful cross-country correlation between the share who answer yes and fluidity. For this reason, I do not further analyze responses to this question.

Table 5. Training and labor market fluidity

	Panel A. Cross-country correlation						
	Days on training (fraction of year)			Hours on training (fraction of year)			Model
	Raw	Controls	Direct	Raw	Controls	Direct	
Fluidity	0.448***	0.386***	0.388***	0.360***	0.305***	0.312***	0.277***
	(0.091)	(0.083)	(0.066)	(0.050)	(0.038)	(0.031)	(0.009)
JJ			0.000			0.001	
			(0.002)			(0.001)	
Age		-0.000***	-0.000***		-0.000***	-0.000***	
		(0.000)	(0.000)		(0.000)	(0.000)	
College		0.006***	0.007***		0.003***	0.004***	
		(0.002)	(0.002)		(0.001)	(0.001)	
N	135,563	115,897	63,634	135,318	115,676	63,494	3,990,963

	Panel B. Within-country correlation (hours as fraction of year)						
	Education		Occupation		Sector		Model
	Baseline	FE	Baseline	FE	Baseline	FE	
Fluidity	0.305	0.380	0.317	0.458**	0.328***	0.419***	0.277***
	(0.836)	(0.822)	(0.226)	(0.222)	(0.079)	(0.096)	(0.009)
N	204,207	204,207	148,155	148,155	148,782	148,782	3,990,963

Note: Panel A: Men aged 25–54. Regression of training outcome on labor market fluidity at the country-level, with or without controls. Raw: Controls for year. Controls: Controls for age, education, occupation, sector and year. Direct: Controls for age, education, occupation, sector, year and JJ mobility in previous year. Data: Days or hours on vocational training in the past 12 months, expressed as a fraction of potential work days/hours (5*52 or 40*52, respectively). Hours and days on training are top-coded at 13 weeks of full time training per year. Model: Fraction of time devoted to training, $i(a, h, z)$. Regressions are weighted using the provided survey weights, renormalized to give each country the same aggregate weight. Standard errors are clustered at the country level. *Panel B.* Men aged 18–64. Regression of training outcome on labor market fluidity at the country-education group/occupation/sector level. Baseline includes country and year fixed effects; FE includes country, year and education group/occupation/sector fixed effects. Data: Hours on vocational training in the past 12 months, expressed as a fraction of potential work hours (40*52). Model: Fraction of time devoted to training, $i(a, h, z)$. Regressions are weighted using the provided survey weights, renormalized to give each country-education group/occupation/sector the same aggregate weight. Standard errors are clustered at the country-education group/occupation/sector-year 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. ** statistically significant at 5%; *** statistically significant at 1%. *Source:* ECHP 1995–2001 and model.

worker fixed effects and time-varying observables, consistent with workers sharing the cost of training (this pattern is true even among those who report that their employer paid for the training). Appendix E.4 finds 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*.

5.2 Disaggregate patterns

The theory also makes rich predictions for how training varies in the cross-section. As highlighted by Figure 10, workers grow their human capital less when employed in less productive firms, as they have less use for it. In more fluid labor markets, however, workers currently in low productive firms expect to be able to move away from such firms faster. Consequently, while workers in general train less in less productive firms, in a relative sense they train more in low productive firms in more fluid labor markets. In contrast, absent separation shocks, training at the top of the job ladder is unaffected by labor market fluidity. Separation shocks moderate this prediction, but the intuition remains: training should be particularly low in less productive firms in less fluid labor markets. By differencing out any country-specific factors, this may provide a more robust test of the predictions of the model.

Testing this prediction is somewhat complicated by the fact that the available data do not contain productivity. They do, however, report firm size, grouped into size bins 1–4, 5–19, 20–49, 50–99, 100–499, and 500+ employees. Pooling across countries, these size categories contain close to equal shares of employment. Under the assumption of a monotone relationship between productivity and size, the six size bins allow me to group firms into (roughly) employment-weighted productivity sextiles. I similarly bin firms based on productivity into employment-weighted sextiles in the model. As an alternative ranking of firms, I compute firm pay by regressing log wages on indicators for the sextiles—controlling for age, education, occupation and country-year fixed effects (age and country fixed effects in the model),

$$w_{it} = \sum_{s=1}^{6} \alpha_s sextile_{it}^{s} + X_{it}\beta + \varepsilon_{it} \tag{15}$$

where $sextile_{it}^{s}$ takes value one if worker i in year t works for an employer in sextile s. My measure of firm pay, $fwage_{it}$, is the estimated coefficients, $\{\alpha^s\}$. Appendix E.5 shows the results from (15), highlighting that larger firms pay better. Firm pay has a standard deviation of 0.114 in the data and 0.123 in the model. I subsequently regress hours on training in the past 12 months on either firm productivity sextile or firm pay, x_{it}, as well as its linear interaction with fluidity, controlling for worker-fixed effects and age,

$$training_{it} = \alpha_0 x_{it} + \alpha_1 x_{it} \times fluidity_c + I_i + X_{it}\beta + \varepsilon_{it}$$

The results in Table 6 offer two main takeaways. First, controlling for worker-fixed effects, workers train more when employed at high-paying, productive (large) firms, consistent with evidence in other data sets (Arellano-Bover, 2020). The reason is that workers have greater use for their skills in more productive firms, and as a consequence train more. In contrast, as I discuss further in Appendix E.6, if the production function had not featured a complementarity between productivity and human capital, one may expect training to decline in productivity (and hence firm pay). Moreover, as highlighted by Figure 4, a larger share of workers are employed at high-paying, productive (large) employers in more fluid labor markets, where *ceteris paribus* they train more. In fact, as shown in Appendix E.7, the model matches this pattern fairly well. These findings relate to the job ladder effect discussed in Section 4.4.

Second, workers in low fluidity countries particularly train less when employed at low paying, unproductive (small) firms. The reason is that a worker currently in a low productive firm is particularly stuck with her current employer in a low fluidity country, where she has less use for her human capital. She responds by training less. This relates to the incentive effect discussed in Section 4.4. Finally, recall from Figure 9 that the mechanism also matches well the higher unemployment rate in less fluid labor markets—the unemployment effect in Section 4.4. I conclude that these aggregate and disaggregate patterns for training lend empirical support for the key predictions of the theory.

TABLE 6. TRAINING IN THE CROSS-SECTION

	Data		Model	
	Prod.	Wage	Prod.	Wage
α_0	0.002**	0.035**	0.006***	0.090***
	(0.001)	(0.013)	(0.000)	(0.003)
α_1	-0.028*	-0.515**	-0.034***	-0.480***
	(0.012)	(0.211)	(0.002)	(0.034)
N	77,386	77,386	3,990,963	3,990,963

Note: Men aged 25–54. Training on firm productivity sextile / firm wage, as well as its interaction with fluidity. Panel A. Hours on training, top-coded at 13 full-time weeks per year. Firm productivity sextile and firm wage imputed based on size. Panel B. $i(a, z, h)$. Firm wage imputed based on productivity. 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 and model.

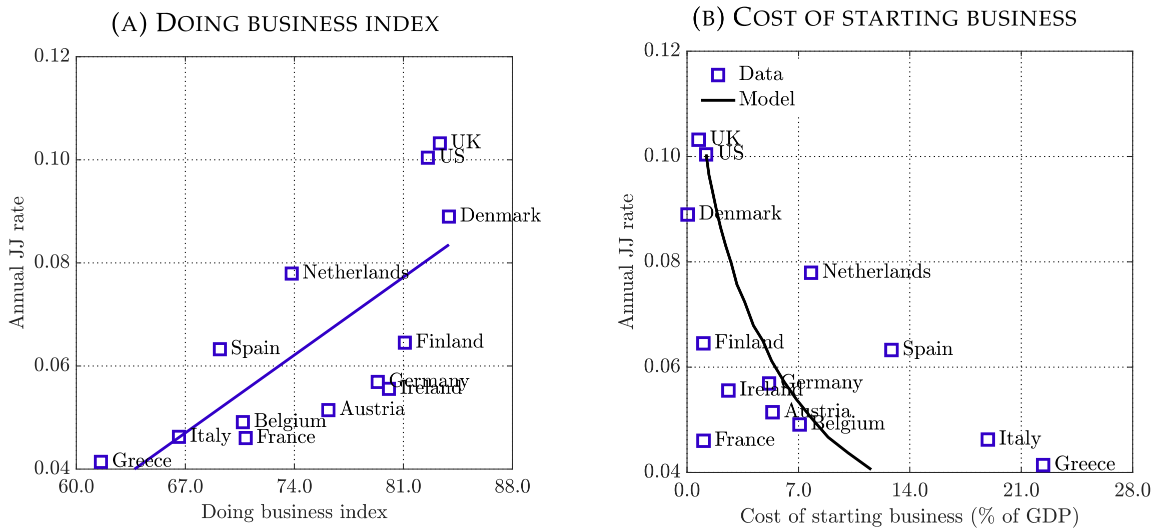
6 Labor market fluidity and policy

Inspired by Hsieh and Klenow (2009), the analysis above adopted a wedge approach to cross-country differences in labor market fluidity in order to focus on the dynamic implications of such differences for workers' optimal behavior. I provide in this section a discussion of some prominent potential factors behind differences in fluidity, building on an extensive literature (Restuccia and Rogerson, 2017).

6.1 Cross-country analysis

Panel A of Figure 12 shows that labor market fluidity is negatively correlated with the World Bank's ease of doing business index, consistent with the argument in Fonseca et al. (2001) that such factors are more important than unemployment benefits and EPL in accounting for cross-country differences in job creation. Panel B plots the cost of starting a firm relative to GNI per capita, as estimated by the World Bank. I construct a model counterpart as the cost of creating a job, c, relative to output per capita.

FIGURE 12. DETERMINANTS OF LABOR MARKET FLUIDITY



Note: Male employees aged 25–54. Panel A. Doing business score. Panel B. Data: Cost of starting a firm relative to GNI per capita. Model: Cost of vacancy, c, relative to total output. Model moments are normalized to match the empirical value for the US by first dividing all country outcomes in the model by the model outcome for the US and then multiplying all country outcomes by the data outcome 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. 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.

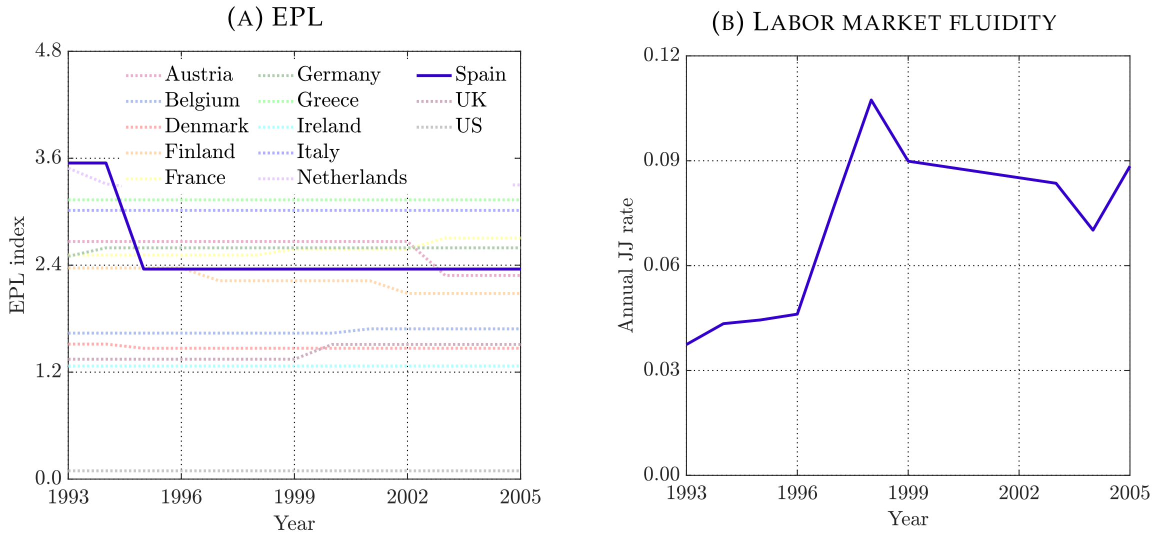
As the levels are non-comparable, I normalize the model measure to the empirical measure for the US. Although it only captures the cost of starting a new firm, it is well-known that young firms contribute a disproportionate share of total job creation. The required wedges are quantitatively consistent with observed dispersion in the cost of creating jobs across countries.

6.2 Within-country analysis

I next turn to within-country variation in labor market policy. In particular, I exploit a significant reduction in EPL in Spain in 1994–1995, which overlaps with the years for which I have training data. Panel A of Figure 13 illustrates the corresponding fall in the OECD's EPL index in Spain over this period. Spain went from having the most stringent EPL in my sample to one of the lowest levels among continental European countries (see Bentolila et al., 2008, for a further discussion of these reforms). Panel B shows that labor market fluidity rose substantially after the reforms, although with some delay.

Table 7 contrasts the empirical change in entry wages, life-cycle wage growth and on-the-job training between a pre and post reform period with the predictions of the model. In the data, I compare the wage profiles of cohorts of workers who entered the labor market before 1995 to those who entered in 1995 or later (labor market entry is measured as when a worker turned 23), and regress log wages on age dummies restricted to not grow after age 50, fully flexible year effects, a dummy for whether the worker

FIGURE 13. CHANGES IN EPL AND LABOR MARKET FLUIDITY IN SPAIN, 1993–2005



Note: Male employees aged 25–54. Panel A. OECD EPL index. Panel B. 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-year level. *Source:* ECHP, EUSILC, and OECD 1993–2005.

entered the labor market after the reforms as well as its interaction with a linear in age,

$$w_{it} \quad = \quad A_{it} \, + \, Y_t \, + \, D_t \, + \, \beta D_t \times a_{it} \, + \, \varepsilon_{it} \tag{16}$$

In the model, I compare a low-fluidity pre-reform steady-state to a high-fluidity post-reform steady-state, and implement regression (16) on pooled pre and post reform simulations. For training outcomes, I compare the years prior to the reform to those after the reforms. I stress that this methodology imposes several strong assumptions, including that cohorts that entered the labor market before the reforms were unaffected, while cohorts that entered after expected the change to be permanent.

TABLE 7. A 1994–1995 SPANISH REFORM TO EPL

	Panel A. Pre-reform		*Panel B. Post-reform*		*Panel C. Change (%)*	
	Data	Model	Data	Model	Data	Model
Annual JJ mobility rate	0.040	0.040	0.075	0.076	87.4%	87.4%
Wage at age 23 (log)			-0.055	-0.038		
Wage at age 35 (log)			0.024	0.031		
Wage at age 50 (log)			0.122	0.117		
Training, fraction of year	0.008	0.050	0.014	0.067	69.4%	33.9%

Note: Men aged 23–55. Wage profiles are based on a regression of log wages on a full set of age effects as well as a separate age intercept and linear slope for the cohorts entering the labor market after the reforms (turning 23 in or after year 1995). Wages for different ages are imputed based on the intercept and linear slope based on regression (16). Model and data moments are constructed identically. 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 survey weights, then to the country-period level. *Source:* ECHP, EUSILC, and model 1993–2015.

Wages of labor market entrants fell by 5.5 log points after the reforms in the data. According to the model, 3.8 log points is due to the rise in labor market fluidity. The fall in entry wages happens as workers share in the cost of higher training through lower wages. Wages subsequently grow faster, such that at age 35 they are 2.4 log points higher in the data versus 3.1 log points in the model. At age 50, they are 12 log points higher in the data and model. Although the magnitude of the change in the policy varies across the two experiments, these results mirror recent findings from a 2001 reduction in EPL in Italy (Daruich et al., 2020). These authors show that earnings of labor market entrants fell by five percent after the reform and did not converge to zero until seven years after entry. Finally, the incidence of training rises significantly after the reforms, in both the model and data.

7 Conclusions

This paper establishes a series of novel findings on cross-country differences in life-cycle careers using comparable cross-country panel micro data from 23 OECD countries. In particular, wages grow more over the life-cycle in labor markets where JJ mobility is more common. To understand these patterns and assess their aggregate economic implications, I propose and estimate a rich theory of labor market search and endogenous accumulation of skills on the job. The theory predicts that if workers are able to faster locate jobs where they can better use their skills, it encourages accumulation of skills. Quantitatively, I find that this mechanism accounts for half of the steeper life-cycle wage growth in more fluid labor markets. Moreover, labor productivity is nine percent lower across the OECD relative to the US. More broadly, my findings highlight that the dynamic consequences of misallocation can be large. They deserve more attention in future work.

References

Abowd, John M and Arnold Zellner, "Estimating gross labor-force flows," *Journal of Business & Economic Statistics*, 1985, *3* (3), 254–283.

Acemoglu, Daron, "Training and Innovation in an Imperfect Labour Market," *The Review of Economic Studies*, 1997, *64* (3), 445–464.

_ **and Jorn-Steffen Pischke**, "Why Do Firms Train? Theory and Evidence," *The Quarterly Journal of Economics*, 1998, *113* (1), 79–119.

_ **and Jörn Steffen Pischke**, "Beyond becker: Training in imperfect labour markets," *Economic Journal*, 1999, *109* (453), 112–142.

_ **and Jorn-Steffen Pischke**, "The Structure of Wages and Investment in General Training," *Journal of Political Economy*, 1999, *107* (3), 539–572.

Arellano-Bover, Jaime, "Consequences of Firm Heterogeneity for Young Workers: First Job and Firm Size Career," 2020.

Bagger, By Jesper, François Fontaine, Fabien Postel-vinay, and Jean marc Robin, "Tenure, Experience, Human Capital, and Wages," *American Economic Review*, 2014, *104* (6), 1551–1596.

Barlevy, Gadi, "The Sullying Effect of Recessions," *Review of Economic Studies*, 2002, *69* (1), 65–96.

Becker, Gary S., "Investment in Human Capital: A Theoretical Analysis," *Journal of Political Economy*, 1962, *70* (5), 9–49.
Ben-Porath, Yoram, "The Production of Human Capital and the Life Cycle of Earnings," *Journal of Political Economy*, 1967, *75* (4), 352–365.
Bentolila, Samuel and Giuseppe Bertola, "Firing Costs and Labour Demand: How Bad is Eurosclerosis?," *The Review of Economic Studies*, 1990, *57* (3), 381.
_ , Juan J. Dolado, and Juan F. Jimeno, "Two-tier employment protection reforms: The Spanish experience," 2008.
Bick, Alexander, Nicola Fuchs-Schündeln, and David Lagakos, "How Do Hours Worked Vary with Income? Cross-Country Evidence and Implications," *American Economic Review*, 2018, *108* (1), 170–199.
Bowlus, Audra J and Huju Liu, "The contributions of search and human capital to earnings growth over the life cycle," *European Economic Review*, 2013, *64*, 305–331.
Burdett, Kenneth and Dale T Mortensen, "Wage Differentials, Employer Size, and Unemployment," *International Economic Review*, 1998, *39* (2), 257–273.
_ , Carlos Carrillo-Tudela, and Melvyn Coles, "The Cost of Job Loss," *Review of Economic Studies*, 2020, *87* (4), 1757–1798.
_ , _ , and Melvyn G. Coles, "Human capital accumulation and labor market equilibrium," *International Economic Review*, 2011, *52* (3), 657–677.
Cahuc, Pierre, Fabien Postel-Vinay, and Jean-Marc Robin, "Wage Bargaining with On-the-Job Search: Theory and Evidence," 2006.
Daruich, Diego, Sabrina Di Addario, and Raffaele Saggio, "The Effects of Partial Employment Protection Reforms: Evidence from Italy," 2020.
Dey, Matthew S and Christopher J Flinn, "An Equilibrium Model of Health Insurance Provision and Wage Determination," *Econometrica*, 2005, *73* (2), 571–627.
Diamond, Peter A, "Aggregate Demand Management in Search Equilibrium," *Journal of Political Economy*, 1982, *90* (5), 881–894.
Doepke, Matthias and Ruben Gaetani, "Why Didn't the College Premium Rise Everywhere? Employment Protection and On-the-Job Investment in Skills," 2020.
Donovan, Kevin, Will Jianyu Lu, and Todd Schoellman, "Labor Market Dynamics and Development," 2020.
Engbom, Niklas, "Misallocative Growth," 2020.
Feng, Ying, David Lagakos, and James E Rauch, "Unemployment and development," 2020.
Flinn, Christopher, Ahu Gemici, and Steven Laufer, "Search, matching and training," *Review of Economic Dynamics*, 2017, *25*, 260–297.
Fonseca, Raquel, Paloma Lopez-Garcia, and Christopher A. Pissarides, "Entrepreneurship, start-up costs and employment," *European Economic Review*, 2001, *45* (4-6), 692–705.
Fu, Chao, "Training, search and wage dispersion," *Review of Economic Dynamics*, 2011, *14* (4), 650–666.
Gervais, Martin, Nir Jaimovich, Henry E. Siu, and Yaniv Yedid-Levi, "What should I be when I grow up? Occupations and unemployment over the life cycle," *Journal of Monetary Economics*, 2016, *83*, 54–70.
Gourieroux, C., A. Monfort, and E. Renault, "Indirect inference," *Journal of Applied Econometrics*, 1993, *8* (1 S), S85–S118.
Gregory, Victoria, "Firms as Learning Environments: Implications for Earnings Dynamics and Job Search," 2019.
Griliches, Zvi, "Capital-Skill Complementarity," *The Review of Economics and Statistics*, 1969, *51* (4), 465–468.
Guner, Nezih, Andrii Parkhomenko, and Gustavo Ventura, "Managers and productivity differences," *Review of Economic Dynamics*, 2018, *29*, 256–282.
Guvenen, Fatih, Burhanettin Kuruscu, and Serdar Ozkan, "Taxation of human capital and wage inequality: A cross-country analysis," *Review of Economic Studies*, 2013, *81* (2), 818–850.
Heathcote, Jonathan, Fabrizio Perri, and Giovanni L. Violante, "Unequal we stand: An empirical analysis of economic inequality in the United States, 1967-2006," *Review of Economic Dynamics*, 2010, *13* (1), 15–51.

Heckman, James J, Lance Lochner, and Christopher Taber, "Explaining Rising Wage Inequality: Explorations with a Dynamic General Equilibrium Model of Labor Earnings with Heterogeneous Agents," *Review of Economic Dynamics*, 1998, *1* (1), 1–58.

Herkenhoff, Kyle, Jeremy Lise, Guido Menzio, and Gordon M Phillips, "Production and Learning in Teams," 2018.

Hobijn, Bart and Aysegul Sahin, "Job-finding and separation rates in the OECD," *Economics Letters*, 2009, *104* (3), 107–111.

Hopenhayn, Hugo and Richard Rogerson, "Job Turnover and Policy Evaluation: A General Equilibrium Analysis," *Journal of Political Economy*, oct 1993, *101* (5), 915–938.

Hornstein, Andreas, Per Krusell, and Giovanni L Violante, "Frictional wage dispersion in search models: A quantitative assessment," *American Economic Review*, 2011, *101* (7), 2873–2898.

Hsieh, Chang-Tai and Peter J. Klenow, "Misallocation and Manufacturing TFP in China and India," *Quarterly Journal of Economics*, 2009, *124* (4), 1403–1448.

Huggett, Mark, Gustavo Ventura, and Amir Yaron, "Sources of lifetime inequality," *American Economic Review*, 2011, *101* (7), 2923–2954.

Jolivet, Grégory, Fabien Postel-Vinay, and Jean Marc Robin, "The empirical content of the job search model: Labor mobility and wage distributions in Europe and the US," *European Economic Review*, 2006, *50* (4), 877–907.

Jovanovic, Boyan and Yaw Nyarko, "Learning by Doing and the Choice of Technology," *Journal of Political Economy*, 1996, *64* (6), 1299–1310.

Kambourov, Gueorgui and Iourii Manovskii, "Occupational specificity of human capital," *International Economic Review*, 2009, *50* (1), 63–115.

Lagakos, David, Benjamin Moll, Tommaso Porzio, Nancy Qian, and Todd Schoellman, "Life cycle wage growth across countries," *Journal of Political Economy*, 2018, *126* (2), 797–849.

Lazear, Edward P., "Job Security Provisions and Employment," *Quarterly Journal of Economics*, 1990, *105* (3), 699–726.

Lazear, Edward P, "Firm-Specific Human Capital: A Skill-Weights Approach," *Journal of Political Economy*, 2009, *117* (5), 914–940.

Lentz, Rasmus and Nicolas Roys, "Training and Search On the Job," 2016.

Ljungqvist, Lars and Thomas J Sargent, "The European Unemployment Dilemma," *Journal of Political Economy*, 1998, *106* (3), 514–550.

__ **and Thomas J. Sargent**, "Two Questions about European Unemployment," *Econometrica*, 2008, *76* (1), 1–29.

Manuelli, Rodolfo E. and Ananth Seshadri, "Human capital and the wealth of nations," *American Economic Review*, 2014, *104* (9), 2736–2762.

McCall, John J, "Economics of Information and Job Search," *The Quarterly Journal of Economics*, 1970, *84* (1), 113–126.

Michelacci, Claudio and Josep Pijoan-Mas, "Intertemporal labour supply with search frictions," *Review of Economic Studies*, 2012, *79* (3), 899–931.

Mincer, Jacob, *Schooling, Experience, and Earnings*, New York: NBER Press, 1974.

Mortensen, Dale T and Christopher A Pissarides, "Job Creation and Job Destruction in the Theory of Unemployment," *The Review of Economic Studies*, 1994, *61* (3), 397–415.

Nickell, Stephen, "Unemployment and Labor Market Rigidities: Europe versus North America," *Journal of Economic Perspectives*, 1997, *11* (3), 55–74.

Petrongolo, Barbara and Christopher A. Pissarides, "Looking into the Black Box : A Survey of the Matching Function," *Journal of Economic Literature*,, 2001, *39* (2), 390–431.

Poschke, Markus, "Wage Employment, Unemployment and Self-Employment across Countries," 2019.

Poterba, James M and Lawrence H Summers, "Reporting Errors and Labor Market Dynamics," *Econometrica*, 1986, *54* (6), 1319–1338.

Pries, Michael and Richard Rogerson, "Hiring Policies, Labor Market Institutions, and Labor Market Flows," *Journal of Political Economy*, 2005, *113* (4), 811–839.

Restuccia, Diego and Richard Rogerson, "The causes and costs of misallocation," *Journal of Economic Perspectives*, 2017, *31* (3), 151–174.

Rosen, Sherwin, "Learning and Experience in the Labor Market," *The Journal of Human Resources*, 1972, *7* (3), 326–342.

Rubinstein, Ariel, "Perfect Equilibrium in a Bargaining Model," *Econometrica*, 1982, *50* (1), 97–109.
Rubinstein, Yona and Yoram Weiss, "Post Schooling Wage Growth: Investment, Search and Learning," in "Handbook of the Economics of Education," Vol. 1 2006, pp. 1–67.
Topel, Robert H and Michael P Ward, "Job Mobility and the Careers of Young Men," *Quarterly Journal of Economics*, 1992, *107* (2), 439–479.
Wasmer, Etienne, "General versus Specific Skills in Labor Markets with Search Frictions and Firing Costs," *The American Economic Review*, 2006, *96* (3), 811–831.
Yamaguchi, Shintaro, "Job Search , Bargaining , and Wage Dynamics," *Journal of Labor Economics*, 2010, *28* (3), 595–631.

Online Appendix—Not for Publication

A Data

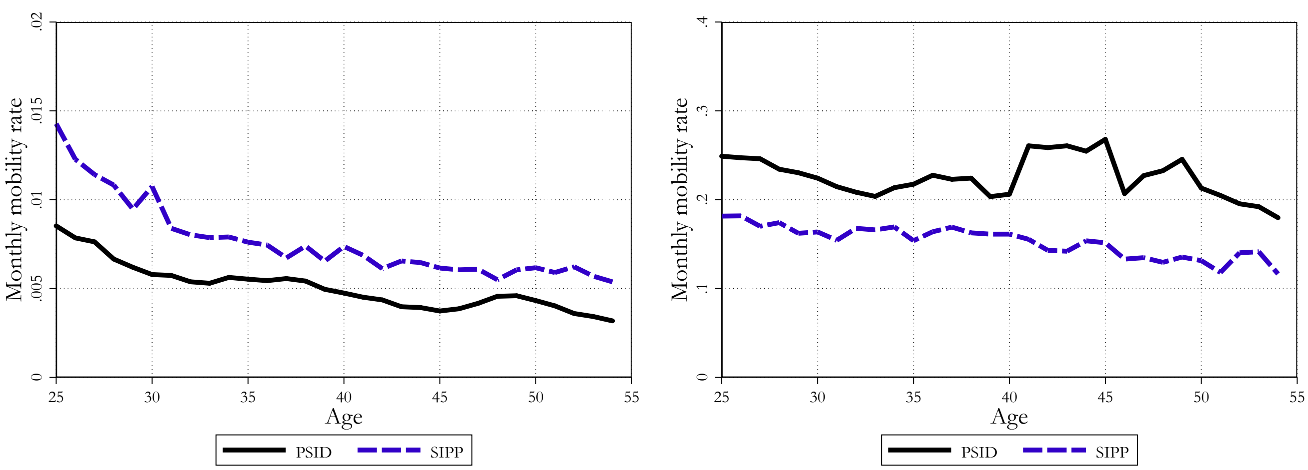
This section describes the data sources in some more detail and provides additional empirical results.

A.1 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 14 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 14. MONTHLY EU AND UE RATES, PSID VERSUS SIPP

(A) EU (B) UE



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.2 Data sources

Table 8 summarizes the annual data set and Table 9 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.[35] 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 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.

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.

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.

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

TABLE 8. 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.

SIPP. 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.

A.3 Life-cycle labor market states

Figure 15 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

Table 9. 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**

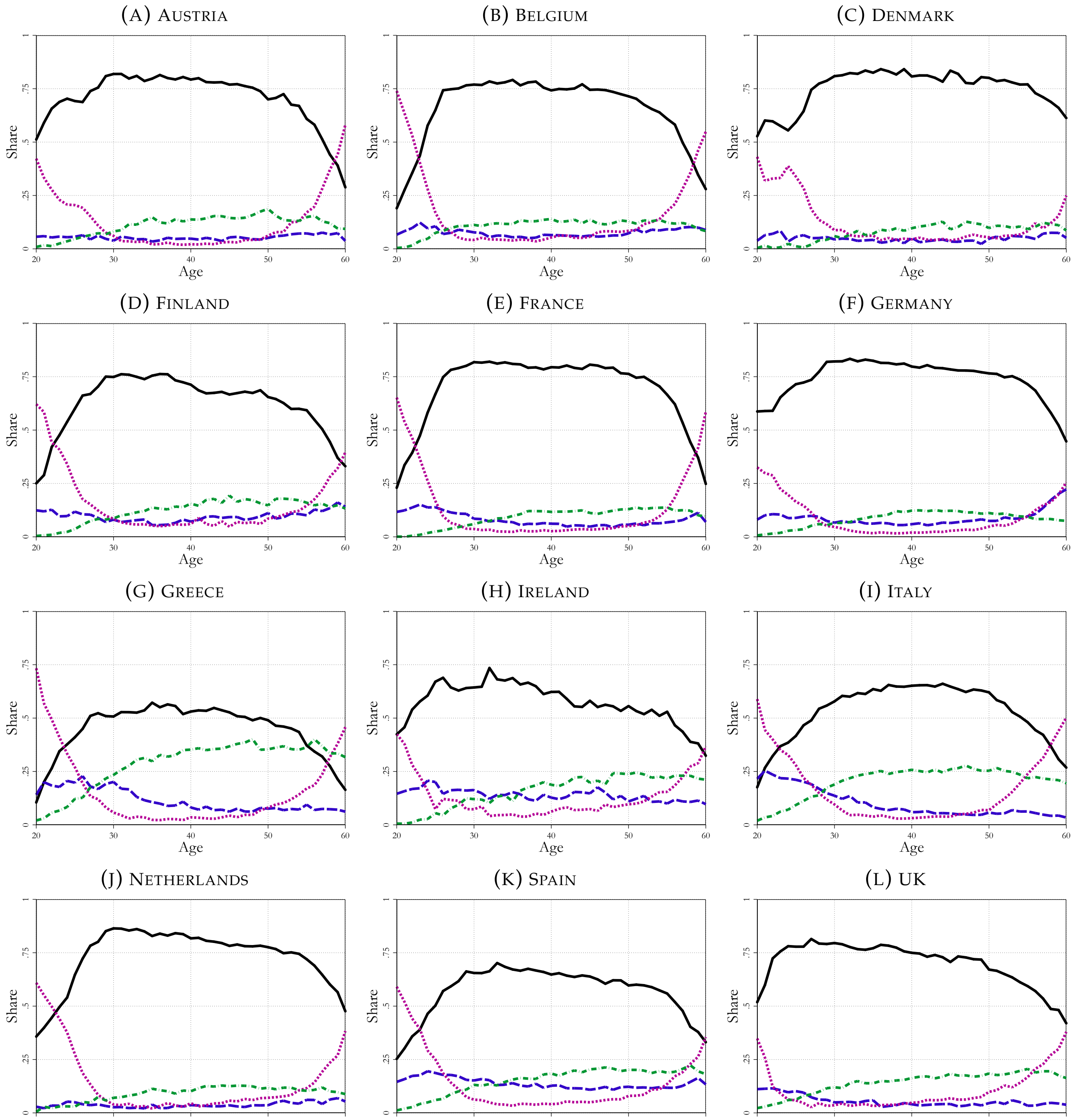
Note: Men aged 25–54. T: Number of months; NT: Number of individual-months; N: Number of individuals.

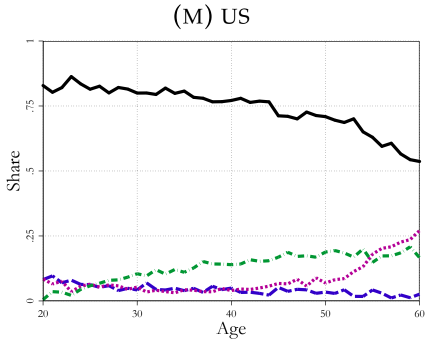
those who participate in the labor market are also more likely to have formed their own households (the SIPP, in contrast, shows an increase in male labor force participation rates between age 20–25). By not focusing on the head of household like the PSID, the other surveys may be less prone to this.

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 D.3, 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 16 plots labor force participation rates for men 25–54, men aged 25 and men aged 54 against labor market fluidity. While there is dispersion across countries in participation, it is only weakly correlated with labor market fluidity. Figure 17 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.

FIGURE 15. LIFE-CYCLE LABOR MARKET STATES

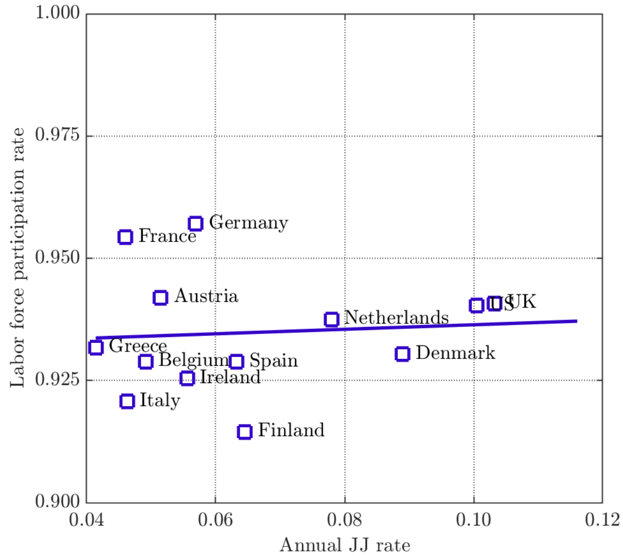




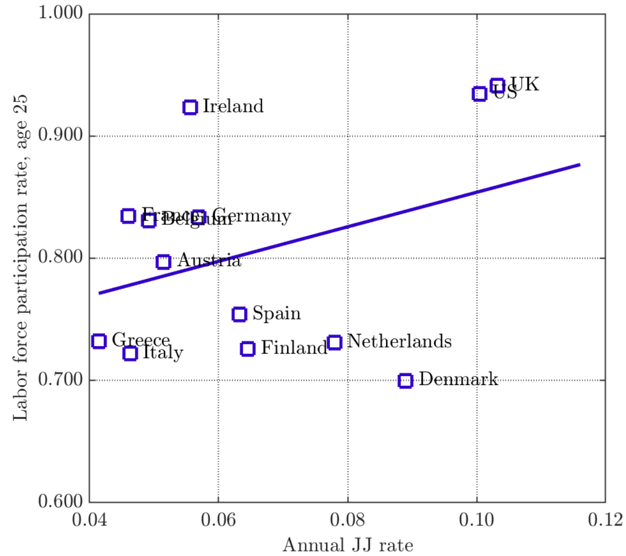
Note: Share of men aged 20–60 by labor market status. Solid black: wage employed. Dash-dotted green: self-employed. Dashed blue: unemployed. Dotted purple: not-in-the labor force. Labor market states follow ILO standard. All moments: Constructed by first collapsing the data to the country-year-age level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

FIGURE 16. LABOR FORCE PARTICIPATION RATES AND LABOR MARKET FLUIDITY

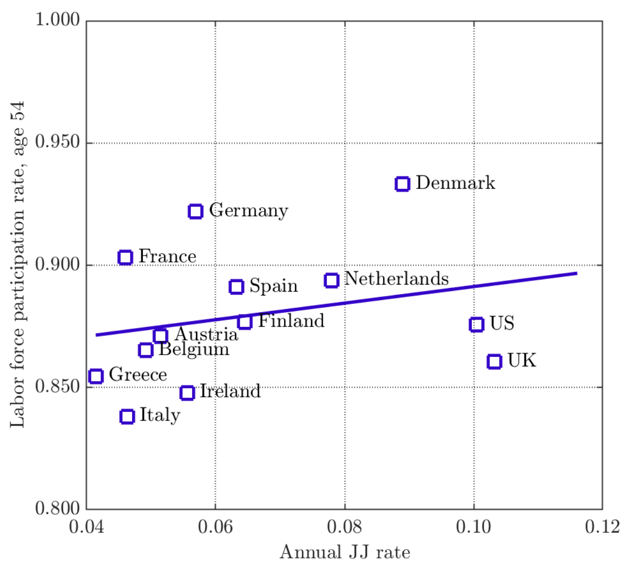
(A) ALL



(B) AGE 25

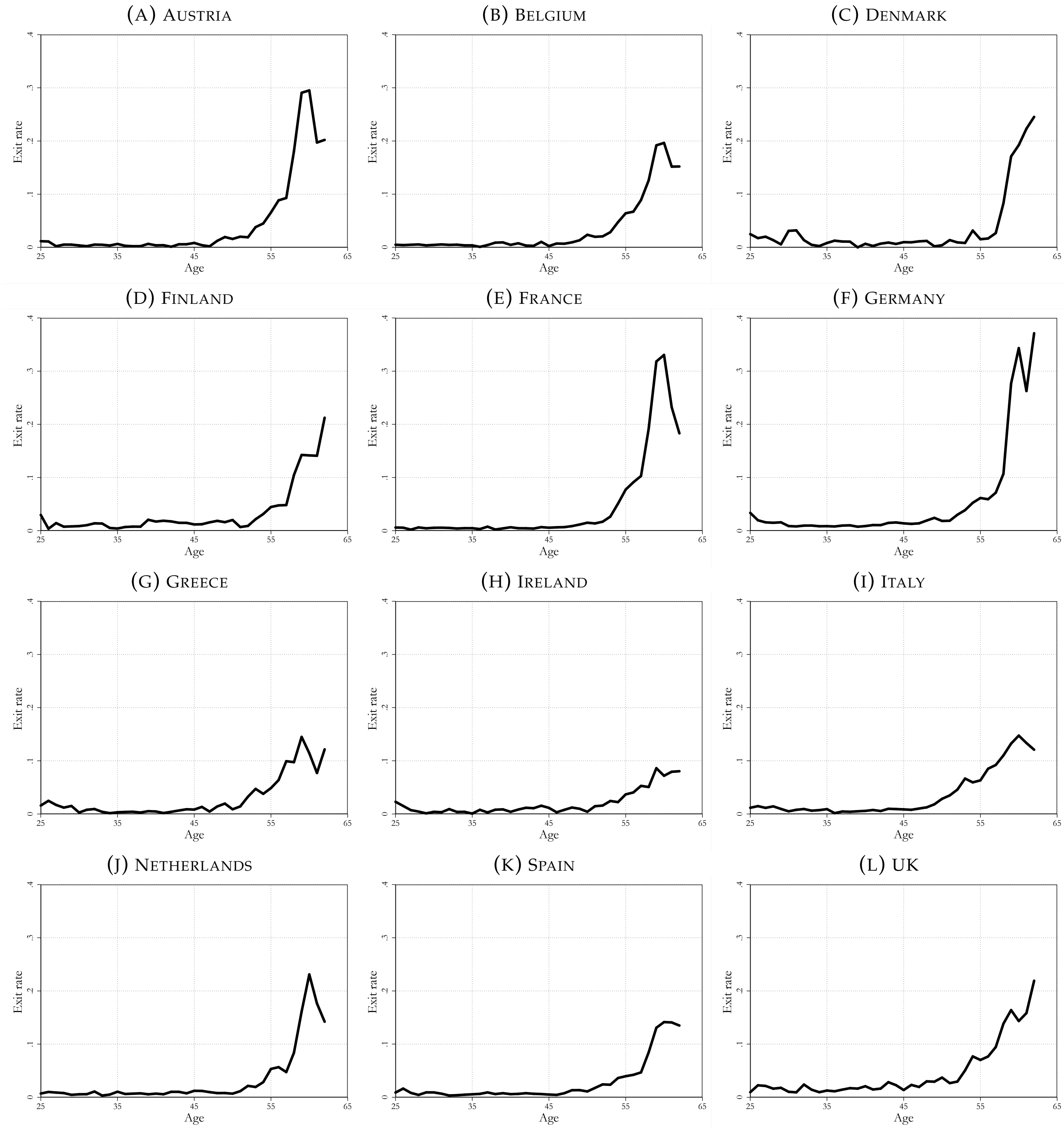


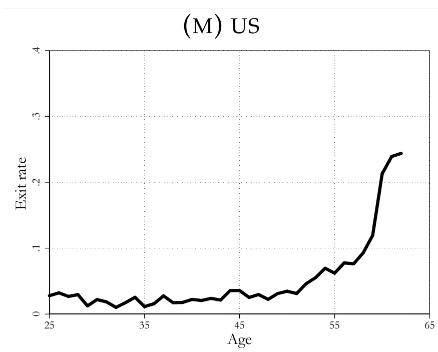
(C) AGE 54



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 17. 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.

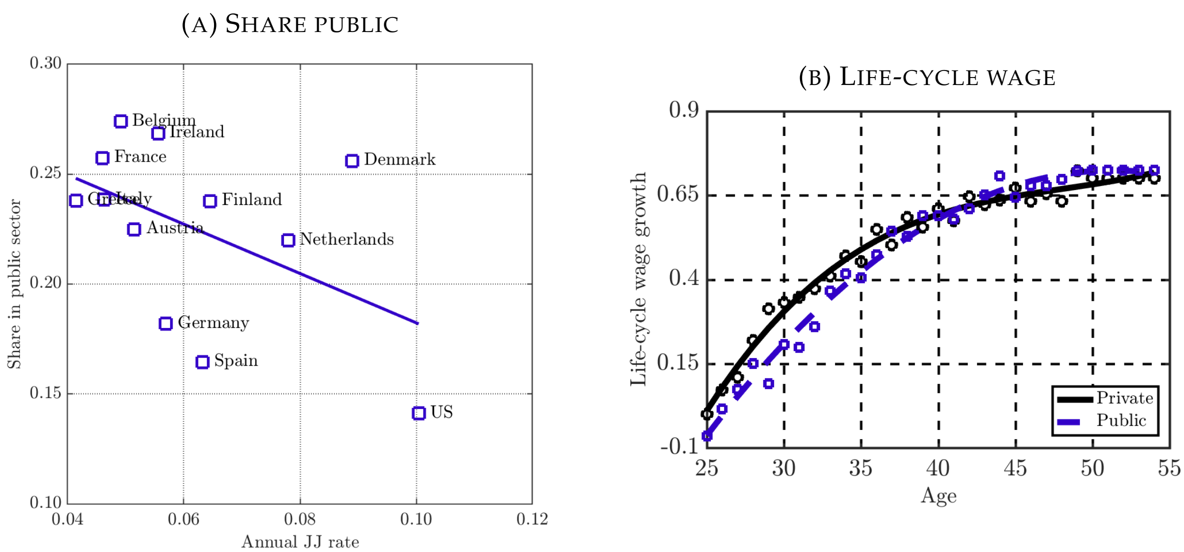
A.4 The public sector

The left panel of Figure 18 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,

$$w_{it} \quad = \quad A_{it} + PA_{it} + Y_{c(i)t} + I_i + \varepsilon_{it} \tag{17}$$

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 (17) 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.

FIGURE 18. PUBLIC SECTOR



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 (17). 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.

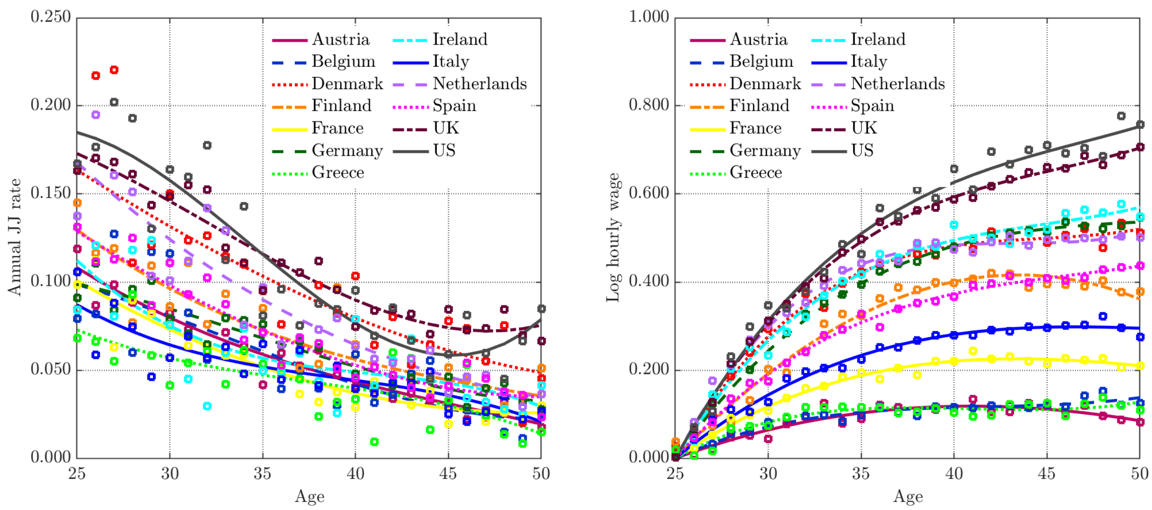
A.5 Empirical life-cycle dynamics

Panal A of Figure 19 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.

Panel B plots wage growth between ages 25–50 across countries, assuming that wages do not grow 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).[36]

FIGURE 19. LABOR MARKET FLUIDITY AND LIFE-CYCLE WAGE GROWTH

(A) JJ MOBILITY | (B) WAGE GROWTH



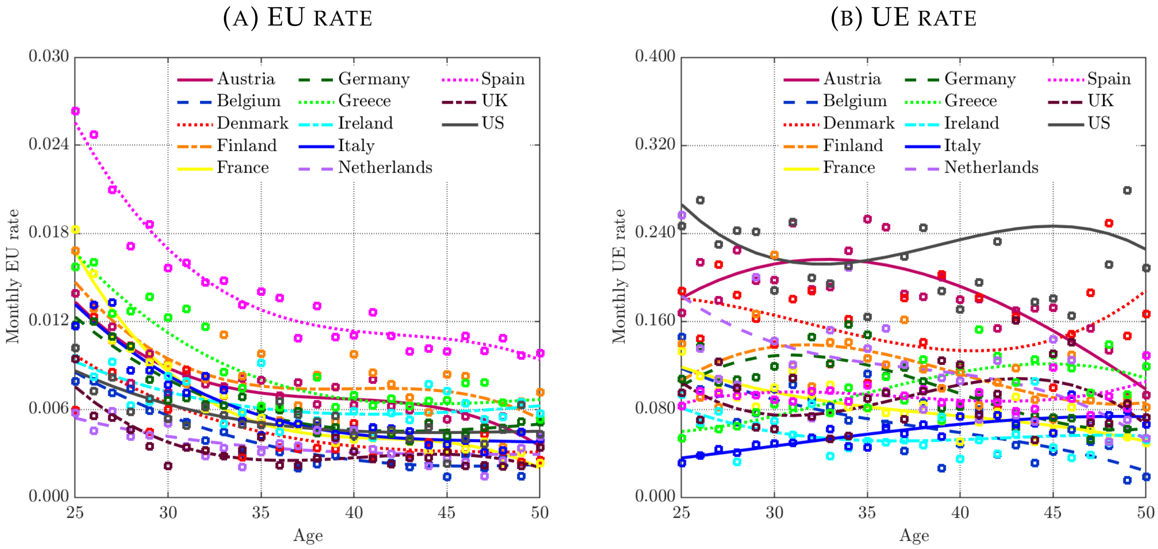
Note: Male employees aged 25–54. JJ mobility: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months. Employment in the past 12 months includes self-employment due to data limitations. Constructed by 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.

Panel A of Figure 20 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.

Panel B 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.

[36] Where our studies overlap, my wage profiles 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.

FIGURE 20. EU AND UE RATES AND LABOR MARKET FLUIDITY



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.

A.6 The role of composition, full sample

Table 10 replicates the regression results for life-cycle wage growth and labor market fluidity controlling for compositional differences for the full sample of 23 countries. Results are very similar to the core sample.

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

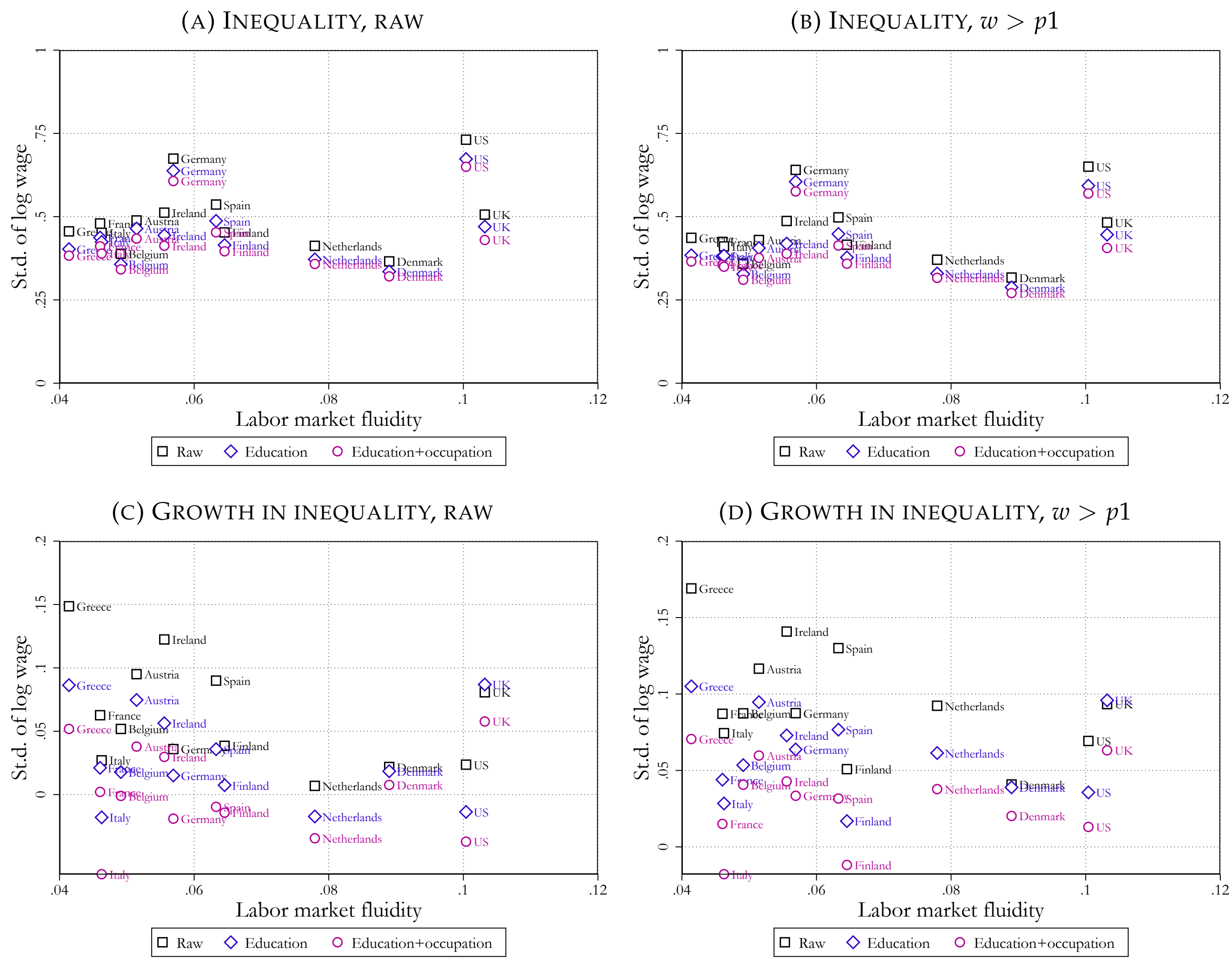
	Panel A. Ages 25–54			*Panel B. 1% depreciation*			*Panel C. Ages 22–59*		
	Baseline	Educ	Occup	Baseline	Educ	Occup	Baseline	Educ	Occup
α	0.242***	0.217**	0.219**	0.242***	0.217**	0.219**	0.257***	0.228***	0.231***
	(0.081)	(0.083)	(0.078)	(0.081)	(0.083)	(0.078)	(0.078)	(0.078)	(0.076)
N	474,919	472,836	449,644	474,919	472,836	449,644	562,239	559,214	531,729

Note: Male employees. Panel A. Wages restricted to not grow after age 50. Panel B. Ages 25–54 with wages restricted to depreciate 1% annually after age 50. Panel C. 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.

A.7 Raw and residual life-cycle inequality

Figure 21 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).

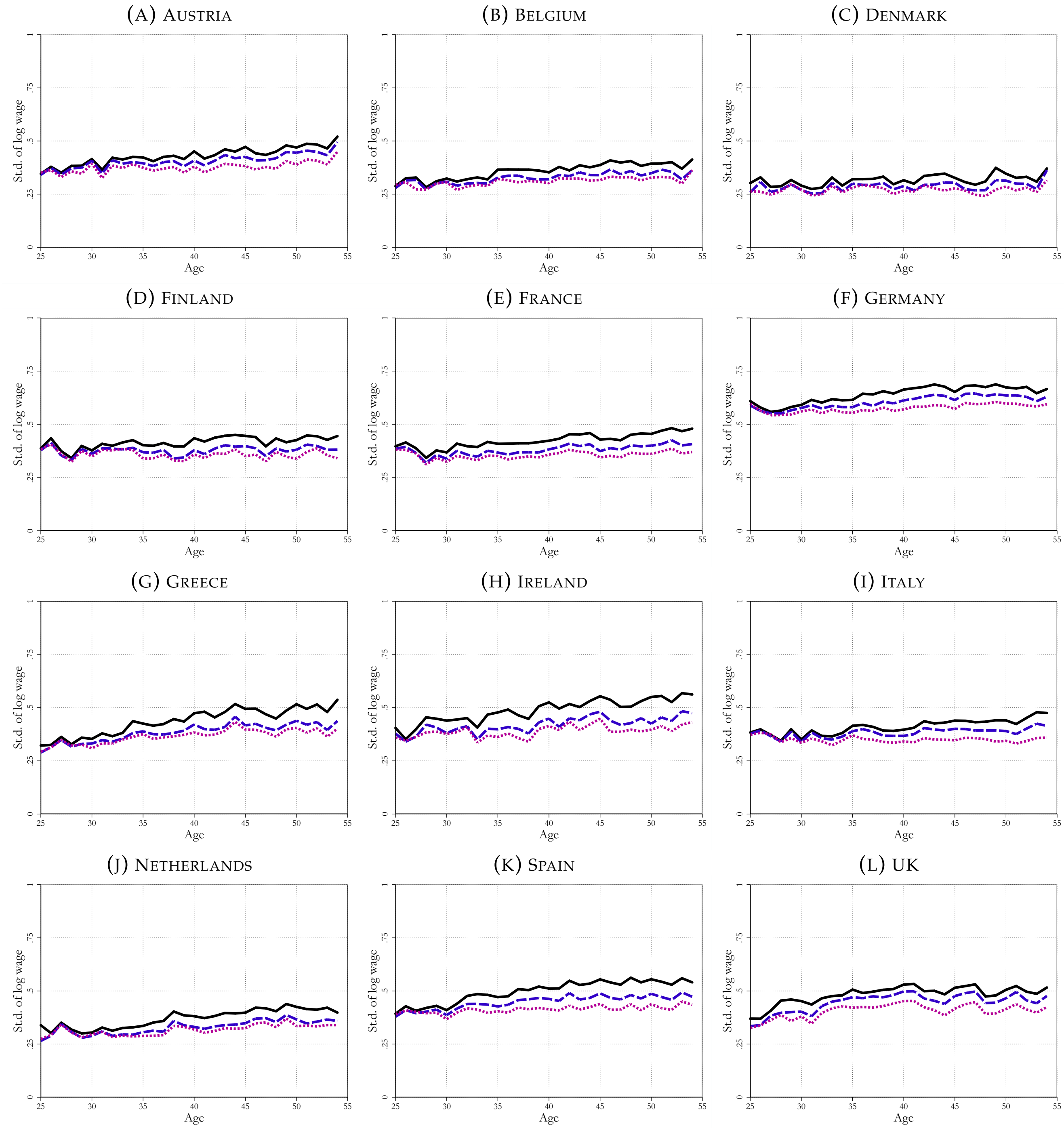
FIGURE 21. INEQUALITY AND LABOR MARKET FLUIDITY, ALTERNATIVE MEASURES

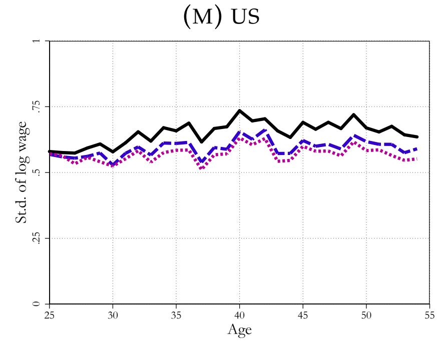


Note: Male employees aged 25–54. Panel A. Cross-sectional standard deviation of residual log hourly real wages. Panel B. Cross-sectional standard deviation of residual log hourly real wages dropping the bottom 1% of residual wages in each country. Panel C. Growth in standard deviation of residual log 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 22 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 22. 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

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

B.1 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 5 for a description of the data). Table 11 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. The "sector" columns additionally also controls for sector, exploiting individuals who switch sectors for identification. In years when a worker spends more time on training, she is paid less per hour. This is not driven by confounding movements of workers across sectors, and a correlation between the incidence of training and wages across sectors. Quantitatively, when a worker spends one percent more of her work time on training, she is paid 0.28 percent less per hour.

TABLE 11. WAGES AND TRAINING

	Panel A. Days		*Panel B. Hours*	
	Raw	Sector	Raw	Sector
β	-0.126***	-0.136***	-0.210***	-0.226***
	(0.041)	(0.041)	(0.066)	(0.067)
N	80,903	78,875	80,711	78,683

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

B.2 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.3 Details on the simplified two-period economy

Denote by $W(r,i)$ the value to a young worker of being in a low productive firm 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,

$$W(r,i) = (1-i)z_1 r + \Big((1-p)rz_1 + p(z_1 + \beta(z_2 - z_1))\Big)\left(1 + \frac{\mu}{\eta}(z_1 i)^\eta\right) \quad (18)$$

The worker is paid piece rate r on net output $(1-i)z_1$ (training need not be optimal at this point). 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, the worker receives a job offer from a poaching, high-productive firm, 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 an incumbent firm of employing a young worker under some piece rate r and training policy i (again, not necessarily the optimal one). It satisfies,

$$F(r,i) = (1-r)(1-i)z_1 + (1-r)(1-p)z_1\left(1 + \frac{\mu}{\eta}(z_1 i)^\eta\right) \quad (19)$$

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

Adding the value of the worker and firm, the joint value of a match between a young worker and an incumbent firm, $J(i) = W(r,i) + F(r,i)$, is given by

$$J(i) = (1-i)z_1 + (z_1 + p\beta(z_2 - z_1))\left(1 + \frac{\mu}{\eta}(z_1 i)^\eta\right) \quad (20)$$

which is independent of how it is split between the worker and firm, r.

Differentiating the joint value (20) with respect to the job finding rate, p, holding training fixed, $\left.\frac{\partial J(i)}{\partial p}\right|_i = \beta(z_2 - z_1)(1 + \mu(z_1 i)^\eta/\eta) > 0$. 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 incumbent firm. Ex ante, an incumbent firm benefits from the opportunity of the worker leaving by having to pay the worker less.

Taking first-order conditions of the joint value of a match (20)

$$i = \frac{1}{z_1}\Big(\big(z_1 + p\beta(z_2 - z_1)\big)\mu\Big)^{\frac{1}{1-\eta}}$$

If there is poaching, the cost of doing so, c, must equal its expected return,

$$c = q(1-\beta)(z_2 - z_1)\left(1 + \frac{\mu}{\eta}(z_1 i)^\eta\right) \quad (21)$$

A poaching firm contacts a worker at rate q and gets slice $1-\beta$ of the surplus. If the worker invested 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* (20) *given a mass of vacancies;*
2. *The mass of vacancies is consistent with free entry* (21)*;*
3. *And the economy is time invariant.*

Uniqueness of the equilibrium. Define $i_w(v)$ and $i_e(v)$ based on (12)–(13) to be

$$\begin{aligned} i_w(v) &= \left(\mu\left(z_1 + v^\alpha \beta(z_2-z_1)\right)\right)^{\frac{\eta}{1-\eta}} \\ i_e(v) &= \frac{\eta}{\mu}\left(\frac{cv^{1-\alpha}}{(1-\beta)(z_2-z_1)} - 1\right) \end{aligned} \tag{22}$$

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 $\lim_{v\to\infty}\left(\frac{i_e(v)}{i_w(v)}\right)^{\frac{1-\eta}{\eta}}$,

$$\lim_{v\to\infty} \frac{\left(\frac{\eta}{\mu}\left(\frac{cv^{1-\alpha}}{(1-\beta)(z_2-z_1)}-1\right)\right)^{\frac{1-\eta}{\eta}}}{\left(z_1+v^\alpha\beta(z_2-z_1)\right)\mu} = \lim_{v\to\infty} v^{(1-\alpha)\frac{1-\eta}{\eta}-\alpha}\frac{\left(\frac{\eta}{\mu}\left(\frac{c}{(1-\beta)(z_2-z_1)}-\frac{1}{v^{1-\alpha}}\right)\right)^{\frac{1-\eta}{\eta}}}{\left(\frac{1}{v^\alpha}+\beta(z_2-z_1)\right)\mu} \tag{23}$$

In the limit $v\to\infty$, the second term in (23) 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,

$$\frac{\partial i_w(v)}{\partial v} = \frac{\eta}{1-\eta} i_w^{\frac{2\eta-1}{\eta}} \mu\alpha v^{\alpha-1}\beta(z_2-z_1) \tag{24}$$

$$\frac{\partial i_e(v)}{\partial v} = \frac{1-\alpha}{v}\left(i_e + \frac{\eta}{\mu}\right) \tag{25}$$

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. Substituting using (24)–(25), I hence require that,

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

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

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

Using (22) to substitute for i,

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

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

$$\frac{\eta}{1-\eta} \frac{\alpha}{1-\alpha} - 1 \; < \; 0 \iff \frac{\alpha}{1-\alpha} \; < \; \frac{1-\eta}{\eta} \tag{26}$$

B.4 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,

$$\max_{v,i} \left\{ (1-i)z_1 + \left(z_1 + v^{\alpha}(z_2 - z_1)\right) \left(1 + \frac{\mu}{\eta}(z_1 i)^{\eta}\right) - cv \right\} \tag{27}$$

with first order conditions,

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

Proposition 1. *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.*

Proof. Compare the first-order condition for optimal investment and the free entry condition in the decentralized equilibrium to those in the planned economy,

$$i(v) = \frac{1}{z_1} \left(\mu \left(z_1 + v^{\alpha}\beta(z_2 - z_1)\right)\right)^{\frac{1}{1-\eta}} \tag{28}$$

$$i_{sp}(v) = \frac{1}{z_1} \left(\mu \left(z_1 + v^{\alpha}(z_2 - z_1)\right)\right)^{\frac{1}{1-\eta}} \tag{29}$$

$$v(i) = \left((1-\beta) \frac{(z_2 - z_1)}{c} \left(1 + \frac{\mu}{\eta}(z_1 i)^{\eta}\right)\right)^{\frac{1}{1-\alpha}} \tag{30}$$

$$v_{sp}(i) = \left(\alpha \frac{z_2 - z_1}{c} \left(1 + \frac{\mu}{\eta}(z_1 i)^{\eta}\right)\right)^{\frac{1}{1-\alpha}} \tag{31}$$

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). $\square$

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 poaching firm, such a high bargaining power of workers is inconsistent with positive job creation in equilibrium.

C Estimation

I pick parameters 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 in the main text, 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.[37] 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 productivity. This corresponds to my empirical measure, which assigns equal weight to each age 25–54.

D Results

This section provides additional quantitative results.

D.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

[37] 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. The approximation to six age groups account for the "jumpiness" of some of the model life-cycle outcomes.

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.

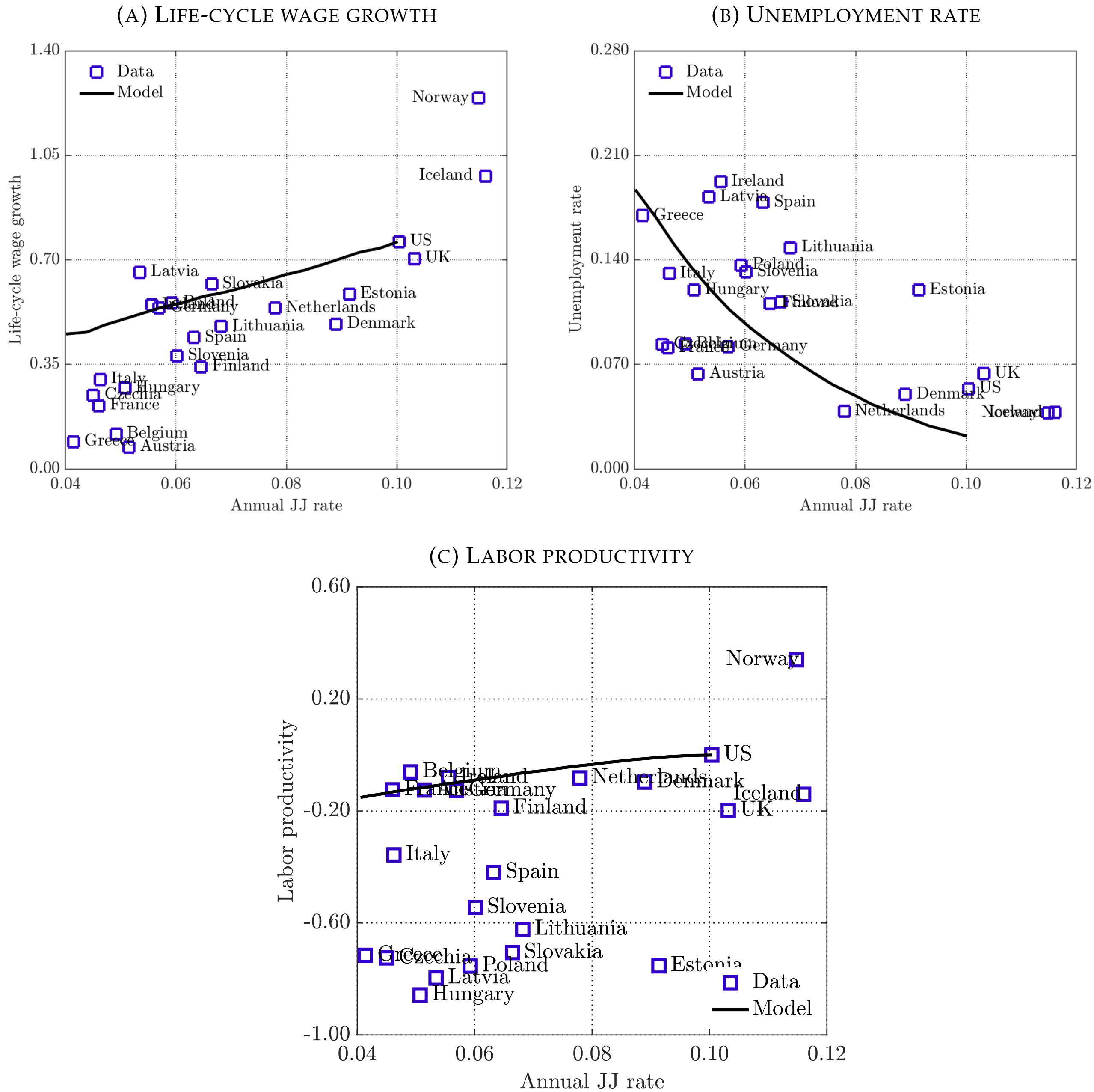
Table 12 reports results from the benchmark model specification in the paper, which does not impose the empirical restriction of no wage growth after age 50, and an alternative specification that imposes no wage growth after age 50. Results are virtually identical.

TABLE 12. 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.

FIGURE 23. THE IMPACT OF LABOR MARKET FLUIDITY, MODEL VERSUS DATA



Note: Men aged 25–54. Panel A. Wage growth between age 25–50. Data: Based on (1) with worker fixed effects, year effects and age effects restricted to not grow after age 50. Panel B. Data: Collapsed to the country-year-age level using the provided survey weights, then to the country-level. Model: Collapsed to the country-age level, then to the country-level. Panel C. Data: Log real output per hour in 2014 in 2004 PPP-adjusted US dollars. Regulation (model): Output per worker net of training and job creation costs including the wedge, Δ, $((1-u)\int(1-i(a,z,h))zhdG(a,z,h)-(c+\Delta)V)/(1-u)$. Tax (model): Output per worker net of training and job creation costs excluding the wedge per worker, $((1-u)\int(1-i(a,z,h))zhdG(a,z,h)-cV)/(1-u)$. Both model series are in logs and normalized to 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 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.2 Full sample results

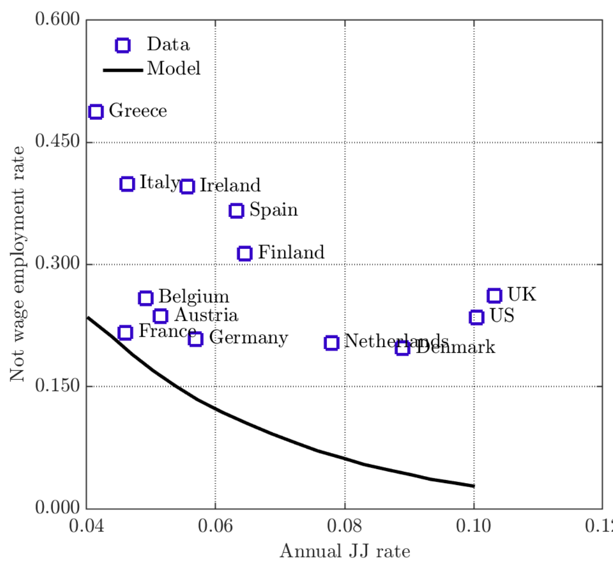
Figure 23 plots life-cycle wage growth, unemployment and labor productivity against labor market fluidity in the model and the data for the full sample of 23 OECD countries. Results are similar.

D.3 Wage employment

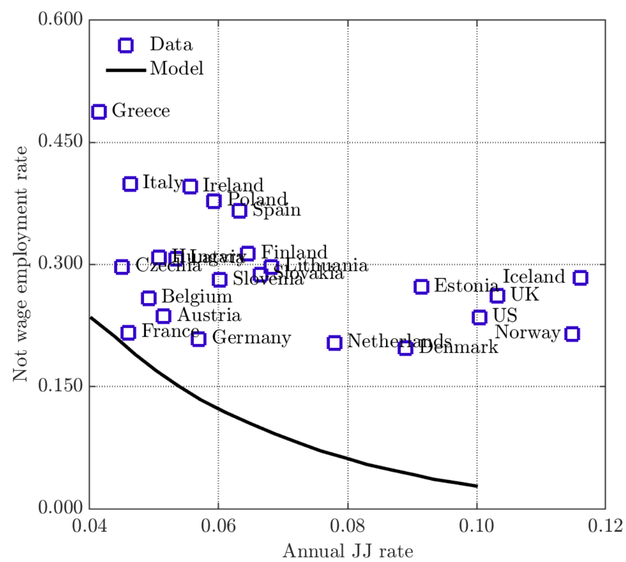
As noted in Appendix A.3, the share of self-employed workers is higher in less fluid labor markets. The model is consistent with this pattern if self-employment is akin to unemployment—something workers do when they cannot find a wage employment job. Figure 24 illustrates this by plotting the share of 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 (Poschke, 2019), it would be interesting to have a deeper theory of self-employment. That, however, is beyond this paper.

FIGURE 24. NOT-WAGE-EMPLOYMENT (UNEMPLOYED, SELF-EMPLOYED AND NON-PARTICIPANTS) AND LABOR MARKET FLUIDITY

(A) CORE



(B) ALL



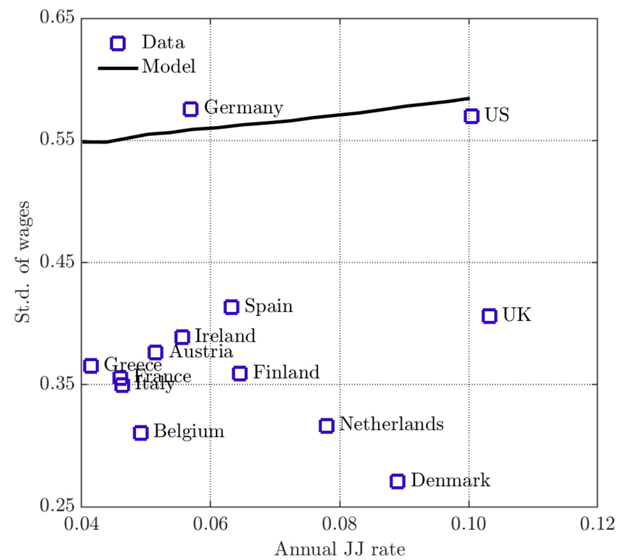
Note: Men aged 25–54. Not wage employment rate: Share of men aged 25–54 that is *not* wage employed, i.e. unemployed, self-employed and non-participants. Data: Constructed by first collapsing the data to the country-year-age level using the provided survey weights, then to the country-level. Model: Constructed 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.4 Additional outcomes

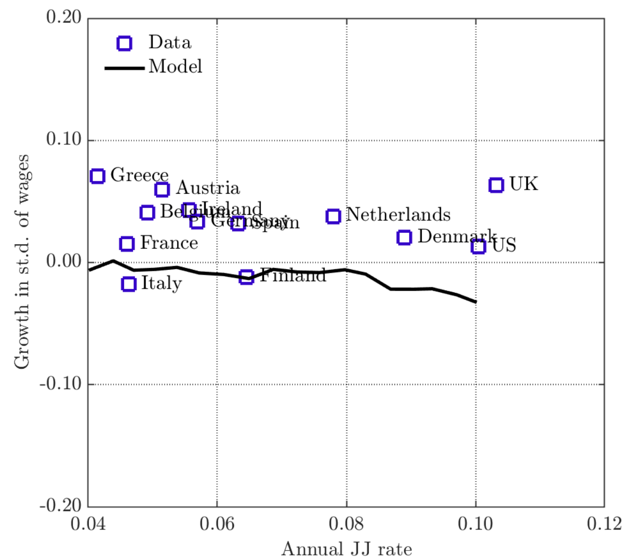
This section compares additional model predictions with the cross-country variation. Panel A of Figure 25 plots the level of inequality against labor market fluidity, illustrating only a minor increase in inequality with labor market fluidity in both the model and the data. As shown in Panel B, the higher inequality in more fluid labor markets is not accounted for by greater life-cycle growth in inequality, in either the model or the data. Panel C shows that 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 25. THE IMPACT OF LABOR MARKET FLUIDITY, MODEL VERSUS DATA

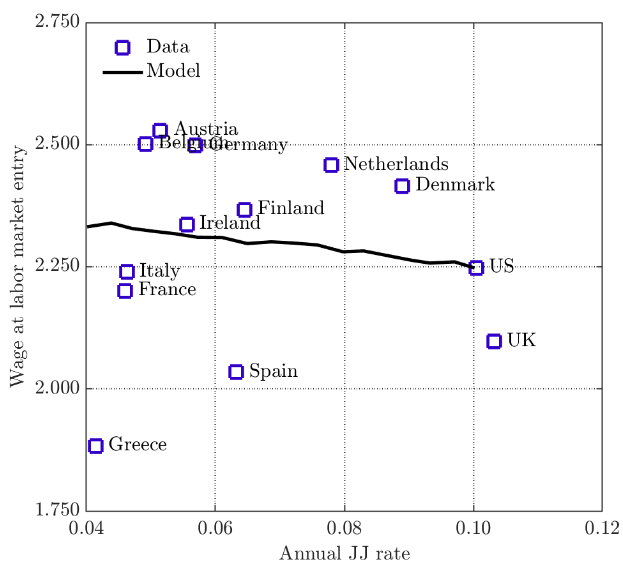
(A) INEQUALITY



(B) GROWTH IN INEQUALITY

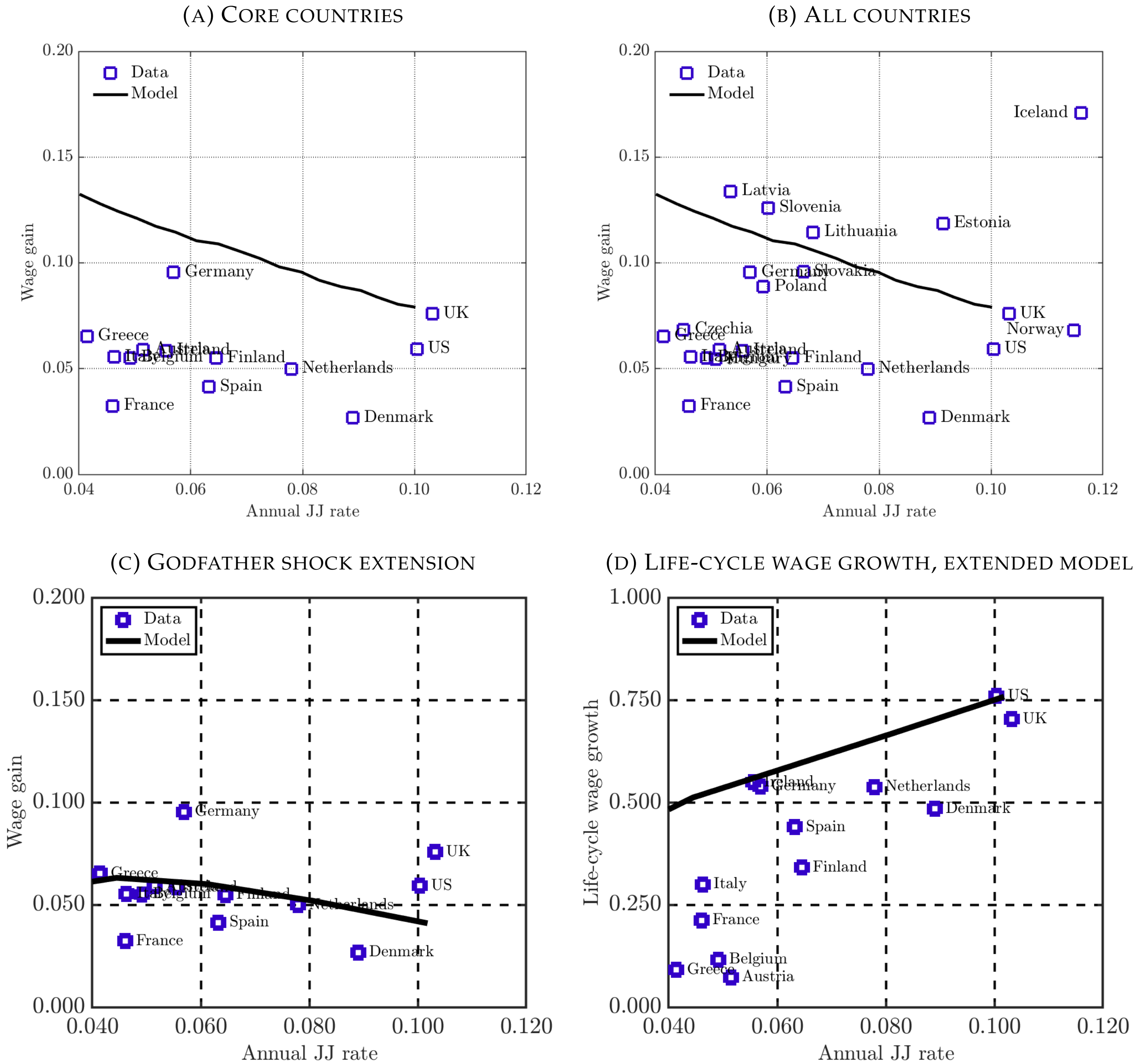


(C) ENTRY WAGES



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 26. WAGE GAIN FROM JJ MOVE, MODEL VERSUS DATA



Note: Men aged 25–54. Panels A–C. 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. Panel D. 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. Panels A–B. Benchmark model. Panel C–D. Extended model that incorporates *godfather* shocks. See text for more details. 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. 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.

Panels A and B of Figure 26 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.

To illustrate this point, Panel C 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 in Panel D (as well as other outcomes) remains essentially unchanged.

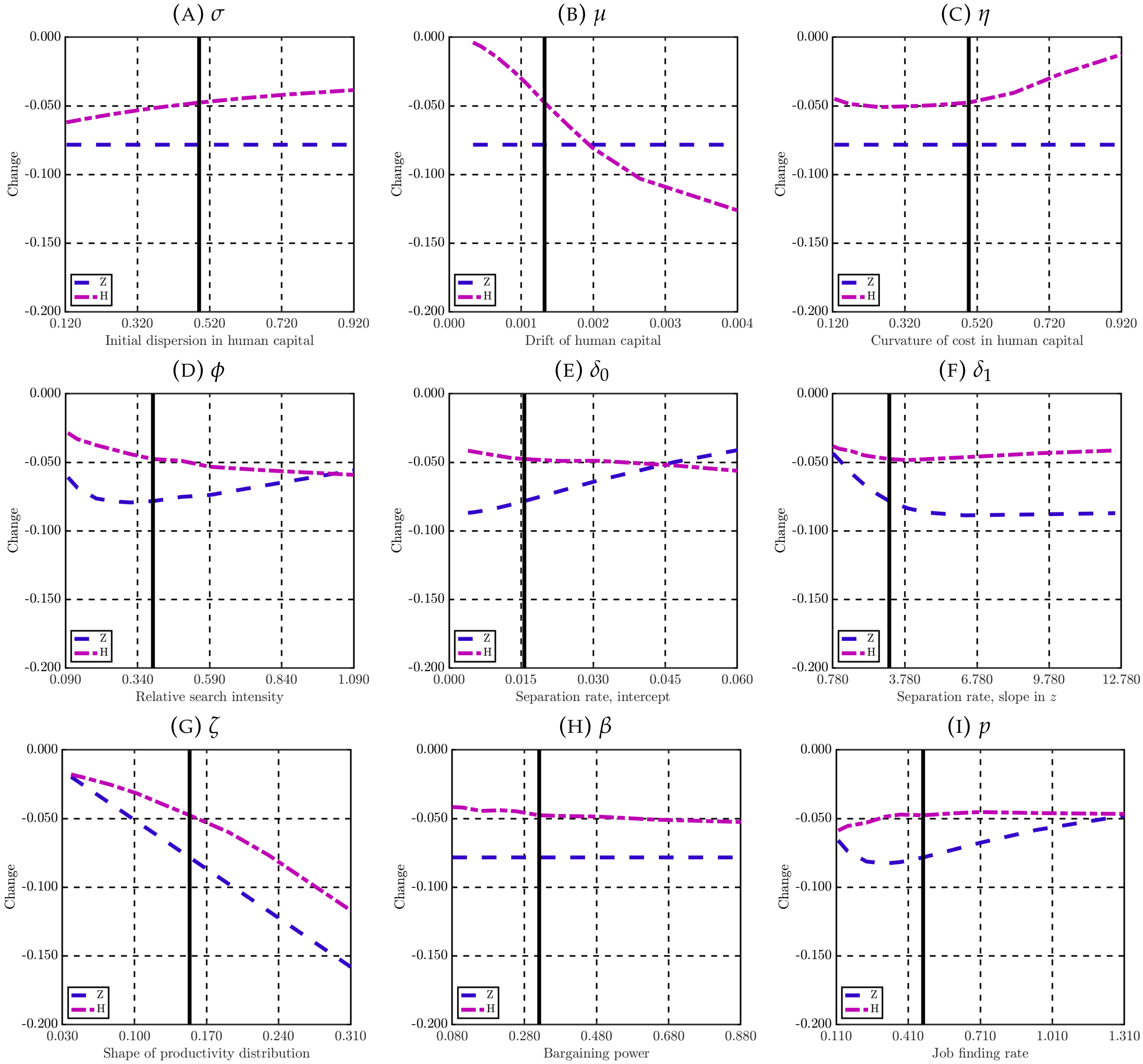
D.5 Sensitivity analysis

Figure 27 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 27. 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.

D.6 Unemployment and labor productivity

Table 13 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 relationship 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 that 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 28 illustrates the EU and UE flows across countries in the model and data.

TABLE 13. 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.

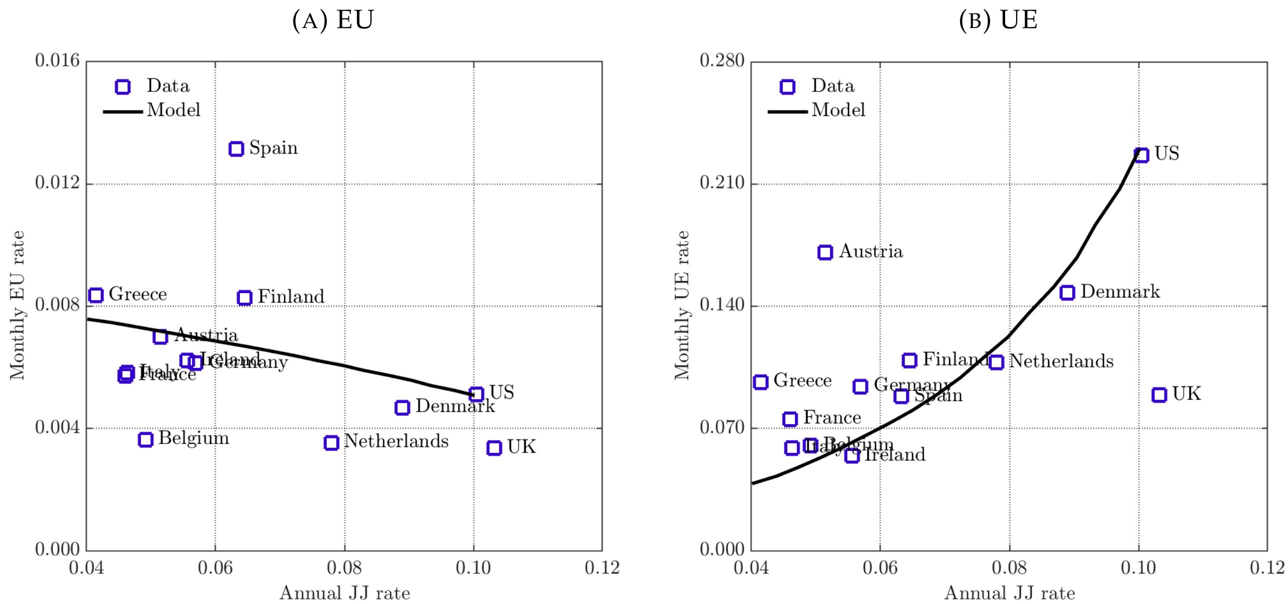
E Training

This appendix contains additional details on training.

E.1 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 14 reports results from

FIGURE 28. THE IMPACT OF LABOR MARKET FLUIDITY ON UE AND EU RATES, MODEL VERSUS DATA



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.

a regression of various training measures on fluidity without top-coding. The point estimates grow in magnitude, but the takeaway remains the same.

E.2 Training over the life-cycle

Figure 29 plots training over the life-cycle—days on training in the left panel and hours on training in the right panel, both expressed as a fraction of total work days/hours per year. The model moment is $\frac{1}{A}\int i(a,z,h)\tilde{g}(z|a,h)dze(a,h)dh$. As noted in the main text, the model significantly overstates the level of training in the data. As the level difference makes it difficult to assess the *relative* behavior of training over the life-cycle, I normalize the model moments to the empirical moment by first dividing by the model moment at age 25 and then multiplying by empirical moment at age 25. Since comparable training data is missing for the US, I use Denmark and construct the corresponding model moments by matching labor market fluidity in Denmark, holding all parameters fixed at their estimated US values. While the model overstates the amount of training in the data, it captures well the relative decline in training with age.

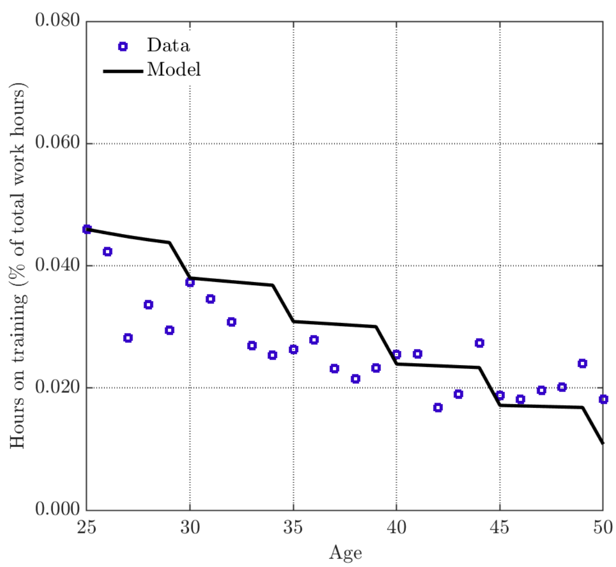
TABLE 14. TRAINING AND LABOR MARKET FLUIDITY WITHOUT TOP-CODE

	Panel A. Days (fraction of year)			*Panel B. Hours (fraction of year)*			*Panel C. Whether trained*		
	Raw	Controls	Direct	Raw	Controls	Direct	Raw	Controls	Direct
Fluidity	1.947***	1.648***	1.692***	1.383***	1.143***	1.089***	9.915***	9.438***	9.545***
	(0.253)	(0.196)	(0.119)	(0.148)	(0.128)	(0.127)	(1.196)	(1.366)	(1.280)
JJ			-0.007			-0.004			-0.011
			(0.011)			(0.005)			(0.012)
Age		-0.002***	-0.003**		-0.001**	-0.002**		-0.005***	-0.004***
		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
College		0.022***	0.030***		0.005**	0.007***		0.108***	0.106***
		(0.005)	(0.006)		(0.002)	(0.002)		(0.027)	(0.029)
N	135,563	115,897	63,634	135,318	115,676	63,494	135,989	116,261	63,852

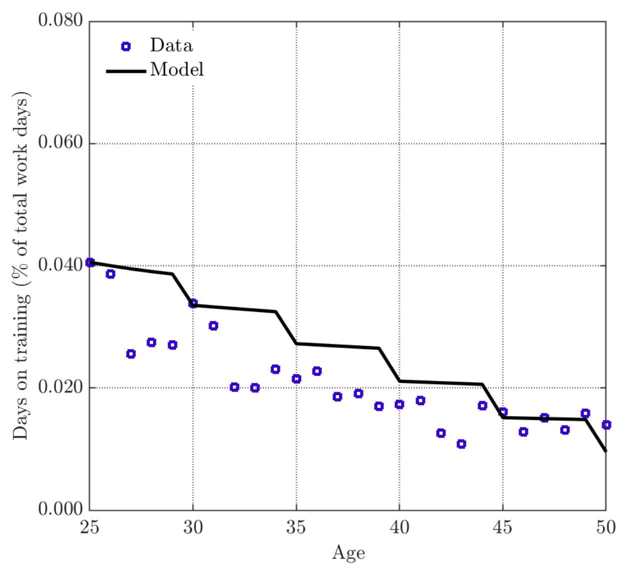
Note: Men aged 25–54. Projection of training outcome on labor market fluidity without or with controls. Panel A. Days on vocational training in the past 12 months, expressed as a fraction of potential work days (5*52). Panel B. Hours on vocational training in the past 12 months, expressed as a fraction of potential work hours (40*52). Panel C. Whether worker undertook any vocational training since January last 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.

FIGURE 29. TRAINING OVER THE LIFE-CYCLE, MODEL VS DATA

(A) DAYS ON TRAINING



(B) HOURS ON TRAINING



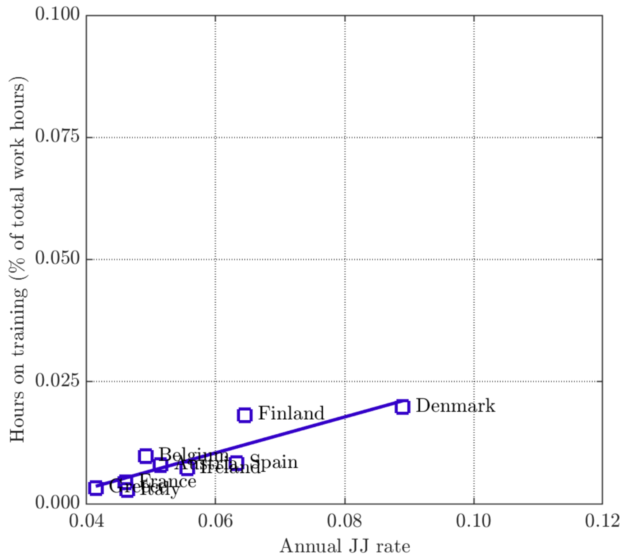
Note: Men aged 25–54. Panel A. Days on vocational training in the past 12 months, expressed as a fraction of potential work hours (40*52). Panel B. Hours on vocational training in the past 12 months, expressed as a fraction of potential work hours (40*52). Both panels. Model moment is average investment, $\frac{1}{A}\int i(a,z,h)\tilde{g}(z|a,h)dze(a,h)dh$, normalized to the empirical moment by first dividing by the model moment at age 25 and then multiplying by empirical moment at age 25. Hours and days on training are top-coded at 13 weeks of full time training per year, and refer to Denmark as the highest fluidity country with training data. Model moments are for a hypothetical country with the same aggregate labor market fluidity as Denmark, holding all other parameters fixed at their estimated US values. 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.

E.3 Additional training outcomes

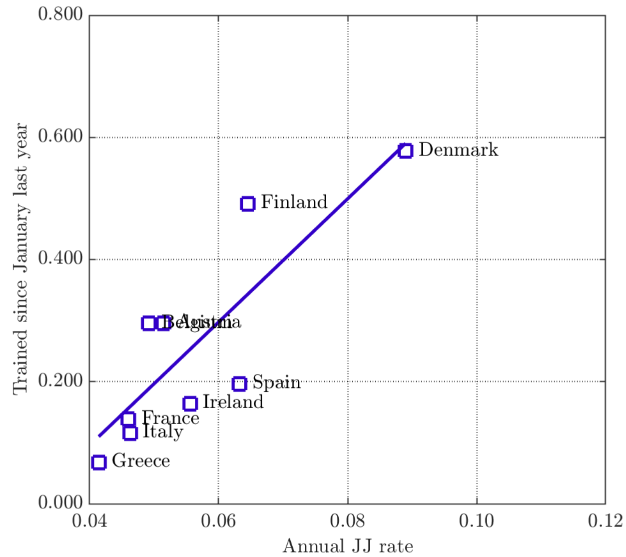
Figure 30 plots hours on training in the past 12 months, whether the worker did any training since January in the year prior to the survey and the share of workers who report that their employer paid for the training against labor market fluidity. If anything, the share rises with labor market fluidity, but the pattern is not statistically significant.

FIGURE 30. TRAINING AND LABOR MARKET FLUIDITY, DATA

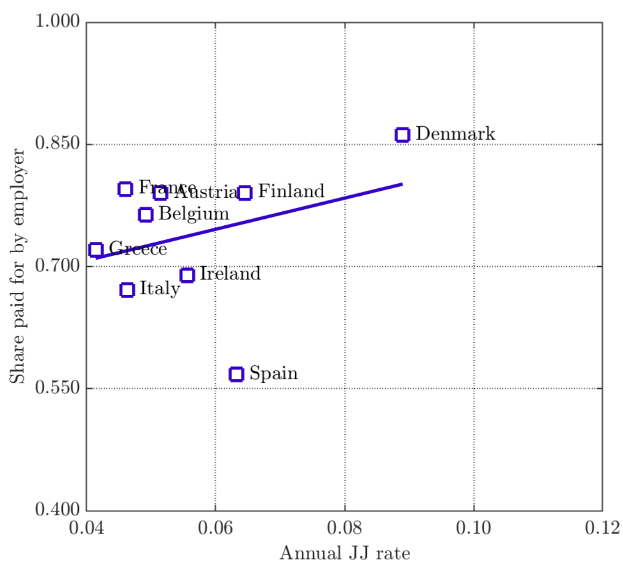
(A) HOURS ON TRAINING



(B) WHETHER TRAINED



(C) SHARE PAID FOR BY EMPLOYER



Note: Men aged 25–54. Panel A. 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. Panel B. Whether worker undertook any vocational training since January last year. Panel C. Share of workers who report that their employer paid for their vocational training since January last 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.

E.4 Training and subsequent mobility: the generality of human capital

This subsection uses the panel data on training and mobility to offer support for the notion that human capital is general. In particular, I hypothesize that if *firm-specific* human capital is important, then the incidence of training should be associated with a subsequent decline in the probability that the worker leaves the firm. The reason is that firm-specific human capital raises the value of the current match relative to alternative matches.

Table 15 relates JJ in the past 12 months to training in the year prior to that, i.e. 13–24 months ago (I have alternatively related mobility to training in the current year as well as two years ago with similar results). The first column shows the raw correlation with only country and year controls, the second adds age, education, occupation and sector controls, and the third controls for worker-fixed effects and year effects.[38] 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.

TABLE 15. JJ MOBILITY AND LAGGED TRAINING

	Panel A. Days (fraction of year)			*Panel B. Hours (fraction of year)*			*Panel C. Whether trained*		
	Raw	Controls	Within	Raw	Controls	Within	Raw	Controls	Within
Training	0.068*	0.044	0.014	0.115**	0.058	0.034	0.001	0.001	-0.004
	(0.036)	(0.033)	(0.040)	(0.053)	(0.047)	(0.062)	(0.004)	(0.003)	(0.004)
N	49,114	48,289	46,247	49,011	48,190	46,134	49,285	48,460	46,434

Note: Men aged 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. 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). Panel C. Whether worker undertook any vocational training since January last year. 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.

E.5 Firm wage and firm size/productivity

Table 16 reports results from the first stage regression (15) projecting pay on firm size bins (data) / match productivity bins (model) with controls. Larger firms pay better, consistent with previous research. As expected more productive matches on average pay better. In fact, the magnitude of the empirical and model relationship is about the same.

E.6 Training and firm size: the complementarity in production

The following intuition is clearest in the simple two period model, so I will restrict attention to that (but it carries through numerically to the general model). Recall from (**??**) that optimal investment is given by

$$i \quad = \quad \frac{1}{z_1}\left(\mu\left(z_1 + p\beta\frac{z_2 - z_1}{2}\right)\right)^{\frac{1}{1-\eta}} \tag{32}$$

[38] The same conclusion holds with age instead of year controls.

TABLE 16. INFERRING FIRM PAY

	Data	Model
α^2	0.101***	0.078***
	(0.005)	(0.001)
α^3	0.188***	0.131***
	(0.006)	(0.001)
α^4	0.214***	0.182***
	(0.006)	(0.001)
α^5	0.265***	0.260***
	(0.006)	(0.001)
α^6	0.338***	0.370***
	(0.006)	(0.001)
N	77,793	5,154,592

Note: Men aged 25–54. Projection of pay on firm size (data) / match productivity (model), each binned into 6 roughly equally large bins (in an employment-weighted sense), controlling for age, education, occupation and country-year (data) / age and country (model). Standard errors are clustered at the individual-level. *** statistically significant at 1%. *Source:* ECHP 1995–2001.

Whether training rises or falls with match productivity, z_1, is ambiguous because of the opposing effects of the first and second terms.

Consider instead a model with no complementary in production, $z + h$. Given the normalization $h_0 = 1$, the natural extension of the Ben-Porath (1967) investment problem would be

$$\max_{i \in [0,1]} \left\{ (1-i)(z_1+1) + z_1 + \frac{p}{2}\beta(z_1 - z_1) + 1 + \frac{\mu}{\eta}\Big(i(z+1)\Big)^{\eta} \right\}$$

with first-order condition

$$i \;=\; \frac{1}{z_1+1}\mu^{\frac{1}{1-\eta}} \tag{33}$$

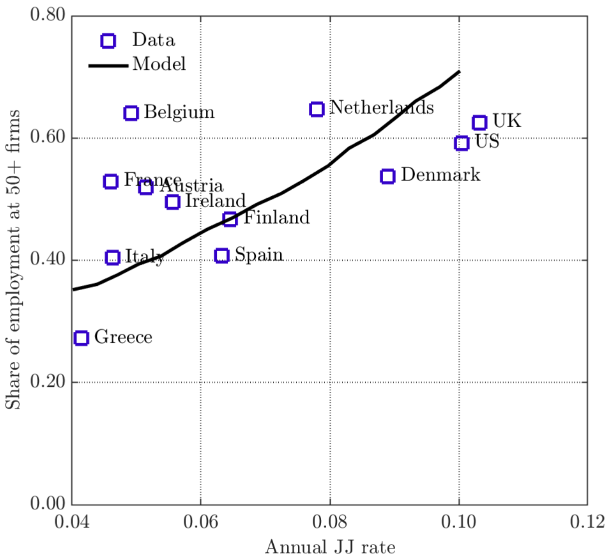
which is unambiguously declining in current productivity, z_1. Hence, one may hypothesize that this model would be inconsistent with the positive correlation between firm level pay and training. While a more thorough assessment is left for future work, I note that the current model matches well the empirical relationship between training and firm pay.

E.7 Share of employment at large firms

As noted in Figure 4, a larger share of workers work at large, higher paying firms in more fluid labor markets, where workers always train more.[39] Given that the model abstracts from size, to compare this prediction with the model, I first note that the average share of workers in 50+ firms across these countries is very close to 50 percent in the data. Hence in the model, I compute the share of workers in the upper half of employment-weighted match productivity, constructed in the pooled data set of all the simulated countries. Figure 31 plots the share of workers in upper half of firm size in the data / upper half of match productivity in the model. Given that firm size is likely an imperfect proxy for match productivity, the mechanism does a decent job matching the empirical patterns.

[39]The data on firm size is only available in the cross-sectional version of the EUSILC, which does not allow me to track individuals over time. It is also missing from the BHPS, so I use the available data from the EUSILC for the UK. The GSOEP

FIGURE 31. SHARE OF WORKERS IN 50+ FIRMS, MODEL VS DATA



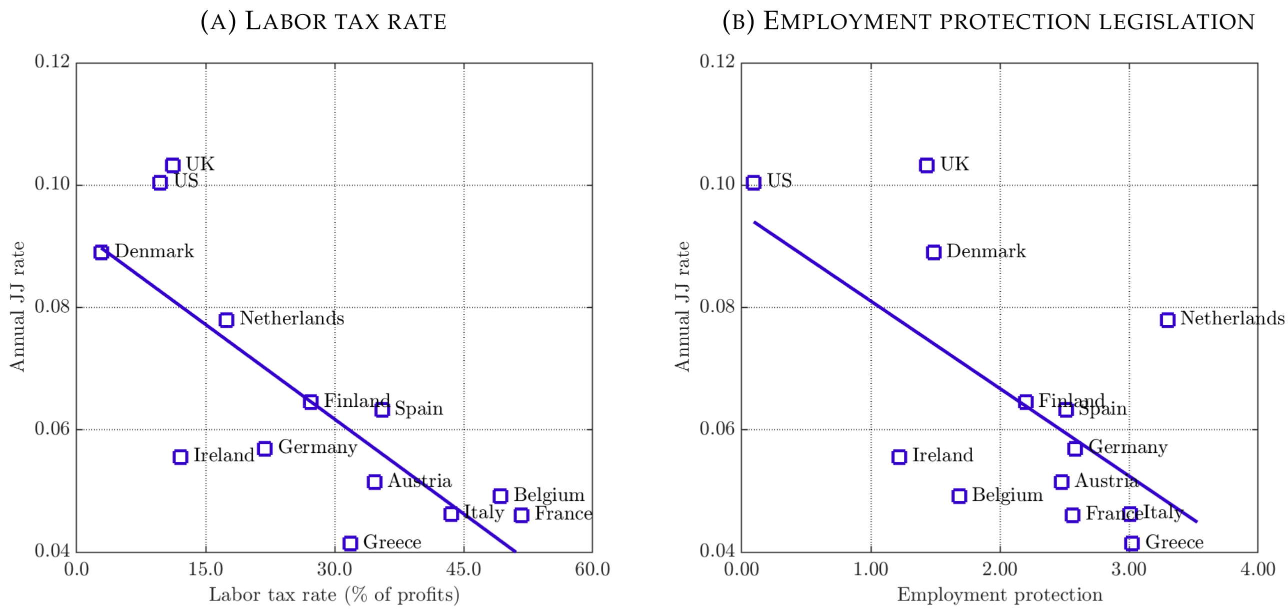
Note: Male wage employees aged 25–54. Data: Share of workers at 50+ employee firms. Model: Share of workers in the upper half of employment-weighted match productivity, constructed across all simulated countries. The upper half of employment-weighted match productivity corresponds closely to the average share of workers at 50+ firms across these countries (51.1%). 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, EUSILC and PSID 1994–2015.

codes firm size in non-comparable bins, and the PSID only asks for firm size in 1999 and from 2003 onwards.

F Labor market fluidity and policy

Figure 32 plots the correlation between labor market fluidity and the average labor tax rate leveled on firms, as well as the OECD's EPL index. These measures are less strongly correlated with labor market fluidity than the World Bank's measures of the cost of doing business, consistent with the argument in Fonseca et al. (2001).

FIGURE 32. DETERMINANTS OF LABOR MARKET FLUIDITY



Note: Male employees aged 25–54. Panel A. Average tax rate on labor on firms. Panel B. Employment protection legislation index. 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.