Labor Market Fluidity, On-the-Job Learning, and Career Growth Across Countries

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Abstract

Using worker-level panel data from 15 advanced economies, I document that life-cycle wage growth is steeper in countries with higher rates of job-to-job mobility. This relationship is not accounted for solely by wage gains at job changes: wages also grow faster within continuing employment spells. Moreover, young workers in more fluid labor markets are more likely to work at large, training-intensive firms. I interpret these facts through an estimated equilibrium model of careers in which firms differ in productivity and in the quality of the learning environments they provide. Lower fluidity depresses human capital accumulation by slowing young workers' movement into high-learning firms and by lowering the return to skill accumulation through a greater prospect of future mismatch. Moving from a low- to a high-fluidity country in my sample raises life-cycle wage growth by 19.4 log points and output per worker by 33.4 log points. Changes in on-the-job skill accumulation play a central role in both effects.

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1 Introduction

A large literature studies how labor market institutions and frictions shape the allocation of workers across firms and, in turn, aggregate productivity (Bentolila and Bertola, 1990; Hopenhayn and Rogerson, 1993; Ljungqvist and Sargent, 1998). This work has emphasized firms' job-creation and job-destruction decisions, as well as the static misallocation of labor across producers induced by these institutions. Yet labor markets do more than allocate a fixed stock of skills across firms. They also assign workers—especially young workers—to jobs that shape the experience and skills they accumulate over their careers. This dynamic margin implies that mobility barriers may depress productivity not only by misallocating workers across firms at a point in time, but also by altering the human capital workers carry into the future.

This paper quantifies the career consequences of policies and frictions that reduce labor mobility. I combine worker-level panel data from 15 advanced economies with an equilibrium model of careers in which firms differ both in contemporaneous productivity and in the quality of the learning environment they provide. The empirical analysis establishes three facts. First, countries with higher rates of job-to-job mobility—which I refer to as more *fluid* labor markets—exhibit greater life-cycle wage growth. Second, this relationship is not accounted for solely by wage gains at job-to-job transitions: wages also grow faster within continuing employment spells. Third, young workers in more fluid labor markets sort more into large and training-intensive firms, where young workers experience the fastest wage growth. The model matches these patterns and finds an important effect on labor market fluidity on skill accumulation. Moving from a typical low-fluidity country to a typical high-fluidity country in my sample raises output per worker by 33.4 log points, more than two-and-a-half times the corresponding static allocative effect.

To document cross-country differences in career outcomes, I assemble worker-level panel data for 15 advanced economies in Western Europe and the United States covering 1993–2024. The panel structure allows me to measure, consistently across countries and over time, the share of employed workers who were hired directly from another employer in the previous 12 months. Cross-country differences in this poaching measure are substantial. In the least fluid economy, fewer than five percent of workers were poached from another employer in the past 12 months, while in the most fluid economy, more than 17 percent were.

Using these data, I establish three empirical facts about cross-country differences in careers. First, life-cycle wage growth rises with labor market fluidity. I estimate wage profiles using the panel dimension of the data, controlling for individual fixed effects and country-year fixed effects, under an identifying restriction on late-life wage growth to separate age, time and individual (cohort) effects. Starting from a similar level at age 20–29, real wages over the next 30 years grow less than 15 log points in the least fluid countries compared with more than 50 log points in the most fluid countries. This relationship is robust to controls for education, gender, and occupational composition, and is especially pronounced among college-educated workers.

Second, the association between fluidity and life-cycle wage growth is not simply the cumulative effect of wage gains at job-to-job transitions. Such transitions are associated with wage gains in the data, so the direct job-ladder channel is relevant. Yet young workers' wages also grow faster in more fluid countries during years in which they remain with the same employer. In addition, entry wages among workers hired from nonemployment rise more steeply over the life cycle in more fluid labor markets. Together, these findings suggest that the steeper wage profiles observed in more fluid labor markets are not explained solely by more frequent moves to higher-paying employers or by outside offers used in within-firm wage bargaining.

Third, more fluid labor markets allocate young workers toward firms associated with faster early-career wage growth. Motivated by recent evidence that firms differ in their *learning environment* and that firm quality shapes human-capital accumulation (Gregory, 2026; Acabbi, Alati and Mazzone, 2026), I document that young workers experience faster wage growth at larger firms and at firms that provide on-the-job training. I then show that young workers in more fluid labor markets are more likely to work at such firms. These patterns suggest that fluidity affects the early-career allocation of workers not only across productive matches, but also across jobs with different implications for skill accumulation.

Guided by these facts, I develop and estimate an equilibrium model of careers in which jobs differ along two dimensions: current productivity and the quality of the learning environment. The model extends Gregory (2026) to a general-equilibrium setting with endogenous job creation by heterogeneous firms. Workers enter the labor market unemployed, search both while unemployed and while employed, and accumulate human capital at a rate that depends on their employer's learning environment. As in Bagger et al. (2014), output is the product of the productivity of the firm and the human capital of the worker. Wages are determined by bargaining and respond to outside offers, as in Cahuc, Postel-Vinay and Robin (2006).

A central insight of the theory is that the value of working in a high-learning environment when young depends on how effectively workers expect to use the resulting skills later in their careers. If future mismatch is likely, early skill accumulation is less valuable. By reducing expected future mismatch, a more fluid labor market therefore increases young workers' valuation of high-learning jobs and induces them to sort more strongly into such firms. In equilibrium, this higher valuation raises the surplus from high-learning jobs and strengthens firms' incentives to create them. Finally, because offers arrive more frequently in fluid labor markets, young workers reach high-learning jobs more quickly. Labor market fluidity therefore affects wage growth through three channels: the speed at which workers move toward more productive matches, their allocation across learning environments, and the arrival rate of outside offers that improve workers' bargaining positions within ongoing matches.

I estimate the model on a benchmark economy with intermediate labor market fluidity, targeting moments on wage growth, job mobility, employment dynamics, firm size, and training incidence. These moments jointly discipline the returns to experience, the distribution of learning environments, the offer arrival process, and firms' incentives to create different types of jobs. Although the model is overidentified, it reproduces the main patterns of wage growth, mobility, and sorting across firm types over the life cycle. Decomposing model-implied wage growth, I find that human capital accumulation is the single largest source of career wage growth.

I use the estimated model to quantify how policies and frictions that reduce labor market fluidity affect life-cycle and aggregate outcomes. I discipline cross-country differences in fluidity by varying two primitives: vacancy-creation costs and the efficiency of on-the-job search. Vacancy-creation costs capture, in reduced form, policies and frictions that raise the cost of creating jobs and help match cross-country differences in job-finding rates from unemployment. Employed-search efficiency governs the rate at which employed workers receive outside offers and convert them into job-to-job transitions.

Differences in labor market fluidity over the observed range have large effects on careers. Moving from a low-fluidity economy to a high-fluidity economy—from one standard deviation below to two standard deviations above mean fluidity, roughly the range spanned by the countries in my sample—raises life-cycle wage growth by 19.4 log points. A decomposition attributes this increase to faster human-capital accumulation, higher match productivity, and higher piece-rate components of wages, which contribute 8.8, 4.4, and 6.3 log points, respectively.

These career effects translate into large aggregate differences. Output per worker is 33.4 log points higher, human capital per worker is 18.7 log points higher, and match productivity is 12.7 log points higher. The total output effect is therefore more than two-and-a-half times the corresponding static allocative effect. Decomposing the human-capital channel, roughly four-fifths of the increase comes from young workers reaching high-learning firms more easily, holding fixed their relative valuation of learning environments and the baseline vacancy distribution. The remaining one-fifth reflects general-equilibrium adjustments: lower expected future mismatch raises young workers' valuation of learning environments relative to current productivity, and firms respond by creating more high-learning vacancies.

The central lesson is that labor market frictions distort not only the allocation of labor, but also the production of human capital. The standard concern is that low mobility prevents workers from reaching the firms where they are most productive. This paper shows that the same frictions also change the jobs in which young workers build their skills. When future mismatch is likely, high-learning jobs become less valuable and harder to reach. The cost of low fluidity is therefore not only a lower wage today, but also a lower stock of skills tomorrow.

Related literature. This paper first contributes to work on labor market institutions, reallocation, and aggregate productivity. Classic models show that firing costs, employment protection, and related labor market institutions alter job creation, job destruction, unemployment dynamics, and the allocation of labor across producers (Bentolila and Bertola, 1990; Hopenhayn and Rogerson, 1993; Bertola and Rogerson, 1997; Ljungqvist and Sargent, 1998; Pries and Rogerson, 2005).

Related empirical work documents large differences in labor market fluidity and job reallocation across countries and over time, and links these differences to business demographics, firm size, industry composition, and labor market regulation (Davis and Haltiwanger, 2014; Haltiwanger, Scarpetta and Schweiger, 2014). A closely related development literature uses harmonized labor-force surveys to document cross-country differences in labor market flows, firm-size distributions, and labor market churn, and studies how frictions in worker reallocation shape structural transformation (Donovan, Lu and Schoellman, 2023). I show that these same forces also shape the accumulation of human capital over the career. The paper therefore complements the standard allocative view with a dynamic channel: labor market frictions affect not only where existing skills are used, but also where new skills are produced.

Second, the paper contributes to research on job mobility and wage dynamics.[1] Search models with employer heterogeneity and on-the-job search explain wage dispersion and wage growth through mobility, employer competition, and wage bargaining (Diamond, 1982; Mortensen and Pissarides, 1994; Burdett and Mortensen, 1998; Postel-Vinay and Robin, 2002; Cahuc, Postel-Vinay and Robin, 2006). Empirical work shows that job changes are especially important early in the career, while structural work decomposes wage growth into returns to experience, tenure, search, and employer heterogeneity (Topel and Ward, 1992; Bagger et al., 2014). Closest in spirit, cross-country estimates of job-search models relate differences in mobility across Europe and the United States to wage distributions (Jolivet, Postel-Vinay and Robin, 2006). My contribution is to study whether cross-country differences in labor market fluidity explain differences in life-cycle wage growth. The key distinction is that mobility affects not only wage levels through better matches and bargaining, but also wage growth by changing where young workers accumulate skills.

Third, the paper relates to human-capital theory, firm-sponsored training, and life-cycle wage profiles. The idea that workers invest in skills early in life and reap the returns later is central to human-capital theory (Mincer, 1962; Becker, 1962; Ben-Porath, 1967). A related tradition emphasizes that jobs themselves differ in the learning opportunities they provide (Rosen, 1972; Rubinstein and Weiss, 2006). In seminal contributions to firm-sponsored training in imperfect labor markets, Acemoglu (1997) and Acemoglu and Pischke (1999) show that frictions and wage compression can make firms internalize part of the returns to general training. Moen and Rosén (2004) study how poaching and coordination affect the efficiency of general human-capital investment, and Lentz and Roys (2024) embed active general and specific training decisions in an on-the-job search model with heterogeneous firms. Recent work uses cross-country differences in life-cycle wage growth to measure human-capital accumulation and assess its aggregate implications (Lagakos et al., 2018; Ma, Nakab and Vidart, 2024), while other work studies how labor-income taxation shapes incentives to accumulate human capital over the life cycle (Guvenen, Kuruscu and Ozkan, 2014). I build on this perspective but focus on advanced economies and on labor market

[1] An earlier draft of this paper documented the first two facts of this paper, but did not attempt to explain them through the lens of a quantitative model of firm heterogeneity in productivity and learning environments.

fluidity as a determinant of on-the-job human-capital accumulation. The analysis shows that differences in career wage growth across rich countries are closely linked to the functioning of labor markets, not only to schooling, tax policy, or aggregate technology.

Finally, the paper contributes to the growing literature on firm heterogeneity in pay, sorting, and learning. Matched employer–employee studies document that firms differ systematically in pay, productivity, and the workers they employ (Abowd, Kramarz and Margolis, 1999; Card, Heining and Kline, 2013; Lise, Meghir and Robin, 2016; Song et al., 2019). More recent work emphasizes that firms also differ in their ability to promote worker learning and that these differences matter for life-cycle earnings inequality (Gregory, 2026; Arellano-Bover and Saltiel, 2026; Arellano-Bover, 2024; Ma, Nakab and Vidart, 2025*a*). Closely related, Acabbi, Alati and Mazzone (2026) document that workers accumulate more human capital at more productive firms and show that recessions distort worker–firm sorting, flatten the human-capital ladder, and generate persistent output losses. Related work on firm-provided training documents that training varies with development and with firm characteristics, and studies how training investments affect human capital and aggregate income (Ma, Nakab and Vidart, 2024, 2025*b*). I use this insight to study cross-country differences in careers. The paper documents that young workers sort more into high-learning firms in fluid labor markets and embeds this sorting margin in an equilibrium model of vacancy creation and on-the-job search. It differs from Acabbi, Alati and Mazzone (2026) by focusing on persistent cross-country differences in labor market fluidity rather than cyclical fluctuations, and by allowing firm productivity and learning environments to be distinct dimensions of heterogeneity. This allows me to quantify how labor market institutions affect not only sorting and wages, but also the aggregate stock of human capital.

The paper proceeds as follows. Section 2 establishes three motivating facts on cross-country differences in life-cycle career outcomes. Section 3 presents the theory, and Section 4 estimates the model. Section 5 uses the estimated model to interpret the observed cross-country patterns and quantify their aggregate implications. Section 6 concludes.

2 Three Facts on Cross-Country Differences in Career Outcomes

I document three facts about cross-country differences in worker career outcomes. The facts link labor market fluidity to life-cycle wage growth and to the allocation of young workers across firms with different learning environments. They motivate the quantitative model in the next section by showing that fluidity matters not only for the frequency of job changes, but also for wage growth within jobs and for the types of firms where young workers begin their careers.

2.1 Data

I use individual-level panel data from the European Community Household Panel (ECHP), the European Union Statistics on Income and Living Conditions (EU-SILC), and the Panel Study of Income Dynamics (PSID). The European data span the ECHP years, 1993–2001, and the EU-SILC years, 2003–2024, subject to country-specific gaps. The PSID provides data from 1993 to 2023. Together, these data provide information on employment histories, wages, and worker and firm characteristics for 15 advanced economies after the access and data-quality restrictions described below.

ECHP. The ECHP ran from 1993 to 2001 and covered 15 Western European countries: Austria (starting in 1995), Belgium, Denmark, Finland (starting in 1994), France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden (starting in 1997), and the U.K. Five features of the data are relevant for the analysis.

First, Germany participated in the ECHP only from 1994 to 1996, but partly overlapping data from the German Socio-Economic Panel (SOEP) for 1994–2001 are included in the ECHP files. Because the German component of the original ECHP suppresses the interview month for confidentiality reasons, I cannot compute labor market fluidity in those data. Since the ECHP and SOEP samples cover different respondents, I use both sources for the other outcomes in order to maximize sample size.

Second, Luxembourg participated in the ECHP only from 1994 to 1996. For 1995–2001, the ECHP includes complementary data from the Panel Socio-Economique Liewen zu Lëtzebuerg (PSELL). These data do not report the start date of the current job for 1995–1997 and do not record the survey month throughout. I therefore cannot compute labor market fluidity in the PSELL, and hence cannot compute it for Luxembourg in 1997–2001. Since the ECHP and PSELL samples cover different respondents, I use both sources for the other outcomes in order to maximize sample size.

Third, each country's statistical agency must grant researchers access to its national components of the ECHP and EU-SILC. The Netherlands has not granted me access to its ECHP or EU-SILC files, so I exclude the Netherlands from the analysis.

Fourth, Sweden did not directly participate in the ECHP, instead providing complementary data from a national survey. Because this survey lacks a panel dimension, it cannot be used for the main analyses below. I therefore exclude Sweden from the ECHP sample.

Fifth, the U.K. participated in the ECHP only from 1994 to 1996, with overlapping data from the British Household Panel Survey (BHPS) for 1994–2001. Although the BHPS contains the variables needed to construct the main outcomes, the implied fluidity series displays implausibly large year-to-year fluctuations. I therefore exclude the BHPS when computing labor market fluidity.

EU-SILC. The EU-SILC was designed as the successor to the ECHP. The files used here cover 2004–2024, with several exceptions. Denmark and Luxembourg also provide data for 2003, while Denmark and Ireland end in 2023. Data for Greece start in 2006, data for Germany start in 2015 and are unavailable in 2020, and data for the U.K. end in 2018.

Eurostat releases the EU-SILC in separate cross-sectional and longitudinal files, even though the underlying data are collected as a panel. The two files contain different variables; for example, firm size and sector are included only in the cross-sectional file. I use the cross-sectional file to impute sector and firm size in the longitudinal file based on demographic characteristics that are available in both files.

The question needed to compute labor market fluidity is not asked in the EU-SILC after 2020. My EU-SILC-based measure of fluidity therefore ends in 2020.

PSID. The PSID provides annual data from 1993 to 1997 and biennial data thereafter. To compute labor market fluidity, I rely on retrospective questions about employment status in each month of the calendar year before the survey year. Specifically, I use the subsequent survey to recover employment status in the calendar months around the previous survey. Starting in 2001, the PSID asks about employment status in each month of the previous two calendar years, which allows me to compute labor market fluidity. The 1999 and 2001 surveys, however, record employment status only for the previous calendar year, so I cannot compute labor market fluidity for 1997–2000.

The PSID records firm size only from 2005 onward, apart from additional measures in 1993 and 1999. Because the survey's earnings questions have changed over time, I harmonize earnings as total wage, salary, and self-employment income in order to maintain consistency with the European data.

2.2 Sample Selection and Variable Definitions

In most of the analysis, I focus on men and women aged 20–59 who are older than the imputed completion age for their highest degree. I set the completion age to 17 for workers with less than an upper secondary degree, 19 for workers with an upper secondary degree, and 23 for workers with a tertiary degree.[2] The cross-country share of young workers enrolled in school is not systematically correlated with labor market fluidity.

Because the data do not consistently distinguish private from public employment, or wage employment from self-employment, I classify private-sector wage employees, public-sector wage employees, and self-employed workers as employed. The non-employed are all other individuals. Although I cannot systematically distinguish public from private employment across all data sets,

[2] I do not consistently observe the age at which respondents completed schooling. The cutoffs therefore assign a common labor-market-entry age within each broad education group. The results are not driven by cross-country differences in student enrollment among young workers.

I can do so in the ECHP. In those data, public employees are concentrated in a small number of one-digit occupations, primarily public administrators and teachers. Since occupation is observed consistently across surveys and over time, I can verify that the results below are similar within occupations that consist primarily of private-sector employees. Excluding the self-employed also produces similar patterns.

I recode education into three categories: less than upper secondary, upper secondary, and tertiary. Occupation is standardized into one-digit ISCO codes. Income is total wage and salary income, inclusive of overtime pay and bonuses, plus self-employment income, all measured over the previous calendar year. Hourly wages are total income divided by total hours worked, where total hours are the product of weeks worked and usual hours per week. Nominal wages are first converted to real 2007 local wages using the national CPI, and then to real U.S. dollars using 2007 PPP-adjusted exchange rates.

Labor market fluidity. The available data do not allow me to construct monthly job-to-job mobility consistently across countries and years. I instead measure the annual *poaching rate*: the share of currently employed workers who started working for their current employer in the past 12 months and were never non-employed during that period. In the regressions below, I express the poaching rate in percentage points. This measure is available in the European data through 2020 and in the U.S. data through 2023, subject to the survey-specific gaps described above. Appendix A shows that although fluidity fluctuates within countries over time, the ranking of countries is persistent.

Life-cycle wage growth. I estimate life-cycle wage growth from the panel dimension of the data. Specifically, I project log hourly wages on individual fixed effects, country-year fixed effects, and country-age effects. The country-age effects are restricted to be flat after age 45, which resolves the perfect collinearity among individual, year, and age fixed effects:

$$\log w_{it} \quad = \quad \alpha_i \; + \; \gamma_{ct} \; + \; \xi_{ca} \; + \; \varepsilon_{it}. \tag{1}$$

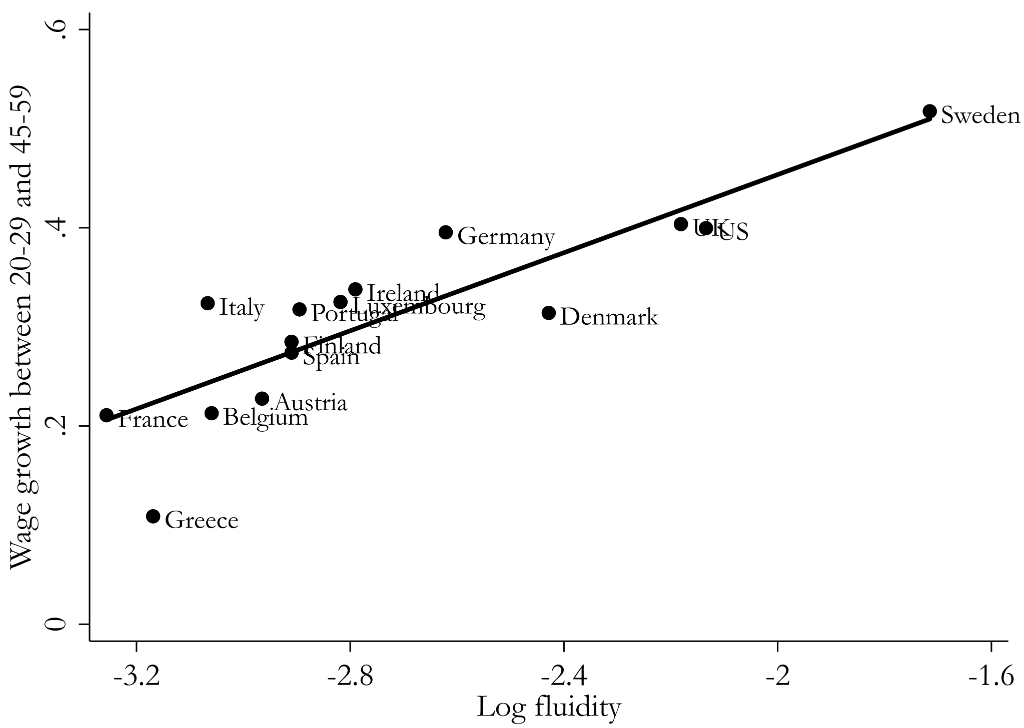
The objects of interest are the country-specific age effects, ξ_{ca}. Appendix A plots the estimated life-cycle profiles by country, highlighting that profiles have a similar concave shape everywhere. I summarize each country's profile by the increase in log wages between ages 20–29 and ages 50–59.

2.3 Wages Grow More Over the Life Cycle in More Fluid Labor Markets

I now present three empirical facts that motivate the model. The first fact establishes the cross-country relationship between fluidity and career wage growth. The second shows that the relationship is not only the direct consequence of wage gains at job changes. The third links fluidity to the types of firms at which young workers accumulate experience.

Figure 1 plots wage growth between ages 20–29 and 50–59, based on the estimates from (1), against the share of workers who were poached in the past year. Three observations stand out. First, countries differ substantially in labor market fluidity: in the least-fluid countries, fewer than five percent of employed workers are poached in a given year, while in the most-fluid countries the annual poaching rate exceeds 15 percent. Second, countries also differ substantially in life-cycle wage growth. Between ages 20–29 and 50–59, real hourly wages grow by less than 15 log points in Greece, holding fixed aggregate growth over calendar time, but by more than 50 log points in Sweden. Third, life-cycle wage growth is steeper in countries with more frequent job-to-job mobility. Thus, the same age profile that is relatively flat in low-fluidity countries is much steeper in economies where employed workers more often move directly to a new employer.

Figure 1: Life-Cycle Wage Growth and Labor Market Fluidity



Notes: Wage growth is the estimated increase in log hourly wages between ages 20–29 and 50–59 after removing individual and country-year fixed effects as in (1). Labor market fluidity is the annual poaching rate. *Source:* ECHP 1993–2001; EU-SILC 2003–2024; PSID 1993–2023.

The limited role of composition. A natural concern is that these patterns reflect differences in workforce composition. To assess this possibility, I project wages on the interaction between aggregate labor market fluidity and the restricted life-cycle age profile, while controlling for individual fixed effects, country-year fixed effects, and restricted age effects interacted with education

Table 1: Life-Cycle Wage Growth, Entry Wages, and Labor Market Fluidity

	(1)	(2)	(3)	(4)	(5)	(6)
	Life-cycle wage growth		By education		Entry wages	
	Raw	Residual	Non-college	College	Raw	Residual
Fluidity	0.011***	0.010***	0.007***	0.014***	0.139	0.103
	(0.001)	(0.002)	(0.002)	(0.002)	(0.115)	(0.103)
Observations	1,854,494	1,854,494	1,146,018	708,476	281,782	281,782
Years	30	30	30	30	30	30
Countries	15	15	15	15	15	15

(college versus non-college), gender, and one-digit occupation:

$$\log w_{it} \quad = \quad \beta * \ln\left(\text{fluidity}_c\right) * a_{it} \; + \; \alpha_i \; + \; \gamma_{ct} \; + \; \xi_{ae} \; + \; \xi_{ag} \; + \; \xi_{ao} \; + \; \varepsilon_{it}.$$

Table 1 summarizes the results. Column (1) shows that a one percent higher poaching rate is associated with 0.011*25=0.275 percent higher wage growth between ages 20 and 45. Although college-educated workers, men, and workers in some occupations tend to experience more wage growth over the life cycle, workforce composition along these dimensions does not sufficiently covary with labor market fluidity to change the estimate much according to column (2). That is, differences in composition do not account for the pattern in Figure 1.

Heterogeneity. Although composition does not drive the result, heterogeneity across subpopulations helps discipline potential explanations. Columns (3) and (4) of Table 1 show that the relationship is positive for both education groups but is larger for college graduates. Since college-educated workers are less likely to be directly affected by minimum wages or collectively bargaining agreements, this pattern points away from explanations based primarily on wage floors or centralized pay-setting institutions.

Entry wages. The final two columns of Table 1 relate wages at ages 20–29 to labor market fluidity. Entry wages are modestly higher in more fluid labor markets, but the relationship is not statistically significant. Thus, workers in high-fluidity countries do not start at lower wages and then catch up. Rather, workers across these advanced economies enter the labor market at broadly similar pay levels, but wages subsequently grow faster in more fluid labor markets.

Table 2: Wage Growth Within and Between Jobs and Labor Market Fluidity

	(1)	(2)
	Baseline	With JJ control
Age 20–39 × fluidity	0.012**	0.010*
	(0.006)	(0.006)
JJ transition in last 12 months		0.037***
		(0.010)
Observations	618,104	618,104
Years	23	23
Countries	15	15

2.4 Wages Also Grow More Within Jobs

Across all countries in the sample, job-to-job transitions are associated with wage gains. It is therefore natural to ask whether the steeper life-cycle wage profiles in high-fluidity countries are simply the mechanical consequence of workers making more such transitions. To assess the importance of this direct effect, I project year-on-year wage growth on an indicator for whether the worker is younger than 40 interacted with labor market fluidity, controlling for country-year, age-year, education-year, gender-year, and occupation-year effects. I then add an indicator for whether the worker made a job-to-job transition in the past 12 months:

$$\Delta \log w_{it} \quad = \quad \beta * \mathbf{1}_{a<40} * \ln \text{fluidity}_c \; + \; \alpha * \text{JJ}_{it} \; + \; \xi_{cy} \; + \; \xi_{ay} \; + \; \xi_{ey} \; + \; \xi_{gy} \; + \; \xi_{oy} \; + \; \varepsilon_{it}. \qquad (2)$$

Equation (2) relates the excess wage growth of young workers relative to older workers within a country to aggregate labor market fluidity.

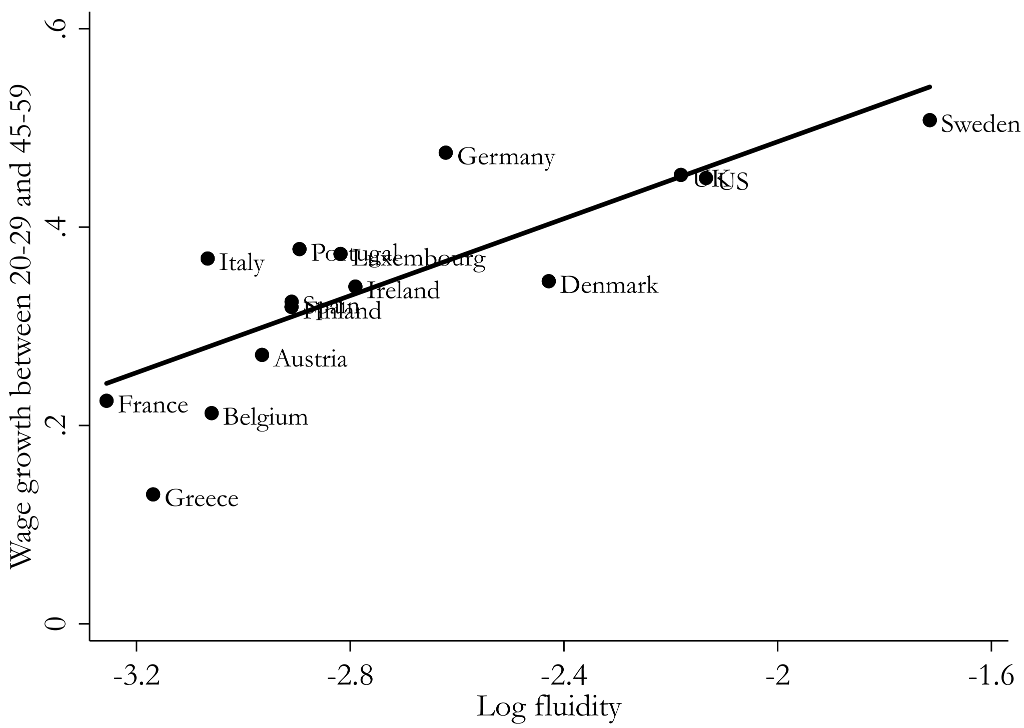
Table 2 summarizes the results. Consistent with Figure 1, young workers experience faster wage growth in more fluid countries: the baseline coefficient is 0.012, so a one-percentage-point higher poaching rate is associated with 1.2 log point more annual wage growth for workers aged 20–39 relative to older workers. Job-to-job transitions themselves are associated with sizable wage gains of 3.7 log points. However, adding the transition indicator reduces the fluidity coefficient only from 0.012 to 0.010. Thus, direct gains at the moment of a job change explain only a small part of the cross-country relationship. Put differently, wages also grow more within employment spells in more fluid labor markets.

Wage growth of hires from nonemployment. In many bargaining models of the labor market—including the theory in the next section—changes in the arrival rate of outside offers also affect wage growth on the job. Workers can use outside offers to renegotiate wages with their current employer, so a more fluid labor market may raise wages even for workers who ultimately stay put.

Could this bargaining channel account for the steeper wage growth in more fluid labor markets?

These model imply that job loss resets a worker's bargaining position. Consequently, if accumulated bargaining rents were the main mechanism, one would expect a substantially weaker relationship between life-cycle wage growth and fluidity among hires from nonemployment. Figure 2 plots wage growth among hires from nonemployment, defined as workers who were nonemployed at some point in the past 12 months, against labor market fluidity. The relationship with fluidity is slightly weaker, but remains clearly positive. This evidence suggests that the relevant mechanism is not only the renegotiation of wages with incumbent employers.

Figure 2: Life-Cycle Wage Growth and Labor Market Fluidity, Hires from Nonemployment



Notes: Wage growth is the estimated increase in log hourly wages between ages 20–29 and 50–59 after removing individual and country-year fixed effects as in (1). The sample is restricted to workers who were nonemployed at some point in the past 12 months. Labor market fluidity is the annual poaching rate. *Source:* ECHP 1993–2001; EU-SILC 2003–2024; PSID 1993–2023.

2.5 Young Workers Sort Toward Larger, Training-Intensive Firms

Why then do wages grow more on the job in more fluid labor markets? A recent literature emphasizes heterogeneity across firms in their *learning environments* (Gregory, 2026): some firms allow workers to accumulate skills more rapidly than others. If young workers in more fluid labor markets are more likely to match with such firms, this allocation channel can help explain the steeper life-cycle wage growth in those countries.

Table 3: Wage Growth at Large and Training Firms

	(1)	(2)	(3)	(4)
	Large		Training	
	20-39	40-59	20-39	40-59
Estimate	0.024***	0.002	0.016***	-0.001
	(0.005)	(0.004)	(0.005)	(0.005)
Observations	239,523	344,958	91,265	78,831
Years	24	24	7	7
Countries	14	14	12	12

Wage growth at large/training firms. I regress wage growth on an indicator for whether the respondent works at a large firm (50+ employees) or a firm that offers on-the-job training, separately for young workers (age 20–39) and older workers (40–59). The latter measure is only available in the 1993–2001 ECHP. I control for individual fixed effects and country-year fixed effects

$$\Delta \log w_{it} \;=\; \beta * \text{large/training}_{it} \;+\; \xi_i \;+\; \xi_{cy} \;+\; \varepsilon_{it}. \tag{3}$$

Table 3 shows that young workers experience faster wage growth while working at large firms or at firms that offer training. Because the specification includes individual fixed effects, the estimates compare wage growth for the same worker across different firm environments. For workers aged 20–39, wage growth is 2.4 log points higher at large firms and 1.6 log points higher at training firms. Older workers, by contrast, experience little differential wage growth across large versus small firms or training versus non-training firms.

Dynamic effects. One concern is that these wage gains reflect a temporary boost to wages. To study the dynamics of wages around the time of a training event, I borrow from the literature on job displacement to relate wages up to two years prior to the worker being at a large/training firm to up to two years after the event, controlling for subsequent and earlier training events, country-year fixed effects, and individual fixed effects

$$w_{it} \;=\; \xi_i + \sum_{\tau=-2}^{2} \beta_\tau \times \text{large/train}_{it-\tau} + \alpha_{cy} + \varepsilon_{it}. \tag{4}$$

I also allow the post-even coefficients to be different for those who remain with the same firm as at the time of the training event, and those who subsequently are at a new firm

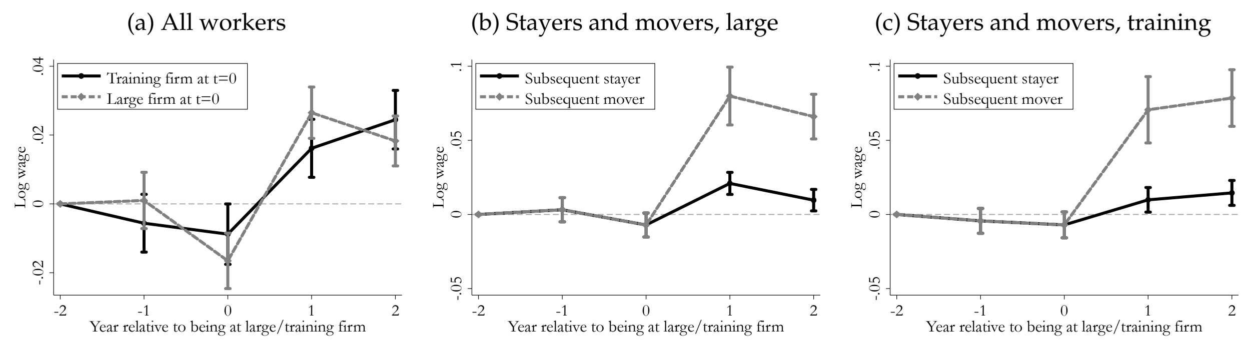
$$w_{it} \;=\; \xi_i + \sum_{\tau=-2}^{0} \beta_\tau \times \text{large/train}_{it-\tau} \tag{5}$$

$$+ \quad \sum_{\tau=1}^{2} \left(\beta_\tau^{\text{mover}} + \beta_\tau^{\text{stayer}} + \left(\beta_\tau^{\text{mover}} + \beta_\tau^{\text{stayer}} \right) \times \text{large/train}_{it-\tau} \right) + \alpha_{cy} + \varepsilon_{it}.$$

Figure 3a reports the results from (4) using either whether the worker works for either a large or a training firm at time $t = 0$, controlling for the size/training status in adjacent years. In the first year after working at a large/training firm, wages are higher and remains to in the subsequent year. The evidence that wages rise after working at a large firms is consistent with findings in Arellano-Bover (2024) that young workers who start at a large firm do better later in their careers.

Panel (b) decomposes the effects of being at a large firm at time $t = 0$ on those who subsequently switch employer and those who stay based on (5), and panel (c) does the same for those at a training firm at time $t = 0$. Although both stayers and movers experience wage gains after a training event, the results are stronger among those who subsequently switch employer. The estimation of the structural model in the next section explicitly targets these wage gains from being at a training firm to identify dispersion in learning environment.

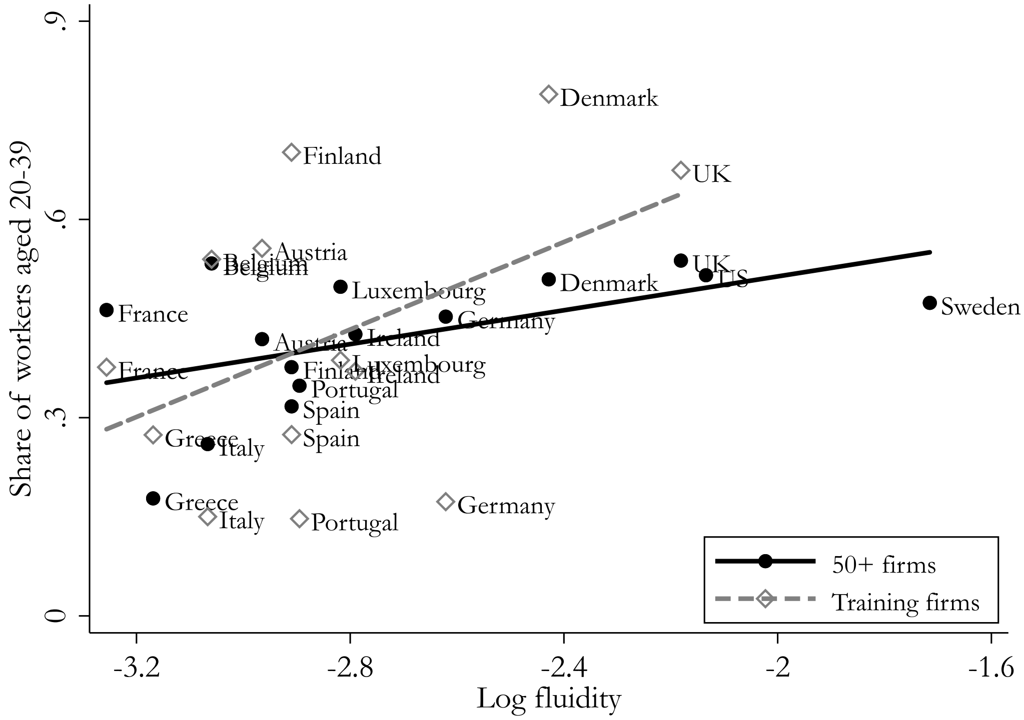
Figure 3: The Dynamics of Wages around a Training Event



The allocation of workers to large/training firms. I next ask whether the allocation of workers across firm types differs across countries. Figure 4 shows that young workers in more fluid labor markets are more likely to work at large firms and at firms that offer training. Combining this sorting pattern with the wage-growth results in Table 3 gives the central empirical message of the section: high-fluidity countries do not simply have more job changes, they also allocate young workers toward firms that generate faster subsequent wage growth. The evidence is consistent with two related mechanisms: greater fluidity may make it easier for young workers to locate firms where they can accumulate skills, and greater fluidity may increase young workers' willingness to trade off current pay for future wage growth.

Taken together, the three facts point to a dynamic allocation channel. More fluid labor markets are associated with steeper life-cycle wage profiles; this association remains after controlling for direct wage gains from job-to-job transitions; and young workers in more fluid countries are more likely to work at firms where young workers' wages grow faster. The model below is designed to

Figure 4: Employment Shares at Large and Training Firms and Labor Market Fluidity



Notes: Large firms have 50 or more employees. Training firms are employers that offer on-the-job training; the training measure is available in the ECHP. Employment shares are computed for workers aged 20–39. Labor market fluidity is the annual poaching rate. *Source:* ECHP 1993–2001; EU-SILC 2003–2024; PSID 1993–2023.

quantify this channel by allowing mobility, firm heterogeneity, and human-capital accumulation to interact over the life cycle.

3 Model

This section develops a stationary search model in which firms differ both in productivity and in the learning opportunities they provide. The model links aggregate labor-market fluidity to the types of jobs workers accept early in their careers and, through those choices, to subsequent human-capital accumulation and wages. Apart from the different focus, a key difference to Gregory (2026) is that the model is set in general equilibrium.

3.1 Environment

The economy is populated by a unit mass of workers and a mass M of firms.

Demographics. Workers enter the economy at age $a = 0$ as unemployed with normalized human capital $h = 0$. Age is continuous. Workers age deterministically at unit speed until retirement at age A, at which point they receive zero continuation value and are replaced by new entrants. The stationary age distribution is therefore uniform on $[0, A]$ with density $1/A$.

Preferences. Workers and firms are risk neutral and value a unique final good discounted at rate ρ. An unemployed worker of age a with human capital h receives the consumption-equivalent flow value $e^{b(a)+h}$.

Technology. Firms differ along two permanent dimensions: productivity z and learning environment x. Let $\Gamma(z, x)$ denote the cumulative distribution function (CDF) of firm types and $\gamma(z, x)$ its probability density function (PDF).

A worker who has human capital h and who is employed in a firm with productivity z produces a flow of the homogeneous final good

$$y = e^{z+h}.$$

Following Bagger et al. (2014), I assume that human capital is general, in the sense that it can used across all firms. Gregory (2026) allow also for firm-specific human capital in her rich partial equilibrium estimation exercise, finding that 94 percent of accumulated skills on-the-job is general. To facilitate my general equilibrium estimation exercise, I abstract from firm-specific human capital.

While employed at a firm with learning environment x, a worker of age a accumulates human capital according to

$$dh = \psi(a)x\,dt.$$

Human capital does not depreciate and remains fixed during unemployment.

Worker search. The labor market is frictional. Unemployed workers search randomly with age-specific intensity $\phi^u(a)$, normalized so that $A^{-1}\int_0^A \phi^u(a)da = 1$. Consequently, the arrival rate of offers for an unemployed worker of age a is $\phi^u(a)p$, where p is the equilibrium job-finding rate per unit of search intensity. Unemployed workers optimally decide whether to accept the offer.

Employed workers also search randomly for better jobs, generating outside offers at rate $(\phi^e + \phi^f)\phi^u(a)p$. With relative efficiency $\phi^e \geq 0$, employed workers generate *directed* outside offers—outside offers that they accept only if it offers a higher value than their current job. With relative intensity ϕ^f, employed workers generate *undirected* outside offers—outside offers that they accept regardless of the value they offer. The case $\phi^f = 0$ can generate job-to-job wage cuts, for example when a worker moves to a better learning environment at a less productive firm, but this channel alone is too weak to match the large share of job-to-job moves with wage cuts in the data. Allowing $\phi^f > 0$ gives the model an additional source of such transitions. One microfoundation for such offers is that workers anticipate a pending job loss, and engage in precautionary job search.

Finally, at rate $\delta(a)$, the worker separates to unemployment. Workers may also quit to unemployment whenever doing so is optimal.

Firm job creation. A firm of type (z, x) posts $v(z, x)$ vacancies subject to a convex cost

$$\frac{cv(z,x)^{1+\eta}}{1+\eta}$$

Conditional on meeting a firm, a worker draws a type from the vacancy-weighted PDF

$$f(z,x) \quad = \quad \frac{M}{V} v(z,x)\gamma(z,x) \tag{6}$$

Let F denote the CDF induced by f.

Matching. Let U denote the aggregate search effort supplied by unemployed workers

$$U \quad = \quad \int_0^A \phi^u(a) \int u(a,h)\, dh\, da, \tag{7}$$

where $u(a, h)$ is the measure of unemployed workers of age a with human capital h. Let $m(a, h)$ be the number of workers with age a and human capital h. Aggregate search intensity is

$$S \quad = \quad \int_0^A \phi^u(a) \int u(a,h) + (\phi^f + \phi^e)\big(m(a,h) - u(a,h)\big)\, dh\, da \quad = \quad U + (\phi^f + \phi^e)(1-U). \tag{8}$$

Aggregate vacancies are the sum of jobs created across firms

$$V \quad = \quad M \int v(z,x)\, d\Gamma(z,x). \tag{9}$$

The job-finding rate for workers p and the worker-finding rate for vacancies q follow from a standard Cobb-Douglas matching function

$$p \quad = \quad \chi \left(\frac{V}{S}\right)^{\alpha} \qquad \text{and} \qquad q \quad = \quad \chi \left(\frac{V}{S}\right)^{\alpha-1}. \tag{10}$$

Bargaining. Wages are determined through the bargaining protocol of Cahuc, Postel-Vinay and Robin (2006), with worker bargaining weight $\beta \in [0, 1]$ and with pay delivered through a piece rate w of output, we^{z+h}. When a worker is hired from unemployment, or when an undirected outside offer leads to a new acceptable job, the bargaining benchmark is unemployment.

When an employed worker receives a directed outside offer, the bargaining benchmark is the firm that loses the worker. If the poaching firm has the higher joint match value, the worker moves and the incumbent firm becomes the benchmark. If the incumbent firm has the higher joint match value but the outside offer can credibly improve the worker's current payoff, the worker stays and the poaching firm becomes the benchmark. Finally, if the worker can credibly threaten to quit the job under the current contract, the firm may make the worker a take-leave offer to stay.[3]

3.2 Value Functions, Piece Rates, and Match Surplus

Because human capital enters all flow payoffs multiplicatively through e^h and the law of motion $dh = \psi(a)x\,dt$ is independent of the level of h, all values are homogeneous of degree one in e^h. I therefore write the value of unemployment as $e^h W(a)$, the value of employment to the worker as $e^h V^w(a,z,x,w)$, and the value of the current match to the incumbent firm as $e^h V^f(a,z,x,w)$. All value functions have terminal value zero at retirement. Let

$$\lambda(a) \quad \equiv \quad \delta(a) + \phi^f \phi^u(a) p$$

denote the rate at which the incumbent match is destroyed by either an exogenous separation or an undirected outside offer.

Joint match value and acceptance sets. For any wage in the interior of the contract set defined below, the joint match value is the sum of the worker and incumbent-firm values,

$$J(a,z,x) \quad = \quad V^w(a,z,x,w) + V^f(a,z,x,w). \tag{11}$$

The joint value does not depend on the current piece rate because the piece rate only divides the value of a continuing match. The set of offers that are acceptable from unemployment is

$$\mathcal{A}(a) \quad = \quad \{(z,x) : J(a,z,x) > W(a)\}\,, \tag{12}$$

Meanwhile the separation region is

$$\mathcal{S}(a) \quad = \quad \{(z,x) : J(a,z,x) \leq W(a)\}\,, \tag{13}$$

[3]Because pay is a piece rate of output that never exceeds one, the firm always earns nonnegative flow profits at the current wage. It therefore has no credible threat to lay off the worker.

The set of outside offers that induce a voluntary job-to-job transition from a current match (z, x) is

$$\mathcal{M}(a,z,x) \quad = \quad \{(\tilde{z},\tilde{x}) : J(a,\tilde{z},\tilde{x}) > J(a,z,x)\}\,. \tag{14}$$

Piece-rate policies. The piece rate a hire from unemployment receives is given by

$$V^w\big(a,z,x,w^U(a,z,x)\big) \quad = \quad W(a) + \beta\big(J(a,z,x) - W(a)\big). \tag{15}$$

The pay of a worker employed in firm (z, x) with renegotiation benchmark $(\tilde{z}, \tilde{x})$, $J(a,z,x) \geq J(a,\tilde{z},\tilde{x})$, satisfies

$$V^w\big(a,z,x,w^p(a,z,x,\tilde{z},\tilde{x})\big) \quad = \quad J(a,\tilde{z},\tilde{x}) + \beta\big(J(a,z,x) - J(a,\tilde{z},\tilde{x})\big). \tag{16}$$

If an incumbent worker would quit to unemployment at the current piece rate while the match still generates positive surplus, the incumbent firm makes a take-it-or-leave-it offer. Let $w^Q(a,z,x)$ denote the lowest piece rate that keeps the worker in the match. It satisfies

$$V^w\big(a,z,x,w^Q(a,z,x)\big) \quad = \quad W(a). \tag{17}$$

Renegotiation sets and the interior wage region. Define the unemployment-threat renegotiation set as the set of employment states at which the worker would prefer weakly to leave for unemployment under the existing wage contract

$$\mathcal{R}(a) \quad = \quad \{(z,x,w) : (z,x) \in \mathcal{A}(a),\ w \leq 1,\ V^w(a,z,x,w) \leq W(a)\}\,. \tag{18}$$

The Bellman equations for V^w and V^f are imposed on the no-renegotiation interior of the employment state space

$$\mathcal{C}(a) \quad = \quad \{(z,x,w) : (z,x) \in \mathcal{A}(a),\ w \leq 1,\ V^w(a,z,x,w) > W(a)\}\,. \tag{19}$$

Directed outside offers that do not dominate the current match can nevertheless be useful for wage renegotiation. Given a current interior employment state $(z,x,w) \in \mathcal{C}(a)$, define

$$\begin{aligned} \mathcal{N}(a,z,x,w) \quad = \quad & \Big\{(\tilde{z},\tilde{x}) \in \mathcal{A}(a) : (\tilde{z},\tilde{x}) \notin \mathcal{M}(a,z,x), \\ & \qquad V^w\big(a,z,x,w^p(a,z,x,\tilde{z},\tilde{x})\big) > V^w(a,z,x,w)\Big\}. \end{aligned} \tag{20}$$

This is the set of outside offers that are not sufficiently attractive to induce mobility, but are sufficiently attractive to raise the worker's promised value at the incumbent firm. Offers outside $\mathcal{M}(a,z,x)$ and $\mathcal{N}(a,z,x,w)$ are discarded and the piece rate remains unchanged.

The value of unemployment. Using the unemployment-benchmark piece-rate rule (15), the value of unemployment satisfies

$$
\begin{aligned}
\rho W(a) &= e^{b(a)} + \frac{\partial W(a)}{\partial a} + \phi^u(a) p \int\limits_{(z,x)\in\mathcal{A}(a)} \left[V^w\big(a, z, x, w^U(a,z,x)\big) - W(a) \right] dF(z,x) \\
&= e^{b(a)} + \frac{\partial W(a)}{\partial a} + \phi^u(a) p \beta \int\limits_{(z,x)\in\mathcal{A}(a)} \big(J(a,z,x) - W(a) \big) \, dF(z,x), \qquad (21)
\end{aligned}
$$

with terminal condition $W(A) = 0$. Unemployed workers receive flow value $e^{b(a)}$ in the normalized economy and meet potential employers at rate $\phi^u(a)p$.

The worker's value of employment. For a worker who remains in the continuation region $(z,x,w) \in \mathcal{C}(a)$, the normalized value of employment satisfies

$$
\begin{aligned}
&\big(\rho - \psi(a)x\big) V^w(a,z,x,w) \\
&= w e^z + \frac{\partial V^w(a,z,x,w)}{\partial a} + \delta(a) \left[W(a) - V^w(a,z,x,w) \right] \\
&+ \phi^f \phi^u(a) p \int\limits_{(\tilde{z},\tilde{x})\in\mathcal{A}(a)} \left[V^w\big(a, \tilde{z}, \tilde{x}, w^U(a,\tilde{z},\tilde{x})\big) - V^w(a,z,x,w) \right] dF(\tilde{z},\tilde{x}) \\
&+ \phi^f \phi^u(a) p \int\limits_{(\tilde{z},\tilde{x})\in\mathcal{S}(a)} \left[W(a) - V^w(a,z,x,w) \right] dF(\tilde{z},\tilde{x}) \\
&+ \phi^e \phi^u(a) p \int\limits_{(\tilde{z},\tilde{x})\in\mathcal{N}(a,z,x,w)} \left[V^w\big(a, z, x, w^p(a,z,x,\tilde{z},\tilde{x})\big) - V^w(a,z,x,w) \right] dF(\tilde{z},\tilde{x}) \\
&+ \phi^e \phi^u(a) p \int\limits_{(\tilde{z},\tilde{x})\in\mathcal{M}(a,z,x)} \left[V^w\big(a, \tilde{z}, \tilde{x}, w^p(a,\tilde{z},\tilde{x},z,x)\big) - V^w(a,z,x,w) \right] dF(\tilde{z},\tilde{x}), \qquad (22)
\end{aligned}
$$

subject to $V^w(A,z,x,w) = 0$. The first line gives the current piece-rate payment and aging. Exogenous separations send the worker to unemployment. Undirected outside offers destroy the incumbent match: acceptable offers lead to a new job with the unemployment-benchmark piece rate w^U, while unacceptable offers leave the worker unemployed. Directed offers either induce renegotiation through $w^p(a,z,x,\tilde{z},\tilde{x})$, induce mobility through $w^p(a,\tilde{z},\tilde{x},z,x)$, or are discarded. If $(z,x) \notin \mathcal{A}(a)$, the worker separates to unemployment. For $(z,x,w) \in \mathcal{R}(a) \cup S(a)$, $V(a,z,x,w) = W(a)$.

The firm's value. In the continuation region $(z,x,w) \in \mathcal{C}(a)$, the firm's normalized value from employing the worker satisfies

$$
\big(\rho - \psi(a)x\big) V^f(a,z,x,w)
$$

$$
\begin{aligned}
&= (1-w)e^z + \frac{\partial V^f(a,z,x,w)}{\partial a} + \delta(a)\left[0 - V^f(a,z,x,w)\right] \\
&+ \phi^f \phi^u(a) p \left[0 - V^f(a,z,x,w)\right] \\
&+ \phi^e \phi^u(a) p \int_{(\tilde{z},\tilde{x}) \in \mathcal{M}(a,z,x)} \left[0 - V^f(a,z,x,w)\right] dF(\tilde{z},\tilde{x}) \\
&+ \phi^e \phi^u(a) p \int_{(\tilde{z},\tilde{x}) \in \mathcal{N}(a,z,x,w)} \left[V^f\left(a,z,x,w^p(a,z,x,\tilde{z},\tilde{x})\right) - V^f(a,z,x,w)\right] dF(\tilde{z},\tilde{x}), \qquad (23)
\end{aligned}
$$

subject to $V^f(A,z,x,w) = 0$. The firm receives its share of output while the match continues. It receives zero continuation value if the worker separates, if an undirected offer destroys the incumbent match, or if a directed outside offer in $\mathcal{M}(a,z,x)$ poaches the worker. Directed offers in $\mathcal{N}(a,z,x,w)$ keep the worker at the incumbent firm but change the division of the match value through the policy w^p. If $(z,x) \notin \mathcal{A}(a)$, the match dissolves, leaving the firm with zero value. If $(z,x,w) \in \mathcal{R}(a)$, $V^f(a,z,x,w) = J(a,z,x) - W(a)$.

Joint match value. Adding (22) and (23) and using the piece-rate rules gives the recursive equation for the joint match value on the continuation region $(z,x) \in \mathcal{A}(a)$

$$
\begin{aligned}
(\rho + \lambda(a) - \psi(a)x) J(a,z,x) &= e^z + \frac{\partial J(a,z,x)}{\partial a} + \lambda(a) W(a) \\
&+ \phi^f \phi^u(a) p \beta \int_{(\tilde{z},\tilde{x}) \in \mathcal{A}(a)} \left(J(a,\tilde{z},\tilde{x}) - W(a)\right) dF(\tilde{z},\tilde{x}) \\
&+ \phi^e \phi^u(a) p \beta \int_{(\tilde{z},\tilde{x}) \in \mathcal{M}(a,z,x)} \left(J(a,\tilde{z},\tilde{x}) - J(a,z,x)\right) dF(\tilde{z},\tilde{x}), \qquad (24)
\end{aligned}
$$

with terminal condition $J(A,z,x) = 0$ for all (z,x). If the joint match value falls below $W(a)$, the worker exits to unemployment. Quit-threat renegotiation through w^Q and outside-offer renegotiation through w^p do not enter (24) because they change only the division of value inside the incumbent match. Directed offers in $\mathcal{M}(a,z,x)$ do enter because the worker moves to a match with higher joint value and receives share β of the gain. For potential matches outside the continuation region, $(z,x) \notin \mathcal{A}(a)$, the effective continuation value is $W(a)$ because the worker separates to unemployment.

The reservation boundary. I fix the flow value of leisure $b(a)$ so that, for each age, workers are indifferent between unemployment and employment at a reference firm $(\underline{z}, \underline{x})$. Evaluating (24) at this reference match gives

$$
(\rho - \psi(a)\underline{x}) W(a) = e^{\underline{z}} + \frac{\partial W(a)}{\partial a} + (\phi^f + \phi^e)\phi^u(a) p \beta \int_{(z,x) \in \mathcal{A}(a)} \left(J(a,z,x) - W(a)\right) dF(z,x).
$$

Combining this condition with (21) yields

$$e^{\underline{z}} = e^{b(a)} - \psi(a)\underline{x}W(a) + p\phi^u(a)\beta(1-\phi^f-\phi^e) \int_{(z,x)\in\mathcal{A}(a)} \big(J(a,z,x) - W(a)\big)\, dF(z,x). \quad (25)$$

Equation (25) illustrates two forces behind the reservation threshold. First, lower search efficiency on the job, $\phi^e + \phi^f$, raises the reservation threshold. The reason is that it raises the forgone option value of search associated with accepting employment. Second, greater learning on the job lowers the threshold, due to the dynamic gains associated with accepting employment.

Vacancy creation. Let $R(z,x)$ denote the expected value to a type-(z,x) firm of a contact generated by one of its vacancies. The firm's first-order condition is

$$cv(z,x)^{\eta} = \underbrace{q}_{\text{worker-contact rate}} \times \underbrace{R(z,x)}_{\text{expected return to a contact}}. \quad (26)$$

A contact can be with an unemployed worker, with an employed worker who receives an undirected offer, or with an employed worker who receives a directed offer. Unemployed workers and workers hit by undirected offers bargain against unemployment. A directed on-the-job-search contact is successful only if the vacancy firm has a higher joint value than the worker's incumbent match. Using the joint value and the bargaining split, the return to contacting a worker can be written as

$$\begin{aligned} R(z,x) = \frac{1-\beta}{S} \int_0^A \phi^u(a) \int e^h \Big[& \mathbf{1}\{(z,x)\in\mathcal{A}(a)\}\big(u(a,h) + \phi^f e(a,h)\big)\big(J(a,z,x) - W(a)\big) \\ & + \phi^e \int \mathbf{1}\{(z,x)\in\mathcal{M}(a,\tilde{z},\tilde{x})\}\big(J(a,z,x) - J(a,\tilde{z},\tilde{x})\big) g(a,\tilde{z},\tilde{x},h)\, d\tilde{z}\, d\tilde{x} \Big] dh\, da, \end{aligned} \quad (27)$$

where $g(a,z,x,h)$ is the measure of employed workers of age a at firm (z,x) with human capital h.

3.3 Aggregation and Equilibrium

Define the total measure of employed workers of age a with human capital h

$$e(a,h) = \int g(a,z,x,h)\, dz\, dx,$$

and the measure of quits to unemployment generated by matches that cease to be acceptable as workers age

$$Q(a,h) \quad = \quad \lim_{\Delta a \downarrow 0} \frac{1}{\Delta a} \int_{(z,x) \notin \mathcal{A}(a+\Delta a)} g(a,z,x,h)\, dz\, dx.$$

Then the measure of unemployed satisfies the Kolmogorov Forward (KF) equation

$$0 \quad = \quad -\frac{\partial u(a,h)}{\partial a} + \Big(\delta(a) + \phi^f \phi^u(a) p F(\mathcal{S}(a))\Big)\, e(a,h) - p\phi^u(a) F(\mathcal{A}(a)) u(a,h) + Q(a,h) \tag{28}$$

with boundary condition

$$u(0,h) \quad = \quad A^{-1}\Psi_0(h),$$

where Ψ_0 is degenerate at the normalized entrant human-capital level $h = 0$. The inflow to unemployment consists of exogenous separations, unacceptable undirected offers in $\mathcal{S}(a)$, and deterministic exits from matches that fall out of the continuation region.

In the continuation region, $(z,x) \in \mathcal{A}(a)$, the measure of employed workers satisfies

$$\begin{aligned} 0 \quad = & \quad -\frac{\partial g(a,z,x,h)}{\partial a} - \frac{\partial}{\partial h}\left(\psi(a) x g(a,z,x,h)\right) \\ & - \quad g(a,z,x,h)\left(\lambda(a) + \phi^e \phi^u(a) p F(\mathcal{M}(a,z,x))\right) \\ & + \quad f(z,x) p \phi^u(a) \left[u(a,h) + \phi^f e(a,h) + \phi^e \int_{\mathcal{A}(a)} \mathbf{1}\{(z,x) \in \mathcal{M}(a,\tilde{z},\tilde{x})\} g(a,\tilde{z},\tilde{x},h)\, d\tilde{z}\, d\tilde{x} \right] \end{aligned} \tag{29}$$

with boundary condition

$$g(0,z,x,h) \quad = \quad 0.$$

The outflow term includes exogenous separations, all undirected offers, and directed offers that move the worker to a higher-value match. The inflow term includes hires from unemployment, hires generated by acceptable undirected offers, and directed job-to-job moves from lower-value incumbent matches. The flux of employed mass that reaches the boundary $\mathcal{A}(a)$ is transferred to unemployment through $Q(a,h)$.

Definition 3.1 (Equilibrium)**.** A stationary equilibrium consists of normalized value functions $W(a)$, $V^w(a,z,x,w)$, $V^f(a,z,x,w)$, and $J(a,z,x)$ for $a \in [0,A]$; acceptance, separation, mobility, outside-offer renegotiation, unemployment-threat renegotiation, and continuation sets $\mathcal{A}(a)$, $\mathcal{S}(a)$, $\mathcal{M}(a,z,x)$, $\mathcal{N}(a,z,x,w)$, $\mathcal{R}(a)$, and $\mathcal{C}(a)$; wage policies $w^U(a,z,x)$, $w^Q(a,z,x)$, and $w^p(a,z,x,\tilde{z},\tilde{x})$; a vacancy policy $v(z,x)$; a job-finding rate p and worker-finding rate q; aggregate search intensity S; aggregate vacancies V; an offer distribution $f(z,x)$; and stationary distributions $u(a,h)$ and $g(a,z,x,h)$ such that:

1. Given the job-finding rate and offer distribution, the unemployment value solves (21), the worker value solves (22), the firm value solves (23), and the joint match value satisfies (11) and (24);
2. Given the value functions, the acceptance, separation, mobility, outside-offer renegotiation, unemployment-threat renegotiation, and continuation sets are given by (12), (13), (14), (20), (18), and (19);
3. Given the value functions and bargaining protocol, the wage policies satisfy (15)–(17);
4. Given the value functions, the number of workers, and the worker-finding rate, firms' vacancy policy is given by (26);
5. Given acceptance and mobility policies, the offer distribution, and the job-finding rate, the distribution of workers solve (28)–(29) and aggregate search intensity is given by (8);
6. Given firms' vacancy policies, the offer distribution follows from (6), and aggregate vacancies from (9);
7. Given aggregate search intensity and aggregate vacancies, the job-finding and worker-finding rates follow from (10).

3.4 Fluidity and Human Capital Accumulation

My quantitative analysis varies the vacancy-posting cost c to study how labor-market fluidity affects life-cycle outcomes. An increase in c lowers firms' incentive to post vacancies and reduces the equilibrium job-finding rate p. Before turning to the quantitative exercises, I illustrate the partial-equilibrium effect of a lower p on the jobs accepted by unemployed workers. To simplify, suppose $A \to \infty$ and $\psi(a) = \psi$ and $\phi^u(a) = 1$ for all a, so that the value functions and policies do not depend on age.

Let $\overline{z}(x)$ be the minimum productivity required for a job with learning environment x to be acceptable. A worker is indifferent between unemployment and the job $(\overline{z}(x), x)$ when $J(\overline{z}(x), x) = W$. Evaluating the decentralized match-value equation at this boundary gives

$$(\rho - \psi x)W \quad = \quad e^{\overline{z}(x)} + \beta(\phi^f + \phi^e)p \int_{(\tilde{z},\tilde{x})\in\mathcal{A}} \left(J(\tilde{z}, \tilde{x}) - W\right) dF(\tilde{z}, \tilde{x}).$$

Using (21) and (25), we get the following expression for the indifference curve

$$\overline{z}(x) \quad = \quad \log(e^{\underline{z}} - \psi W(x - \underline{x}))\,.$$

Differentiating this with respect to x,

$$\overline{z}'(x) \quad = \quad -\frac{\psi W}{e^{\underline{z}} - \psi W(x - \underline{x})} \quad = \quad -\frac{\psi W}{e^{\overline{z}(x)}} \quad < \quad 0.$$

Thus the indifference curve is downward sloping. Holding fixed the total separation rate $\lambda = \delta + \phi^f p$, the derivative with respect to the job-finding rate is

$$\left.\frac{\partial \overline{z}'(x)}{\partial p}\right|_{\lambda=\delta+\phi^f p \text{ fixed}} \quad = \quad -\frac{\psi e^{\underline{z}}}{\left(e^{\underline{z}} - \psi W(x - \underline{x})\right)^2} \left.\frac{\partial W}{\partial p}\right|_{\lambda=\delta+\phi^f p \text{ fixed}}.$$

The value of unemployment W is increasing in p. Workers can never be made worse off from receiving more offers, since they can always discard additional offers. Using a version of this logic, it is easy to show that they are strictly better off as long as some of the additional offers are accepted. Thus, a higher p steepens the indifference curve: for a given deterioration in the learning environment, workers require larger productivity compensation in a more fluid economy. The intuition is that workers in fluid labor markets expect to be less mismatched in the future, which raises the value of human capital and makes high-learning jobs more attractive.

3.5 Efficiency of the Tradeoff Between Productivity and Learning Environment

Next, I briefly illustrate an inherent inefficiency in human capital accumulation. To that end, consider a planner who chooses only workers' acceptance, quitting, and mobility decisions, taking vacancy creation as given. Piece rates and renegotiation policies do not enter the planner problem because they only divide the value of a continuing match. Let $W^P(a)$ denote the planner's normalized value of an unemployed worker and let $J^P(a,z,x)$ denote the planner's normalized value of assigning a worker of age a to a firm of type (z,x). The planner's acceptance and mobility sets are

$$\mathcal{A}^P(a) \quad = \quad \{(z,x) : J^P(a,z,x) > W^P(a)\},$$

and

$$\mathcal{M}^P(a,z,x) \quad = \quad \{(\tilde{z},\tilde{x}) : J^P(a,\tilde{z},\tilde{x}) > J^P(a,z,x)\}.$$

The planner's unemployment value solves

$$\rho W^P(a) \quad = \quad e^{b(a)} + \frac{\partial W^P(a)}{\partial a} + \phi^u(a) p \int_{\mathcal{A}^P(a)} \left(J^P(a,z,x) - W^P(a)\right) dF(z,x).$$

The planner's match value solves

$$\begin{aligned}\big(\rho+\lambda(a)-\psi(a)x\big)J^P(a,z,x) &= e^z+\frac{\partial J^P(a,z,x)}{\partial a}+\lambda(a)W^P(a)\\ &+ \phi^f\phi^u(a)p\int_{\mathcal{A}^P(a)}\big(J^P(a,\tilde z,\tilde x)-W^P(a)\big)\,dF(\tilde z,\tilde x)\\ &+ \phi^e\phi^u(a)p\int_{\mathcal{M}^P(a,z,x)}\big(J^P(a,\tilde z,\tilde x)-J^P(a,z,x)\big)\,dF(\tilde z,\tilde x).\end{aligned}$$

These equations differ from the decentralized equations only in the coefficient on the gains from future offers. In the decentralized economy, those gains enter with weight β, because after a worker moves, the future employer captures share $1-\beta$ of the future match surplus. The incumbent worker-firm pair therefore does not internalize the full social value of the worker's future matches. The planner instead attaches weight one to those gains. Jarosch (2023) highlights a similar insight in the context of jobs that vary in their security.

This wedge has direct implications for the tradeoff between firm productivity and learning. Productivity z raises output only while the worker remains at the current firm. Learning environment x raises human capital, which is portable and affects output in all future matches. Since part of the return to portable human capital is captured by future employers, the decentralized allocation undervalues x relative to z.

Let $\bar z^D(a,x)$ and $\bar z^P(a,x)$ denote the decentralized and planner acceptance frontiers. Locally,

$$\frac{\partial \bar z^k(a,x)}{\partial x} = -\frac{J_x^k(a,\bar z^k(a,x),x)}{J_z^k(a,\bar z^k(a,x),x)}, \qquad k\in\{D,P\}.$$

Because the planner internalizes the full future return to portable human capital, while the decentralized worker-incumbent pair internalizes only the worker's share of future match surplus, the planner is willing to give up more current productivity in exchange for a better learning environment. Thus, under the usual monotonicity conditions,

$$\left|\frac{\partial \bar z^P(a,x)}{\partial x}\right| > \left|\frac{\partial \bar z^D(a,x)}{\partial x}\right|.$$

Equivalently, the decentralized economy accepts too few high-learning, low-productivity jobs and too many low-learning, high-productivity jobs relative to the planner.

4 Calibration

This section calibrates the model to a hypothetical average-fluidity benchmark economy. The calibration proceeds in two steps. I first set or normalize parameters that are standard or directly pinned down by individual moments. I then estimate the remaining parameters by matching moments that discipline job mobility, wage growth, firm size, and worker sorting.

4.1 Calibration Strategy

I proxy the continuous time model for age with four 10-year bins: 20–30, 30–40, 40–50 and 50–60.

Externally set and normalized parameters. Panel A of Table 5 reports the parameters set outside the internal calibration. These include a monthly discount rate $\rho = 0.003$, corresponding to an annual real interest rate of approximately four percent, worker bargaining power $\beta = 0.5$, and matching-function elasticity $\alpha = 0.5$. To simplify the estimation, I also fix three objects that map closely into individual moments.

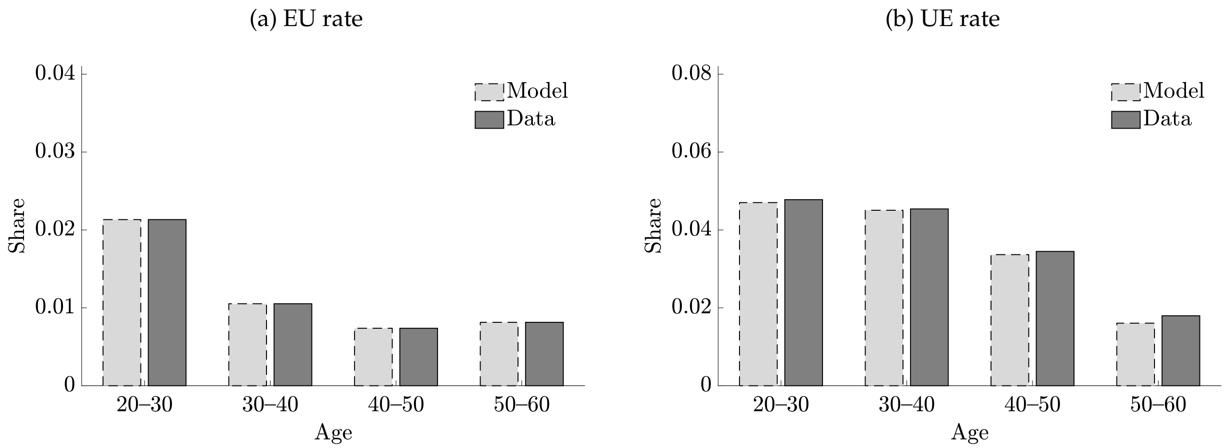
First, the worker-level data identify employment shares in broad firm-size bins but do not identify average firm size. Comparable cross-country data on average firm size are also limited. Moreover, in the quantitative exercises below, M mainly scales the economy and has little effect on the relative changes of interest. I hence set the mass of firms per worker to $M = 0.05$, which given an employment rate of about 75 percent in the average-fluidity country for workers aged 20–59, implies an average firm size of 15 employees.

Second, I set the exogenous separation hazards $\delta(a)$ to match employment-to-unemployment (EU) rates by age. The model also generates a small number of endogenous separations when workers age into the separation region, but these separations are negligible in the calibrated economy. Consequently, the model fits closely the empirical EU rate by age in Figure 5a.

Third, I set the unemployment job-arrival rates $\phi^u(a)p$ to match unemployment-to-employment (UE) rates by age. Age variation in workers' reservation thresholds implies that not all posted jobs are accepted in equilibrium, but the share of rejected offers is modest in the calibrated economy. Moreover, as for the number of firms, $\phi^u(a)p$ mostly affect the scale of the employment pool, with second-order effects on the relative changes I consider below. Let UE_a denote the UE rate for age group a. Under the normalization $A^{-1}\int \phi^u(a)da = 1$, the average job-finding rate is $p = A^{-1}\sum_a UE(a)$, and the age-specific search efficiencies are $\phi^u(a) = UE(a)/p$. Given p and $[\phi^u(a)]_{a=1}^{A}$, I solve for $J(z,x,a)$, $W(a)$, $\mathcal{A}(a)$, $\mathcal{M}(z,x,a)$, $u(h,a)$, $g(z,x,h,a)$, and $f(z,x)$. Ex post, I recover the scalar vacancy-cost parameter c so that p is consistent with equilibrium. Without vacancy data, the matching efficiency χ and the vacancy-cost scale c are not separately identified, so I normalize $\chi = 1$. Because most jobs are accepted, the model matches well the UE rate by age in Figure 5b.

Internally calibrated parameters. I estimate eight parameters of the model internally in a joint estimation to minimize a weighted sum of squared deviations between 42 model and data moments. Since the targeted moments are either rates or log differences, the objective is comparable across moments. Panel B of Table 5 reports estimated parameter values. Although the parameters

Figure 5: EU and UE Rates



are estimated jointly, the discussion below highlights the empirical variation that most directly disciplines each parameter.

On-the-job search efficiency for higher-paying jobs, ϕ^e, is disciplined by the job-to-job (JJ) mobility rate. To mirror the empirical measure, the model JJ rate is the share of currently employed workers who started a new job in the previous 12 months without experiencing unemployment during that period. I construct the measure by recording employment status at monthly intervals and classifying workers as employed or unemployed at each observation. Because the age distribution in the model differs from that in the data, I compute the rate within age bins 20–29, 30–39, 40–49, and 50–59 in both the model and the data, and then aggregate by weighting each age group equally. This moment receives a total weight of five.

Forced-reallocation search efficiency, ϕ^f, is disciplined by two sets of moments. First, I target JJ mobility by ages 20–29, 30–39, 40–49, and 50–59. If most job-to-job mobility takes the voluntary form, JJ falls more with age, since older workers tend to be better matched. If on other hand all mobility is involuntary, job-to-job mobility falls little with age (it still declines through the falling $\phi^u(a)$). These moments receive an aggregate weight of five.

Second, I target wage growth of JJ movers relative to stayers. To construct the corresponding model moment, I condition on workers employed in month 17, paralleling the timing of the survey, which is typically fielded in May. A JJ mover is a worker who changes employer at some point between months 6 and 17 while remaining employed in every month over that interval; a stayer is someone who remained with their employer throughout the past 12 months. I compute total income and total months worked separately in months 1–12 and 13–24, and define wages as income per month worked. I compute the average wage in year t and year $t-1$ (in levels) of JJ movers and stayers at the age group level, compute the log difference in wages within age group-mobility cells, and difference movers to stayers within age groups. I target this moment for workers aged 20-29, 30-39, 40-49 and 50-59. Combined, these moments receive an aggregate weight of 10.

The underlying distribution of firm productivity z and learning environment x is jointly normal. Although I cannot test this assumption, I target the distribution of within-individual residual wages of workers age 20-29, which the model matches well.[4] Since the overall productivity scale is indeterminate, I normalize mean productivity to $\mu_z = 0$. I estimate the dispersion of productivity, σ_z; the mean learning environment, μ_x; the dispersion of learning environments, σ_x; and the correlation between productivity and the learning environment, ϱ_{zx}.

I discipline μ_x using wages at age 50–59 relative to age 20–29 with a weight of one.

The dispersion of learning environments, σ_x, is disciplined by wage growth at training relative to non-training firms. I define training firms as the employment-weighted top 41 percent of firms ranked by x, matching the employment share at training firms in the data. As above, the employer is recorded in month 17 in the model. I condition on workers who have remained with the same employer for at least the past 12 months and who are aged 20-39. I compute average wages between months 1–12 and 13–24, compute the mean (in levels) at the age group level, take the log difference, and aggregate across age groups using equal weights, applying the same procedure in the data and the model. This moment receives total weight of 10.

The dispersion of productivity, σ_z, is disciplined by pay across the firm size bins in bins 1-4, 5-19, 20-49 and 50+, as well as the wage distribution among workers age 20–29. To mimic the data, I record firm size in month 17 and define the wage as total income in months 1–12 divided by total months worked in months 1–12. I compute average wages by firm-size category and age group, take logs, difference large relative to small firms, and aggregate across age groups using equal weights, applying the same procedure in the data and the model. To construct the residual wage distribution, I take out individual fixed effects in the data. Each of these moments receives an aggregate weight of one.

The curvature of the vacancy cost, η, governs how costly it is for firms to grow large. I set η to match the employment share at firms with at least 50 employees, separately by age groups 20–29, 30–39, 40–49, and 50–59, weighing these moments to receive an aggregate weight of one.

The correlation between productivity and learning environment, ϱ_{zx}, is disciplined by the share of training firms within firm-size categories 1–4, 5–19, 20–49, and 50 or more employees. A higher ϱ_{zx} implies a higher training share among large, high-productivity firms. As with the other moments, I compute training shares first by firm-size category and age group, and then aggregate to the firm-size level by weighting all age groups equally in both the model and the data. These moments receive a total weight of one.

[4] Since the model abstracts from permanent worker heterogeneity in learning ability, I target only the wage distribution among young workers.

Table 4: Elasticity of Moments to Parameters

Moment	ϕ^e	ϕ^f	μ_x	σ_x	σ_z	η	ϱ_{zx}	ψ
JJ mobility rate	**0.14**	0.74	-0.01	-0.03	0.03	-0.05	-0.00	0.00
Wage growth of JJ movers to stayers	0.39	**-1.06**	0.05	0.57	1.66	-0.10	-0.03	0.04
Life-cycle wage growth	0.09	0.05	**0.82**	0.52	0.24	-0.01	0.02	-0.49
Δw at training to non-training firms	0.08	0.12	-0.06	**0.96**	-0.02	0.03	-0.02	-0.27
Wage at 50+ firms relative to 1–4 firms	0.08	-0.07	-0.31	-0.35	**5.96**	4.60	-0.02	4.64
Employment share of 50+ firms	0.08	-0.05	-0.01	-0.04	1.72	**-0.61**	0.03	1.78
Training share at 50+ relative to 1-4 firms	-0.05	0.05	1.23	0.87	-5.80	-0.79	**0.05**	-5.94
$(w_{30-40} - w_{20-30}) / (w_{40-50} - w_{30-40})$	0.10	0.09	0.05	-0.15	-1.10	0.07	-0.00	**0.19**

Note: To compute wage at training to non-training firms, curvature, I first compute the difference in wage growth at training to non-training firms of workers age 20–29 relative to workers age 30–39, and the difference in wage growth at training to non-training firms of workers age 30–39 to 40–49. Subsequently, I difference these two differences to obtain a measure of the convexity of the profile.

I assume that age-specific learning ability takes the form

$$\psi(a) = \mu \left(\frac{A-a}{A-1} \right)^{\psi}.$$

Thus, $\psi(1) = \mu$ and $\psi(A) = 0$, with μ governing average learning ability and ψ governing the speed at which learning ability declines with age. Because mean learning ability is not separately identified from the mean learning environment, I normalize $\mu = 1$. The curvature parameter ψ is disciplined by three sets of moments. First, I target annual wage growth at training firms by age groups 20–29, 30–39 and 40–49. A high value of ψ implies that the human-capital gain from working at training firms declines sharply with age, and therefore that the wage-growth premium from such firms also declines sharply with age. These moments receive an aggregate weight of five.

Second, I include wages at ages 30–39, 40–49, and 50–59 relative to ages 20–29. A high value of ψ generates rapid human-capital accumulation early in the life cycle and slower accumulation later, producing a more concave wage profile. These moments receive an aggregate weight of one.

Third, I add the share of hires from unemployment at training firms by age. If ψ is high, the value of being at a training firm falls quickly with age, so that older unemployed workers are less likely to accept a job at a high training firm relative to their younger peers. These moments receive an aggregate weight of one.

Table 4 summarizes the identification logic by displaying the elasticity of some of these moments to the estimated parameters, with the particularly informative moment in bold. The parameters move the designated moments in the expected direction, although identification is clearly joint in the sense that some parameters move multiple moments strongly. The minimum distance also displays multiple local minima, but starting from a wide range of random points, many converge to the global minimum.

Conditional on the calibrated parameter vector, I infer the flow value of leisure $b(a)$ at each age so that workers are indifferent between unemployment and a $(\underline{z}, \underline{x})$ match, where I set $\underline{z} = 0$ and $\underline{x} = \mu_x$. Panel C of Table 5 reports the implied values of c and $b(a)$.

4.2 Parameter Estimates and Model Fit

Table 5 summarizes the parameter values, and Table 6 reports the fit to the targeted moments. Employed workers receive directed outside offers at 7.5 percent of the frequency of unemployed workers, while forced-reallocation offers arrive at 18.0 percent of that rate. Combined, this implies that employed workers receive outside offers at about 26 percent of the rate of unemployed workers, which is broadly in line with typical estimates.

Because $\sigma_x \times 100 = 0.110$, a one-standard-deviation improvement in the learning environment raises annual human-capital growth by $12 \times 0.110 = 1.32$ percentage points.

The estimated standard deviation of firm productivity is 0.236. Although this value is below the empirical dispersion in value added across firms, value-added dispersion is larger in the model because older workers with more human capital tend to work at more productive firms. In the data, value-added dispersion also reflects differences in capital intensity, pricing power, and other firm-level factors that the model abstracts from. The estimated vacancy-cost curvature, $\eta = 0.878$, implies a close to quadratic vacancy cost, consistent with common findings.

Productivity and the learning environment are weakly positively correlated, with $\varrho_{zx} = 0.028$. Gregory (2026) draw a similar conclusion. Finally, the estimate of ψ implies that learning ability falls from one at age 20–29 to zero at age 50–59 at a close to linear rate.

The implied vacancy cost is $c = 6357$, but even if expressed relative to output, it has no meaning since χ is a free parameter (that is, χ could be reduced, generating a corresponding fall in c). The flow value of leisure first falls with age and then rises. To keep workers of all age groups indifferent between unemployment and employment at the same point $(\underline{z}, \underline{x})$, the flow value of leisure must fall with age initially since workers perceive a high value of being employed and accumulating skills.

Table 6 summarizes the moments that particularly inform each parameter. Although the calibration targets more moments than there are internally calibrated parameters, the model matches the aggregate JJ rate well, slightly understates the wage-growth gain of JJ movers relative to stayers, and slightly overstates both life-cycle wage growth and wage growth at training relative to non-training firms.

Figure 6 reports the fit for the remaining moments. The model reproduces the age profile of JJ mobility and the wage gains from JJ moves. It also captures the faster wage growth of young workers at training firms relative to older workers, as well as the higher incidence of training firms among large firms. The age pattern in training-firm wage growth and the life-cycle wage profile

Table 5: Parameter Values

Parameter	Description	Value
Panel A. Preset or Normalized Parameters		
ρ	Discount rate	0.003
β	Worker bargaining weight	0.500
α	Matching elasticity	0.500
M	Mass of firms	0.050
$\delta(a)$	Separation hazard by age	
	Age 20–30	0.021
	Age 30–40	0.011
	Age 40–50	0.007
	Age 50–60	0.008
$\phi^u(a)$	Relative efficiency of unemployed search	
	Age 20–30	1.312
	Age 30–40	1.247
	Age 40–50	0.947
	Age 50–60	0.493
p	Job finding rate per unit of search intensity	0.036
χ	Matching efficiency	1.000
μ	Mean learning ability	1.000
Panel B. Internally Calibrated Parameters		
ϕ^e	Relative efficiency of directed on-the-job search efficiency	0.075
ϕ^f	Relative efficiency of undirected on-the-job search efficiency	0.180
μ_x	Mean learning environment ($\times 100$)	0.143
σ_x	Std. dev. learning environment ($\times 100$)	0.110
σ_z	Std. dev. productivity	0.236
η	Vacancy cost curvature	0.878
ϱ_{zx}	Correlation between z and x	0.028
ψ	Speed of decline in learning ability with age	1.500
Panel C. Implied Parameters		
c	Vacancy cost scale	6357
$e^{b(a)}$	Flow value of leisure	
	Age 20–30	1.087
	Age 30–40	0.825
	Age 40–50	0.780
	Age 50–60	0.893

Table 6: Targeted Moments

Parameter	Moment	Data	Model
ϕ^e	JJ mobility rate	0.072	0.073
ϕ^f	JJ mobility rate by age	See Figure 6a	
	Wage growth of JJ movers to stayers by age	See Figure 6b	
μ_x	Wage growth over the life-cycle (20–29 to 50–59)	0.310	0.323
σ_x	Wage growth at training to non-training firms	0.014	0.017
σ_z	Log wage by firm size	See Figure 6c	
	Wage distribution of young workers (20–29)	See Figure 6d	
η	Employment share at 50+ firms by age	See Figure 6e	
ϱ_{zx}	Employment share of training firms by firm size	See Figure 6f	
ψ	Empl. share of hires from unempl. at training firms by age	See Figure 6g	
	Wage growth at training to non-training firms by age	See Figure 6h	
	Life-cycle wage profile	See Figure 6i	

discipline ψ; the firm-size pattern in training incidence disciplines ϱ_{zx}.

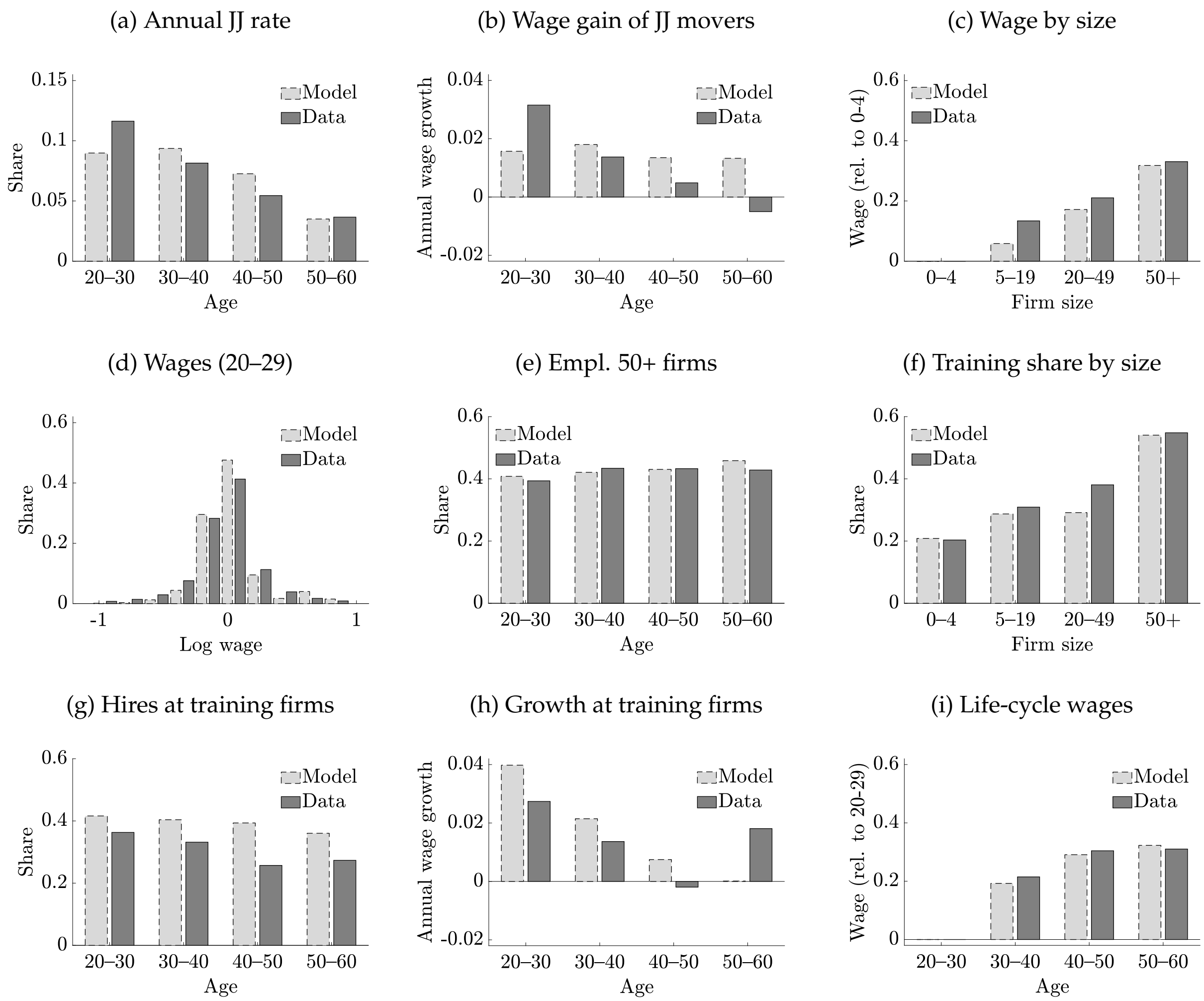
4.3 Model Mechanics

Before I turn to the main cross-country exercises, I use the calibrated model to analyze life-cycle wage and employment dynamics. Figure 7 decomposes life-cycle wage growth into growth in human capital, match productivity, and the piece-rate component of wages. My estimates indicate that human capital accumulation is the single most important factor behind life-cycle wage growth, contributing roughly 60 percent of wage growth. Growth in match productivity and the piece rate account in roughly equal proportion for the remaining growth.

Figure 8 compares the underlying firm distribution, the distribution of vacancies, and the age-conditional distribution of employment. Recall that the flow value of leisure b_a is set so that workers are indifferent between unemployment and employment in a $(z, x) = (0, \mu_x)$ match. Some low-productivity, low-learning-environment firms in the lower-left tail cannot profitably hire workers and therefore do not post vacancies. The vacancy-weighted distribution is consequently tilted toward firms with higher productivity and stronger learning environments.

The indifference curves in panels (c) and (d) illustrate how worker preferences over productivity and learning environments change over the life cycle. Young workers place greater value on learning environments than older workers, who receive lower returns from human-capital accumulation. Young workers initially sort toward firms with stronger learning environments and higher productivity. Later in the life cycle, as the return to learning declines, workers increasingly trade off learning opportunities for higher current productivity and wages.

Figure 6: Targeted Moments



5 Results

I now turn to my main quantitative exercise: understanding the role of labor market frictions in driving the observed cross-country differences in career outcomes.

5.1 Cross-Country Calibration and Validation

I recalibrate two parameters—the cost of job creation c and the relative efficiency of directed search by employed workers, ϕ^e—to match the UE and JJ rates in hypothetical countries with minus one standard deviation log fluidity relative to the mean ("low fluidity"), plus one standard deviation log fluidity relative to the mean ("high fluidity"), and plus two standard deviations log fluidity relative to the mean ("super fluid"). I obtain the corresponding UE rates from a linear projection on log fluidity. In practice, I set p to the UE rate, choose ϕ^e to match labor market fluidity, and

Figure 7: The Sources of Life-Cycle Wage Growth

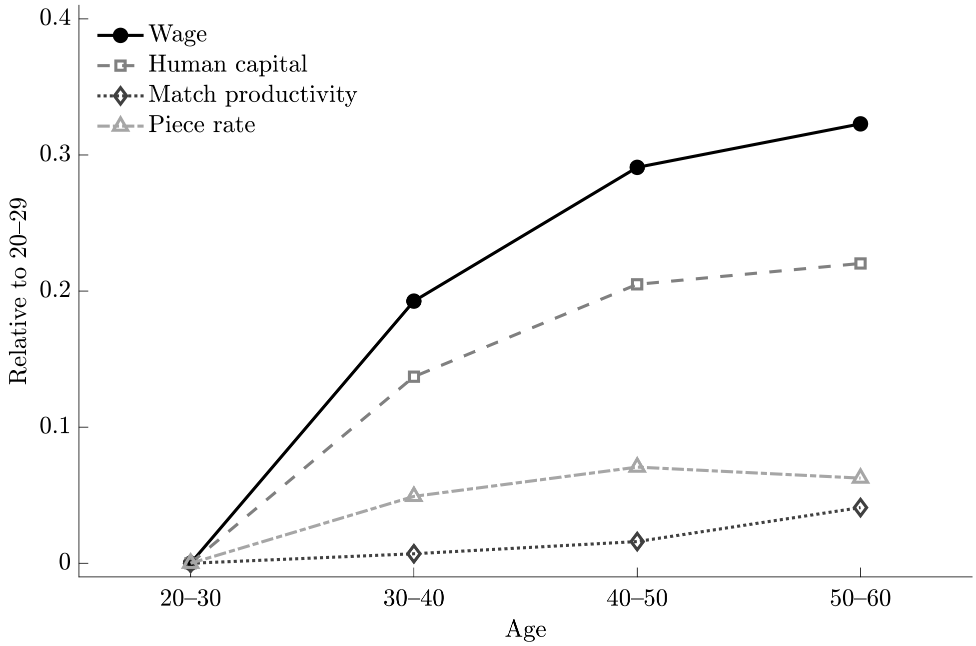
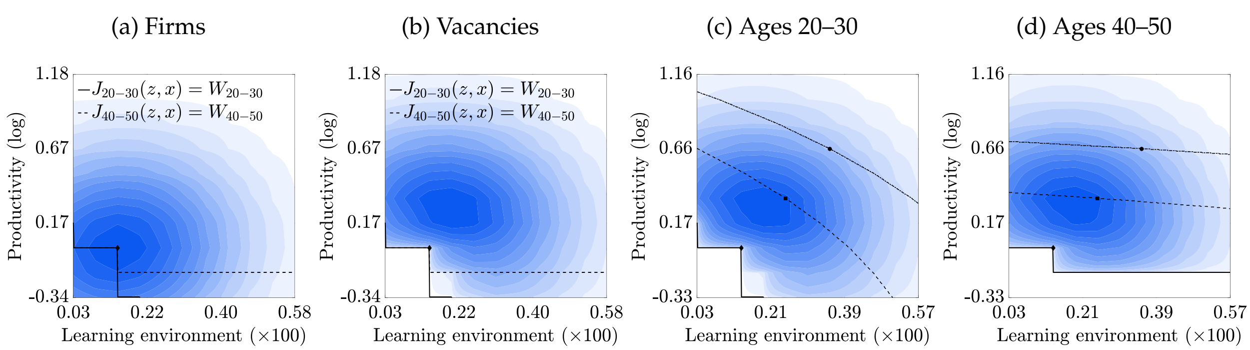


Figure 8: Distributions and Indifference Curves



recover the vacancy-creation cost c so that p is an equilibrium outcome. All other parameters are held fixed in the analysis below, including the total separation rate $\delta(a) + \phi^u(a)\phi^f p$.

Figure 9 summarizes the targeted moments as well as additional outcomes across countries. Because the total separation rate is held fixed, the higher job-finding rate in high-fluidity countries implies a modestly lower separation rate to unemployment, broadly consistent with the data (panel (b)). The higher UE rate and modestly lower EU rate imply a higher employment rate in high-fluidity countries, as shown in panel (c). Panel (d) shows no systematic relationship between the average wage gain for JJ movers and fluidity. According to panel (e), young workers in more fluid labor markets tend to work for larger firms, although the model somewhat overstates the empirical relationship. Panel (f) shows that young workers in more fluid labor markets are also more likely to work for firms that offer training, although the model understates this empirical relationship.[5] I conclude that variation in these two parameters generates cross-country patterns for a range of outcomes that are broadly consistent with the data.

Figure 9: Cross-Country Calibration Moments and Additional Outcomes

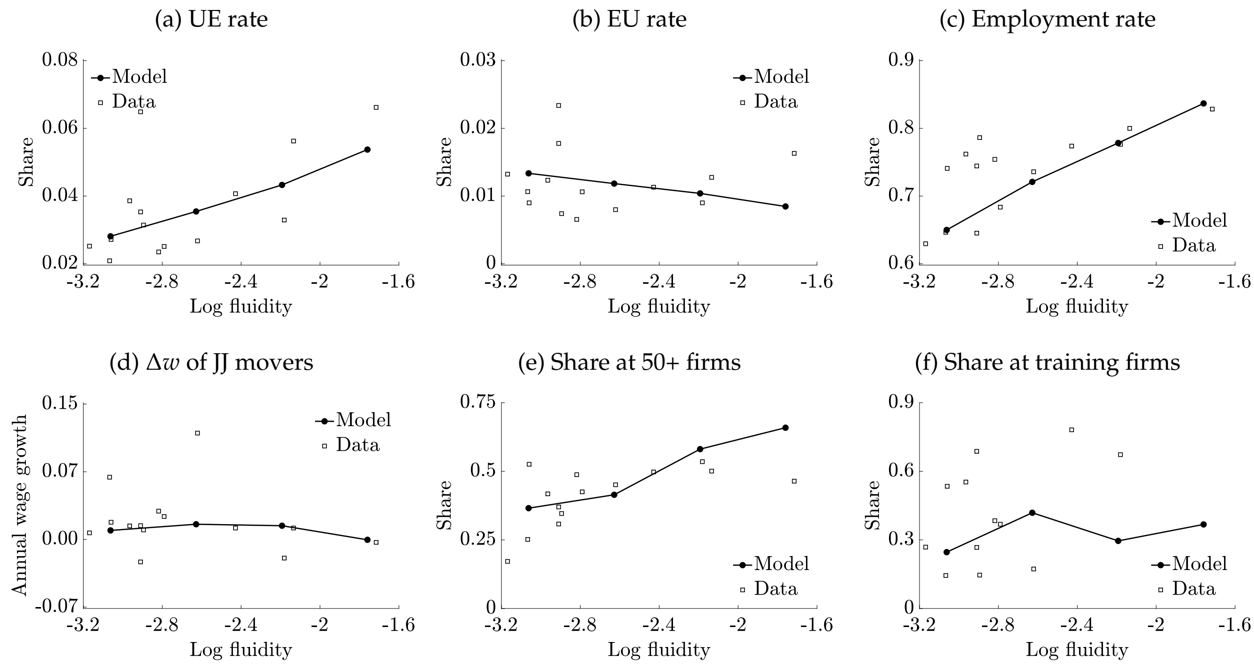


Table 7 summarizes the calibrated cross-country parameters. The job-finding rate p rises from 2.9 percent per month in the low-fluidity country to 5.5 percent per month in the super-fluidity country. Relative search efficiency for directed outside offers rises sharply with fluidity, from 0.000 to 0.523. One interpretation is that employed workers respond to a higher job-finding rate by searching harder. Finally, the vacancy-creation cost falls by roughly 303 log points when moving from the low-fluidity country to the super-fluidity country. These large changes in parameter values are required to rationalize the large observed differences in labor market flows.

5.2 The Impact on Life-Cycle Outcomes

I start by quantifying the impact of the functioning of the labor market on life-cycle outcomes. Panel (a) of Figure 10 plots wage growth between ages 20–29 and 50–59 in the model and data. Moving from the low-fluidity to the super-fluidity labor market, life-cycle wage growth rises by 19.4 log points in the model, somewhat understating the empirical relationship. Panel (b) shows wage growth of hires from nonemployment, defined equivalently in the model and data as some-

[5] I construct this measure by tagging firms characterized by (z, x) as training or non-training firms in the baseline economy so that 41% of employment is at training firms, consistent with the data, and then holding each firm's training type fixed across countries.

Table 7: Cross-Country Differences in Labor Market Structure

	Low	Middle	High	Super
Labor market fluidity	0.047	0.073	0.113	0.173
Job finding rate per unit of search: p	0.029	0.036	0.044	0.055
Mean total separation rate: $\lambda(a) \equiv \delta(a) + \phi^f \phi^u(a) p$	0.018	0.018	0.018	0.018
Mean job loss rate: δ	0.013	0.012	0.010	0.008
Search efficiency for undirected offers: φ^f	0.174	0.180	0.180	0.180
Search efficiency for directed offers: φ^e	0.000	0.075	0.233	0.523
Vacancy cost: $\log c$ (relative to baseline)	0.714	0.000	-0.946	-2.311

one who was nonemployed in at least one month in the past 12 months. Life-cycle wage growth of hires from nonemployment rises even more with fluidity than overall wage growth, even though as I show below greater skill accumulation accounts for only just under half of the pattern in panel (a). The reason is that young hires from unemployment get paid a particularly low piece rate in high fluidity countries, as they greatly value the skills they accumulate on the job. In contrast, older hires from unemployment get paid a more similar piece rate across countries.

Figure 10: Cross-Country Life-Cycle Outcomes

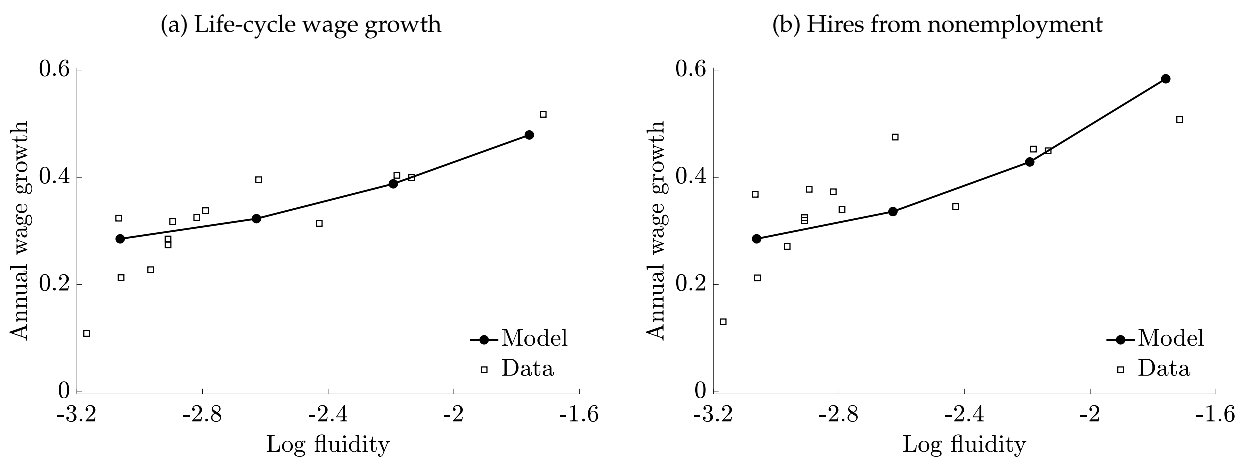


Table 8 summaries our results for life-cycle outcomes. Growth in log output between ages 20–29 and 50–59 is 13.3 log points higher in the most relative to the least fluid country. Recall that log output is additively separable in log match productivity and log human capital. Human capital growth rises by 8.8 log points and match productivity growth by 4.4 log points. Hence, greater human capital accumulation is the most important factor behind greater growth in output per worker over the life-cycle in more fluid labor markets. Recall that wages are in turn log-additively separable into the log piece rate and log output. The piece rate grows 6.3 log points more in the super-fluidity country than in the low-fluidity country. Combining these forces, wages grow by 19.4 log points more in the super-fluidity country than in the low-fluidity country.

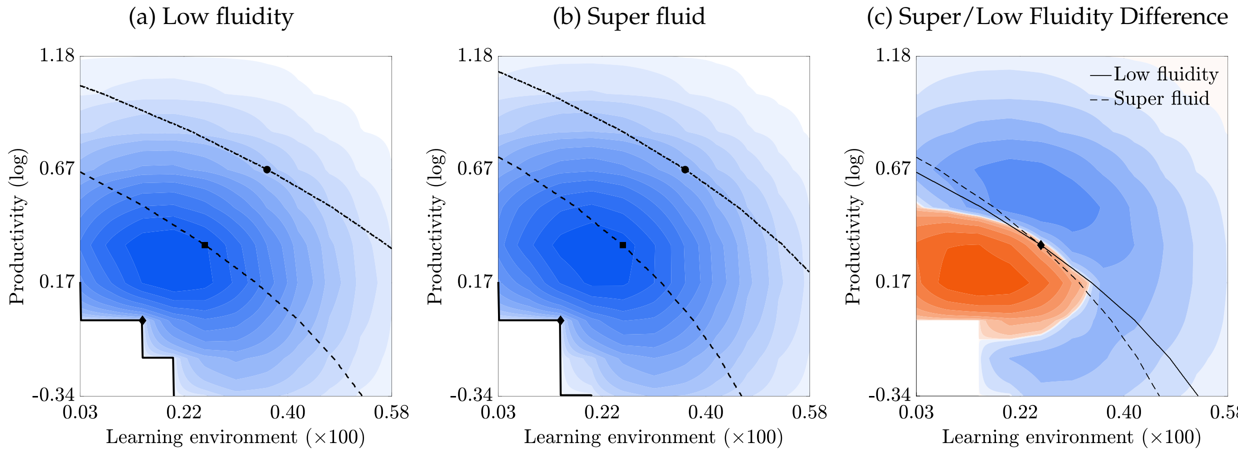
Table 8: The Impact of Labor Market Fluidity on Life-Cycle Outcomes

	Low (-1σ)	Baseline	High ($+1\sigma$)	Super ($+2\sigma$)
Panel A. All changes (pp)				
Output	-3.2	0.0	4.0	10.1
Human capital	-2.4	0.0	2.6	6.4
Match productivity	-0.7	0.0	1.4	3.7
Piece rate	-0.6	0.0	2.5	5.7
Wage	-3.8	0.0	6.5	15.6
Panel B. Fixed acceptance, mobility and vacancy policies				
Output	-2.8	0.0	3.3	7.4
Human capital	-2.2	0.0	2.2	4.9
Match productivity	-0.6	0.0	1.1	2.5
Piece rate	0.0	0.0	-0.6	-2.4
Wage	-2.8	0.0	2.7	5.0

Figure 11 illustrates young workers' job acceptance behavior and firms' vacancy creation decisions in the low-fluidity (panel (a)) and super-fluidity (panel (b)) countries. With higher fluidity, young workers are better able to locate both a high productivity and high learning environment firm. The lower frictions in turn encourages high productivity, high learning environment firms to raise job creation relative to their low productivity, low learning environment competitors. In addition, young workers value skill accumulation more in high-fluidity countries because lower expected mismatch later in life raises the expected usefulness of those skills. Consequently, workers in high-fluidity countries are willing to accept a larger fall in match productivity for the same increase in the learning environment, consistent with the theoretical predictions. This further encourages high learning environment firms to create jobs. Panel (c) illustrates the shift in the distribution of vacancies toward high productivity, high learning environment firms with labor market fluidity (blue intensity indicates a larger mass in the super-fluidity country, while red indicates a larger mass in the low-fluidity country).

To separate the role of the mechanical effect of workers relocating slower to high learning environment jobs from changes in behavior, I consider a fixed-policy counterfactual in which workers' and firms' policies are held at their baseline values while p and ϕ^e vary as estimated. Panel B summarizes the outcomes under this counterfactual. Moving from the low-fluidity to the super-fluidity country, life-cycle growth in log output per worker is 10.2 log points under fixed policies. Hence changes in workers' and firms' behavior account for a little over 23 percent of the total effect of 13.3 log points steeper growth in output. Changes in behavior also account for roughly 19 percent of the greater growth in human capital in more fluid labor markets, and about 30 percent of the greater growth in match productivity. Under fixed policies, wages grow by only 7.8 log points more in the most relative to the least fluid economy, so changes in behavior account for

Figure 11: Changes in Vacancy Distribution and Indifference Curves of Young Workers



over 59 percent of the effect on life-cycle wage growth.

5.3 The Impact on Aggregate Outcomes

I next turn to the impact of labor market fluidity on output and wage levels. Figure 12a shows that wages of young workers are modestly higher in more fluid labor markets, broadly consistent with the data. Figure 12b shows that output per worker is higher in more fluid labor markets. In fact, the gap in the level of output is larger than what a naive calculation based on Table 8 would suggest. The reason is that Figure 12b reports the log of averages, whereas Table 8 reports the average of logs. Increased sorting of high-skill workers to high-productivity matches in high-fluidity countries generates a larger effect on the log average.

Figure 12: Cross-Country Aggregate Outcomes

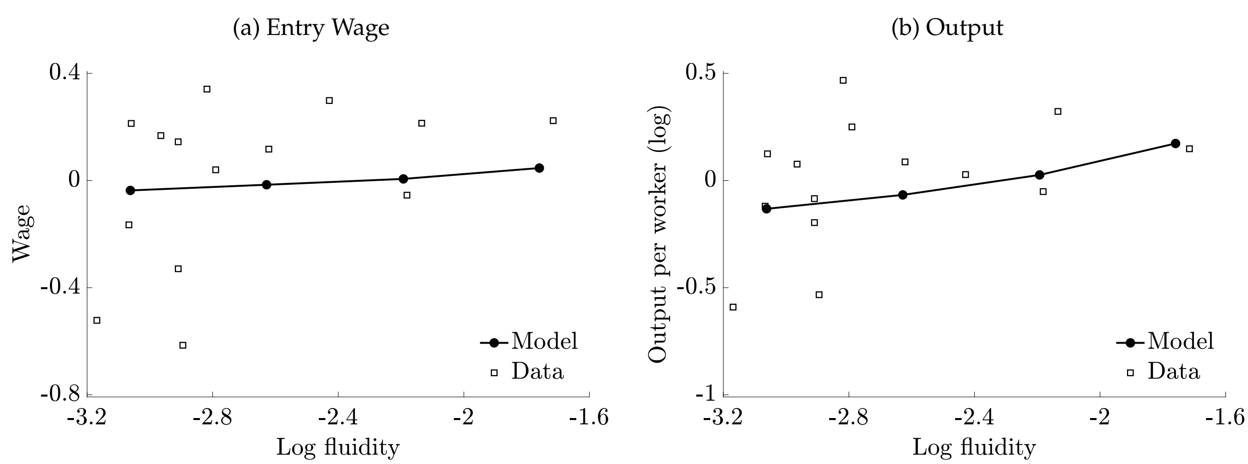


Table 9 summarizes and decomposes the effect on entry wages. Human capital is 4.9 log points higher in the super-fluidity country than in the low-fluidity country among workers aged 20–29. Although workers enter the economy as unemployed with the same level of human capital in all countries, by age 20–29 they have already had time to accumulate additional skills in the high fluidity country. Match productivity is 7.3 log points higher, because the more fluid labor market gives them more opportunities to find a good match. However, the piece rate is 4.3 log points lower0. The piece rate is lower because young workers in high-fluidity countries are willing to work for less initially, anticipating a higher payoff later in life as they accumulate more skills and are less mismatched. Due to these offsetting forces, wages are only modestly higher among young workers in more fluid labor markets, consistent with the data.

Table 9: The Impact of Labor Market Fluidity on Entry Wages

	Low (-1σ)	Baseline	High ($+1\sigma$)	Super ($+2\sigma$)
Panel A. All changes (pp)				
Output	-2.1	0.0	3.8	10.1
Human capital	-1.3	0.0	1.4	3.6
Match productivity	-0.8	0.0	2.3	6.5
Piece rate	0.1	0.0	-1.7	-4.2
Wage	-2.1	0.0	2.2	6.2
Panel B. Fixed acceptance, mobility and vacancy policies				
Output	-1.7	0.0	2.7	7.1
Human capital	-1.2	0.0	1.3	2.9
Match productivity	-0.5	0.0	1.4	4.2
Piece rate	-0.8	0.0	2.0	5.4
Wage	-2.6	0.0	4.8	12.7

Table 10 summarizes and decomposes the cross-country variation in log average outcomes per worker. Output per worker is 33.4 log points higher in the super-fluidity country than in the low-fluidity country. Greater human capital per worker is the most important factor behind higher output in high-fluidity countries. Moving from the low-fluidity to the super-fluidity country, average human capital per worker rises by 18.7 log points. Match productivity is 12.7 log points higher in the super-fluidity country than in the low-fluidity country. Aggregate wages are 35.7 log points higher in the super-fluidity country than in the low-fluidity country. In other words, output and wages rise broadly proportionally, with the piece rate rising by only 0.5 log points.

Under fixed policies, output per worker is 25.0 log points higher, so changes in workers' and firms' behavior again account for just over one-quarter of the aggregate output effect. Average human capital per worker is 15.0 log points higher; that is, changes in policies account for slightly less than 20 percent of the aggregate human-capital effect. Finally, wages are 32.4 log points higher, so that changes in policies account for just over 9 percent of the higher wage level in more fluid countries.

Table 10: The Impact of Labor Market Fluidity on Aggregate Outcomes

	Low (-1σ)	Baseline	High ($+1\sigma$)	Super ($+2\sigma$)
Panel A. All changes (%)				
Output	-6.3	0.0	9.8	27.1
Human capital	-4.7	0.0	5.4	14.0
Match productivity	-1.6	0.0	3.9	11.1
Piece rate	-0.3	0.0	0.2	0.2
Wage	-6.8	0.0	10.5	28.9
Panel B. Fixed acceptance, mobility and vacancy policies				
Output	-5.5	0.0	7.6	19.5
Human capital	-4.3	0.0	4.6	10.7
Match productivity	-1.2	0.0	2.8	7.6
Piece rate	-1.0	0.0	2.0	4.6
Wage	-6.7	0.0	10.2	25.7

5.4 Sensitivity

To assess the sensitivity of my results, I begin with the following exercise. I vary each parameter by $\pm 10\%$ around its estimated value, holding all other parameters fixed. I then trace the impact of this variation on the change in key outcomes between the most and least fluid labor markets, and report the corresponding semi-elasticities in Table 11.

Dispersion in the learning environment, σ_x, is the most important parameter governing the response of output and human capital growth over the life cycle to differences in labor market fluidity. When dispersion in the learning environment is low, workers gain little from being better able to relocate to good learning environments in high-fluidity countries, shrinking cross-country gaps in life-cycle output and human capital growth. The rate at which learning ability declines with age, ψ, is also important. If ψ is high, older workers benefit little from finding firms with better learning environments in high-fluidity countries, since they cannot learn much. Consequently, the impact of differences in fluidity on life-cycle output and human capital growth is dampened.

Cross-country differences in life-cycle output and human capital growth are also affected by dispersion in match productivity, σ_z, although it affects output and human capital growth in opposite directions. Higher dispersion in match productivity amplifies cross-country differences in output growth, because it implies substantial benefits from moving more toward high-productivity jobs over careers in high-fluidity countries. At the same time, high dispersion in match productivity means that productivity considerations dominate learning-environment considerations in workers' mobility choices. As a result, higher σ_z reduces differences in skill accumulation.

Finally, the curvature of the vacancy cost, η, also affects cross-country differences. If η is high, it reduces firms' willingness to shift vacancies toward high-learning-environment jobs as workers' relative valuation of such jobs rises with fluidity. Consequently, a higher η reduces cross-country differences in output and human capital growth. The other parameters are less consequential for the impact of fluidity on life-cycle output and human capital growth.[6]

Table 11: Difference in Life-Cycle Growth Between Most and Least Fluid Labor Market

	ϕ^e	ϕ^f	μ_x	σ_x	σ_z	η	ϱ_{zx}	ψ
Output	+0.000	+0.000	+0.051	+0.066	+0.014	-0.038	+0.003	-0.047
Human capital	+0.000	+0.000	+0.034	+0.047	-0.020	-0.016	+0.003	-0.042
Wage	+0.000	+0.000	+0.066	+0.175	+0.021	-0.051	+0.010	-0.039

Note: Output is the difference in log average output among the employed at age 20–30 and 50–60. Human capital is the difference in log average human capital among the employed at age 20–30 and 50–60. Wage is the difference in the log average wage at age 20–30 and 50–60. All outcomes are the difference between the super-fluid and low-fluidity country over the percent change in the parameter, computed by varying the parameter $\pm10\%$ around its estimated value.

Figure 13 illustrates how these four parameters affect the moments that particularly inform them, as well as cross-country differences in the aggregate stock of human capital. Each panel varies the designated parameter only, holding all other parameters fixed at their estimated values, and traces the impact on the moment that especially informs that parameter as well as on the cross-country difference in human capital per worker between the most and least fluid labor markets. The dashed black vertical line shows the parameter estimate. The dashed black horizontal line extending to the right y-axis shows the difference in human capital per worker between the most and least fluid countries, which is roughly 18 log points under my baseline estimate. The dashed black horizontal line extending to the left y-axis shows the value of the targeted moment under the baseline parameter estimate. The dotted gray horizontal line starting from the left y-axis shows the empirical value of the targeted moment. Finally, the dotted gray horizontal line extending to the right y-axis shows the implied cross-country difference in aggregate human capital under the parameter value that would exactly match the empirical target, holding all other parameters fixed.

Concretely, panel (a) considers dispersion in the learning environment, σ_x, which is particularly informed by the wage gains at training firms relative to non-training firms. As the graph shows, the model overstates the empirical target under the baseline estimate. One possibility would be to increase the weight on this moment, at the cost of a worse fit in other dimensions. *Ceteris paribus*, this would reduce the estimated dispersion in the learning environment, which in turn would lead to *smaller* cross-country differences in human capital. The gap between the dashed black line and the dotted gray line extending to the right y-axis shows this.

Panel (b) repeats this analysis for the decline in learning ability with age, ψ, which as I discussed above is particularly informed by several sets of moments. In panel (b), I graph one of these moments: the concavity of the life-cycle wage profile. Everything else the same, more front-

[6] Mean learning environment, μ_x, is also important, but its role is mechanical because I impose a lower bound on the learning environment, guided by the view that it seems unreasonable for many firms to offer a much worse learning environment than unemployment. A low μ_x means that most firms are at the lower bound, leaving little dispersion in the learning environment. In any case, μ_x is very tightly identified by life-cycle wage growth.

loaded wage growth—a more concave wage profile—suggests a more rapidly declining learning ability with age, i.e. a high ψ. The model understates the concavity of the life-cycle wage profile in the data. If the model had been forced to match it—again at the cost of a worse fit in other dimensions—I would infer a higher ψ, dampening cross-country differences in human capital.

Panel (c) conducts the same analysis for dispersion in match productivity, σ_z, which is particularly informed by the wage premium from working at large firms. Everything else the same, a higher σ_z is associated with larger pay differences across firms. The model matches this target well. If the empirical moment had been lower, I would infer a lower σ_z, which in turn would amplify cross-country differences in human capital.

Finally, panel (d) considers the curvature of the vacancy cost, η, which is particularly informed by the employment share at large firms. If η is higher, high productive firms do not grow as large. The model matches the target well. If the employment share of large firms had been smaller, the model would infer a lower η, which would shrink cross-country differences in human capital.

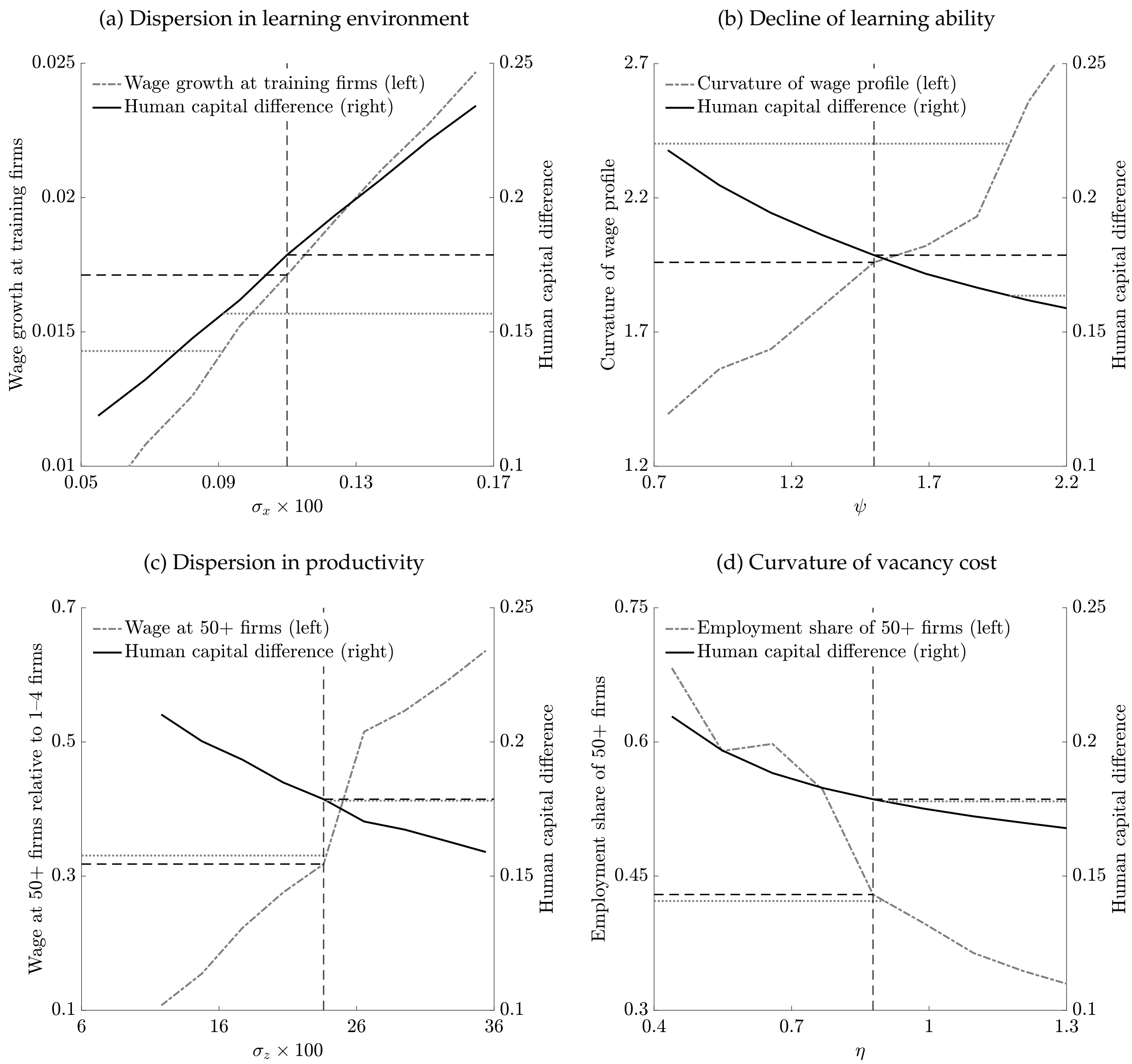
A general lesson from these exercises is that the estimated effect of labor market fluidity on life-cycle and aggregate outcomes is not hardwired into the model. If the empirical moments had looked different, I would infer very different parameter values, which in turn would substantively change the estimated impact of labor market fluidity.

6 Conclusion

This paper shows that labor market fluidity shapes careers through both reallocation and human capital accumulation. Using panel data from 15 advanced economies, I document that workers in more fluid labor markets experience steeper life-cycle wage growth, that this pattern is not explained only by wage gains at job-to-job transitions, and that young workers in more fluid economies are more likely to work at large and training-intensive firms. These facts motivate an equilibrium model in which firms differ not only in contemporaneous productivity but also in the quality of their learning environment. In the model, fluidity raises the value of early-career skill investment because workers expect to use those skills in better matches later in life.

The quantitative results imply that the costs of low labor market fluidity are substantial. Moving from the low-fluidity to the super-fluidity economy raises life-cycle wage growth by 19.4 log points and aggregate output per worker by 33.4 log points. Human capital accumulation accounts for the largest part of the aggregate gain, while better matching and wage bargaining provide additional channels. These findings suggest that policies and frictions that limit mobility can have long-lasting effects beyond their immediate impact on job creation and reallocation: by making future mismatch more likely, they reduce the incentives and opportunities for young workers to accumulate valuable skills.

Figure 13: Sensitivity Analysis of Aggregate Human Capital



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A Data Appendix

Figure 14 plots annual poaching rates by year across countries. Although the poaching rates fluctuate, the general ranking of countries remain persistent with a few exceptions. In particular, Portugal experienced a rapid rise in poaching rates in the last few years of the data.

Figure 15 plots estimated life-cycle wage profiles by country. All countries display a similar pattern of rapid wage growth earlier in careers.

Figure 14: Annual Poaching Rate

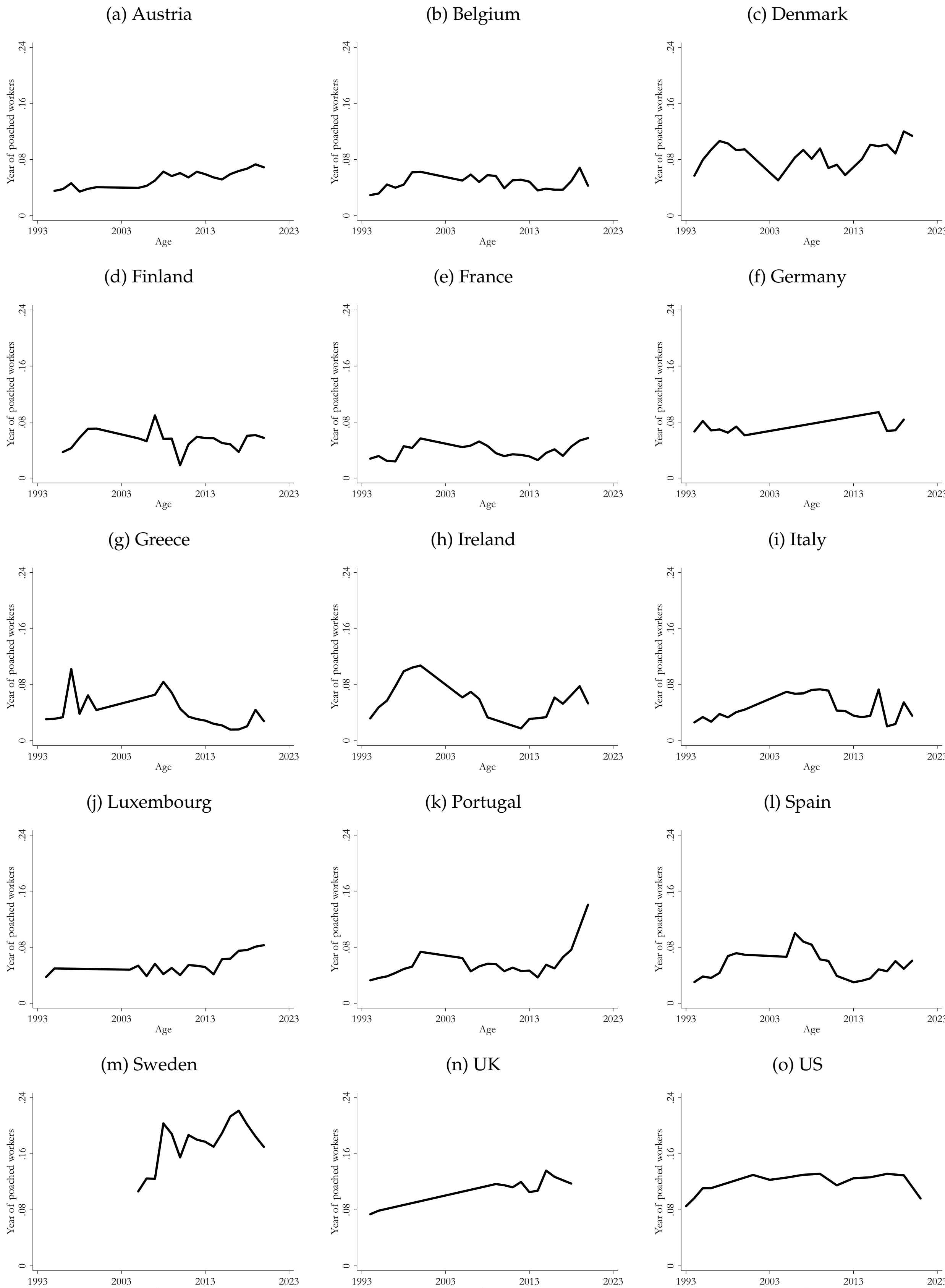

Figure 15: Life-Cycle Wage Profile