Labor Market Fluidity and Human Capital Accumulation

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Abstract

I argue that by reducing workers’ ability to find a job that fully utilizes their skills, policies and regulations that raise firms’ cost of doing business discourage workers from accumulating human capital. Consistent with this view, rich panel data from 23 OECD countries indicate that life-cycle wage growth and on-the-job training are greater in more fluid labor markets while firms’ cost of doing business is lower. A quantitative version of the model implies that aggregate productivity is 30 percent lower in the least fluid labor market relative to the US, primarily due to a lower stock of human capital.

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1 Introduction

A large literature studies differences in labor market flows across countries. This research finds that such flows vary markedly between countries, and that policies and institutions that impede such flows may lead to misallocation of factors of production.\(^1\) The literature, however, has tended to focus on the effect of such policies on firms’ job creation and destruction decisions, with less attention paid to their impact on worker flows and the behavior of workers. Yet workers’ responses to such large differences in the functioning of the labor market may have a first-order effect on aggregate economic outcomes.

My main contribution is to quantify the impact of policies that raise firms’ cost of doing business on workers’ on-the-job accumulation of skills. To that end, I proceed in three steps. I start by developing an equilibrium search model in the Diamond (1982)–Mortensen and Pissarides (1994) tradition with on-the-job training. The marginal product of a worker’s human capital differs across firms, but frictions in the labor market prevent workers from immediately reallocating to their most productive use. I make one key modification to an earlier literature on training in frictional labor markets (Acemoglu, 1997; Acemoglu and Pischke, 1998, 1999): I allow workers to move directly from one employer to another without an intervening spell of unemployment, motivated by empirical evidence that such job-to-job (JJ) mobility is a pervasive feature of workers’ careers (Topel and Ward, 1992).\(^2\)

In the model that I develop, a young worker enters the labor market with few skills and in a job that does not utilize her skills particularly well. Through on-the-job training, she gradually builds her skills. Other firms try to poach her, such that over time she reallocates toward jobs that use her skills efficiently—she climbs the job ladder (Burdett and Mortensen, 1998). As a result, life-cycle growth in both the quantity and price of human capital are endogenous equilibrium objects.

I examine in the model the impact on worker careers of policies that raise firms’ cost of doing business. Such policies include, for instance, registration requirements on new businesses, construction permits, and time spent filing taxes. A higher cost of doing business discourages firms from creating jobs, in turn limiting workers’ ability to climb the job ladder. Because workers have a harder time finding a job that uses their skills efficiently, the expected value of human capital declines, disincentivizing on-the-job training. Consequently, the aggregate stock of human capital falls with the cost of doing business.

In the second step of my analysis, I provide empirical support for the predictions of the theory by building an internationally comparable worker-level panel data set covering almost one million obser-


\(^2\)Acemoglu and Pischke (1998) briefly discuss the effect of allowing for poaching—what they refer to as raids—noting that “whether raids are possible or not, may have important consequences for training.” They do not pursue this further, though.
vations across 23 OECD countries for over 20 years. These data offer a unique cross-country perspective on life-cycle labor market dynamics. I document three facts consistent with the theory. First, wages grow more over the life-cycle in more fluid labor markets, where my notion of labor market fluidity is the share of workers who made a JJ move at some point in the past year. Second, on-the-job training is more prevalent in more fluid labor markets. This pattern is particularly notable as it is at odds with predictions of earlier theoretical work (Acemoglu and Pischke, 1999). Third, labor market fluidity correlates only weakly with measures of employment protection legislation and the generosity of unemployment benefits, but strongly negatively with measures of the cost to firms of doing business.

While differences in the cost of doing business are qualitatively consistent with these cross-country patterns, an important question is their quantitative relevance. To assess this, the third and final part of the paper estimates by Simulated Method of Moments (SMM) 11 parameters targeting 108 moments in the US. The model fits the data well and the parameters appear to be well-identified. JJ mobility declines over the life-cycle, as workers gradually find a good job. Wages grow rapidly early in careers, as young workers have significant scope to climb the job ladder and face high returns to training. Human capital accounts for a majority of life-cycle wage and productivity growth, in line with typical findings in the literature (Bagger et al., 2014). Wage inequality rises with age, also primarily accounted for by human capital. It takes place despite the fact that workers do not differ in permanent learning ability, which the literature has argued is essential in matching increasing inequality with age (Huggett et al., 2006). The reason is that workers’ optimal training decisions act to propagate transitory luck in the labor market.

I use the estimated framework to quantify the impact of policies and regulations that raise firms’ cost of doing business on workers’ careers. An issue, however, is that the empirical index of the cost of doing business is not easily mapped into a number for quantitative analysis. Hence, I pursue a wedge-like approach in the spirit of Hsieh and Klenow (2009)—I calibrate wedges to the cost of creating jobs such that the model matches empirical cross-country differences in labor market fluidity. This approach is motivated by the observation that while multiple factors likely impact firms’ cost of doing business, they all map into labor market fluidity from the perspective of understanding workers’ optimal behavior (Pries and Rogerson, 2005). Holding all parameters fixed, I evaluate the impact of such wedges on life-cycle growth in human capital, match productivity and wages. Although the implied wedges to the cost of doing business lack quantitative counterpart in the data, I offer reassuring evidence that they align well with measured differences in the cost of starting a business across countries.

Cross-country differences in the cost of doing business account for over half of the steeper life-cycle wage growth in more fluid labor markets across OECD countries. Differences in human capital accumulation is the single most important factor behind this pattern. A higher cost to firms of doing business
has large negative aggregate consequences. Labor productivity is 30 percent lower in the least fluid labor market relative to the US. Of this, 40 percent is due to the direct effect of greater labor misallocation, as workers climb the job ladder less. The remaining 60 percent is due to the indirect effect on the economy’s stock of human capital, as workers optimally train less on-the-job. In summary, my findings highlight that policies and regulations that raise firms’ cost of doing business have large negative consequences on both workers’ life-cycle wage growth and aggregate economic outcomes.

**Previous literature.** This paper contributes to three strands of the literature. First, a literature studies on-the-job training in frictional labor markets (Pigou, 1912; Becker, 1964). Stevens (1994) and Acemoglu (1997) show that training is generally inefficient as future employers appropriate part of the returns; Moen and Rosén (2004) overturn this conclusion in a directed search framework. Acemoglu and Pischke (1998, 1999) argue that training may decrease with mobility. Wasmer (2006) notes that high turnover increases incentives to accumulate general rather than specific skills—a distinction which I abstract from.

A related literature quantifies the role of human capital and search in life-cycle outcomes (Yamaguchi, 2010; Bagger et al., 2014; Gregory, 2019; Engbom, 2020). Bowlus and Liu (2013) are closest to this paper in that they allow for endogenous training, but in a partial equilibrium setting.

Second, a literature documents cross-country differences in labor market outcomes. Whereas much work has focused on differences in hours worked or unemployment (see Nickell, 1997, for an overview of this literature), fewer papers provide a systematic assessment of differences in life-cycle wage growth or labor market flows, particularly JJ mobility. Lagakos et al. (2018) show that richer countries have steeper life-cycle wage growth across 18 countries at different stages of development, while Donovan et al. (2020) study differences in labor market flows across rich and poor countries. The latter confirm my findings among the set of developed countries for which our data overlap, but find that poor countries are characterized by higher labor market flows. One reason could be that factors other than low frictions contribute to high flows in poor countries, such as high embodied growth due to conditional convergence or volatile firm-level idiosyncratic shocks (Asker et al., 2014).

Third, a vast literature assesses the sources of cross-country income differences (see Jones, 2016, for a survey). Seminal work by Klenow and Rodríguez-Clare (1997), Prescott (1998) and Hall and Jones (1999) find that differences in total factor productivity (TFP) play a key role behind income differences. Erosa

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4See, for instance, Panel B of their Table 2, which “provides the regression estimates from a sample that includes only EU countries, Switzerland, the U.K., and the United States. For this sample, we also find a positive relationship between labor market flows and development” (Donovan et al., 2020, p.14). This finding is reassuring given that they rely on different data.
et al. (2010) and Manuelli and Seshadri (2014) challenge this conclusion, arguing that human capital accounts for a significant share of cross-country differences. The latter is closest to this paper in that they also allow for on-the-job accumulation of skills, but differ in two key regards. First, they assume that all life-cycle wage growth is due to human capital, which my estimates imply overstates its importance. Second, they continue to require large, exogenous differences in underlying TFP, whereas I argue that policies that raise firms’ cost of doing business give rise to such differences endogenously. My assessment of the dynamic consequences of policies that lead to static misallocation is in the spirit of Restuccia and Rogerson (2017, p.170), who write that "whereas much of the literature has focused on static misallocation, we think the dynamic effects of misallocation deserve much more attention going forward." In particular, following recent work on firm dynamics and misallocation (David and Venkateswaran, 2019), I use rich panel data to shed new light on cross-country differences in worker life-cycle dynamics.

Section 2 develops the theory and Section 3 introduces the data. Section 4 estimates the model, Section 5 quantifies the impact of labor market fluidity.

2 Model

This section develops an equilibrium search model in the Diamond (1982)–Mortensen and Pissarides (1994) tradition with on-the-job search and endogenous on-the-job training to assess how policies that impact firms’ cost of doing business in turn affect worker behavior. I start with a discrete-time, two period model that highlights the intuition, and subsequently enrich the model to quantify the interaction.

2.1 Environment

Consider a two-period economy without aggregate shocks that is in steady-state. A unit mass of workers enter, work for two periods and exit. The economy also consists of some positive mass of firms. Workers and firms have linear preferences over a single output good and do not discount the future.

Workers are endowed with initial skills $h_0$. Skills are general, in the sense that they may be used at all firms. The focus on general human capital is motivated by mounting evidence of the limited scope for firm-specific human capital (Kambourov and Manovskii, 2009; Lazear, 2009; Bagger et al., 2014). Workers may grow their skills through training on the job. To grow human capital at rate $\mu_i$, an investment of $c(h, i) = \exp^{\eta h^{1+\eta}}/(1 + \eta)$ is required, where $\eta > 0$. All costs are in terms of the final good.

Technology. The single good of the economy is produced by one worker-one firm matches. A large number of potential firms may pay flow cost $c$ in return for the opportunity to meet with a worker. If
a firm contacts a worker, the two draw an idiosyncratic productivity \( z \) from distribution \( \Gamma \). For now, I assume that productivity can take one of two values with equal probability. I normalize without loss of generality the first productivity to zero, \( z_1 = 0 \), and denote by \( Z = e^{z_2} > 1 \). Match output is,

\[
y = e^{z + h}
\]

That is, as in Acemoglu and Pischke (1998) and Bagger et al. (2014), human capital and technology are complements. The view that some matches use a worker’s human capital more effectively is the first key assumption of this paper. As discussed further by Acemoglu (1997), a large empirical literature going back to Griliches (1969) has found evidence of complementarities between physical and human capital.

**Market structure and timing.** The second key assumption of this paper is that the employed may search for jobs, motivated by substantial empirical evidence of the importance of job shopping for workers’ careers (Topel and Ward, 1992). In fact, to highlight the intuition, I focus for now exclusively on employed search. To that end, I assume that workers enter the labor market in a low productive match, and that firms compete for workers going into the second period. Figure 1 illustrates the timing.

**Figure 1. Timing of events**

Search is random. The labor market is subject to frictions such that if firms create vacancies \( \nu \), then total meetings are \( m(\nu) = \nu^a \), where \( a \in (0, 1) \) denotes the elasticity of meetings with respect to vacancies.\(^5\) Denote by \( p \) the job finding rate of young workers and by \( q \) the worker finding rate of firms,

\[
p = \nu^a, \quad q = \nu^{a-1}
\]

**Discussion of the cost of training.** Before proceeding, I pause to make two observations with respect to the assumed cost function of training, \( c(h, i) = e^{\eta h i^2 + \eta} / (1 + \eta) \). First, it differs slightly from the standard Ben-Porath (1967) specification, which assumes that the cost of training is forgone production,\(^5\)While one could add a scalar (“matching efficiency”) to the matching technology, without data on vacancies it would not be separately identified from the cost of creating jobs, \( c \). Hence I abstract from it to save on notation. In the discrete time formulation here, note the implicit assumption that parameter values are such that the resulting finding rates are probabilities, i.e. less than one. This is not an issue in the extended, continuous time model in Section 4.
i.e. it would scale also in the productivity of the firm, \(z\), in the current environment. I opt not to scale the cost of training in the productivity of the firm, because doing so results in workers training more when they are working in low productive matches. The reason is that the expected value of human capital rises less than one-for-one with current productivity, since workers expect to move across differentially productive firms over time. In contrast, my data suggest that workers train more when employed at larger, better-paying employers. While similar cross-country results hold under a Ben-Porath (1967) specification, I prefer my specification as it is consistent with the data in this dimension.

Second, I find that the cost of training must rise with human capital in order to match the concavity of the life-cycle wage profile in the data. Although a similar result could likely be accomplished by introducing decreasing returns to scale in human capital accumulation, I opt to build this feature into the cost side. One interpretation of this specification is that training takes place after-hours, such that it comes at the cost of forsaken leisure (whose value rises with human capital).

2.2 Contracting

I adopt the bargaining protocol of Dey and Flinn (2005) and Cahuc et al. (2006), which has become a benchmark in the literature for its tractability and empirical relevance. In particular, I assume limited commitment: the firm can commit to pay the worker a wage \(w\) and offer an investment schedule \(i(z, h)\), but the worker cannot commit to work for the firm forever and the firm cannot commit to employ the worker forever. In cases where either the worker or the firm would like to quit the match—either side has a credible threat to abandon the match—however, the two sides are allowed to renegotiate the contract.

The assumption that firms can commit to training is the last key assumption of this paper. As will become clear, it assures that a match between a worker and firm acts so as to maximize its joint surplus. As noted by Acemoglu and Pischke (1999, p.545), "the assumption that contractual problems are absent [...] is reasonable when firms have long-term reputations." Indeed, casual empiricism suggests that many firms such as Deloitte, Goldman Sachs and McKinsey & Company have successfully established a reputation as good training environments, allowing them to hire young workers to work long hours for relatively low hourly pay. Moreover, given that employment relationships on average last for many months, workers and firms arguably engage in a repeated game. It seems reasonable that a worker and firm should be able to figure out a way to maximize their joint surplus, in the spirit of Coase (1960).6

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6My preferred interpretation is that the firm commits to offer the worker a certain number of training courses, etc. For simplicity, I also assume that the worker is able to commit to undertake the provided training. Given the setup, however, I believe that this assumption could be relaxed. In particular, by not taking an already paid for training course, the worker would effectively be leaving money on the table, and hence she would not have an incentive to do so. Moreover, as will become clear, in equilibrium the firm will offer the worker the bilaterally optimal amount of training. Given that the worker would have to
Consistent with this view, I find that wages at labor market entry are lower in more fluid labor markets.

In practice, the bargaining protocol works in the following way. Consider a worker without a job who meets a firm $z$. If the firm and the worker agree to match, the worker gets a share $\beta$ of the difference between the value of the match and the value of unemployment, henceforth the surplus. Consider next a worker employed at a firm with productivity $z$ who meets a potential new employer with productivity $z'$. A second price auction starts between the two firms for the worker. This is won by the bidder with the higher valuation of the worker’s services, and it leaves the worker with the full value of working for the least productive firm as her outside option. The worker and winning firm bargain over the differential surplus such that the worker receives a slice $\beta$ of the differential surplus.\footnote{Subject to the constraint that the worker cannot be made worse off by receiving a new offer.}

The bargaining protocol determines how surplus is split, but not the timing of payment. Following Barlevy (2002) and Bagger et al. (2014), I assume that wages are paid as a piece-rate $w = e^{r}$ of gross output, $w = e^{r+z+h}$. This assumption has no implication for the training decision or more broadly the equilibrium allocation, because as will become clear, the allocation is independent of how value is split. The timing of payment matters, however, for life-cycle wage profiles. Nevertheless, within the context of the estimated model in Section 4, I find similar life-cycle wage profiles and cross-country differences in life-cycle wage growth under the alternative assumption that wages are paid as a fixed wage $w = R$, a piece rate of human capital, $w = Re^h$, or a piece rate of net output, $w = R(e^{z+h} - c(h,i))$.

2.3 The joint value

Denote by $W(R, i)$ the value to a young worker of being in a low productive match with investment $i$ and piece rate $R$. Without loss of generality, I normalize initial human capital, $h_0 = 0$, and abstract from it for now as an argument in the value function to simplify the notation. The value $W(R, i)$ solves,

$$W(R, i) = R + \left( (1-p)R + \frac{p}{2} + \frac{p}{2}(1 + \beta(Z - 1)) \right) (1 + \mu i)$$  

The worker is paid piece rate $R$ in the current period and receives training $i$ (not necessarily the optimal level). The firm pays the cost of investment, but as will become clear this assumption is innocuous. The worker’s human capital rises to $e^{\mu i} \approx 1 + \mu i$ in the second period. The worker receives no new job offer with probability $1 - p$, in which case she continues to be paid piece rate $R$. With probability $p/2$, the worker receives a job offer from another low productive firm. I impose the tie-breaking rule that an indifferent worker switches employer (this only impacts the measured JJ mobility, though). The worker would likely be an easy exercise to show that she has no incentive to train more.
extracts the full surplus of the current match, i.e. she gets an updated piece rate equal to the productivity of the match, $e^0 = 1$. Finally, with probability $p/2$, the worker receives a job offer from a high-productive match, in which case she switches employer and gets a piece rate that reflects the full value of the least productive match, $e^0 = 1$, plus a share $\beta$ of the differential value, $Z - 1$.

Denote by $F(R, i)$ the value to a low productive firm of employing a young worker who is paid piece rate $R$ under some investment policy $i$ (not necessarily the optimal one). It satisfies,

$$F(R, i) = 1 - R - \frac{1}{1 + \eta} i^{1+\eta} + (1 - p)(1 - R)(1 + \mu i)$$

(2)

The firm makes profits $1 - R$ in the current period but has to pay for the training. With probability $1 - p$, the worker receives no outside offer and the firm makes profits $1 - R$ per unit of human capital in the second period. If the worker receives an outside offer, the firm makes no profit in the second period.\footnote{Even if the worker had remained, the firm would have had to pay the worker her full marginal product to keep her.}

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

$$J(i) = 1 - \frac{1}{1 + \eta} i^{1+\eta} + \left(1 + \frac{p}{2}\beta(Z - 1)\right)(1 + \mu i)$$

(3)

**Proof.** All proofs are in Appendix A. \qed

Differentiating the joint value (3) with respect to the job finding rate, $p$, holding investment fixed, \[ \frac{\partial J(i)}{\partial p} \bigg|_{i} = \frac{1}{2} \beta(Z - 1)(1 + \mu i) > 0. \] Hence, ceteris paribus, the joint value increases in the rate at which the worker switches employer (assuming $\beta > 0$). Although the incumbent employer ex post loses value when the worker leaves, the worker is compensated by the poaching firm with the full value of the incumbent match plus a share $\beta$ of the differential surplus. From the joint perspective of the incumbent match, the gain to the worker more than offsets the loss to the firm. Ex ante, an incumbent firm benefits from the opportunity of the worker leaving by having to pay the worker less.

**Proposition 2.** The optimal amount of training offered by the firm maximizes the bilateral surplus,

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

(4)

This conclusion differs from Acemoglu and Pischke (1998) and arises because of different assumptions regarding contracting on investment. They assume that the firm cannot commit to offer the worker
investment. As a result, in their environment a worker would never take a lower starting wage in return for higher training, since the firm will fail to deliver the promised training. In contrast, as discussed above, I assume that the firm can commit to offer investment. As a result, the match will undertake the bilaterally optimal investment, with the worker sharing the cost through a lower wage.9

Differentiating the training policy (4) with respect to the job finding rate, \( \partial i / \partial p = i^{1-\eta} \beta Z^{\eta-1} > 0. \) Hence, from the decision-theoretic perspective of an incumbent match (i.e. holding equilibrium outcomes fixed), a higher job finding rate raises a match’s optimal training. Although as in Acemoglu and Pischke (1998) a higher probability that the worker meets a new employer lowers the value of human capital to the firm, it increases the value of human capital to the worker. When workers’ bargaining power, \( \beta, \) is strictly positive, the latter effect outweighs the former. The reason is that a higher arrival rate of outside offers allows the worker to use her skills at an employer that values them higher. Because the incumbent match gets (partly) compensated for this, it raises the value of human capital to the incumbent match. As a result, the match invests more in response to a higher arrival rate of outside offers, and the worker compensates the firm for higher investment through a lower initial wage. Allowing for JJ mobility is critical to this argument as it gives the worker the chance to re-bargain using the value of the current match as benchmark, and not the value out of unemployment.

2.4 The decentralized equilibrium

Entrepreneurs create jobs up to the point where the cost of doing so, \( c, \) equals the expected return,

\[
c = q \frac{1}{2} (1 - \beta) (Z - 1) (1 + \mu i)
\]  

(5)

At rate \( q, \) a recruiting firm gets paired with a young worker and with probability 0.5 the match draws a good productivity. Only in this case is the recruiting firm successful and it gets slice \( 1 - \beta \) of the differential output of the match, \( Z - 1. \) If the worker invested amount \( i \) in training in the first period, human capital in the second period is \( 1 + \mu i. \)

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

1. The value function and investment policy maximizes (3) given a mass of vacancies;

9Hence, I also abstract from wage constraints such as a binding minimum wage, motivated by a lack of systematic correlation between labor market fluidity and the minimum wage across countries. Moreover, the patterns documented in the next section are equally, or if anything more, pronounced among college graduates (see Appendix B). As college educated are typically less bound by a minimum wage, this suggests that the minimum wage is not the main driver of the patterns documented here.
2. The mass of vacancies is consistent with free entry (5);

3. And the economy is time invariant.

The equilibrium is characterized by two curves. The first is a training curve, which can be derived from the first-order condition (4) by substituting for the job finding rate using the matching function,

\[ i(v) = \left(1 + \frac{\beta Z - 1}{2}\right) \mu \] (6)

The second curve is a job creation curve, derived by substituting the worker finding rate \( q = v^{\alpha - 1} \) in the free entry condition (5),

\[ v(i)^{1-\alpha} = \left(1 - \beta \right) \frac{Z - 1}{2c} (1 + \mu i) \] (7)

Figure 2 graphs the training and job creation curves (6)–(7) in \( v-i \) space. At zero vacancies, the training curve (6) is positive. It subsequently rises in vacancies. A higher job finding rate raises the return to human capital since workers expect to use it more efficiently, encouraging investment. At zero investment, the job creation curve (7) is positive. Optimal job creation subsequently increases in the investment rate of workers. This reflects the fact that if workers invest more, matches produce more output, and recruiting firms get a share of this. The training and job creation curves may in fact cross multiple times.

Figure 2. COMPARATIVE-STATIC IMPACT OF A HIGHER COST OF HIRING

(A) LOW COST

(B) HIGH COST

Note: The comparative-static equilibrium impact of a higher cost of creating jobs, \( c \). Training: Equation (6). Job creation: Equation (7).

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

The key parameters governing whether the economy may display multiple stationary equilibria are the curvature of the matching technology, \( \alpha \), and the cost of investing, \( \eta \). If it is cheaper to scale up
training (i.e. \( \eta \) is lower), a given increase in job creation of firms leads to a stronger optimal increase in training of workers. If the worker finding rate declines less with an increase in vacancies (i.e. \( \alpha \) is higher), a given increase in training of workers leads to a stronger optimal increase in job creation of firms.

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

In response to a higher cost of vacancy creation, firms create fewer vacancies for any given level of investment of workers. That is, the job creation curve in Figure 2 shifts to the left. The lower job finding rate, in turn, reduces the expected value of human capital to workers, lowering investment.

### 2.5 The planning problem

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

\[
\max_{v,i} \left\{ 1 - \frac{1}{1 + \eta} (1 + \frac{1}{2} \alpha (Z - 1)) \left( 1 + \mu i \right) - cv \right\}
\]

with first order conditions,

\[
i_{sp}^\eta(v) = \left( 1 + \alpha Z - \frac{1}{2} \right) \mu,
\quad v_{sp}^{1 - \alpha}(i) = \alpha Z - 1 \frac{1}{2c} (1 + \mu i)
\]

**Lemma 1 (Hosios (1990) condition).** Suppose \( \eta > \alpha / (1 - \alpha) \) and that training in the decentralized economy equaled the constrained first best, \( i(v) = i_{sp}(v) \). Then the decentralized equilibrium attains the constrained first best number of vacancies iff the elasticity of matches w.r.t. vacancies equals firms’ bargaining power, \( \alpha = 1 - \beta \).

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

**Lemma 2 (Stevens (1994)/Acemoglu (1997)).** Suppose \( \eta > \alpha / (1 - \alpha) \) and that job creation in the decentralized economy equaled the constrained first best, \( v(i) = v_{sp}(i) \). Then the decentralized equilibrium attains the constrained first best amount of investment iff workers’ bargaining power is one, \( \beta = 1 \).
Due to a positive externality of investment on future employers, for a given number of vacancies the decentralized economy in general features less investment in human capital relative to the social optimum, as in Stevens (1994) and Acemoglu (1997). Only if incumbent matches enjoy the full marginal benefit from additional training upon a JJ move would they undertake the socially optimal level of investment.

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

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

# 3 Data

This section offers empirical support of the theory. To that end, I build an internationally comparable worker-level panel data set covering 23 OECD countries and almost one million observations.

## 3.1 Data sources

The empirical analysis relies on data from the following sources and time periods: the US Panel Study of Income Dynamics (PSID) 1994–2015; the German Socio-Economic Panel (GSOEP) 1991–2011; the British Household Panel Survey (BHPS) 1991–2008; the European Community Household Panel (ECHP) 1994–2001; and the European Union Statistics on Income and Living Conditions (EUSILC) 2003–2014. While a cross-country comparison inevitably is subject to issues of comparability, an important advantage of these data sets is that they are modeled after the PSID, facilitating the international comparison.

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

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

**BHPS.** The BHPS began in 1991 and was discontinued in 2008. It is similar to the PSID. The sample has expanded over time, but I focus on the original core sample. As the PSID/GSOEP, the BHPS contains demographic characteristics on the respondent, as well as annual information on gross income and hours worked. The BHPS also contains information on start and end dates on all labor market spells since the last survey, which I use to construct a monthly calendar of labor market events as in the PSID/GSOEP. I use survey weights throughout my analysis to adjust for nonrandom attrition and non-response.

**ECHP.** The ECHP was run 1994–2001 across the original set of European Union countries. Because of confidentiality restrictions, however, data from Germany and Portugal are not released to researchers. The data from Sweden are only available for a few years and miss several key variables, forcing me to exclude Sweden. Luxembourg switched to collecting data via a separate, national survey after three years in the ECHP, dropping several key variables in the process. As the Luxembourg sample for the first three years in the ECHP is small, I drop also Luxembourg from my analysis (similar results hold including the few available years, though). While data from the UK are available in the ECHP, several years are missing so I opt to use the larger and consistently collected BHPS instead. The ECHP follows the same individuals annually for up to eight years. The survey is similar to the PSID, including a similar set of variables. In particular, it asks for a monthly calendar of events in the prior calendar year and the start date of the current employment spell. I weigh all results using the provided survey weights.
EUSILC. The EUSILC is the successor to the ECHP starting in 2003. It gradually expanded the set of countries covered to eventually include all EU members plus a set of affiliated countries. The survey is annual and uses a rotating panel design, which differs somewhat in length across countries. Most countries follow the same individuals for up to four years, but France follows individuals for eight years and Norway for six. As the other surveys, it contains the standard demographic and income variables, including gross annual labor income and hours worked during the previous calendar year. It also contains a monthly calendar of labor market events for the prior calendar year. It differs slightly from the other surveys in that it does not contain the start date of the current employment spell, instead recording whether the individual switched employer in the past 12 months. All results use survey weights.

SIPP. To estimate the model, I additionally use data from the US Survey of Income and Program Participation (SIPP). The annual frequency of the PSID is not ideal to estimate the wage gain upon a JJ move, and hence I use the SIPP for this. The SIPP has been conducted in separate panels since the mid-1980s, but a break in the survey in 1996 implies that data on job-to-job mobility in the earlier panels are not directly comparable to that in the later panels. To align with the time period covered by the other data sets used by this paper, I focus on SIPP data from 1996–2012 (i.e. the 1996, 2001, 2004 and 2008 panels).

Each panel of the SIPP follows a group of individuals over time. Data are collected in "waves", with the respondent in each wave being asked to recall labor market events during the prior four months. The survey asks for information regarding up to four employment spells during the past four months (two as employee and two as self-employed), including start dates and end dates (if applicable), income, hours, occupation, sector, etc. It also contains standard demographic characteristics. I use the provided survey weights throughout my analysis to make results representative of the overall US population.

3.2 Variable definitions

For each data set (apart from the SIPP), I construct two samples. The first is an annual sample of wage outcomes, which I use in my analysis of life-cycle wage growth. As is common, I define the wage as the sum of gross labor income during the prior calendar year divided by annual hours worked. The latter is constructed as the product of months or weeks worked times usual weekly hours. I top code usual weekly hours at 98 hours to be consistent with the PSID. I include in labor income also income from self-employment, to be consistent with the BHPS which does not distinguish across sources of labor.

---

10 In the PSID, each subcomponent of total income is top-coded at separate thresholds that vary across years. I use a Pareto imputation to top-coded subcomponents in each year before I sum each component to get total income (Heathcote et al., 2010). The BHPS records income and hours from September to September instead of by calendar year.
income. I do, however, restrict my wage analysis to those who are wage employed at the time of the survey—henceforth employees—as the model has little to say about self-employment. I have repeated my analysis excluding income from self-employment whenever possible (all countries but the UK) with virtually identical results, i.e. differences in self-employment income among wage employees do not drive the patterns. Nominal variables are converted to real 2004 local currency using the national CPI index, and then to real US dollars using the PPP-adjusted exchange rate in 2004.

The second sample is a monthly sample of labor force status, with additional information on the ongoing employment spell in the month the respondent takes the survey. I use this to compute monthly labor market flows. The monthly calendar of events asks for labor market status in each month during the prior calendar year. By linking subsequent years, I obtain labor force status in each month during the 12 months prior to the survey month. In particular, a worker is said to make an EU transition if she is employed in the current month but unemployed in the subsequent month. She makes an UE transition if she is unemployed in the current month but employed in the subsequent month. The PSID does not allow a distinction between wage and self-employment in the monthly calendar of events, and hence to be consistent all monthly flows include the self-employed as employed. In the other data sets as well as in the US SIPP, however, flows from employment to (and from) self-employment are an order of magnitude smaller than those to (and from) unemployment, so I believe that this issue is second-order.

The available data sets do not allow the construction of a satisfactory monthly measure of JJ mobility, because the surveys in general ask for information on only (up to) two employment spells in the prior year. As a consequence, at most one JJ move can be observed during the past 12 months, even though the respondent might have made multiple transitions. For young, highly mobile workers in particular, this restriction is not innocuous. Nevertheless, I am able to construct a consistent measure of JJ mobility across countries as the fraction of employees who started working for their current employer at some point in the past 11 months while having been employed in every of the past 12 months. Note in particular that this accounts for intervening months of non-employment between job switches—it is not equivalent to the fraction of employed workers who were at a different employer 12 months earlier.

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

I drop observations with missing year of birth, gender or employment status, as well as individuals whose reported year of birth deviates by more than five years across panel years. This excludes very few observations. I focus on men, as female labor force participation likely varies across countries for reasons that the theory abstracts from.\footnote{In a separate, ongoing project I study cross-country gender differences in careers.} To sidestep issues associated with labor force entry and retirement, I primarily focus on ages 25–55, but present additional samples as robustness. As I discuss in Appendix B, male labor force participation rates are consistently high across countries between ages 25–55.

<table>
<thead>
<tr>
<th>Source</th>
<th>Years</th>
<th>T</th>
<th>NT</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A. Core Western European countries plus the US</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Austria</td>
<td>ECHP/EUSILC</td>
<td>1995–2014</td>
<td>18</td>
<td>39,700</td>
</tr>
<tr>
<td>Belgium</td>
<td>ECHP/EUSILC</td>
<td>1994–2014</td>
<td>19</td>
<td>36,070</td>
</tr>
<tr>
<td>Denmark</td>
<td>ECHP/EUSILC</td>
<td>1994–2013</td>
<td>18</td>
<td>25,883</td>
</tr>
<tr>
<td>Finland</td>
<td>ECHP/EUSILC</td>
<td>1996–2014</td>
<td>16</td>
<td>48,432</td>
</tr>
<tr>
<td>France</td>
<td>ECHP/EUSILC</td>
<td>1994–2014</td>
<td>16</td>
<td>58,981</td>
</tr>
<tr>
<td>Germany</td>
<td>GSOEP</td>
<td>1991–2011</td>
<td>21</td>
<td>60,346</td>
</tr>
<tr>
<td>Greece</td>
<td>ECHP/EUSILC</td>
<td>1994–2008</td>
<td>10</td>
<td>24,803</td>
</tr>
<tr>
<td>Iceland</td>
<td>EUSILC</td>
<td>2004–2014</td>
<td>10</td>
<td>10,407</td>
</tr>
<tr>
<td>Ireland</td>
<td>ECHP/EUSILC</td>
<td>1994–2014</td>
<td>17</td>
<td>25,018</td>
</tr>
<tr>
<td>Italy</td>
<td>ECHP/EUSILC</td>
<td>1994–2014</td>
<td>15</td>
<td>85,926</td>
</tr>
<tr>
<td>Netherlands</td>
<td>ECHP/EUSILC</td>
<td>1994–2014</td>
<td>18</td>
<td>61,312</td>
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<tr>
<td>Norway</td>
<td>EUSILC</td>
<td>2003–2014</td>
<td>10</td>
<td>22,994</td>
</tr>
<tr>
<td>Spain</td>
<td>ECHP/EUSILC</td>
<td>1994–2014</td>
<td>19</td>
<td>92,355</td>
</tr>
<tr>
<td>UK</td>
<td>BHPS</td>
<td>1991–2008</td>
<td>18</td>
<td>32,910</td>
</tr>
<tr>
<td>US</td>
<td>PSID</td>
<td>1994–2015</td>
<td>13</td>
<td>19,047</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td>238</td>
<td>644,184</td>
<td>198,768</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Panel B. Other OECD countries</strong></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Czech Republic</td>
<td>EUSILC</td>
<td>2005–2014</td>
<td>9</td>
<td>27,761</td>
</tr>
<tr>
<td>Estonia</td>
<td>EUSILC</td>
<td>2004–2014</td>
<td>10</td>
<td>19,682</td>
</tr>
<tr>
<td>Hungary</td>
<td>EUSILC</td>
<td>2005–2014</td>
<td>10</td>
<td>37,406</td>
</tr>
<tr>
<td>Latvia</td>
<td>EUSILC</td>
<td>2007–2014</td>
<td>7</td>
<td>12,684</td>
</tr>
<tr>
<td>Lithuania</td>
<td>EUSILC</td>
<td>2005–2014</td>
<td>9</td>
<td>13,495</td>
</tr>
<tr>
<td>Poland</td>
<td>EUSILC</td>
<td>2005–2014</td>
<td>9</td>
<td>46,972</td>
</tr>
<tr>
<td>Slovak Republic</td>
<td>EUSILC</td>
<td>2005–2013</td>
<td>8</td>
<td>15,404</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td>71</td>
<td>221,112</td>
<td>96,101</td>
</tr>
</tbody>
</table>

Note: Men aged 25–55. \(T\): Number of years; \(NT\): Number of individual-years; \(N\): Number of individuals.

I focus on employees and flows in and out of unemployment, as the theory abstracts from self-employment and non-participation. Flows in and out of non-participation are small, however, and do not vary systematically with aggregate labor market fluidity among prime aged men. I include all wage
employees, regardless of full-time status, but similar results hold among those working 30+ hours a week. Because sector classification is not made available to researchers in the EUSILC, I cannot condition on being in the private sector. I note, however, that my wage regressions control for differential patterns of selection (in levels) across countries over the life-cycle via worker fixed effects. Moreover, Appendix B assesses the role of the public sector, with two main takeaways. First, in the available data, the share of prime aged male employees that work in the public sector is about 25 percent and it declines with labor market fluidity, driven by the US. Second, life-cycle wage profiles are steeper in the public sector, but the difference is small. Hence, accounting for the lower share of public employees in more fluid labor markets would if anything make the patterns documented here somewhat more pronounced.

My analysis focuses primarily on 15 developed Western European countries and the US for which I have at least 10 years of data. I report robustness results including an additional eight OECD countries in the former East Communist bloc for which I have fewer years of data. Table 1 summarizes the annual data set. Note that the sample contains gaps. The core sample includes almost six hundred fifty thousand observations, with another two hundred thousand observations for the other OECD countries.

3.4 A cross-country perspective on life-cycle dynamics

Figure 3 plots the share of employees who made a JJ move at some point in the previous year—my measure of labor market fluidity—over the life-cycle by country. Across all countries, JJ mobility has a common shape: it is high early in careers, and subsequently declines substantially as individuals age. There are significant differences in the level of labor market fluidity across countries, with some countries displaying higher fluidity at all ages. These high fluidity countries include the Anglo-Saxon countries (UK and US), as well as Iceland and Norway. On the other end of the spectrum, Belgium, Austria and Greece have JJ mobility rates that are less than half those in the US at all ages.

Appendix B plots the EU and UE rates over the life-cycle across countries. The EU rate shares a common shape across countries, with high rates of job loss early in careers and subsequent declines. Aggregate cross-country differences are less pronounced than for JJ mobility, with Spain as an exception. The UE rate is roughly flat between ages 25–55 in most countries, although its shape is somewhat more heterogeneous across countries than the EU and JJ rates. Aggregate labor market fluidity is negatively correlated with the aggregate EU rate and positively correlated with the aggregate UE rate.

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12 Most prime aged men work full time (conditional on working) and there is no systematic covariation between usual weekly hours of prime aged men and labor market fluidity. This is reassuring given that the theory abstracts from an intensive margin.

13 The EUSILC also contains a few years of data from five non-OECD countries: Bulgaria, Cyprus, Malta, Romania and Serbia. I have confirmed that my empirical facts hold also including these non-OECD countries, but I prefer to focus in this paper on the set of relatively comparable OECD countries. This has the added convenience that the OECD provides easily accessible, internally consistent measures of GDP per hour, price levels, PPP-adjusted exchange rates, etc., online for its member countries.
I next construct life-cycle wage profiles by regressing separately by country the log hourly real wage of individual $i$ in year $t$, $w_{it}$, on age effects, $A_{it}$, year effects, $Y_t$, and individual fixed effects, $I_i$,

$$w_{it} = A_{it} + Y_t + I_i + \epsilon_{it} \quad (9)$$

The inclusion of individual fixed effects in regression (9) addresses important concerns about differences in sample attrition across countries biasing the cross-country comparison of life-cycle wage growth. In my benchmark, I compute wage growth by age. Appendix B separates results by education groups—which is isomorphic to wage growth by potential experience—with similar results.

**Figure 3. Share of workers who made a JJ move in the past year**

(A) Low fluidity countries

(B) Medium-low fluidity countries

(C) Medium-high fluidity countries

(D) High fluidity countries

Note: Male employees aged 25–55. Core sample of developed countries with at least 10 years of data. Labor market fluidity/JJ mobility: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months, constructed by first collapsing all male employees aged 25–55 to the country-age-year level, then to the country level. Due to data limitations, employment in the past 12 months includes self-employment. Source: BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.
Whenever an individual gets one year older, time also increases by one year, and vice versa. That is, age, time and individual fixed effects are collinear. Hence, a restriction is needed to identify regression (9). I follow Heckman et al. (1998) and Lagakos et al. (2018) in imposing that wages do not grow at the end of life. In particular, I assume that wages depreciate at some annual rate \(d\) after some age \(\bar{A}\). This restriction is sufficient to separate individual, time and age effects. Effectively, systematic fluctuations in wages among individuals older than \(\bar{A}\) identify the year effects. The age effects can then be recovered from within-individual conditional fluctuations in wages among those aged less than \(\bar{A}\).

**Figure 4. Wage growth between ages 25–50**

Note: Male employees aged 25–55. Core sample of developed countries with at least 10 years of data. Log hourly real wage profile based on regression (9) with individual fixed effects, unrestricted time effects and restricted age effects, restricting wages past age 50 to not grow. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months, constructed by first collapsing all male employees aged 25–55 to the country-age-year level, then to the country level. Due to data limitations, employment in the past 12 months includes self-employment. Source: BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

Figure 4 plots wage growth between ages 25–50 across countries, assuming that wages do not grow
after age 50. Across all countries, life-cycle wage profiles share a common shape, with wages growing rapidly early in careers. In contrast to the common shape, there is a remarkable degree of heterogeneity across countries in the overall wage growth over the life-cycle, as emphasized by Lagakos et al. (2018).

**FIGURE 5. LIFE-CYCLE WAGE GROWTH AND LABOR MARKET FLUIDITY**

(A) AGES 25–55 WITH 0% DEPRECIATION, CORE

(B) AGES 25–55 WITH 1% DEPRECIATION, CORE

(C) AGES 25–60 WITH 0% DEPRECIATION, CORE

(D) AGES 25–55 WITH 0% DEPRECIATION, ALL

Note: Male employees aged 25–55. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months, constructed by first collapsing all male employees aged 25–55 to the country-age-year level, then to the country level. Due to data limitations, employment in the past 12 months includes self-employment. Life-cycle wage growth: Log hourly real wage profile based on regression (9) with worker fixed effects, time effects and restricted age effects. Top left: Core sample, ages 25–54 restricting wages past age 50 to not grow. Top right: Core sample, ages 25–54 restricting wages past age 50 to depreciate 1% annually. Bottom left: Core sample, ages 25–59 restricting wages past age 50 to not grow. Bottom right: All countries, ages 25–54 restricting wages past age 50 to not grow. Source: BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

Broadly, where our studies overlap, the wage profiles I document align well with Lagakos et al. (2018). The main exception is Germany, which they find has the highest wage growth (steeper than the US). I confirm this finding in a specification that includes workers aged 20–60, which may be closer to their specifications that include all workers with 0–40 years of experience. As discussed further in Appendix B, my patterns remain robust to such alternative specifications. Nevertheless, I prefer to focus on ages 25–55 due to higher non-participation rates prior to 25 and after age 55 (see Appendix B), which the theory abstracts from. Another difference is that my panel data allow me to control for selection on unobservables using worker fixed effects.
3.5 Three cross-country facts

I now use these data to establish three facts on cross-country labor market outcomes.

Fact I. Wages grow more over the life-cycle in more fluid labor markets. Figure 5 shows that life-cycle wage growth is higher in more fluid labor markets. The top left panel plots wage growth between ages 25–50, assuming that wages do not grow between ages 50–54. By ending the analysis at age 55, the scope for cross-country differences in retirement to drive results is mitigated. The top right panel does the same instead assuming that wages depreciate by one percent annually between ages 50–54. The bottom left panel includes workers to age 59, assuming that wages do not grow between ages 50–59. Finally, the bottom right panel adds to the core sample also the OECD countries with fewer years of data.

Table 2 summarizes these correlations. The first row shows that the correlation between life-cycle wage growth and labor market fluidity is around 0.8 across specifications. The second row shows the point estimate from a linear projection of wage growth on fluidity. It is strongly statistically significant, although the sample size is small. Imposing a different depreciation rate $d$ shifts the wage profiles, but does not affect the conclusion that fluidity and wage growth are positively correlated. In addition, similar results hold if I exclude the bottom one percent of wages, top one percent or both in each country-survey, or restrict attention to full-time workers (30+ hours in a usual week). Appendix B highlights the robustness of these results across a range of additional specifications.

<table>
<thead>
<tr>
<th>Panel A. Core 15 Western European countries + the US</th>
<th>Panel B. All 23 OECD countries</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho$ 0.873 0.873 0.819 0.855 0.845</td>
<td>0.820 0.820 0.634 0.847 0.783</td>
</tr>
<tr>
<td>1.817 1.400 1.473 1.754 1.755</td>
<td>1.614 1.244 1.961 1.392 1.596</td>
</tr>
<tr>
<td>$R^2$ 0.762 0.762 0.671 0.731 0.714</td>
<td>0.672 0.672 0.402 0.717 0.613</td>
</tr>
<tr>
<td>$N$ 15 15 15 15 15</td>
<td>23 23 23 23 23</td>
</tr>
<tr>
<td>$A$ 50 50 50 50 50</td>
<td>50 50 50 50 50</td>
</tr>
<tr>
<td>$d$ 0% 1% 0% 0% 0%</td>
<td>0% 1% 0% 0% 0%</td>
</tr>
<tr>
<td>Sample All All All 30+ 1–99</td>
<td>All All All 30+ 1–99</td>
</tr>
</tbody>
</table>

Note: Male employees 25–60. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months, constructed by first collapsing all male employees aged 25–55 to the country-age-year level, then to the country level. Due to data limitations, employment in the past 12 months includes self-employment. Life-cycle wage growth: Log hourly real wage growth based on regression (9) with individual fixed effects, time effects and restricted age effects. $\rho$: Correlation between life-cycle wage growth and labor market fluidity. $\beta$: Slope in linear regression of wage growth on labor market fluidity and a constant, with standard error below. $N$: Number of countries in sample. $A$: Upper age threshold beyond which wages are assumed to depreciate at a fixed rate. $d$: Depreciation rate of wages past age $A$. All: All male employees of the given age group; 30+: Working 30+ hours in a usual week; 1–99: Trims the bottom and top 1% of wages in each country-survey. * statistically significant at 1%. Source: BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.
Appendix B finds similar results within education and occupation groups. It also illustrates that wages at labor market entry are, in fact, lower in more fluid labor markets. While this is consistent with the theory, I caution, however, that the negative relationship is not statistically significant across all specifications and it requires taking a stand on a PPP-adjustment. Hence, I interpret this particular pattern cautiously as not being inconsistent with the model.

**Fact II. On-the-job training is greater in more fluid labor markets.** Figure 6 provides tentative support for the prediction that workers train more on-the-job in more fluid labor markets. It plots the share of workers whose employer provides free or subsidized training against labor market fluidity, based on a question asked by the ECHP (i.e. only available for a subsample of country-years). I caution that it is likely difficult to capture well on-the-job training in survey data, as some training may not be perceived as such. Nevertheless, to the extent that the reported measure is positively correlated with other, non-reported training, the observed measure may still be useful. Moreover, an important advantage of the ECHP is that it is conducted by the same statistical agency based on an identical survey (although translated to the local language). This facilitates the cross-country comparison. According to the available measure, training is higher in more fluid labor markets. This is particularly notable as it is at odds with predictions from earlier theories of training in frictional labor markets (Acemoglu and Pischke, 1999).

**Fact III. Fluidity is higher in countries with lower costs of doing business.** Lastly, Figure 7 assesses potential factors behind cross-country differences in labor market fluidity. In the interest of space, I
focus here on a few obvious potential candidates. The top left panel shows a negative correlation between fluidity and measures of employment protection legislation, but the relationship is noisy. The top right panel suggests no systematic relationship between fluidity and the average unemployment benefit replacement rate. In contrast, the bottom panels show a positive correlation between fluidity and the World Bank’s doing business index across the set of core countries (left) and all countries (right). In countries where it is easier to do business, labor market fluidity is higher. This is consistent with Fonseca et al. (2001), who argue that differences in the cost of starting businesses are more important in driving cross-country variation in labor market outcomes than labor market policies.

**FIGURE 7. DETERMINANTS OF LABOR MARKET FLUIDITY**

(A) INDEX OF EPL

(B) AVERAGE UB REPLACEMENT RATE

(C) DOING BUSINESS SCORE, CORE

(D) DOING BUSINESS SCORE, ALL

*Note:* Male employees aged 25–55. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months, constructed by first collapsing all male employees aged 25–55 to the country-age-year level, then to the country level. Due to data limitations, employment in the past 12 months includes self-employment. EPL: Index of employment protection legislation compiled by the OECD. UB: Average unemployment benefit replacement rate compiled by the OECD. Doing business score: World Bank’s score of overall cost of doing business downloaded from [https://www.doingbusiness.org](https://www.doingbusiness.org) (high value indicates a low cost). Source: BHPS, ECHP, EUSILC, GSOEP, OECD, PSID and World Bank 1991–2015.
4 Estimation

The cross-country evidence in the previous section is qualitatively consistent with the theory proposed in Section 2. Yet an important outstanding question is the quantitative relevance of differences in the cost of doing business and their aggregate welfare consequences. To address these questions, this section extends the theory and brings it to the data targeting the US as a benchmark high-fluidity country.

4.1 Empirical extensions

Time is continuous and infinite, there are no aggregate shocks and I focus on the long-run steady-state.

Demographics and preferences. Workers exit the labor market exponentially at rate $\kappa$. This perpetual youth assumption simplifies by avoiding age as a state (Yaari, 1965; Blanchard, 1985). An equal mass of young workers enter at a point in time such that the overall number of workers is fixed. The consumption flow of the final good is discounted at rate $\rho$. Unemployed workers enjoy flow value of leisure $b(h)$.

Ex ante heterogeneity. Initial skills $h_0$ are drawn i.i.d. from distribution $\Lambda$. Human capital depreciates at rate $\xi$ in both unemployment and employment (subject to remaining above some lowest point, $h$).

Continuous offer distribution. The offer distribution $\Gamma$ has continuous support $[0, \infty)$.

Godfather shocks. At rate $\nu$, employed workers receive a job offer drawn from the offer distribution $\Gamma$ that they have to accept, bargaining with the employer as though they are coming from unemployment. Such godfather shocks provide a parsimonious way to generate JJ transitions with wage cuts (Jolivet et al., 2006). Microfoundations include, for instance, the need to move to accompany a spouse.

Unemployment. Workers become unemployed at rate $\delta(z)$. The dependence on match productivity $z$ captures in reduced-form the view that less productive matches are more likely to separate in response to idiosyncratic shocks. It allows the model to match the decline in EU mobility with age. Search from employment may differ in efficiency by factor $\phi$.

Value of unemployment. The value of unemployment for a worker with human capital $h$, $U(h)$, is

$$\left(\rho + \kappa\right)U(h) = b(h) - \xi U'(h) + p\beta \int_0^\infty J(z, h)^+ d\Gamma(z)$$

---

15 An earlier version of this paper solved a more sophisticated life-cycle model in which age is a state, and found very similar result as the current framework. The reason is that mobility and training primarily take place during the first 10–15 years of careers. Under standard rates of discounting, retirement 30–40 years later have very little impact on these decisions.
where \( J^+ = \max\{J, 0\} \) and \( J(z, h) \) is the surplus value of a match between a firm with productivity \( z \) and a worker with human capital \( h \). The unemployed worker enjoys flow value of leisure \( b(h) \). She meets potential employers at rate \( p \), who are sampled from the offer distribution \( \Gamma \). She accepts the job if it provides a positive surplus and she gets a slice \( \beta \) of the surplus.

**Surplus value of a match.** The surplus value of a match \( J(z, h) \) solves

\[
(p + \kappa + \delta(z)) J(z, h) = e^{z+h} + v \left( \beta \int_0^\infty (J'(z', h)^+ d\Gamma(z') - J(z, h)) \right) + \phi p \int_z^\infty J(z', h) - J(z, h) d\Gamma(z') \]

\[
+ \max_i \left\{ (\mu_i - \xi) \left( \frac{\partial J(z, h)}{\partial h} - e^{\eta h} \frac{z + \eta}{1 + \eta} \right) - b(h) + \xi U'(h) - p \beta \int_0^\infty (J'(z', h)^+ d\Gamma(z')) \right\}
\]

The match produces output \( e^{z+h} \), the worker permanently exits at rate \( \kappa \) and the match breaks up exogenously at rate \( \delta(z) + v \). If due to a godfather shock, the worker immediately draws a new job offer from the offer distribution \( \Gamma \) and bargains with the new employer as if from unemployment. The worker finds a new potential job at rate \( \phi p \) also drawn from \( \Gamma \). If the new job is better than the current, she switches employer and gets a slice \( \beta \) of the differential surplus. The match optimally invests in training. Finally, \( J(z, h) \) is the surplus, so the value of unemployment has to be subtracted.

**Surplus value of a worker.** Given investment and reservation rules, the surplus value to a worker with human capital \( h \) of being employed in a match with productivity \( z \) while paid piece rate \( r \), \( W(r, z, h) \), is

\[
(p + \kappa + \delta(z)) W(r, z, h) = e^{r+z+h} + (\mu i(z, h) - \xi) \frac{\partial W(r, z, h)}{\partial h} + v \left( \beta \int_0^\infty (J'(z', h)^+ d\Gamma(z') - W(r, z, h)) \right) + \phi p \int_0^z (J'(z', h) + \beta \left( J(z, h) - J(z', h) \right) - W(r, z, h)) d\Gamma(z') + \phi p \int_z^\infty (J(z, h) + \beta \left( J(z', h) - J(z, h) \right) - W(r, z, h)) d\Gamma(z') - b(h) + \xi U'(h) - p \beta \int_0^\infty (J(z, h)^+ d\Gamma(z))
\]

The worker receives flow payment \( e^{r+z+h} \) and grows her human capital at rate \( \mu i(z, h) - \xi \) (she implicitly pays for the training through a lower wage). At rate \( \phi p \), she receives outside job offers from offer distribution \( \Gamma \). If the new productivity is lower than the current, she remains with her current firm, but potentially with an updated piece rate. If the new match is better than the current, she switches jobs.

**Wage policies.** Four wage policies determine wages. The wage out of unemployment, \( r^u(z, h) \), is defined by \( \beta J(z, h) = W(r^u(z, h), z, h) \). The wage a worker with human capital \( h \) receives when simul-
A worker with human capital $h$ is given by $W(r^I(z', h), z, h) = J(z', h) + \beta \left( J(z, h) - J(z', h) \right)$. The reservation wage that leaves a worker with human capital $h$ indifferent between remaining with a firm with productivity $z$ and quitting for unemployment, $r^I(z, h)$, satisfies $W(r^I(z, h), z, h) = 0$. The reservation wage that leaves a firm with productivity $z$ indifferent between firing a worker with human capital $h$ and keeping her, $r^f(z, h)$, is given by $W(r^f(z, h), z, h) = J(z, h)$.

**Evolution of states.** Let $g(z, h)$ be the distribution of workers over productivity $z$ and human capital $h$. Assume that the flow value of leisure $b(h)$ is such that all workers have the same reservation threshold $z$, $b(h) : U(h) \equiv J(z, h)$ for all $h$. Then for $z \geq z$, $g(z, h)$ solves the Kolmogorov Forward Equation (KFE)

$$
0 = -\left( \kappa + \delta(z) + v + \phi \rho (1 - \Gamma(z)) \right) g(z, h) - \left( \mu i(z, h) - \xi \right) \frac{\partial g(z, h)}{\partial h} + \gamma(z) \left( p \frac{u(h)}{e} + v \int_{z}^{\infty} g(z', h) dz' + \phi \rho \int_{z}^{\infty} g(z', h) dz' \int_{z}^{\infty} \frac{dG(z', h)}{dh} \right)
$$

where $u(h)$ the number of unemployed with human capital $h$, given by

$$
0 = -\left( \kappa + p \right) u(h) + \xi u'(h) + \int_{z}^{\infty} \delta(z) g(z, h) dz
$$

and $e = 1 - \int u(h) dh$ is the number of employed. Workers flow out due to permanent exit at rate $\kappa$, exogenous separations at rate $\delta(z)$, godfather shocks at rate $v$, and up the job ladder at rate $\phi \rho (1 - \Gamma(z))$. With probability $\gamma(z)$, workers who receive an offer contact a match with productivity $z$, which they accept if they are either unemployed, received a godfather shock or are employed lower down the job ladder. Finally, the density changes due to changes in human capital.

**Free entry.** Let $S = u + \phi e$ be the efficiency mass of voluntary searching workers. Free entry requires

$$
c = (1 - \beta) \int_{0}^{\infty} \left( q \left( \int \frac{u(h)}{S} J(z, h) dh + \frac{\phi e}{S} \int_{z}^{\infty} J(z, h) dG(z', h) \right) + \frac{ve}{V} \int_{0}^{\infty} J(z, h) dG(z', h) \right) d\Gamma(z)
$$

In return for a flow cost of a vacancy $c$, a firm meets a voluntary mover at rate $q = (V - ve) / S^{a-1}$. The first term is the probability that the potential hire is unemployed, distributed over human capital according to $u(h)$. The second term is the probability that the worker is employed, distributed over human capital and productivity according to $G(z, h)$. At rate $ve / V$ the vacancy contacts an involuntary

$^{16}$I assume that parameters are such that $V \geq ve$. I exclude those hit by a godfather shock—moving to accompany a spouse etc—from the matching function to avoid the arrival rate of such shocks from rising with job creation, which I find unreasonable.
mover. The worker has to accept the offer and bargains as though from unemployment. In either case, the new potential match draws a productivity from $\Gamma(z)$ and the firm gets a slice $1 - \beta$ of any match that is formed. The definition of a stationary equilibrium is similar to the simple model and hence omitted.

### 4.2 Methodology

I set externally three parameters. The discount rate, $\rho$, corresponds to a five percent annual real interest rate. I assume that all workers enter the labor force at age 24 and that the exit rate from the labor force, $\kappa$, is such that the average career is 35 years. Note that I will keep both the entry age and the exit rate fixed across countries in my counterfactual experiments, consistent with the lack of systematic covariation between labor force entry and exit ages and labor market fluidity in Appendix B. The available data do not allow me to identify the elasticity of matches with respect to vacancies, $\alpha$, so I set $\alpha = 1 - \beta$. The implied value for $\alpha$ is within the range of typical estimates (Petrongolo and Pissarides, 2001).

I estimate internally 11 parameters using SMM (Gourieroux et al., 1993) targeting 108 moments. I solve the continuous time model on a discretized grid for productivity and human capital for a large number of potential parameter values $\mathcal{P}$. Subsequently, I pick the parameter vector that minimizes the sum of weighted squared percentage deviations between a set of moments in the model and the data,

$$p^* = \arg \min_{p \in \mathcal{P}} \sum_i \left( \frac{m_i^{\text{model}}(p) - m_i^{\text{data}}}{m_i^{\text{data}}} \right)^2$$

As discussed further below, some moments particularly inform some parameters. I set weights such that each set of moments particularly informing one parameter receives the same total weight (that is, if $n$ moments particularly inform parameter $p$, each of these moments receives a weight $1/n$). The one exception is aggregate fluidity, which I assign five times this weight given its key role in the analysis.

By avoiding maximums, I reduce the time it takes to solve the model for one parameter draw to only a few seconds. To subsequently compute moments, I invert a system of linear equations, which is faster than simulation. It is difficult, however, to derive a law of motion for labor market fluidity. Hence, I compute it based on a simulated discrete-time, monthly approximation for 13 months for 800,000 individuals uniformly distributed between ages 25–55, where each age group is initialized from its age-conditional distribution over employment state, human capital and match productivity. This corresponds with my empirical measure, which assigns equal weight to each age 25–55.

I assume that initial match productivity, $z$, is drawn from an exponential distribution with shape $\zeta$ (i.e. $e^z$ is Pareto distributed with tail index $1/\zeta$). I assume that initial human capital, $h_0$, is drawn from an
exponential distribution with shape $\sigma$. I parameterize the separation rate, $\delta(z) = \delta_0 e^{-\delta_1(z - z_0) / (z - \bar{z})}$, where $z_0$ is the maximum productivity on the discretized grid for productivity. The flow value of leisure $b(h)$ is set such that workers of each human capital level are indifferent between unemployment and working at the second lowest grid point for productivity. This leaves 11 parameters to estimate internally,

$$p = \{ \sigma, \mu, \eta, \zeta, p, \phi, \nu, \delta_0, \delta_1, \zeta, \beta \}$$

While the estimation is joint, it is nevertheless useful to provide a heuristic discussion of what moments particularly inform what parameter. Dispersion in initial human capital, $\sigma$, is informed by the overall standard deviation of wages. If this is larger, inequality is greater. The drift of human capital, $\mu$, targets wage growth between ages 25–50, while the curvature of the training cost, $\eta$, and the depreciation rate of human capital, $\zeta$, are set to match the curvature of the life-cycle wage profile.

The job finding rate $p$ targets the aggregate unemployment rate. Of course, $p$ is an endogenous outcome, but the cost of a vacancy, $c$, is effectively a free parameter. I set this ex post to rationalize the job finding rate. The relative search efficiency of employed workers, $\phi$, is set to target the aggregate JJ mobility rate. If $\phi$ is higher, JJ is greater. I target for the rate of godfather shocks, $\nu$, the life-cycle profile of JJ mobility. With age, individuals move up the job ladder, thus reducing the probability of a subsequent job move. If $\nu$ is larger, the JJ mobility rate falls less with age, as a larger share of JJ moves are independent of a worker’s current rank in the job ladder. The intercept in the separation rate, $\delta_0$, is particularly informed by the aggregate EU rate. The slope $\delta_1$ is informed by the life-cycle EU rate. Workers gradually move up the job ladder with age, which hence reduces the risk of separation.

The shape, $\zeta$, of the productivity distribution is informed by the standard deviation of wages over the life-cycle. If it is larger, i.e. the tail of the productivity distribution is fatter, inequality grows more with age. Finally, workers’ bargaining power, $\beta$, is informed by average wage gains upon a JJ move, because if it is larger, wage gains from moving to a more productive match are more front loaded.

### 4.3 Estimates and model fit

Table 3 summarizes the parameter estimates, expressed at a monthly frequency. The fit is excellent. While it is not known whether the condition for uniqueness in Proposition 3 extends to the richer model, the high estimated curvature of the training cost, $\eta$, suggests that the equilibrium may be unique. Moreover, I have not uncovered any evidence of multiplicity. The estimated depreciation rate of human capital, $\zeta$, is particularly informed by the standard deviation of wages over the life-cycle. If it is larger, i.e. the tail of the productivity distribution is fatter, inequality grows more with age.

---

17I normalize the flow value of leisure such that workers are indifferent between unemployment and employment at the second grid point on the discretized grid for human capital to avoid any potential numerical issues associated with the boundary of the grid. Hence, the estimated job finding rate $p$ is higher than the actual UE rate, since some job offers are not accepted.
capital, $\xi$, implies that a full year of unemployment is associated with a 10 percent decline in human capital. The relative search intensity of employed workers, $\phi$, is high, as the "slippery" nature of the job ladder—$\delta_1 > 0$—implies that workers who have found a good job tend to stay there for long and reject many offers in the meantime (for comparison, Jarosch, 2015, estimates $\phi = 0.74$). Godfather shocks, $\nu$, are rare. Workers’ bargaining power $\beta$ is 0.42, with an implied labor share of 84 percent (for comparison, Bagger et al., 2014, estimate $\beta \approx 0.3$ with an implied labor share of 81–85 percent). The parameters appear to be well informed from the targeted moments, as I discuss further in Appendix C.

**Table 3. Parameter values**

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>Targeted moment</th>
<th>Model</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A. Externally set</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\nu$ Permanent exit rate</td>
<td>0.002</td>
<td>35 year average career</td>
<td>0.851</td>
<td>0.820</td>
</tr>
<tr>
<td>$\rho$ Discount rate</td>
<td>0.004</td>
<td>5% annual real interest rate</td>
<td>0.774</td>
<td>0.748</td>
</tr>
<tr>
<td>$\alpha$ Elasticity of matches w.r.t. vacancies</td>
<td>0.577</td>
<td>Hosios (1990) condition, $1 - \beta$</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Panel B. Internally estimated</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma$ Initial human capital dispersion</td>
<td>0.577</td>
<td>Std. of wages</td>
<td>0.851</td>
<td>0.820</td>
</tr>
<tr>
<td>$\mu$ Drift of human capital</td>
<td>0.014</td>
<td>Life-cycle wage growth</td>
<td>0.774</td>
<td>0.748</td>
</tr>
<tr>
<td>$\eta$ Curvature of training cost</td>
<td>8.088</td>
<td>Life-cycle wage profile</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\xi$ Depreciation rate of human capital</td>
<td>0.009</td>
<td>Life-cycle wage profile</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$p$ Job finding rate</td>
<td>0.254</td>
<td>Unemployment rate</td>
<td>0.059</td>
<td>0.054</td>
</tr>
<tr>
<td>$\phi$ Relative search efficiency of employed</td>
<td>0.859</td>
<td>Labor market fluidity</td>
<td>0.097</td>
<td>0.096</td>
</tr>
<tr>
<td>$\nu$ Rate of godfather shock</td>
<td>0.001</td>
<td>Life-cycle labor market fluidity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\delta_0$ Separation rate, intercept</td>
<td>0.045</td>
<td>Monthly EU rate</td>
<td>0.005</td>
<td>0.005</td>
</tr>
<tr>
<td>$\delta_1$ Separation rate, slope in $z$</td>
<td>7.594</td>
<td>Life-cycle EU rate</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\zeta$ Shape of productivity distribution</td>
<td>0.099</td>
<td>Life-cycle inequality profile</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta$ Worker bargaining power</td>
<td>0.423</td>
<td>Wage gain upon a JJ move</td>
<td>0.036</td>
<td>0.036</td>
</tr>
</tbody>
</table>


Figure 8 illustrates the model fit to life-cycle dynamics. It matches well the decline in the JJ rate with age, as workers gradually find a good job. It also matches well the decline in the EU rate, as workers gradually move away from low productive matches with a high likelihood of breaking up. To a first order, the UE rate is flat over the life-cycle in both the model and data. Wages grow rapidly early in careers, as workers have much scope to move up the job ladder and bargain up their wage, and face low costs of training. Inequality grows over the life-cycle, as some lucky individuals find highly productive jobs early in careers and invest in skills in response. The model matches the gradual decline in the wage gains upon JJ mobility, although the life-cycle profile was not targeted. The reason is that as individuals move up with job ladder with age, an increasing share of JJ moves are due to godfather shocks.
Figure 8. Model fit

(A) Annual JJ rate

(B) Monthly EU rate

(C) Monthly UE rate

(D) Mean log wage

(E) St.d. of log wage

(F) Wage gain upon a JJ move

Note: Men aged 25–50. JJ rate: Share of employees who started working for their current employer in the past 11 months and have been employed in all of the past 12 months. EU rate: Share of employed workers who are unemployed in the subsequent month. UE rate: Share of unemployed workers who are employed in the subsequent month. Mean wage: Average log hourly wage (in the data based on regression (9) between ages 25–54 assuming zero wage growth between ages 50–54). St.d. of wage: Standard deviation of log hourly wage, constructed after first dropping observations earnings less than half the federal minimum wage an hour in 2004 USD (i.e. $3.13). Wage gain upon a JJ move: Difference between log wage in the subsequent month and the current month among those who are employed at different employers in the two months. All model moments are re-centered to match the empirical mean in order to facilitate visual comparison of the life-cycle dynamics; for the level of the respective moments, see Table 3. Source: Model, PSID and SIPP 1994–2015.
4.4 Understanding life-cycle wage dynamics

Before proceeding, I illustrate the implications of my estimates for the sources of life-cycle wage dynamics, as this both has some independent interest and serves as a useful illustration of the workings of the model. Figure 9 uses the estimated model to decompose the sources of life-cycle growth in average wages and inequality in the US. Recall that log wages are \( \ln w = z + h + r \) while log output equals \( \ln y = z + h \). The left panel shows that human capital is the most important source of life-cycle wage and output growth. Wages grow faster than output because the piece rate increases over the life-cycle.\(^{18}\)

The right panel shows that a large share of the life-cycle increase in inequality is due to human capital. Some lucky individuals find a high productive job early in careers. Due to the slippery nature of the job ladder, once an individual has found her way to the upper part of the job ladder, she expects to remain there for an extended period of time. This may involve staying with the same firm or making a JJ move even further up the ladder, but the important aspect is that the probability of a reset through unemployment is low. She optimally responds to this by investing significantly in human capital. Other, less fortunate individuals do not find a productive job early and respond by investing little.

\[\text{FIGURE 9. DECOMPOSING LIFE-CYCLE WAGES, MODEL}\]

\[\text{(A) MEAN}\]

![Graph of mean productivity, human capital, and piece rate over age, normalized to zero at age 25.]

\[\text{(B) STANDARD DEVIATION}\]

![Graph of standard deviation productivity, human capital, piece rate, and covariances over age.]

\[\text{Note:}\] Left panel: Average log match productivity, log human capital and log piece rate by age, normalized to zero at age 25. Recall that output is \( \ln y = z + h \) and wages are \( \ln w = z + h + r \). Right panel: St.d. of log match productivity, st.d. of log human capital, st.d. of log piece rate, and sum of all covariances based on a variance decomposition of log wages, \( \ln w = r + z + h \). Source: Model.

I note in particular that the increase in inequality takes place despite no permanent differences in learning ability, which the previous literature has argued is essential to produce an increase in earnings\(^{18}\) This contrasts with Bagger et al. (2014), who estimate a flat piece rate over the life-cycle in Denmark. While several features differ between the two papers (including the fact that they use Danish data), the most conceptually distinct feature of the current model is that workers share the cost of investing in training early in careers through a lower piece rate, whereas in their model training comes "for free" through learning-by-doing.

\(^{18}\)
dispersion over the life cycle (Huggett et al., 2006). Moreover, it contrasts with Bagger et al. (2014), who attribute increasing inequality to rising dispersion in match productivity. Because they allow for neither permanent differences in learning ability nor training to respond to luck in the labor market (except to differ depending on employment versus unemployment), they infer that the increase in wage dispersion must be due to increasing dispersion in match productivity. In contrast, when training is endogenous, it acts to propagate labor market luck. This is consistent with recent evidence that some firms offer systematically higher wage growth, although here it arises endogenously through agents’ optimizing behavior instead of through exogenous differences in firms’ learning environment (Gregory, 2019).

5 Labor market fluidity and human capital accumulation

I now turn to the effect of differences in firms’ cost of doing business on worker careers, motivated by the positive correlation between the World Bank’s doing business index and labor market fluidity documented in Section 3. An issue, however, is that the doing business index is not easily mapped into a model object for quantitative analysis. Hence, I pursue a wedge-like approach in the spirit of Hsieh and Klenow (2009), adjusting the cost of creating vacancies, $c$, to match cross-country differences in labor market fluidity. This approach acknowledges that while multiple factors likely impact firms’ cost of doing business, they all map into labor market fluidity from the perspective of understanding workers’ optimal behavior (Pries and Rogerson, 2005). Holding all other parameters fixed, I assess the impact of such wedges to firms’ cost of creating jobs on life-cycle wage growth and aggregate outcomes.¹⁹

I focus most of my discussion on the core set of 15 Western European countries plus the US for which I have at least 10 years of data. Appendix D provides the same graphs for the full set of 23 OECD countries with similar conclusions. Appendix C shows that the model could have predicted much different effects of a change in the cost of doing business, had the estimated parameter values been different. That is, the estimated effects are not hard-wired into the model. Nevertheless, it also argues that the differences in parameter values required to substantially change my conclusions would substantially worsen the fit of the model to the data. This provides confidence in the estimated effects presented below.

5.1 Micro consequences of the cost of doing business

The top left panel of Figure 10 shows that life-cycle wage growth is significantly greater in more fluid labor markets. The top right panel illustrates that inequality increases modestly with labor market fluidity.¹⁹

¹⁹I allow the flow value of leisure to adjust such that each human capital group is indifferent between unemployment and employment at the least productive firm on the grid for productivity. Not doing this, however, only marginally affect results.
idity, in both the model and the data. Appendix D finds, however, that this pattern is not due to steeper life-cycle growth in inequality in more fluid labor markets, at odds with the progressive taxation mechanism emphasized by Guvenen et al. (2013) being the driver of the patterns documented here. The EU rate in the bottom left panel is lower in more fluid labor markets, as workers more quickly leave low productive matches with a high chance of breaking up, while the UE rate in the bottom right panel is higher in more fluid labor markets, as firms create more vacancies.

**Figure 10. Micro outcomes**

![Figure 10: Micro outcomes](image)

**Note:** Men aged 25–55. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months, constructed by first collapsing all male employees aged 25–55 to the country-age-year level, then to the country level. Due to data limitations, employment in the past 12 months includes self-employment. Wage growth (data): Based on regression (9) for ages 25–54 assuming no wage growth after age 50. EU rate: Share of employed who are unemployed in the subsequent month. UE rate: Share of unemployed who are employed in the subsequent month. EU/UE flows include as employed the self-employed due to data limitations; unemployment follows standard ILO definition. Model moments are re-centered to match the empirical mean to improve readability. **Source:** Model, BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

Table 4 summarizes these predictions. For each outcome in Figure 10, the first row shows the cor-
relation between the moment in the data and model. The correlation ranges from 0.24 for inequality to 0.87 for life-cycle wage growth. The second row shows the point estimate from a regression of the moment in question on a constant and labor market fluidity in the data, with the corresponding standard error in the third row. The positive relationship between life-cycle wage growth and fluidity is strongly statistically significant, as is that with the UE rate. The relationship with inequality is not statistically significant, while that with the EU rate is weakly statistically significant. The last row shows the point estimate from the same regression on model generated data. Differences in the cost of doing business account for 55 percent of the covariation between life-cycle wage growth and labor market fluidity in the data \( \beta_{\text{model}} / \beta_{\text{data}} = 0.554 \). Hence, while important, other forces are also at work. Possible candidates include unions or minimum wages, which would be interesting to pursue further in future work. Differences in the cost of doing business account for a large share of the empirical covariance between inequality, the EU rate and the UE rate, on the one hand, and labor market fluidity, on the other.

### Table 4. Micro outcomes, model versus data

<table>
<thead>
<tr>
<th>Panel A. Core 15 Western European countries + the US</th>
<th>Panel B. All 23 OECD countries</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Delta )Wage</td>
<td>St.d.</td>
</tr>
<tr>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>( \rho )</td>
<td>0.874</td>
</tr>
<tr>
<td>( \beta_{\text{data}} )</td>
<td>11.730***</td>
</tr>
<tr>
<td>(1.817)</td>
<td>(0.992)</td>
</tr>
<tr>
<td>( \beta_{\text{model}} )</td>
<td>6.504</td>
</tr>
</tbody>
</table>

*Correlation between moment in model and data. \( \beta_{\text{data}} \): Point estimate from linear projection on labor market fluidity and a constant (standard error in parenthesis). \( \beta_{\text{model}} \): Point estimate from linear projection on labor market fluidity and a constant. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months, constructed by first collapsing all male employees aged 25–55 to the country-age-year level, then to the country level. Due to data limitations, employment in the past 12 months includes self-employment. \( \Delta \)Wage: Log wage difference between age 50 and 25; empirical wage profile based on regression (9) for ages 25–54 assuming no wage growth after age 50. St.d.: Standard deviation of log hourly wage. EU/UE rates: Monthly EU/UE rate, including the self-employed as employed due to data limitations. * statistically significant at 10%; ** statistically significant at 5%; *** statistically significant at 1%. Source: Model, BHPS, ECHP, EUSILC, GSOEP, and PSID 1991–2015.

Appendix D shows that: (i) there is no pronounced, systematic relationship between wage growth in years of a JJ move and aggregate labor market fluidity; (ii) as expected given the in and outflows from unemployment, the unemployment rate is higher in less fluid labor markets; and (iii) wages of labor market entrants are higher in less fluid labor markets. The model matches these patterns well.

### 5.2 Supporting evidence of the mechanism

Figure 11 provides supporting evidence for the mechanism. The left panel plots training in the model and the data against labor market fluidity. The model moment is the average amount spent on training

---

\( ^{20} \)Although a projection of labor market fluidity on the minimum wage reveals no robust pattern.
per worker, \( \int c(h, i(h, z))dG(z, h) \), while the data moment is the share of workers who report that their employer provides free or subsidized training. Differences in firms’ cost of doing business account for a third of the empirical covariation between on-the-job training in the data. The right panel shows that variation in the calibrated cost of a vacancy, \( c \), in the model is of a similar order of magnitude as observed differences in the cost of starting firms across countries, expressed as a fraction of income per capita. This provides reassuring evidence that the calibrated wedges to the cost of doing business are realistic.

**Figure 11. Training and the cost of doing business**

Note: Male employees aged 25–55. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months, constructed by first collapsing all male employees aged 25–55 to the country-age-year level, then to the country level. Due to data limitations, employment in the past 12 months includes self-employment. Training (data): Log share of workers whose employer provides free or subsidized training. Training (model): Training per worker, \( \log \int c(h, i(h, z))dG(z, h) \). Cost of starting business (data): As estimated by the World Bank relative to income per capita. Cost of doing business (model): Cost of a vacancy, \( c \), relative to net output per capita (output minus costs of vacancies and investment). Model moments are re-centered to match the empirical mean. Source: Model, BHPS, ECHP, EUSILC, GSOEP, PSID and World Bank 1991–2015.

### 5.3 Macro consequences of the cost of doing business

Figure 12 projects versions of labor productivity on labor market fluidity in the model and data, where the empirical measure is real output per hour in 2014 in 2004 PPP-adjusted USD. An important caveat is that the model is estimated for men, while productivity is only available at the economy level. The model measure is gross output per worker in the top left panel and net output per worker in the top right panel, subtracting spending on training and vacancy creation. This measure of net output reflects the view that the wedges to firms’ cost of doing business capture red tape. The bottom left panel plots net output under the alternative view that these wedges represent payment for governmental services, i.e. it adds the wedge times total vacancy creation to net output in the top right panel. The bottom right panel additionally includes the flow value of leisure of unemployed workers. This is the appropriate
measure of welfare given linear utility. Note that this specification adopts the view that the value of leisure reflects utility value of leisure, as opposed to, for instance, government funded unemployment insurance. Under the latter alternative view, the patterns for welfare would be more pronounced.

**Figure 12. Macro Outcomes**

Across all alternative views of productivity and welfare, a higher cost of doing business is associated with substantial negative effects. Gross and net labor productivity in the top panels are 30 percent lower in the least fluid labor market relative to the US. While the data are consistent with these predictions,
they are noisy. One reason could be that the model is estimated for prime aged men, while the empirical moments cover the entire population, as noted above. Moreover, other forces are likely at work too. To the extent that they primarily have level effects, life-cycle wage growth may provide a more direct test of the mechanism emphasized here. The patterns for gross and net output per worker are effectively indistinguishable. The reason is that while vacancy creation rises with fluidity, the cost of a vacancy falls. Nevertheless, adding back the amount spent on the wedges in the bottom left panel, a higher cost of doing business continues to result in large negative productivity consequences. Accounting also for the value of leisure, welfare remains 20 percent lower in the least fluid labor market relative to the US.

5.4 Direct versus indirect effects

How important is the dynamic incentive effect of misallocation on human capital accumulation versus the direct effect of lower match productivity? The left panel of Figure 13 illustrates that aggregate match productivity is over 10 percent lower in the least fluid labor market relative to the US, as workers move up the job ladder at a slower pace. The stock of human capital is over 15 percent lower, as workers in less fluid labor markets train less, since they expect to use their human capital less efficiently.

The right panel shows that human capital is also the biggest factor behind lower life-cycle wage growth in less fluid labor markets. Less growth in match productivity and the piece rate are also important. The latter grows by more in more fluid labor markets as workers start at a lower piece rate to share the cost of higher training with their employer, but grow it faster as they receive more outside offers.

5.5 The role of labor market fluidity

When the cost of doing business changes, the job finding rates from both unemployment and employment change. While this is in line with the data in Figure 10, it is nevertheless of interest to assess the relative importance of each channel. To quantify this, I consider the following counterfactual scenario. I hold the job finding rate from unemployment, \( p \), fixed at the estimated value for the US, but instead adjust relative search efficiency from employment, \( \phi \), so as to match observed cross-country variation in labor market fluidity.\(^{21}\) Figure 14 shows that both a lower job finding rate from unemployment and from employment contribute meaningfully to lower labor productivity and life-cycle wage growth in less fluid labor markets, with a slower rate of climbing the job ladder the single most important factor.

\(^{21}\)Because workers still move away from low productive jobs with a higher chance of breaking up at a slower rate when the search intensity from employment, \( \phi \), is lower, the incidence of unemployment remains higher in low-\( \phi \) countries. Nevertheless, over 90 percent of unemployment differences disappear once differences in the job finding rate from unemployment are shut down, such that remaining differences in the incidence of unemployment play a second-order role in driving results.
Figure 13. Decomposing the effect, model

(A) Aggregate productivity

(B) Life-cycle wage growth

Note: Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months, constructed by first collapsing all male employees aged 25–55 to the country-age-year level, then to the country level. Due to data limitations, employment in the past 12 months includes self-employment. Aggregate productivity: Log aggregate (gross) output per worker, log aggregate match productivity, and log average human capital. Life-cycle wage growth: Average growth in log wages between age 25–50, average growth in the log piece rate between age 25–50, average growth in the log human capital between age 25–50. All moments are relative to the US. Source: Model.

Figure 14. The role of a higher rate of climbing the job ladder, $\phi$, model

(A) Aggregate productivity

(B) Life-cycle wage growth

Note: Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months, constructed by first collapsing all male employees aged 25–55 to the country-age-year level, then to the country level. Due to data limitations, employment in the past 12 months includes self-employment. Aggregate productivity: Log average output per worker. Life-cycle wage growth: Average growth in log wages between age 25–50. All moments are relative to the most fluid labor market. Benchmark: Baseline results reported above. $\phi$ only: Effect of counterfactually only changing $\phi$ holding $p$ fixed at its estimated US value in order to match observed cross-country differences in labor market fluidity. In both cases, the flow value of leisure $b(h)$ is allowed to adjust such that workers exit at the second lowest grid point for productivity. Source: Model.
5.6 The case for job creation subsidies

Lastly, I briefly assess whether policy could improve outcomes within the context of the estimated US economy. That is, relative to the earlier analysis, I now treat the cost of a vacancy, $c$, as a technological constraint and ask whether given this a policy maker may want to intervene. As highlighted in Section 2, the decentralized equilibrium is generically inefficient, suggesting that a policy maker may want to do so. One potential policy would be to subsidize on-the-job training. Such training, however, often takes an informal nature, likely making it difficult to verify for a policy maker. Hence, I instead consider whether a policy maker would want to subsidize job creation as a way of implicitly raising incentives to train. I assume that a policy maker has the ability to raise funds in a lump sum fashion to subsidize the creation of vacancies (which given linear preferences has no impact on behavior).

Figure 15 plots on the x-axis the cost of the subsidy, expressed as a fraction of gross output per capita in the benchmark US economy. The y-axis graphs the percentage change in net output per capita relative to the benchmark, defined as the sum of total flow output, including the flow value of leisure for workers currently unemployed, minus the total costs of vacancy creation, investment and the total cost to the government of the subsidy program. With linear utility, this is the relevant measure of welfare. A subsidy to job creation of two percent of GDP would raise welfare by 0.6 percent. Hence, while there is scope for policy to improve outcomes, the welfare gains from this policy are fairly modest.

**Figure 15. Change in welfare as a function of subsidy to job creation, model**

*Note:* Change in welfare: Percentage change in flow output per capita including the flow value of leisure of unemployed workers minus the total cost of vacancy creation, investment and the total cost of the government subsidy program relative to net output in the benchmark US economy. Subsidy as fraction of gross output: Cost of the subsidy program relative to gross output per capita in the benchmark US economy, constructed as the sum of flow output across employed workers. *Source:* Model.
6 Conclusion

This paper argues that policies that raise firms’ cost of doing business in turn reduce the stock of human capital in the economy. The reason is that it lowers labor market fluidity, which makes it harder for workers to find jobs that fully utilize their skills, discouraging human capital accumulation. Differences in the cost of doing business account for over half of lower life-cycle wage growth in less fluid labor markets across OECD countries. The single most important factor behind this is less human capital accumulation on-the-job. Aggregate productivity is 30 percent lower in the least fluid labor market relative to the US, of which 60 percent is due to a lower stock of human capital.

In their summary of the misallocation literature, Restuccia and Rogerson (2017) argue that the dynamic consequences of static misallocation deserve much more attention. This paper has taken a step in that direction, finding that such dynamic responses may substantially amplify the effect of policies causing static misallocation. Yet many related questions remain unanswered. For instance, it would be very interesting to study how static misallocation due to gender and race discrimination as documented by Hsieh et al. (2019) may by amplified through individuals’ and firms’ dynamic responses.

References


A Proofs — FOR ONLINE PUBLICATION

A.1 Proof of proposition

Define \( \tilde{J}(i, r) = W(r, i) + F(r, i) \) as the joint value of a match between a young worker and a low-productive firm under some (not necessarily optimal) level of investment \( i \). Adding (1) and (2),

\[
\tilde{J}(i, r) = r + \left( (1 - p)r + \frac{p}{2} + \frac{p}{2}(1 + \beta(Z - 1)) \right) (1 + \mu i)
\]

which does not depend on the piece rate \( r \). The same logic extends to high-productive matches.

A.2 Proof of proposition

The problem of the firm is to chose investment to maximize its value,

\[
F(r, i) = \max_i \left\{ 1 - r(i) - \frac{1}{1 + \eta} i^{1 + \eta} + (1 - p)(1 - r(i))(1 + \mu i) \right\}
\]

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

\[
W(r, i) = U + \beta(J(i) - U)
\]

\[
r(i) = U + \beta(J(i) - U) - \left( (1 - p)r(i) + \frac{p}{2} + \frac{p}{2}(1 + \beta(Z - 1)) \right) (1 + \mu i)
\]

where \( U \) is the value of being unemployed. Substituting for \( r(i) \) in (10) using (11) and simplifying

\[
F(r, i) = (1 - \beta) \max_i \left\{ 1 - \frac{1}{1 + \eta} i^{1 + \eta} + \left( 1 + \frac{p}{2} \beta(Z - 1) \right) (1 + \mu i) \right\}
\]

Hence, the firm’s choice of investment coincides with that which maximizes the joint value,

\[
J(i) = \max_i \left\{ 1 - \frac{1}{1 + \eta} i^{1 + \eta} + \left( 1 + \frac{p}{2} \beta(Z - 1) \right) (1 + \mu i) \right\}
\]
A.3 Proof of proposition 3

Define $i_w(v)$ and $i_e(v)$ based on (6)–(7) to be

$$
i_w(v) = \left( \left( 1 + v^\alpha \beta \frac{Z-1}{2} \right) \mu \right)^{\frac{1}{\eta}}$$

$$i_e(v) = \frac{1}{\mu} \left( \frac{2cv^{1-\alpha}}{(1-\beta)(Z-1) - 1} \right)$$

Then,

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

Hence, if $\lim_{v \to \infty} i_e(v) i_w(v) > 1$, there is at least one equilibrium. Consider the limit $\lim_{v \to \infty} \left( \frac{i_e(v)}{i_w(v)} \right)^{\frac{\eta}{2}}$,

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

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

$$(1-\alpha)\eta - \alpha > 0$$

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

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

$$\frac{\partial i_w(v)}{\partial v} = \frac{1}{\eta} i_w^{1-\eta} \alpha v^{\alpha-1} \beta \frac{Z-1}{2} \mu$$

$$\frac{\partial i_e(v)}{\partial v} = \frac{1}{\nu} \left( i_e + \frac{1}{\mu} \right)$$

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

$$\frac{1}{\nu} \left( i_e + \frac{1}{\mu} \right) > \frac{1}{\eta} i_e^{1-\eta} \alpha v^{\alpha-1} \beta \frac{Z-1}{2} \mu$$

$$i_e + \frac{1}{\mu} > \frac{1}{\eta} i_e^{1-\eta} \alpha \frac{1}{1-\alpha} v^{\alpha} \beta \frac{Z-1}{2} \mu$$
Since \( i + \frac{1}{\mu} > i \), surely the above inequality is true if

\[
i > \frac{1}{\eta} i^{1-\eta} \frac{\alpha}{1-\alpha} v^\alpha \beta \frac{Z-1}{2} \mu
\]

\[
i^n > \frac{1}{\eta} \frac{\alpha}{1-\alpha} v^\alpha \beta \frac{Z-1}{2} \mu
\]

\[
\left(1 + v^\alpha \beta \frac{Z-1}{2}\right) \mu > \frac{1}{\eta} \frac{\alpha}{1-\alpha} v^\alpha \beta \frac{Z-1}{2} \mu
\]

\[
1 + v^\alpha \beta \frac{Z-1}{2} > \frac{1}{\eta} \frac{\alpha}{1-\alpha} v^\alpha \beta \frac{Z-1}{2}
\]

\[
1 > \left(\frac{1}{\eta} \frac{\alpha}{1-\alpha} - 1\right) v^\alpha \beta \frac{Z-1}{2}
\]

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

\[
\frac{1}{\eta} \frac{\alpha}{1-\alpha} - 1 < 0
\]

\[
\frac{\alpha}{1-\alpha} < \eta
\]

### A.4 Proof of proposition 4

Holding investment fixed, an increase in the cost of job creation shifts the job creation curve to the left in Figure 2, \( \frac{\partial i}{\partial c} |_i < 0 \). Holding fixed vacancy creation, an increase in the cost of job creation has no impact on the training curve, \( \frac{\partial i}{\partial c} |_v = 0 \). As established above, the unique equilibrium is characterized by the job creation curve crossing the training curve from below. Hence, in equilibrium job creation falls by more and training declines. As the job finding rate of workers falls, average match quality declines. As training falls, average human capital declines.

### A.5 Proof of lemmas 1–2 and proposition 5

This follows immediately from comparing the first-order condition for optimal investment and the free entry condition in the decentralized equilibrium to those in the planned economy,

\[
i(v)^{\eta} = \left(1 + v^\alpha \beta \frac{Z-1}{2}\right) \mu
\]

\[
i^\eta_{sp}(v) = \left(1 + v^\alpha \frac{Z-1}{2}\right) \mu
\]

\[
v(i)^{1-\alpha} = (1 - \beta) \frac{(Z-1)}{2c} (1 + \mu i)
\]

\[
v^{1-\alpha}_{sp}(v) = \frac{\alpha}{2c} \frac{Z-1}{2c} (1 + \mu i)
\]
Suppose that the decentralized economy created total vacancies equal to the constrained first best, \( v_{sp} = v \). Then only for \( \beta = 1 \) would investment coincide with the first-best solution. To ensure that \( v_{sp} = v \) would in turn require that \( \alpha = 0 \), which is inconsistent with the assumption that \( \alpha \in (0, 1) \) (moreover, even if \( \alpha = 0 \) was allowed, it would imply that there was no vacancy creation in this equilibrium).

B  Data — FOR ONLINE PUBLICATION

This section provides additional empirical results.

**Figure 16. Monthly EU rate**

(A) LOW FLUIDITY COUNTRIES

(B) MEDIUM-LOW FLUIDITY COUNTRIES

(C) MEDIUM-HIGH FLUIDITY COUNTRIES

(D) HIGH FLUIDITY COUNTRIES

*Note:* Men 25–55. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months, constructed by first collapsing all male employees aged 25–55 to the country-age-year level, then to the country level. Due to data limitations, employment in the past 12 months includes self-employment. EU rate: Share of employed workers who are unemployed in the subsequent month. Employment includes self-employment due to data limitations; unemployment follows standard ILO definition. *Source:* BHPS, ECHIP, EUSILC, GSOEP and PSID 1991–2015.
B.1 EU and UE rates

Figure 16 plots the monthly EU rate over the life-cycle across countries. The EU rate shares a common shape across countries, with high rates of job loss early in careers and subsequent declines. Aggregate cross-country differences are less pronounced than for JJ mobility, with Spain as an exception. Moreover, there is no evidence that high-fluidity countries also have higher EU mobility rates. In fact, the correlation between the aggregate EU rate and labor market fluidity is negative.

**Figure 17. Monthly UE rate**

Note: Men 25–55. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months, constructed by first collapsing all male employees aged 25–55 to the country-age-year level, then to the country level. Due to data limitations, employment in the past 12 months includes self-employment. UE rate: Share of unemployed workers who are employed in the subsequent month. Employment includes self-employment due to data limitations; unemployment follows standard ILO definition. Source: BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

Figure 17 plots the monthly UE rate over the life-cycle across countries. Three observations are noteworthy. First, the profiles appear to be somewhat noisier than the other mobility rates, likely because the
sample of unemployed is much smaller than the sample of employed. Second, the life-cycle pattern of UE mobility is somewhat more heterogeneous across countries. Most countries display modest declines in the UE rate over the life-cycle, but a few countries have more pronounced declines, while others see increases. Third, there are significant differences also in the UE rate across countries. Moreover, the aggregate UE rate is positively correlated with aggregate labor market fluidity.

B.2 PSID relative to the SIPP

The EU rate in the PSID is lower than what researchers typically find in the CPS, but in line with what other research has found in the SIPP (Menzio et al., 2016). To highlight this, Figure 18 compares the monthly EU and UE rates in the PSID against the SIPP. The EU rate is essentially identical across the two surveys. The UE rate is higher in the PSID (closer to the CPS numbers). In fact, given the EU rate, the UE rate in the PSID is somewhat "too high", in the sense that a flow-balance approach would imply an unemployment rate of middle aged men of only about two percent, relative to 3.5 percent in the raw data. A plausible factor behind this discrepancy is flows in and out of non-participation. As discussed in Section 4, I target the unemployment rate as opposed to the UE rate in estimation, as I prefer to get the former right rather than the latter. Nevertheless, the PSID and SIPP broadly paint a similar picture of significantly lower mobility rates than in, for instance, the CPS. This is consistent with well-known issues with classification error leading to substantially overstated gross worker flows in the CPS (Abowd and Zellner, 1985; Poterba and Summers, 1986).

**Figure 18. Monthly EU and UE rates, PSID versus SIPP**

- **(A) EU**
  - EU rate: Share of employed workers who are unemployed in the subsequent month.

- **(B) UE**
  - UE rate: Share of unemployed workers who are employed in the subsequent month.

*Note: Men 25–55. EU rate: Share of employed workers who are unemployed in the subsequent month. UE rate: Share of unemployed workers who are employed in the subsequent month. Employment includes self-employment due to data limitations; unemployment follows standard ILO definition. Source: PSID and SIPP 1994–2015.*
B.3 The public sector

The left panel of Figure 19 shows that the share of prime aged male employees that work in the public sector is about 25 percent and that it declines with labor market fluidity, although the relationship is driven by the US. The right panel plots the estimated life-cycle wage profile of private and public employees based on a regression of log hourly real wages, $w_{it}$, of individual $i$ in year $t$ on separate age effects for the private, $A_{it}$, and public sector, $PA_{it}$, country-year effects, $Y_{ct}$, and worker fixed effects, $I_i$,

$$w_{it} = A_{it} + PA_{it} + Y_{c(i)t} + I_i + \varepsilon_{it}$$  \hspace{1cm} (16)

I focus on the sample of 25–55 year olds and restrict wages to not grow after age 50. While in principle this restriction is only required for one of the two sectors, to treat both identically I impose it in both. Inclusion of worker fixed effects in (16) controls for differences in worker composition across sectors, i.e. identification of the level wage difference is based on workers switching between sectors. Note also that the required data for this exercise are only available from the ECHP, GSOEP and PSID. Young workers earn less when employed in the public sector, but the public sector is associated with steeper within-worker residual life-cycle growth in wages. Hence, the fact that the share of public sector employees declines with labor market fluidity tends to, ceteris paribus, flatten the relationship between life-cycle wage growth and labor market fluidity. The differences in life-cycle wage growth, however, are modest, so it is unlikely that this would have a major impact on the patterns documented in this paper.

**Figure 19. Public sector**

![Figure 19. Public sector](image)

*Note: Male employees aged 25–55. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months, constructed by first collapsing all male employees aged 25–55 to the country-age-year level, then to the country level. Due to data limitations, employment in the past 12 months includes self-employment. Share public: Share of employees that work in public sector. Life-cycle wage: Wage profile for ages 25–54 with wages restricted to not grow past age 50 based on regression (16) with worker-fixed effects and country-year effects. Source: ECHP, GSOEP and PSID 1991–2015.*
B.4 Additional empirical specifications

Table 5 provides results from a range of alternative specifications of life-cycle wage growth on labor market fluidity. For reference, the first column repeats the benchmark specification in the main body of the paper (age 25–55, no growth after age 50). The second column instead assumes a two percent annual depreciation rate of wages after age 50. The third column includes individuals from age 20, assuming constant wages after age 50. The fourth column extends the sample to cover age 20–60, assuming constant wages after age 50. The fifth column shows results for age 20–60, assuming a one percent annual depreciation rate after age 50. Panel B repeats the same analysis for the full sample. The main finding that life-cycle wage growth is greater in more fluid labor markets remains robust across all specifications.

These specifications as well as those in the main body of the paper assume an upper age threshold of $\bar{A} = 50$. This choice is motivated by the causal observation that wages in the cross-section appear to flatten out after this point. Additionally, it aims to avoid identifying the year effects only off workers with a weak attachment to the labor force such as those older than 55, since it is possible that such workers drop out of the labor force when hit by a negative shock (but remain if hit by a positive shock). I have confirmed that similar results hold assuming instead an upper age threshold of $\bar{A} = 45$.

<table>
<thead>
<tr>
<th>Panel A. Core 15 Western European countries + the US</th>
<th>Panel B. All 23 OECD countries</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho$</td>
<td>$\beta$</td>
</tr>
<tr>
<td>0.873</td>
<td>11.730*</td>
</tr>
<tr>
<td>0.740</td>
<td>15.713*</td>
</tr>
<tr>
<td>0.670</td>
<td>10.715*</td>
</tr>
<tr>
<td>0.670</td>
<td>7.618*</td>
</tr>
<tr>
<td>0.740</td>
<td>(1.817)</td>
</tr>
<tr>
<td>0.670</td>
<td>(3.296)</td>
</tr>
</tbody>
</table>

Note: Male employees 20–60. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months, constructed by first collapsing all male employees aged 25–55 to the country-age-year level, then to the country level. Due to data limitations, employment in the past 12 months includes self-employment. Life-cycle wage growth: Log hourly real wage growth based on regression (9) with individual fixed effects, time effects and restricted age effects. $\rho$: Correlation between life-cycle wage growth and labor market fluidity. $\beta$: Slope in linear regression of wage growth on labor market fluidity and a constant, with standard error below. $N$: Number of countries in sample. $\bar{A}$: Upper age threshold beyond which wages are assumed to depreciate at a fixed rate. $d$: Depreciation rate of wages past age $\bar{A}$. All: All male employees of the given age group. * statistically significant at 1%. Source: BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

B.5 Education and occupation controls

More educated workers typically have greater life-cycle wage growth. Hence, one factor behind the differences in life-cycle wage growth could be differences in educational or occupation composition across
countries. While this may ultimately be due to labor market fluidity, the mechanism differs from that emphasized here (see, e.g., Laing et al., 1995). To assess the scope for this, I consider a version of regression (9) that pools all countries and years with separate country-year effects, separate age profiles by country (restricted following the approach above), and common education-age or occupation-age profiles across all countries. This specification hence controls for differential life-cycle wage growth by education or occupation, together with differences in education or occupation composition across countries.

**Figure 20. Life-cycle wage growth and labor market fluidity with controls**

- **(A) Education-slopes**
- **(B) Occupation-slopes**
- **(C) Less than college**
- **(D) College or more**

Note: Male employees aged 25–55. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months, constructed by first collapsing all male employees aged 25–55 to the country-age-year level, then to the country level. Due to data limitations, employment in the past 12 months includes self-employment. Log hourly real wage profile based on core sample of 15 West European countries and the US with 10+ years of data for male employees ages 25–54 with wages restricted to not grow past age 50 based on regression (9). Top panels: Residual life-cycle wage growth from a pooled regression of all countries and years with separate country-year effects, country-age effects, individual fixed effects and flexible education-age effects (left) or occupation-age effects (right). Both are restricted to not grow past age 50. Bottom panels: Life-cycle wage growth and labor market fluidity within education groups. Source: BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.
The top panels of Figure 20 plot residual life-cycle wage growth from this exercise controlling for education or occupation. The cross-country correlation between life-cycle wage growth and labor market fluidity is not accounted for by systematic differences in educational or occupational composition.

The bottom panels correlate wage growth with labor market fluidity constructed separately for those with less than a college degree and those with a college degree or more. The main pattern of rising life-cycle wage growth with labor market fluidity holds within each education group. The pattern is equally or, if anything, more pronounced for higher educated. This argues against wage setting mechanisms such as union bargaining or minimum wages being the main driver of the patterns documented here, as one would expect those to have less of an impact on higher educated groups. Note also that since age and potential experience are perfectly correlated within education groups, Figure 20 also effectively provides life-cycle profiles by potential experience (I do not have data on actual experience).

### B.6 Wages of labor market entrants

The theory predicts that wages at labor market entry are lower in more fluid labor markets, as young workers share the cost of higher human capital investment with their employers. To assess whether this prediction receives empirical support, I regress log entry wages on aggregate labor market fluidity,\(^{22}\)

\[
    w_{it} = \alpha \text{fluidity}_{c} + X_{it} \beta + \epsilon_{it} \tag{17}
\]

I weigh the regression such that each country receives the same aggregate weight and include as labor market entrants those aged 22–24. I include in \(X_{it}\) only year effects, as it is not possible to control for selection via individual-fixed effects since they would be collinear with aggregate labor market fluidity. Moreover, since I am now comparing wage levels across countries (instead of growth in wages over the life-cycle), a PPP-adjustment is required. I use the PPP-adjusted exchange rate for actual individual consumption from the OECD for 2004 to convert real local currency to real USD.

Table 6 summarizes the results from regression (17) with labor market fluidity in either levels or logs. Panel A shows results with heteroscedasticity robust standard errors and Panel B with standard errors clustered at the country-level. Conceptually, one would probably like to do the latter, but standard rules of thumb suggest that the number of observations is too small to make this valid. The point estimate is consistently negative, i.e. entry wages are systematically lower in more fluid labor markets. The magnitudes imply that entry wages are about five percent lower in the most relative to the least fluid labor market. Yet the large standard errors highlight that these should be interpreted cautiously, as there is a

\(^{22}\)I thank Todd Schoellman for suggesting that I analyze this.
lot of noise in the data. One interpretation is that other factors that contribute to cross-country differences in income act as a level effect, such that life-cycle wage growth provides a more direct test of the particular mechanism in this paper.

Table 6. Entry wages relative to labor market fluidity

<table>
<thead>
<tr>
<th></th>
<th>Panel A. Robust</th>
<th>Panel B. Clustered</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Level</td>
<td>Log</td>
</tr>
<tr>
<td>( \hat{\alpha} )</td>
<td>-0.740**</td>
<td>-0.053*</td>
</tr>
<tr>
<td></td>
<td>(0.289)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>N</td>
<td>22,422</td>
<td>22,422</td>
</tr>
<tr>
<td>Clusters</td>
<td>15</td>
<td>15</td>
</tr>
</tbody>
</table>

Note: Men aged 22–24. Regression (17) of log entry wages on aggregate labor market fluidity in either levels or logs, controlling for year effects. Panel A: Heteroscedasticity robust standard errors. Panel B: Clustered standard errors at the country level. * statistically significant at 5%; ** statistically significant at 1%. Source: BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

B.7 Life-cycle labor market states

Figure 21 plots the distribution of men across four labor market states—wage employment, self employment, unemployment and non-participation—over the life-cycle, offering three main takeaways. First, workers enter the labor market at a declining pace up to age 30. There is no pronounced covariation between age of entry and labor market fluidity, although the US (and somewhat less the UK) appears to be an outlier. The way the PSID is collected, however, may bias participation rates at young ages if those who participate in the labor market are also more likely to have formed their own households (the SIPP, in contrast, shows an increase in male labor force participation rates between age 20–30). By not focusing on the head of household like the PSID, the other surveys may be less prone to this.

Second, participation rates remain high and roughly constant until age 50, after which they start to decline. The decline becomes pronounced after around age 55. Third, the share of wage employed falls gradually after age 30, while the share of self-employed rises. The current framework cannot speak to this. While the share of self-employment remains modest across all countries, it would nevertheless be interesting to study this further (see, for instance, Engbom, 2020, for a joint model of labor market search and entrepreneurship).
**Figure 21. Life-cycle labor market states**

*Note: Share of men aged 20–60 by labor market status. Solid black: wage employed; Dash-dotted green: self-employed; Dashed blue: unemployed; Dotted purple: not-in-the labor force. Computed by first collapsing the data to the age-year-country level, then collapsing to the country-age-level. Labor market states follow standard ILO definition. Source: BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.*
C Estimation — FOR ONLINE PUBLICATION

Figure 22 plots how the objective function—the sum of squared percentage deviations between model and data moments—varies as each of the estimated parameters varies around its estimated value, holding the other parameters fixed at their estimated values. Intuitively, a parameter is well informed if the gradient is steep around the optimum (although a rigorous assessment would also have to take into account underlying uncertainty in the empirical moments). The parameters appear to be well-identified based on this criterion. The only exception is possibly the curvature of the cost of investing, which is steep for lower $\eta$ but relatively flat for larger $\eta$.

Figure 23 plots on the y-axis the change in aggregate match productivity, $Z$, and human capital, $H$, in response to a change in the cost of creating jobs, $c$, such that the model generates a 67% fall in the job finding rate, $p$, for different values of the parameter on the x-axis around its estimated value, holding the other parameters fixed at their estimated values. Two observations stand out.23

First, it is theoretically possible for the model to generate much smaller or larger changes in aggregate outcomes in response to changes in the cost of creating jobs. For instance, had the estimated curvature of the cost function, $\eta$, been much lower, the effects of a higher cost of creating jobs on the aggregate stock of human capital could have been over twice as large. Similarly, if the job finding rate $p$ had been much larger, the effects could have been only half as large.

Second, Figures 22–23 jointly suggest that the estimated effects of changes in the cost of doing business on aggregate outcomes are robust, in the sense that while much different results are a theoretical possibility, they would come at the cost of a substantially worse fit to the targeted moments.

23It is also interesting that the effect of a change in the cost of doing business does not vary much with workers’ bargaining power, $\beta$, for modest variation in $\beta$. 
Figure 22. Gradient of objective function around the optimum

(A) $\sigma$

(B) $\mu$

(C) $\eta$

(D) $\zeta$

(E) $\phi$

(F) $v$

(G) $\delta_0$

(H) $\delta_1$

(I) $\zeta$

(J) $\beta$

(K) $p$

Note: Gradient of objective function (solid purple) around the parameter estimate (dashed blue). Source: Model.
FIGURE 23. CHANGE IN AGGREGATE PRODUCTIVITY AND HUMAN CAPITAL IN RESPONSE TO A 67% DECLINE IN THE JOB FINDING RATE AS A FUNCTION OF EACH PARAMETER

(A) $\sigma$

(B) $\mu$

(C) $\eta$

(D) $\xi$

(E) $\phi$

(F) $\nu$

(G) $\delta_0$

(H) $\delta_1$

(I) $\zeta$

(J) $\beta$

(K) $p$

Note: Change in aggregate match productivity $Z$ (solid purple) and aggregate human capital $H$ (dash-dotted green) in response to an increase in the cost of job creation, $c$, such that the job finding rate falls by 67% as each of the parameters varies around its estimated value (dashed blue) holding all other parameters fixed. Source: Model.
This section provides additional quantitative results.

### D.1 Additional outcomes

Figure 24 plots several additional outcomes in the model and the data. The top left panel shows that the standard deviation of log wages on average rises over the life-cycle across countries. There is, however, no systematic relationship between life-cycle growth in inequality and labor market fluidity. In contrast, if the patterns documented in this paper had been due to the progressive taxation mechanism emphasized by Guvenen et al. (2013), one would have expected steeper life-cycle growth in inequality in more fluid labor markets. Hence, that mechanism does not appear to be the primary driver between the patterns documented here. The top right panel plots residual wage growth between year \( t \) and \( t - 1 \) for workers who made a JJ move in year \( t \) relative to workers who did not move (controlling for age and year). The differential wage gains in the year of a JJ move are not systematically correlated with fluidity.

The bottom left panel projects the unemployment rate of prime aged men on labor market fluidity in the model and the data. Not surprisingly given the cross-country patterns for in and outflows in Figure 10, the unemployment rate is higher in less fluid labor markets.\(^{24}\) The bottom right panel shows that the labor share is higher in more fluid labor markets, although the mechanism emphasized here only accounts for a fraction of the empirical pattern.

Table 7 reports the slope coefficient from a linear projection of log wages at labor market entry on a constant and labor market fluidity (plus year effects in the data), in either levels or logs. Differences in the cost of doing business match well the empirical patterns for entry wages, although as discussed in Appendix B the empirical patterns are associated with substantial uncertainty. One interpretation is that other factors that contribute to cross-country differences in income act as a level effect, such that life-cycle wage growth provides a more direct test of the particular mechanism in this paper.

<table>
<thead>
<tr>
<th>Panel A. Data</th>
<th>Panel B. Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level</td>
<td>Log</td>
</tr>
<tr>
<td>Slope coefficient</td>
<td>-0.740</td>
</tr>
</tbody>
</table>

Note: Men aged 22–24 in the data; entry year (age 24) in the model. Regression (17) of log entry wages on aggregate labor market fluidity in either levels or logs, controlling for year effects. Source: Model, BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.

\(^{24}\)In results available on request, I find that the wage employment rate is lower in less fluid labor markets, i.e. the pattern for unemployment is not driven by issues associated with distinguishing between unemployment and not in the labor force.
FIGURE 24. ADDITIONAL OUTCOMES

(A) LIFE-CYCLE GROWTH IN INEQUALITY

(B) WAGE GAIN IN YEAR OF JJ MOVE

(C) UNEMPLOYMENT RATE

(D) LABOR SHARE

Note: Men aged 25–55. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months, constructed by first collapsing all male employees aged 25–55 to the country-age-year level, then to the country level. Due to data limitations, employment in the past 12 months includes self-employment. Life-cycle growth in inequality: Difference in cross-sectional std. of log hourly wage between age 25 and 55. Wage gain in year of JJ move: Median change in log hourly wage between year $t$ and year $t-1$ for workers who made a JJ move in year $t$ relative to median wage change of workers who did not make a JJ move in year $t$. Unemployment rate: Share of unemployed men aged 25–55 following standard ILO definition. Labor share: Labor’s total share of income including imputed self-employment values based on average 1991–2014 from the EU Klem database. Model moments are re-centered to match the empirical mean to improve readability. Source: Model, BHPS, ECHP, EU Klem, EUSILC, GSOEP and PSID 1991–2015.

D.2 Full sample results

Figures 25–26 repeat the analysis for the full set of 23 countries in my sample. Patterns are consistent across the core and full samples.
Note: Men aged 25–55. Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months, constructed by first collapsing all male employees aged 25–55 to the country-age-year level, then to the country level. Due to data limitations, employment in the past 12 months includes self-employment. Wage growth (data): Based on regression (9) for ages 25–54 assuming no wage growth after age 50. EU rate: Share of employed who are unemployed in the subsequent month. UE rate: Share of unemployed who are employed in the subsequent month. EU/UE flows include as employed the self-employed due to data limitations; unemployment follows standard ILO definition. Model moments are re-centered to match the empirical mean to improve readability. Source: Model, BHPS, ECHP, EUSILC, GSOEP and PSID 1991–2015.
**Figure 26. Macro outcomes, full sample**

**Note:** Labor market fluidity: Share of employees who started working for their current employer at some point in the past 11 months while having been employed in all of the past 12 months, constructed by first collapsing all male employees aged 25–55 to the country-age-year level, then to the country level. Due to data limitations, employment in the past 12 months includes self-employment. Labor productivity (data): Log average real output per hour between 1991–2015 in 2004 PPP-adjusted USD. Gross labor productivity (model): Log average output per worker. Net labor productivity (model): Log of total output minus costs of investment and vacancy creation divided by employment. Net labor productivity + wedge (model): Net labor productivity plus total spending on the wedge on the cost of doing business, \( V_i(c_i - c_{US}) \), where \( V_i \) are total vacancies in country \( i \) and \( c_i \) the estimated cost of a vacancy in country \( i \). Cost of starting business (data): Total cost of starting a business expressed as a fraction of annual income per capita, as estimated by the World Bank. Cost of doing business (model): Cost of a vacancy, \( c \), relative to net output per capita, constructed as total output minus total costs of vacancies and investment. Data moments are normalized relative to the US; Model moments are re-centered to match the empirical mean to improve readability. **Source:** Model, BHPS, ECHP, EUSILC, GSOEP, OECD, PSID and World Bank 1991–2015.