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Abstract

This paper analyzes the macroeconomic effects of employment protection legislation (EPL) through workers' optimal human capital choices and the resulting changes in labor market fluidity. In a general equilibrium model, stringent EPL shifts investment from general to firmspecific human capital, reducing aggregate labor mobility across employers. Using Japanese microdata to discipline the model's human capital accumulation process, we show that although EPL increases overall human capital accumulation, the resulting decline in labor market fluidity lowers average matching efficiency and generates sizable output losses following structural changes that require labor reallocation.

Keywords: Labor market fluidity; Human capital; Employment protection; Job tenure

JEL classification: E24, J24, J62

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1 Introduction

Labor market fluidity is crucial to achieving efficient labor allocation. The literature identifies many factors that influence it.[1] For example, the efficiency with which workers and firms are matched in the labor market is an important determinant, as it directly influences the number of realized job-to-job transitions. In addition to the matching efficiency in the labor market, workers' incentives to change their jobs also influence labor market fluidity, as long as we measure labor market fluidity by the number of realized job-to-job transitions. That is, labor market fluidity could stagnate even in an economy with perfectly efficient labor markets if workers do not have incentives to change their jobs for some reason. Therefore, to understand the significant differences in labor market fluidity across countries, it is key to understanding what determines not only labor market efficiency but also workers' incentives to change their employers.

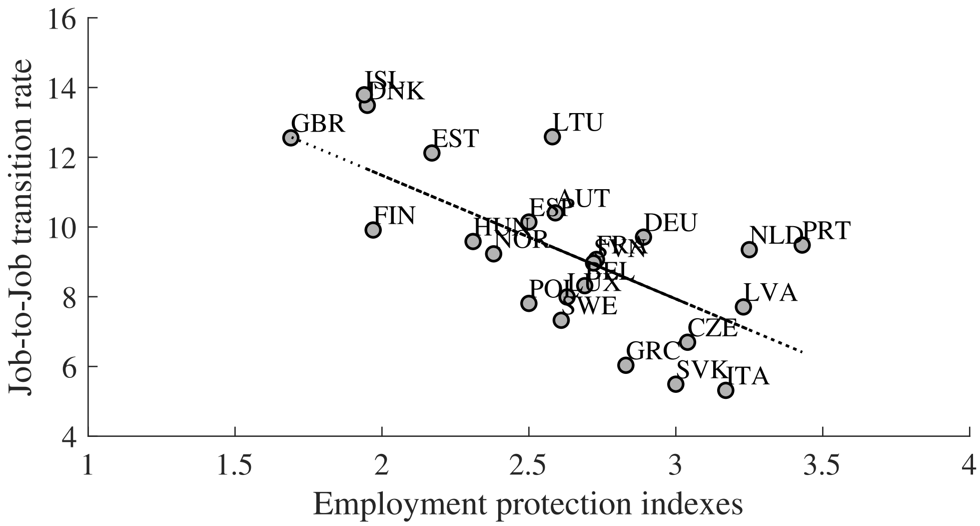
In this paper, we analyze the macroeconomic effects of employment protection legislation (EPL) through workers' optimal human capital choices and the resulting changes in labor market fluidity. In particular, we focus on the possibility that EPL stagnates labor market fluidity by disincentivizing workers from moving across employers. Empirically, more stringent EPL is associated with more stagnant labor market fluidity. Figure 1 shows the relationship between the employment protection index compiled by OECD (horizontal axis) and job-to-job transition rates (vertical axis) across European countries. The figure indicates a clear negative relationship between them, implying that countries with more stringent EPL are associated with more stagnated labor market fluidity. While the figure indicates just a correlation rather than a causal relationship between them, some empirical studies show that more stringent EPL negatively impacts job-to-job transition, implying that EPL hampers labor market fluidity.[2]

As highlighted in previous empirical studies, stringent EPL reduces job turnover, including dismissals, by increasing firing costs for firms (e.g., Autor et al., 2007). While the effect of EPL in reducing dismissals is relatively straightforward, its impact on hindering labor market fluidity measured by job-to-job transitions is less immediately apparent. When workers leave their current employer to move to a new firm as part of their career development, they typically believe the new employer offers better opportunities, such as higher wages or improved working conditions. However, EPL does not alter this *relative* attractiveness, as it applies uniformly to all firms within

[1] For example, Molloy et al. (2016) discusses various factors affecting labor market fluidity in the context of the decline in labor market fluidity in the U.S. economy.

[2] See, for example, Bassanini and Garnero (2013) for cross-country analysis for OECD countries.

Figure 1: Employment Protection and Labor Market Fluidity



Note: The horizontal and vertical axes represent the employment protection index complied by OECD and the job-to-job transition rates for European countries.

Source: OECD

the same country. This suggests that EPL is inherently neutral with regard to workers' incentives to switch employers, as well as labor market fluidity measured by job-to-job transitions.

To examine the relationship between EPL and labor market fluidity, we focus on the Japanese economy, one of the countries with the most stringent EPL and stagnated labor market fluidity, and compare it with the U.S. economy by the following two-step approach. First, in the empirical analysis using Japanese household-level microdata, we show that employer tenure brings a sizable wage premium for workers in Japan. This empirical result contrasts with the U.S. economy, where the wage premium for employer tenure is almost negligible. While the size of the wage premium associated with employer tenure has also been arguable in the U.S. until the early 2000s, several empirical papers establish that it is almost negligible in the U.S. when controlling for endogenous job selection and industry or occupational tenure. Hence, while we observe a similar wage growth pattern over the life cycle in many advanced economies (Lagakos et al., 2018), our empirical analysis implies that its driving force can be different across countries.

In the second step, given the above empirical results, we conduct a quantitative analysis to examine the effects of EPL by constructing a dynamic general equilibrium model focusing on the difference between firm-specific human capital and general human capital (FSHC and GHC). Following the spirit of Becker (1964), in the model, workers optimally accumulate FSHC and GHC in the face of the tradeoff between generality and efficiency: FSHC is valuable only for the current employer; however, FSHC is more efficiently accumulated than GHC because it is customized to the current employer's business. As EPL lowers the probability of being dismissed, it influences workers' choice between FSHC and GHC, thus affecting the observed wage premium for employer tenure and, consequently, labor market fluidity.

The quantitative exercise indicates that stringent EPL leads to stagnated labor market fluidity by raising the wage premium for employer tenure. Specifically, stringent EPL quantitatively accounts for the large wage premium for employer tenure in Japan relative to the U.S., as it encourages workers to shift their human capital accumulation from GHC to FSHC. This is intuitive because the reduced layoff probability due to stringent EPL decreases the risk of workers losing FSHC. A higher share of FSHC, in turn, disincentivizes individual workers to leave their current employers, given that they would lose all accumulated FSHC upon separation. Our quantitative exercise shows that stringent EPL in Japan leads workers to prioritize FSHC and consequently changes the aggregate stationary distribution of human capital. This aggregate shift quantitatively accounts for the stagnated labor market fluidity observed in Japan, implying that stringent EPL, rather than other labor market characteristics, is the dominant driver of the stagnation.

The quantitative analysis provides several macroeconomic policy implications. First, although eliminating EPL slightly reduces social welfare through the human capital accumulation channel, the overall impact via this channel appears limited. Our quantitative analysis suggests that while eliminating EPL hinders the accumulation of FSHC, as emphasized in previous studies, the associated welfare loss may be limited when accounting for (i) workers' endogenous shift from FSHC to GHC to hedge against job separation risk, and (ii) improved matching quality resulting from increased labor market fluidity. Second, eliminating EPL has a more adverse impact on older workers than on younger and future workers, as the former have already accumulated substantial FSHC under the expectation that EPL would remain in place. This suggests that, despite its long-term benefits for younger and future generations, eliminating EPL may be politically challenging. Third, reduced labor market fluidity can result in significant output losses by slowing the economy's adjustment to structural changes. Therefore, the overall desirability of EPL should be assessed in light of its adverse effects, which become particularly pronounced during periods of structural transformation.

This study is closely related to the literature on human capital accumulation through on-the-job training. Following Becker (1964)'s seminal work, Altonji and Shakotko (1987) and Topel (1991) examine the role of employer tenure in the U.S. While Parent (2000) and Kambourov and Manovskii (2008) show that employer tenure plays a limited role in a wage profile recently in the U.S. economy, Hashimoto and Raisian (1985), Yamada and Kawaguchi (2015), and Kimura et al. (2019) show that the wage premium on employer tenure is much larger in Japan than in the U.S., suggesting that FSHC plays an important role there.[3] In the quantitative macroeconomics literature, Kuruscu (2006), Guvenen and Kuruscu (2010), and Guvenen et al. (2014) model endogenous human capital accumulation through on-the-job training. Wasmer (2006) endogenizes workers' choice between FSHC and GHC as in our model and predicts that EPL will lead workers to rely more on FSHC. Consistent with this theoretical prediction, MacLeod and Nakavachara (2007) and Tang (2012) demonstrate that stringent EPL encourages the development of industries where FSHC plays a significant role. Regarding the role of specific human capital, Kambourov and Manovskii (2009) and Kambourov (2009) note that it influences workers' incentives to change their jobs, while they do not model workers' endogenous choice between specific and general human capital. Engbom (2022) examines human capital accumulation across countries, given the cross-country differences in labor market fluidity. Our paper complements his, as our paper introduces the difference between FSHC and GHC and examines differences in labor market fluidity resulting from variations in human capital accumulation induced by EPL. Doepke and Gaetani (2024) also focuses on the effects of EPL on human capital accumulation as we do, and shows that EPL accounts for the difference in college premium between the U.S. and Germany.

In the remainder of this paper, Section 2 presents the empirical analysis using Japanese household-level microdata to examine the wage premium associated with job experience and tenure. Section 3 develops a dynamic optimization problem for workers, while Section 4 conducts a quantitative policy exercise to evaluate the effects of EPL on labor market fluidity. Finally, Section 5 offers policy implications and concluding remarks.

2 Empirical Analysis

This section estimates the wage premium associated with job experience and employer tenure in Japan using household-level microdata. We begin by examining the relationship between wages and total job experience, and then decompose the wage premium into components attributable to employer tenure (or industry and occupation tenure) and to general work experience. To

[3]See also Kimura et al. (2022) and Nakamura (2024) for wage premiums for employer tenure in Japan.

estimate the wage premium on job experience and tenure, we use household-level microdata, "Japan Household Panel Survey (JHPS/KHPS)," from 2004 to 2020, constructed by the Panel Data Research Center at Keio University. See Appendix A for more details about our dataset.

2.1 Wage Premium on Job Experience

The wage rate grows over the life cycle as job experience is accumulated. While the pattern of wage increases over the life cycle varies across countries, wage increases along with job experience are observed in most countries (e.g., Lagakos et al., 2018). The wage premium for job experience reflects human capital accumulation through various job experiences, including on-the-job training, other general training by employers, and skill development through adult education.

To examine the relationship between wages and job experience in Japan, we estimate the wage premium for job experience by the following equation,

$$\log(wage_{i,t}) = f(expr_{i,t}) + Y_t + Control_{i,t} + \varepsilon_{i,t} \tag{1}$$

where $f(expr_{i,t})$ is a function of total job experience. We construct $expr_{i,t}$ following previous studies, including Lagakos et al. (2018). See Appendix A for more details on how to construct $wage_{i,t}$ and $expr_{i,t}$. We also include a time dummy Y_t and a vector of control variables $Control_{i,t}$, including a dummy for education, gender, and marital status.

Column (1) in Table 1 shows the baseline estimation result of equation (1), using a quadratic function of $expr$ as $f(expr)$. As in the previous studies, it indicates that job experience has positive and statistically significant effects on the wage rate and that the relationship between the wage rate and job experience is concave (i.e., the coefficient for $expr^2$ is negative). The dashed red line in the left panel of Figure 2 presents the wage-experience relationship based on the estimation result in column (1) of Table 1. It suggests that the wage rate rises along with job experience and that the rate of increase diminishes, particularly for those with longer job experience.

While the baseline estimation employs a quadratic function of job experience for $f(expr)$ in the econometric model (1), this functional form may not be flexible enough to capture the non-linearity of the wage-experience relationship. As a robustness check of this concern, we examine a more flexible functional form for $f(expr)$. Specifically, following the methodology used in Lagakos et al. (2018), we construct dummy variables with respect to a five-year bin for job experience, $dum(ex)_{i,t}$

Table 1: Empirical Relationship between Wages and Job Experience/Tenure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	log(w)	log(w)	log(w)	log(w)	log(w)	log(w)	log(w)
expr	0.048***	0.032***	0.030***	0.030***	0.030***	0.023***	0.021***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$expr^2/100$	-0.069***	-0.056***	-0.045***	-0.045***	-0.046***	-0.031***	-0.035***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
tenu		0.020***	0.029***	0.017***	0.016***		-0.002
		(0.001)	(0.004)	(0.005)	(0.005)		(0.008)
$tenu^2/100$		-0.007***	-0.048***	-0.025**	-0.022*		0.019
		(0.003)	(0.008)	(0.012)	(0.013)		(0.018)
ind				0.013***	0.012***		-0.004
				(0.004)	(0.004)		(0.007)
$ind^2/100$				-0.020*	-0.019		0.016
				(0.011)	(0.012)		(0.018)
occ					0.002		0.025***
					(0.003)		(0.007)
$occ^2/100$					-0.002		-0.058***
					(0.010)		(0.017)
N	21,731	21,463	21,463	20,609	20,397	9,772	8,369
R^2	0.288	0.397	0.376	0.374	0.377	0.121	0.184
Method	OLS	OLS	IV	IV	IV	OLS	IV
Job Type	Regular	Regular	Regular	Regular	Regular	Non-Reg.	Non-Reg.

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The table shows the estimation results for the wage premium for job experience/tenure in Japan. The independent variable log(*wage*) is a log of monthly wages. The explanatory variables, *expr*, *tenu*, *ind* and *occ*, are the length of total job experience, employer tenure, industry tenure, and occupational tenure, respectively. The IV estimation uses the instrumental variable proposed by Altonji and Shakotko (1987), as explained in footnote 6. All variables are based on household-level microdata, "Japan Household Panel Survey (JHPS/KHPS)," from 2004 to 2020, constructed by the Panel Data Research Center at Keio University.

Figure 2: Wages and Job Experience and Employer Tenure

Note: The left panel shows the estimation result of equation (1). The dashed red line and the black line with circles show the wage-experience relationship based on the estimation result in column (1) of Table 1 and that using dummy variables based on the five-year bin. The middle and right panels show (log of) wage premiums over the life cycle for employer tenure and job experience, based on the estimation results for the econometric model (2). The OLS estimation (the dashed red lines) and IV estimation (the blue bold lines) are based on columns (2) and (3) in Table 1, respectively. The IV estimation uses an instrumental variable proposed by Altonji and Shakotko (1987).

where $ex = 1, \cdots, 7$ by,

$$dum(ex)_{i,t} = \begin{cases} 1 & \text{if } 1 + 5 \times (ex - 1) \leq i\text{'s job experience in time } t < 5 \times ex \\ 0 & \text{otherwise} \end{cases}$$

and $dum(ex = 8)_{i,t} = 1$ if i's job experience in time $t > 35$. Then, we estimate relative wages for each bin by using those dummy variables as $f(expr)$ in the econometric model (1). The black line with circles in the left panel of Figure 2 shows the wage-experience relationship using dummy variables based on the five-year bin. It shows that the wage-experience relationship is almost identical to that based on a quadratic function (the red dashed line), implying that a quadratic function is flexible enough to capture the non-linearity.

The estimated size of wage premiums for job experience in Japan is quantitatively consistent with the cross-country characteristics pointed out by Lagakos et al. (2018). They show that the wage premium for job experience is positively associated with income level across countries. For example, the wage premium for those with job experience of 20-24 years is 88.7% in the U.S. and 105.3% in Germany, while it is only 71.8% in Brazil and 41.1% in Mexico. Based on our estimation result using Japanese microdata, the wage premium on job experience for the 20-24-year-old bin is 100.0% in Japan. While Japan is not included in the analysis by Lagakos et al. (2018), our estimation result suggests that the slope of the Japanese wage-experience relationship is between the U.S. and Germany and broadly consistent with the relationship between the wage premium and the income level suggested by their estimation.

2.2 Wage Premium on Employer Tenure

While the wage premium for job experience is accumulated mainly through human capital accumulation, the classical literature pioneered by Becker (1964) pointed out that there are two types of human capital, namely, (i) firm-specific human capital (FSHC), which is valuable only at the current employer, and (ii) general human capital (GHC), which is valuable at any employers. Given the definition of FSHC and GHC, the wage premium for (i) employer tenure at a particular employer and (ii) total job experience is used as a proxy for FSHC and GHC in the literature, respectively. Thus, while the effects of $f(expr)$ in the econometric model (1) contain those associated with both FSHC and GHC, we can decompose human capital accumulation over the life cycle into FSHC and GHC by estimating the relationship between wages and job experience and employer tenure. Specifically, we estimate,

$$\log(wage_{i,t}) = f(expr_{i,t}) + g(tenu_{i,t}) + Y_t + Control_{i,t} + \varepsilon_{i,t} \tag{2}$$

where $f(expr_{i,t})$ and $g(tenu_{i,t})$ are functions of job experience and employer tenure, respectively. Then, we evaluate the accumulation process of FSHC and GHC by measuring the marginal effects of job experience and employer tenure, i.e., $f(expr_{i,t})$ and $g(tenu_{i,t})$.

Previous empirical literature, however, argues that the decomposition between FSHC and GHC through estimating the wage premium for job experience/tenure using the econometric model (2) is possibly biased for the following two reasons. First, as noted by Altonji and Shakotko (1987), even if we observe the positive correlation between wages and employer tenure, it may represent not only the wage premium on employer tenure, including FSHC accumulation, but also workers' endogenous responses to match quality with employers. More specifically, wages and employer tenure can be positively correlated even without the wage premium for employer tenure, as employees tend to stay longer at particular employers who pay higher wages. Second, as noted by Parent (2000) and Kambourov and Manovskii (2008), the estimated wage premium for employer tenure may reflect the wage premium for job experience within a particular industry or occupation rather than with a specific employer. That is, the econometric model (2) may not precisely distinguish the wage premiums for industry or occupation tenure from those for employer tenure, as some workers change their industry or occupation when switching employers. Indeed, Kambourov and Manovskii (2008), using household-level microdata from the U.S. (PSID), show that once industry and occupational tenure are controlled for, the wage premium for employer tenure is almost negligible in the U.S. In our sample data, among workers who switched employers, 41% also changed either their industry or occupation, while 22% changed both. This implies that employer tenure is highly correlated with industry and occupation tenure in Japan, potentially leading to an overestimation of the effect of employer tenure.

Given those discussions in the previous studies, we estimate the relationship between wages and job experience/tenure in Japan. First, we add employer tenure as an additional explanatory variable to the econometric model (1) and estimate the wage premium for job experience/tenure through the econometric model (2). Second, to deal with the above endogeneity problems noted by Altonji and Shakotko (1987), we estimate the wage premium for job experience/tenure using an instrument variable proposed in their study. Third, we include industry and occupational tenure as additional explanatory variables to estimate the wage premium associated with employer tenure, controlling for the effects of industry and occupational tenure on wages. Specifically, we estimate the econometric model,

$$\log(wage_{i,t}) = f(expr_{i,t}) + g(tenu_{i,t}) + h(ind_{i,t}) + k(occ_{i,t}) + Y_t + Control_{i,t} + \varepsilon_{i,t} \tag{3}$$

where $f(expr_{i,t})$, $g(tenu_{i,t})$, $h(ind_{i,t})$, and $k(occ_{i,t})$ are a function of job experience, employer tenure, industry tenure, and occupational tenure, respectively. We use a quadratic function for those functions, given that it is flexible enough to capture the non-linear relationship between wages and job experience, as shown in the left panel of Figure 2. We construct $tenu_{i,t}$, $ind_{i,t}$, and $occ_{i,t}$ following previous empirical studies, including Kambourov and Manovskii (2008). Appendix A provides details on how these variables are constructed, as well as on the industry and occupational classifications in our dataset.

Columns (2) and (3) in Table 1 show the estimation results for the econometric model (2). Column (2) uses a standard OLS, while column (3) uses an instrumental variable proposed by

Altonji and Shakotko (1987).[4] The estimation results show that employer tenure has sizable effects on wage premiums over the life cycle in Japan and that the coefficients on employer tenure are statistically significant even when using the IV estimation. The middle and right panels in Figure 2 show (log of) wage premiums over the life cycle for employer tenure (the middle panel) and job experience (the right panel). These panels indicate that while the OLS estimation overestimates the wage premium for employer tenure, particularly for those with more than 20 years of employer tenure, there exists a sizable wage premium for employer tenure over the life cycle.[5] For example, based on the IV estimation in column (3), 20-25 years of employer tenure increases the wage rate by around 40%.[6]

While columns (2) and (3) indicate a significant wage premium for employer tenure, those estimation results may spuriously capture the effects of industry or occupational tenure. To address this potential omitted variable bias, columns (4) and (5) in Table 1 estimate the econometric model (3), which includes industry and/or occupational tenure as additional explanatory variables. Here, we use the IV estimation proposed by Altonji and Shakotko (1987) as in column (3). The estimation results in columns (4) and (5) indicate that the coefficients for job experience, employer tenure, and industry tenure are statistically significant, while those for occupational tenure are not, implying that the first three variables significantly impact the wage rate over the life cycle in Japan.

Regarding the relative importance of the four factors in equation (3)—job experience, employer tenure, industry tenure, and occupational tenure—Table 2 shows the wage premium for workers with 10-15 years of job experience and decomposes it into these four factors based on the estimation results. The table implies that employer tenure provides a substantial wage premium over the life cycle in Japan, even after controlling for industry and occupational tenure. More specifically, the

[4]Based on Altonji and Shakotko (1987), the instrumental variable $\tilde{tenu}_{i,t}$ is constructed by $\tilde{tenu}_{i,t} = tenu_{i,t} - 1/T \sum_{\tau=1}^{T} tenu_{i,j,\tau}$ where $tenu_{i,j,\tau}$ is job tenure for employer j in year τ, and T is the length of job tenure for employer j. By construction, this instrumental variable is orthogonal to (time-invariant) matching quality with a particular employer. We construct the instrumental variable $\tilde{ind}_{i,t}$ and $\tilde{occ}_{i,t}$ in the same manner.

[5]The result that OLS overestimates the wage premiums only for workers with long employer tenure is intuitive. Workers with better match quality tend to have longer tenures, so those employed by the same employer for more than 20 years are mostly individuals with a good match quality with their current employer. As a result, their wage premiums reflect not only employer tenure but also the higher match quality. In contrast, workers with shorter employer tenures may also include those with relatively poorer match quality, thus leading a simple OLS estimation to identify a steeper wage profile over the life cycle mistakenly.

[6]The substantial wage premium for employer tenure observed in this study differs from the findings in Nakamura (2024), which report a smaller wage premium for employer tenure using JHPS/KHPS data. A key distinction lies in the sample selection criteria: While Nakamura's study examines a relatively broad group of workers, including all types of workers who work more than 500 hours annually, this study focuses exclusively on regular workers who work more than 1,200 hours annually.

Table 2: (Log of) Wage Premium for 10-15 Years of Job Experience

		Experience	Employer	Industry	Occupation	Total
		(1)	(2)	(3)	(4)	(1)-(4)
Japan	Regular	.24	.22	–	–	.46
		.24	.13	.09	.02	.48
	Non-regular	.16	.00	-.02	.17	.31
U.S.		.33	.01	.05	.10	.49

Note: The table shows the wage premium for workers with 10-15 years of job experience and decomposes it into the four factors in equation (3), namely job experience, employer tenure, industry tenure, and occupational tenure, based on the estimation results in Table 1. The first and second rows are derived from the estimation results for regular workers in columns (3) and (5) of Table 1, while the third row is derived from those for non-regular workers in column (7). The last row reports the wage premium for each factor in the U.S., based on the estimation results in Kambourov and Manovskii (2008). Specifically, we use their estimates based on the 1-digit occupational classification, as it is comparable to the classifications used in our dataset. See Appendix A for details on the occupational classification in our dataset.

first row of Table 2, derived from column (3) of Table 1, indicates that job experience and employer tenure contribute wage premiums of 0.24 and 0.22, respectively, resulting in a total wage premium of 0.46. The second row of Table 2, based on column (5) of Table 1, indicates that employer tenure continues to contribute a significant wage premium (=0.13) even after accounting for industry and occupational tenure, while industry and occupation tenure contribute an additional 0.11 to the wage premium.

The estimation results in Tables 1 and 2 indicate that employer tenure has a sizable impact on the wage premium over the life cycle in Japan.[7] This sizable wage premium for employer tenure is, however, in stark contrast to findings based on U.S. data. The last row in Table 2 presents the wage premium for job experience, employer tenure, industry tenure, and occupational tenure in the U.S., based on the estimation results in Kambourov and Manovskii (2008).[8] While the wage premium in total is nearly identical across Japan and the U.S., the composition of its components differs significantly. Specifically, the wage premiums for job experience and occupational tenure are considerably higher in the U.S. than in Japan, whereas the premium for employer tenure is almost negligible in the U.S. According to the traditional interpretation of the wage premiums for employer tenure and other forms of job experience, this contrasting result suggests substantial differences in

[7]As a robustness check, we conduct a subsample analysis to check how the wage premiums for employer tenure change over time. The estimation results of the subsample analysis in Appendix B show that, while the wage premiums for employer tenure have become slightly lower recently, employer tenure still brings about sizable wage premiums in Japan.

[8]Specifically, we use their estimates based on the 1-digit occupational classification, as it is comparable to the classifications used in our dataset. See Appendix A for details on the occupational classification in our dataset.

the relative importance of FSHC and GHC in human capital accumulation between Japan and the U.S. Namely, in the U.S., GHC overwhelmingly dominates human capital accumulation, while in Japan, both FSHC and GHC play significant roles.

What drives the difference in human capital accumulation between Japan and the U.S.? Given that Japan and the U.S. represent countries with the most and least stringent EPL, respectively, this paper hypothesizes that stringent EPL incentivizes Japanese workers to prioritize accumulating FSHC over GHC. While we quantitatively test this hypothesis using a structural model in the next section, as a preliminary analysis, columns (6) and (7) in Table 1 estimate the econometric model (3) for *non-regular* workers in Japan, who are exempt from the stringent EPL applied exclusively to regular workers. The estimation results for non-regular workers indicate that their wage profile is much flatter for non-regular workers than regular workers (column 6 in Table 1) and that employer tenure has no statistically significant effect on wages for non-regular workers, whereas occupational tenure does (column 7 in Table 1). The wage premium for non-regular workers in the third row of Table 2, which is based on the estimation results in column (7) of Tables 1, indicates that the wage premium for employer tenure is almost negligible, while the premium for occupational tenure is substantially large. This contrasts with the findings for regular workers but aligns more closely with the results for U.S. workers. Thus, these findings suggest that the stringency of EPL may play a significant role in determining the relative importance of FSHC and GHC. The next section uses a structural model in which individuals optimally decide to accumulate FSHC and GHC, allowing us to examine how EPL influences human capital accumulation and, consequently, labor market fluidity.

3 Dynamic Model with Human Capital Accumulation

What explains the contrasting difference in the wage premium for job experience and employer tenure between Japan and the U.S. in the previous section? And, what are their macroeconomic implications for labor market fluidity? To answer these questions, in what follows, we conduct a quantitative exercise to explore the role of EPL using a dynamic model with human capital accumulation.

The model is a dynamic general equilibrium model that incorporates human capital accumulation and the possibility of switching employers through an on-the-job search. The economy consists of the household and firm sectors. The household sector comprises a continuum of individuals that exhibit heterogeneity in terms of their firm-specific and general human capital (FSHC and GHC) and match quality, as well as their employment status. The distinction between FSHC and GHC aligns with the human capital literature, notably pioneered by Becker (1964). That is, FSHC holds value only for the current employer and becomes worthless once individuals leave their current employer, either due to a layoff or a voluntary move to another firm. In each period, employed individuals earn wages and accumulate human capital. In doing so, they can choose whether to invest more intensively in FSHC or GHC. They also face a risk of job separation, with probability d, which includes dismissals as well as other involuntary exits, such as those driven by family circumstances. All workers have the option to voluntarily leave their current employer at any time to take a job elsewhere. The firm sector consists of a continuum of homogeneous firms. When jobs are exogenously destructed, firms must decide whether to dismiss the affected workers or retrain them so they can be reallocated to new positions within the firm. In general equilibrium, firing costs affect firms' dismissal decisions and, in turn, influence labor market fluidity through their impact on human capital accumulation.

3.1 Household Sector

The individual is risk-neutral and maximizes the lifetime utility:

$$\mathbb{E}\sum_{t=0}^{\infty}\beta^t(1-\lambda)^t c_t$$

where β is a discount factor and c_t is consumption. Since the household is assumed not to save, their consumption equals income in every period, $c_t = y_t$, as in Kambourov and Manovskii (2009).[9] Since the workers are exogenously and stochastically retired with probability λ and subsequently replaced with new workers, their consumption is discounted by the survival probability $1-\lambda$.

Match Quality and Wage Premiums

All individuals are categorized into two groups: employed and unemployed. Employed individuals are characterized by three state variables, namely, FSHC, GHC, and match quality, denoted as h_s, h_g, and z, respectively. The match quality $z \leq 1$, which determines how well their human capital fits their current employer's business, starts with $z = 1$ and follows the exogenous stochastic

[9]Note that assuming no savings under a linear utility function is close to assuming a complete market economy with savings.

process,

$$z' = \begin{cases} \max\{z-\kappa, \underline{z}\} & \text{with prob. } q \\ z & \text{with prob. } 1-q \end{cases} \tag{4}$$

The above process implies that match quality starts at the highest level (i.e., $z = 1$) and gradually deteriorates every period. More specifically, in every period, the match quality z deteriorates by κ with probability q or stays at the previous level with probability $1-q$, until it reaches the lower bound of match quality, $\underline{z} > 0$.

The employed individuals with total human capital $h_s + h_g$ and matching quality z earn wage income,

$$wz\exp(h_s + h_g), \tag{5}$$

where w is the wage rate. As discussed below, the values of h_s and z are specific to the current employer, as they are reset to their initial values (i.e., $h_s = 0$ and $z = 1$) upon separation from the current employer. Therefore, equation (5) implies that when mapping the model-implied wage premiums over the life cycle to data, the log of wage premiums is decomposed as

$$\log(\textit{wage premium}) \equiv \underbrace{\log(z) + h_s}_{\textit{Employer tenure}} + \underbrace{h_g}_{\textit{Others}}, \tag{6}$$

and then the parameter values are calibrated so that the dynamics of the first two terms, $\log(z) + h_s$, align with wage premiums for employer tenure in data, while those of the last term, h_g, align with the sum of transferable human capital captured by the sum of wage premiums for job experience, industry tenure, and occupation tenure in data.

Value Functions 1: Human Capital Accumulation

Employed individuals accumulate FSHC and GHC as follows. First, all employed individuals have one unit of time for human capital accumulation. Then, as in Wasmer (2006), employed individuals can choose how much FSHC or GHC to accumulate in each period. Specifically, when the employed individuals allocate h and $1-h$ unit of time for accumulating FSHC and GHC, respectively, their h_s and h_g are accumulated following the law of motion,

$$h'_s = (1-\delta_s)h_s + A_s h^\alpha \quad \text{and} \quad h'_g = (1-\delta_g)h_g + A_g(1-h)^\alpha \tag{7}$$

where $\alpha < 1$ is a curvature of the human capital investment function, δ_s and δ_g are the depreciation rates of FSHC and GHC, and A_s and A_g are the efficiencies of FSHC and GHC accumulation. We assume that workers acquire both FSHC and GHC through on-the-job training or adult education while working, with the distinction between these two forms of capital lying in their applicability to a specific employer. Consequently, the condition $A_s > A_g$ is necessary for individuals to have an incentive to accumulate FSHC, as it implies that focusing on FSHC allows workers to accumulate human capital more efficiently by tailoring their skills specifically to the needs of their current employer.[10] Under this framework, employed individuals optimally allocate their time h in light of a trade-off between efficiency and generality: FSHC can be accumulated more efficiently but loses its value when workers leave their current employer, whereas GHC is accumulated less efficiently but retains its value across employers.

Given the above trade-off regarding human capital accumulation, the value functions for employed and unemployed individuals are formulated as follows. First, the employed individual optimally chooses the time allocation h so as to maximize the value function,

$$H_W(h_s, h_g, z) = c + \beta(1-\lambda) \cdot \max_h \mathbf{E}_{z'} \left[J_W(h_s', h_g', z') \right] \tag{8}$$

subject to (4), (7), and the budget constraint $c = wz \exp(h_s + h_g) + T$, where T is a public lump-sum transfer. Here, $J_W(h_s, h_g, z)$ is the value function related to job changes for employed individuals (defined later). Second, as unemployed individuals do not accumulate human capital, they are not subject to any optimization problems at this stage. Thus, their value function is expressed as,

$$H_N(h_g) = \beta(1-\lambda) \cdot J_U(h_g') \tag{9}$$

subject to $h_g' = (1-\delta_g)h_g$. Here, $J_U(h_g)$ is the value function for the unemployed individuals before job findings (defined later).

Note that, unlike some previous studies, our model does not incorporate the endogenous

[10] FSHC and GHC can be viewed either as distinct types of skills or as the same type of skill with different applicability. For instance, learning Microsoft Office could be GHC or FSHC, depending on whether the skill is developed in a way that is broadly applicable across various businesses or tailored specifically to the current employer's business needs. Also note that while the model primarily assumes that FSHC accumulation increases wage income by enhancing workers' labor productivity, FSHC is not necessarily confined to activities that directly boost their productivity. In particular, under long-term employment arrangements, workers often engage in activities that do not directly enhance labor productivity but just increase wage premiums for employer tenure, such as networking for internal promotion. FSHC in the model can also be interpreted to include such non-productive activities aimed at increasing wage premiums for employer tenure, as our primary focus is on workers' decision-making under the significant wage premiums for employer tenure.

allocation of time between working and accumulating human capital. This modeling choice is based on two main considerations. First, our focus is restricted to workers' on-the-job decisions between FSHC and GHC, rather than the broader life-cycle aspects of human capital accumulation. For example, Guvenen et al. (2014) explicitly models time allocation over the life cycle and shows that younger individuals allocate more time to accumulating human capital—partly through full-time schooling—rather than working. While such life-cycle considerations, including schooling decisions, are certainly important, they fall outside the scope of this study.[11] Second, it remains debatable whether wage premiums on the job stem from the *proactive* accumulation of human capital at the expense of work or from *nearly automatic* accumulation through work experience. Our simplified framework, which assumes a fixed amount of time available for human capital accumulation, does not contradict the former interpretation but is more aligned with the latter.[12]

Value Functions 2: Job Search

First, consider the value function for unemployed individuals. The value function for unemployed workers who search for a new job, $J_N(h_g)$ in (9), is formulated as,

$$J_U(h_g) = m \cdot H_W(0, h_g, 1) + (1 - m) \cdot \left[b \exp(h_g) + H_N(h_g) \right] \tag{10}$$

where m is a job-finding probability and $b \exp(h_g)$ is an unemployment benefit for unemployed workers with h_g, and $H_W(h_s, h_g, z)$ and $H_N(h_g)$ are the value functions for employed and unemployed individuals defined in equations (8) and (9). The unemployment benefit equals b times the wage rate that the worker would obtain if they find a job. The above value function for unemployed individuals in equation (10) implies that when they find a new job with a probability m, they have to start with zero FSHC (i.e., $h_s = 0$) but the highest match quality $z = 1$. On the other hand, if they

[11]Our focus on the choice between FSHC and GHC is also reflected in the functional form of the human capital production function in equation (7). Specifically, we use a Ben-Porath type production function, $h' = (1 - \delta)h + Ah^\beta i^\alpha$, where h is the stock of human capital and i is the time allocated for its accumulation. For parameter values, however, we set $\beta = 0$ and $\alpha = 0.85$, whereas most previous studies that do not differentiate between FSHC and GHC typically assume $\alpha = \beta \in [0.85, 1.00)$. We do not adopt $\beta > 0$ because it would lead workers to concentrate on accumulating either FSHC or GHC, unless the two types of human capital are highly non-substitutable. If, however, they are highly non-substitutable, the model cannot account for economies with negligible FSHC, such as the U.S. This motivates our choice of $\beta = 0$. Since previous literature adopts $\beta > 0$ to model the endogenous allocation of time between work and human capital accumulation, extending such frameworks to distinguish between FSHC and GHC represents an interesting but challenging direction for future research.

[12]When adopting the former modeling strategy, the interpretation of wage premiums over the life cycle becomes more nuanced. For example, Kuruscu (2006) argues that wage growth over the life cycle primarily reflects a decline in the time allocated to human capital accumulation, rather than an increase in the stock of human capital.

cannot find a job with a probability $1 - m$, they obtain the unemployment benefit and their value function is that for the unemployed ones in equation (9).

Next, consider the value function for employed individuals. In the model, employed individuals possibly have incentives to move away from their current employer through an on-the-job search, as they are subject to exogenous deterioration in matching quality with their current employers. However, as in traditional work by Becker (1964), FSHC is valuable only while working for the current employer. Thus, workers decide whether to leave or stay with their current employer in the face of the trade-off between improving matching quality and losing FSHC. Given this trade-off, the value function for currently employed individuals, $J_W(h_s, h_g, z)$ in equation (8), is formulated as:

$$J_W(h_s, h_g, z) = d \cdot J_U(h_g) - d_D \cdot \xi(h_s, h_g, z) + (1 - d) \cdot \max\left\{H_W(h_s, h_g, z),\ H_W(0, h_g, 1)\right\} \tag{11}$$

where d is the probability of job separation. The job separation rate is the sum of dismissal probability, d_D, and job separations for other exogenous reasons, d_O:

$$d \equiv d_D + d_O.$$

We assume that workers who are dismissed must pay $\xi(h_s, h_g, z)$ for re-skilling themselves to enter the unemployment pool. $\xi(h_s, h_g, z)$ and d_D are endogenously determined by firms' optimal dismissal behavior in general equilibrium, while d_O is an exogenous parameter. The value function $J_W(h_s, h_g, z)$ in equation (11) shows that, with probability d, individuals are dismissed or leave their employer for other reasons and then become unemployed, receiving the value $J_U(h_g)$ in equation (10). With probability $1 - d$, they remain employed and then decide whether to stay with their current employer or move to another. The last bracket captures this discrete choice problem under the aforementioned trade-off. That is, when they stay with their current employer, they can maintain FSHC h_s while their matching quality remains at z. On the other hand, when they leave their current employer, they lose all FSHC (i.e., $h_s = 0$) while their matching quality improves to the highest value at $z = 1$.

Stationary Distribution

Let $g_s(h_s, h_g, z)$ and $g_g(h_s, h_g, z)$ be the policy functions for FSHC and GHC accumulation, h'_s and h'_g, to solve the optimization problem for employed individuals in (8). Furthermore, let $e_W(h_s, h_g, z)$

be the policy function for changing jobs for employed individuals in the discrete choice problem in (11), which takes the value of 1 when individuals change their jobs and takes the value of 0 otherwise.

Given those policy functions, the stationary distributions for employed and unemployed individuals, $\mu_w(h_s, h_g, z)$ and $\mu_n(h_g)$, are defined as follows.

Definition 1 *The stationary distribution for employed and unemployed individuals, $\mu_w(h_s, h_g, z)$ and $\mu_n(h_g)$, satisfy*

$$\begin{aligned}
\mu_w(h'_s, h'_g, z') &= (1-\lambda)\int_{h_s,h_g,z}\Big[(1-d)\cdot(1-e_W(h_s,h_g,z))\cdot Pr(z'|z)\cdot \mathbf{1}_{\{h'_s=g_s(h_s,h_g,z)\wedge h'_g=g_g(h_s,h_g,z)\}} \\
&+ \Big\{d\cdot m + (1-d)\cdot e_W(h_s,h_g,z)\Big\}\cdot Pr(z'|z=1)\cdot \mathbf{1}_{\{h'_s=g_s(0,h_g,1)\wedge h'_g=g_g(0,h_g,1)\}}\Big]d\mu_w(h_s,h_g,z) \\
&+ (1-\lambda)\int_{h_g} m\cdot Pr(z'|z=1)\cdot \mathbf{1}_{\{h'_s=g_s(0,h_g,1)\wedge h'_g=g_g(0,h_g,1)\}}d\mu_n(h_g) \\
\mu_n(h'_g) &= (1-\lambda)\left[\int_{h_s,h_g,z} d\cdot(1-m)\cdot \mathbf{1}_{\{h'_g=(1-\delta)h_g\}}d\mu_w(h_s,h_g,z) + \int_{h_g}(1-m)\cdot \mathbf{1}_{\{h'_g=(1-\delta)h_g\}}d\mu_n(h_g)\right] \\
\mu_w(0,0,1) &= \lambda\left[\int_{h_s,h_g,z} d\mu_w(h_s,h_g,z) + \int_{h_g} d\mu_n(h_g)\right]
\end{aligned}$$

where $Pr(z'|z)$ is the conditional probability that the matching quality becomes z' in the next period, given that the matching quality is z in the current period.

In the definition of stationary distribution, the first and second equations are the law of motion for employed and unemployed individuals, respectively. The last equation is the case for exogenous retirement. We can compute the stationary distribution by applying the law of motion to an arbitrary initial distribution until it converges.

Given the stationary distributions for employed individuals, $\mu_w(h_s, h_g, z)$, the number of workers who change their jobs x^e are defined as,

$$x^e = \int_{h_s,h_g,z}(1-d)\cdot e_W(h_s,h_g,z)\, d\mu_w(h_s,h_g,z) \tag{12}$$

and the aggregate labor supply is defined as,

$$L = \int_{h_s,h_g,z} z\exp(h_s+h_g)\, d\mu_w(h_s,h_g,z) \tag{13}$$

Then, we define the aggregate job-to-job transition rate in the model as x^e/L and use it as a proxy for labor market fluidity.

3.2 Firm Sector

It is assumed that there is a continuum of homogeneous firms $i \in [0,1]$. Each firm operates a linear production technology, $y_i = An_i$, where n_i is the labor input for firm i. Note that n_i does not represent the number of workers per se, but rather a measure of *substantive* labor that incorporates workers' firm-specific human capital (h_s), general human capital (h_g), and match quality (z). Given the labor supply function in equation (5), the substantive labor input n_i is defined as,

$$n_i \equiv \int_{h_s,h_g,z} z\exp(h_s + h_g)\, l_i(h_s,h_g,z)\, dh_s dh_g dz$$

where $l_i(h_s,h_g,z)$ is the mass of firm i's employees with h_s, h_g, and z. Then, we make the following assumption regarding information frictions for firms.

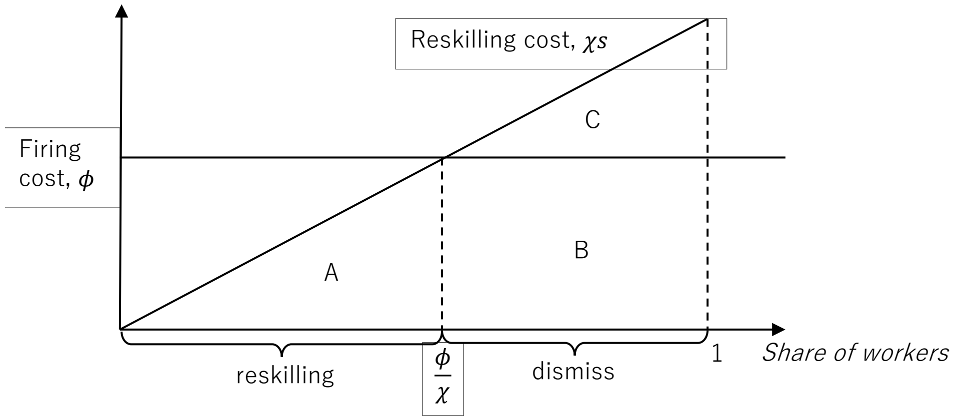
Assumption 1 *Firms do not observe h_s, h_g, or z individually; instead, they observe only each worker's substantive labor supply n_i.*

This assumption implies that (i) firms choose n_i rather than $l_i(h_s,h_g,z)$, and (ii) they set a wage rate w per unit of substantive labor input n_i, without differentiating across h_s, h_g, or z.[13] In what follows, we discuss the firm's optimal labor-force choice, as well as its optimal dismissal behavior, in more detail under this informational assumption.

At each point in time, a fraction ψ of jobs is assumed to be exogenously destructed. In the face of exogenous job destruction, firms have two options: (i) dismissing workers in destructed jobs by paying severance pay ϕ and hiring new workers, or (ii) reallocating these workers to new positions within the firm by retraining them, as in Mortensen and Pissarides (1998). The severance pay ϕ serves as a measure of the stringency of employment protection legislation (EPL). Regarding the second option, to reflect the heterogeneity in retraining costs across employees observed in the real economy, the marginal retraining cost is assumed to follow a uniform distribution over $[0,\chi]$. Given that firms cannot observe workers' characteristics, h_s, h_g, or z, as described in Assumption 1, firms retrain workers starting with those whose retraining costs are lower. This means that the

[13]If firms were able to observe h_s, h_g, or z individually, they could offer more complex and efficient wage contracts. For example, they might set a higher wage rate for h_s than for h_g in order to encourage workers to accumulate FSHC. However, because such wage contracts are difficult to implement in practice—and would significantly complicate the model—we abstract from these possibilities.

Figure 3: Optimal Dismissal Behavior



Note: The figure describes the firm's optimal dismissal behavior with severance payment ϕ and retraining costs χs. The figure shows that the marginal cost of retraining becomes higher than the firing cost ϕ when $s \geq \phi/\chi$, which implies that the optimal dismissal probability is $d_D = 1 - \phi/\chi$. Then, in the figure, the minimized cost per labor unit corresponds to the area of A + B.

marginal cost of retraining increases linearly with the amount of substantive labor being retrained. Accordingly, when firms retrain a fraction $\bar{s}$ and dismiss a fraction $1 - \bar{s}$ of the substantive labor force affected by job destruction, the total cost incurred from exogenous job destruction is given by:

$$\left[\int_0^{\bar{s}} \chi s \, ds + (1 - \bar{s})\phi\right] \times \psi n_i, \tag{14}$$

where χs is the marginal cost for retraining s fraction of substantive labor.[14] Taking the first order condition to minimize the employment protection cost with respect to $\bar{s}$, the optimal choice of $\bar{s}$ is $s^* = \phi/\chi$, as described in Figure 3. The figure shows that the marginal cost of retraining becomes higher than the firing cost ϕ when $s \geq \phi/\chi$ and that the minimized cost per labor unit is $\phi(1-\phi/(2\chi))$, which corresponds to the area of A + B in the figure. This optimal dismissal behavior implies that the dismissal probability is:

$$d_D = \left(1 - \frac{\phi}{\chi}\right)\psi. \tag{15}$$

Given the assumption that firms cannot condition dismissal or retraining decisions on h_s, h_g, and z, the above value of dismissal probability d_D is uniformly applied to all workers in the household sector.

[14]Here, it is assumed that $0 \leq \phi \leq \chi$ to have an internal solution.

The firm calculates the cost of hiring a labor force by considering employment protection costs due to severance payments ϕ, retraining costs χ, and the exogenous job destruction rate ψ. Specifically, the labor cost for hiring one unit of substantive labor is given by:

$$w + \tau \quad \text{where} \quad \tau \equiv \phi\left(1 - \frac{\phi}{2\chi}\right)\psi, \tag{16}$$

Note that when $\phi = 0$ (i.e., without severance payments), $\tau = 0$, that is, wages w are the only labor cost as in a standard model without employment protection.

Given the labor cost in (16), the firm chooses the optimal level of substantive labor input. To simplify the analysis, we abstract from wage bargaining and long-term contracts by assuming that: (i) firms hire workers in a competitive labor market, and (ii) the wage rate w remains fixed until separation.[15] With these assumptions, as well as Assumption 1 and a linear production technology, $y_i = An_i$, the firm maximizes its profit, $An_i - (w + \tau)n_i$, which gives the optimality condition:

$$w = A - \tau. \tag{17}$$

This implies that an increase in the employment protection cost τ proportionally reduces the wage rate w in equilibrium and that the firm's zero profit condition is always satisfied.

3.3 General Equilibrium

Given the optimal behaviors by households and firms in the previous two subsections, a competitive general equilibrium is characterized. First, the dismissal behavior described in Figure 3 implies that the average retraining cost for dismissed workers is $(\chi + \phi)/2$. Since dismissed workers receive the severance payment ϕ, the expected retraining cost (net of the severance pay) that dismissed workers must pay to enter the unemployment pool, $\xi(h_s, h_g, z)$ in equation (11), is:

$$\xi(h_s, h_g, z) = d_D \cdot \frac{\chi - \phi}{2} z \exp(h_s + h_g). \tag{18}$$

[15]Without these assumptions, firms and workers may have an incentive to renegotiate the wage rate, although the outcome of such renegotiation is ambiguous. On the one hand, firms may seek to lower w by exploiting the non-transferability of FSHC. On the other hand, workers may attempt to raise w by taking advantage of the firing cost ϕ, which prevents firms from dismissing them. In practice, wage renegotiation is common but tends to have only limited effects on wages, as firms and workers typically agree on a wage table that functions as a long-term contract. Our assumptions offer a parsimonious approach to capturing this arrangement.

This retraining cost incurred by dismissed workers themselves corresponds to the area of C in Figure 3. Second, given the substantive labor input for each firm i, the aggregate labor input N is defined as:

$$N \equiv \int_0^1 n_i di \tag{19}$$

Then, the competitive general equilibrium is defined as follows:

Definition 2 *The competitive general equilibrium is characterized by: (i) the dismissal probability d_D^*, the retraining cost function $\xi^*(h_s, h_g, z)$, the wage rate w^*, and the lump-sum transfer T^*, (ii) the policy functions $g_s(h_s, h_g, z)$, $g_g(h_s, h_g, z)$, and $e_W(h_s, h_g, z)$, and (iii) the stationary distributions $\mu_w(h_s, h_g, z)$ and $\mu_n(h_s, h_g, z)$, such that: (1) d_D^* satisfies (15), (2) $\xi^*(h_s, h_g, z)$ satisfies (18), (3) w^* satisfies (17), (4) T^* satisfies $\int_{h_g} b\exp(h_g)d\mu_n(h_g) = T^* \int_{h_s,h_g,z} d\mu_w(h_s, h_g, z)$, (5) given d^*, w^*, $\xi^*(h_s, h_g, z)$, and T^*, the policy functions solve the workers' optimization problems, (6) the stationary distributions are defined by Definition 1, and (7) the labor market clears, $L = N$.*

In a quantitative analysis, we conduct comparative statics to assess the effects of EPL by computing the competitive equilibrium under different values of firing costs, ϕ, and comparing the equilibrium values.

To conduct a welfare analysis, we need to define a welfare measure in the equilibrium. Given the linear utility function for workers, a natural welfare measure is the aggregate consumption C, which is defined as:

$$C \equiv \int_{h_g} b\exp(h_g)d\mu_n(h_g) + \int_{h_s,h_g,z} \left[w^* z\exp(h_s + h_g) - T^* - d^*\xi(h_s, h_g, z)\right] d\mu_w(h_s, h_g, z)$$

Then, we have the following proposition regarding aggregate consumption in equilibrium.

Proposition 1 *The aggregate consumption in equilibrium is expressed by:*

$$C = \left(1 - \frac{\chi\psi}{2}\right)L$$

where L is the equilibrium aggregate labor supply defined in equation (13).

This proposition indicates that aggregate consumption C is proportional to aggregate labor supply L. The term $\chi\psi/2$ captures the total economy-wide cost of retraining workers in destructed jobs, which corresponds to the area A + B + C in Figure 3. The proposition implies that the severance pay ϕ does not directly influence the aggregate consumption C but affects it only indirectly through its impact on L. As you can see in Figure 3, since the severance pay ϕ is a pure transfer from firms to dismissed workers, it does not alter the aggregate retraining cost but merely redistributes the burden of payment between firms and dismissed workers.

A caveat regarding our general equilibrium framework is that the firm sector in this framework cannot capture the adverse effects of EPL on labor allocation across firms. Specifically, the previous literature, pioneered by Hopenhayn and Rogerson (1993), emphasizes that EPL causes resource misallocation across firms by constraining firms' optimal adjustment of labor force in response to idiosyncratic productivity. Labor (mis)allocation across firms does not matter in our framework because we assume homogeneous firms with respect to their productivity. Introducing heterogeneity in firms' idiosyncratic productivity, in addition to household heterogeneity, and analyzing the associated costs and benefits of EPL remains a challenging yet important direction for future research.

4 Quantitative Simulation

This section conducts a quantitative simulation to examine the effects of EPL on labor market fluidity. First, parameter values are calibrated using the Japanese economy as a calibration target. In particular, those associated with human capital accumulation are calibrated so that the wage premiums for employer tenure and others are consistent with the estimation results using the Japanese data in the previous section. Second, the effects of EPL are examined by comparative statics. Since EPL is represented by the firing cost, ϕ, we investigate the effects of EPL by examining what would happen to human capital accumulation and labor market fluidity if ϕ is completely eliminated as in the U.S. Third, the effects of EPL and the resulting changes in labor market fluidity are also analyzed through transition dynamics following a structural shock. In particular, the analysis focuses on a turbulence shock, which captures an increase in skill mismatch among workers due to a structural change.

4.1 Baseline Simulation

We first calibrate the parameter values using the Japanese economy as a calibration target. Then, we describe the job-to-job transitions in the equilibrium. All the calibration values are summarized in Table 3.

Table 3: Parameter Values by Calibration

Parameter	Value	Target value etc.
Discount rate, β	0.96	$\beta = 1/1.04$
Retirement prob., λ	1/40	Ave. working periods = 40 years
Unemployment benefit, b	0.40	40% of current wages
Job-finding rate, m	0.43	Unemployment rate = 3.0%
Curvature for HC inv., α	0.85	Guvenen et al. (2010)
Matching quality, κq	0.0071	Job-to-job transition = 4.8%
Aggregate productivity, A	1.32	$w = 1.0$ (Standardization)
Firing cost, ϕ	1.00	Severance pay = 1-year salary
retraining cost, χ	1.46	Tenure > 10Y = 47.4% (Japan)
Job destruction rate, ψ	0.048	Tenure > 10Y = 27.9% (U.S.)
Exo. job separation, d_O	0.009	Separations other than dismissals
Depreciation for GHC, δ_g	0.030	Estimation results
Depreciation for FSHC, δ_s	0.087	Estimation results
Efficiency: FSHC inv., A_s	0.173	Estimation results
Efficiency: GHC inv., A_g	0.088	Estimation results

4.1.1 Calibration

Some parameters are calibrated to standard values or to be consistent with macroeconomic data in Japan. The retirement probability λ is set to 0.025, meaning the average working periods equal 40 years, and the discount rate β is set to 1/1.04. The unemployment benefit is assumed to be 40% of wages (i.e., $b = 0.4$), and the matching probability m is set to 0.43 so that the unemployment rate equals 3.0%. The curvature of the human capital production function α is set to 0.85 following the discussion in Guvenen and Kuruscu (2010). The probability of deteriorating the matching quality is calibrated to 0.71% so that the job-to-job transition rate equals 4.8%, the aggregate value taken from the Labor Force Survey in Japan. Regarding the parameters associated with job destruction and dismissals, the severance pay is assumed to be one-year salary, $\phi = 1.0$, and d_O is set to 0.9%, both of which are based on Japanese data. Then, given $d_D = (1 - \phi/\chi)\psi$ in equilibrium, ψ and χ are calibrated so that: (i) d_D with $\phi = 0$, i.e., ψ, equals a dismissal probability in the U.S (= 4.8%), (ii) d_D with $\phi = 1.0$ equals a dismissal probability in Japan (= 1.5%).[16]

[16]More specifically, the calibration strategy for the parameters associated with job destruction and dismissals is as follows. First, in Japan, the ratio of workers with an employer tenure of more than 10 years is 47.4%, implying that the total job separation rate is 7.2%, as $(1 - 0.072)^{10} \approx 0.474$. Then, since 21.2% of job separations are due to an employer's

Figure 4: Wages and Job Experience/Tenure

Note: The left and middle panels in the figure show FSHC and GHC accumulation in the model (the bold blue and red lines), along with the wage premium for job experience/tenure based on the estimation results in column (2) in Table 1 (the dashed black lines). In the right panel, the dashed black line shows the wage premium for job experience in Japan based on the estimation results in column (1) in Table 1. The blue area in the right panel represents the wage premium over the life cycle due to FSHC accumulation and changes in matching quality, while the red area represents the wage premium due to GHC accumulation.

The parameter values for efficiency of human capital accumulation and its depreciation, A_g, A_s, δ_g, and δ_s, are calibrated so that the human capital accumulation in the model is consistent with the observed wage premiums in Japan. The features for FSHC and match quality (i.e., h_s and z) in our model imply that both are identified as wage premiums for employer tenure. They differ in that h_s is endogenously accumulated and disappears when workers leave the current employer, while z is exogenously exacerbated and improves when workers leave the current employer. Despite those differences, both h_s and z are reset to their initial values (i.e., $h_s = 0$ and $z = 1$) upon separation from the current employer, thus making their values specific to the current employer. Therefore, when mapping the model-implied wage premiums to data, the log of wage premiums is decomposed as in equation (6). The parameter values for human capital accumulation are calibrated so that the dynamics of the first two terms, $\log(z) + h_s$, align with wage premiums for employer tenure, while those of the last term, h_g, align with the sum of transferable human capital captured by the sum of wage premiums for job experience, industry tenure, and occupation

reasons in Japan, we assume that 1.5% out of the total job destruction rate 7.2% is due to dismissals. Given that the job-to-job transition rate equals 4.8%, the remaining 0.9% is assumed to be due to private reasons such as family reasons. Second, in the U.S., the ratio of workers whose employer tenure is more than 10 years is 27.8%, which implies that the total job separation rate is 12.0%, i.e., $[1 - 0.12]^{10} \approx 0.278$. Then, given the fact that the layoff-quit ratio is around 1.5 in the U.S. (See, BLS, 2018), we assume that 4.8% out of 12.0% is due to dismissals.

tenure. Specifically, the parameter values are calibrated so that the model-implied dynamics of wage premiums are consistent with the estimation results in column (5) in Table 1.

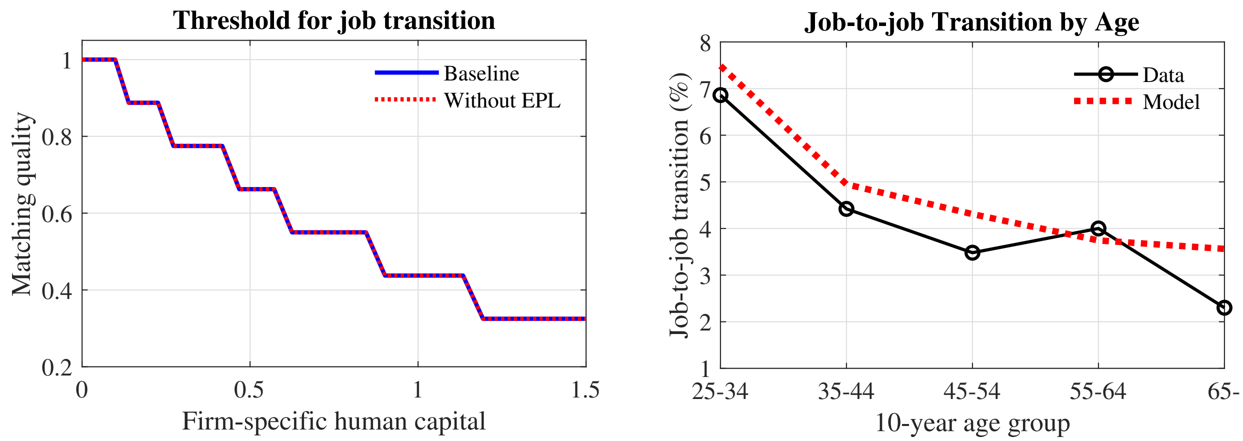
Figure 4 shows FSHC and GHC accumulation in the model under our calibration values (the bold blue and red line in the left and middle panels), along with the wage premiums for employer tenure and others based on the estimation results in Table 1 (the dashed black lines in the left and middle panels). The left and middle panels in the figure indicate that, with appropriately chosen parameter values for A_g, A_s, δ_g, and δ_s, the optimal human capital accumulation can fairly well account for the observed wage premium for employer tenure and others in Japan. Furthermore, the right panel in Figure 4 indicates that the wage premium for total job experience in Japan (the dashed black line), based on the estimation results in column (1) in Table 1, can also be well accounted for by the model, even though it is not directly targeted in the calibration. In the right panel, the blue area represents the wage premium over the life cycle due to FSHC accumulation and changes in matching quality in the model, while the red area represents the wage premium due to GHC accumulation. The panel suggests that FSHC and changes in matching quality account for around one-fourth of human capital accumulation over the life cycle in Japan.

4.1.2 Job-to-Job Transition in Equilibrium

Regarding job-to-job transition in the model, the left panel in Figure 5 describes the threshold for job transition in equilibrium. The x-axis and y-axis represent the level of FSHC and the matching quality, respectively, and the threshold lines are defined as indicating that workers transit to another employer when their matching quality falls below the threshold lines. Thus, the downward-sloping threshold lines imply that the more a worker accumulates FSHC, the more a worker hesitates to change his/her job. The fact that workers with more FSHC hesitate to change their jobs is intuitive, as workers lose all FSHC when leaving their current employer. That is, for workers who have accumulated substantial FSHC, the opportunity cost for leaving their current employer is high.

The job-to-job transition in the model accounts for the job-to-job transition rate by age in the data. The right panel in Figure 5 displays the job-to-job transition rates by age in Japan, along with those in the model. In the model, the downward-sloping threshold shown in the left panel of Figure 5 leads to the declining job-to-job transition rate with respect to workers' age (the red dashed line). This trend is intuitive, as workers accumulate more FSHC over their life cycle, thereby facing higher opportunity costs when considering a transition to another employer as they age. The declining trend of the job-to-job transition rate by age aligns broadly with observations from

Figure 5: Job-to-job Transition



Note: In the left panel, the x-axis and y-axis represent the level of FSHC and the matching quality, and the threshold lines indicate that workers leave their current job for another job when their matching quality falls below the threshold lines.

Japanese data (the black line with circles), suggesting that the job-to-job transition in the model effectively captures a key incentive for workers to change jobs over the life cycle.

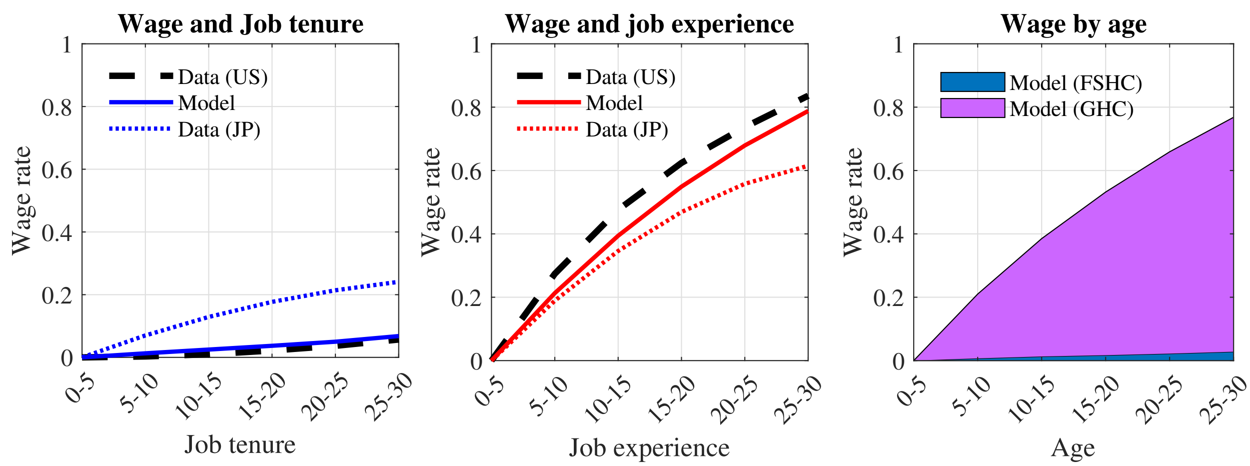
4.2 Comparative Statics: EPL and Labor Market Fluidity

This subsection conducts a policy exercise to examine how EPL influences labor market fluidity. Specifically, we perform comparative statics with respect to the firing cost ϕ, which represents the stringency of EPL in the model. In the baseline case, calibrated to the Japanese economy, ϕ is set to 1.0, reflecting Japan's stringent EPL. In the counterfactual case, ϕ is set to zero—consistent with the U.S. dismissal rate of 4.8%—to explore the implications of eliminating stringent EPL. Importantly, all other parameter values are assumed to remain unchanged from the baseline, allowing us to isolate the marginal effects of EPL. Hereafter, the counterfactual case with zero firing cost is referred to as "the economy without EPL." In this exercise, firms optimally choose d_D and w under different levels of firing costs, thereby affecting workers' human capital accumulation and their incentives to switch employers.

Human Capital Accumulation without EPL

The left and middle panels in Figure 6 show the accumulation of FSHC and GHC over the life cycle in the economy without EPL (the bold blue and red lines), along with the wage premium in the U.S.

Figure 6: Wages and Job Experience/Tenure without EPL



Note: The figure shows FSHC and GHC accumulation over the life cycle in the economy without EPL (the bold blue and red lines), along with the wage premium for the U.S. based on the estimation results in Kambourov and Manovskii (2008) (the dashed black lines) and the baseline case (the dotted blue and red lines).

economy based on the estimation results in Kambourov and Manovskii (2008) (the dashed black lines) and the baseline case (the dotted blue and red lines). The figure indicates that, compared with the baseline case, the human capital accumulation relies more on GHC rather than FSHC in the economy without EPL and that, consequently, it closely replicates the life-cycle wage premiums observed in the U.S. The shift from FSHC to GHC in response to eliminating EPL is intuitive: A higher dismissal probability raises the risk for workers to lose their FSHC due to dismissals, thus discouraging them from accumulating FSHC. As a result, FSHC plays a very limited role in the economy without EPL. Specifically, the left panel shows that it brings only around 10% wage premium for 20-year employer tenure, which is close to what we observe in the U.S. economy. Hence, the right panel indicates that almost all human capital accumulation is accounted for by GHC rather than FSHC in the model. Overall, Figure 6 implies that a dismissal probability can quantitatively account for the different roles of FSHC across the two countries.

Labor Market Fluidity without EPL

The policy exercise also indicates that eliminating EPL increases the job-to-job transition rate, i.e., a measure of labor market fluidity, while increasing the unemployment rate. Table 4 shows some labor market measures in the baseline case (the first row) and the counterfactual case without EPL (the second case), along with the U.S. data (the third row). Note that the values for the baseline

Table 4: Policy Exercise for Eliminating Employment Protection

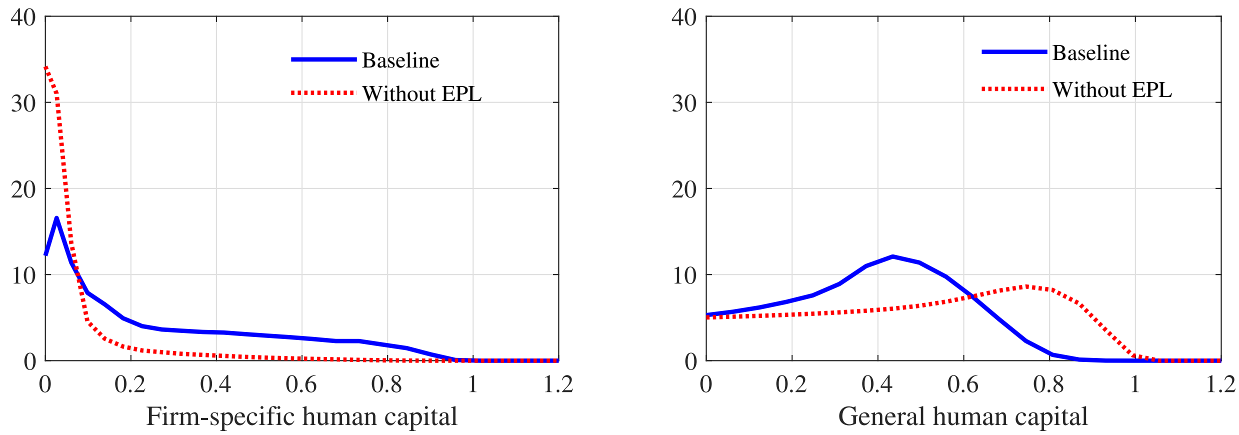
		Dismissal	Quits		Unemp.
			Job Chg.	Others	
Japan	Baseline	1.5	4.8	0.9	3.0
	No EPL	4.8	6.5	0.9	6.8
U.S.		4.8	7.2		5.5

Note: The table shows the dismissal probability (the first column), the job-to-job transition rate (the second column), and the quit rate for other reasons (the third column) in the baseline case (the first row) and the counterfactual case without EPL (the second case), along with the U.S. data (the third row).

case are equal to those in the Japanese data, as the parameter values are calibrated so that the model replicates those Japanese data. In our comparative statics analysis, the dismissal rate in the first column, set to 1.5% in the baseline, is exogenously changed to that in the U.S., 4.8%, in the counterfactual case without EPL. The table indicates that when the dismissal probability increases, (i) the job-to-job transition rate (the second column) also increases by 1.7% from 4.8% to 6.5%, and (ii) the unemployment rate increases from 3.0% to 6.8%. The first result implies that EPL suppresses job turnovers by not only directly reducing the dismissal rate but also adversely affecting labor market fluidity measured by the job-to-job transition rate.

Why does EPL suppress labor market fluidity? To understand the underlying mechanism behind this result, Figure 7 shows the stationary distribution of FSHC (the left panel) and GHC (the right panel). The figure implies that the shift from FSHC to GHC in response to eliminating EPL is key to understanding EPL's adverse effects on labor market fluidity. The stationary distribution of human capital $\mu_w(h_s, h_g, z)$ indicates that there are more workers who have accumulated a significant amount of FSHC h_s, rather than GHC h_g, in the baseline case (the blue bold line) than in the hypothetical case without EPL (the red dotted line). The difference in the stationary distribution between the baseline and the hypothetical case without EPL is consistent with the changes in human capital accumulation over the life cycle described in Figures 4 and 6. Given that more workers accumulate a substantial amount of FSHC in the baseline economy, the downward sloping threshold in the left panel of Figure 5 implies a stagnated *aggregate* job-to-job transition rate in the baseline economy. Conversely, the economy without EPL is associated with a higher aggregate job-to-job transition rate, as fewer workers accumulate FSHC in the counterfactual case without EPL. Furthermore, the left panel of Figure 5 indicates that the thresholds for job transitions *given the level of FSHC* are identical between the baseline and the case without EPL, implying that

Figure 7: Stationary Distribution of Firm-specific and General Human Capital



Note: The figure shows the (marginal) stationary distribution of FSHC (the left panel) and GHC (the right panel) in the baseline economy and the counterfactual case without EPL.

the distributional change in human capital accumulation entirely accounts for the aggregate change in job-to-job transition in comparative statics.[17]

Quantitatively, Table 4 implies that the workers' endogenous responses to EPL can account for the gap in labor market fluidity between Japan and the U.S. Specifically, the quit rate increases from 5.7% to 7.4% in our comparative statics, which is close to 7.2% observed in the U.S. As noted in the introduction, while EPL clearly suppresses labor market fluidity in cross-country data (Figure 1), it is not straightforward why EPL suppresses labor market fluidity. In particular, given that the same EPL should be equally applied to all firms within the same countries, EPL does not directly influence the *relative* attractiveness between employers. This paper contributes to this discussion by modeling human capital accumulation, EPL, and job changes in a unified framework and pointing out that the endogenous response of human capital accumulation to the degree of EPL is key to understanding the EPL's adverse effects on labor market fluidity.

4.3 Welfare Analysis

In this subsection, we conduct a welfare analysis to examine how the elimination of EPL affects social welfare through human capital accumulation and labor market fluidity. This is a relevant policy question for some advanced economies with stringent EPL such as continental European

[17] Also, while it is not shown in the figures, the threshold for job transition is almost flat with respect to GHC, h_g, and remains almost the same between the baseline and the counterfactual case without EPL.

Table 5: Welfare Analysis

	Firm-specific HC	General HC	Matching	Total
	(1)	(2)	(3)	(1)+(2)+(3)
Baseline	26.8	73.2	–	100.0
No EPL 1	6.0	87.2	2.9	96.0
No EPL 2	5.5	90.3	2.9	98.6

Note: The table shows the result of the welfare analysis. Given the functional form of the labor supply function, EPL's effects on the (log of) total labor supply are decomposed into those on FSHC, GHC, and matching quality.

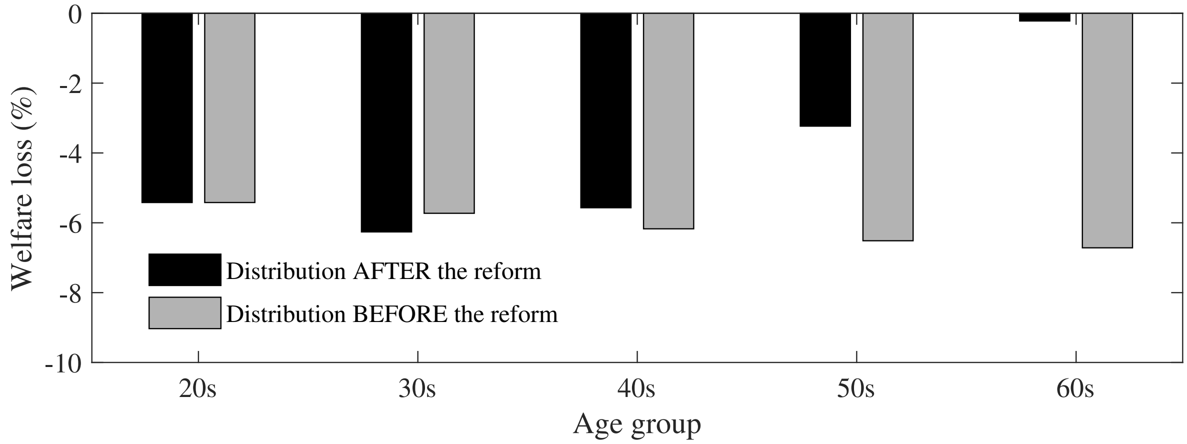
countries and Japan. As discussed in Section 3, we can use the aggregate labor supply as a measure of social welfare. Furthermore, given the functional form of the wage function, $z\exp(h_s + h_g)$, we can decompose EPL's effects on the (log of) total labor supply into those on FSHC, GHC, and matching quality.[18]

Table 5 presents the results of the welfare analysis. In the table, social welfare in the baseline scenario is normalized to a hundred, while the contribution of matching quality in the baseline is normalized to zero. First, the table indicates that eliminating EPL has both negative and positive effects on social welfare: a decline in FSHC results in a -20.8 percentage points change (column 1), while an increase in GHC contributes +14.0 percentage points (column 2). This finding is consistent with Figures 6 and 7, which illustrate the shift from FSHC to GHC in response to the removal of EPL. Second, the elimination of EPL positively impacts social welfare by improving matching quality (+2.9 percentage points, column 3). This suggests that enhanced labor market fluidity leads to better labor allocation and, consequently, improves social welfare. Third, the overall welfare effects of eliminating EPL are slightly negative, though not substantial, as the positive and negative impacts largely offset each other. EPL enhances social welfare by promoting the accumulation of FSHC and reducing the unemployment rate, as highlighted in previous studies. However, the welfare analysis suggests that these benefits may be limited when accounting for (i) workers' endogenous shift from FSHC to GHC to hedge against job separation risk, and (ii) improved matching quality resulting from increased labor market fluidity.

There are some caveats for the welfare analysis in Table 5. First, as noted in the previous section, FSHC in the model possibly includes components that do not directly improve labor productivity. If this is the case, a decline in FSHC following the elimination of EPL does not necessarily reduce

[18]Specifically, we can decompose log of labor supply by $\log(l_s) = \log(z) + h_s + h_g$ and aggregate each component in the right-hand side.

Figure 8: Welfare Analysis by Age



Note: The figure shows the welfare impact of eliminating EPL by age group. The black and gray bars indicate the welfare effects based on the stationary distribution after and before eliminating EPL.

social welfare, suggesting that the benefits of EPL may be overestimated. Second, Table 4 indicates that the comparative statics overpredict the rise in the unemployment rate compared with empirical data from the U.S. economy. While the model does not incorporate firms' endogenous adjustments of hiring to eliminating EPL, the absence of EPL may raise the value of new matching and thereby induce firms to increase job postings, helping to mitigate the resulting rise in the unemployment rate.[19] To incorporate this possibility, in the third row of Table 5 ("No EPL 2") adjusts the job finding probability m, in addition to the severance payment ϕ, to align the unemployment rate with the U.S. level of 5.5%.[20] The results imply that under this adjustment, the total welfare loss from eliminating EPL is reduced to less than half. These two caveats imply that the welfare gain attributed to EPL may be somewhat overestimated in Table 5.

While the overall welfare effects of eliminating EPL are slightly negative, they do not uniformly impact across age groups. Figure 8 illustrates the welfare impact of eliminating EPL by age group. The black and gray bars represent the welfare effects evaluated under the stationary distribution after and before the elimination of EPL, respectively. First, the black bars indicate that the negative welfare effects are smaller for older workers. This result reflects the fact that enhanced labor

[19] Also, with firm heterogeneity with respect to productiviy, Hopenhayn and Rogerson (1993) argues that the employment rate is higher in the economy without EPL due to firms' endogenous increases in hiring.

[20] Another way to incorporate changes in the job finding rate is to allow for endogenous job postings by firms and introduce a matching function, as in a Diamond-Mortensen-Pissarides model. This approach would endogenize the increase in the job finding rate following the elimination of EPL. However, we do not adopt this framework and instead assume a competitive hiring market with a zero-profit condition, as there is no tractable and sufficiently simple way to characterize the firm's value of new matching while accounting for future human capital accumulation of workers.

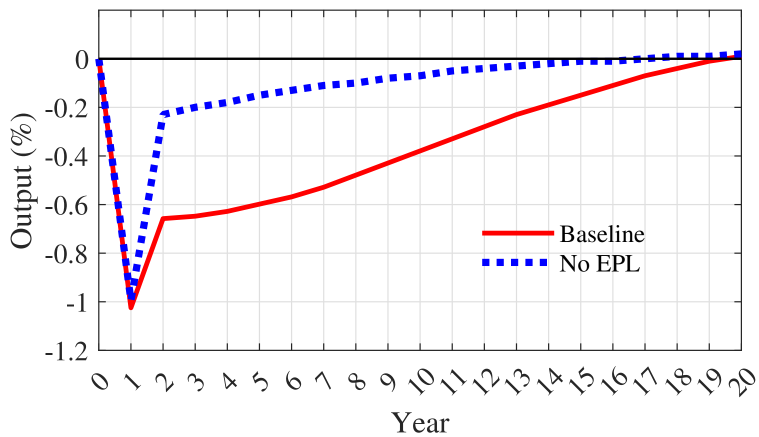
market fluidity is more beneficial for older workers than for younger workers. While younger workers can transition to another employer even in an economy with EPL, older workers may be less able to do so due to their accumulated FSHC. Thus, matching quality is likely to improve more for older workers than for younger ones if EPL is eliminated. Second, the gray bars show that when measuring the welfare effects using the stationary distribution *before* eliminating EPL, older workers are adversely affected more than younger workers. Therefore, if EPL were to be eliminated suddenly, older workers would face greater negative impacts compared to younger workers. This finding is intuitive; older workers have already accumulated a substantial amount of FSHC under the assumption that EPL would remain in place. A sudden elimination of EPL would negatively impact their welfare by increasing the risk of losing that FSHC. These two policy scenarios, represented by the black and gray bars, suggest that the long-term and short-term welfare effects by age group could be substantially different.

Finally, it is important to emphasize that the welfare analyses presented here highlight only a specific aspect of EPL. The model used is a stylized model that focuses on human capital accumulation by workers. Therefore, while the welfare effects of EPL reported in Table 5 are slightly negative and their magnitude is small, they do not necessarily indicate that EPL's overall impact on social welfare is either negative or small. Rather, they suggest that EPL's impact on social welfare *through a human capital accumulation channel* is minimal when increased labor market fluidity is taken into account. Clearly, EPL influences both worker behavior and business decisions through various other channels, such as mitigating unemployment risk and affecting labor reallocation across firms. Consequently, while this paper's welfare analysis enhances our understanding of the effects of EPL on welfare, a more comprehensive analysis is needed to fully assess the overall effects of EPL on social welfare.

4.4 Recovery from Structural Changes

While the previous subsections examined the effects of EPL on macroeconomic variables in the stationary equilibrium through comparative statics, this subsection discusses how EPL influences economic dynamics in response to structural changes. Specifically, the quantitative exercise below focuses on the impact of a turbulence shock, which represents an increase in skill mismatch among workers due to structural shifts, as in Kambourov and Manovskii (2009), and investigates how EPL affects the recovery path following the turbulence shock. In the simulation, we assume that the matching quality z in equation (5) deteriorates unexpectedly by one percentage point for all workers

Figure 9: Recovery from Turbulence Shocks



Note: The figure shows the output response to the turbulence shock in the economies with and without EPL. The quantitative exercise assumes that the matching quality z in equation (5) unexpectedly and suddenly deteriorates by one percentage point for all workers ("the turbulence shock") in period 1.

(the "turbulence shock") and analyze the transition dynamics back to the stationary equilibrium under different EPL regimes.

Figure 9 illustrates the output response to the turbulence shock in economies with and without EPL. In the baseline economy with EPL (bold red line), output drops by one percentage point in the first period due to the shock, partially rebounds in the following year, and then gradually converges back to its pre-shock level. In contrast, in the counterfactual economy without EPL (dashed blue line), output rebounds more strongly in the year after the shock, recovering approximately 80% of the initial decline. Although both economies return to their pre-shock output levels within 20 years, the baseline economy experiences a much larger cumulative output loss due to its slower recovery. Specifically, the cumulative output loss over 20 years is 7.7% in the baseline economy, compared to just 2.3% in the economy without EPL.

The difference in labor market fluidity is key to understanding the contrasting recovery paths across the two economies. In the model, there are two main channels through which aggregate matching quality can recover following the turbulence shock: (i) workers voluntarily quit their current jobs—where matching quality has deteriorated—and transition to new jobs with higher matching quality; and/or (ii) workers with poor matches are retired or dismissed and replaced by new workers with better matches. In the baseline economy with EPL, many workers have accumulated substantial FSHC, making them reluctant to leave their current jobs despite the decline in matching quality. By contrast, in the economy without EPL, most workers accumulate little FSHC, making them more willing to leave deteriorated matches and transition to new jobs. As a result, aggregate matching quality recovers more rapidly in the absence of EPL.

This quantitative analysis suggests that stringent EPL reduces labor market fluidity and delays labor reallocation, potentially leading to substantial output losses following structural changes. Indeed, empirical evidence indicates that, in the wake of the structural shifts brought about by the COVID-19 pandemic, employment recovery was faster in economies with more flexible labor markets. This exercise suggests that although stringent EPL modestly promotes human capital accumulation, as shown in Table 5, its overall desirability should be evaluated in light of the adverse effects stemming from reduced labor market fluidity—particularly those that become pronounced during periods of structural transformation.

5 Policy Implications and Concluding Remarks

This paper investigates how employment protection legislation (EPL) affects labor market fluidity by changing the wage premium for employer tenure. In the empirical part using the Japanese household-level microdata, we show that, in contrast to the U.S. economy, a sizable wage premium for employer tenure exists in Japan. Then, through the quantitative exercise using a structural model, we find that EPL suppresses labor market fluidity, as it encourages workers to shift their human capital accumulation from general human capital (GHC) to firm-specific human capital (FSHC). The quantitative exercise shows that a large amount of FSHC under stringent EPL disincentivizes workers to change their employers, thus accounting for the stagnated job-to-job transitions observed in Japan relative to the U.S. The welfare effect of eliminating EPL is slightly negative but not large, as it reduces FSHC but increases GHC and improves matching quality.

Our quantitative exercise implies that EPL can be a key determinant explaining the cross-country differences in labor market fluidity. Specifically, while EPL primarily aims at lowering the income risk for households by reducing dismissal probability, the decline in dismissal probability due to EPL reduces labor market fluidity by disincentivizing workers from leaving their current employer. Under a stagnant labor market, workers tend to remain with their current employer, even in the face of deteriorated matching quality, which adversely affects aggregate productivity due to labor misallocation across businesses, particularly after structural changes. Our quantitative analysis implies that it is difficult to enhance labor market fluidity while maintaining the stringent

EPL for regular workers.

While this study focuses on EPL and human capital accumulation, a more comprehensive welfare analysis of EPL through a general equilibrium analysis is promising for future work. In our quantitative analysis focusing on human capital accumulation, EPL has only a small impact on social welfare, as it encourages FSHC accumulation but discourages GHC accumulation and job-to-job transitions. In reality, however, the stagnated labor market fluidity due to EPL should adversely affect aggregate productivity through resource misallocation. In addition, since we assume risk-neutral households for simplicity, the welfare analysis in this paper cannot consider the benefit of EPL to reduce the household's unemployment risk. The welfare analysis of EPL that incorporates those various effects of EPL is challenging but promising for future work.

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Appendix A: Data Appendix

This appendix describes the dataset for our estimation in Section 2. Our estimation for wage premiums in Japan uses "Japan Household Panel Survey (JHPS/KHPS)," from 2004 to 2020, constructed by the Panel Data Research Center at Keio University. The JHPS/KHPS is an annual survey of Japanese households starting in 2004. The survey asks more than 3,000 individuals every year about various items, including job status, hours worked, and annual labor income. The microdata of JHPS/KHPS is available upon request for academic purposes. See their website (https://www.pdrc.keio.ac.jp/en/paneldata/datasets/jhpskhps/) for more information about the JHPS/KHPS dataset, including their purpose and methods.

Definitions of Variables

First, based on previous empirical studies using JHPS/KHPS (e.g., Kimura et al., 2022), the monthly wage rate $wage_{i,t}$ is defined as,

$$wage_{i,t} = \frac{\text{Annual labor income}_{i,t} \div 12}{\text{Weekly hours worked}_{i,t} \div 7 \times 30}$$

Second, to construct a variable for job experience $expr_{i,t}$, we assume that individual i has kept working since graduation if he/she is employed at the time of joining the survey, following previous studies including Lagakos et al. (2018). That is, job experience $expr_{i,t}$ in the initial year of the survey is defined as,

$$expr_{i,t} = t - \text{Year of graduation}_i$$

if they are employed in their initial year t. Based on the academic history information, the year of graduation is calculated by assuming that people graduate from middle school at 15, high school at 18, college at 22, and graduate school at 24. If individual i is not employed at the time of joining the survey, we drop individual i from the sample. Then, after the initial year, $expr_{i,t} = expr_{i,t-1} + 1$ if they are employed in year t, and $expr_{i,t} = expr_{i,t-1}$ otherwise. Finally, we drop individual i from the sample in the baseline estimation if: (i) their yearly hours worked are less than 1,200 hours, (ii) they are self-employed, or (iii) they are non-regular workers.

Finally, we construct the variable for employer tenure $tenu_{i,t}$, industry tenure $ind_{i,t}$, and occupational tenure $occ_{i,t}$ as follows. First, in the initial year for individual i for the survey, employer tenure $tenu_{i,t}$ is calculated using "Year of starting working at the current employer",

$$tenu_{i,t} = t - \text{Year of starting working at the current employer}_i$$

if he/she is employed in time t. Since we lack information on industry and occupational tenure at the time each individual joins the survey, we assume $ind_{i,t} = occ_{i,t} = tenu_{i,t}$ for the initial year. This assumption follows Kambourov and Manovskii (2008). It is a conservative assumption for the effects of employer tenure on wage premiums, as it raises a degree of covariation between employer tenure and industry/occupational tenure.[21] Then, after the initial year, $tenu_{i,t} = tenu_{i,t-1} + 1$ if they continue working with the same employer in year t; otherwise, $tenu_{i,t} = 0$. Similarly, after the initial year, if they continue working in the same industry or occupation in year t, then $ind_{i,t} = ind_{i,t-1} + 1$ and $occ_{i,t} = occ_{i,t-1} + 1$, respectively; otherwise, $ind_{i,t} = 0$ and $occ_{i,t} = 0$.

Industry and Occupational Classifications

The JHPS/KHPS dataset provides its own occupational and industry categories. On the occupational side, respondents are assigned to 12 categories: (i) workers in agriculture, forestry, and fisheries; (ii) mining; (iii) sales; (iv) service; (v) managers and administrators; (vi) clerical workers; (vii) transportation and communication; (viii) production, construction, maintenance, and transport; (ix) information-processing technicians; (x) professional and technical workers other than information-processing technicians; (xi) security); and (xii) others. On the industry side, the establishments at which respondents work are grouped into 18 industry categories: (i) agriculture; (ii) fisheries, forestry, and marine products; (iii) mining; (iv) construction; (v) manufacturing; (vi) wholesale and retail trade; (vii) food and drinking services and accommodation; (viii) finance and insurance; (ix) real estate; (x) transportation; (xi) information services and survey/research services; (xii) telecommunications and broadcasting; (xiii) electricity, gas, water, and heat supply; (xiv) medical and welfare services; (xv) education and learning support; (xvi) other services; (xvii) public administration; and (xviii) others.

The U.S. and Japanese classifications are not perfectly harmonized, reflecting differences in institutional context and survey design. Nevertheless, the U.S. 1-digit classifications and the occupational and industry groupings used in our Japanese survey are comparable in terms of granularity,

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[21] An alternative assumption can be $ind_{i,t} = occ_{i,t} = expr_{i,t}$, rather than $ind_{i,t} = occ_{i,t} = tenu_{i,t}$, which is less conservative for the effects of employer tenure. Indeed, if we use this alternative assumption, the effects of employer tenure become much larger and the effects of job experience become statistically insignificant and almost negligible.

Figure 10: Wages and Job Experience and Employer Tenure

Note: The figure shows the wage premiums for employer tenure (the left panel) and total job experience (the right panel) over the life cycle in Japan, based on the estimation results using equation (2) in the main text. In the figure, the dotted red lines, the blue bold lines, and the dashed black lines represent the wage premiums for the subsample of 2004-2008, 2009-2013, and 2014-2018, respectively.

as both rely on relatively coarse classifications—typically on the order of 10 to 30 categories—that aggregate jobs into broad functional and industrial sectors. Accordingly, while Kambourov and Manovskii (2008) report estimates based on 1-digit, 2-digit, and 3-digit classifications, we use their 1-digit estimates for the purpose of comparing occupational- and industry-tenure wage premiums across the two countries in Table 2 of the main text.

Appendix B: Subsample Analysis of Employer Tenure

In this appendix, we investigate whether the wage premiums associated with employer tenure in Japan have changed over the sample periods. Specifically, we examine whether the sizable wage premiums for employer tenure still persist, as some empirical studies, such as Kimura et al. (2022), argue that these premiums have significantly declined in Japan. To address this, we divide the sample into three 5-year periods: 2004–2008, 2009–2013, and 2014–2018, and perform subsample estimations for job experience and employer tenure based on equation (2).[22]

[22]In this subsample analysis, we use OLS instead of IV estimation because the IV method proposed by Altonji and Shakotko (1987) requires sufficiently long sample periods to capture extended employer tenure for each individual. Additionally, we do not control for industry and occupation tenure, as longer sample periods are needed to disentangle the effects of employer, industry, and occupation tenure. Indeed, when we conduct this subsample analysis using all the variables in equation (3), the coefficients on all explanatory variables other than total job experience become statistically insignificant due to multicollinearity.

To examine differences in wage premiums across subsamples, Figure 10 presents the wage premiums for employer tenure (left panel) and total job experience (right panel) over the life cycle. In the figure, the dotted red lines, bold blue lines, and dashed black lines correspond to the estimation results for the subsamples of 2004–2008, 2009–2013, and 2014–2018, respectively. First, the figure shows that wage premiums for employer tenure have slightly decreased, particularly for individuals with tenure exceeding 20 years. This finding aligns with previous studies that suggest a decline in wage premiums for employer tenure in Japan. Second, and more importantly, the figure indicates that employer tenure continues to yield substantial wage premiums. Therefore, the subsample analysis supports the main text's empirical findings: unlike in the U.S. economy, wage premiums for employer tenure remain a significant factor for regular workers in Japan.