Employment Protection and Entrepreneurship in a Schumpeterian Growth Model*

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Abstract

This paper investigates the effects of employment protection legislation (EPL) on entrepreneurship, firm dynamics, and economic growth in a general equilibrium model with Schumpeterian growth. In the general equilibrium model, EPL changes firms' innovation behavior and dismissal attitudes, which in turn affects households' human capital accumulation and entrepreneurship. The parameter values for firm growth and household human capital accumulation are estimated using Japanese firm-level and household-level microdata. The quantitative exercise reveals that eliminating EPL has a significant impact on firm dynamics and economic growth (around 20-30 bps), as it stimulates entrepreneurship by promoting the shift from firm-specific human capital to general human capital accumulation. Policies to directly support entrepreneurs stimulates entrepreneurship but have limited impacts on economic growth as long as stringent EPL exists.

Keywords: Entrepreneurship; Employment protection legislation (EPL); Schumpeterian growth; Firm Dynamics; Firm-specific human capital.

JEL Classification codes: E24, J32, M13, O41

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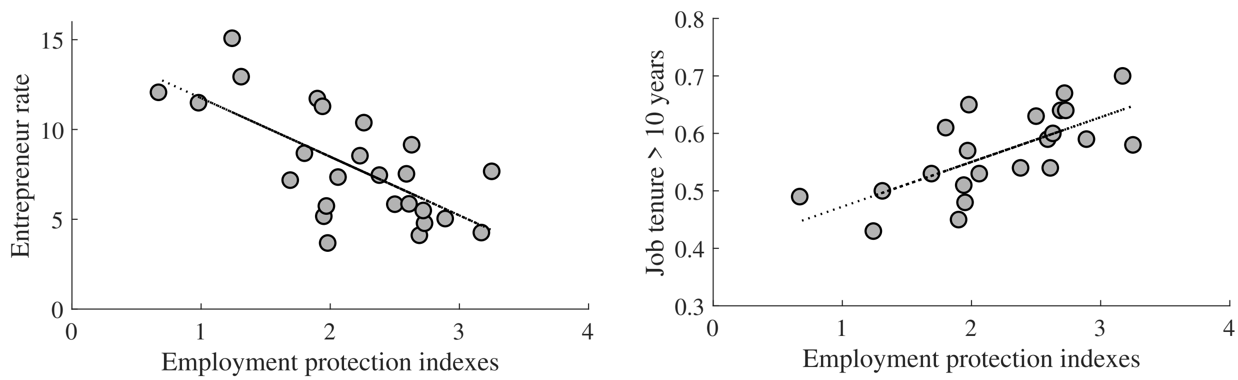
1 Introduction

While employment protection legislation (EPL) is commonly adopted in many countries, its economic impacts are manifold. The primary motivation for introducing EPL is to hEPL households reduce the risk of unemployment and thus accumulate human capital. However, in the firm sector, it raises the cost of employment, thereby possibly having adverse effects on wages or employment (e.g., Lazear, 1990; Hopenhayn and Rogerson, 1993; Autor et al., 2006). Among those various effects of EPL, its impact on entrepreneurship, and consequently on economic growth, is of particular importance, given that the impact on economic growth, even if small, is cumulatively large in the long run. Since EPL possibly influences economic growth through various channels in the firm and household sectors, modeling an interaction between those effects via various channels is key to quantitatively understanding the whole picture of its economic impact.

This paper investigates the quantitative impacts of EPL on economic growth, firm dynamics, and entrepreneurship in a Schumpeterian growth model. While EPL primarily changes firms' attitudes to employment and innovation by changing their dismissal cost, those changes in firms' behavior, in turn, influence households' entrepreneurial decisions, thus affecting economic growth through creative destruction. A general equilibrium model with Schumpeterian growth is a rich and tractable framework that can model such an interaction between the household and firm sectors; therefore, it is a good laboratory to quantitatively investigate the underlying mechanisms that EPL influences entrepreneurship, firm dynamics, and economic growth while taking into account the influences through the general equilibrium effects.

In light of these motivations, we construct a model by particularly focusing on empirical regularities associated with (i) firm growth by age, and (ii) the "escape-entry effects." First, regarding firm growth by age, previous empirical studies point out that the growth rate of young firms tends to be higher than that of old ones on average. While understanding to what extent the growth rate of young firms is higher than others is crucial to assess the impact of entrepreneurship on economic growth, it is an empirical question; therefore, in this paper, we estimate the growth-age relationship using confidential firm-level microdata

Figure 1: Effects of Employment Protection on Entrepreneurship and Job Tenure



Note: The left panel shows cross-country scatter plots between the employment protection indexes constructed by OECD (x-axis) and the entrepreneur ratios (y-axis). The right panel shows a relationship between the employment protection indexes and the number of workers whose job tenure is longer than ten years. Both panels focus on advanced economies whose GDP per capita is larger than 20 thousand USD. See the Appendix for more about data definition and formal regression analyses.

Source: OECD, Global Entrepreneurship Monitor

for Japanese firms and use indirect inference for setting parameters so that the model accounts for the estimated results. Second, Aghion et al. (2009) points out the "escape-entry effects," namely, existing firms try harder to innovate to keep their leading position for their products in the face of an increase in firm entries. Given that activating entrepreneurship increases firm entries, this escape-entry effect is also crucial in considering the effect of entrepreneurship on economic growth. Furthermore, stringent EPL should urge existing firms to pursue the escape-entry effect more aggressively, as EPL increases the cost of dismissals due to creative destruction.

Empirically, EPL negatively impacts entrepreneurship while leading to longer job tenure. The left panel in Figure 1 shows cross-country scatter plots between the employment protection indexes constructed by OECD and the entrepreneur ratios in the Global Entrepreneurship Monitor among advanced economies. This panel shows a clear negative relationship between them, suggesting that EPL has some negative impacts on entrepreneurship.[1] Second, the right panel in Figure 1 shows the cross-country scatter

[1]While Figure 1 focuses on advanced economies whose GDP per capita is larger than 20 thousand USD, more formal regression analysis shows that the negative relationship is observed among the full sample, including emerging market economies, after controlling for the level of GDP per capita. See the Appendix

plots between the employment protection indexes and the number of workers whose job tenure is longer than ten years. The panel shows a clear positive relationship between them, suggesting that more stringent EPL leads to longer job tenure on average. Previous studies emphasize that EPL encourages workers to accumulate firm-specific human capital (FSHC) through the positive impact on job tenure, i.e., long-term employment. Therefore, when modeling the household side in this paper, we explicitly model the accumulation of FSHC and general human capital and examine how EPL affects entrepreneurship through its impact on each type of human capital accumulation by using a discrete occupational choice model.

In the quantitative analysis, we set the baseline economy to the Japanese economy, one of the countries with the most stringent EPL, and examine the impact of EPL through comparative statics by asking: What if EPL is eliminated in Japan? First, consistent with the data, we find that EPL decreases the entrepreneurial rate. Under stringent EPL, individuals tend to accumulate FSHC rather than general one. Given that FSHC is lost when quitting a current job, EPL indirectly increases the opportunity cost for quitting the current job and starting their own business. In other words, while entrepreneurship is a kind of experimentation as Kerr et al. (2014) describes, the cost for experimentation is really high given the accumulated FSHC. Second, EPL depresses economic growth by suppressing entrepreneurship, as well as incumbent firms' innovation. Specifically, the comparative statics show that if EPL in Japan were to be eliminated entirely like in the U.S., the economic growth rate would rise by 0.2 to 0.3 percentage points. Increased entrepreneurship promotes economic growth by not only activating creative destruction associated with firm entries but also increasing young firms with more growth potential. General equilibrium effects are important in assessing the impact of EPL on entrepreneurship and economic growth. For instance, if we focus only on the firm sector and ignore the general equilibrium effects of increased entrepreneurship in the household sector, the impact on economic growth would be underestimated to be about two-thirds. Finally, policies to directly support entrepreneurs have much smaller effects on economic growth compared with eliminating EPL. The policy experiments suggest that as long as stringent EPL exists,

for more details on those regression analyses.

policy support for entrepreneurs does not fully exert its effects due to incumbent firms' reactions to increased firm entries.

Literature Review

First, this paper is built upon the fast-growing literature on quantitative studies using a Schumpeterian growth model with firm dynamics (e.g., Klette and Kortum, 2004; Lentz and Mortensen, 2008, 2016; Akcigit and Kerr, 2018; Akcigit et al., 2021). In particular, given that recent empirical studies emphasize the relationship between firm age and growth (e.g., Huynh and Petrunia, 2010; Haltiwanger et al., 2013; Decker et al., 2014; Adelino et al., 2017), we follow Acemoglu et al. (2018) to model the age-growth relationship in a Schumpeterian growth model and estimate it by Japanese firm-level microdata. In terms of motivation, Mukoyama and Osotimehin (2019) and Koeniger (2005) are closely related to this paper, as they also examine the effects of EPL on economic growth in an endogenous growth model.

Second, this paper is also related to the literature on entrepreneurship. On the modeling side, this paper models an individual's discrete choice between entrepreneurs and paid workers as in a standard entrepreneurship model.[2] Unlike existing models, our model does not focus exclusively on individual entrepreneurial decisions by assuming a partial equilibrium model in which the labor market does not clear (e.g., Jones and Pratap, 2020; Catherine, 2022) or by having a separate and large corporate sector (e.g., Salgado, 2019; Gaillard and Kankanamge, 2023), as this paper's main focus is on the macroeconomic impact of entrepreneurship on economic growth. On the impact of EPL on entrepreneurship and firm dynamics, Autor et al. (2007) and Haltiwanger et al. (2014) show that stringent EPL suppresses firm entries using the U.S. and cross-country data, respectively, and Bozkaya and Kerr (2014) point out the adverse effects of EPL on venture capital activity among European countries.

Third, this paper is related to the literature on human capital accumulation. Following Becker (1964)'s seminal work, Hashimoto and Raisian (1985) and Kimura et al. (2019)

[2]See Buera et al. (2015) for a survey on entrepreneurship models.

empirically show that FSHC plays an important role in Japan. Also, as for the relative importance of FSHC across countries, Tang (2012) shows that countries with more stringent EPL have a comparative advantage in industries where FSHC is important, which suggests that stringent EPL encourages FSHC accumulation in line with theoretical works by Wasmer (2006). Few studies in the literature, however, investigate the relationship between FSHC and entrepreneurship.

The rest of the paper proceeds as follows. Section 2 describes a general equilibrium model for the quantitative analysis. Section 3 calibrates the model parameters by indirect inference and conducts comparative statics to assess the impact of employment protection. Finally, in Section 4, concluding remarks are provided.

2 Motivating Facts

Before proposing a general equilibrium model, we show two key empirical facts associated with firm age to motivate our quantitative analysis. First, we investigate firm growth by age. Previous empirical studies such as Haltiwanger et al. (2013) and Huynh and Petrunia (2010) show that younger firms' growth rate is significantly higher than older ones' growth rate, even after controlling for firm size. Understanding to what extent the growth rate of young firms is higher than others is crucial to assess the impact of entrepreneurship on economic growth, as active entrepreneurship is expected to increase the share of younger firms. Second, we examine the role of R&D investment by firm age to investigate the "escape-entry effects" argued by Aghion et al. (2009). They point out that incumbent firms try harder to innovate to keep their leading position for their products in the face of an increase in firm entries. Hence, in contrast to R&D investment aiming to grow through creative destruction, R&D investment to pursue the escape-entry effects is a defensive investment to avoid losing the current market share. Given those different types of R&D investment, the following empirical analysis examines whether the role of R&D is different across firms of different ages.

The relationship between firm growth and age, as well as the role of R&D investment, are examined by using firm-level microdata. Specifically, we use confidential firm-level microdata for Japanese firms in the "Basic Survey of Japanese Business Structure and Activities" by the Ministry of Economy, Trade and Industry (METI) from 1997 to 2021. The dataset contains yearly financial information for all firms in Japan that hire more than 50 employees.[3] While the dataset does not contain many small firms whose employees are less than 50, excluding very small firms is in line with this paper's research motivation because our main focus in this paper is on innovation and its effects on economic growth.[4]

2.1 Firm Growth by Age

To estimate the relationship between firm growth and age, the annual growth rate of sales is used as a proxy for firm growth. Let $\Delta\text{Sale}_{i,t}$ be the annual growth rate of sales for firm i in year t. Then, all firms are categorized into 15 five-year bins according to their age. Specifically, we construct dummy variables $dum(\bar{a})_{i,t}$ where $\bar{a} = 1, \cdots, 15$,

$$dum(\bar{a})_{i,t} = \begin{cases} 1 & \text{if } 1 + 5(\bar{a} - 1) \leq \text{Firm } i\text{'s age in time } t \leq 5\bar{a} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

and the relationship between firm growth and age is estimated by running the following regression,

$$\Delta\text{Sale}_{i,t} = \alpha + Y_t + \sum_{\bar{a}=1}^{15} \beta_{\bar{a}} \times dum(\bar{a})_{i,t} + \gamma X_{i,t-1} + \varepsilon_{i,t} \tag{2}$$

where Y_t is the year dummy to control for the effects of business cycle fluctuations on firm growth, and $X_{i,t-1}$ is a vector of control variables, including firm size and dummy variables for cohort and industry.[5] The coefficients of our interest are $\beta_1, \cdots, \beta_{15}$, which capture the difference in sales growth by age group.

Table 1 shows the estimation results of $\beta_{\bar{a}}$ in the regression analysis of (2). The estimation

[3]Based on the Statistics Act in Japan, the microdata is available only for academic researchers after a scrutinizing process by METI regarding research purposes. For other empirical studies using this confidential firm-level microdata, see, for example, Fukao et al. (2017).

[4]Previous studies with similar motivation, such as Lentz and Mortensen (2008) and Akcigit and Kerr (2018), also exclude very small firms from their sample due mainly to data availability. For instance, Akcigit and Kerr (2018) limit their sample to firms with 500 and more employees.

[5]See Appendix D for more details about the specifications for estimating the relationship between firm age and growth using microdata.

Table 1: Empirical Relationship between Firm Growth and Age

$\bar{a}$	1	2	3	4	5	6	7	8	9	10
$\beta_{\bar{a}}$	.048** (.006)	.032** (.005)	.021** (.005)	.019** (.004)	.012** (.004)	.005 (.004)	.003 (.003)	.001 (.003)	.001 (.003)	.002 (.002)

Note: The table shows the estimation results of $\beta_{\bar{a}}$ in the regression analysis for the empirical relationship between firm growth and age specified in (2). In addition to the dummy variables for age, $\sum_{\bar{a}=1}^{15} \beta_{\bar{a}} \times dum(\bar{a})_{i,t}$, the estimation includes the capital stock in $t-1$, as well as industry and cohort dummies, as control variables. Appendix D provides more details about the estimation, including the results using other specifications, and the estimation results in this table correspond to column (4) in table 9 in Appendix D. Robust standard errors are shown in parentheses. ** and * mean that the coefficients are statistically significant at the .01 and .05 levels, respectively.

results in the table imply that the growth rate of younger firms is significantly higher than that of older firms, as in previous empirical studies for other countries. For instance, the growth rate of sales for firms in group 1, i.e., firm age is from 1 year to 5 years, is higher than that for firms older than 75 years by 4.8% on average. The estimation results also suggest that the average growth rate of sales gradually decreases as they get old and that the age effect on firm growth becomes statistically insignificant when firm age surpasses 25-30 years old.

To capture this empirical feature about firm growth by age, the model in the next section assumes that all new entrants are growing firms that have an opportunity for growth through creative destruction and then gradually become non-growing firms without growth potential. To identify the parameter values associated with innovation, as well as the transition rate from growing to non-growing firms, the estimation results about firm growth by age in table 1 contain crucial information. Hence, in the estimation of parameters using indirect inference, those estimated coefficients about the age effects on firm growth, $\beta_1, \cdots, \beta_{15}$, are used as moment conditions to be matched.

2.2 R&D Investment and Growth by Firm Age

Next, we investigate the role of R&D investment by firm age. While R&D investment is long recognized as a driver of growth through creative destruction (e.g., Klette and Kortum, 2004), it is also used by incumbent firms for keeping their leading position, as pointed out by Aghion et al. (2009). To investigate whether R&D investment has a different role for firms of different ages, we estimate the effects of R&D investment on the growth rate of sales by firm age,

$$\Delta \text{Sale}_{i,t} = \alpha + Y_t + \beta_Y \mathbf{1}_{\{Age<30\}} \times \text{R\&D\_rate}_{i,t-1} + \beta_O \mathbf{1}_{\{Age>30\}} \times \text{R\&D\_rate}_{i,t-1} + \gamma X_{i,t-1} + \varepsilon_{i,t} \quad (3)$$

where $\text{R\&D\_rate}_{i,t-1}$ is the average R&D investment for the last three years for firm i in year $t-1$ divided by its total asset. The vector of control variables includes capital stock in $t-1$, as well as industry and cohort dummies. The indicator function $\mathbf{1}_{\{Age<30\}}$ and $\mathbf{1}_{\{Age>30\}}$ are equal to one if the firm age is lower (higher) than 30 years; therefore, β_Y and β_O capture the effects of R&D investment on sales for young and old firms, respectively. The threshold for firm age is set to 30 years because the estimation regarding firm growth and age in table 1 suggests that firms younger than 30 years seem to have different growth potential than those older than 30 years.

Table 2 shows the estimation results for the regression analysis of (3). Column (1) indicates that when we do not distinguish between young and old firms, R&D investment has positive and statistically significant effects on sales growth. Also, column (2) indicates that when we distinguish between firms younger and older than 30 years, R&D investment has positive effects on sales growth only for firms older than 30 years. However, this estimation result by firm age drastically changes when we drop firms with large negative sales growth from the sample. Specifically, column (3) suggests that when firms whose sales growth is less than -30% are dropped from the sample, R&D investment has positive effects on sales growth only for firms younger than 30 years, in contrast to column (2). Such a drastic change is a bit surprising because the share of firms with sales growth less than -30% is only around 3.5%. Column (4) shows that the results are almost the same when we drop firms whose sales growth is less than -20% from the sample. Hence, in sum, the estimation results in table 2 indicate that: (i) R&D investment has positive effects on sales growth for old firms but explains only the difference between firms with large negative sales growth and others among them, and (ii) except for those with large negative sales growth, R&D investment increases young firms' sales growth.

Table 2: R&D Investment and Growth

	(1) $\Delta\ln(Sale)$	(2) $\Delta\ln(Sale)$	(3) $\Delta\ln(Sale)$	(4) $\Delta\ln(Sale)$
R&D_rate	0.055**			
	(0.019)			
$\mathbf{1}_{\{Age<30\}}\times$ R&D_rate		0.023	0.122**	0.154**
		(0.037)	(0.037)	(0.039)
$\mathbf{1}_{\{Age>30\}}\times$ R&D_rate		0.077**	0.029	0.010
		(0.018)	(0.018)	(0.018)
Sample	Full	Full	$\Delta\ln(Sale) > -.3$	$\Delta\ln(Sale) > -.2$
Observations	522,039	522,039	503,845	484,658
R^2	0.059	0.059	0.058	0.053

Note: The table shows the estimation results for the regression analysis of (3). R&D_rate$_{i,t-1}$ is the average R&D investment for the last three years for firm i in year $t-1$ divided by its total asset. The indicator function $\mathbf{1}_{\{Age<30\}}$ and $\mathbf{1}_{\{Age>30\}}$ are equal to one if the firm age is lower (higher) than 30 years. The estimation also includes firm size (capital stock) in $t-1$, as well as industry, year, and cohort dummies, as control variables. Robust standard errors are in parentheses. ** and * mean that the coefficients are statistically significant at the .01 and .05 levels, respectively.

To investigate more on the different roles of R&D investment across firms with different ages, we run the following quantile regression for R&D investment and sales growth,

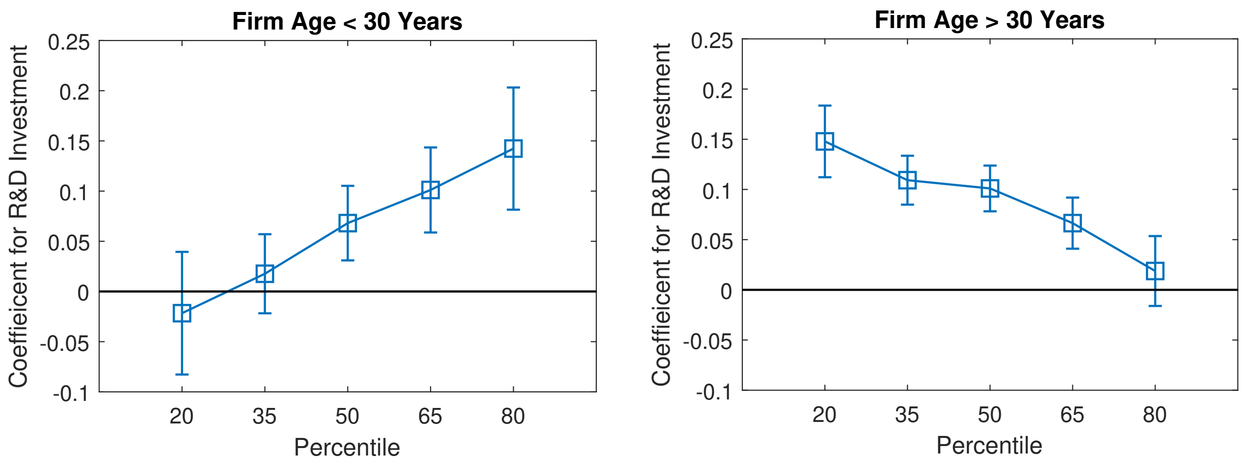
$$\widehat{\Delta\text{Sale}}_{i,t} = \alpha_Q + \beta_Q \widehat{\text{R\&D\_rate}}_{i,t-1} + \varepsilon_{i,t} \tag{4}$$

where $\widehat{\Delta\text{Sale}}_{i,t}$ and $\widehat{\text{R\&D\_rate}}_{i,t-1}$ are sales growth and the R&D investment to asset ratio for firm i after controlling for firm size, as well as dummy variables for the year, industry, cohort, and firm age.[6] The coefficient β_Q in the quantile regression of (4) captures the effects of R&D investment on the Q-percentile of sales growth.

Figure 2 shows the estimated β_Q in (4) with 95% confidence intervals for firms younger than 30 years (the left panel) and those older than 30 years (the right panel). The horizontal axis represents the percentile in the quantile regression, $Q = 20, 35, 50, 65,$ and 80 percentile. The figure indicates that β_Qs are significantly different between firms of different ages.

[6]Specifically, first, we regress sales growth and the R&D investment to asset ratio on firm size, as well as dummy variables for the year, industry, cohort, and firm age. Then, $\widehat{\Delta\text{Sale}}_{i,t}$ and $\widehat{\text{R\&D\_rate}}_{i,t-1}$ are constructed from residuals in those regressions.

Figure 2: Quantile Regression for R&D Investment and Firm Growth



Note: The figure shows the marginal impact of R&D investment on Q-percentile of sales growth, i.e., β_Q in (4), with 95% confidence intervals for firms younger than 30 years (the left panel) and those older than 30 years (the right panel). The horizontal axis represents the percentile in the quantile regression, $Q = 20, 35, 50, 65$, and 80 percentile.

Specifically, for firms younger than 30 years, R&D investment has larger, positive, and statistically significant effects on the upper tails of sales growth (i.e., $Q \geq 50$) but no effects on its lower tails. Oppositely, for firms older than 30 years, R&D investment has larger, positive, and statistically significant effects only on the lower tails of sales growth (i.e., $Q < 80$) but no effects on its lower tails (i.e., $Q = 80$). Hence, the estimation results in figure 2 imply that: (i) for firms older than 30 years, R&D investment prevents large negative sales growth (i.e., the lower tails) but does not lead to large positive sales growth (i.e., the upper tails), and (ii) for firms younger than 30 years, R&D investment does not prevent large negative sales growth but potentially leads to large positive sales growth.

In sum, the estimation results in table 2 and figure 2 imply that old firms conduct R&D investment mainly to avoid a large drop in their sales (i.e., the escape-entry effect) while younger firms conduct it mainly to grow further. For firms older than 30 years, R&D investment explains the difference between those with large negative sales growth and others (table 2) and raises only the lower tails of sales growth (figure 2), suggesting that it enables them to keep their current position and avoid a large drop in sales. On the other hand, for firms younger than 30 years, R&D investment cannot reduce the probability of large negative sales growth but potentially leads to higher sales growth, suggesting that it enables them to grow further through creative destruction. As discussed in detail in the next section, such differences in the role of R&D investment by firm age are described in our general equilibrium model by assuming that: (i) firms' innovation on their own existing products reduces the probability of losing their leading position for the products (i.e., the escape-entry effects), and (ii) only young firms have growth potential through creative destruction.

3 Model

This section provides a quantitatively tractable model to assess the effects of EPL on entrepreneurship, firm dynamics, and economic growth. The economy consists of the firm and household sectors. In the firm sector, businesses have single or multiple product lines and grow via creative destruction, as in a standard Schumpeterian growth model. In the household sector, households accumulate firm-specific and general human capital and face a discrete choice problem regarding entrepreneurship. General equilibrium is characterized to be consistent with firms' and households' optimization, given wages, layoff probability, and firm values.

3.1 Firm

The firm sector follows a standard Schumpeterian growth model with firm dynamics such as Klette and Kortum (2004) and Akcigit and Kerr (2018). The firm sector consists of final-good firms and intermediate-good firms. Intermediate good firms, which are heterogeneous with respect to the number of product lines and the quality of each product line, grow through creative destruction (i.e., external innovation) and quality improvement of existing product lines (i.e., internal innovation). Finally, in terms of their growth potential, there are two types of firms, namely, growing and non-growing firms as in Acemoglu et al. (2018), which capture the fact that the growth rate of young firms tends to be higher than that of old ones.

Final Good Firm

The final good firms produce final goods, Y, by aggregating intermediate goods,

$$Y = \frac{1}{1-\rho}\int_0^1 q_j^{\rho} k_j^{1-\rho} dj, \tag{5}$$

where q_j and k_j are quality and quantity of intermediate good j. They maximize their profit, $Y - \int_0^1 p_j k_j dj$, in a competitive market, given the price of each intermediate good, p_j. Here, without loss of generality, the price of the final goods is normalized to one. Then, the demand function for each intermediate good,

$$k_j = q_j p_j^{1/\rho} \tag{6}$$

is provided as a result of the final good firms' profit maximization.

Internal Innovation and the Escape-entry Effect

The intermediate-good firms have single or multiple product lines and produce intermediate goods k_j with quality q_j at product line j. For each product line, they continuously conduct internal innovation for the following two purposes. First, internal innovation improves the existing product line's quality q_j and increases its profitability. Second, while all the existing product lines are subject to the risk of being taken by other incumbent firms or entrants via creative destruction (as described in details below), internal innovation reduces such a risk by keeping their leading position. Aghion et al. (2009) call the second benefit from internal innovation "the escape-entry effect" and empirically show that an increase in entries encourages incumbent firms' internal innovation.

Those two benefits from internal innovation are modeled as follows. First, the product lines are categorized as improving lines or non-improving lines, depending on the current internal R&D expenditure for the product lines. Then, as in Garcia-Macia et al. (2019), it is assumed that only the non-improving product lines are vulnerable to creative destruction.

More specifically, when the firm spends

$$C_I(\tilde{z}_j, q_j) = \tilde{\xi}\tilde{z}_j^{\tilde{\eta}} q_j \tag{7}$$

units of final goods for internal R&D investment, the product line j is an improving line with probability $\tilde{z}_j$. Therefore, with probability $\tilde{z}_j$, the product line j's quality is continuously improving from q_j to $(1+\tilde{\gamma})q_j$, i.e., $q_j(t+\Delta t) = (1+\tilde{\gamma}\Delta t)q_j(t)$, where $\tilde{\gamma}$ is a step size for internal innovation. Moreover, the improving line does not face the risk of being taken by others through creative destruction, thanks to the escape-entry effects. On the other hand, with probability $1-\tilde{z}_j$, the product line j is a non-improving line; therefore, the quality of the product line j remains at q_j, and it is susceptible to the risk of being taken by others with probability τ. Here, τ is the rate of creative destruction in the economy, which is determined as a result of external innovation as described below.

Employment Protection and Labor Cost

The intermediate-good firms produce the intermediate goods k_j at each product line j by the technology

$$k_j = \bar{q} l_j \tag{8}$$

where $\bar{q} \equiv \int_0^1 q_j dj$ is the average quality of all intermediate goods. To hire a unit of labor force l_j, they have to pay wages, w. In addition, when they dismiss workers, they have to incur some costs due to employment protection. Here, EPL is modeled as a firing tax as in Hopenhayn and Rogerson (1993) and Mukoyama and Osotimehin (2019). More specifically, the intermediate-good firms have to pay the firing tax ϕw when dismissing each unit of the labor force.

In the model, intermediate-good firms dismiss their employees in the following two cases. First, when their product lines do not survive due to creative destruction, they must dismiss all employees at the lost product lines.[7] Second, at surviving product lines, a

[7] This assumption implies that firms cannot avoid the firing tax by reallocating employees at the lost product lines to their other product lines. That is, it is too costly for firms to reallocate workers across different product lines because of, for instance, differences in a necessary skill set. See Mukoyama and Osotimehin (2019) for the case allowing a more general labor reallocation policy.

fraction ψ of jobs are exogenously destructed at each point in time. In the face of exogenous job destruction, firms have two choices, namely, (i) dismissing employees with destructed jobs by paying the firing tax and replacing them with new workers, or (ii) re-skilling them to return to their previous positions. Reflecting the fact that the cost for re-skilling varies across employees in the real economy, the marginal cost for re-skilling is linearly increasing with respect to the number of workers to be re-skilled and their wage rates. Hence, when firms re-skill $\bar{s}$ and dismiss $1 - \bar{s}$ of workers with destructed jobs, the total cost due to the exogenous job destruction is assumed to be,

$$\left[\int_0^{\bar{s}} \chi s \, ds + (1 - \bar{s})\phi\right] w \times \psi l_j. \tag{9}$$

where $w\chi s$ is the marginal cost for re-skilling s fraction of workers.[8] Taking the first order condition to minimize the employment protection cost with respect to $\bar{s}$, the optimal choice of $\bar{s}$ is $s^* = \phi/\chi$ and the minimized cost is $\phi(1 - \phi/(2\chi))w \times \psi l_j$.

The intermediate-good firms calculate the cost of hiring a labor force by considering the employment protection cost they have to incur in those two cases to dismiss their employees. Given their internal R&D expenditure in (7), the product line j is an improving line (a non-improving line) with probability $\tilde{z}_j$ (with probability $1 - \tilde{z}_j$). Since the firm loses non-improving product lines with probability τ due to creative destruction, the expected labor cost to hire each unit of the labor force at the product line j is,

$$\omega_j w \quad \text{where} \quad \omega_j \equiv 1 + (1 - \tilde{z}_j)\tau\phi + \left[1 - (1 - \tilde{z}_j)\tau\right]\phi\left(1 - \frac{\phi}{2\chi}\right)\psi, \tag{10}$$

where the second and third term of ω_j is the employment protection cost associated with creative destruction and exogenous job destruction, respectively. When $\phi = 0$ (i.e., no firing tax), $\omega_j = 1$, i.e., wages are the only labor cost as in a standard model without employment protection. Note that the total labor cost $\omega_j w$ is increasing with respect to the wage rate w, the firing tax ϕ, the re-skilling cost χ, and the rate of creative destruction τ. Also, it is decreasing with respect to $\tilde{z}_j$ thanks to the escape-entry effects, which implies that

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

employment protection encourages firms to conduct more internal R&D for the purpose of avoiding the employment protection cost due to creative destruction.

Profit Maximization

The intermediate-good firm optimally chooses the labor force at product line j, l_j, so as to maximize the profit at product line j,

$$\max_{l_j} \left\{ p_j k_j - \omega_j w l_j \right\} \tag{11}$$

subject to the demand function (6), the internal R&D expenditure (7), the production function (8), and the labor cost (10). As a result of profit maximization, the optimal choice of employment and sales, as well as the optimized profit, is linear with respect to the quality of the product line q_j, namely,

$$p_j k_j = \left[\frac{(1-\rho)\bar{q}}{\omega_j w} \right]^{\frac{1-\rho}{\rho}} q_j \qquad \text{and} \qquad l_j = \left[\frac{(1-\rho)\bar{q}}{\omega_j w} \right]^{\frac{1}{\rho}} \frac{q_j}{\bar{q}} \tag{12}$$

and the optimized profit,

$$\pi_j q_j \ \text{ where } \ \pi_j \equiv \rho \left[\frac{(1-\rho)\bar{q}}{\omega_j w} \right]^{\frac{1-\rho}{\rho}}. \tag{13}$$

Note that π_j is possibly different across product lines because the labor cost ω_j depends on $\tilde{z}_j$ (and so the internal R&D expenditure for the product line j).

External Innovation

Intermediate good firms can increase the number of their product lines through external innovation. To describe the heterogeneity in terms of growth potential across firms, it is assumed that there are two types of firms, growing and non-growing firms, and that only the growing firms have opportunities for external innovation. Given that empirical works indicate that younger firms grow more than older firms (e.g., Haltiwanger et al., 2013; Decker et al., 2014), all firms are assumed to be growing ones at the time of entry, and then gradually become non-growing ones at the rate of ν. Non-growing firms do not become growing firms again, i.e., the non-growing state is an absorbing state, as in Acemoglu et al. (2018).

External innovation for the growing firms is modeled as follows. First, following Klette and Kortum (2004), the external innovation opportunities increase along with the number of product lines, n. Second, as in Akcigit and Kerr (2018), firms have to incur a fixed cost for external innovation proportional to the number of product lines, Φn.[9] Specifically, the growing firms can increase a product line at the instantaneous Poisson flow rate of $(1-\tilde{x})\hat{Z}$ by spending

$$C_E(\hat{z}, n) = \left[\hat{\xi}\hat{z}^{\hat{\eta}} + \Phi\right] n\bar{q} \tag{14}$$

units of final goods for external R&D investment. Here, $\hat{z} \equiv \hat{Z}/n$ is an innovation effort per product line, and $1 - \tilde{x}$ is the share of non-improving product lines in the economy, i.e., the share of product lines vulnerable to external innovation. Also, note that the cost for external innovation is increasing with $\bar{q}$ to be consistent with the balanced growth path.

When the firm succeeds in external innovation over product j, it improves the quality of product j by $\hat{\gamma}\bar{q}$, i.e., $q_j(t + \Delta t) = q_j(t) + \hat{\gamma}\bar{q}$, and adds the product line j to its product line portfolio by taking over the leading position from a previous leading firm. External innovation is assumed to be undirected in the sense that the expected quality of a newly acquired product line is equal to $(1 + \hat{\gamma})\bar{q}$.

Value Function

The optimal choice for internal and external R&D expenditure is characterized by the intermediate good firms' value function. To describe the value function, some new variables are defined. First, as the state variable for the firm who owns n product lines, the set of quality of all their product lines is expressed as,

$$\mathbf{q} \equiv \{q_1, \cdots, q_n\}.$$

[9] As shown in Akcigit and Kerr (2018), the fixed cost is introduced mainly for analytical traceability.

Second, the set of quality of improving product lines is denoted by $\tilde{\mathbf{q}}$. Hence, the set of quality of non-improving product lines is $\mathbf{q}\backslash\tilde{\mathbf{q}}$. Since all product lines can be improving lines or non-improving lines, $\tilde{\mathbf{q}}$ is an element of the power set of $\mathbf{q}$, i.e., $\tilde{\mathbf{q}} \in \mathbf{2}^{\mathbf{q}}$, and the probability to realize $\tilde{\mathbf{q}}$ is $\left[\prod_{q_j \in \tilde{\mathbf{q}}} \tilde{z}_j\right] \cdot \left[\prod_{q_j \in \mathbf{q}\backslash\tilde{\mathbf{q}}} \left(1 - \tilde{z}_j\right)\right]$. Finally, let $\tilde{\mathbf{q}}' \equiv \mathbf{q}\backslash\tilde{\mathbf{q}} \cup (1+\tilde{\gamma})\tilde{\mathbf{q}}$. Note that, without any other events, the set of quality of product lines $\mathbf{q}$ in t becomes $\tilde{\mathbf{q}}'$ in $t + \Delta t$.

Let $V_g(\mathbf{q})$ and $V_n(\mathbf{q})$ be the value function for a growing and a non-growing firm, respectively. Given the interest rate r, the rate of creative destruction τ, and the share of improving products in the economy $\tilde{x}$, the growing firm that owns n product lines chooses internal and external innovation intensity, $\tilde{z}_j$ and $\hat{z}$, so as to maximize the value function $V_g(\mathbf{q})$,

$$rV_g(\mathbf{q}) = \max_{\hat{z}, \{\tilde{z}_j\}_j} \left\{ \begin{array}{l} \displaystyle\sum_{\tilde{\mathbf{q}} \in \mathbf{2}^{\mathbf{q}}} \left(\prod_{q_j \in \tilde{\mathbf{q}}} \tilde{z}_j\right) \cdot \left(\prod_{q_j \in \mathbf{q}\backslash\tilde{\mathbf{q}}} \left(1 - \tilde{z}_j\right)\right) \left[\begin{array}{l} V_g\left(\tilde{\mathbf{q}}'\right) - V_g(\mathbf{q}) + \displaystyle\sum_{q_j \in \mathbf{q}\backslash\tilde{\mathbf{q}}} \tau \left\{ V_g(\tilde{\mathbf{q}}'\backslash q_j) - V_g(\tilde{\mathbf{q}}')\right\} \\ + (1-\tilde{x}) n \hat{z} \left\{ \mathbb{E}_{q_k} V_g\left(\tilde{\mathbf{q}}' \cup (q_k + \hat{\gamma}\bar{q})\right) - V_g(\tilde{\mathbf{q}}')\right\} \\ + \nu \left\{ V_n(\tilde{\mathbf{q}}') - V_g(\tilde{\mathbf{q}}')\right\} \end{array} \right] \\ \\ + \displaystyle\sum_{q_j \in \mathbf{q}} \left[\pi_j q_j - \tilde{\xi} \tilde{z}_j^{\tilde{\eta}} q_j\right] - \left[\hat{\xi} \hat{z}^{\hat{\eta}} + \Phi\right] n \bar{q} \end{array} \right\}.$$

The first line of the right-hand side shows that without any other events, the set of quality becomes from $\mathbf{q}$ to $\tilde{\mathbf{q}}'$ from time t to $t + \Delta t$, and that with the Poisson arrival rate of τ, the firm possibly loses a product line j when it is a non-improving line, i.e., $q_j \in \mathbf{q}\backslash\tilde{\mathbf{q}}$. The second line shows that the firm can acquire a new product line with the Poisson arrival rate at $(1 - \tilde{x})n\hat{z}$ where $(1 - \tilde{x})$ is a share of non-improving products in the economy. The third line describes the possibility that the firm becomes a non-growing firm with probability ν. Finally, the fourth line shows that the firm obtains the flow of profits subtracted by the internal and external R&D expenditure.

Similarly, the non-growing firm chooses internal innovation intensity, $\tilde{z}_j$, so as to maximize the value function $V_n(\mathbf{q})$,

$$rV_n(\mathbf{q}) = \max_{\{\tilde{z}_j\}_j} \left\{ \begin{array}{l} \sum_{\tilde{\mathbf{q}} \in 2^{\mathbf{q}}} \left(\prod_{q_j \in \tilde{\mathbf{q}}} \tilde{z}_j \right) \cdot \left(\prod_{q_j \in \mathbf{q} \setminus \tilde{\mathbf{q}}} \left(1 - \tilde{z}_j\right) \right) \left[V_n\left(\tilde{\mathbf{q}}'\right) - V_n(\mathbf{q}) + \sum_{q_j \in \mathbf{q} \setminus \tilde{\mathbf{q}}} \tau \left\{ V_n(\tilde{\mathbf{q}}' \setminus q_j) - V_n(\tilde{\mathbf{q}}') \right\} \right] \\ + \sum_{q_j \in \mathbf{q}} \left[\pi_j q_j - \tilde{\xi} \tilde{z}_j^{\tilde{\eta}} q_j \right] \end{array} \right\}.$$

Note that since the non-growing firm has no opportunity for external innovation, it chooses only the intensity of internal innovation.

Proposition 1 *Let the optimal internal and external innovation intensity for growing firms denote $\tilde{z}_{g,j}$ and $\hat{z}$ and the optimal internal innovation intensity for non-growing firms denote $\tilde{z}_{n,j}$. Assume that the fixed cost for external innovation Φ satisfies*

$$\Phi = \hat{\xi}(\hat{\eta} - 1)\hat{z}^{\hat{\eta}}. \tag{15}$$

Under this assumption regarding Φ, we have: (i) the value function is linear with respect to $\mathbf{q}$, i.e., $V_x(\mathbf{q}) = A \sum_{q_j \in \mathbf{q}} q_j$, where A is constant and takes the same value for $V_g(\mathbf{q})$ and $V_n(\mathbf{q})$, (ii) the optimal internal innovation for growing and non-growing firms is the same and independent of q_j, i.e., $\tilde{z}_{g,j} = \tilde{z}_{n,j} \equiv \tilde{z}$, and (iii) the optimal internal and external innovation, $\tilde{z}$ and $\hat{z}$, and the constant value of A for the value function $V(\mathbf{q}) = A \sum_{q_j \in \mathbf{q}} q_j$ are characterized by:

$$\tilde{\xi}\tilde{\eta}\tilde{z}^{\tilde{\eta}-1} = \frac{\partial \pi}{\partial \tilde{z}} + (\tilde{\gamma} + \tau)A \quad \text{and} \quad \hat{\xi}\hat{\eta}\hat{z}^{\hat{\eta}-1}\bar{q} = (1 - \tilde{x})v^e \tag{16}$$

and

$$rA = \pi - \tilde{\xi}\tilde{z}^{\tilde{\eta}} + \tilde{z}\tilde{\gamma}A - (1 - \tilde{z})\tau A \tag{17}$$

where $v^e = (1 + \hat{\gamma})A\bar{q}$ is the expected value for acquiring a new product line through external innovation by growing firms.

The proof is provided in Appendix. Note that π_j specified in (13) is also independent of q_j in equilibrium because $\tilde{z}_j$ and consequently ω_j in (10) are independent of q_j. The idea to introduce a fixed cost Φ to make the value function linear and tractable follows Akcigit and Kerr (2018). As in their model, the value of the fixed cost is chosen to completely offset the value from external innovation. While the choice of the value of the fixed cost is arbitrary, this assumption is not counter-intuitive because operating laboratories for external innovation should incur some operational costs. Given the linearity of the value function, the two equations in (16) are the first-order conditions for internal and external innovation intensity, respectively. In both of them, the left- and right-hand side represents the marginal cost and benefit of innovation expenditure. Equation (17) is the value function under the guess for linearity. Intuitively, the optimal $\tilde{z}_j$ characterized by the first equation in (16) does not depend on q_j because both the cost and benefit for internal innovation are linear with respect to q_j, as shown in the proof in the appendix. Proposition 1 implies that there are three equations in (16) and (17) for three unknowns, $\tilde{z}_j, \hat{z}$, and A; therefore, while it is difficult to solve the system of equations analytically due to their non-linearity, it is straightforward to compute the solution numerically.

The following corollary shows that the internal and external innovation expenditure in Proposition 1, and consequently the layoff probability d, are the same across all product lines, i.e., independent of q_j.

Corollary 1 *The layoff probability d_j is independent of q_j and satisfies*

$$d = (1 - \tilde{z})\tau + [1 - (1 - \tilde{z})\tau]\, \psi \left(1 - \frac{\phi}{\chi}\right). \tag{18}$$

The first and second terms correspond to layoff due to creative destruction and exogenous job destruction, respectively. The layoff probability is independent of q_j because the optimal internal innovation intensity $\tilde{z}_j$ is independent of q_j. This property is important to compute general equilibrium because, otherwise, the layoff probability is different for workers who work at different product lines, thus affecting their decision on entrepreneurship and human capital accumulation.

Firm Dynamics and Aggregation

While individual firms solve their optimization problem by taking as given the share of improving product lines $\tilde{x}$, the wage rate w, and the rate of creative destruction τ, those aggregate equilibrium variables are determined to be consistent with the firm's optimization policy as follows. First, since the optimal internal R&D, $\tilde{z}$, is independent of $\mathbf{q}$ and the firm type, the share of improving product lines in the economy is equal to the optimal internal innovation intensity,

$$\tilde{x} = \tilde{z}. \tag{19}$$

Second, the wage rate w is determined to clear the aggregate labor market. The aggregate labor demand is $\int_0^1 l_j dj$ where the individual line's labor demand l_j is determined by (12). Hence, given the labor supply L, the wage rate w is characterized by,

$$L = \left[\frac{(1-\rho)\bar{q}}{\omega w}\right]^{\frac{1}{\rho}} \tag{20}$$

Here, note that ω_j is not indexed by j anymore because the optimal $\tilde{z}_j$ is the same across all product lines. The aggregate labor supply L is assumed to be exogenous at this point but endogenously determined in general equilibrium later.

Third, the rate of creative destruction τ is determined as the sum of external innovation by incumbent growing firms and new entrants, as in a standard Schumpeterian growth model. To characterize the aggregate rate of creative destruction, the share of product lines owned by growing firms is an important state variable because only the growing firms have opportunities for external innovation.[10] Specifically, let F_g denote the share of product lines owned by growing firms. Then, the aggregate rate of creative destruction τ is determined by,

$$\tau = F_g\hat{z} + x^e \tag{21}$$

where x^e is the entry rate. The entry rate is exogenous at this point but endogenously determined in general equilibrium later. Also, there are two important notes on x^e here. First, x^e is not a realized entry rate but the share of entrants to non-improving product lines. Therefore, the realized entry rate is $(1-\tilde{x})x^e$. Second, it is not the *firm* entry rate but the *product* entry rate, i.e., the number of entrants' product lines divided by the mass of

[10]The aggregation method to use the share of product lines owned by different types of firms follows Lentz and Mortensen (2016).

non-improving product lines. Since the total mass of product lines is normalized to one and all entrants have only one product line, the firm entry rate is x^e/M_f, where M_f is the mass of firms in the economy. In the quantitative analysis, we numerically compute the mass of firms and use the firm entry as one of the calibration targets.

To characterize τ in (21), the share of product lines owned by growing firms, F_g, should be pinned down. Given the entry rate and the optimal external R&D, an instantaneous change in F_g from t to $t + \Delta t$ is determined by,

$$\dot{F}_g = (1 - \tilde{x})\hat{z}F_g + (1 - \tilde{x})x^e - (1 - \tilde{x})\tau F_g - \nu F_g \tag{22}$$

The share of product lines owned by growing firms F_g increases by external innovation by growing firms (the first term) or new entries (the second term), and decreases by creative destruction (the third term) and the transition to non-growing firms (the fourth term). In stationary equilibrium, F_g is characterized by setting $\dot{F}_g = 0$.

Finally, the aggregate economic growth g is characterized as the average quality improvement, i.e., growth of $\bar{q}$, through internal and external innovation. Specifically, the aggregate growth rate g on the balanced growth path is characterized as follows.

Proposition 2 *The aggregate growth rate in the stationary equilibrium is* $g = \tilde{z}\tilde{\gamma} + (1 - \tilde{z})\tau\hat{\gamma}$.

The first and second term is economic growth stemming from internal and external innovation, respectively. On the balanced growth path, the final goods, the wage rate, and the expected firm value for entrants, Y, w, and v^e, grow at the rate of g; therefore, in computing the equilibrium, define the stationary variables for them by dividing by $\bar{q}$, i.e., $\tilde{w} = w/\bar{q}$, $\tilde{Y} = Y/\bar{q}$, and $\tilde{v}^e = v^e/\bar{q}$. This result for the aggregate economic growth is similar to a standard Schumpeterian growth model, except that while internal innovation $\tilde{z}$ promotes economic growth through the quality improvement of product lines, it possibly suppresses them by discouraging external innovation through the escape-entry effects. The quantitative exercise will examine how employment protection affects economic growth by changing internal and external R&D investments, as well as household entrepreneurship, in general equilibrium.

Firm-side Equilibrium

In sum, the firm-side equilibrium is defined as follows.

Definition 1 *(Firm-side equilibrium) Assume that the interest rate r, the aggregate labor supply L, and the entry rate x^e are exogenously given. Then, a firm-side equilibrium consists of $\tilde{z}_j, \omega_j, k_j, p_j, l_j$, and π_j for all $q_j \in [0,1]$, as well as $\hat{z}, A, v^e, \tilde{x}, \tau, w, F_g, \Phi, Y, d$ and g such that: (i) the production, prices, labor demand, and profit at each product line, k_j, p_j, l_j, and π_j, satisfy (6), (12), and (13); (ii) the employment protection cost ω_j satisfies (10); (iii) the expected value for acquiring a new product line, v^e, is determined by Lemma 2; (iv) the internal and external innovation intensity, $\tilde{z}$ and $\hat{z}$, are characterized by the first order conditions (16); (v) the constant value of A for the value function $V(\mathbf{q}) = A \sum_{q_j \in \mathbf{q}} q_j$ satisfies (17); (vi) the share of improving lines, $\tilde{x}$, is equal to $\tilde{z}$; (vii) the aggregate rate of creative destruction, τ, satisfies (21); (viii) the wage rate w is determined by (20); (ix) the share of product lines owned by growing firms, F_g, is characterized by (22) and $\dot{F}_g = 0$; (x) the fixed cost for external innovation Φ satisfies (15); (xi) the final goods produced satisfy (5); (xii) the layoff rate d satisfies (18); (xiii) the aggregate growth rate g is characterized by Proposition 2.*

3.2 Household

The household sector consists of a continuum of households that are heterogeneous with respect to their firm-specific and general human capital (FSHC and GHC). They stochastically age every period, and once the age reaches some point, they are exogenously retired and are replaced by new ones with no human capital. In every period, workers obtain wages and accumulate human capital; however, they face the risk of being fired with probability d. Also, in every period, all households have an opportunity to become an entrepreneur and get entrepreneurial income. However, once workers leave their current employer due to layoff or to become an entrepreneur, they lose their FSHC while keeping GHC.

Human Capital Accumulation

All individuals are classified into two groups: employed and non-employed. Employed individuals work for a particular employer including their own firm and obtain wage income, while non-employed individuals do not. As shown later, non-employed individuals include dismissed workers and failed entrepreneurs. Employed individuals are characterized by two state variables, namely, FSHC and GHC, h_s and h_g. On the other hand, since non-employed individuals do not currently work for a particular employer, they are characterized only by GHC, h_g. Here, the difference between h_s and h_g follows the previous human capital literature pioneered by Becker (1964). That is, the FSHC h_s is valuable only for the current employer; therefore, it becomes worthless once employed individuals leave the current employer due to layoff or to become an entrepreneur.

The labor supply function determines the labor force that the employed individuals can supply based on h_s and h_g,

$$l_s(h_s, h_g) = \bar{h}(1 + h_s + h_g) \tag{23}$$

where $\bar{h}$ is a scale parameter. The labor supply function $l_s(h_s, h_g)$ implies that FSHC and GHC, h_s and h_g, are perfectly substitutable and that labor supply is equal to $\bar{h}$ when no human capital is accumulated.

Employed individuals accumulate FSHC and GHC as follows. First, all employed individuals have one unit of time to be used 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,

$$h'_s = (1 - \delta_s)h_s + A_s h^{\alpha} \quad \text{and} \quad h'_g = (1 - \delta_g)h_g + A_g(1 - h)^{\alpha} \tag{24}$$

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. Here, it is assumed $A_s > A_g$ and/or $\delta_s < \delta_g$; otherwise, individuals do not have an incentive to accumulate h_s because h_s is perfectly substitutable with h_g while disappearing when leaving the current employer. Hence, employed individuals optimally choose the time allocation of h in the face of the following trade-off: h_s is efficiently accumulated and hardly depreciated but becomes worthless when leaving the current employer, while h_g is inefficiently accumulated and quickly depreciated but remains valuable even after leaving the current employer. Specifically, the employed individual optimally chooses the time allocation h so as to maximize the value function,

$$H_W(a, y, h_s, h_g) = c + \beta \max_{h'_s, h'_g} \left[(1 - \lambda) X_W(a, h'_s, h'_g) + \lambda X_W(a + 1, h'_s, h'_g) \right] \tag{25}$$

subject to (23), (24), and $c \leq wl_s(h_s, h_g) + y$, where w is the wage rate and y is non-labor income. a represents the age, and individuals stochastically age with probability λ. Since employed individuals include the self-employed, the non-labor income is equal to the founder's financial income for self-employed individuals, i.e., entrepreneurs, and zero for employees of firms. $X_W(a, h_s, h_g)$ is the value function for the employed individuals before the discrete entrepreneurial choice (defined later).

As non-employed individuals do not accumulate human capital, they do not face any optimization problems at this stage and their value function is formulated as,

$$H_N(a, y, h_g) = c + \beta \left[(1 - \lambda) X_N(a, h'_g) + \lambda X_N(a + 1, h'_g) \right] \tag{26}$$

subject to $h'_g = (1 - \delta) h_g$ and $c \leq y$, where y is non-labor income and $X_W(h_s, h_g)$ is the value function for the non-employed individuals before the discrete entrepreneurial choice (defined later). Given that the non-employed individuals include dismissed workers and failed entrepreneurs, the non-labor income y for the non-employed is, if any, equal to an unemployment benefit.

When the age a reaches $\bar{a}$, both the employed and non-employed are retired and replaced new individuals with no human capital. Specifically, we assume

$$X_W(\bar{a}, h_s, h_g) = X_N(\bar{a}, h_g) = X_W(0, 0, 0) \tag{27}$$

for all h_s and h_g.

Entrepreneurial Choice

All households have an opportunity to become an entrepreneur. Given the accumulated two types of human capital, the value functions for the employed and non-employed individuals before the discrete entrepreneurial choice are,

$$X_W(a, h_s, h_g) = \mathbb{E}_z \max\left\{J_E(a, h_g, z), J_W(a, h_s, h_g)\right\} \tag{28}$$

and

$$X_N(a, h_g) = \mathbb{E}_z \max\left\{J_E(a, h_g, z), J_U(a, h_g)\right\}, \tag{29}$$

where $J_E(a, h_g, z)$, $J_W(a, h_s, h_g)$, and $J_U(a, h_g)$ are the value function for the entrepreneur, the employed worker, and the unemployed worker who searches for a job.

Here, z is the success probability for entrepreneurs. That is, individuals who start their startups, i.e., choose $J_E(a, z, h_g)$, succeed in their startups with probability z. Hence, the discrete choice problems in (28) and (29) imply that, after observing the success probability z for the current period, employed workers choose between working at their current employer or starting their own startups, while non-employed individuals choose between searching for a new job as unemployed workers or starting a business.

Value Functions for Entrepreneurs and Employed/non-employed Individuals

When individuals start a business, they first have to pay the initial entry cost, κ. Then, they succeed in their businesses with probability z. In the case of success, they obtain the founder's benefit equal to the expected firm value for entrants v^e and become an employee for their own firm, i.e., the employed individuals. On the other hand, in the case of failure, they get nothing and just become non-employed individuals. While this assumption reflects the fact that failed entrepreneurs are not eligible for unemployment benefits, it will be relaxed in the policy experiment section. Under those assumptions, the value function for the potential entrepreneur $J_E(a, h_g, z)$ in (28) and (29) is,

$$J_E(a, h_g, z) = z \cdot H_W(a, v^e - \kappa, 0, h_g) + (1 - z) \cdot H_N(a, -\kappa, h_g) \tag{30}$$

where $H_W(a, y, h_s, h_g)$ and $H_N(a, y, h_g)$ is the value function for employed and non-employed individuals defined in (25) and (26). The value function $J_E(a, h_g, z)$ implies that when they succeed, they obtain a large amount of non-labor income as an entrepreneurial income subtracted by entry cost $y = v^e - \kappa$ and they work at their own firm. On the other hand, when they fail, they just lose the entry cost κ and become non-employed. Given the value function $J_E(a, h_g, z)$ in (30), the entrepreneurial decisions in (28) and (29) can be interpreted as a sort of "free entry condition" used in a firm dynamics model. That is, while the standard free entry condition assumes that the firm value for entrants v^e should be equal to the entry cost κ, the entrepreneurial decisions in (28) and (29) takes into account other costs and benefits for starting a business, particularly the opportunity cost for quitting a current job, in addition to v^e and κ.[11]

Next, the value function for unemployed workers who search for a new job, $J_U(a, h_g)$ in (29), is formulated as,

$$J_U(a, h_g) = m \cdot H_W(a, 0, 0, h_g) + (1 - m) \cdot H_N(a, 0, h_g) \tag{31}$$

where m is a job-finding probability. The value function $J_U(a, h_g)$ implies that unemployed individuals find a new job with probability m while they remain unemployed with probability $1 - m$. Reflecting the fact that unemployment benefits last for no longer than one year in most countries, they are assumed not to be eligible for unemployment benefits even if they cannot find a job. Note that even when they find a new job, they start with zero FSHC, i.e., $h_s = 0$, because they are new to the new employer.

Lastly, the value function for currently employed individuals, $J_W(a, h_s, h_g)$ in (28), is formulated as,

$$J_W(a, h_s, h_g) = d \cdot \left[m \cdot H_W(a, 0, 0, h_g) + (1 - m) \cdot H_N(a, b, h_g) \right] + (1 - d) \cdot H_W(a, 0, h_s, h_g) \tag{32}$$

[11] Compared with a standard entrepreneurship model such as Buera et al. (2011), where entrepreneurs remain as a manager of their own firms, the entry decision based on the firm value v^e rather than the expected value of future profits may be too simplified to disregard some important aspects of entrepreneurship including bankruptcy risks after starting businesses; however, given the relatively complicated innovation structure of the firm sector, it is necessary for tractability to cut the link between firms' decisions and the founder's individual state.

where d is the layoff probability and b is unemployment benefits. The value function $J_W(h_s, h_g)$ implies that the employed individuals are dismissed with probability d while they can keep working for the current employer with probability $1 - d$. When they are dismissed and cannot find a new job, they are eligible for unemployment benefit b. Note that the probability of being dismissed d is assumed to include voluntary quits in addition to layoff, as the difference between them is murky in reality.[12] That is, while voluntary quit is driven by various motivations, it is often caused by dissatisfaction with the current treatment associated with low performance; therefore, the situation should be similar to layoffs in many cases.

Stationary Distribution

Let $g_s(a, h_s, h_g)$ and $g_g(a, h_s, h_g)$ be the policy function for FSHC and GHC accumulation, h'_s and h'_g, to solve the optimization problem for employed individuals in (25). Also, let $e_W(a, h_s, h_g, z)$ and $e_N(a, h_g, z)$ be the policy functions for entrepreneurship by employed and non-employed individuals in the discrete choice problem of (28) and (29), respectively, which take the value of 1 when individuals choose to start their own startups and take the value of 0 otherwise. Then, define the stochastic aging function as

$$\lambda(a, a') \equiv \begin{cases} 1 - \lambda & \text{if } a' = a \\ \lambda & \text{if } a' = a + 1 \ \& \ 1 \leq a' \leq \bar{a} - 1 \\ 0 & \text{otherwise} \end{cases}$$

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

Definition 2 *The stationary distribution for employed and non-employed individuals,* $\mu_w(h_s, h_g)$

[12] Engbom (2022) takes a similar approach to the distinction between voluntary quit and layoffs.

and $\mu_n(h_g)$, satisfy

$$\begin{aligned}
\mu_w(a', h_s', h_g') &= \sum_a \lambda(a, a') \Bigg\{ \int_z \int_{h_s, h_g} (1 - e_W(a, h_s, h_g, z)) \cdot (1 - d) \cdot \mathbf{1}_{\{h_s' = g_s(a, h_s, h_g) \wedge h_g' = g_g(a, h_s, h_g)\}} \\
&+ \Big[(1 - e_W(a, h_s, h_g, z)) \cdot d \cdot m + z \cdot e_W(a, h_s, h_g, z) \Big] \cdot \mathbf{1}_{\{h_s' = g_s(a, 0, h_g) \wedge h_g' = g_g(a, 0, h_g)\}} \\
& d\mu_w(a, h_s, h_g) \; dP(z) \\
&+ \int_z \int_{h_g} \Big[(1 - e_N(a, h_g, z)) \cdot m + z \cdot e_N(a, h_g, z) \Big] \cdot \mathbf{1}_{\{h_s' = g_s(a, 0, h_g) \wedge h_g' = g_g(a, 0, h_g)\}} d\mu_n(a, h_g) \; dP(z) \Bigg\} \\
\mu_n(a', h_g') &= \sum_a \lambda(a, a') \Bigg\{ \int_z \int_{h_s, h_g} \Big[(1 - e_W(a, h_s, h_g, z)) \cdot d \cdot (1 - m) + (1 - z) e_W(a, h_s, h_g, z) \Big] \\
&\times \; \mathbf{1}_{\{h_g' = (1 - \delta) h_g\}} \; d\mu_w(a, h_s, h_g) \; dP(z) \\
&+ \int_z \int_{h_g} \Big[(1 - e_N(a, h_g, z)) \cdot (1 - m) + (1 - z) e_N(a, h_g, z) \Big] \cdot \mathbf{1}_{\{h_g' = (1 - \delta) h_g\}} d\mu_n(a, h_g) \; dP(z) \Bigg\} \\
\mu_w(0, 0, 0) &= \lambda \left[\int_{h_s, h_g} d\mu_w(\bar{a} - 1, h_s, h_g) + \int_{h_g} d\mu_n(\bar{a} - 1, h_g) \right]
\end{aligned}$$

where $P(z)$ is the probability distribution for the success probability of entrepreneurship, z. The first and second equation is the law of motion for employed and non-employed individuals, respectively. The last equation is the case for exogenous retirement.

Household-side Equilibrium

Given the stationary distributions for employed and non-employed individuals, $\mu_w(a, h_s, h_g)$ and $\mu_n(a, h_g)$, the number of entrants x^e are defined as,

$$x^e = \sum_a \int_z z \cdot \left[\int_{h_s, h_g} e_W(a, h_s, h_g, z) d\mu_w(a, h_s, h_g) + \int_{h_g} e_N(a, h_g, z) d\mu_n(a, h_g) \right] dP(z) \tag{33}$$

and the aggregate labor supply is defined as,

$$\begin{aligned} L &= \sum_a \Bigg\{ \int_z \int_{h_s,h_g} (1 - e_W(a,h_s,h_g,z)) \cdot \Big[(1-d)\cdot l_s(h_s,h_g) + d\cdot m \cdot l_s(0,h_g)\Big] \\ &+ z \cdot e_W(a,h_s,h_g,z) \cdot l_s(0,h_g)\, d\mu_w(a,h_s,h_g)\, dP(z) \\ &+ \int_z \int_{h_g} \Big[(1-e_N(a,h_g,z))\cdot m + z\cdot e_N(a,h_g,z)\Big] \cdot l_s(0,h_g)\, d\mu_n(h_g)\, dP(z) \Bigg\} \end{aligned} \tag{34}$$

The first line is the labor supply by employed individuals who do not lose their job, while the second line is by non-employed individuals who find new jobs. Then, the household-side equilibrium is defined as follows.

Definition 3 *(Household-side equilibrium) Assume that the interest rate r, the layoff probability d, the expected firm value for entrants v^e, the wage rate w, and the growth rate g are exogenously given. Then, a household-side equilibrium consists of (1) policy functions $g_s(a,h_s,h_g), g_g(a,h_s,h_g), e_W(a,h_s,h_g,z)$, and $e_N(a,h_g,z)$, (2) probability distributions $\mu_w(a,h_s,h_g)$ and $\mu_n(a,h_g)$, and (3) a tuple (x^e, L) such that: (i) the policy functions for firm-specific and general human capital, $g_s(a,h_s,h_g)$ and $g_g(a,h_s,h_g)$ solve the employed individuals' optimization problem (25); (ii) the policy function for entrepreneurship choice, $e_W(a,h_s,h_g,z)$ and $e_N(a,h_g,z)$, solve the discrete choice problem for the employed individuals (28) and the non-employed individuals (29); (iii) the probability distributions $\mu_w(a,h_s,h_g)$ and $\mu_n(a,h_g)$ are stationary distributions defined in Definition 2; (iv) the number of entrants x^e is determined by (33); (v) the aggregate labor supply L is determined by (34).*

Note that on the balanced growth path, as in the firm-side equilibrium, consumption, the wage rate, and the expected firm value for entrants, c, w, and v^e, as well as all the value functions, grow at the rate of aggregate economic growth rate g; therefore, in computing the equilibrium, define the stationary variables for them and the value functions by dividing by $\bar{q}$, i.e., $\tilde{w} = w/\bar{q}$, $\tilde{c} = c/\bar{q}$, $\tilde{v}^e = v^e/\bar{q}$, and the value functions divided by $\bar{q}$. As a result, the discount factor for the household becomes $(1+g)(1-\lambda)\beta$ on the balanced growth path.

In the following quantitative analysis, the optimal policy functions and the stationary distribution in the household-side equilibrium can be computed by a standard value function iteration method.

3.3 General Equilibrium

We close Section 3 by defining a general equilibrium in the economy. To define general equilibrium, it is necessary to describe the firm sector as a discrete-time model rather than a continuous-time model to be consistent with the household sector. As shown in the appendix, while a discrete-time version of the model looks much more complicated and cumbersome, the firm-side equilibrium is characterized by exactly the same first-order conditions as in a continuous-time version.

The general equilibrium is characterized as follows. First, for tractability, it is assumed that the interest rate r is fixed, i.e., a small open economy assumption, and $\beta = 1/(1+r)$. Then, the firm-side equilibrium can be characterized by taking as given the entry rate and aggregate labor supply, while the household-side equilibrium can be characterized by taking as given the layoff probability, the expected firm value for entrants, the wage rate, and the growth rate. In the following general equilibrium, those aggregate variables are endogenously and simultaneously determined.

Definition 4 *(Competitive equilibrium) A competitive small open economy equilibrium consists of a tuple* $(d^*, v^{e*}, w^*, g^*, x^{e*}, L^*)$ *such that: (i) given the mass of entries* x^{e*} *and the aggregate labor supply* L^**, the firm-side equilibrium is consistent with the layoff probability* d^**, the expected firm value for entrants* v^{e*}*, the wage rate* w^**, and the growth rate* g^**; and (ii) given* d^*, v^{e*}, w^**, and* g^**, the household-side equilibrium is consistent with* x^{e*} *and* L^**.*

As you can see in the definition, in the general equilibrium, the labor market clears by the equilibrium wage rate and labor supply/demand w^* and L^*. Furthermore, while the labor market is the only market in the general equilibrium, the firm and household sectors also interact with each other through entrepreneurship and firm dynamics. For instance, when the entrants x^e increase in the household sector, the firm sector should face more creative destruction. More active creative destruction increases the layoff probability d but decreases the entrant's expected firm value v^e, thus, in turn, influencing the entrepreneurial motive in the household sector, i.e., affecting x^e. In the following section, we quantitatively assess the effects of employment protection on entrepreneurship, firm dynamics, and economic growth through comparative statics by taking into account those interactions between the firm and household sector in general equilibrium.

4 Quantitative Analysis

This section conducts a quantitative analysis using the model in the previous section, focusing on the effects of employment protection legislation (EPL) on entrepreneurship, firm dynamics, and economic growth. First, we calibrate the model parameters based on Japanese firm-and household-level microdata. In so doing, key parameters in the firm sector are calibrated by indirect inference using firm-level microdata in Japan. Then, the effects of EPL are examined by comparative statics. Given that Japan is one of the countries with very stringent EPL, the quantitative exercise assesses the effects of EPL by asking: What if Japan entirely eliminates EPL as in the U.S.?

4.1 Calibration and Indirect Inference

Before conducting a quantitative exercise, we calibrate the parameter values based on Japanese data. First, some firm parameters are calibrated using macro data or previous empirical studies. Then, the rest of them are calibrated by indirect inference so as to minimize the gap between model-implied moments and empirical moments obtained from data. Finally, household parameters are calibrated using household-level microdata.

Calibration for Firm Parameters

While most firm parameters are estimated by indirect inference, some are calibrated following previous empirical studies and macro data. First, the curvature of the innovation production function is calibrated as $\tilde{\eta} = \hat{\eta} = 2$ as in previous studies, including Acemoglu et al. (2018). Second, the production function parameter ρ is calibrated to be consistent with the labor share in Japan. Based on the Ministry of Finance's "Financial Statements Statistics of Corporations by Industry" in 2019, Labor cost/(Labor cost + Profit) = 0.803; therefore, given that the labor share in the model is $\omega w L/Y = (1-\rho)^2$, the production function parameter is calibrated as $\rho = 0.104$.[13] Third, the interest rate r is set to 0.04 following the previous literature. Finally, the aggregate labor supply is normalized to one, i.e., $L = 1$. While the aggregate labor supply is normalized to one in the baseline, the equilibrium value of L in comparative statics is determined so that the labor maker clears in general equilibrium.

Given those calibrated and normalized values, the rest of the firm parameters are calibrated by indirect inference as in Lentz and Mortensen (2008), Acemoglu et al. (2018), and Akcigit and Kerr (2018). Specifically, we calibrate by indirect inference the following nine parameter values in the firm sector: $x^e, \tilde{\gamma}, \hat{\gamma}, \tilde{\xi}, \hat{\xi}, \psi, \chi, \nu$, and ϕ.[14] The following subsections discuss which moment conditions are used in our indirect inference to identify parameter values and describe how to compute the model-implied values and the target empirical moments in data. We first compute the model-implied values for firm growth by age to be matched with the estimation results in table 1 and then discuss other moment conditions by referring to previous empirical studies or macro data.

Model-implied Firm Growth by Age

Next, we compute the model-implied values for firm growth by age to be matched with the empirical moments estimated by microdata. To compute the model-implied values for firm growth by age, it is necessary to construct the firm's stationary distribution by age over the state variables, i.e., a set of quality of their product lines $\mathbf{q}$ and the firm type (growing or non-growing). Nonetheless, as long as our interest is only on firm growth by age, the stationary distribution does not need to track the whole set of quality $\mathbf{q}$ because the optimal internal and external R&D is independent of q_j. Instead, the stationary distribution needs to track the number of products n, in addition to firm age a, in order to take into account the following survival bias: The growth rate of young firms is possibly estimated to be higher than that of old firms (i.e., the upward bias) because the estimated $\beta_{\bar{a}}$ in equation (2) is the relationship between firm age and growth *given the survival of firms*. That is, even

[13] The value for the production function parameter is close to $\rho = 0.106$ in Akcigit and Kerr (2018), .

[14] Note that while the entry rate x^e is not a parameter, it is calibrated to be consistent with data in the baseline and then adjusted in comparative statics.

though firm growth through both internal and external innovation is independent of n, young firms own fewer product lines and thus tend to exit more, thus leading to the above survival bias.

Let $\varpi_G(n,a)$ and $\varpi_N(n,a)$ be the mass of growing and non-growing firms with n product lines and age a. Also, define $\tilde{\tau} \equiv (1-\tilde{z})\tau$ and $\tilde{\hat{z}} \equiv (1-\tilde{z})\hat{z}$ for expositional reasons. Then, the stationary distributions are defined as follows.

Definition 5 *The stationary distribution for growing and non-growing firms, $\varpi_G(n,a)$ and $\varpi_N(n,a)$, on the number of product lines n and firm age a, satisfy:*

1. For all (n,a) where $n > 1$ and $a > 1$,

$$\varpi_G(n,a) = \left(1 - n\tilde{\tau} - n\tilde{\hat{z}}\right)\cdot\varpi_G(n,a-1) + (n-1)\tilde{\hat{z}}\cdot\varpi_G(n-1,a-1) + (n+1)\tilde{\tau}\cdot\varpi_G(n+1,a-1) - \nu\cdot\varpi_G(n,a-1)$$
$$\varpi_N(n,a) = \left(1 - n\tilde{\tau} - n\tilde{\hat{z}}\right)\cdot\varpi_N(n,a-1) + (n+1)\tilde{\tau}\cdot\varpi_N(n+1,a-1) + \nu\cdot\varpi_G(n,a-1).$$

2. For all (n,a) where $n = 1$ and $a > 1$

$$\varpi_G(1,a) = \left(1 - \tilde{\tau} - \tilde{\hat{z}}\right)\cdot\varpi_G(1,a-1) + 2\tilde{\tau}\cdot\varpi_G(2,a-1) - \nu\cdot\varpi_G(1,a-1)$$
$$\varpi_N(1,a) = \left(1 - \tilde{\tau} - \tilde{\hat{z}}\right)\cdot\varpi_N(1,a-1) + 2\tilde{\tau}\cdot\varpi_N(2,a-1) + \nu\cdot\varpi_G(1,a-1)$$

3. For $n = 1$ and $a = 1$, $\varpi_G(1,1) = (1-\tilde{z})x^e$ and $\varpi_N(1,1) = 0$.

In Definition 5, the law of motion for $\varpi_G(n,a)$ in case 1 indicates that firms with n product lines should be those who: (i) had n product lines and experienced no events, (ii) had $n-1$ product lines and succeeded in external innovation, (iii) had $n+1$ product lines and lost a product line due to creative destruction, or (iv) had n product lines and transited from growing firms to non-growing firms at the rate of ν. The stationary distributions for firms can be numerically computed by iteratively applying the law of motion in Definition 5 to an arbitrary initial probability distribution.

Given the stationary distributions for growing and non-growing firms, $\varpi_G(n,a)$ and $\varpi_N(n,a)$, the model-implied expected firm growth by age is computed as follows. First, to be consistent with the estimation using the dummy variables defined in (1), let $g(\bar{a})$ be the model-implied average growth rate of firms with ages between $1+5(\bar{a}-1)$ and $5\bar{a}$. That is, for instance, $g(1)$ is the model-implied average growth rate of firms of their ages between 1 year old and 5 years old, and $g(2)$ is that for firms of their ages between 6 years old and 10 years old, and so on. The following proposition specifies $g(\bar{a})$ for the five-year age group of $\bar{a}$.

Proposition 3 *The model-implied average growth rate, given survival, for firms with ages between* $1+5(\bar{a}-1)$ *and* $5\bar{a}$ *on the balanced growth path is determined by,*

$$g(\bar{a}) = \frac{\sum_n \sum_{a=1+5(\bar{a}-1)}^{5\bar{a}} (1-\mathbf{1}_{\{n=1\}}\tilde{\tau}) \left\{\varpi_G(n,a)\cdot g_G(n) + \varpi_N(n,a)\cdot g_N(n)\right\}}{\sum_n \sum_{a=1+5(\bar{a}-1)}^{5\bar{a}} (1-\mathbf{1}_{\{n=1\}}\tilde{\tau}) \left\{\varpi_G(n,a) + \varpi_N(n,a)\right\}} \tag{35}$$

where

$$g_G(n) = \tilde{\hat{z}}(1+\hat{\gamma}) + \tilde{z}\tilde{\gamma} - \mathbf{1}_{\{n>1\}}\tilde{\tau} \quad \textit{and} \quad g_N(n) = \tilde{z}\tilde{\gamma} - \mathbf{1}_{\{n>1\}}\tilde{\tau} \tag{36}$$

Proposition 3 implies that even though the expected growth for growing and non-growing firms with n product lines, $g_G(n)$ and $g_N(n)$ in (36), are independent of firm age a, the average growth rate by the age group $g(\bar{a})$ is possibly decreasing with respect to $\bar{a}$, i.e., young firms' growth rate is higher than old firms' growth rate, for the following two reasons. First, since younger firms are more likely to own only a single product line, their average growth rate is possibly higher due to survival bias. Specifically, as the last term in (36) implies, the downsizing due to creative destruction has negative impacts on the average growth rate only when they survive, i.e., only when they have multiple product lines. Hence, the expected growth rate *given survival* for growing and non-growing firms with only a single product line, i.e., $g_G(1)$ and $g_N(1)$, is higher than that of those who own multiple product lines due to survival bias. Second, given that all new entrants are growing firms and gradually become non-growing firms over time, younger firms are more likely to be growing ones, i.e., $\varpi_G(n,a)/\varpi_N(n,a)$ is decreasing with respect to a. Since only growing firms have an opportunity for external innovation, younger firms tend to grow more through external innovation than older firms. The second reason implies that the model-implied average growth by age $g(\bar{a})$ should be useful to identify the parameters associated with external innovation, $\hat{\gamma}$ and $\hat{\xi}$, as well as the transition probability ν.

Given the estimation results for $\beta_{\bar{a}}$ in (2) and the model-implied average growth rate of firms by age $g(\bar{a})$ in Proposition 3, we use $\{g(\bar{a}) - g(15)\}$ for $\bar{a} = 1, \cdots, 10$ as the model-implied moments to be matched with $\beta_{\bar{a}}$ for $\bar{a} = 1, \cdots 10$. The model-implied moment to be matched is $\{g(\bar{a}) - g(15)\}$ rather than $g(\bar{a})$ because the estimated $\beta_{\bar{a}}$ is the age effects on firm growth *relative to* the base group.

Other Target Moments

This subsection discusses other moment conditions for indirect inference. Unlike the previous subsection, the target values are based on previous empirical studies or macro data rather than the estimation using microdata.

Entry rate The entry rate is used as one of the moments to be matched, given that it contains relevant information to identify x^e. Based on the estimation in the "White Paper on Small and Medium Enterprises in Japan," the average entry and exit rate from 2008-2018 is 4.4%. On the other hand, the model-implied entry rate is

$$\frac{(1-\tilde{z})x^e}{\sum_a \sum_n [\varpi_G(n,a) + \varpi_N(n,a)]} \tag{37}$$

where the denominator is the total mass of firms. Note that the mass of *product lines* is normalized to one, but the mass of *firms* is not equal to one because some firms own multiple product lines.

Aggregate growth rate Given that the aggregate economic growth rate g stems solely from internal and external innovation in the model, it contains valuable information to identify innovation parameters. The average GDP growth rate in Japan from 1997 to 2019, 0.7%, is used for the targeted value to match with g.

R&D to GDP ratio The aggregate R&D expenditure to GDP ratio in the model is,

$$\frac{F_g \hat{\xi} \hat{z}^{\hat{\eta}} + \tilde{\xi} \tilde{z}^{\tilde{\eta}}}{Y} \tag{38}$$

where F_g is the share of product lines owned by growing firms in (22). The target value is set to 3.2% based on OECD data for Japan.

Internal R&D ratio According to Nagaoka and Walsh (2009), Japanese firms use 66% of their R&D expenditure for "enhancement of existing business line." Hence, this number is used as the target value for the internal R&D to total R&D ratio,

$$\frac{\tilde{\xi}\tilde{z}^{\tilde{\eta}}}{F_g\hat{\xi}\hat{z}^{\hat{\eta}} + \tilde{\xi}\tilde{z}^{\tilde{\eta}}} \tag{39}$$

which contains relevant information to identify innovation parameters.

Layoff probability Since the layoff probability d in the model takes into account not only dismissed workers but also those who leave the current employer voluntarily, the target value for d is computed by statistics for job tenure. Expressly, since the OECD database shows that the share of workers whose tenure is longer than 10 years is 47.4% in Japan, the target value for d is set to 0.072 ($= 1 - 0.47^{1/10}$).

Internal R&D ratio and layoff probability *without EPL* In the model, firms dismiss their employees when: (i) losing product lines due to creative destruction, or (ii) facing exogenous job destruction at surviving product lines. Case (i) is governed by $(1 - \tilde{z})\tau$, while case (ii) is governed by the exogenous job destruction rate ψ and the re-skilling cost χ. A key difference between case (i) and (ii) is that the number of dismissed workers in case (i) can be reduced through the escape-entry effects by increasing internal innovation intensity $\tilde{z}$, while that in case (ii) cannot. Hence, the response of internal R&D, as well as the total layoff probability, to changes in EPL should contain relevant information to identify those parameters. Hence, the internal R&D ratio in (39) and the layoff probability d in the case *without EPL*, i.e., $\phi = 0$ are used for identifying the parameters associated with the labor market, namely ϕ, ψ, and χ. More specifically, under the assumption that there is no EPL in the U.S., the following values in the U.S. are used for the target values: (i) according to Nagaoka and Walsh (2009), the U.S. firms use 48% of their R&D expenditure for "enhancement of existing business line," and (ii) the U.S. Bureau of Labor Statistics indicates that the share of workers whose tenure is longer than 10 years as of 2022 is 28.0% in the U.S.[15]

Estimation Results

Given the model-implied values and the target values for the moment conditions, the nine parameter values, $(x^e, \tilde{\gamma}, \hat{\gamma}, \tilde{\xi}, \hat{\xi}, \psi, \chi, \nu, \phi)$, are estimated so as to minimize the gap between them. Following the previous studies, the loss function to measure the gap is defined as,

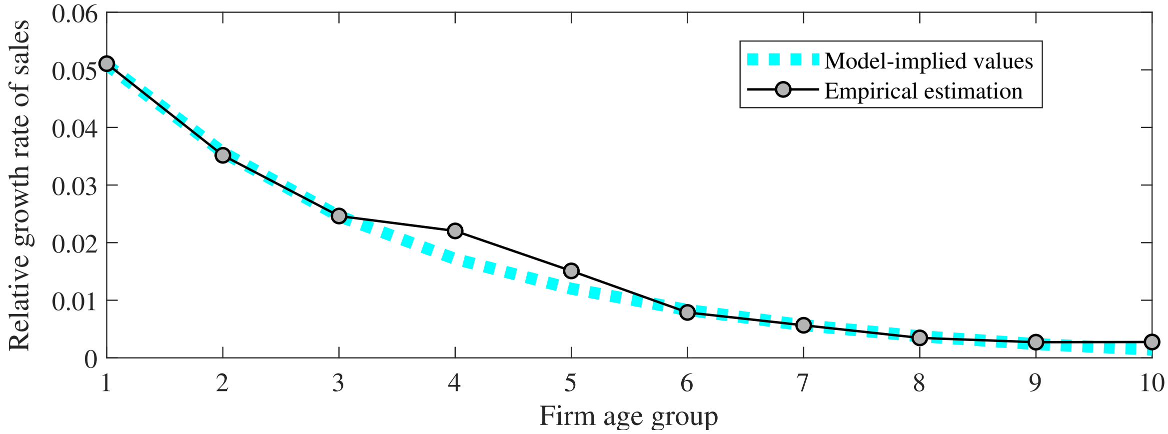
$$\sum_{i=1}^{17} \frac{|\text{model}(i) - \text{data}(i)|}{|\text{data}(i)|} \tag{40}$$

where model(i) and data(i) are the model-implied values and the target values in data for moment i, respectively. Since there are 17 moments (10 moments from firm growth by age and 7 from others), the 9 estimated parameters are over-identified. A numerical algorithm iteratively computes the model-implied values under different parameter values by simulation and searches for the parameter values to minimize the loss function (40).

Figure 3 shows the relationship between firm age and growth in data and the model. The thin line with circles represents the estimated $\beta_{\bar{a}}$ in (2) while the thick dashed line represents the model-implied average growth rate by age $g(\bar{a})$ in (35). First, the estimated $\beta_{\bar{a}}$ (i.e., the thin line with circles) implies that the growth rate of younger firms is higher than that of older firms as in previous empirical studies. For instance, the growth rate of sales for firms in group 1, i.e., firm age is from 1 year to 5 years old, is higher than that for firms older than 75 years old by 5.1% on average. The estimation result also suggests that the average growth rate of sales gradually decreases as they get old and that the age effect on firm growth becomes almost flat when firm age surpasses 30-35 years old. See Appendix D for more details about the estimation results including those using various specifications. Second, figure 3 shows that the relationship between firm growth and age is fairly well replicated in the model under the estimated parameters. In particular, the model

[15]Note that this estimation strategy uses the result of comparative statics in the next section. Hence, in the comparative statics, the layoff probability and the internal R&D ratios without EPL match the empirical values in the U.S. almost by definition because they are used as the target moments in estimation.

Figure 3: Firm Growth by Age: Model and Data



Note: In the figure, the horizontal axis represents the five-year age group $\bar{a}$, while the vertical axis shows the relative growth rate of sales for each age group. The thin line with circles represents estimated $\beta_{\bar{a}}$ in (2) based on column 1 in Table 9 in Appendix D, while the thick dashed line represents the model-implied average growth rate by age $g(\bar{a})$ in (35).

Table 3: Model-implied Values and Empirical Moments

Moment	With EPL					Without EPL	
	Entry	growth	R&D	Int. R&D	Layoff	Int. R&D	Layoff
Model	4.4	0.7	3.2	61.8	7.2	47.5	12.0
Data	4.4	0.7	3.2	66.0	7.2	48.0	12.0

Note: The table shows the model-implied values under the estimated parameters in Table 4 for each moment, along with the empirical targets in the data.

can account for the fact that the growth rate is higher for younger firms and gradually decline as firms get old. Table 3 shows the model-implied values under the estimated parameters for other moments along with the empirical targets in data. The table indicates that the model-implied values of other moments under the estimated parameters also closely match the empirical counterparts.

Table 4 shows the estimated parameter values by indirect inference. Some comments are in order. First, the cost for external innovation $\hat{\xi}$ is around 25 times larger than that for internal innovation $\tilde{\xi}$. Second, as a flip-side of the higher cost, the step size for external innovation $\hat{\gamma}$ is estimated to be much larger than internal innovation $\tilde{\gamma}$. The higher cost and

Table 4: Parameter Values Estimated by Indirect Inference

x^e	$\tilde{\gamma}$	$\hat{\gamma}$	$\tilde{\xi}$	$\hat{\xi}$	ψ	χ	ν	ϕ
.049	.09	11.18	.14	3.57	.040	.477	.033	.318

Note: The table shows the estimation results by indirect inference for the number of entrants x^e, the step-size for internal and external innovation, $\tilde{\gamma}$ and $\hat{\gamma}$, the innovation capacity for internal and external innovation, $\tilde{\xi}$ and $\hat{\xi}$, the exogenous job destruction rate ψ, the re-skilling cost χ, the transition rate from growing firms to non-growing firms ν, and the firing tax ϕ. The parameter values are estimated so as to minimize the loss function in (40) by the Nelder-Mead algorithm.

larger step size for external innovation are consistent with previous studies.[16] Compared with previous literature, however, the step size for internal innovation is relatively low in our estimation ($\tilde{\gamma}$ =0.09%), probably because internal innovation is modeled as a continuous improvement of quality with the escape-entry effects in this model. That is, while internal innovation has two benefits, namely, quality improvement and the escape-entry effects, the first benefit is estimated to be larger in most previous studies as they do not take into account the second benefit, i.e., the escape-entry effects.

Calibration for Household Parameters

Finally, the parameter values for the household sector are calibrated as follows. First, some parameters and equilibrium values are calibrated to be consistent with those in the firm sector. The growth rate g and the layoff probability d are calibrated to the target values for indirect inference in the firm sector. Also, the wage rate w and the expected firm value for entrants v^e are calibrated to the firm-side equilibrium values under the estimated parameters in table 4. The discount rate is calibrated as $\beta = 1/(1+r)$ with $r = 0.04$.

Second, the parameters associated with the labor market and human-capital accumulation are calibrated to conventional values or to fit Japanese data. The stochastic retirement probability λ is set to 1/40, which implies that workers retire after working for 40 years, and the unemployment benefit is set to 40% of previous wages, $b = 0.4w \cdot l_s(h_s, h_g)$. The job-finding rate for unemployed workers m in (31) is calibrated to fit the unemployment rate in

[16]For instance, Akcigit and Kerr (2018) obtain similar estimation results even though their identification strategy is based on patent data.

Japan. In the model, the unemployment rate is calculated by the number of unemployed workers,

$$\sum_a \int_z \Big[\int_{h_s,h_g} (1 - e_W(a,h_s,h_g,z)) \cdot d(1-m) + (1-z)e_W(a,h_s,h_g,z)\, d\mu_w(a,h_s,h_g)$$
$$+ \int_{h_g} (1 - e_N(a,h_g,z)) \cdot (1-m) + (1-z)e_N(a,h_g,z)\, d\mu_n(a,h_g) \Big] dP(z)$$

divided by the total mass of households

$$M_h \equiv \sum_a \int_z \Big[\int_{h_s,h_g} d\mu_w(a,h_s,h_g) + \int_{h_g} d\mu_n(a,h_g) \Big] dP(z). \tag{41}$$

The job finding rate m is set to 0.74 so that the equilibrium unemployment rate is equal to the unemployment rate in Japan for the last decade, 3.0%. On the parameters for human-capital accumulation by the human-capital investment function (24), the curvature α is set to 0.8 based on previous studies including Guvenen et al. (2014).

Then, the other four parameters regarding human capital accumulation, $(\delta_s, \delta_g, A_s, A_g)$, in (24) are calibrated following the estimation results using household-level microdata in Japan. Specifically, we parameterize FSHC and GHC accumulation over the life cycle in Japan by estimating the relationship between wages and job experience/tenure. As both FSHC and GHC are thought to be mainly accumulated through job experience, the length of (i) job tenure at a particular employer and (ii) total job experience, are used as a proxy for FSHC and GHC in the literature, respectively. Hence, by estimating the relationship between wages and job experience/tenure, we can decompose human capital accumulation over the life cycle into FSHC and GHC. To estimate the relationship between wages and job experience/tenure in Japan, we use household-level microdata, "Japan Household Panel Survey (JHPS/KHPS)" provided by the Panel Data Research Center at Keio University. The JHPS/KHPS is an annual survey of Japanese households starting in 2004, which asks various items including job status, hours worked, and annual labor income.[17] According to previous empirical studies, the non-linear relationship between

[17] See Appendix E for more details about the JHPS/KHPS dataset.

wages and job experience/tenure is estimated by,

$$\log(wage_{i,t}) = \alpha + \beta_{11} expr_{i,t} + \beta_{12} expr_{i,t}^2 + \beta_{21} tenu_{i,t} + \beta_{22} tenu_{i,t}^2 + Y_t + D_{edu,i} + D_{sex,i} + \varepsilon_{i,t} \quad (42)$$

where $expr_{i,t}$ and $tenu_{i,t}$ are total experience and job tenure for individual i in time t, and $Y_t, D_{edu,i}$, and $D_{sex,i}$ are dummy variables for a year, education, and male/female. See Appendix E for more details about the estimation results including robustness checks. Based on the estimation result for (42), figure 4 shows the relationship between wages and job experience/tenure in Japan (the black dashed lines in the left and middle panels). The figure indicates that both experience and job tenure have a positive impact on wages in Japan. More specifically, 10-year job tenure and 10-year job experience are associated with 27.0% and 25.3% higher wages, respectively, implying that workers who work at the same employer for ten years get 52.3% higher wages than those without any job tenure and experience. The figure also indicates that while the return from job experience and tenure are both diminishing over the life cycle, the relationship for job experience (the middle panel) is highly concave while that for job tenure is close to linear (the left panel). To replicate this feature in the model, it is assumed in our calibration that GHC is depreciated every year while FSHC is not. Specifically, the depreciation rate for FSHC and GHC is set to 0% and 4.5% i.e., $\delta_s = 0.0$ and $\delta_g = 0.045$ so that the non-linearity of human capital accumulation fits the estimation results. Then, A_g and A_s are chosen to account for the return from 10-year job experience and 10-year job tenure. Given those parameters with respect to human capital accumulation, the scale parameter $\bar{h}$ in the labor supply function (23) is calibrated so that the aggregate labor supply L is equal to 1.0 to be consistent with the normalization assumption in the firm-side equilibrium.

Figure 4 indicates that the process of human capital accumulation is well replicated under those calibrated values and that FSHC plays an important role in human capital accumulation in Japan. The blue and red lines in the left and middle panels of figure 4 represent the process of FSHC and GHC accumulation based on the optimal policy function, and the panels show that those lines very closely follow the relationships based on the estimation results for (42). Based on the optimal choice of human capital accumulation

Figure 4: Firm-specific and General Human Capital Accumulation

Note: The figure shows the estimated and model-implied relationship between wages and job experience/tenure in Japan. The dashed black lines in the left and middle panels show the wage rate relative to zero job tenure or zero job experience, based on the estimation results in column (4) of table 10 in Appendix E. To estimate the relationship between wages and job experience/tenure in Japan, we use household-level microdata, "Japan Household Panel Survey (JHPS/KHPS)" provided by the Panel Data Research Center at Keio University. See Appendix E for more details about the data and the estimation results. The blue and red lines in the left and middle panels represent the process of FSHC and GHC accumulation based on the optimal policy function. Based on the optimal choice of human capital accumulation in the model, the right panel shows the average FSHC and GHC by age. Note that total human capital by age (the right panel) is not equal to the sum of FSHC and GHC shown in the left and middle panels because some workers lose their FSHC due to layoff or by quitting their current job to become entrepreneurs.

Table 5: Parameter Values by Calibration

Parameter	Value	Target value etc.
Firm parameter		
Production function, ρ	0.104	$\omega wL/Y = 0.803$
Innovation elasticity, $\hat{\eta}, \tilde{\eta}$,	2.0	Acemoglu et al. (2018)
Interest rate, r	0.04	Standard value
Aggregate labor supply, L	1.0	Normalization
Household parameter		
Discount rate, β	0.96	$\beta = 1/(1+r)$
Stochastic aging, λ	1/10	One unit = 10 years
Unemployment benefit, b	0.40	40% of current wages
Job-finding rate, m	0.74	Unemployment rate = 3.0%
Curvature for HC inv., α	0.80	Guvenen et al. (2014)
Depreciation for FSHC, δ_g	0.00	Estimation results for (42)
Depreciation for general HC, δ_g	0.053	Estimation results for (42)
Efficiency: FSHC inv., A_s	0.066	Wage with 10-year tenure = 33%
Efficiency: general HC inv., A_g	0.056	Wage with 10-year exp. = 29%
Scale parameter for labor, $\bar{l}^s$	0.060	$L = 1.0$ (Firm-side equilibrium)
Entry cost, κ	0.134	Entry rate $x^e = 0.049$ (See table 4)
Dist. of success prob., σ_z	0.192	The failure rate = 50%
Mass of households, M_h	9.86	Entry cost = 1.5× Labor income

in the model, the right panel of figure 4 shows the average FSHC and GHC by age. The panel indicates that FSHC (the blue area) accounts for 1/3-1/2 of total human capital on average, suggesting the importance of FSHC for workers in Japan.[18]

Finally, on the parameter values regarding entrepreneurship, first, we assume that the success probability for entrepreneurship z follows a truncated normal distribution, $z \sim \mathbb{N}(0, \sigma_z)$ for $z \geq 0$. In this setting, as the volatility σ_z becomes larger, the probability for higher z becomes larger too, thereby lowering the failure rate (and vice versa). Therefore, σ_z is calibrated so that the failure rate is equal to 50%, following the failure rate within

[18] Note that total human capital by age (the right panel) is not equal to the sum of FSHC and GHC shown in the left and middle panels of figure 4 because some workers lose their FSHC due to layoff or by quitting their current job to become entrepreneurs.

the first 5 years in the U.S. and other countries.[19] Second, given σ_z and v^e, the entry cost κ is calibrated so that the aggregate entry rate x^e in (33) is equal to the estimated value of x^e in table 4. Note that since x^e is estimated using the entry rate as a target moment, the calibrated value for the entry cost κ is also consistent with the entry rate. Third, as the aggregate labor supply L is normalized to one, the average labor income for households is equal to w/M_h where M_h is the mass of households in (41). Hence, given that the average cost for starting businesses in Japan is around 1.5 times the average wages, the mass of households M_h is calibrated to satisfy $\kappa = 1.5 \times w/M_h$.[20] As a summary of calibration for household parameters, Table 5 shows the calibrated values and calibration strategy for each parameter.

4.2 Comparative Statics: Effects of Employment Protection

This subsection gives the main quantitative result of this paper, namely, the results of comparative statics to assess how EPL influences entrepreneurship, firm dynamics, and economic growth. The basic idea for comparative statics is close to Akcigit et al. (2021). Given that the baseline economy is calibrated to Japan, a country with the most stringent EPL among advanced economies, the policy exercise asks: What if the EPL in Japan is entirely eliminated as in the U.S.? For this purpose, we set the layoff tax ϕ to zero in the hypothetical case and compare the economic growth rate, entrepreneurship, and firm dynamics with those in the baseline.

Computational Strategy

In conducting comparative statics, we need to compute the aggregate variables consistent with the firm- and household-side equilibrium in the hypothetical economy without EPL. Specifically, the following six aggregate variables should be computed in the general equilibrium specified in definition 4: the aggregate labor supply L, the mass of entrants x^e,

[19] The failure rate within the first 5 years is not that different across advanced economies and around 50%.

[20] The average labor income for male employees working at companies with more than 30 employees is about 6 million JPY, according to the National Tax Agency in Japan. On the other hand, the average cost of starting a business in Japan is around 9 million JPY, according to a survey by Japan Finance Corporation.

the layoff probability d, the expected value for entrants v^e, the wage rate w, the growth rate g. A sketch of the computational strategy to quantitatively solve the general equilibrium problem is as follows.

1. Set the layoff tax to zero, i.e., $\phi = 0$, and start the iteration with $(L_0, x_0^e, d, v_0^e, w_0, g_0)$ at the baseline equilibrium.

2. At the i-th iteration, given $(d_{i-1}, v_{i-1}^e, w_{i-1}, g_{i-1})$, solve the household problem and compute (L_*^s, x_*^e) in the household side equilibrium specified in Definition 3.

3. Similarly, given (L_{i-1}^s, x_{i-1}^e), solve the firm problem and compute (d_*, v_*^e, w_*, g_*) in the firm-side problem specified in Definition 1.

4. If $\max_x |x_* - x_{i-1}| < 1.0e^{-4}$ where $x \in (L, x^e, d, v^e, w, g)$, then stop the iteration and use $(L_*, x_*^e, d_*, v_*^e, w_*, g_*)$ as general-equilibrium values for comparative statics under $\phi = 0$. Otherwise, set $x_i = (x_* + x_{i-1})/2$ and return to Step 2 with $i \to i + 1$.

Intuitively, we repeatedly compute the firm- and household-side equilibrium by taking the other equilibrium values as given. Then, in each iteration, the aggregate variables are adjusted gradually in order for them to converge smoothly to the new equilibrium values.

Employment Protection, Firm Dynamics, and Human Capital

Table 6 shows the comparative statics results for the elimination of EPL. The table shows (1) the layoff probability d, (2) the internal R&D ratio defined in (39), (3) the entry rate of firms x^e/M_f, (4) the aggregate growth rate g, and (5) the expected firm value for entrants v^e, in the baseline case (the first row) and the hypothetical cases without EPL, i.e., $\phi = 0$ (the second and third row). The general equilibrium simulation in the second row takes into account the changes in the number of entrants and aggregate labor supply in the household sector, while the partial equilibrium simulation in the third row does not, i.e., the firm-sector equilibrium. The firm value in the fifth column is normalized to one in the baseline to highlight the effects of EPL.

Column (1) shows that when EPL is eliminated, the layoff probability d increases, as expected, from 7.2% to 12.0%. There are several reasons. First, without the firing tax

Table 6: Results of Comparative Statics: Firm Dynamics and Growth

	(1) Layoff	(2) In. R&D	(3) Entry rate	(4) Growth	(5) Firm val.
Baseline ($\phi > 0$)	7.2	61.8	4.4	0.70	1.00
No EPL ($\phi = 0$) in GE	12.0	47.0	6.4	0.96	0.97
No EPL ($\phi = 0$) in PE	11.1	43.5	5.3	0.86	1.10

Note: The table shows the results of comparative statics for the layoff probability d, the internal R&D ratio defined in (39), the entry rate of firms x^e/M_f, the aggregate growth rate g, and the expected firm value for entrants v^e in the baseline case (the first row) and the hypothetical cases without EPL, i.e., $\phi = 0$ (the second and third row). The general equilibrium simulation in the second row takes into account changes in the number of entrants, as well as aggregate labor supply, in the household sector, while the partial equilibrium simulation in the third row does not.

in the model, firms tend to choose layoff rather than re-skilling in the face of exogenous job destruction. Second, firms have less incentive to protect their product lines through the escape-entry effect, thus lowering the internal R&D ratios (column 2) and increasing layoffs associated with creative destruction. Third, more firm entries (column 3) intensify creative destruction, thus increasing layoffs associated with creative destruction too. As discussed in the section for indirect inference, the layoff probability and the internal R&D ratio in the case without EPL are used as the target values in indirect inference; therefore, they closely match the numbers in the U.S.

As for the effects on firm dynamics, column (3) shows that eliminating EPL would increase the entry rate of firms by more than 1.4 times from 4.4% to 6.4%. Eliminating EPL increases new entrants through the following two channels. First, thanks to the weak escape-entry effects due to the lower internal R&D by incumbent firms, firm entries become easier for new entrants. Second, eliminating EPL leads to a higher layoff probability and lower labor costs, thus encouraging individuals to start a business in the household sector. In the partial equilibrium in the third row, only the first effect is materialized because the general equilibrium effects of the increased entrepreneurship in the household sector are not taken into account. Given that the entry rate in the partial equilibrium simulation increases only by 0.9% points from the baseline, the general equilibrium effects induce a quantitatively substantial impact on firm dynamics.

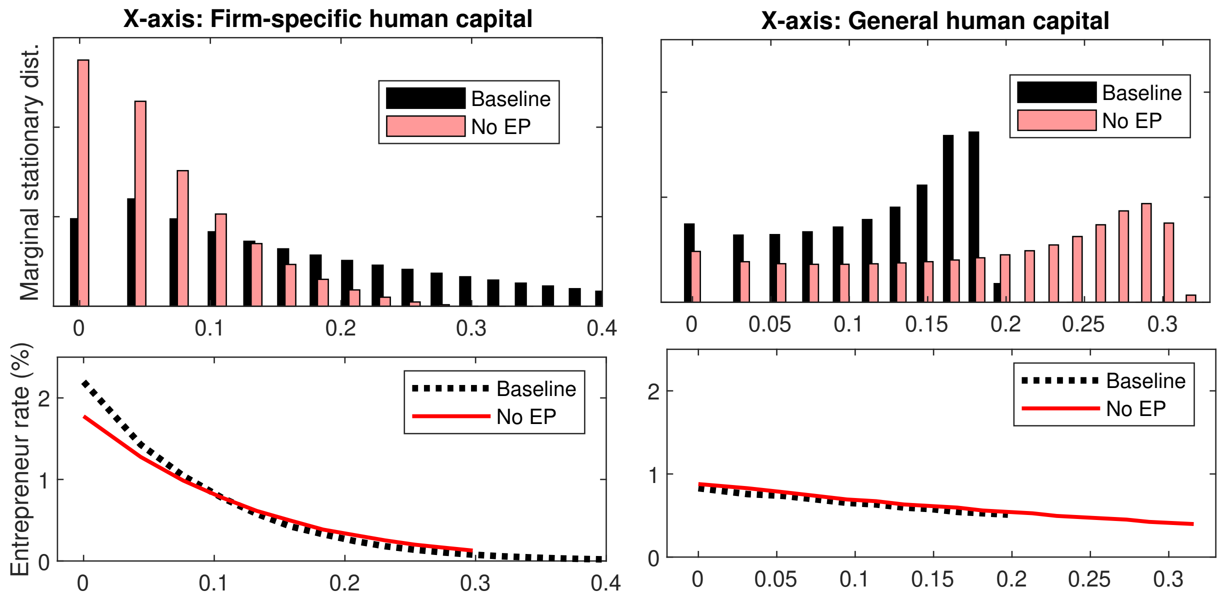
Human capital accumulation is key to understanding the effects of EPL on firm dynam-

Figure 5: Human Capital Accumulation without EPL

Note: The left and middle panels show the model-implied process of FSHC and GHC accumulation in the hypothetical case without EPL (the bold blue and red lines) along with those in the baseline case with EPL (the dotted blue and red lines). Also, the dashed black lines in those two panels represent the empirical relationship based on Kambourov and Manovskii (2008)'s estimation using the U.S. household-level microdata. The right panel shows the model-implied average FSHC and GHC by age.

ics through general equilibrium effects. The left and middle panels of figure 5 show the model-implied process of FSHC and GHC accumulation in the hypothetical case without EPL (the bold blue and red lines) along with those in the baseline case with EPL (the dotted blue and red lines). The left and middle panels of figure 5 indicate that eliminating EPL substantially affects human capital accumulation, particularly the choice between FSHC and GHC. Specifically, without EPL, workers tend to accumulate more GHC and less FSHC. Given that FSHC is valuable only at the current employer, the shift from FSHC to GHC is intuitive because the greater risk of being dismissed encourages individuals to accumulate GHC rather than FSHC. The reduction in the importance of FSHC in the hypothetical case without EPL is consistent with the previous empirical studies, where FSHC plays a limited role in the U.S. (e.g., Hashimoto and Raisian, 1985; Topel, 1991; Parent, 2000). Specifically, the model-implied process of FSHC and GHC accumulation in the hypothetical case without EPL closely follows the empirical relationship based on Kambourov and Manovskii (2008)'s estimation using the U.S. household-level microdata (the dashed black lines). The right panel of figure 5 indicates that as a result of the changes

Figure 6: Stationary Distribution and Entrepreneur Rate



Note: The figure shows the marginal stationary distribution (the first row) and the entrepreneur rate (the second row) with respect to firm-specific human capital (the left panel) and general human capital (the right panel). In the panels for stationary distributions in the first row, the black and pink bars show those for the baseline case with EPL and the hypothetical case without EPL, respectively. In the panels for the entrepreneur rate in the second row, the black dashed lines and the red bold lines represent the entrepreneur rate in the baseline and the hypothetical case without EPL, respectively.

in workers' choice between FSHC and GHC accumulation, GHC accounts for most human capital and FSHC plays a very limited role in human capital accumulation in the hypothetical case without EPL.[21]

The shift from FSHC to GHC increases new entries by decreasing the opportunity cost of starting a business. Figure 6 shows the marginal stationary distribution (the two panels in the first row) and the entrepreneurial rate (the two panels in the second row) with respect to FSHC (the left panels) and GHC (the right panels). As is consistent with figure 5, the stationary distributions imply that individuals accumulate more FSHC in the baseline (the black bars) and that they would shift their human capital accumulation

[21] Lazear (1979) provides a theoretical model where EPL encourages a long-term contract with back-loaded wage profiles, which makes job tenure have a positive impact on wages even without FSHC. Even in this case, however, employed individuals face a large opportunity cost for quitting a current job, thus leading to a similar conclusion.

from FSHC to GHC when EPL is eliminated (the pink bars). Also, in both cases with and without EPL, the policy function of the entrepreneurial choice is significantly decreasing with respect to FSHC (the left-bottom panel) while it is almost flat with respect to GHC (the right-bottom panel). The employed individuals who accumulated FSHC hesitate to start a business, as they lose most of their human capital when quitting their current job. In other words, the entrepreneurial rate is decreasing with respect to FSHC because the opportunity cost of stating a business is high. [22] Hence, the figure implies that eliminating EPL would increase the *aggregate* entrepreneurial rate, as it decreases the opportunity cost of starting a business by promoting the shift from FSHC to GHC accumulation.

While eliminating EPL stimulates entrepreneurship through other channels, figure 6 implies that the effects through those other channels are not quantitatively large. For instance, eliminating EPL can increase new entries, as it lowers labor costs and raises the entrepreneurial benefit. Also, the higher layoff rate makes employed workers unstable and less attractive, thus making starting a business relatively more attractive. The two panels in the second row of figure 6 imply, however, that the policy functions of the entrepreneurial choice *given the level of human capital* are almost identical between the baseline (the black dashed lines) and the hypothetical case without EPL (the red bold lines).[23] Hence, while those other channels to stimulate firm dynamics exist in the model, they do not substantially affect the individual's entrepreneurial choice, which implies that the increase in new entries in response to eliminating EPL is mainly accounted for by the shift from FSHC to GHC.

Does Employment Protection Suppress Economic Growth?

As a result of the effects on firm entries, eliminating EPL would raise economic growth by around 20-30 bps from 0.70% to 0.96% (column 4 in table 6). Given that EPL encourages incumbent firms to pursue the escape-entry effects, eliminating EPL weakens such an

[22] The entrepreneur rate is slightly decreasing with respect to GHC because it increases the wage rate and so makes it more attractive to keep working as an employed worker.

[23] The slope of the entrepreneur rate with respect to FSHC is slightly steeper for the baseline than that for the case without EPL. Given that the probability of losing FSHC is higher for the case without EPL, FSHC is more valuable in the baseline; therefore, the entrepreneurial rate is more responsive to FSHC in the baseline.

incentive, thus facilitating incumbent firms' and new entrants' external innovation through expanding their opportunities. Furthermore, without EPL, the increase in firm entries stimulates creative destruction by itself but also by increasing the share of young firms, i.e., firms with more growth potential. Specifically, eliminating EPL increases the share of product lines owned by growing firms F_g rises from 64.1% to 71.4%, thus facilitating economic growth through creative destruction.

Given the effects on economic growth, eliminating EPL should have positive cumulative effects on household consumption in the long run, while they are ambiguous in the short run. In the short run, eliminating EPL may have adverse effects on household consumption, as it decreases the substantive aggregate labor supply L by increasing the unemployment rate (from 3.0% to 4.9%) and discouraging FSHC accumulation (see the right panel of figure 5). The higher unemployment rate is consistent with the fact that the average unemployment rate in the U.S. is higher than that in Japan. In the long run, however, since the wage rate and the aggregate productivity grow at the same rate, the wage rate grows at 0.96% on the balanced growth path in the hypothetical case without EPL, which is higher than 0.70% in the baseline; therefore, in the long run, eliminating EPL should have positive cumulative effects on household consumption in the long run.

General Equilibrium vs. Partial Equilibrium

Table 6 implies that the general equilibrium effects play an important role in assessing the effects of EPL on firm dynamics and economic growth. Specifically, in the partial equilibrium in the third row, where changes in the number of entrants and aggregate labor supply in the household sector are not taken into account, the positive effects on the economic growth rate become around two-thirds of those in general equilibrium. In other words, if we focus only on the firm sector and ignore the general equilibrium effects through stimulating entrepreneurship in the household sector, the impact on economic growth would be substantially underestimated. Also, layoff probability is low in the partial equilibrium analysis, which implies that layoffs and new entries increase by influencing each other in a general equilibrium.

On the contrary, the partial equilibrium analysis focusing only on the household sector, rather than the firm sector, overestimates the EPL's effects on entrepreneurship. In the partial equilibrium analysis, which ignores the general equilibrium effects through wages and firm values, the increase in the number of entrepreneurs is overestimated by more than double. In general equilibrium, the firm value decreases from the baseline (column 5 in table 6). Given that EPL increases labor costs for firms, this result is counter-intuitive at first glance, but eliminating EPL exposes incumbent firms to a higher risk of losing their product lines, as the increase in firm entries intensifies creative destruction.[24] Previous studies, including Klette and Kortum (2004), also point out the possibility that more entries may suppress incumbents' firm value due to intensified creative destruction. Therefore, when ignoring the general equilibrium effects, the benefits of starting a business are overestimated in partial equilibrium. The substantial difference in the number of entrepreneurs between the general and the partial equilibrium in table 6 implies that such general equilibrium effects through wages and firm value are quantitatively important in assessing the effects of EPL on entrepreneurship.

4.3 Policy Experiment: How to Stimulate Growth without Easing EPL?

This section conducts some policy experiments to investigate how to stimulate entrepreneurship and economic growth without eliminating EPL. This is an important policy question, as eliminating EPL is politically difficult in many countries. Previewing the results of the policy experiments, however, policies to directly support entrepreneurs have much smaller effects on economic growth compared with eliminating EPL. The policy experiments suggest that as long as stringent EPL exists, policy support for entrepreneurs does not fully exert its effects due to incumbent firms' reactions to increased firm entries.

In the policy experiment, the following two policies to support entrepreneurs are examined. First, we examine the policy effects of extending unemployment benefits to failed entrepreneurs. This policy exercise is inspired by Hombert et al. (2020), which empirically shows that granting unemployment benefits to failed entrepreneurs significantly

[24] In partial equilibrium in table 6, where the increase in firm entries due to increased entrepreneurs in the household sector is not taken into account, the firm value increases by around 11%, suggesting that an increase in firm entries significantly decreases the firm value.

Table 7: Results of Policy Experiment

	Entrepreneur	In. R&D	Entry rate	Firm value	Growth
Baseline	1.00	61.8	4.40	1.00	0.70
Unemp. benefit	1.11	64.1	4.64	0.96	0.72
Entre. leave	1.33	68.4	5.11	0.88	0.76

Note: The table shows the results of comparative statics for policy support for entrepreneurs.

increases new entries in France. Also, Japan also introduced a similar policy to encourage entrepreneurship in 2022. Granting unemployment benefits to failed entrepreneurs is expected to stimulate entrepreneurship, as it mitigates an income risk in the case of failure. To examine the effects of unemployment benefits on failed entrepreneurs in the policy experiment, the failed entrepreneur's value function in (30) is changed from $H_N(-\kappa, h_g)$ to $H_N(b-\kappa, h_g)$ where b is unemployment benefits. Second, we examine what if workers can temporarily leave their current employer to start their own startups while having the option to return to their previous job in the case of failure. The idea of the "entrepreneurial leave" is inspired by Gottlieb et al. (2022), which empirically shows that a temporary leave with the option to return to the previous job hEPLs stimulate entrepreneurship in Canada. To examine the effects of the entrepreneurial leave in the policy experiment, the policy function for failed entrepreneurs in (30) is changed from $H_N(-\kappa, h_g)$ to $H_W\left(-wl_s(h_s, h_g), h_s, h_g\right)$, reflecting that workers lose their labor income for one period but can return to the previous job in the case of failure. Similarly to granting unemployment benefits to failed entrepreneurs, the entrepreneurial leave is expected to stimulate entrepreneurship by reducing the income risk after failure.

Table 7 shows the results of those two policies to support entrepreneurs. First, the first column indicates that the number of entrepreneurs increases as expected when the policy support for entrepreneurs is introduced. Specifically, it increases by 11% and 33% for the case with unemployment benefits to failed entrepreneurs and the entrepreneurial leave, respectively. Entrepreneurial leave stimulates entrepreneurship more than unemployment benefits because it enables employed individuals to keep their FSHC even in the case of failure. In other words, given that the income loss associated with quitting a current job mainly stems from losing FSHC, temporary payments from unemployment benefits are not enough to compensate for the loss. Furthermore, given that unemployment benefits should increase the fiscal burden, introducing entrepreneurial leaves may be a more efficient way to stimulate entrepreneurship (but costly for the corporate sector). Second, table 7 shows that support to entrepreneurs decreases the average firm value. As in the case of eliminating EPL in table 6, more fierce creative destruction causes such a decline in firm value, thereby discouraging entrepreneurship. Hence, the policy experiment suggests that if we disregard the general equilibrium effects through the decline in firm value, the policy effects of support for entrepreneurs would be significantly overestimated.

Finally, while policy support to entrepreneurs hEPLs stimulate entrepreneurship, its effects on economic growth are relatively small (only a few bps). A key to understanding the small policy effects on economic growth is incumbent firms' reaction to increased firm entries. In general, as pointed out in Klette and Kortum (2004), an increase in new entrants discourages incumbent firms' external innovation and consequently suppresses economic growth, as it raises the probability for incumbent firms to lose their existing product lines. Furthermore, as long as stringent EPL exists, an increase in new entrants strongly encourages incumbent firms to pursue the escape-entry effects more by increasing internal R&D. In fact, table 7 shows that the internal R&D ratios increase by several percentage points when policy support for entrepreneurs is introduced. When incumbent firms pursue the escape-entry effects more aggressively, growth opportunities through external innovation become more limited, thus suppressing economic growth as well. While not shown in the table, support for entrepreneurs has larger effects on economic growth if it is combined with eliminating EPL, implying that as long as stringent EPL exists, policy support for entrepreneurs does not fully exert its policy effects.

5 Concluding Remarks

This paper investigates the effects of employment protection legislation (EPL) on entrepreneurship, firm dynamics, and economic growth in a Schumpeterian growth model. EPL has various effects not only on firms' innovation and employment attitudes but also on households' human capital accumulation and entrepreneurship, thus having non-trivial impacts on economic growth through general equilibrium effects. In the quantitative exercise, we estimate the parameter values for firm growth and household human capital accumulation by indirect inference using firm-level and household-level microdata in Japan and find that: (i) eliminating EPL in Japan has sizable effects on economic growth (around 20-30 bps) by encouraging entrepreneurship, (ii) a partial equilibrium analysis focusing only on the household sector or the firm sector possibly under- or overestimate the effects of EPL, and (iii) Policies to directly support entrepreneurs stimulates entrepreneurship but have limited impacts on economic growth, as long as stringent EPL exists.

There are some strands for future research. While this paper focuses on the effects of EPL on economic growth through entrepreneurship, it should have adverse effects on economic growth through other channels. In particular, it should have effects on occupational mobility, thus possibly causing a misallocation of the labor force across firms. On the other hand, employment protection should improve the household's welfare by mitigating their income risk due to dismissals. While this paper assumes risk-neutral households for tractability, the cost-benefit analysis using an incomplete market model with a more realistic risk-averse utility function is necessary to discuss the optimal level of EPL. This paper is just the first step in analyzing the effects of EPL on economic growth and should be followed by future research investigating those important issues.

References

Acemoglu, D., U. Akcigit, H. Alp, N. Bloom, and W. Kerr (2018): "Innovation, Reallocation, and Growth," *American Economic Review*, 108, 3450–3491.

Adelino, M., S. Ma, and D. Robinson (2017): "Firm Age, Investment Opportunities, and Job Creation," *Journal of Finance*, 72, 999–1038.

Aghion, P., R. Blundell, R. Griffith, P. Howitt, and S. Prantl (2009): "The Effects of Entry on Incumbent Innovation and Productivity," *The Review of Economics and Statistics*, 91, 20–32.

Akcigit, U., H. Alp, and M. Peters (2021): "Lack of Selection and Limits to Delegation: Firm Dynamics in Developing Countries," *American Economic Review*, 111, 231–275.

Akcigit, U. and W. R. Kerr (2018): "Growth through Heterogeneous Innovations," *Journal of Political Economy*, 126, 1374–1443.

Autor, D. H., J. J. Donohue, and S. J. Schwab (2006): "The Costs of Wrongful-Discharge Laws," *The Review of Economics and Statistics*, 88, 211–231.

Autor, D. H., W. R. Kerr, and A. D. Kugler (2007): "Does Employment Protection Reduce Productivity? Evidence From US States," *Economic Journal*, 117, 189–217.

Becker, G. S. (1964): *Human Capital: A Theoretical and Empirical Analysis with Special Reference to Education*, NBER Books, National Bureau of Economic Research, Inc.

Bozkaya, A. and W. R. Kerr (2014): "Labor Regulations and European Venture Capital," *Journal of Economics & Management Strategy*, 23, 776–810.

Buera, F. J., J. P. Kaboski, and Y. Shin (2011): "Finance and Development: A Tale of Two Sectors," *American Economic Review*, 101, 1964–2002.

——— (2015): "Entrepreneurship and Financial Frictions: A Macrodevelopment Perspective," *Annual Review of Economics*, 7, 409–436.

Catherine, S. (2022): "Keeping options open: What motivates entrepreneurs?" *Journal of Financial Economics*, 144, 1–21.

Decker, R., J. Haltiwanger, R. Jarmin, and J. Miranda (2014): "The Role of Entrepreneurship in US Job Creation and Economic Dynamism," *Journal of Economic Perspectives*, 28, 3–24.

Engbom, N. (2022): "Labor Market Fluidity and Human Capital Accumulation," NBER Working Papers 29698.

Fukao, K., K. Ikeuchi, Y. G. Kim, and H. U. Kwon (2017): "Innovation and Employment Growth in Japan: Analysis Based on Microdata from the Basic Survey of Japanese Business Structure and Activities," *The Japanese Economic Review*, 68, 200–216.

Gaillard, A. and S. Kankanamge (2023): "Gross Labor Market Flows, Self-Employment, and Unemployment Insurance," Working paper.

Garcia-Macia, D., C. Hsieh, and P. J. Klenow (2019): "How Destructive Is Innovation?" *Econometrica*, 87, 1507–1541.

Gottlieb, J. D., R. R. Townsend, and T. Xu (2022): "Does Career Risk Deter Potential Entrepreneurs?" *Review of Financial Studies*, 35, 3973–4015.

Guvenen, F., B. Kuruscu, and S. Ozkan (2014): "Taxation of Human Capital and Wage Inequality: A Cross-Country Analysis," *Review of Economic Studies*, 81, 818–850.

Haltiwanger, J., R. S. Jarmin, and J. Miranda (2013): "Who Creates Jobs? Small versus Large versus Young," *The Review of Economics and Statistics*, 95, 347–361.

Haltiwanger, J., S. Scarpetta, and H. Schweiger (2014): "Cross country differences in job reallocation: The role of industry, firm size and regulations," *Labour Economics*, 26, 11–25.

Hashimoto, M. and J. Raisian (1985): "Employment Tenure and Earnings Profiles in Japan and the United States," *American Economic Review*, 75, 721–735.

Hombert, J., A. Schoar, D. Sraer, and D. Thesmar (2020): "Can Unemployment Insurance Spur Entrepreneurial Activity? Evidence from France," *Journal of Finance*, 75, 1247–1285.

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

Huynh, K. P. and R. J. Petrunia (2010): "Age Effects, Leverage and Firm Growth," *Journal of Economic Dynamics and Control*, 34, 1003–1013.

Jones, J. B. and S. Pratap (2020): "An Estimated Structural Model of Entrepreneurial Behavior," *American Economic Review*, 110, 2859–2898.

Kambourov, G. and I. Manovskii (2008): "Rising Occupational And Industry Mobility In The United States: 1968-97," *International Economic Review*, 49, 41–79.

KERR, W. R., R. NANDA, AND M. RHODES-KROPF (2014): "Entrepreneurship as Experimentation," *Journal of Economic Perspectives*, 28, 25–48.

KIMURA, T., Y. KURACHI, AND T. SUGO (2019): "Decreasing Wage Returns to Human Capital: Analysis of Wage and Job Experience Using Micro Data of Workers," Bank of Japan Working Paper Series 19-E-12.

KLETTE, T. J. AND S. KORTUM (2004): "Innovating Firms and Aggregate Innovation," *Journal of Political Economy*, 112, 986–1018.

KOENIGER, W. (2005): "Dismissal costs and innovation," *Economics Letters*, 88, 79–84.

LAGAKOS, D., B. MOLL, T. PORZIO, N. QIAN, AND T. SCHOELLMAN (2018): "Life Cycle Wage Growth across Countries," *Journal of Political Economy*, 126, 797–849.

LAZEAR, E. P. (1979): "Why Is There Mandatory Retirement?" *Journal of Political Economy*, 87, 1261–1284.

——— (1990): "Job Security Provisions and Employment," *The Quarterly Journal of Economics*, 105, 699–726.

LENTZ, R. AND D. MORTENSEN (2008): "An Empirical Model of Growth Through Product Innovation," *Econometrica*, 76, 1317–1373.

——— (2016): "Optimal Growth Through Product Innovation," *Review of Economic Dynamics*, 19, 4–19.

MUKOYAMA, T. AND S. OSOTIMEHIN (2019): "Barriers to Reallocation and Economic Growth: The Effects of Firing Costs," *American Economic Journal: Macroeconomics*, 11, 235–270.

NAGAOKA, S. AND J. P. WALSH (2009): "Commercialization and Other Uses of Patents in Japan and the U.S.: Major findings from the RIETI-Georgia Tech inventor survey," RIETI Discussion Paper Series 09-E-010.

PARENT, D. (2000): "Industry-Specific Capital and the Wage Profile: Evidence from the National Longitudinal Survey of Youth and the Panel Study of Income Dynamics," *Journal of Labor Economics*, 18, 306–323.

Salgado, S. (2019): "Technical Change and Entrepreneurship," Working paper.

Tang, H. (2012): "Labor market institutions, firm-specific skills, and trade patterns," *Journal of International Economics*, 87, 337–351.

Topel, R. H. (1991): "Specific Capital, Mobility, and Wages: Wages Rise with Job Seniority," *Journal of Political Economy*, 99, 145–176.

Wasmer, E. (2006): "General versus Specific Skills in Labor Markets with Search Frictions and Firing Costs," *American Economic Review*, 96, 811–831.

Appendixes

Appendix A: Empirical Relationship between Employment Protection, Entrepreneurship, and Job Tenure across Countries

Figure 1 shows cross-country scatter plots between employment protection legislation (EPL) and entrepreneurship (the left panel) and those between EPL and job tenure (the right panel). This appendix explains how to construct the data including data sources and conducts more formal regression, including the one using a full sample rather than only advanced economies where GDP per capita is higher than $20 thousand.

First, as a measure of employment protection, we use the summary indicator for individual and collective dismissals of regular workers (EPLRC version 2) in the "OECD Employment Protection Legislation Database, 2020 edition". The average value for 2000-2020 gives cross-country data on employment protection for 65 countries. Second, as a measure of entrepreneurship, we use survey data from the Global Entrepreneurship Monitor (GEM) on "Total early-stage Entrepreneurial Activity (TEA) Rate," which is defined as a "Percentage of 18-64 population who are either a nascent entrepreneur or owner-manager of a new business." The average value for 2001-2020 gives cross-country data on entrepreneurship for 115 countries. Third, as a measure of job tenure, we use the share of workers whose tenure is longer than 10 years in the "OECD Employment and Labour

Table 8: Employment protection, Entrepreneurship, and Job Tenure

	Entrepreneur rate			Job Tenure	
	(1)	(2)	(3)	(4)	(5)
EPL index	-2.60*	-3.08**	-3.27**	.067**	.073**
	(1.11)	(0.97)	(0.73)	(.017)	(.017)
log(GDP)		-2.81**			.026
		(0.65)			(.016)
Sample	Full	Full	GDP> $20K	Full	Full
N	65	64	25	36	36

Note: Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$. The table reports the estimation results for the effects of the employment protection index constructed by OECD.

Market Statistics." The average value for 2010-2020 gives cross-country data on job tenure for 36 countries.

The regression analysis in Table 8 shows that EPL suppresses entrepreneurship while it leads to longer job tenure on average. As is consistent with Figure 1, the negative relationship between EPL and entrepreneurship is clear only among advanced economies (column 3), it is statistically significant after controlling for the income level (column 2).

Appendix B: Proof of Proposition 1

This appendix provides proofs for propositions 1. The proof uses a guess-and-verify strategy. Under the guess that the value function for growing and non-growing firms $V_g(\mathbf{q})$ and $V_n(\mathbf{q})$ in the main text are linear with respect to $\mathbf{q} \equiv \{q_1, \cdots, q_n\}$ with a constant parameter A, i.e.,

$$V_g(\mathbf{q}) = V_g(\mathbf{q}) = A \sum_{q_j \in \mathbf{q}} q_j,$$

the value function for the growing firms can be rewritten as,

$$rA\sum_{q_j\in\mathbf{q}} q_j = \max_{\hat{z},\{\tilde{z}_j\}_j}\left\{\begin{array}{l}\sum_{\tilde{\mathbf{q}}\in 2^{\mathbf{q}}}\left(\prod_{q_j\in\tilde{\mathbf{q}}}\tilde{z}_j\right)\cdot\left(\prod_{q_j\in\mathbf{q}\backslash\tilde{\mathbf{q}}}\left(1-\tilde{z}_j\right)\right)\left[\tilde{\gamma}A\sum_{q_j\in\tilde{\mathbf{q}}}q_j-\tau A\sum_{q_j\in\mathbf{q}\backslash\tilde{\mathbf{q}}}q_j+(1-\tilde{x})n\hat{z}(1+\hat{\gamma})A\bar{q}\right] \\ +\sum_{q_j\in\mathbf{q}}\left[\pi_j q_j-\tilde{\xi}\tilde{z}_j^{\tilde{\eta}}q_j\right]-\left[\hat{\xi}\hat{z}^{\hat{\eta}}+\Phi\right]n\bar{q}\end{array}\right\}.$$

Since the last term in the first row is independent of q_j, the first order condition for $\hat{z}$ gives the second equation in (16).

By focusing on a particular product line X, $q_X\in\mathbf{q}$, and defining $\mathbf{q}_{-\mathbf{X}}\equiv\mathbf{q}\backslash q_X$, the first two terms in the first row can be rewritten as,

$$\begin{aligned}&\sum_{\tilde{\mathbf{q}}\in 2^{\mathbf{q}}}\left(\prod_{q_j\in\tilde{\mathbf{q}}}\tilde{z}_j\right)\cdot\left(\prod_{q_j\in\mathbf{q}\backslash\tilde{\mathbf{q}}}\left(1-\tilde{z}_j\right)\right)\left[\tilde{\gamma}A\sum_{q_j\in\tilde{\mathbf{q}}}q_j-\tau A\sum_{q_j\in\mathbf{q}\backslash\tilde{\mathbf{q}}}q_j\right]\\ =&\sum_{\tilde{\mathbf{q}}\in 2^{\mathbf{q}_{-\mathbf{X}}}}\left(\prod_{q_j\in\tilde{\mathbf{q}}}\tilde{z}_j\right)\cdot\left(\prod_{q_j\in\mathbf{q}_{-\mathbf{X}}\backslash\tilde{\mathbf{q}}}\left(1-\tilde{z}_j\right)\right)\left[\tilde{\gamma}A\sum_{q_j\in\tilde{\mathbf{q}}}q_j-\tau A\sum_{q_j\in\mathbf{q}\backslash\tilde{\mathbf{q}}}q_j+\tilde{z}_X\tilde{\gamma}Aq_X-(1-\tilde{z}_X)\tau Aq_X\right]\end{aligned}$$

Thus, the first order condition for any z_j is,

$$\frac{\partial\pi_j}{\partial\tilde{z}_j}q_j-\tilde{\xi}\tilde{\eta}\tilde{z}_j^{\tilde{\eta}-1}q_j+(\tilde{\gamma}+\tau)Aq_j=0$$

By deleting q_j, we obtain the first equation in (16). Note that z_j is independent of q_j because both the cost and benefit are linear with respect to q_j.

Finally, given that the optimal $\tilde{z}$ is independent of q_j and that the optimal $\hat{z}$ is characterized by the second equation in (16), the value function for the growing firm can be rewritten as,

$$rA\sum_{q_j\in\mathbf{q}}q_j=\left\{\begin{array}{l}\sum_{\tilde{\mathbf{q}}\in 2^{\mathbf{q}}}\tilde{z}^m\left(1-\tilde{z}\right)^{n-m}\left[\tilde{\gamma}A\sum_{q_j\in\tilde{\mathbf{q}}}q_j-\tau A\sum_{q_j\in\mathbf{q}\backslash\tilde{\mathbf{q}}}q_j\right]\\ +\left(\pi-\tilde{\xi}\tilde{z}^{\tilde{\eta}}\right)\sum_{q_j\in\mathbf{q}}q_j-\left[\hat{\xi}\hat{z}^{\hat{\eta}}+\Phi\right]n\bar{q}+(1-\tilde{x})n\hat{z}(1+\hat{\gamma})A\bar{q}\end{array}\right\}.$$

where m is the number of improving product lines, i.e., $m = \#\tilde{\mathbf{q}}$. Then, under the assumption for the fixed cost Φ

$$\Phi = \hat{\xi}(\hat{\eta} - 1)\hat{z}^{\hat{\eta}},$$

the last two terms in the second row disappear because the fixed cost completely offsets the value from external innovation. Also, we can show,

$$\begin{aligned}\sum_{\tilde{\mathbf{q}} \in 2^{\mathbf{q}}} \left[\tilde{z}^m (1-\tilde{z})^{n-m} \sum_{q_j \in \tilde{\mathbf{q}}} q_j \right] &= \sum_{m=0}^{n} \left[\tilde{z}^m (1-\tilde{z})^{n-m} {}_{n-1}C_{m-1} \right] \sum_{q_j \in \mathbf{q}} q_j \\ &= \tilde{z} \sum_{q_j \in \mathbf{q}} q_j\end{aligned}$$

The last equation uses the formula of the expected value for the binomial distribution. By using this result to rewrite the first and second terms in the first row, we can show that the right-hand side of the value function is linear with respect to $\sum_{q_j \in \mathbf{q}} q_j$, which verifies the guess for linearity. Furthermore, by deleting $\sum_{q_j \in \mathbf{q}} q_j$ from both sides of the equation, we have the equation (17) in Proposition 1, namely,

$$rA = \pi - \tilde{\xi}\tilde{z}^{\tilde{\eta}} + \tilde{z}\tilde{\gamma}A - (1-\tilde{z})\tau A$$

Note that the value function for growing firms and non-growing firms is characterized by the same constant value A because the fixed cost Φ completely offsets the value from external innovation.

Appendix C: Discrete-time Model for the Firm Sector

In the main text, the firm-side equilibrium in Definition 1 is characterized by a continuous-time model for explanatory simplicity. However, given that the household-side equilibrium in Definition 3 is characterized by a discrete-time model, the general equilibrium in Definition 4 is also defined in a discrete-time setting. In this appendix, we show that the firm-side equilibrium in a discrete-time model is characterized by exactly the same first-order conditions as in a continuous-time model. Thus, using either a continuous- or discrete-time version of the model does not matter for defining the general equilibrium in this paper.

Let $\tilde{\mathbf{q}}$, $\check{\mathbf{q}}$, $\hat{\mathbf{q}}$, and $\bar{\mathbf{q}}$ be the vector of quality of products for the improving product lines, the lost product lines, the newly acquired product lines, and the average quality in the economy, and define

$$\mathbf{q}' \equiv \mathbf{q} \backslash \tilde{\mathbf{q}} \cup (\mathbf{1} + \tilde{\gamma})\tilde{\mathbf{q}} \backslash \check{\mathbf{q}} \cup (\hat{\mathbf{q}} + \hat{\gamma}\bar{\mathbf{q}}).$$

Then, the value function for growing and non-growing firms in a discrete-time model is

$$V_g(\mathbf{q}) = \max_{\hat{z}, \{\tilde{z}_j\}_j} \left\{ \begin{array}{l} \displaystyle\sum_{\tilde{\mathbf{q}} \in \mathbf{2^q}} \left(\prod_{q_j \in \tilde{\mathbf{q}}} \tilde{z}_j \right) \cdot \left(\prod_{q_j \in \mathbf{q} \backslash \tilde{\mathbf{q}}} \left(1 - \tilde{z}_j\right) \right) \times \sum_{\check{\mathbf{q}} \in \mathbf{2}^{\mathbf{q} \backslash \tilde{\mathbf{q}}}} \tau^l (1-\tau)^{n-m-l} \times \sum_{k=0}^{n} {}_nC_k \left[(1-\tilde{x})\hat{z}\right]^k \left[1 - (1-\tilde{x})\hat{z}\right]^{n-k} \\ \times \beta \mathbb{E}_{\hat{\mathbf{q}}} \left[(1-\nu) V_g(\mathbf{q}') + \nu V_n(\mathbf{q}') \right] \\ \displaystyle + \sum_{q_j \in \mathbf{q}} \left[\pi_j q_j - \tilde{\xi} \tilde{z}_j^{\tilde{\eta}} q_j \right] - \left[\hat{\xi} \hat{z}^{\hat{\eta}} + \Phi \right] n \bar{q} \end{array} \right\}$$

and

$$V_n(\mathbf{q}) = \max_{\hat{z}, \{\tilde{z}_j\}_j} \left\{ \begin{array}{l} \displaystyle\sum_{\tilde{\mathbf{q}} \in \mathbf{2^q}} \left(\prod_{q_j \in \tilde{\mathbf{q}}} \tilde{z}_j \right) \cdot \left(\prod_{q_j \in \mathbf{q} \backslash \tilde{\mathbf{q}}} \left(1 - \tilde{z}_j\right) \right) \times \sum_{\check{\mathbf{q}} \in \mathbf{2}^{\mathbf{q} \backslash \tilde{\mathbf{q}}}} \tau^l (1-\tau)^{n-m-l} \times \beta V_n \left\{ \mathbf{q} \backslash \tilde{\mathbf{q}} \cup (\mathbf{1} + \tilde{\gamma}) \tilde{\mathbf{q}} \backslash \check{\mathbf{q}} \right\} \\ \displaystyle + \sum_{q_j \in \mathbf{q}} \left[\pi_j q_j - \tilde{\xi} \tilde{z}_j^{\tilde{\eta}} q_j \right] \end{array} \right\},$$

where $n = \#\mathbf{q}$, $m = \#\tilde{\mathbf{q}}$, $l = \#\check{\mathbf{q}}$, and $k = \#\hat{\mathbf{q}}$. The discrete-time version looks slightly messier than the continuous-time version because it is necessary to take into account the possibility that the firm loses (and acquires) multiple product lines and consider the joint distributions for its probability.

As in the continuous time version of the model, we use a guess-and-verify strategy. Under the guess that the value function for growing and non-growing firms $V_g(\mathbf{q})$ and $V_n(\mathbf{q})$ are linear with respect to $\mathbf{q} \equiv \{q_1, \cdots, q_n\}$ with a constant parameter A, i.e.,

$$V_g(\mathbf{q}) = V_g(\mathbf{q}) = A \sum_{q_j \in \mathbf{q}} q_j,$$

the second row of the growing firm's value function can be rewritten as,

$$\beta A\left[\sum_{q_j\in\mathbf{q}} q_j - \sum_{q_j\in\check{\mathbf{q}}} q_j + \tilde{\gamma}\sum_{q_j\in\tilde{\mathbf{q}}} q_j + (1+\hat{\gamma})k\bar{q}\right] \tag{43}$$

where $k = \#\hat{\mathbf{q}}$. Hence, using the formula of the expected value for the binomial distribution, the first order condition with respect to $\hat{z}$ gives the second equation in (16) in the main text by redefining $\tilde{A} = \beta A$.

Also, as in the continuous-time version, by focusing on a particular product line X, $q_X \in \mathbf{q}$, and defining $\mathbf{q}_{-\mathbf{X}} \equiv \mathbf{q}\backslash q_X$, the first three terms in (43) can be rewritten as,

$$\sum_{\tilde{\mathbf{q}}\in 2^{\mathbf{q}}}\left(\prod_{q_j\in\tilde{\mathbf{q}}}\tilde{z}_j\right)\cdot\left(\prod_{q_j\in\mathbf{q}\backslash\tilde{\mathbf{q}}}\left(1-\tilde{z}_j\right)\right)\times\sum_{\check{\mathbf{q}}\in 2^{\mathbf{q}\backslash\tilde{\mathbf{q}}}}\tau^l(1-\tau)^{n-m-l}\times\beta A\left[\sum_{q_j\in\mathbf{q}} q_j - \sum_{q_j\in\check{\mathbf{q}}} q_j + \tilde{\gamma}\sum_{q_j\in\tilde{\mathbf{q}}} q_j\right]$$

$$= \sum_{\tilde{\mathbf{q}}\in 2^{\mathbf{q}_{-\mathbf{X}}}}\left(\prod_{q_j\in\tilde{\mathbf{q}}}\tilde{z}_j\right)\cdot\left(\prod_{q_j\in\mathbf{q}_{-\mathbf{X}}\backslash\tilde{\mathbf{q}}}\left(1-\tilde{z}_j\right)\right)\times\sum_{\check{\mathbf{q}}\in 2^{\mathbf{q}_{-\mathbf{X}}\backslash\tilde{\mathbf{q}}}}\tau^l(1-\tau)^{n-m-l}\times\beta A\left[\sum_{q_j\in\mathbf{q}} q_j - \sum_{q_j\in\check{\mathbf{q}}} q_j + \tilde{\gamma}\sum_{q_j\in\tilde{\mathbf{q}}} q_j + \tilde{z}_X\tilde{\gamma}q_X - (1-\tilde{z}_X)\tau q_X\right]$$

Thus, the first order condition for $\tilde{z}$ gives the first equation in (16).

Finally, by applying the formula of the expected value for the binomial distribution, we can derive

$$r\tilde{A} = \pi - \tilde{\xi}\tilde{z}^{\tilde{\eta}} + \tilde{z}\tilde{\gamma}\tilde{A} - (1-\tilde{z})\tau\tilde{A}$$

where $\tilde{A} = \beta A$ and $r = 1/\beta - 1$. Therefore, in the discrete-time version, the firm-side equilibrium can be characterized by the same equations in Proposition 1.

Appendix D: Age-growth Relationship in Japanese Firm-level Microdata

As is shown by table 1 in the main text, the estimation using Japanese firm-level microdata indicates that the growth rate of young firms is higher than that of old firms and gradually declines as they age. This appendix provides more details about the firm-level microdata used for estimation and shows more results of regression analyses on the firm age-growth relationship.

In the estimation, we use confidential firm-level microdata for Japanese firms in the

"Basic Survey of Japanese Business Structure and Activities" by the Ministry of Economy, Trade and Industry (METI) from 1997 to 2021. The dataset contains yearly financial information for all firms in Japan that hire more than 50 employees. Based on the Statistics Act in Japan, the microdata is available only for academic researchers after a scrutinizing process by METI regarding research purposes.

To investigate the relationship between firm age and growth, first, we construct dummy variables with respect to firm age, $dum(\bar{a})_{i,t}$ where $\bar{a} = 1, \cdots, 15$,

$$dum(\bar{a})_{i,t} = \begin{cases} 1 & \text{if } 1 + 5(\bar{a} - 1) \leq \text{Firm } i\text{'s age in time } t \leq 5\bar{a} \\ 0 & \text{otherwise} \end{cases} \tag{44}$$

Here, given that all firms register their year of establishment T_{est}, firm i's age in time t is calculated by $t - T_{est}$. Based on equation (44), all firms belong to one of the age groups $\bar{a}$. Similarly, we construct time-invariant dummy variables with respect to year of establishment (i.e., cohort), $dum(\bar{e})_i$ where $\bar{e} = 1, \cdots, 12$,

$$dum(\bar{e})_{i,t} = \begin{cases} 1 & \text{if } 1 + 5(\bar{e} - 1) \leq \text{Firm } i\text{'s year of establishment} \leq 5\bar{e} \\ 0 & \text{otherwise} \end{cases} \tag{45}$$

Finally, we construct the industry dummies, $dum(x)$, based on two digits industry codes. Using those dummy variables with respect to firm age, cohort, and industry, the relationship between firm age and its growth is estimated by running the following regression,

$$\Delta \text{Sale}_{i,t} = \alpha + Y_t + \sum_{\bar{a}=1}^{15} \beta_{\bar{a}} dum(\bar{a})_{i,t} + \sum_{\bar{e}=1}^{12} \delta_{\bar{e}} dum(\bar{e})_{i,t} + \phi_x dum(x)_i + \gamma \text{size}_{i,t-1} + \varepsilon_{i,t} \tag{46}$$

where Y_t is a time dummy. To control for firm size, we include shareholder's capital or employment in $t-1$ as a proxy for firm size, $\text{size}_{i,t-1}$. The coefficients of our interest are $\beta_1, \cdots, \beta_{15}$, which capture the difference in sales growth by age.

Table 9 shows the estimation results for the relationship between firm age and growth in (46). Column (1) shows the estimation results without controlling for any effects, while columns (2)-(5) show those with some control variables. In particular, those in column

Table 9: Empirical Relationship between Firm Growth and Age

	(1) $\Delta \ln(Sale)$	(2) $\Delta \ln(Sale)$	(3) $\Delta \ln(Sale)$	(4) $\Delta \ln(Sale)$	(5) $\Delta \ln(Sale)$
$\bar{a}$=1	0.049**	0.047**	0.048**	0.048**	0.050**
	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)
$\bar{a}$=2	0.034**	0.031**	0.032**	0.032**	0.034**
	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)
$\bar{a}$=3	0.025**	0.022**	0.021**	0.021**	0.024**
	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)
$\bar{a}$=4	0.025**	0.022**	0.019**	0.019**	0.021**
	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)
$\bar{a}$=5	0.019**	0.017**	0.012**	0.012**	0.014**
	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)
$\bar{a}$=6	0.012**	0.010**	0.005	0.005	0.007
	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)
$\bar{a}$=7	0.010**	0.008**	0.003	0.003	0.004
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
$\bar{a}$=8	0.007**	0.006**	0.001	0.001	0.002
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
$\bar{a}$=9	0.005**	0.004**	0.001	0.001	0.002
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
$\bar{a}$=10	0.005**	0.004**	0.002	0.002	0.003
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
$\bar{a}$=11	0.002	0.001	-0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
$\bar{a}$=12	0.002*	0.002	0.001	0.001	0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
ln_cap				0.001**	
				(0.000)	
ln_emp					0.005**
					(0.000)
Industry	No	Yes	Yes	Yes	Yes
Cohort	No	No	Yes	Yes	Yes
Obs.	667,607	667,607	667,607	667,607	667,607
R^2	0.050	0.053	0.053	0.053	0.054

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

Note: The table shows the estimation results of the regression analysis for the empirical relationship between firm growth and age specified in (46). The estimation uses confidential firm-level microdata for Japanese firms in the "Basic Survey of Japanese Business Structure and Activities" by the Ministry of Economy, Trade and Industry (METI) from 1997 to 2021. ** and * mean that the coefficients are statistically significant at the .01 and .05 levels, respectively.

(4) are the baseline estimation results where we control for firm size by stockholder's capital, as well as cohort and industry effects by the dummy variables. In the main text, the estimated $\beta_{\bar{a}}$ in column (4) is shown in table 1 and figure 3 and used as the empirical moment conditions to match in indirect inference. As explained in the main text, all the estimation results in table 9 imply that the growth rate of younger firms is higher than that of older firms, as in previous empirical studies. For instance, the growth rate of sales for firms in group 1, i.e., firm age is from 1 year to 5 years old, is higher than that for firms older than 75 years old by 4.8% on average in the baseline estimation in column (4). The estimation result also suggests that the average growth rate of sales gradually decreases as they get old and that the relationship between firm age and growth becomes almost flat and statistically insignificant when firm age surpasses 20-30 years. On the other hand, the coefficient for firm size is positive and statistically significant after controlling for firm age, which implies that the growth rate of small firms tends to be higher than that of large firms, which is against the Gibrat law but consistent with previous empirical studies.

Those features about the relationship between firm age and growth are almost unchanged under various specifications. Columns (1) and (2) are the estimation results without controlling for the cohort effects. While the estimated coefficients are slightly larger and more statistically significant for middle-aged firms, the main quantitative results are almost the same. Also, the estimation using employment as a proxy for firm size (Column 5) provides similar estimation results with respect to the relationship between firm age and growth.

Appendix E: Wage and Job Experience/Tenure in Japan

This appendix provides details about the estimation of the relationship between wages and job experience/tenure, which is used as a calibration target for human capital accumulation. While wages increase over the life cycle for various reasons, human capital accumulation is thought to be a primary reason in the literature. More specifically, as Becker (1964) pointed out, 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. As both FSHC and GHC are thought to be mainly accumulated through job experience, the length of (i) job tenure at a particular employer and (ii) total job experience are used as a proxy for FSHC and GHC in the literature, respectively. Then, by estimating the relationship between wages and job experience/tenure, we can decompose human capital accumulation over the life cycle into FSHC and GHC.

To estimate the relationship between wages and job experience/tenure in Japan, we use household-level microdata, "Japan Household Panel Survey (JHPS/KHPS)" provided by the Panel Data Research Center at Keio University. The JHPS/KHPS is an annual survey of Japanese households starting in 2004, which asks various items including job status, hours worked, and annual labor income.[25] Based on previous empirical studies using JHPS/KHPS (e.g., Kimura et al., 2019), the variables for estimation are constructed as follows. First, the hourly wage rate $wage_{i,t}$ is defined as,

$$wage_{i,t} = \frac{\text{Annual labor income}_{i,t} \div 12}{\text{Weekly hours worked}_{i,t} \div 7 \times 30} \tag{47}$$

Second, job experience $expr_{i,t}$ is constructed as follows. At the moment that individual i joins the survey, it is assumed that he/she kept working since graduation if they work then. That is, job experience $expr_{i,t}$ in the initial year is defined as,

$$expr_{i,t} = t - \text{Year of graduation}_i \tag{48}$$

if he/she works in time t. Based on information about the academic history, the year of graduation is calculated by assuming that people graduate from mid-school at 15, high school at 18, college at 22, and graduate school at 24. If individual i does not work when he/she joins the survey, we drop individual i from the dataset. Then, after the initial year, $expr_{i,t} = expr_{i,t-1} + 1$ if they work in year t, and $expr_{i,t} = expr_{i,t-1}$ otherwise. Finally, in the initial year for individual i for the survey, job tenure $tenu_{i,t}$ is calculated using "Year of

[25]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.

starting working at the current employer",

$$tenu_{i,t} = t - \text{Year of starting working at the current employer}_i \tag{49}$$

if he/she works in time t. Then, after the initial year, $tenu_{i,t} = tenu_{i,t-1} + 1$ if they keep working at the employer in year t, and $tenu_{i,t} = 0$ otherwise. Following previous empirical studies, we restrict our sample to regular employees younger than 60 who work for more than 100 hours a month. Also, individuals who work in the agricultural sector, public sector, and non-profit organizations are excluded. Then, the relationship between wages and job experience/tenure is estimated by,

$$\log(wage_{i,t}) = \alpha + f(expr_{i,t}) + g(tenu_{i,t}) + Y_t + D_{edu,i} + D_{sex,i} + \varepsilon_{i,t} \tag{50}$$

where $f(x)$ and $g(x)$ are some functions of x, and Y_t, $D_{edu,i}$, and $D_{sex,i}$ are dummy variables for a year, education, and male/female.

Table 10 shows the estimation results for (50) where $f(x)$ and $g(x)$ are linear or quadratic functions. Column (1) shows that job experience has positive effects on the wage rate and that one-year job experience increases the wage rate by 1.9% on average. Column (2) indicates that the relationship between wages and job experience is concave, which suggests that the return from job experience is diminishing as in previous studies (e.g., Lagakos et al., 2018; Kimura et al., 2019). In those estimations, however, $expr_{i,t}$ captures the effects of both FSHC and GHC; therefore, we need to add job tenure as a proxy for FSHC to distinguish between them. Column (3) shows that job tenure also has positive effects on wages, and column (4) indicates that the return from job experience and tenure are both significantly diminishing. The estimation result in column (4) is our baseline estimation to be used as a calibration target in the main text. The middle and right panels in figure 7, as well as figure 4 in the main text, indicate that while the return from job experience and tenure are both diminishing, the relationship between wages and job experience is more concave than that between wages and job tenure, implying that FSHC plays a more important role later in the carriers. To account for this feature in the model, it is assumed in our calibration that GHC is depreciated by around 5% every year while FSHC is not.

Table 10: Empirical Relationship between Wages and Job Experience/Tenure

	(1)	(2)	(3)	(4)
	$\log(wage_{i,t})$	$\log(wage_{i,t})$	$\log(wage_{i,t})$	$\log(wage_{i,t})$
expr	0.019**	0.050**	0.005**	0.031**
	(0.000)	(0.002)	(0.000)	(0.002)
$expr^2$		-0.067**		-0.057**
		(0.004)		(0.004)
tenu			0.022**	0.029**
			(0.000)	(0.001)
$tenu^2$				-0.020**
				(0.004)
Obs.	12,778	12,778	12,699	12,699
R^2	0.263	0.283	0.375	0.398

Standard errors in parentheses

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

Note: The table shows the estimation results * $p < 0.05$, **$p < 0.01$

To check the robustness of the estimation results in table 10, first, we examine a more flexible functional form for $f(x)$ and $g(x)$ in (50). Specifically, following the methodology used in Lagakos et al. (2018), we construct dummy variables with respect to a five-year bin for job experience and job tenure and estimate relative wages for each bin. Let $dum(ex)_{i,t}$ where $ex = 1, \cdots, 7$ be dummy variables such as,

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

and $dum(ex = 8)_{i,t} = 1$ if i's job experience in time $t > 35$. Similarly, let $dum(tn)_{i,t}$ where $tn = 1, \cdots, 7$ be dummy variables such as,

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

and $dum(tn = 8)_{i,t} = 1$ if i's job tenure in time $t > 35$. Then, $f(x)$ and $g(x)$ in (50) are defined as,

$$f(expr_{i,t}) = \sum_{ex=1}^{7} dum(ex)_{i,t} \quad \text{and} \quad g(tenu_{i,t}) = \sum_{tn=1}^{7} dum(tn)_{i,t}$$

and estimate relative wages for each bin with respect to job experience/tenure.

Figure 7 shows the estimation results using the 5-year bin for job experience and tenure. First, the left panel in figure 7 shows the relationship between wages and job experience without controlling for job tenure. That is, in this case, only $dum(ex)_{i,t}$ is included in the regression. Hence, the relationship in the left panel contains the effects of both FSHC and GHC. The panel indicates that the estimation results using the 5-year bin (the blue line with circles) are concave and almost identical to those using a quadratic function (the red dotted line), i.e., the estimation results in column 2 of table 10 .[26] Second, the middle and

[26]The estimation result shows that the wage rate for those with 20 years of experience relative to those with no experience is around 0.66, which suggests that 20 years of experience is associated with 94% higher wages, i.e., $e^{0.66} - 1 = 0.94$. This result is quantitatively consistent with the main findings in Lagakos et al. (2018). Figure 3 in their paper shows that relative wage for 20 years of experience is positively correlated with real GDP per capita. Given that Japan's PPP GDP per capita is 36000 in 2011, the estimation result for Japan in figure 7 is very close to their regression line.

Figure 7: Wage and Job Experience/Tenure

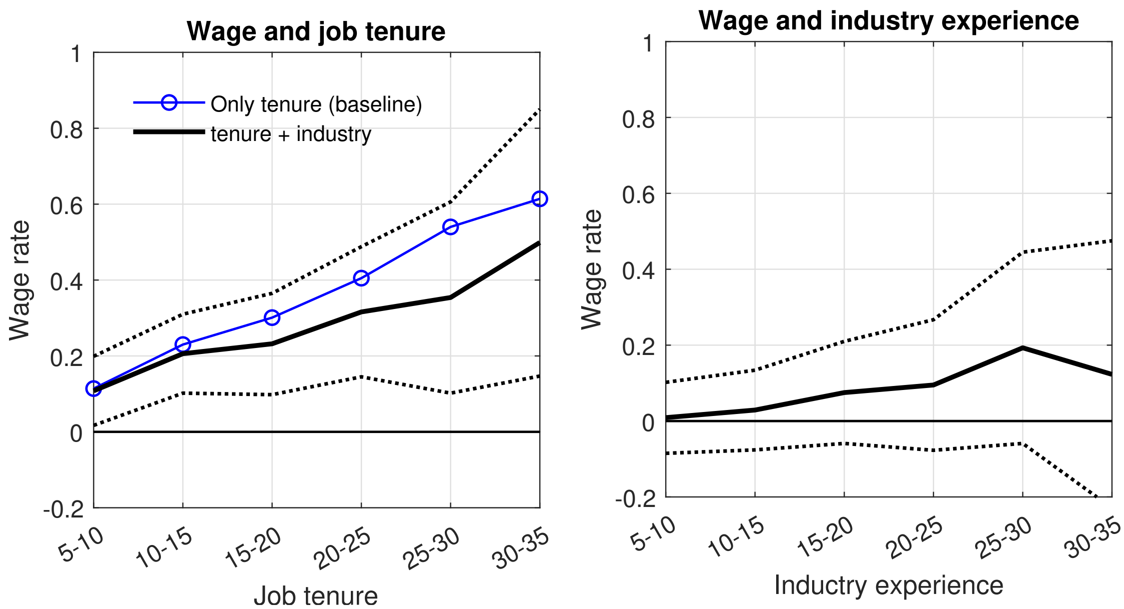
Note: The figure shows the estimation results using a quadratic function (the dashed red lines), the 5-year bin for job experience and tenure (the blue lines with circles), and Topel's method (the green lines with x-marks). The left panel shows the relationship between wages and job experience without controlling for job tenure, which conceptually contains the effects of both FSHC and GHC. The middle and right panels show the relationship between wages and job tenure/experience, respectively.

right panels in figure 7 show the estimation results for the relationship between wages and job experience/tenure using the 5-year bin. In this case, both $dum(ex)_{i,t}$ and $dum(tn)_{i,t}$ are included in the regression to separately estimate the marginal contribution of job experience and tenure (i.e., GHC and FSHC). Those panels indicate that estimation results using the 5-year bin (the blue line with circles) are very close to those using a quadratic function (the red dotted line), i.e., the estimation results in column 4 of table 10. Those estimation results in figure 7 show that the baseline estimation results using a quadratic function are robust to changes in functional forms of $f(x)$ and $g(x)$ in (50).

Next, we conduct a robustness check for possible endogeneity problems. Particularly, in the empirical literature, the coefficient for job tenure based on (50) is possibly biased upward. That is, positive shocks to wages may be positively correlated with job tenure because a good job tends to last longer. To resolve this endogeneity problem, Topel (1991) proposes a two-step procedure to estimate the effects of job experience and tenure on wage growth using only continued job data in the first step and then estimate the contribution of job experience on wages using job experience at the moment of job changes. The green lines with x-marks show the estimation results based on the two-step procedure proposed by Topel (1991). The middle panel in the figure shows that the estimated relationship between wages and job tenure is almost the same as that using a quadratic function and the 5-year bin (the red dotted line and the blue line with circles), suggesting that the endogeneity problem in the baseline estimation based on (50) does not severely affects the estimation results.[27] In countries with stringent EPL like Japan, a job with longer job tenure does not necessarily correspond to a good one because employers cannot dismiss their employees for poor performance. Hence, compared with the case in countries with lax EPL like the U.S., it is less likely that the endogeneity problem severely affects the estimation results.

[27]While our main focus is on the relationship between wages and job tenure, it is notable that the relationship between wages and job experience estimated by Topel (1991)'s method is substantially different from that in the baseline, particularly later in the career (the right panel in figure 7). The primary reason for this gap is that Topel (1991)'s method cannot account for the diminishing return from job experience, as it assumes linearity. Also, while the method uses job experience at the moment of job changes to estimate the relationship between wages and job experience, most job changes concentrate early in the career, thereby making it difficult to estimate the relationship for later in the career.

Figure 8: Job Tenure and Industry Experience



Note: The figure shows the estimation results for the relationship between wages and job tenure (the left panel) and industry experience (the right panel) with 95% confidence intervals. We run the regression (50) by adding industry experience as an additional variable for explaining the wage profile.

Finally, some empirical studies including Parent (2000) cast doubt on the role of FSHC by arguing that the positive effects of job tenure capture industry-specific HC rather than FSHC. To examine this criticism, we run the regression (50) by adding industry experience as an additional variable for explaining the wage profile. Specifically, the dummy variables for industry experience are constructed in a similar way to those for job experience and tenure. Let $dum(ind)_{i,t}$ where $ind = 1, \cdots, 7$ be dummy variables such as,

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

and $dum(ind = 8)_{i,t} = 1$ if i's industry experience in time $t > 35$. Then, we include $\sum_{ind=1}^{7} dum(ind)_{i,t}$ in addition to $\sum_{ex=1}^{7} dum(ex)_{i,t}$ and $\sum_{tn=1}^{7} dum(tn)_{i,t}$ as an explanatory variable. Figure 8 shows the estimation results for the relationship between wages and job tenure (the left panel) and industry experience (the right panel) with 95% confidence intervals. First, the left panel shows that including industry experience as an additional explanatory variable slightly flattens the estimated wage profile for job tenure (the bold black line) but does not significantly change it from the baseline (the blue line with circles). Second, as a flip side of the estimation results in the left panel, the right panel shows that there are no statistically significant effects of industry experience on wages, after controlling for job experience and tenure. Hence, in contrast to the U.S. wage profile analyzed in Parent (2000), job tenure plays a more important role than industry experience in determining the wage profile of Japanese workers. One caveat is that when both job tenure and industry experience are included as explanatory variables, the standard error becomes relatively large due to collinearity between them. Specifically, the lower bound for the relationship between job tenure and wages is close to flat around 0.1, implying that the estimation results do not statistically reject the possibility that industry experience plays an important role in wage profile.