Unleashing Innovation and Entrepreneurship: Ripple Effects of Employment Protection Reforms*

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Abstract

This study investigates the effects of employment protection legislation (EPL) on entrepreneurship, firm dynamics, and economic growth in a general equilibrium model that incorporates endogenous Schumpeterian growth. The model implies that more stringent EPL encourages households to accumulate more firm-specific human capital, which raises the opportunity cost to start a business. Using Japanese firm- and household-level microdata to calibrate parameter values, the quantitative exercise reveals that EPL reform aimed at its elimination could stimulate entrepreneurship in the household sector, thus boosting economic growth through more creative destruction in the firm sector. A partial equilibrium model that disregards the general equilibrium effects can overestimate or underestimate the policy effects of the EPL reform on entrepreneurship and economic growth. Policies that directly support firm entries or incumbents' research and development investment 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

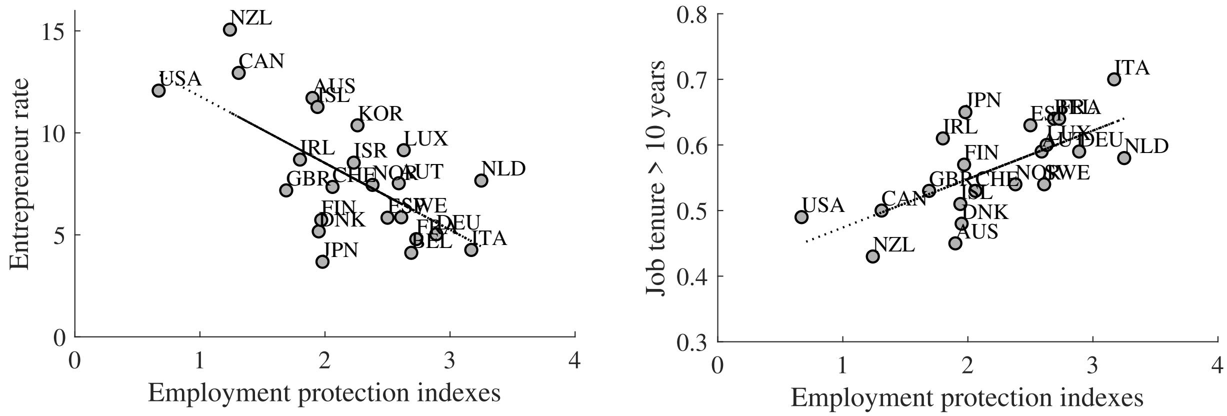
While employment protection legislation (EPL) is commonly adopted in many countries, its economic impacts are manifold. The primary motivation for introducing EPL is to help households reduce the risk of unemployment and thus accumulate human capital. Nonetheless, in the firm sector, it raises the cost of employment, thereby possibly adversely affecting wages or employment (e.g., Lazear, 1990; Autor et al., 2006). Among the various effects of EPL, its impact on economic growth is of particular importance, given that it has a cumulatively large impact on output in the long run. However, it is somewhat challenging to quantify its macroeconomic effects, particularly on economic growth, as EPL widely influences economic behaviors in both the firm and household sectors; thus, it is necessary to consider their interaction in general equilibrium. Hence, although some empirical studies indicate the negative effects of EPL on productivity growth, the aggregate impact on growth remains a relatively underexplored research area.[1]

This study investigates the quantitative impacts of EPL on economic growth, firm dynamics, and entrepreneurship in a Schumpeterian growth model. While EPL reform 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 firm entries and creative destruction. A general equilibrium model that incorporates Schumpeterian growth and households' entrepreneurial decisions offers a rich and tractable framework for modeling such an interaction between the firm and household sectors. Hence, in contrast to most previous studies elaborating only on the household or firm sector, it serves as a good laboratory to quantitatively investigate the ripple effects of EPL on entrepreneurship, firm dynamics, and economic growth while considering the general equilibrium effects.

Given the above motivation, we construct a model by particularly focusing on empirical facts associated with (i) firm growth by age, and (ii) the "escape-entry effects." First, regarding firm growth by age, previous empirical studies highlight that, on average, younger firms grow faster than older ones. As more active entrepreneurship increases the share of younger firms in the economy, understanding to the extent to which the growth rate of young firms is higher than others is crucial to assessing the impact of entrepreneur-

[1]For example, see Bassanini et al. (2009) for an empirical study on EPL and productivity growth.

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 Appendix A for more about data definition and formal regression analyses.

Source: OECD, Global Entrepreneurship Monitor

ship on economic growth. In this study, we estimate the growth-age relationship using confidential firm-level microdata for Japanese firms and use indirect inference for setting parameters so that the model accounts for the estimated results. Second, Aghion et al. (2009) notes the "escape-entry effects," namely, existing firms try harder to innovate to retain their leading position for their existing 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 Organization for Economic Co-operation and Development (OECD) employment protection indexes and the entrepreneur ratios among advanced economies. This panel shows a clear negative relationship between them, suggesting that EPL has some negative impacts on entrepreneurship.[2] Second, the right panel in Figure 1 shows the cross-country scatter

[2]While Figure 1 focuses on advanced economies whose GDP per capita is larger than 20 thousand USD,

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, on average, leads to longer job tenure. 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 study, we explicitly model the accumulation of FSHC and general human capital (GHC) 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? Our main findings are summarized as follows. First, consistent with Figure 1, we find that EPL decreases the entrepreneurial rate. Under stringent EPL, individuals tend to accumulate FSHC rather than GHC. Given that FSHC is lost when quitting a current job, EPL indirectly increases the opportunity cost for households to quit their current job and start a business. In other words, while entrepreneurship is a kind of experimentation (Kerr et al., 2014), EPL raises the cost of the experimentation by encouraging the accumulation of 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 approximately 0.4% points. Increased entrepreneurship promotes economic growth by not only activating creative destruction associated with new entries but also increasing young firms with more growth potential. As mentioned above, the quantitative analysis is disciplined by calibrating parameters to be consistent with the estimation result on firm growth by age using Japanese firm-level microdata. Furthermore, in assessing the macroeconomic impact of EPL, general equilibrium effects play an important role. 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

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 Appendix A for more details on those regression analyses.

would be underestimated to be about two-thirds.[3] Finally, the policy experiments suggest that policies directly supporting firm entries or incumbents' research and development (R&D) investment have limited impacts on economic growth as long as stringent EPL exists.

Literature Review

First, this study is built upon the fast-growing literature on an endogenous growth model with firm dynamics pioneered by Klette and Kortum (2004), particularly quantitative studies using firm-level microdata (e.g., Lentz and Mortensen, 2008; Akcigit and Kerr, 2018; Peters, 2020; Akcigit et al., 2021; Konig et al., 2022). 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; Klenow and Li, 2020), we follow Acemoglu et al. (2018) to model the age-growth relationship in a Schumpeterian growth model and calibrate parameters by Japanese firm-level microdata. This study mainly differs from the previous literature in that we focus on the general equilibrium effects of EPL, including those through entrepreneurship in the household sector.

Second, this study contributes to the literature on the adverse effects of ELP. Among numerous quantitative analyses following the seminal work by Hopenhayn and Rogerson (1993), this study is closely related to Koeniger (2005), Mukoyama and Osotimehin (2019) and Aghion et al. (2023), as they also examine the effects of EPL on economic growth within an endogenous growth model. Empirically, Griffith and Macartney (2014) shows that while EPL encourages innovation as a whole, it decreases the share of radical innovation. 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) highlight the adverse effects of EPL on venture capital activity among European countries, both of which are consistent with our quantitative analysis.

Third, this study models an individual's discrete choice between entrepreneurs and paid workers as in a standard entrepreneurship model (e.g., Buera et al., 2015). In contrast to existing models, our model does not focus exclusively on individual entrepreneurial

[3]Note that, as in previous studies such as Hopenhayn and Rogerson (1993), this study exclusively focuses on the adverse effects of EPL on economic growth, disregarding the potential benefits associated with EPL. Thus, our goal is to quantify the adverse effects rather than discuss the optimal level of EPL.

decisions by using a partial equilibrium model (e.g., Jones and Pratap, 2020; Catherine, 2022) or by having a separate and large firm sector (e.g., Salgado, 2019; Gaillard and Kankanamge, 2023), as our focus is on the impact of entrepreneurship on economic growth.

Fourth, this study is related to the literature on human capital accumulation. Following Becker (1964)'s seminal work, Hashimoto and Raisian (1985), Kimura et al. (2019), and Katagiri (2023) empirically show that FSHC plays an important role in Japan, contrasting to Parent (2000) and Kambourov and Manovskii (2008) showing that FSHC plays a limited role in the U.S. Tang (2012) shows that countries with stringent EPL have a comparative advantage in industries where FSHC is important, consistent with the theoretical work by Wasmer (2006). However, few studies in the literature investigate the relationship between FSHC and entrepreneurship.

The reminder of the paper proceeds as follows. Section 2 provides two motivating facts on the relationship between firm age and growth. Section 3 describes a general equilibrium model for the quantitative analysis. Section 4 calibrates the model parameters by indirect inference and conducts comparative statics to assess the impact of employment protection. Finally, in Section 5, concluding remarks are provided.

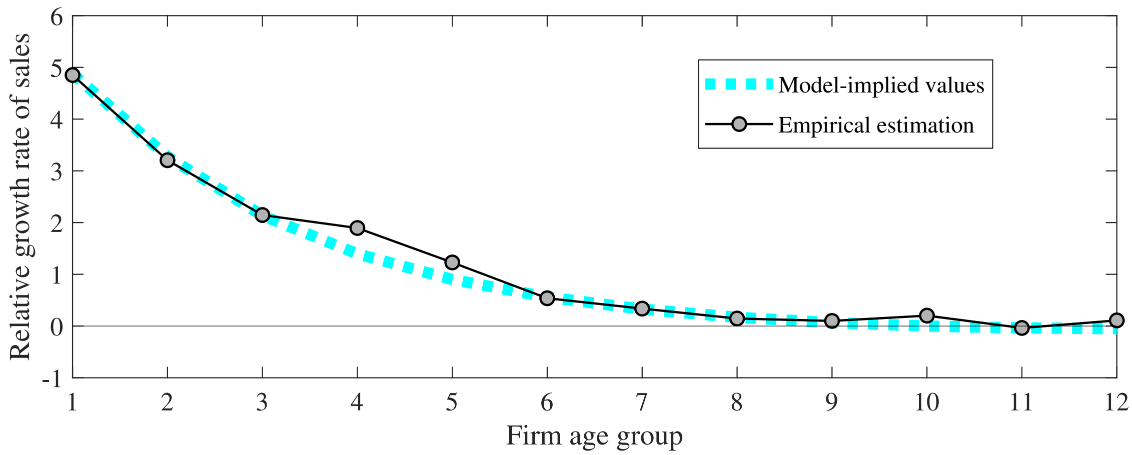
2 Motivating Facts

Before proposing a general equilibrium model, we present two key empirical facts associated with firm age to motivate our quantitative analysis. That is, the relationship between firm growth and age, as well as the role of R&D investment by firm age, are examined by using confidential firm-level microdata in Japan. See Appendix B for more details regarding the data and the estimation results using various specifications.

2.1 Firm Growth by Age

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. Given that active entrepreneurship is expected to naturally increase the share of younger firms, it is crucial to understand the extent to which the growth rate of young firms is higher

Figure 2: Firm Growth by Age: Model and Data



Note: In the figure, the horizontal axis represents the 5-year age group, and the vertical axis shows the relative growth rate of sales for each age group. The thin line with circles represents estimated coefficients based on column 1 in Table 7 in Appendix B. The thick dashed line represents the model-implied average growth rate by age based on indirect inference. See Appendix F for more detail on how to compute the model-implied values containing the same survival bias as in data.

than that of older firms to assess the impact of entrepreneurship on economic growth.

The relationship between age and growth in Japan is estimated using Japanese firm-level micro data, by constructing firms into 5-year age groups and comparing the differences in sales growth across these groups. The thin line with circles in Figure 2 displays the estimation results, indicating a significant difference in the growth rate between younger and older firms, consistent with findings from previous empirical studies in other countries. For example, 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 4.9% on average. Additionally, the estimation results suggest a gradual decrease in the average growth rate of sales as firms age. The age effect on firm growth becomes statistically insignificant when the firm age surpasses 25–30 years.

To account for the empirical feature of firm growth by age, the model in the next section assumes that all new entrants are growing firms with an opportunity for growth through creative destruction and then gradually transform into non-growing firms without growth potential. The parameter values related to innovation, as well as the transition from growing to non-growing firms, are identified using the estimation results of firm growth by age presented in Figure 2. These results serve as empirical moments to be matched in calibration through indirect inference. Importantly, note that the estimation results in Figure 2 may be influenced by survival bias, as younger firms facing negative shocks tend to exit more frequently than older firms. To address the problem of survival bias in calibration, we compute the model-implied values *containing the same survival bias* as in data and calibrate the model parameters to match them with the estimation results in Figure 2. Additionally, as a robustness check for potential survival bias, Appendix B conducts a median regression using a sample that includes exiting firms, confirming that the quantitative implications remain unchanged.

2.2 R&D Investment and Growth by Firm Age

Second, we examine the role of R&D investment by firm age, aiming to investigate the "escape-entry effects" discussed by Aghion et al. (2009). They highlight that incumbent firms intensify their innovation efforts to maintain their leading position in response to an increase in firm entries. Hence, unlike R&D investment aiming to grow through creative destruction, R&D investment for the escape-entry effects is a defensive investment to prevent the loss of current market share. Given those different types of R&D investment, we conduct quantile regression analysis for R&D investment and sales growth to examine whether the role of R&D varies among firms of different ages.

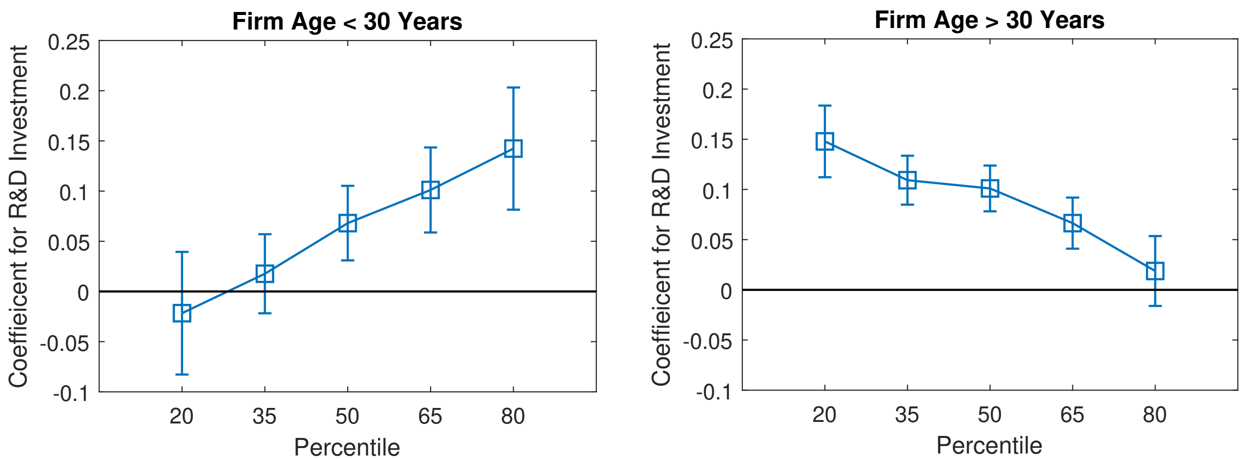
$$\widehat{\Delta\mathrm{Sale}}_{i,t} = \alpha_Q + \beta_Q \widehat{\mathrm{R\&D\_rate}}_{i,t-1} + \varepsilon_{i,t} \tag{1}$$

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

Figure 3 shows the estimated β_Q in (1) with 95% confidence intervals for firms younger than 30 years (the left panel) and those older than 30 years (the right panel). The threshold for firm age is set to 30 years because the estimation regarding firm growth and age in Figure 2 suggests that firms younger than 30 years seem to have different growth potential

[4]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, $\widehat{\Delta\mathrm{Sale}}_{i,t}$ and $\widehat{\mathrm{R\&D\_rate}}_{i,t-1}$ are constructed from residuals in those regressions.

Figure 3: 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 (1), 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.

than those older than 30 years. The horizontal axis represents the percentile in the quantile regression, $Q = 20, 35, 50, 65$, and 80 percentile. The figure indicates that β_Qs significantly differ between firms of different ages. 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. Conversely, 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., $Q \leq 65$).

Figure 3 is interpreted as implying that older firms conduct R&D investment mainly to avoid a large drop in their sales (i.e., the escape-entry effect), whereas younger firms conduct it mainly to grow further. In other words, for firms older than 30 years, R&D investment helps them maintain their current position by avoiding a substantial decline in sales, i.e., the lower tails. Conversely, for firms younger than 30 years, R&D investment does not reduce the probability of large negative sales growth but potentially leads to higher sales growth, i.e., the upper tails. Appendix B conducts additional empirical analyses on the role of R&D investment by firm age and obtains the same implications. As discussed in detail in the next section, such differences in the role of R&D investment by firm age are incorporated into the model by assuming that: (i) firms' innovation on their existing products reduces the probability of losing their leading position (i.e., the escape-entry effects), and (ii) only younger firms have growth potential through creative destruction.[5]

3 Model

This section provides a quantitatively tractable model to assess the effects of EPL on entrepreneurship, firm dynamics, and economic growth. The economy comprises 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. In general equilibrium, the firm and household sectors interact through not only labor market clearing but also firm dynamics and entrepreneurship. Specifically, firms' dismissal behavior influences households' behavior, including entrepreneurial decisions, by changing the layoff probability they face. Entrepreneurship, in turn, determines the firm entry rate, thus affecting economic growth through creative destruction.

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 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). Additionally, there are two types of firms concerning their growth potential, namely growing and non-growing firms, a concept akin to Acemoglu et al. (2018). This distinction captures the empirical observation that the growth rate of young firms tends to surpass that of older ones.

[5] These estimation results are broadly consistent with findings in Klenow and Li (2020).

Final Good Firm

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

$$Y = \frac{1}{1-\rho} \int_0^1 q_j^{\rho} k_j^{1-\rho} dj, \tag{2}$$

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,

$$k_j = q_j p_j^{1/\rho} \tag{3}$$

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

Internal Innovation and the Escape-entry Effect

Intermediate-good firms operate with either single or multiple product lines, producing intermediate goods denoted as k_j with quality q_j at product line j. For each product line, these firms consistently engage in internal innovation for two primary purposes. First, internal innovation serves to enhance the quality q_j of the existing product line, thereby increasing its profitability. Second, while all existing product lines face the risk of being acquired by other incumbent firms or new entrants through creative destruction (as detailed below), internal innovation mitigates such a risk by maintaining their leading position. Aghion et al. (2009) term this second benefit derived from internal innovation as "the escape-entry effect," and empirically demonstrate that an increase in entries encourages incumbent firms to pursue internal innovation.

The two benefits arising from internal innovation are modeled as follows: First, the product lines are classified into improving lines or non-improving lines, based on the current internal R&D expenditure for each product line. Then, following the approach employed in Garcia-Macia et al. (2019), it is assumed that only the non-improving product lines are susceptible to creative destruction. More specifically, when the firm spends

$$C_I(\tilde{z}_j, q_j) = \tilde{\xi} \tilde{z}_j^{\tilde{\eta}} q_j \tag{4}$$

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, owing to the escape-entry effects. In contrast, 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

$$k_j = \bar{q} l_j \tag{5}$$

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 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.[6] Second, at surviving product lines, a fraction ψ of jobs are exogenously destructed at each point in time. In the face of exogenous job destruction, firms have two choices: (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 assumed to be

[6] 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 example, differences in a necessary skill set. See Mukoyama and Osotimehin (2019) for the case allowing a more general labor reallocation policy.

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,

$$\left[\int_0^{\bar{s}} \chi s \, ds + (1-\bar{s})\phi\right] w \times \psi l_j. \tag{6}$$

where $w\chi s$ is the marginal cost for re-skilling s fraction of workers.[7] 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 $\phi(1-\phi/(2\chi))w \times \psi l_j$.

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 (4), the product line j is an improving line (a non-improving line) with probability $\tilde{z}_j$ (with probability $1-\tilde{z}_j$). As 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,

$$\omega_j w \quad \text{where} \quad \omega_j \equiv 1 + (1-\tilde{z}_j)\tau\phi + \left[1-(1-\tilde{z}_j)\tau\right]\phi\left(1-\frac{\phi}{2\chi}\right)\psi, \tag{7}$$

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), $\omega_j = 1$, that is, 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. Furthermore, it is decreasing with respect to $\tilde{z}_j$ owing to the escape-entry effects, which implies that employment protection encourages firms to conduct more internal R&D for the purpose of avoiding the employment protection cost due to creative destruction.

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

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,

$$\max_{l_j} \left\{ p_j k_j - \omega_j w l_j \right\} \tag{8}$$

subject to the demand function (3), the internal R&D expenditure (4), the production function (5), and the labor cost (7). Due to 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,

$$p_j k_j = \left[\frac{(1-\rho)\bar{q}}{\omega_j w} \right]^{\frac{1-\rho}{\rho}} q_j \quad \text{and} \quad l_j = \left[\frac{(1-\rho)\bar{q}}{\omega_j w} \right]^{\frac{1}{\rho}} \frac{q_j}{\bar{q}} \tag{9}$$

and the optimized profit,

$$\pi_j q_j \ \text{ where } \ \pi_j \equiv \rho \left[\frac{(1-\rho)\bar{q}}{\omega_j w} \right]^{\frac{1-\rho}{\rho}}. \tag{10}$$

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).[8]

External Innovation

Intermediate good firms can expand the number of their product lines through external innovation. To capture 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 growing firms have opportunities for external innovation. Empirical evidence in Section 2 indicates that (i) on average, the growth rate of younger firms is higher than that of older firms, and (ii) older firms conduct R&D investment mainly to avoid a large drop in their sales (i.e., the escape-entry effect), whereas younger firms conduct it mainly to grow further. Considering those empirical findings, it is assumed that all firms are growing

[8] As in previous studies, including Acemoglu et al. (2018), firms set the price as a monopolist under the implicit assumption that the process of creative destruction is a two-stage game.

firms at the time of entry, and then gradually transition to the non-growing state at an exogenous rate of ν. Following Acemoglu et al. (2018), the non-growing state is treated as an absorbing state, meaning that non-growing firms do not revert to becoming growing firms.[9]

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.[10] Specifically, the growing firms can increase a product line at the instantaneous Poisson flow rate of $(1-\tilde{x})\hat{Z}$ by spending

$$C_E(\hat{z}, n) = \left[\hat{\xi}\hat{z}^{\hat{\eta}} + \Phi\right] n\bar{q} \tag{11}$$

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, that is, the share of product lines vulnerable to external innovation. Furthermore, 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 $\hat{\gamma}\bar{q}$, that is, $q_j(t + \Delta t) = q_j(t) + \hat{\gamma}\bar{q}$, 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

[9]While the exogenous transition from the growing state to the non-growing state follows Acemoglu et al. (2018), it is a somewhat strong assumption, given that it implies that all older firms inevitably experience a decline in their growth rate. Nevertheless, modeling the underlying mechanism that induces higher growth for younger firms is evidently quite challenging and beyond the scope of this study. Hence, instead of endogenizing the transition, we opt to maintain the assumption of exogenous transition and discipline the quantitative analysis by calibrating the exogenous transition rate ν, as well as innovation parameters, to be consistent with the estimation results using Japanese firm-level microdata.

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

quality of all their product lines is expressed as,

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

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 $\mathbf{q}\backslash\tilde{\mathbf{q}}$. As all product lines can be improving lines or non-improving lines, $\tilde{\mathbf{q}}$ is an element of the power set of $\mathbf{q}$, that is, $\tilde{\mathbf{q}} \in \mathbf{2^q}$, 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,

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

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, that is, $q_j \in \mathbf{q}\backslash\tilde{\mathbf{q}}$. 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 because the non-growing firm has no opportunity for external innovation, it chooses only the intensity of internal innovation. As in previous studies on the Schumpeterian growth model, the optimal behavior of growing and non-growing firms is characterized as follows.

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*

$$\Phi = \hat{\xi}(\hat{\eta} - 1)\hat{z}^{\hat{\eta}}. \tag{12}$$

Under this assumption regarding Φ: (i) the value function is linear with respect to $\mathbf{q}$, $V_x(\mathbf{q}) = A \sum_{q_j \in \mathbf{q}} q_j$, 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, $\tilde{z}_{g,j} = \tilde{z}_{n,j} \equiv \tilde{z}$, 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:

$$\tilde{\xi}\tilde{\eta}\tilde{z}^{\tilde{\eta}-1} = \frac{\partial \pi}{\partial \tilde{z}} + (\tilde{\gamma} + \tau)A \quad \textit{and} \quad \hat{\xi}\hat{\eta}\hat{z}^{\hat{\eta}-1}\bar{q} = (1 - \tilde{x})v^e \tag{13}$$

and

$$rA = \pi - \tilde{\xi}\tilde{z}^{\tilde{\eta}} + \tilde{z}\tilde{\gamma}A - (1 - \tilde{z})\tau A \tag{14}$$

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 C. Note that π_j specified in (10) is also independent of q_j in equilibrium because $\tilde{z}_j$ and consequently ω_j in (7) 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 (13) show the first-order conditions for internal and external innovation intensity, respectively. In both of them, the left- and right-hand sides represent the marginal cost and benefit of innovation expenditure. Equation (14) is the value function under the guess for linearity. Intuitively, the optimal $\tilde{z}_j$ characterized by the first equation in (13) 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 (13) and (14) for three unknowns, $\tilde{z}_j, \hat{z}$, and A; therefore, while the system of equations cannot be analytically solvable 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, that is, independent of q_j.

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

$$d = (1 - \tilde{z})\tau + [1 - (1 - \tilde{z})\tau]\,\psi\left(1 - \frac{\phi}{\chi}\right). \tag{15}$$

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.

3.2 Household

The household sector comprises a continuum of households that exhibit heterogeneity in terms of their firm-specific and general human capital (FSHC and GHC) as well as their employment status. These households are exogenously and stochastically retired with probability λ, subsequently replaced with new households devoid of human capital. Each period, employed individuals earn wages and accumulate human capital; however, they face the risk of being laid off with a probability of d. Moreover, all households have the opportunity to become entrepreneurs each period and obtain entrepreneurial income. The household is risk-neutral and maximizes the lifetime utility:

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

where β is a discount factor and c_t is consumption.

Human Capital Accumulation

All individuals are categorized into two groups: employed and non-employed. Employed individuals work for a specific employer, including their own firm, and receive wage income. In contrast, non-employed individuals do not engage in wage-earning activities. As demonstrated later, individuals transition to the non-employed category when they are either dismissed or face failure in their own businesses. Employed individuals are characterized by two state variables, namely, FSHC and GHC, denoted as h_s and h_g, respectively. In contrast, non-employed individuals are characterized solely by GHC, as they are not currently employed by a specific employer. The distinction between h_s and h_g aligns with established human capital literature, notably pioneered by Becker (1964). In this framework, FSHC h_s holds value exclusively for the current employer; hence, it becomes worthless once employed individuals leave the current employer due to layoff or to become an entrepreneur.

The employed individuals supply the labor force, $l_s(h_s, h_g)$, based on h_s and h_g,

$$l_s(h_s, h_g) = \bar{h}(1 + h_s + h_g) \tag{16}$$

where $\bar{h}$ is a scale parameter. The linear 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. In Appendix H, a more general CES form of labor supply function is examined as a robustness check.

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,

$$h_s' = (1-\delta_s)h_s + A_s h^\alpha \quad \text{and} \quad h_g' = (1-\delta_g)h_g + A_g(1-h)^\alpha \tag{17}$$

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, whereas 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,

$$H_W(h_s, h_g) = w \cdot l_s(h_s, h_g) + \beta(1+g)(1-\lambda) \cdot \max_{h_s', h_g'} X_W(h_s', h_g') \tag{18}$$

subject to (16) and (17), where w is a wage rate, β is a discount rate, and g is a growth rate.[11] Individuals are stochastically retired with probability λ and replaced by an individual with zero FSHC and GHC. $X_W(h_s, h_g)$ 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 are not subject to any optimization problems at this stage. Thus, their value function is expressed as,

$$H_N(h_g) = \beta(1+g)(1-\lambda) \cdot X_N(h_g') \tag{19}$$

subject to $h_g' = (1-\delta)h_g$, where $X_N(h_g)$ is the value function for the non-employed individ-

[11] In Appendix H, as a robustness check, the household is assumed to endogenously adjust hours worked and/or time allocation for human capital accumulation in the optimization problem.

uals before the discrete entrepreneurial choice (defined later).

Entrepreneurial Choice

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

$$X_W(h_s, h_g) = \mathbb{E}_z \max \left\{ J_E(h_g, z), J_W(h_s, h_g) \right\} \tag{20}$$

and

$$X_N(h_g) = \mathbb{E}_z \max \left\{ J_E(h_g, z), J_U(h_g) \right\}, \tag{21}$$

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

Here, z is the success probability for entrepreneurs. Individuals who start their startups, that is, those who choose $J_E(z, h_g)$, succeed in their startups with probability z. Hence, the discrete choice problems in (20) and (21) 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, whereas 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

First, consider the value function for unemployed individuals. The value function for unemployed workers who search for a new job, $J_U(h_g)$ in (21), is formulated as,

$$J_U(h_g) = m \cdot H_W(0, h_g) + (1 - m) \cdot \left[b(h_g) + H_N(h_g) \right] \tag{22}$$

where m is a job-finding probability and $b(h_g)$ is an unemployment benefit, and $H_W(h_s, h_g)$ and $H_N(h_g)$ are the value functions for employed and non-employed individuals defined in (18) and (19). Note that even when they find a new job, they have to start with zero FSHC (i.e., $h_s = 0$) because they are new to the new employer.

Next, consider a potential entrepreneur. The value function for the potential entrepreneur $J_E(h_g, z)$ in (20) and (21) is expressed as,

$$J_E(h_g, z) = -\kappa + z \cdot \left[v^e + H_W(0, h_g)\right] + (1-z) \cdot \left[m \cdot H_W(0, h_g) + (1-m) \cdot H_N(h_g)\right]. \tag{23}$$

In the event of success with a probability of z, they obtain a substantial amount of non-labor income as the founder's benefit. This benefit is calculated as the expected firm value for entrants, denoted as v^e, subtracted by the entry cost κ. Furthermore, successful entrepreneurs transition to working at their own firms. Of note, even in cases of success, they commence with zero FSHC ($h_s = 0$) because they must leave their current employer when initiating a business. Conversely, in the case of failure with a probability of $1-z$, entrepreneurs incur only the entry cost κ as a loss and subsequently engage in a job search. Unlike unemployed individuals described in (22), entrepreneurs are assumed not to be eligible for unemployment benefits $b(h_g)$, which is a common feature in many countries. Given the value function $J_E(h_g, z)$ in (23), the entrepreneurial decisions in (20) and (21) can be interpreted as a form of "free entry condition" employed in firm dynamics models. While the standard free entry condition assumes that the firm value for entrants v^e should equal the entry cost κ, the entrepreneurial decisions in (20) and (21) consider additional costs and benefits associated with starting a business. This includes the opportunity cost of quitting a current job, entailing the loss of FSHC, in addition to considering v^e and κ.[12]

Lastly, the value function for currently employed individuals, $J_W(h_s, h_g)$ in (20), is formulated as,

$$J_W(h_s, h_g) = d \cdot \left[\phi w l_s(h_s, h_g) + J_U(h_g)\right] + (1-d) \cdot H_W(h_s, h_g) \tag{24}$$

where d is the layoff probability. When they are dismissed with probability d, they obtain the severance pay $\phi w l_s(h_s, h_g)$ and become unemployed. Thus, the higher firing tax ϕ in the firm sector is good for workers not only because it lowers the layoff probability d but also because it increases the severance pay.[13]

[12]In contrast to a standard entrepreneurship model like Buera et al. (2011), where entrepreneurs continue as managers of their own firms, the entry decision in this model is significantly simplified, relying solely on the firm value v^e instead of considering the expected value of future profits. However, it is essential to note that, given the assumption of a linear utility function for households, obtaining the firm value in success is almost equivalent to the household's optimization decision of securing a stream of profits in the future.

[13]The probability of being dismissed d is assumed to include voluntary quits in addition to layoff, reflecting

3.3 General Equilibrium

Section 3 is closed by defining a general equilibrium in the economy.[14] As only a rough sketch of equilibrium characterization is provided here, see Appendix E for a more formal characterization of equilibrium and its computation strategy.

Firm-side equilibrium On the firm side, given the mass of entries x^e and the aggregate labor supply L, the aggregate firm dynamics based on firms' optimal behavior provide the layoff probability d, the expected firm value for entrants v^e, the wage rate w, and the growth rate g. We call this equilibrium consisting of (d, v^e, w, g) given (x^e, L) "the firm-side equilibrium." As only the growing firms have opportunities for external innovation, the equilibrium rate of creative destruction τ is characterized by $\tau = F_g\hat{z} + x^e$, where F_g is the share of product lines owned by growing firms and x^e is the entry rate. The aggregate economic growth g is characterized as the average quality improvement, that is, 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* $g = \tilde{z}\tilde{\gamma} + (1-\tilde{z})\tau\hat{\gamma}$.

This proposition is intuitive, as the first and second terms are economic growth stemming from internal and external innovation, respectively. This result for the growth rate is similar to a standard Schumpeterian growth model, except that although internal innovation $\tilde{z}$ promotes economic growth through quality improvement, it possibly suppresses economic growth by discouraging external innovation through the escape-entry effect.

Household-side equilibrium On the household side, given the interest rate r, the layoff probability d, the expected firm value for entrants v^e, the wage rate w, and the growth rate

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the fact that the difference between them is murky in reality. 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 involuntary layoffs in many cases. Engbom (2022) takes a similar approach to the distinction between voluntary quit and layoffs.

[14] 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 Appendix D, while a discrete-time version of the model looks far more complicated and cumbersome, the firm-side equilibrium is characterized by exactly the same first-order conditions as in a continuous-time version.

g, the optimal household behavior leads to the policy functions for FSHC and GHC accumulation and entrepreneurial decisions, as well as the associated stationary distribution of FSHC and GHC, which provide the equilibrium mass of entrants x^e and aggregate labor supply L. Specifically, given the stationary distributions for employed and non-employed individuals, $\mu_w(h_s, h_g)$ and $\mu_n(h_g)$, the aggregate labor supply is given by,

$$L = \int_{h_s, h_g} l_s(h_s, h_g) \, d\mu_w(h_s, h_g) \tag{25}$$

We call this equilibrium consisting of (x^e, L) given (d, v^e, w, g) "the household-side equilibrium."[15] 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.

General equilibrium First, for simplicity, it is assumed that the interest rate r is fixed, that is, a small open economy assumption, and $\beta = 1/(1+r)$. Then, in the general equilibrium, all the aggregate variables are endogenously and simultaneously determined to be consistent with both the firm- and household-side equilibrium.

Definition 1 *(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 provides 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 provides x^{e*} and L^*.*

As evident from the definition, the general equilibrium in the model is characterized by the labor market clearing through the equilibrium wage rate and labor supply/demand, denoted as w^* and L^*. Despite the labor market being the sole market in this general equilibrium framework, the firm and household sectors interact dynamically through entrepreneurship and firm dynamics. For example, an increase in entrants (x^e) in the household sector intensifies creative destruction in the firm sector. This heightened creative destruction leads to an increase in the layoff probability (d) but a decrease in the

[15] The definition of aggregate labor supply in (38) implicitly assumes, for tractability in general equilibrium analysis, that the composition across FSHC and GHC at a firm or a product line is immaterial. Exploring the effects of their composition at the firm level is an interesting avenue for future research.

entrant's expected firm value (v^e), thereby influencing the entrepreneurial motive in the household sector (i.e., affecting x^e). In the subsequent section, we conduct a quantitative assessment of the effects of EPL on entrepreneurship, firm dynamics, and economic growth through comparative statics by considering the intricate interactions between the firm and household sectors within the general equilibrium framework.

4 Quantitative Analysis

This section undertakes a quantitative analysis using the model from the previous section, with a primary focus on investigating the impacts of employment protection legislation (EPL) on entrepreneurship, firm dynamics, and economic growth. Initially, the model parameters are calibrated based on Japanese firm- and household-level microdata. The calibration process involves utilizing firm-level microdata in Japan for indirect inference to determine key parameters in the firm sector. Subsequently, the effects of EPL are examined through comparative statics. Given that Japan is characterized by particularly stringent EPL, the quantitative exercise assesses the effects of entirely eliminating EPL in Japan, akin to the conditions observed in the U.S.

4.1 Calibration and Indirect Inference

In our calibration based on Japanese data, first, some firm parameters are calibrated using macro data or the estimation results of previous empirical studies. Then, the remaining firm parameters are calibrated through indirect inference to minimize the gap between model-implied moments and empirical moments obtained from data. Finally, household parameters are calibrated using estimations derived from household-level microdata.

Calibration for Firm Parameters

Some parameters 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 $\rho = 0.104$.[16] Third, the interest rate r is set to 0.04 as a standard value. 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 remaining 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 the remaining nine parameter values, $(x^e, \tilde{\gamma}, \hat{\gamma}, \tilde{\xi}, \hat{\xi}, \psi, \chi, \nu, \phi)$, to minimize the gap between the model-implied values and the target values for the moment conditions.[17] Following the previous studies, the loss function to measure the gap is defined as,

$$\sum_{i=1}^{17} \frac{|\text{model}(i) - \text{data}(i)|}{|\text{data}(i)|} \tag{26}$$

where model(i) and data(i) are the model-implied values and the target values in data for moment i, respectively. Regarding the moment conditions, first, we utilize the estimation results on firm growth by age in Figure 2 for age group 1 to 10 (i.e., firm age from 1 year to 50 years). Then, we also use the seven moments listed in Table 1: (i) the entry rate, (ii) the aggregate growth rate, (iii) the R&D to GDP ratio, (iv) the internal R&D ratio, (v) the layoff probability, and (vi) the internal R&D ratio and layoff probability without EPL. The first five moment conditions with EPL are matched with Japanese data, whereas the last two moments without EPL are matched with the U.S. data. As there are 17 moments (10 moments from firm growth by age and 7 from others), the 9 estimated parameters are over-identified. Appendix F provides detailed definitions for each moment in the data, outlines the procedure for computing their model-implied values, and discusses which moments are intended to identify specific parameter values. 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 (26).

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

[17]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.

Table 1: 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	67.2	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 2 for each moment, along with the empirical targets in the data. See Appendix F for more detail on definitions of each moment and the computation of model-implied values and target empirical moments in the data.

The results from indirect inference demonstrate that the model-implied values closely replicate the empirical target moments. First, in Figure 2 in Section 2, the thick dashed line represents the model-implied average growth rate by age, whereas the estimated values are illustrated by the thin line with circles. The figure demonstrates that the model successfully replicates the relationship between firm growth and age under the estimated parameters. Specifically, the model captures the observed pattern where growth rates are higher for younger firms and gradually decline as firms age.[18] Second, Table 1 presents model-implied values under the estimated parameters for other moments alongside empirical targets from the data. This comparison reveals that the model-implied values for other moments closely align with their empirical counterparts.

Table 2 presents the estimated parameter values obtained through indirect inference. Several observations are noteworthy. First, the cost for external innovation $\hat{\xi}$ is around 25 times larger than that for internal innovation $\tilde{\xi}$. Second, in return for the higher cost, the step size for external innovation $\hat{\gamma}$ is estimated to be substantially larger than internal innovation $\tilde{\gamma}$. The higher cost and larger step size for external innovation are consistent with previous studies.[19] Compared with the extant literature, it is worth noting that the step size for internal innovation is relatively small in our estimation ($\tilde{\gamma}$ =0.1%). This divergence can be attributed to our modeling of internal innovation as a continuous improvement of quality, incorporating the escape-entry effects. While internal innovation has two benefits—quality improvement and the escape-entry effects—most previous studies,

[18] As emphasized in Section 2, in Figure 2, both the empirical estimation and the model-implied values are subject to the same survival bias. See Appendix F for the way of computing the model-implied values containing the same survival bias as in data.

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

Table 2: Parameter Values Estimated by Indirect Inference

x^e	$\tilde{\gamma}$	$\hat{\gamma}$	$\tilde{\xi}$	$\hat{\xi}$	ψ	χ	ν	ϕ
.052	.001	.116	.157	3.875	.029	1.259	.043	.555

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 (26) by the Nelder-Mead algorithm.

not accounting for the latter, possibly estimate the first benefit to be larger.

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 in indirect inference. In addition, the wage rate w and the expected firm value for entrants v^e are calibrated to the firm-side equilibrium values under the calibrated parameters in Table 2. 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 the estimation results using the Japanese household-level microdata. 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 potential wages, $b(h_g) = 0.4w \cdot l_s(0, h_g)$. The job-finding rate for unemployed workers m in (22) is calibrated to 0.70 so that the unemployment rate equals that in Japan for the last three decades, 3.0%. On the parameters for human-capital accumulation by the human-capital investment function (17), the curvature α is set to 0.8 based on previous studies including Guvenen et al. (2014).

The other four parameters regarding human capital accumulation, $(\delta_s, \delta_g, A_s, A_g)$, in (17) are calibrated using the estimation results for the relationship between wages and job experience/tenure in Japan. Following the previous literature, the effects of (i) the length of job tenure for a particular employer and (ii) the total and industry job experience, are used as a proxy for FSHC and GHC, respectively. In a companion paper, Katagiri (2023) estimates the relationship between wages and job experience/tenure in Japan using household-level microdata and shows that 10- and 20-year work experience brings approximately 45% and 73% higher wages, respectively, in Japan. Furthermore, it shows that around 40% of the wage increase is accounted for by the effects of job tenure (i.e., FSHC) in contrast to the U.S. case, where job tenure plays an almost negligible role (e.g., Kambourov and Manovskii, 2008).[20] To replicate those features in the model, our calibration assumes that $\delta_s = 0.0$ and $\delta_g = 0.02$ 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. Appendix G explains the relationship between wages and job tenure/experience in Japan in more detail and shows that the process of human capital accumulation is well replicated under the calibrated values. Given those parameters with respect to human capital accumulation, the scale parameter $\bar{h}$ in the labor supply function (16) 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.

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 the first 5 years in the U.S. and other countries.[21] Second, given σ_z and v^e, the entry cost κ is calibrated so that the aggregate entry rate x^e in (37) is equal to the estimated value of x^e in Table 2. Note that because x^e is estimated using the entry rate of firms in Japan as a target moment, the calibrated value for the entry cost κ is also consistent with the entry rate. Third, given that the mass of firms is normalized to one, the mass of households, M_h, is set to 16.3. As a summary of calibration for household parameters, Table 3 shows the calibrated values and calibration strategy for each parameter.

[20] Doepke and Gaetani (2023) identify significant effects of job tenure on wages in a German labor market as well, suggesting that FSHC plays a crucial role in advanced economies other than the U.S.

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

Table 3: 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 retirement, λ	1/40	retired in 40 years
Unemployment benefit, b	0.40	40% of current wages
Job-finding rate, m	0.70	Unemployment rate = 3.0%
Curvature for HC inv., α	0.80	Guvenen et al. (2014)
Depreciation for FSHC, δ_g	0.00	Wage with 20-year tenure = 29%
Depreciation for general HC, δ_g	0.02	Wage with 20-year job exp. = 73%
Efficiency: FSHC inv., A_s	0.150	Wage with 10-year tenure = 18%
Efficiency: general HC inv., A_g	0.066	Wage with 10-year job exp. = 45%
Scale parameter for labor, $\bar{l}^s$	0.029	$L = 1.0$ (Firm-side equilibrium)
Entry cost, κ	0.263	Entry rate $x^e = 0.052$ (See Table 2)
Dist. of success prob., σ_z	0.20	The failure rate = 50%
Mass of households, M_h	16.3	# of workers relative to # of firms

4.2 Comparative Statics: Effects of Employment Protection

This subsection gives the main quantitative result of this study, specifically the results of comparative statistics assessing the impact of EPL on entrepreneurship, firm dynamics, and economic growth. The underlying concept for comparative statics closely follows that of Akcigit et al. (2021). Given that the baseline economy is calibrated to Japan, a nation characterized by the most stringent EPL among advanced economies, the policy exercise poses the question: What would happen if EPL in Japan were entirely eliminated, as is the case in the U.S.? For this purpose, we set the layoff tax ϕ to zero in the hypothetical case and compare the resulting economic growth rate, entrepreneurship, and firm dynamics with those observed in the baseline. In comparative statics, we compute the general equilibrium in the hypothetical case by iteratively computing the firm- and household-side equilibrium until they converge to be consistent with each other. See Appendix E for details on the computational strategy for the comparative statics.

Firm Sector: Employment Protection, R&D Investment, and Firm Dynamics

Table 4 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 by $\tilde{\xi}\tilde{z}^{\tilde{\eta}}/(F_g\hat{\xi}\hat{z}^{\hat{\eta}} + \tilde{\xi}\tilde{z}^{\tilde{\eta}})$, (3) the entry rate of firms $(1-\tilde{z})x^e/M_f$, (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, that is, $\phi = 0$ (the second and third rows). The general equilibrium simulation in the second row considers the changes in the number of entrants and aggregate labor supply in the household sector, whereas the partial equilibrium simulation in the third row does not (i.e., the firm-sector equilibrium). The partial equilibrium focusing only on the firm sector is denoted by PE_F in Table 4 to distinguish it from that focusing only on the household sector, PE_H. The firm value in the fifth column is normalized to one in the baseline to highlight the effects of EPL.

Column (1) shows that eliminating EPL would lead to an increase in the layoff probability d as expected, rising from 7.2% to 12.0%. There are several reasons: First, without the firing tax, 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

Table 4: Results of Comparative Statics: Firm Sector and Growth

	(1) Layoff	(2) In. R&D	(3) Entry rate	(4) Growth	(5) Firm val.
Baseline ($\phi > 0$)	7.2	67.2	4.4	0.70	1.00
No EPL ($\phi = 0$) in GE	12.0	48.8	7.6	1.12	0.95
No EPL ($\phi = 0$) in PE_F	10.4	39.5	5.7	0.92	1.15

Note: The table shows the results of comparative statics for the layoff probability d, the internal R&D ratio defined by $\tilde{\xi}\tilde{z}^{\tilde{\eta}}/(F_g\hat{\xi}\hat{z}^{\hat{\eta}}+\tilde{\xi}\tilde{z}^{\tilde{\eta}})$, the entry rate of firms $(1-\tilde{z})x^e/M_f$, 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, that is, $\phi = 0$ (the second and third rows). The general equilibrium simulation in the second row considers changes in the number of entrants, as well as aggregate labor supply, in the household sector, whereas the partial equilibrium simulation in the third row does not and focuses only on the firm sector.

layoffs associated with creative destruction. Third, more firm entries (column 3) intensify creative destruction, thus further increasing layoffs associated with creative destruction.[22]

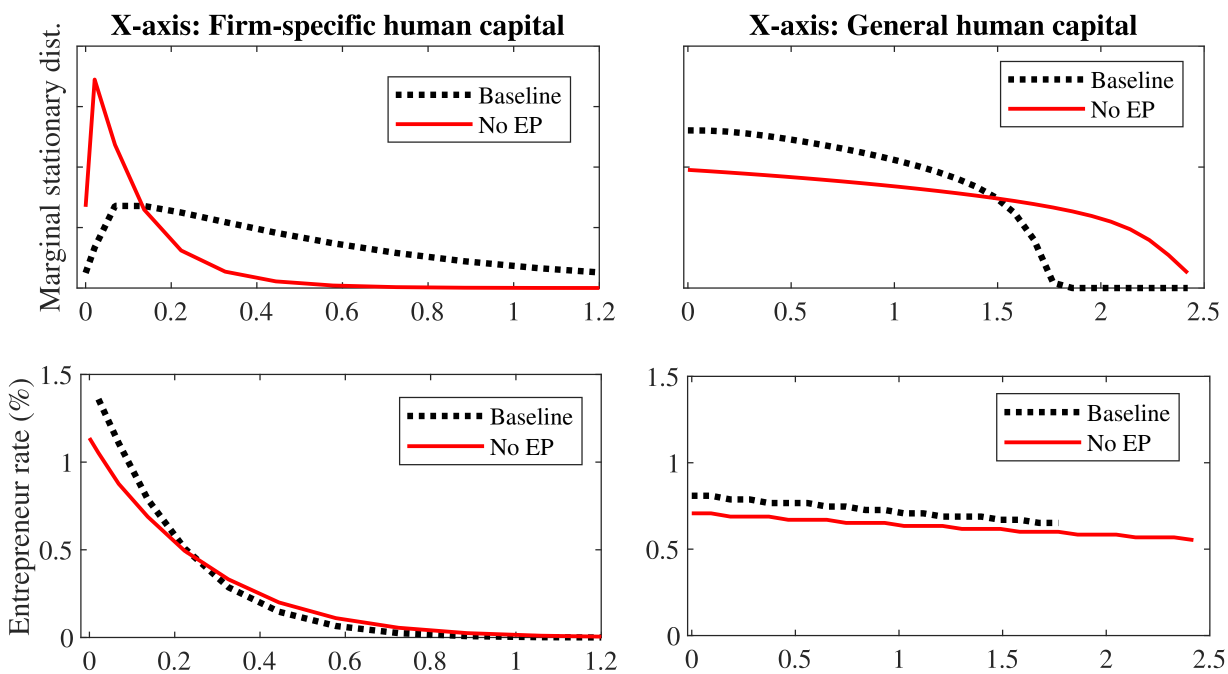
Regarding the effects on firm dynamics, column (3) shows that eliminating EPL would result in a more than 1.7-fold increase in the entry rate of firms, rising from 4.4% to 7.6%. The absence of EPL weakens escape-entry effects due to lower internal R&D by incumbent firms (column 2), thereby facilitating new entrants in establishing firms. Moreover, the removal of EPL stimulates entrepreneurship in the household sector, contributing to a further increase in the entry rate. The partial equilibrium in the third row, which does not consider the general equilibrium effect arising from increased entrepreneurship in the household sector, shows only a modest 1.3% point increase in the entry rate from the baseline. This underscores the crucial role of the general equilibrium effect through entrepreneurship in understanding the impact of EPL reform on firm dynamics.

Household Sector: Employment Protection, Entrepreneurship, and Human Capital

Why does the removal of EPL stimulate entrepreneurship in the household sector? Changes in HC accumulation are key to understanding the effects on entrepreneurship. Specifically, the absence of EPL encourages workers to accumulate more GHC while reducing FSHC,

[22] As discussed in Appendix F, the layoff probability and the internal R&D ratio in the case without EPL are used as the target values in indirect inference. Consequently, the comparative statics results in columns (1) and (2) do not imply a quantitatively good model fit. Rather, they are closely aligned with the corresponding values observed in the U.S. data by construction. In other words, the comparative statics examine the effects of EPL reform on entrepreneurship and economic growth under the assumption that the EPL reform brings these two variables down to the U.S. levels.

Figure 4: 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 panels) and general human capital (the right panels). In all panels, the black dashed lines and red bold lines show those for the baseline case with EPL and the hypothetical case without EPL, respectively. The panels in the second row show the policy functions with respect to only one variable (FSHC or GHC) by fixing the other variable at the average level.

decreasing the share of FSHC in total HC from 43% to 11%. Given that FSHC is valuable only at the current employer, shifting from FSHC to GHC in the face of the higher layoff probability is intuitive. Note that the reduced importance of FSHC in the hypothetical case without EPL is consistent with the previous empirical studies, which show that FSHC plays a limited role in the U.S. (e.g., Kambourov and Manovskii, 2008).[23][24]

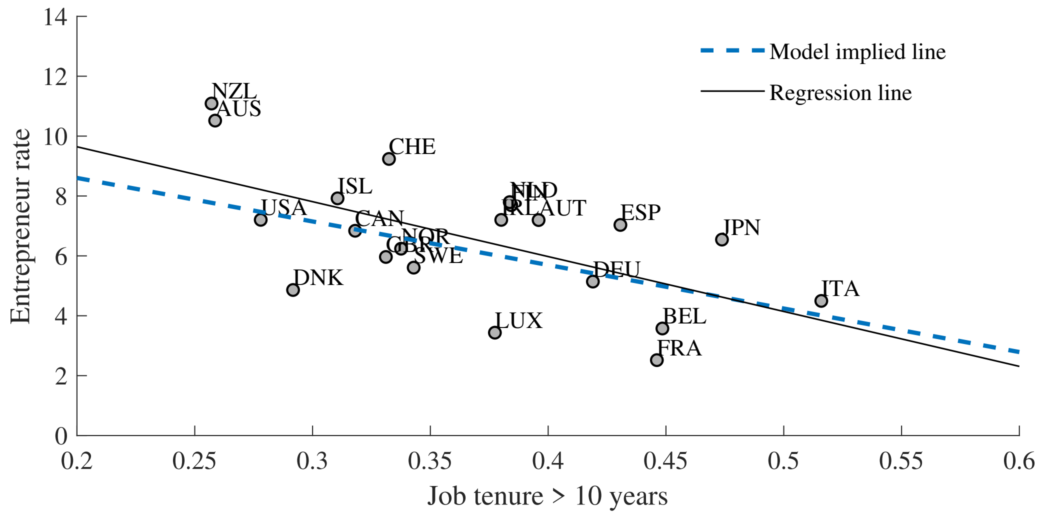
The shift from FSHC to GHC stimulates entrepreneurship through a decrease in the opportunity cost for the household to start businesses, thus increasing firm entries. Figure 4 shows the marginal stationary distribution (the two panels in the first row) and the entrepreneurial rate (the two panels in the second row) with respect to FSHC (the left panels) and GHC (the right panels). First, the stationary distributions in the first row indicate that eliminating EPL would induce individuals to shift their HC accumulation from FSHC to GHC, as evidenced by the dashed black lines compared to the bold red lines. Second, the bottom two panels indicate that the entrepreneurial rate significantly decreases with respect to FSHC (the left-bottom panel), whereas it remains nearly constant with respect to GHC (the right-bottom panel). This result is intuitive because the employed individuals who have accumulated FSHC face a substantial loss of human capital when leaving their current jobs, thus hesitating to start businesses.[25] Combining these two observations, the figure suggests that eliminating EPL decreases the opportunity cost for employed individuals to start businesses by shifting their HC accumulation from FSHC to GHC, thereby stimulating entrepreneurship. Furthermore, the entrepreneurial rates *given the level of human capital* are nearly identical between the two cases with and without EPL. Hence, while eliminating EPL stimulates individual entrepreneurship through various channels in the model, the figure implies that the distributional shift of HC accumulation from FSHC to GHC mainly accounts for the increase in the *aggregate* entrepreneurial rate.

[23] See also Hashimoto and Raisian (1985) and Parent (2000). In a companion paper, Katagiri (2023) shows that the endogenous choice between FSHC and GHC in response to different layoff probability quantitatively accounts for the difference in the relationship between wages and job tenure/experience across Japan and the U.S. and that eliminating EPL enhances labor market fluidity by encouraging the accumulation of GHC, which is beneficial to incumbent firms as well.

[24] Lazear (1979) provides a theoretical model where EPL encourages a long-term contract with back-loaded wage profiles, which leads job tenure to positively impact wages even without FSHC. Nevertheless, employed individuals face a large opportunity cost for quitting a current job, thus leading to a similar conclusion in this study.

[25] The entrepreneur rate is slightly decreasing with respect to GHC because it increases the wage rate, thus it is more attractive to remain an employed worker.

Figure 5: Job Tenure and Entrepreneurship



Note: The figure shows the relationship between the length of job tenure and entrepreneurship in data among advanced economies (the scatter plots) along with the model-implied relationship based on the comparative statics (the blue dashed line).

The changes in the number of entrepreneurs resulting from EPL reform in the comparative statics are quantitatively in line with the relationship between the length of job tenure and the entrepreneur rate in data. Figure 5 illustrates this relationship in data among advanced economies (the scatter plots) along with the model-implied relationship based on the comparative statics (the blue dashed line). As more stringent EPL extends average job tenure by lowering layoff probability, job tenure length is negatively correlated with entrepreneurship in both data and the model. The figure indicates that the model-implied relationship is quantitatively aligned with the empirically observed relationship, suggesting that the EPL reform in the comparative statics accounts for the empirically observed negative effects of EPL on entrepreneurship.

Does Employment Protection Suppress Economic Growth and Welfare?

Column (4) in Table 4 indicates that eliminating EPL would raise economic growth by approximately 40–50 bps, increasing it from 0.70% to 1.12%. Given that EPL encourages incumbent firms to pursue the escape-entry effects, eliminating EPL weakens such an incentive, facilitating both incumbent firms' and new entrants' external innovation through expanding their opportunities. Furthermore, without EPL, more firm entries stimulate creative destruction by themselves but also by increasing the share of younger firms, that is, firms with more growth potential. Specifically, the share of product lines owned by growing firms F_g would rise from 57.2% to 68.9%, thus fostering economic growth through more creative destruction by younger firms.

Given the effects on economic growth, eliminating EPL positively affects households' welfare in the long run, whereas its effects are ambiguous in the short run. Eliminating EPL may adversely affect household consumption in the short run, as it decreases the substantive aggregate labor supply L by disturbing FSHC accumulation, as well as increasing the unemployment rate from 3.0% to 4.9%. The higher unemployment rate, driven by higher layoff probability, is quantitatively consistent with the fact that the average unemployment rate in the U.S. is higher than that in Japan by approximately 2%. In the long run, however, because the wage rate and aggregate productivity grow at the same rate, the EPL reform should have positive cumulative effects on household income and consumption. Specifically, eliminating EPL leads to an approximately 3% point increase in the household's welfare measured by:

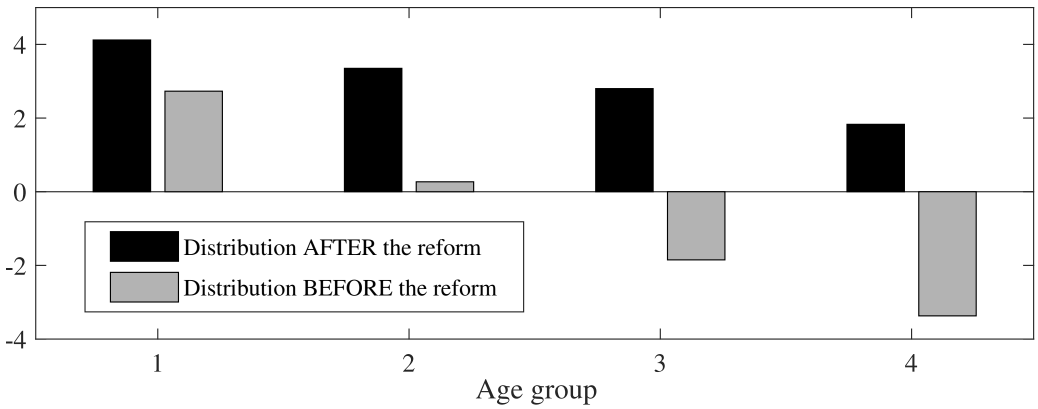
$$\text{Welfare} = \int_{h_s,h_g} H_W(h_s,h_g)\, d\mu_w(h_s,h_g) + \int_{h_g} H_N(h_g)\, d\mu_n(h_g) \tag{27}$$

where $H_W(h_s,h_g)$ and $H_N(h_g)$ are the value functions for employed and non-employed individuals in (18) and (19). Given that we use a linear utility function, the above welfare is equivalent to the discounted sum of lifetime consumption. Note that eliminating EPL *decreases* welfare by approximately 7% in the partial equilibrium because the effects on economic growth, driven by more innovations in the firm sector, are not considered, which suggests that higher future income plays a crucial role in the welfare gain resulting from EPL reform.

Whereas the comparative statics indicate a significant welfare gain from the EPL reform to eliminate it, a more relevant measure for policymakers may be the welfare gain given the stationary distribution of human capital *prior to eliminating EPL*. Given the considerable differences in the distribution across generations, it is worthwhile to calculate the welfare gain by generation.[26] Figure 6 presents the welfare gains by the 10-year age group (from

[26]The welfare gain by age is computed using a slightly modified version of the model, where all individuals are assumed to move from age group i to $i+1$ with probability 1/11. Individuals are retired with the same probability when they are in age group 4, which implies that individuals are retired for 40 years on average

Figure 6: Welfare Gain by Age Group



Note: The figure shows the welfare gain by age group. In the model, all individuals are assumed to move from age group i to $i + 1$ with probability 1/11, and they are retired with the same probability when they are in age group 4, which implies that individuals are on average retired for 40 years as in the baseline model. In the figure, the black and gray bars show the welfare gains by age group using the stationary distribution of human capital after and before eliminating EPL, respectively.

group 1 for twenties to group 4 for fifties and over) using the stationary distribution of human capital after and before eliminating EPL (the black and gray bars). The figure implies that (i) eliminating EPL results in substantial welfare gains for all generations in the long run, but (ii) given the distribution of human capital accumulation before the reform, eliminating EPL would decrease welfare for workers in age groups 3 and 4 (i.e., forties and fifties). This decline in welfare for older generations occurs because they have already accumulated a significant amount of FSHC under the assumption of EPL existence and will not live long enough to benefit from economic growth. Thus, while eliminating EPL would eventually entail some welfare gains for all generations, it requires strong and forward-looking political leadership.

General Equilibrium vs. Partial Equilibrium

Table 4 implies that the general equilibrium effects play an important role in assessing the effects of EPL on firm dynamics and economic growth. Specifically, in partial equilibrium in the third row, where changes in the number of entrants and aggregate labor supply in the household sector are not considered, the positive effects on the economic growth rate

as in the baseline model.

become approximately half 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. Moreover, layoff probability is low in the partial equilibrium analysis, which implies that the changes in layoffs and new entries influence each other in general equilibrium.

By contrast, the partial equilibrium analysis focusing only on the household sector possibly overestimates the effects of EPL on entrepreneurship. Specifically, in the partial equilibrium analysis, which ignores the general equilibrium effects through wages and firm values, the increase in the number of entrepreneurs is significantly overestimated by more than double, that is, 61% in GE vs. 125% in PE. This overestimation occurs because the partial equilibrium analysis fails to consider the *decreases* in firm value resulting from intensified creative destruction (column 5 in Table 4). That is, eliminating EPL intensifies creative destruction by increasing firm entries, exposing incumbent firms to a greater risk of losing their product lines after entry, and discouraging the household from starting businesses.[27] The substantial overestimation of the number of entrepreneurs in partial equilibrium highlights a potential pitfall associated with employing a partial equilibrium model for policy analysis on entrepreneurship.

Robustness Check

We conduct robustness checks with respect to model specifications in the household sector. Specifically, the robustness checks examine the case with (1) a general CES form of labor supply function, (2) endogenous labor supply, or (3) an endogenous choice between working and accumulating human capital. In all cases, the parameter values are recalibrated to match the target values. The same comparative statics for eliminating EPL are then conducted to assess the sensitivity to the changes in (1), (2), and (3). The results of the robustness checks, detailed in Appendix H, indicate that while the policy effects on entrepreneurship and economic growth may vary in magnitude, eliminating EPL consistently stimulates entrepreneurship and firm dynamics, facilitating economic growth.

[27] Some previous studies, including Klette and Kortum (2004), also highlight that more entries are negative to incumbent firms because they decrease incumbent firms' values due to intensified creative destruction.

Table 5: Results of Policy Experiment

	(1) Entrepreneur	(2) In. R&D	(3) Firm value	(4) Growth
Baseline	1.00	67.2	1.00	0.70
Entry subsidy	1.18	71.7	0.92	0.73
R&D subsidy	0.85	67.8	1.00	0.63

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

4.3 Policy Experiment: Can We Stimulate Growth without Easing EPL?

This section conducts policy experiments to investigate ways to stimulate entrepreneurship and economic growth without eliminating EPL. This is an important policy question, given the political challenges associated with eliminating EPL in many countries. In the policy experiment, the following two policies are examined. First, we investigate the impact of a subsidy aimed at directly supporting entrepreneurship by reducing the entry cost κ in (23) by 10%. Second, we examine the effects of granting tax benefits to incumbent firms conducting R&D by reducing the internal and external R&D costs, $\tilde{\xi}$ and $\hat{\xi}$, by 10%.

Table 5 shows the results of policy experiments. Columns (1) and (4) reveal that the entry subsidy policy, supporting entrepreneurs by reducing entry costs, increases the number of entrepreneurs by 18% and raises the economic growth rate by 3bps. Despite the large support, the moderate impact on entrepreneurship and growth is attributed to general equilibrium effects, notably the increase in internal R&D by incumbent firms and the decrease in firm value, both discouraging new entries. First, as long as stringent EPL exists, an increase in new entrants encourages incumbent firms to pursue the escape-entry effects by increasing internal R&D (column 2), thus discouraging new entries. Second, the average firm value decreases due to more fierce creative destruction as in the case of eliminating EPL in Table 4, thereby discouraging entrepreneurship (column 3). This implies that if we disregard the general equilibrium effects through the increase in internal R&D and the decline in firm value, the policy effects on entrepreneurship would be significantly overestimated. Furthermore, while not shown in the table, the entry subsidy has larger effects on economic growth in the absence of EPL, implying that as long as stringent EPL exists, policy support for entrepreneurs does not fully exert its policy effects.

Also, Table 5 shows that uniform tax benefits to incumbent firms' R&D expenditure have almost negligible, even slightly negative, effects on economic growth (-7bps) by discouraging entrepreneurship (-15%). Given that more than 60% of R&D investment by incumbent firms is internal, the R&D subsidy on incumbent firms does not significantly promote growth but helps them survive longer. Consequently, the higher survival rate of incumbent firms decreases new entries by reinforcing the escape-entry effect and deters entrepreneurship by encouraging workers to accumulate more FSHC. The result aligns with findings from Acemoglu et al. (2018), indicating that, although tax policies increase incumbent firms' R&D expenditure, their positive effects are counteracted by discouraging new entrants' innovation.

5 Concluding Remarks

This study explores the impact of employment protection legislation (EPL) on entrepreneurship, firm dynamics, and economic growth within a Schumpeterian growth model. The study reveals that EPL influences not only firms' innovation and employment attitudes but also households' human capital accumulation and entrepreneurship, leading to significant effects on economic growth through general equilibrium dynamics. Through quantitative analysis using microdata from Japan, the findings suggest that eliminating EPL in the country could boost economic growth by approximately 40 basis points, primarily by encouraging entrepreneurship. The study also underscores the potential pitfalls of partial equilibrium analyses that focus solely on the household or firm sectors, indicating that such approaches might underestimate or overestimate the effects of EPL. In addition, policies directly supporting entrepreneurs or incumbent firms' R&D investments may have limited impacts on economic growth as long as stringent EPL remains in place.

Future research should further investigate the adverse effects of EPL on economic growth through other channels, such as impacts on occupational mobility and labor force misallocation across firms. Furthermore, this study exclusively focuses on quantifying the adverse effects of EPL on economic growth, while disregarding the potential benefits associated with EPL. Thus, examining EPL's influence on household welfare, particularly in terms of mitigating income risk due to dismissals, using more realistic risk-averse utility functions in an incomplete market model could provide a comprehensive cost-benefit analysis for discussing the optimal level of EPL.

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Appendix A 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). Appendix A explains how to construct the data, including data sources, and conducts more formal regression,

Table 6: 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.

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 used 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 used 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 used the share of workers whose tenure is longer than 10 years in the "OECD Employment and Labour Market Statistics." The average value for 2010-2020 gives cross-country data on job tenure for 36 countries.

The regression analysis in Table 6 shows that EPL suppresses entrepreneurship while, on average, it leads to longer job tenure. As shown in Figure 1, the negative relationship between EPL and entrepreneurship is clear only among advanced economies (column 3), whereas it is statistically significant for the full sample after controlling for the income level (column 2).

Appendix B Empirical Age-growth Relationship in Japan

As is shown by Figure 2 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. Additionally, the estimation in Figure 3 shows that the R&D investment by younger firms has positive effects on the upper tails of their sales growth, whereas that by older firms positively affects only the lower tails. Appendix B provides further details about the firm-level microdata used for estimation and shows more results of regression analyses on the firm age-growth relationship and the role of R&D investment by age to check the robustness.

Data and Dummy Variables for Estimation

We used 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. For other empirical studies using this confidential firm-level microdata, see, for example, Fukao et al. (2017). While the dataset does not contain many small firms whose employees are less than 50, excluding very small firms is in line with our study's research motivation because our main focus was on innovation and its effects on economic growth.[28]

To estimate the relationship between firm growth and age, the annual sales growth rate was 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. Furthermore, the firm age is calculated by subtracting the year of the firm's foundation obtained in the dataset from the current year. Then, all firms were categorized into 15 five-year bins according to their age to construct dummy variables $dum(\bar{a})_{i,t}$ where $\bar{a} = 1, \cdots, 15$,

$$dum(\bar{a})_{i,t} = \begin{cases} 1 & \text{if } \ 1 + 5(\bar{a} - 1) \leq \text{Firm } i\text{'s age in time } t \leq 5\bar{a} \\ 0 & \text{otherwise} \end{cases} \tag{28}$$

Similarly, we constructed time-invariant dummy variables with respect to year of establishment (i.e., cohort), $dum(\bar{e})_i$ where $\bar{e} = 1, \cdots, 12$,

$$dum(\bar{e})_{i,t} = \begin{cases} 1 & \text{if } \ 1 + 5(\bar{e} - 1) \leq \text{Firm } i\text{'s year of establishment} \leq 5\bar{e} \\ 0 & \text{otherwise} \end{cases} \tag{29}$$

Estimation for the Relationship between Firm Age and Growth

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,

$$\Delta \ln(\text{Sale}_{i,t}) = \alpha + Y_t + \sum_{\bar{a}=1}^{15} \beta_{\bar{a}} dum(\bar{a})_{i,t} + \sum_{\bar{e}=1}^{12} \delta_{\bar{e}} dum(\bar{e})_{i,t} + \gamma X_t + \varepsilon_{i,t} \tag{30}$$

[28] Previous studies with similar motivation, such as Lentz and Mortensen (2008) and Akcigit and Kerr (2018), also exclude significantly small firms from their sample due to data availability. For example, Akcigit and Kerr (2018) limits their sample to firms with 500 or more employees.

where Y_t is a time dummy. In the baseline estimation, the difference in the log of sales, $\Delta \ln(\text{Sale}_{i,t})$, is used as a proxy of firm growth. X_t is a vector of control variables including the log of shareholder's capital in $t-1$ as a proxy for firm size, $\ln(\text{cap}_{i,t-1})$, and the industry dummies based on two-digit industry codes. The coefficients of our interest are $\beta_1, \cdots, \beta_{15}$, which capture the difference in sales growth by age.

Table 7 shows the estimation results for the relationship between firm age and growth in (30). Column (1) shows the estimation results without controlling for any effects, whereas columns (2)–(4) show those with some control variables. All the estimation results in column (1)–(4) of Table 7 imply that the growth rate of younger firms is higher than that of older firms, as in previous empirical studies using other countries' data. For example, 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 around 5% on average. The estimation results also suggest that the average firm growth rate gradually decreases as firms age and that the relationship between firm age and growth becomes almost flat when firm age surpasses 20-30 years. The table shows that those features regarding the relationship between firm age and growth are almost unchanged under various specifications in columns (1)-(4). Specifically, the estimation results controlling for the industry and/or cohort effects in columns (2) and (3), as well as those controlling for firm size in column (4), provide almost the same results as those without controlling for any effects in column (1). In particular, while the coefficient for firm size is positive and statistically significant, the relationship between firm age and growth is almost unchanged from the case without controlling for firm size.

Among those estimation results, the estimation results in column (4), where we control for firm size by stockholder's capital and cohort and industry effects by the dummy variables, are used as the target values in the quantitative analysis. The estimated $\beta_{\bar{a}}$ in column (4) are shown in Figure 2 in the main text and used as the empirical moments to be matched in indirect inference.

Survival Bias and Median Estimation

As highlighted in the main text, the estimation results in columns (1)–(4) are potentially biased due to survival bias, as younger firms facing negative shocks tend to exit and are not retained in the sample compared with older firms. To consider the possibility of survival bias, we conducted a robustness check as follows. First, we used a %change of sales, rather than the first difference in the log of sales, as a measure of firm growth and defined missing firms' growth rate as -100%. Then, we ran a quantile regression for the 50-percentile (i.e., median). We use a median regression instead of a standard OLS in order to avoid overestimating the effects of firms dropping out of the sample. Specifically, given that many small and younger firms cease responding to the survey due to reasons other than exits, counting all missing firms' sales growth as -100% would exaggerate their effects.[29] However, in the case of a median regression, including the exiting firms in the sample influences the estimation results only by increasing the number of firms below the median. In the median estimation, we first residualized the %changes of sales by regressing them on the

[29] In fact, when we include missing firms in the sample and run a standard OLS regression of (30) using %changes of sales as a dependent variable, younger firms' growth rate is significantly lower than older firms' growth rate.

Table 7: Empirical Relationship between Firm Growth and Age

	(1) $\Delta \ln(Sale)$	(2) $\Delta \ln(Sale)$	(3) $\Delta \ln(Sale)$	(4) $\Delta \ln(Sale)$	(5) $\%\Delta(Sale)$
$\bar{a}$=1	0.050**	0.047**	0.049**	0.049**	0.051**
	(0.004)	(0.004)	(0.006)	(0.006)	(0.001)
$\bar{a}$=2	0.034**	0.031**	0.032**	0.032**	0.053**
	(0.002)	(0.002)	(0.005)	(0.005)	(0.001)
$\bar{a}$=3	0.025**	0.022**	0.021**	0.021**	0.050**
	(0.002)	(0.002)	(0.005)	(0.005)	(0.001)
$\bar{a}$=4	0.025**	0.022**	0.019**	0.019**	0.046**
	(0.001)	(0.001)	(0.004)	(0.004)	(0.000)
$\bar{a}$=5	0.019**	0.017**	0.012**	0.012**	0.041**
	(0.001)	(0.001)	(0.004)	(0.004)	(0.000)
$\bar{a}$=6	0.012**	0.010**	0.005	0.005	0.034**
	(0.001)	(0.001)	(0.004)	(0.004)	(0.000)
$\bar{a}$=7	0.010**	0.008**	0.003	0.003	0.031**
	(0.001)	(0.001)	(0.003)	(0.003)	(0.000)
$\bar{a}$=8	0.007**	0.006**	0.001	0.001	0.026**
	(0.001)	(0.001)	(0.003)	(0.003)	(0.000)
$\bar{a}$=9	0.005**	0.004**	0.001	0.001	0.022**
	(0.001)	(0.001)	(0.003)	(0.003)	(0.000)
$\bar{a}$=10	0.005**	0.004**	0.002	0.002	0.020**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.000)
$\bar{a}$=11	0.002	0.001	-0.001	-0.000	0.018**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.000)
$\bar{a}$=12	0.002*	0.002	0.001	0.001	0.014**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.000)
$\ln(cap_{t-1})$				0.001**	
				(0.000)	
Industry	No	Yes	Yes	Yes	-
Cohort	No	No	Yes	Yes	-
Obs.	667401	667401	667401	667401	701793
R^2	0.050	0.053	0.053	0.053	

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

Note: Columns (1)–(4) show the estimation results of the regression analysis for the empirical relationship between firm growth and age specified in (30). Column (5) shows the estimation result for the median regression using a residualized %change of sales as a dependent variable, which includes exiting firms in the sample. All the estimations 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. ** and * mean that the coefficients are statistically significant at the .01 and .05 levels, respectively.

industry and cohort dummies and the stockholder's capital, and used the residualized values as a dependent variable while using the dummy variables of firm ages, $dum(\bar{a})_{i,t}$, as independent variables.

The estimation result for the median regression is shown in column (5) of Table 7. It indicates that even with the inclusion of firms exiting the sample, younger firm's growth rate is significantly higher than old firms' growth rate, at least when comparing the median values. Hence, even though the estimation results in columns (1)–(4) are subject to potential survival bias, it does not substantially impact the quantitative implication regarding the relationship between firm age and growth.

Role of R&D Investment by Firm Age

In the main text, we conducted a quantile regression to examine whether R&D investment has a different role for firms of different ages. The estimation results of the quantile regression imply that for older firms, R&D investment helps them avoid a large decline in sales growth (the lower tails), whereas, for younger firms, it helps them potentially grow further (the upper tails).

To further investigate the role of R&D investment by firm age, we estimated the effects of R&D investment on the growth rate of sales by firm age by the following regression.

$$\Delta \text{Sale}_{i,t} = \alpha + Y_t + \beta_Y \mathbf{1}_{\{Age<30\}} \times \text{R\&D\_rate}_{i,t-1} + \beta_O \mathbf{1}_{\{Age>30\}} \times \text{R\&D\_rate}_{i,t-1} + \gamma X_{i,t-1} + \varepsilon_{i,t} \quad (31)$$

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. As in the quantile regression in the main text, the threshold for firm age is set to 30 years because the estimation regarding firm growth and age in Figure 2 suggests that firms younger than 30 years seem to have different growth potential from those older than 30 years.

Table 8 shows the estimation results for the regression analysis of (31). As in the quantile regression in the main text, the table implies that for older firms, R&D investment is a defensive investment to prevent a decline in sales, whereas for younger firms, it is an aggressive investment to grow further. 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. 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 positively affects sales growth only for firms younger than 30 years. Such a drastic change is a bit surprising because the share of firms with sales growth less than -30% is approximately 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.

Table 8: R&D Investment and Growth

	(1) $\Delta\ln(Sale)$	(2) $\Delta\ln(Sale)$	(3) $\Delta\ln(Sale)$	(4) $\Delta\ln(Sale)$	(5) $\mathbf{1}_{\{\%\Delta(Sale)>0\}}$
R&D_rate	0.055**				
	(0.019)				
$\mathbf{1}_{\{Age<30\}} \times$ R&D_rate		0.023	0.122**	0.154**	-0.410
		(0.037)	(0.037)	(0.039)	(0.294)
$\mathbf{1}_{\{Age>30\}} \times$ R&D_rate		0.077**	0.029	0.010	1.664**
		(0.018)	(0.018)	(0.018)	(0.263)
Sample	Full	Full	$\Delta\ln(Sale) > -.3$	$\Delta\ln(Sale) > -.2$	Full
Observations	521,719	521,719	503,557	484,383	542,614
R^2	0.059	0.059	0.058	0.053	

Note: The table shows the estimation results for the regression analysis of (31). 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. The estimations for (1)-(4) are conducted by OLS, whereas that for (5) is conducted by the logit estimation. Robust standard errors are in parentheses. ** and * mean that the coefficients are statistically significant at the .01 and .05 levels, respectively.

Finally, column (5) shows the result of a logit estimation using the dummy variable for positive sales growth as a dependent variable, which indicates that R&D investment helps firms avoid negative sales growth for older firms. Hence, in summary, the estimation results in Table 8 imply that (i) for older firms, R&D investment helps them avoid negative growth, particularly a large drop in sales, and (ii) for younger firms, it does not help them avoid a negative sales but potentially realize a large positive sales growth.

Appendix C Proof of Proposition 1

Appendix C 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, that is,

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

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

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

As the last term in the first row is independent of q_j, the first order condition for $\hat{z}$ gives the second equation in (13).

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

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

Thus, the first order condition for any z_j is,

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

By deleting q_j, we obtain the first equation in (13). 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 (13), the value function for the growing firm can be rewritten as,

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

where m is the number of improving product lines, that is, $m = \#\tilde{\mathbf{q}}$. 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. Additionally, 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 (14) 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 D Discrete-time Model for the Firm Sector

In the main text, the firm sector's problem is characterized by a continuous-time model for explanatory simplicity. However, given that the household sector's problem is characterized by a discrete-time model, the general equilibrium in Definition 1 is also defined in a discrete-time setting. In Appendix D, 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 study.

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

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

and

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

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 consider 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, that is,

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

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

$$\beta A \left[\sum_{q_j\in\mathbf{q}} q_j - \sum_{q_j\in\check{\mathbf{q}}} q_j + \tilde{\gamma} \sum_{q_j\in\tilde{\mathbf{q}}} q_j + (1+\hat{\gamma})k\bar{q}\right] \tag{32}$$

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 (13) in the main text by redefining $\tilde{A} = \beta A$.

Additionally, as in the continuous-time version, by focusing on a particular product line X,

$q_X \in \mathbf{q}$, and defining $\mathbf{q_{-X}} \equiv \mathbf{q} \backslash q_X$, the first three terms in (32) can be rewritten as,

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

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

Thus, the first order condition for $\tilde{z}$ gives the first equation in (13).

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 E Firm- and Household-side Equilibrium

In Appendix E, first, we formally characterize the firm-side equilibrium and the household equilibrium, which we introduced in the main text. Finally, a computational strategy to compute a general equilibrium in comparative statics is provided.

Firm-side Equilibrium

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, as 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,

$$\tilde{x} = \tilde{z}. \tag{33}$$

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 (9). Hence, given the labor supply L, the wage rate w is characterized by,

$$L = \left[\frac{(1-\rho)\bar{q}}{\omega w} \right]^{\frac{1}{\rho}} \tag{34}$$

Here, note that ω_j is not indexed by j 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. The aggregation method to use the share of product lines owned by different types of firms follows Lentz and Mortensen (2016). 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,

$$\tau = F_g \hat{z} + x^e \tag{35}$$

where x^e is the entry rate. The entry rate is exogenous at this point but endogenously determined in general equilibrium later. In addition, 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, that is, the number of entrants' product lines divided by the mass of non-improving product lines. As 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 (35), 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,

$$\dot{F}_g = (1-\tilde{x})\hat{z}F_g + (1-\tilde{x})x^e - (1-\tilde{x})\tau F_g - \nu F_g \tag{36}$$

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 by Proposition 2 in the main text as $g = \tilde{z}\tilde{\gamma} + (1-\tilde{z})\tau\hat{\gamma}$. 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 $\tilde{v}^e = v^e/\bar{q}$). 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.

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

Definition 2 *(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 (3), (9), and (10); (ii) the employment protection cost*

ω_j satisfies (7); (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 (13); (v) the constant value of A for the value function $V(\mathbf{q}) = A\sum_{q_j\in\mathbf{q}} q_j$ satisfies (14); (vi) the share of improving lines, $\tilde{x}$, is equal to $\tilde{z}$; (vii) the aggregate rate of creative destruction, τ, satisfies (35); (viii) the wage rate w is determined by (34); (ix) the share of product lines owned by growing firms, F_g, is characterized by (36) and $\dot{F}_g = 0$; (x) the fixed cost for external innovation Φ satisfies (12); (xi) the final goods produced satisfy (2); (xii) the layoff rate d satisfies (15); (xiii) the aggregate growth rate g is characterized by Proposition 2.

Household-side Equilibrium

Next, we formally characterize the household-side equilibrium. Let $g_s(h_s, h_g)$ and $g_g(h_s, h_g)$ be the policy functions for FSHC and GHC accumulation, h'_s and h'_g, to solve the optimization problem for employed individuals in (18). Furthermore, let $e_W(h_s, h_g, z)$ and $e_N(h_g, z)$ be the policy functions for entrepreneurship by employed and non-employed individuals in the discrete choice problem of (20) and (21), respectively, which take the value of 1 when individuals choose to start a business and take the value of 0 otherwise.

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

Definition 3 *The stationary distribution for employed and non-employed individuals, $\mu_w(h_s, h_g)$ and $\mu_n(h_g)$, satisfy*

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

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

Given the stationary distributions for employed and non-employed individuals, $\mu_w(h_s, h_g)$ and

$\mu_n(h_g)$, the number of entrants x^e are defined as,

$$x^e = \int_z z \cdot \left[\int_{h_s,h_g} e_W(h_s,h_g,z) d\mu_w(h_s,h_g) + \int_{h_g} e_N(h_g,z) d\mu_n(h_g) \right] dP(z) \tag{37}$$

and the aggregate labor supply is defined as,

$$L \quad = \quad \int_{h_s,h_g} l_s(h_s,h_g) \, d\mu_w(h_s,h_g) \tag{38}$$

Then, the household-side equilibrium is defined as follows.

Definition 4 *(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 $g_s(h_s,h_g)$, $g_g(h_s,h_g)$, $e_W(h_s,h_g,z)$, and $e_N(h_g,z)$, (2) probability distributions $\mu_w(h_s,h_g)$ and $\mu_n(h_g)$, and (3) a tuple (x^e, L) such that: (i) the policy functions for firm-specific and general human capital, $g_s(h_s,h_g)$ and $g_g(h_s,h_g)$ solve the employed individuals' optimization problem (18); (ii) the policy function for entrepreneurship choice, $e_W(h_s,h_g,z)$ and $e_N(h_g,z)$, solve the discrete choice problem for the employed individuals (20) and the non-employed individuals (21); (iii) the probability distributions $\mu_w(h_s,h_g)$ and $\mu_n(h_g)$ are stationary distributions defined in Definition 3; (iv) the number of entrants x^e is determined by (37); (v) the aggregate labor supply L is determined by (38).*

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. In the 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.

General Equilibrium and Computational Strategy

Given the formal definitions of the firm- and household-side equilibrium, the competitive general equilibrium is characterized by Definition 1 in the main text. In conducting comparative statics, we must 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 1: the aggregate labor supply L, the mass of entrants x^e, 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 $(L_0, x^e_0, d, v^e_0, w_0, g_0)$ at the baseline equilibrium.

2. At the i-th iteration, given $(d_{i-1}, v^e_{i-1}, w_{i-1}, g_{i-1})$, solve the household problem and compute (L^s_*, x^e_*) in the household side equilibrium specified in Definition 4.

3. Similarly, given (L^s_{i-1}, x^e_{i-1}), solve the firm problem and compute (d_*, v^e_*, w_*, g_*) in the firm-side problem specified in Definition 2.

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.

Appendix F Target Moments in the Indirect Inference

Appendix F discusses the moment conditions used in our indirect inference in more detail and describes how to compute the model-implied values and the target empirical moments in data.

Model-implied Firm Growth by Age

Firm growth by age estimated by microdata is used as the empirical moment to be matched, given that it should have relevant information to identify the values of innovation parameters. In so doing, we need to compute the model-implied values for the average firm growth rate by age, using the firm's stationary distribution by age over the state variables, that is, 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 survival bias. In general, younger firms facing negative shocks tend to exit more frequently than older firms, as young firms own fewer product lines. Therefore, as discussed in the main text and Appendix B, the growth rate of young firms may be subject to upward bias because the estimated $\beta_{\bar{a}}$ in equation (30) is the relationship between firm age and growth *given survival of firms*.

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 $a > 1$,

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

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 $\varpi_G(n, a)$ and $\varpi_N(n, a)$ 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, or (iii) had $n + 1$ product lines and lost a product line due to creative destruction. Note that there are no firms for case (ii) for non-growing firms because they do not have an opportunity for external innovation. In addition, some firms move from $\varpi_G(n, a)$ to $\varpi_N(n, a)$ because they transit from growing firms to non-growing firms at the rate of ν. The stationary distributions 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 (28), 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 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,*

$$g(\bar{a}) = \frac{\sum_n \sum_{a=1+5(\bar{a}-1)}^{5\bar{a}} (1 - \mathbf{1}_{\{n=1\}}\tilde{\tau}) \left\{\varpi_G(n, a) \cdot g_G(n) + \varpi_N(n, a) \cdot g_N(n)\right\}}{\sum_n \sum_{a=1+5(\bar{a}-1)}^{5\bar{a}} (1 - \mathbf{1}_{\{n=1\}}\tilde{\tau}) \left\{\varpi_G(n, a) + \varpi_N(n, a)\right\}} \tag{39}$$

where

$$g_G(n) = \tilde{\hat{z}}(1 + \hat{\gamma}) + \tilde{z}\tilde{\gamma} - \mathbf{1}_{\{n>1\}}\tilde{\tau} \quad \textit{and} \quad g_N(n) = \tilde{z}\tilde{\gamma} - \mathbf{1}_{\{n>1\}}\tilde{\tau} \tag{40}$$

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 (40), are independent of firm age a, the average growth rate by the age group $g(\bar{a})$ is possibly decreasing with respect to $\bar{a}$, that is, 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 (40) 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; that is, $\varpi_G(n,a)/\varpi_N(n,a)$ is decreasing with respect to a. As 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 (30) 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%. By contrast, the model-implied entry rate is

$$\frac{(1-\tilde{z})x^e}{\sum_a \sum_n [\varpi_G(n,a) + \varpi_N(n,a)]} \tag{41}$$

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,

$$\frac{F_g \hat{\xi} \hat{z}^{\hat{\eta}} + \tilde{\xi} \tilde{z}^{\tilde{\eta}}}{Y} \tag{42}$$

where F_g is the share of product lines owned by growing firms in (36). 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,

$$\frac{\tilde{\xi}\tilde{z}^{\tilde{\eta}}}{F_g\hat{\xi}\hat{z}^{\hat{\eta}} + \tilde{\xi}\tilde{z}^{\tilde{\eta}}} \tag{43}$$

which contains relevant information to identify innovation parameters.

Layoff probability As the layoff probability d in the model considers 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, as 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 $(1-\tilde{z})\tau$, whereas 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 $\tilde{z}$, whereas 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 (43) 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., implying that d is 0.120 (= $1 - 0.28^{1/10}$). Note that this calibration strategy uses the result of comparative statics in Section 4. Hence, in the comparative statics, the layoff probability and the internal R&D ratios without EPL are closely aligned with the empirical observation in the U.S. by construction, as they are used as the target moments in indirect inference.

Appendix G Wage and Job Experience/Tenure in Japan

Appendix G provides details about calibration regarding the relationship between wages and job experience/tenure. 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, (i) the effects of job tenure at a particular employer and (ii) the effects of total and industry 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.

In a companion study, Katagiri (2023) estimates the relationship between wages and job experience/tenure in Japan by:

$$\log(wage_{i,t}) = \alpha + f(expr_{i,t}) + g(Ind\_expr_{i,t}) + h(tenu_{i,t}) + Y_t + D_{edu,i} + D_{sex,i} + \varepsilon_{i,t} \tag{44}$$

where $f(expr_{i,t})$, $g(Ind\_expr_{i,t})$ and $h(tenu_{i,t})$ are some functions of total job experience, job experience in the current industry, and job tenure at the current employer. Y_t, $D_{edu,i}$, and $D_{sex,i}$ are dummy variables for a year, education, and male/female. To estimate (44), I 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.[30] As emphasized in the main text, Katagiri (2023) shows that job tenure, in addition to total job experience, has significant influences on wages over the life cycle, whereas it has almost negligible effects in the U.S. (e.g., Kambourov and Manovskii, 2008; Parent, 2000).[31]

In a quantitative analysis in Section 4, the parameter values for the human capital production function are chosen so that the baseline simulation can replicate the human capital accumulation in Japan implied by the estimation in Katagiri (2023). Figure 7 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 7 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 in Katagiri (2023) (the dashed black lines). Based on the optimal choice of human capital accumulation in the model, the right panel of Figure 7 shows the average FSHC and GHC by age. The panel indicates that the total human capital in the model (the sum of blue and red areas) closely follows human capital by age in Katagiri (2023) (the black dashed line) even though it is not targeted in calibration. In the right panel, 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.

Appendix H Robustness Check

Appendix H conducts some robustness checks with respect to model specifications in the household sector. Specifically, the robustness checks examine the case with (1) a general form of labor supply function, (2) endogenous labor supply, or (3) an endogenous choice between working and accumulating human capital. For all cases, the parameter values are recalibrated to match the

[30] 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.

[31] Katagiri (2023) highlights that the difference between Japan and the U.S. can be well accounted for by the difference in layoff probability using a simple model with endogenous human capital accumulation.

Figure 7: 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, middle, and right panels show the wage rate relative to zero job tenure, zero job experience, and age zero, based on the estimation results in Katagiri (2023). 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.

target values. Then, the same comparative statics for eliminating EPL are conducted to see the sensitivity to the changes in (1), (2), and (3).

Table 9 shows the results of the robustness check. The table shows (1) the number of entrepreneurs, (2) the share of FSHC in total HC for those with 10-year job experience, (3) aggregate labor supply, (4) the entry rate, and (5) the growth rate. The first row shows the comparative statics results for eliminating EPL under the baseline specification as a benchmark, whereas the second to the fourth rows show the results for the same comparative statics under different specifications for robustness checks.

A General Form of Labor Supply Function

The labor supply function (16) in the baseline model assumes that the labor supply is linear with respect to both FSHC and GHC, which implies that they are perfectly substitutable. Considering the possibility that FSHC and GHC are not perfectly substitutable, the following CES labor supply function is assumed,

$$l_s(h_s, h_g) = \bar{h}\left[1 + (h_s^{\zeta} + h_g^{\zeta})^{\frac{1}{\zeta}}\right]$$

where ζ is a parameter for substitutability between FSHC and GHC. As the baseline labor supply function is the cases where $\zeta = 1$, the robustness check here conducts the comparative statics under $\zeta = 0.8$ to check the sensitivity to ζ.

The second row of Table 9 shows the results of comparative statics. It implies that when FSHC and GHC are not perfectly substitutable, the shift from FSHC to GHC in response to eliminating EPL less pronounced compared to the case where they are perfectly substitutable, as shown in the first row. The relatively moderate shift from FSHC to GHC is, however, somewhat inconsistent with the observation in the U.S., where FSHC has a negligible role. Moreover, the increase in entrepreneurs and firm entries is slightly smaller than the benchmark case but still significantly large, thus fostering economic growth by 30–40 basis points.

Endogenous Labor Supply and Human Capital Accumulation

While labor supply and time allocation for human capital accumulation are assumed to be inelastic in the baseline specification, eliminating EPL may have some effects through endogenous responses of labor supply or time allocation for human capital accumulation. Hence, in the second robustness check, the household is assumed to endogenously adjust hours worked N and/or time allocation for human capital accumulation i in the optimization problem (18). Specifically, first, to endogenize the labor supply, the optimization problem is changed to,

$$H_W(h_s, h_g) = \max_N \left[w \cdot N l_s(h_s, h_g) - \iota \frac{N^{1+\mu}}{1+\mu}\right] + \beta(1+g)(1-\lambda) \cdot \max_{h_s', h_g'} X_W(h_s', h_g')$$

where ι and μ are parameters for labor disutility. Here, μ is set to 1.0, while ι is calibrated to normalize the total labor supply to one. As there is no saving decision in this model, the optimal

Table 9: Results of Comparative Statics: Robustness Check

	(1) Entre.	(2) FSHC share	(3) Labor	(4) Entry	(5) Growth
No EPL in GE (benchmark)	1.61	0.11	0.97	7.6	1.12
CES parameter = 0.8	1.43	0.27	0.93	6.9	1.07
Endo. hours worked	1.75	0.05	1.01	8.2	1.14
Endo. HC accumulation	1.87	0.04	1.02	8.5	1.19

Note: The table shows the results of the robustness check. It shows (1) the number of entrepreneurs, (2) the share of FSHC in total HC for those with 10-year job experience, (3) aggregate labor supply, (4) the entry rate, and (5) the growth rate. The first row shows the comparative statics results for eliminating EPL under the baseline specification as a benchmark, whereas the second to the fourth rows show the results for the same comparative statics under different specifications for robustness checks. The second row is the case where FSHC and GHC are not perfectly substitutable. The third row is the case of endogenous hours worked, whereas the fourth row is the case where both hours worked and time allocation for human capital accumulation are endogenous.

hours worked is,

$$N^* = \left[\frac{w \cdot l_s(h_s, h_g)}{\iota}\right]^{\frac{1}{\mu}}, \tag{45}$$

which implies that hours worked is an increasing function of wages and human capital. Second, to endogenize both hours worked and time allocation for human capital allocation, the optimization problem is changed to,

$$H_W(h_s, h_g) = \max_{N,i}\left[w \cdot (1-i)Nl_s(h_s, h_g) - \iota\frac{N^{1+\mu}}{1+\mu} + \beta(1+g)(1-\lambda) \cdot \max_{h_s', h_g'} X_W(h_s', h_g')\right]$$

subject to the law of motion,

$$h_s' = (1-\delta_s)h_s + A_s[iNh]^\alpha \quad \text{and} \quad h_g' = (1-\delta_g)h_g + A_g[iN(1-h)]^\alpha$$

Note that the optimal hours worked are still characterized by N^* in (45) thanks to the envelope theorem, as the time allocation for human capital i is optimally chosen.

The third and fourth rows of Table 9 show the results of comparative statics. They imply that, in both cases, eliminating EPL results in (i) a larger shift from FSHC to GHC than in the benchmark case, and (ii) an increase in labor supply as a result of higher wages. The shift from FSHC to GHC is larger because the endogenous hours worked with quadratic labor disutility make losing FSHC more costly. While they lead to larger effects on entrepreneurship and economic growth than in the benchmark case, the main quantitative message is unchanged from the benchmark case in the first row.