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Firm Age, Productivity, and Intangible Capital[*]

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Abstract

We examine the role of intangible capital in firms' growth in sale through physical productivity (TFPQ), markup, and factor price distortion. Using a large dataset from Japan, we have constructed firm-level panel data of intangible capital consisting of software, organizational capital, and R&D stocks. We find that TFPQ plays a significant role in the firm growth. In addition, the accumulation of intangible capital accounts for a major part of sales growth. Among three types of intangible capital, organization capital is crucial for firm growth.

Keywords: Firm Age, Total Factor Productivity, Intangible Capital, Markup
JEL classification: D24, E22.

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Firm Age, Productivity, and Intangible Capital

1. Introduction

Since the IT revolution in the US during the 1990s, many studies have focused on measuring intangible capital and analyzing its role in firm activities (e.g., Bresnahan et al., 2002). Recently, some researchers have attributed the decline in business dynamism to the concentration of intangible capital (Akcigit and Ates, 2019, 2021; De Ridder, 2019).[2] These studies have theoretically shown the role of intangible capital in aggregate economic growth and firm growth, but empirical studies on the role of intangible capital in firm growth are limited.

In this paper, we explore the roles of intangible capital in a firm's growth and productivity by focusing on the dynamics of its investment in intangible capital over time. While many studies have examined the determinants of the investment in intangible capital, none have focused on its relation to the age of a firm. Figure 1 shows the mean log difference of intangible capital by age for our sample of Japanese firms for the period from 1995 to 2015. Firms are divided into five age groups: age 2-9, age 10-29, age 30-49, age 50-69, and age 70 and over. In the figure, the mean of the youngest firms is the highest in every year of the observation period. The second youngest firms have the second highest investment rate and the other three groups are almost the same. The figure shows that young firms more actively undertake investment in intangible capital even during severe recessions. This figure indicates the importance of focusing on the role of age in the accumulation of intangible capital.[3]

[Insert Figure 1 here]

Studies have explored the roles of young firms in dimensions of activities other than intangible capital. They show that the size of plants and firms grows in terms of sales and employment as they age and that younger plants and firms have higher growth rates in the US. (e.g. Davis et al., 1996). Japanese firms show such an age-size relation as well.[4] Figure 2 shows the log difference in sales and production factors of Japanese firms in our sample. The growth rates in sales and all production factors are higher for younger firms. The growth rates decline

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[2] In this paper, we focus on the intangible capital and firm growth in Japan. In case of Japan, some studies point out that the accumulation of intangible capital is slow and negative in some years. Fukao et al. (2009) find that although the ratio of intangible investment to GDP in Japan has risen from the 1980s to the 2000s, it is lower than in the US. In addition, the growth rate of intangible capital in Japan declined from the late 1980s to the early 2000s. Chun et al. (2012) compare the intangible capital in Japan and Korea at the industry level and find the growth rate in intangibles became negative in some industries in Japan in the 2000s.

[3] In Table A1 in Appendix, we regress the investment rate of intangible capital on firm age, lagged sales, and lagged intangible capital stock to show that the high investment rate of the young firm is not perfectly explained by its small size.

[4] See Fujii et al. (2017) for sales and Liu (2018) for employment.

with age and reach zero around 30 to 40 years after establishment. In addition, the growth rate of sales is higher than the growth rates of production factors that means productivity increases with age to the extent that productivity is measured as the ratio of sales to the weighted average of production factors.[5]

[Insert Figure 2 here]

What is less known is the mechanism that drives such age-size and age-productivity relations. One strand of literature stresses the selection mechanism through which less productive firms exit and more productive firms survive (Baily et al., 1992; Jovanovic, 1982; and Ericson and Pakes, 1995). Another strand of literature examines the role of organizational capital that plants and firms accumulate as they age (Atkeson and Kehoe, 2005; Hsieh and Klenow, 2014). While empirical studies on the selection mechanism are relatively copious, those on organizational capital are still scarce. We provide new empirical evidence on the latter mechanism by using a large panel data set of Japanese firms.

We examine the roles of intangible capital including organizational capital in firms' growths in sales and productivity over time. For this aim, we first construct a model to show the relation between sales and three parameters: physical productivity (or Total Factor Productivity in terms of Quantity: TFPQ), markup, and distortion in the factor prices. While Hsieh and Klenow (2009) show that the log of sales is proportional to the difference between the logs of TFPQ and revenue productivity (or Total Factor Productivity in terms of Revenue: TFPR) under the assumption of a constant markup across firms, we decompose TFPR into the markup and the distortions in factor prices both of which vary across firms and over time. This decomposition is important given the potential effect of intangible capital on market power (Crouzet and Eberly, 2019). Next, we examine how these three parameters evolve with age. We further examine the quantitative effects of the three parameters on sales growth by simulating the hypothetical sales growth by fixing each parameter to its initial value. Then, we proceed to analyze the role of intangible capital in the age-size relations through the three parameters. We construct firm-level panel data of intangible capital that consists of organizational capital, software, and R&D stocks and regress the changes in sales, TFPQ, markup, and the distortion on age and the changes in intangible capital.

Our findings can be summarized as follows: First, sales grow with age up to about 30 years after the establishment of a firm. Second, the TFPQ increases with age and has a dominant positive effect on the sales growth up to about 30 years after establishment of a firm. On the other hand,

[5] This definition of productivity is based on revenue-based productivity (TFPR). We show below that our measure of physical productivity (TFPQ) also increases with age.

the markup increases with age and hence has a negative effect on sales growth, while the distortion decreases with age and has a positive effect on sales growth. Third, intangible capital has significant effects on firm growth through the TFPQ. Among the three types of intangible capital, organizational capital accounts for a major part of the growth in sales. Software and R&D stocks also have some effects on markup and the distortion of the factor prices.

Closely related to the present study are Atkeson and Kehoe (2005) and Hsieh and Klenow (2009, 2014). Atkeson and Kehoe (2005) build a growth model for the life cycle of plants that incorporates the accumulation of plant-specific knowledge, which they call organizational capital. In their model, firms accumulate organizational capital through the learning process as they age. Using manufacturing establishment-level data from Mexico, India, and the US, Hsieh and Klenow (2014) find that establishment size in terms of labor and productivity grow less as establishments age in Mexico and India than in the US. This finding indicates that firms accumulate less organizational capital in India and Mexico than in the US. They further find that the TFPR rises much more steeply with the TFPQ in India and Mexico than in the US. This finding indicates that distortions in taxes, factor costs, financial frictions, and transportation and trade costs become larger with age in India and Mexico than in the US. Both Atkeson and Kehoe (2005) and Hsieh and Klenow (2014) show that plant-specific investment in organizational capital plays a key role in plant growth in terms of size and productivity. However, they do not directly measure organizational capital or other types of intangible capital. We take a different approach from them. We measure firm-level intangible capital to examine whether it actually plays a significant role in the growth over firms' life cycles. As far as we know, the present study is the first that examines the role of intangible capital in the relation between the age and productivity of a firm or a plant.

Bahk and Gort (1993), Power (1998) and Jensen et al. (2001) are also related to the present study in that they examine how productivity evolves with plant age.[6] Bahk and Gort (1993) use data on US manufacturing plants for the period from 1972 to 1986 in order to examine learning-by-doing with a production function in which labor, human capital, physical capital, and vintage are inputs. Power (1998) use data on US manufacturing plants for the period from 1972 to 1988 in order to show that investment in physical capital is not correlated with productivity or its growth. Jensen et al. (2001) examine the evolution of productivity in US manufacturing plants from 1963 to 1992 and show that while recent cohorts enter with higher productivity than earlier entrants did (vintage effect), the surviving cohorts show productivity increases as they age (survival effect) and that these two effects roughly offset each other. These studies indicate that productivity evolves with plant age, but they do not take into consideration the role of intangible capital while we do.

[6] In these papers, plant age is used to explore the role of learning-by-doing. See Thompson (2010) for the survey of the literature on learning-by-doing.

Foster et al. (2016) and Fujii et al. (2017) focus on a specific factor for the age-productivity relation. Foster et al. (2016) show that even in commodity-like markets, plant growth is largely driven by rising demand for the plant's products rather than by initial productivity gaps as it ages. This finding indicates the importance of a demand accumulation process through the accumulation of intangible capital, such as a customer base, but does not directly examine its role.[7] Fujii et al. (2017) investigate how the inter-firm transaction network evolves over the firm's life cycle. They obtain evidence that shows the relation between the age and growth of a firm may be due to the life-cycle pattern of building inter-firm networks. Instead of focusing on a specific type of intangible capital such as a customer base, we examine the role of intangible capital broadly defined in firm growth.

This study is also related to the recent literature on the role of intangible capital in business dynamism in terms of productivity, market concentration, markups, labor share, firm turnover rate, job reallocation, and others. Akcigit and Ates (2019, 2021) stress the decline in knowledge spillover across firms as a reason for the declining business dynamism in the U.S. Although they mention the tacit knowledge and big proprietary data as one of the potential sources for the decline in knowledge spillover, they do not analyze the role of such intangible capital in knowledge spillover or business dynamism. Using data on the universe of French firms and U.S. publicly listed firms, De Ridder (2019) focuses mainly on software and find that the increasing use of intangible capital such as software explains the slowdown of productivity growth, the decline in business dynamism, and the rise of market power. Crouzet and Eberly (2019) also show that intangible capital is associated with market power, productivity gains, and consequently, market concentration. Unlike these studies, we study the role of intangible capital through the lens of firm growth over age.

The remainder of the paper is organized as follows. Section 2 presents the underlying framework for our analysis. We describe the data and measurement method for productivity and intangible capital in Section 3. Section 4 provides the basic facts on the age-sales and age-productivity relations. In Section 5, we evaluate the role of intangible capital in firm growth by conducting regression and simulation analyses based on the estimated parameters. The last section concludes.

2. Framework

In this section, we introduce a framework to express sales through the underlying parameters of TFPQ, demand elasticity (or markup), and distortion in input prices. Thus we do not impose the relations between age and productivity of the firm and other parameters a priori.

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[7] The role of customer base is explored in Gourio and Rudanko (2014).

Using this framework, we explain the possible mechanism that generates the relation between age and sales. We further discuss the roles of intangible capital in the mechanism of the age-sales relation.

We consider a static partial equilibrium model with monopolistic competition. The framework is a natural extension of Hsieh and Klenow (2009; 2014). However, unlike them, we allow for heterogeneous markups across firms and increasing or decreasing returns to scale. By so doing, we can analyze the behavior of a firm more realistically but cannot evaluate the economic welfare that requires aggregation across firms.

In industry s, there is a continuum of goods and each of them is produced by a firm. Below we do not specify industry by subscripts unless it is necessary to avoid confusion. Firm i produces output in year t according to the following production function:

$$Q_{it} = A_{it} K_{it}^{\alpha_K} L_{it}^{\alpha_L} M_{it}^{\alpha_M}, \qquad \alpha_K + \alpha_L + \alpha_M = \gamma, \tag{1}$$

where Q_{it} denotes output. A_{it} denotes the Hicks-neutral technology or the TFPQ and we assume that it is expressed as a function of intangible capital, Int_{it}, and firm age, Age_{it}, so $A_{it} = A(Int_{it}, Age_{it})$. K_{it}, L_{it}, and M_{it} denote capital, labor, and intermediate, respectively. The α_X for input $X = K, L, M$ is the elasticity of output with respect to input X. These elasticities are assumed to be common across all firms within an industry. The summation of the elasticities γ denotes the degree of the returns to scale. Unlike Hsieh and Klenow (2009), we do not impose a constant returns to scale.

The demand for firm i's goods is assumed to take the following form:

$$Q_{it} = B P_{it}^{-\epsilon_{it}}, \tag{2}$$

where P_{it} is the output price at the firm level, B is a constant demand shift parameter for the industry, and ϵ_{it} is the time-variant price elasticity for firm i ($\epsilon_{it} > 1$). Equation (2) leads to:

$$Q_{it} = B^{1-\mu_{it}} (P_{it} Q_{it})^{\frac{\epsilon_{it}}{\epsilon_{it}-1}}. \tag{3}$$

Equation (3) enables us to obtain the output from sales.

Following Hsieh and Klenow (2009), the profit function is the following:

$$\pi_{it} = P_{it} Q_{it} - (1 + \tau_{Kit}) R K_{it} - (1 + \tau_{Lit}) w L_{it} - P_M M_{it}, \tag{4}$$

where R, w, and P_M denote factor prices for each input; and τ_{Kit} and τ_{Lit} represent distortions at the firm level. Positive values of these distortions mean that the firm suffers from unfavorable treatments such as taxes or restrictions, and negative values mean that firms enjoy their favorable treatments such as subsidies.

We assume that the firms maximize their profits for a given technology. Then, the markup can be derived as $\mu_{it} = \epsilon_{it}/(\epsilon_{it} - 1)$. We assume that the demand elasticity, or markup, is also a function of intangible capital and firm age, $\mu_{it} = \mu(Int_{it}, Age_{it})$. In addition, the first order conditions for profit maximization with respect to each of the inputs lead to:

$$\frac{RK_{it}}{P_{it}Q_{it}} = \frac{\alpha_K}{\mu_{it}(1+\tau_{Kit})} \tag{5a}$$

$$\frac{wL_{it}}{P_{it}Q_{it}} = \frac{\alpha_L}{\mu_{it}(1+\tau_{Lit})} \tag{5b}$$

$$\frac{P_M M_{it}}{P_{it}Q_{it}} = \frac{\alpha_M}{\mu_{it}} \tag{5c}$$

We define the input distortion and composite factor price as:

$$\tau_{it} = (1+\tau_{Lit})^{\alpha_L}(1+\tau_{Kit})^{\alpha_K} \tag{6}$$

$$c = \left(\frac{\alpha_L}{w}\right)^{-\alpha_L}\left(\frac{\alpha_K}{R}\right)^{-\alpha_K}\left(\frac{\alpha_M}{P_M}\right)^{-\alpha_M} \tag{7}$$

The factor price distortion also depends on the intangible capital and firm age, $\tau_{it} = \tau(Int_{it}, Age_{it})$. Then, combining equations (5a)-(5c), we obtain:

$$\tau_{it} = \frac{(P_{it}Q_{it})^{\gamma}}{K_{it}^{\alpha_K} L_{it}^{\alpha_L} M_{it}^{\alpha_M} \mu_{it}^{\gamma} c} \tag{8}$$

Combining (5a)–(5c) with the production function (1) and equations (3) and (8), we can express output and sales, respectively, as:

$$Q_{it} = \frac{A_{it}}{\tau_{it}c}\left(\frac{P_{it}Q_{it}}{\mu_{it}}\right)^{\gamma} \tag{9}$$

$$P_{it}Q_{it} = \left(\frac{A_{it}B^{\mu_{it}-1}}{\mu_{it}^{\gamma}\tau_{it}c}\right)^{\frac{1}{\mu_{it}-\gamma}} \tag{10}$$

We use equation (10) to decompose sales into the three parameters of TFPQ, markup, and factor distortion as well as a constant term that contains industry-wide composite factor prices and demand shifters. Equation (10) shows that sales increase with the TFPQ and decrease with the markup and distortions if $\mu_{it} - \gamma > 0$, which we assume hereafter for all i and t.

We consider the three parameters, A_{it}, μ_{it}, and τ_{it}, as functions of age and intangible capital. Age affects the TFPQ via learning-by-doing because firms accumulate knowledge through production experience. Another important channel that enhances the TFPQ is the accumulation of intangible capital. Unlike tangible capital, intangibles take a long time to adjust to the statically optimal level. For example, knowledge capital is accumulated through R&D in which the transaction is limited because it is unobservable.[8]

Markup and factor distortions are also affected by age and intangible capital though many channels. For example, firms can reduce borrowing costs over time as they build reputation in capital markets (Sakai et al., 2010). In extreme cases, zombie firms may enjoy their favorable treatment (Caballero et al., 2008). On the other hand, start-ups may be subsidized. The net effect of age on distortions is, therefore, difficult to predict.[9] Furthermore, age can affect markup as well if older firms obtain a better reputation in the product market. Similarly, intangible capital can affect both factor distortions and markup. The availability of outside financing in intangible capital investment is limited because intangibles cannot be pledged as collateral that leads to higher factor distortions. Advertising and R&D may differentiate their products more for consumers that is likely to lead to a higher markup.

3. Data and measurement

We use data from the Basic Survey of Japanese Business Structure and Activities (BSJBSA). The Ministry of Economy, Trade and Industry (METI) conducts the survey and collects detailed information on enterprises with 50 or more employees and with paid-up capital over 30 million. BSJBSA covers firms in the mining, manufacturing, and wholesale and retailing industries as well as some other non-manufacturing industries. The data that are available to us cover the period from 1994 to 2018. To deal with the revision of industry classification during the period, we use a concordance table from the Japan Industrial Productivity Database constructed by the Research Institute of Economy, Trade and Industry (RIETI).

3.1 Firm age

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[8] If age reflects vintage capital, TFPQ can decrease with age.

[9] Another interesting mechanism is the precision of prediction made by firms. As in Jovanovic (1982) and Arkolakis et al. (2018), old firms can predict their demand more precisely. This channel results in the small variation in markup for older firms.

We first measure the age of firms. In the BSJBSA, firms report years since establishment. Some firms, however, report different establishment years in different survey years. We regard these cases as misreporting and choose the most frequently reported years of establishment for each firm. In addition, we correct the establishment year to the year that the firm first appears in the BSJBSA if the reported establishment year is later than the year it appears. Then we calculate the age by subtracting the establishment year from the survey year. Next, we drop the firms with zero age to exclude partial year effects as in Bernard et al. (2017). Figure 3 shows the distribution of ages in 2015. Due to the threshold of BSJBSA, the numbers of young firms included in the sample are relatively small. The number of firms over 70 years old are also small because many firms in Japan were established in the postwar period.

[Insert Figure 3 here]

3.2 Elasticities of inputs and firm-level parameters

We assume the output elasticities of production function (1), α_K, α_L, α_M, are common across firms within an industry. Then we use the first order condition with respect to intermediates (5c) to estimate the intermediate elasticity α_{Ms} and the markup μ_{it}. As shown in Bond et al. (2021), we cannot estimate the output elasticities and the levels of markups from the sales data. But these parameters are required to recover TFPQ and distortions. To identify the parameters, therefore, we impose the assumption that the firms that fall in the lowest 10 percent of the markup in each industry have a unit markup, $\mu_{it} = 1$. Equation (5c) shows that these firms correspond to the firms that fall in the highest 10 percent of the share of intermediates of cost to sales. We therefore obtain $\widehat{\alpha_{Ms}}$ as the 90th percentile of $P_{Ms}M_{it}/P_{it}Q_{it}$ for each industry.

Once we obtain $\widehat{\alpha_{Ms}}$, we can derive the markup for each firm by taking the ratio of the estimated elasticity to the intermediate share

$$\widehat{\mu_{it}} = \frac{\widehat{\alpha_{Ms}} P_{it} Q_{it}}{P_{Ms} M_{it}}. \tag{11}$$

This method is consistent with the approach developed by De Loecker and Warzynski (2012) in which the markup is derived from the elasticity of output with respect to a variable input divided by the revenue share of that input ($P_{Ms}M_{it}/P_{it}Q_{it}$), although we do not derive $\widehat{\alpha_{Ms}}$ by estimating the production function.[10] This method is a simplified version of De Loecker and Warzynski

[10] See Nishioka and Tanaka (2019) for the application of De Loecker and Warzynski (2012) to the Japanese plant-level data. We do not estimate the production function to obtain the input elasticities because the output quantity data are not available for the BSJBSA that contains non-manufacturing firms as well as manufacturing firms.

(2012). We set the markups for the lower 10 percent of firms as the minimum values conditional on being strictly above one in each industry.[11]

We use the first order conditions (5a) and (5b) to estimate the labor and capital elasticities. We assume that the median values of the factor distortions for each input is zero in each industry. Thus, we obtain the following equations:

$$Med_s[\ln(1+\tau_{Lit})] = 0 \tag{12}$$

$$Med_s[\ln(1+\tau_{Kit})] = 0, \tag{13}$$

where Med_s denotes the industry-level median value. By assuming symmetric distributions for τ_{Lit} and τ_{Kit}, the factor elasticities are estimated with the following equations:

$$\widehat{\alpha_{Ls}} = Med_s\left(\frac{\widehat{\mu_{it}} w_s L_{it}}{P_{it} Q_{it}}\right) \tag{14}$$

$$\widehat{\alpha_{Ks}} = Med_s\left(\frac{\widehat{\mu_{it}} R K_{it}}{P_{it} Q_{it}}\right). \tag{15}$$

We use the reported wage bill of $w_s L_{it}$ to obtain $\widehat{\alpha_{Ls}}$. We use the tangible fixed assets as K_{it} and by following Hsieh and Klenow (2009) set $R = 0.1$ to obtain $\widehat{\alpha_{Ks}}$.

Next, we derive the TFPQ. From equations (1) and (3), we can define its composite with demand shifter as:

$$A'_{it} = \frac{(P_{it} Q_{it})^{\mu_{it}}}{K_{it}^{\alpha_K} L_{it}^{\alpha_L} M_{it}^{\alpha_M}} = A_{it} B^{\mu_{it}-1}. \tag{16}$$

We first calculate this composite term by using the estimated parameters.

$$\widehat{A'_{it}} = \frac{(P_{it} Q_{it})^{\widehat{\mu_{it}}}}{K_{it}^{\widehat{\alpha_{Ks}}} L_{it}^{\widehat{\alpha_{Ls}}} M_{it}^{\widehat{\alpha_{Ms}}}} \tag{17}$$

Taking the first order differences of the logged values, we obtain:

$$\Delta \ln A'_{it} = \Delta \ln A_{it} + \ln B \, \Delta \mu_{it} \tag{18}$$

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[11] For four out of 101 industries, the median shares of intermediates are less than 10%. We dropped these industries because the estimated markups and factor elasticities are extraordinarily high. After this process, our sample includes 97 industries.

We assume that the TFPQ growth rate is composed of the firm fixed effect, year fixed effect, and random shock as:

$$\Delta \ln A_{it} = \delta_i + \delta_t + u_{it} \tag{19}$$

Then, equation (18) can be represented by

$$\Delta \ln A'_{it} = \delta_i + \delta_t + \ln B \, \Delta\mu_{it} + u_{it} \tag{20}$$

We regress $\Delta \ln \widehat{A'_{it}}$ on $\Delta\widehat{\mu_{it}}$ with firm and time fixed effects by using an OLS to obtain the coefficient for $\Delta\widehat{\mu_{it}}$ of $\widehat{\ln B}$.[12] Then we use equation (16) to retrieve the TFPQ from $\widehat{A'_{it}}$ as:

$$\ln \widehat{A_{it}} = \ln \widehat{A'_{it}} - (\widehat{\mu_{it}} - 1) \widehat{\ln B} \, . \tag{21}$$

Further, we estimate the change in the factor distortion by making the log difference in equation (8):

$$\Delta \ln \widehat{\tau_{it}} = \widehat{\gamma_s} \Delta \ln P_{it} Q_{it} - \widehat{\alpha_{Ks}} \Delta \ln K_{it} - \widehat{\alpha_{Ls}} \Delta \ln L_{it} - \widehat{\alpha_{Ms}} \Delta \ln M_{it} - \widehat{\gamma_s} \Delta \ln \widehat{\mu_{it}} \, , \tag{22}$$

where $\widehat{\gamma_s} = \widehat{\alpha_{Ks}} + \widehat{\alpha_{Ls}} + \widehat{\alpha_{Ms}}$ is the estimate of the returns to scale.[13]

3.3 Intangible assets

Corrado et al. (2009) classify intangible assets into three categories: computerized information, innovative property, and economic competencies. Following them, we measure three types of intangibles; software, R&D, and organizational change from the BSJBSA.

First, Software investment is for computerized information processing and involves three types of software: custom software, packaged software, and own account software. We first measure a part of software investment as the ratio of workers engaged in information processing to the total number of employees, multiplied by the total cash earnings. Then, we add to this number the cost of information processing to obtain total software investment. Next, R&D investment is for innovative property. We use the expenses of in-house R&D and contract R&D

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[12] We also estimated equation (20) by using the dynamic-panel-data technique in Arellano and Bond (1991) and Blundell and Bond (1998) and found that the estimated demand parameters were highly correlated with each other. The correlation coefficient was over 0.95.

[13] Although equation (8) includes the composite factor price c_s, we use only the rate of change in $\widehat{\tau_{it}}$ in the empirical analyses below, and therefore do not need to estimate the industry-level variable c_s.

to estimate the value of this investment. Finally, investment in economic competencies includes organizational change. Following Eisfeldt and Papanikolaou (2013) and Lev and Radhakrishnan (2005), we use sales and general administrative (SGA) to measure the cash flows to organizational capital. We assume that firms invest 10 % of their SGA accounts in organizational change.

Then we measure the stock values of each type of intangible capital with the Perpetual Inventory Method. The depreciation rates are 33%, 20%, and 60% for software, R&D, and organization capital, respectively. We follow Corrado et al. (2009) and set these depreciation rates. For firms that first appear in the sample, we set the initial stock value to the investment value divided by the sum of the depreciation rate and the assumed mean of net investment rate, 10% and then discard first three years, 1994-1996. We define the total intangible capital stock as the sum of these three types of stocks. We denote $Software$, $R\&D$, and $Organization$ for each type of intangible capital stock, respectively.

3.4 Summary statistics

We construct a sample by dropping observations that fall in the top and bottom 1% tails of the distribution for any differences in $\ln(P_{it}Q_{it})$, $\ln K_{it}$, $\ln L_{it}$, $\ln M_{it}$, $\ln Software_{it}$, $\ln Organization_{it}$, $\ln(R\&D_{it}+1)$, $\widehat{\mu_{it}}$, $\ln\widehat{A_{it}}$, and $\ln\widehat{\tau_{it}}$. We also drop the top and bottom 1% tails of deviations from industry median values in $\widehat{\mu_{it}}$ from our sample.

Table 1 shows the summary statistics for our sample. The mean age is 44 and is close to the median value, 45. On the other hand, the mean markup is 1.78 and is higher than the median value, 1.30, due to the lower bound of one and therefore the right-skewed distribution. The means and medians of the change rates in most firm-level variables are all close to zero. These rates mean that the Japanese economy has no trend during the sample period, although it went through several business cycles and the domestic and global financial crises.

[Insert Table 1 here]

4. Analysis of sales growth

In this section, we explore the relations between a firm's age and size and the firm-specific parameters of TFPQ, markup, and factor price distortion. We first take the means of the differences for each variable and then accumulate them from age 1 as $\ln PQ_a = \sum_{age_{it}=1}\ln P_{it}Q_{it}/N_1 + \sum_{a'=2}^{a}\left(\sum_{age_{it}=a'}\Delta\ln P_{it}Q_{it}/N_{a'}\right)$, where N_a denotes the number of firm-years it with age a.[14] We also obtain the log of the TFPQ $\ln A_a$, the markup μ_a, and the log of distortion $\ln\tau_a$ in a similar way. Figure 4 shows the relations between the estimated

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[14] We do not define $\ln PQ_a$ as the actual mean of levels, $\sum_{age_{it}=a}\Delta\ln P_{it}Q_{it}/N_a$, to exclude the effects of the differences in initial values.

parameters and age. As noted in the explanation of Figure 2, the log of sales increases with age up to about age 20. The TFPQ also increases with age up to about age 20. While it has a similar path to sales up to about age 20, it decreases rapidly afterward.[15] Because TFPQ is a measure of technological efficiency, Figure 4 shows that young firms improve their technology rapidly. The positive relation between age and the TFPQ is qualitatively the same result as that for the US in Hsieh and Klenow (2014). Markup also increases with age, but its growth rate is smaller than those of sales and the TFPQ when firms are young.[16] In addition, the markup reaches its maximum about 50 years after establishment and does not show a clear decline thereafter. The path of markup means that newly established firms are forced to set a lower price and suffer from low markups for an extended period. Further, the factor price distortion decreases with age. The decline in the distortion is consistent with the reputation hypothesis in the credit market that postulates that firms can reduce borrowing costs over time (e.g., Sakai et al., 2010).

[Insert Figure 4 here]

We find the same results at the plant level from the Census of Manufacture conducted by METI and the Economic Census for Business Activity conducted by the Ministry of Internal Affairs and Communications (MIC) and METI. Figure A2 in Appendix shows the change rates in sales, employment, intermediates, and the ratio of sales to intermediates in 2015 by age group. The ratio of sales to intermediate inputs can be interpreted as a proxy for markup. In the Census of Manufacture and the Economic Census for Business Activity, plants report the period of establishment with a longer-than-annual base. We therefore classify the plants into five age groups; 2-4, 5-10, 11-20, 20-30, and over 30.[17] The sample covers the plants that had four or more employees in 2014 and survived until 2015. In the figure, the rates of change in sales, employment, and intermediate are positive when the plants are young and decrease with plant age. The change in the ratio of sales to intermediate inputs is positive and almost constant for all age groups.

Before exploring the roles of intangible capital, we evaluate the importance of the TFPQ, markup, and distortion in sales by calculating the hypothetical sales that would realize if one of the TFPQ, markup, or distortions did not change with age at the initial level. For this aim, we take the log of equation (10) and replace the firm-year index it with age a to express the log of sales

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[15] Figure A1 in Appendix shows the paths of sales and inputs by cumulating the change rates in output and inputs. Figure A1 suggests that while the sales decline for firms 20 years after establishment, the tangible fixed asset do not decline thereafter. This is the reason why TFPQ decreases rapidly 20 years after establishment.

[16] The positive correlation between age and markup is also found in Peters (2020) who uses firm-level data from Indonesia.

[17] We drop plants with age less than two from our sample because we cannot calculate the rate of change in the variables for those plants.

of the representative firm at age a as a function of the TFPQ, markup, and distortion.

$$\ln PQ(A_a, \mu_a, \tau_a) = \ln B + \frac{1}{\mu_a - \gamma}(\ln A_a - \gamma \ln \mu_a - \ln \tau_a + (\gamma - 1)\ln B - \ln c) \qquad (23)$$

Then we replace one of the arguments, A_a, μ_a, and τ_a, with its initial value, A_1, μ_1, and τ_1, respectively. Figure 5 shows the dynamics of the hypothetical sales if each one of these three factors is fixed at its initial value. The baseline is the simulated path of sales using equation (23) and as such shows how the actual sales evolve with age. The line labelled "initial TFPQ", for example, shows the simulated path of sales when we fix the TFPQ at the initial value: $\ln[PQ(A_1, \mu_a, \tau_a)/PQ(A_1, \mu_1, \tau_1)]$.[18] It shows that if TFPQ were fixed at the initial value and did not increase with age, the growth rate in sales would be much lower. This result indicates that the rise in the TFPQ is central to growth. The hypothetical firm would grow slightly faster if the markup were fixed to the initial level. The rising markup makes sales smaller because the elasticity of demand is assumed to be over one. The changes in the factor price distortion have small effects on sales, but the sales growth is slower for the firms if the factor price distortion does not change.

[Insert Figure 5 here]

5. Roles of intangible capital in firm growth

5.1 Regression results

In this section, we explore the roles of intangible capital in firm growth. Considering the potential effects of intangibles on the TFPQ, markup, and distortion, the accumulation of intangibles with age that is observed in Figure 1 indicates that the age-productivity relation may be accounted for by intangible capital. We first estimate the age effects without controlling for intangible capital. Then we separate the effects of intangible capital from the age effects by including the variables of intangible capital in the estimation. The former age effects include the effects of intangible capital while the latter captures the pure age effect.

We first consider the following equation without intangible capital:

$$Y_{it} = \beta'_{Y1} age_{it} + \beta'_{Y2}(age_{it})^2 + \beta'_{Y3}(age_{it})^3 + \delta'_{Y,i} + \delta'_{Y,st} + u'_{Y,it}, \qquad (24)$$

where $Y_{it} = \ln P_{it}Q_{it}$, $\ln A_{it}$, μ_{it}, and $\ln \tau_{it}$. The independent variables are the first to third

[18] We standardize the sales by the initial value to interpret the simulated paths as the accumulated change rates from establishment.

orders of age. We control for the firm fixed effect and time-varying industry effect. Then we estimate the first difference in (24):

$$\Delta Y_{it} = \beta_{Y1} + \beta_{Y2} age_{it} + \beta_{Y3} (age_{it})^2 + \delta_{Y,st} + u_{Y,it}, \tag{25}$$

We impose the mean of zero to $\delta_{Y,st}$ to identify the first-order age effect (β_{Y1}) with the estimated constant term. In all specifications, the standard errors are clustered at the firm level. Table 2 shows the estimation results from OLS for equation (25). We report the result for $\Delta \ln P_{it} Q_{it}$ as the dependent variable in column (1). It shows that both age and age squared are significant for the log difference in sales. Column (2) shows that they are also significant for the log difference in the TFPQ. Column (3) shows that neither of them is significant for the difference in markup while column (4) shows that only age squared is significant for the log difference in the distortion.

[Insert Table 2 here]

Then we proceed to explore the roles of intangible capital in firm dynamics by considering the following equations:

$$Y_{it} = \beta'_{Y1} age_{it} + \beta'_{Y2} (age_{it})^2 + \beta'_{Y3} (age_{it})^3 + \beta'_{Y,Intan} \ln Intangible_{it} + \delta'_{Y,i} + \delta'_{st} + u'_{Y,it} \tag{26a}$$

$$\begin{aligned} Y_{it} = {} & \beta'_{Y1} age_{it} + \beta'_{Y2} (age_{it})^2 + \beta'_{Y3} (age_{it})^3 + \beta'_{Y,Soft} \ln Software_{it} + \beta'_{Y,O} \ln Organization_{it} \\ & + \beta'_{Y,RD} \ln(R\&D_{it} + 1) + \delta'_{Y,RDzero} * 1_{\{R\&D_{it}=0\}} + \delta'_{Y,i} + \delta'_{st} + u'_{Y,it} \end{aligned} \tag{26b}$$

In both equations, the dependent variables are the log of sales ($\ln P_{it} Q_{it}$), log of TFPQ ($\ln A_{it}$), markup (μ_{it}), and the log of the distortion ($\ln \tau_{it}$). The independent variables are the first to third orders of age and either the log of total intangible capital in (26a) or the logs of the three kinds of intangible capital in (26b). Because a substantial number of firms do not conduct R&D at all, we include a dummy for a positive R&D. We estimate the first difference of (26a) and (26b) as follows:

$$\Delta Y_{it} = \beta_{Y1} + \beta_{Y2} age_{it} + \beta_{Y3} (age_{it})^2 + \beta_{Y,Intan} \Delta \ln Intangible_{it} + \delta_{Y,st} + u_{Y,it} \tag{27a}$$

$$\begin{aligned} \Delta Y_{it} = {} & \beta_{Y1} + \beta_{Y2} age_{it} + \beta_{Y3} (age_{it})^2 + \beta_{Y,Soft} \Delta \ln Software_{it} + \beta_{Y,O} \Delta \ln Organization_{it} \\ & + \beta_{Y,RD} \Delta \ln(R\&D_{it} + 1) + \delta_{Y,RDstart} 1_{\{R\&D_{it}>0 \,\&\, R\&D_{it-1}=0\}} + \delta_{Y,RDzero} * 1_{\{R\&D_{it}=0 \,\&\, R\&D_{it-1}=0\}} \\ & + \delta_{Y,st} + u_{Y,it}. \end{aligned} \tag{27b}$$

None of firms has any $R\&D$ in period t but positive $R\&D$ in period $t-1$ because we assume the multiplicative depreciation. We use one- and two-year lagged values of the corresponding intangible capital variables as instruments and estimate equations (27a) and (27b) with a two-step GMM as well as an OLS.

Before showing the results of the GMM, we briefly summarize the estimation results of the OLS, which we report in Table A2 in Appendix. First, the total intangible capital is significantly and positively correlated with all the dependent variables: the log of sales, log of TFPQ, markup, and the log of distortion. Among the three types of intangibles, the coefficients for organizational capital are the largest. These coefficients indicate that organizational capital plays an important role in firm dynamics.

Table 3 shows the estimation results of the GMM. In columns (1)–(3), the dependent variable is the log difference in sales. Column (1) presents the result of equation (27a) and shows that the coefficient for the log difference in total intangible capital is positive and significant and that the absolute values of the coefficients for age and its squared value are smaller than those in column (1) in Table 2. Column (2) presents the result of equation (27b) and shows that the coefficients for the log differences in organizational capital and R&D are positive and significant. Column (3) gives the result when we include only organizational capital among the three types of intangible capital to deal with the possible multicollinearity that may arise because the investment rates of the three types of intangible capital can be highly correlated with each other. The coefficient for the organizational capital does not significantly change from column (2) and shows that the multicollinearity is not serious for sales growth.

[Insert Table 3 here]

In columns (4)–(6) of Table 3, the dependent variables are the log differences in the TFPQ. Column (4) presents the estimation result of equation (27a). The coefficient for the log difference in the total intangible capital is positive but statistically insignificant. Column (5) presents the result from equation (27b) and shows that among the three types of intangible capital, the coefficient for organizational capital is positive, although its size is small. In columns (7)–(9), the dependent variable is the difference in markup. Column (7) shows that the coefficient for the log difference in total intangible capital is unexpectedly negative and significant. Column (8) shows that the coefficients for the log differences in the three kinds of intangible capital are not significant. In columns (10)–(12) the dependent variables are the log differences in the factor price distortion. Column (10) shows that the coefficient for the log difference of total intangible capital is not significant. Column (11) shows that the coefficients for organizational capital and software are negative and marginally significant.

In sum, we find that the total intangible capital has significant and positive effects on sales. The total intangible capital has a significantly negative effect on the markup that is not consistent with the view that intangible capital helps build a reputation in the product markets. Furthermore, the total intangible capital has a negative effect on the factor price distortion that is consistent with the view that investment in intangible capital removes financial frictions. Among the three types of intangible capital, organizational capital has significantly positive effects on sales, although its quantitative effects are smaller than those of total intangible capital.

5.2 Quantitative effects of intangible capital on sales, TFPQ, markup, and distortion

To quantify the effects of intangible capital on sales growth, we use the results in Tables 2 and A3 to simulate the paths of each of the dependent variables over time by accumulating the constant terms and the coefficients for age and age squared to extract the pure age effect. Specifically, we use equations (25), (27a) and (27b) to calculate the predicted values for age a as $\widehat{Y_a} = \beta_{Y1} a + \beta_{Y2} \sum_{a'=1}^{a} a' + \beta_{Y3} \sum_{a'=1}^{a} (a')^2$. We compare the predicted paths that control for intangible capital in Table 3 to the simulated paths that do not control for intangible capital in Table 2 to observe the quantitative effects of the total intangible capital on the relations between age and sales and the three parameters. Panel A in Figure 6 shows the predicted paths of sales before and after controlling for either total intangible capital or organizational capital. Specifically, we use the coefficients for age and age squared in columns (1) and (3) in Table 3 for the predicted paths of sales after controlling for total intangible capital and organizational capital, respectively, and those coefficients in column (1) in Table 2 for the predicted path of sales before controlling for intangible capital. Similarly, Panels B, C, and D in Figure 6 show the predicted paths of the TFPQ, markup, and the distortion, respectively, before and after controlling for either total intangible capital or organizational capital.[19]

[Insert Figure 6 here]

Panel A in Figure 6 shows that shows that a part of the age effect on sales is mediated by controlling for organization capital or intangible capital. This result shows that intangible capital has quantitatively sizable effects on the evolution of sales with age. Panel B reports the paths of TFPQ and shows that the positive age effect on the TFPQ up to about age 20 is reversed. The path is slightly explained by the organization capital. Panel C shows that controlling for the intangible capital makes clearer the rise in markup up to age 40. This result shows that the accumulation of the intangible capital mitigates the increase in markup with age, though the pure age effects are

[19] Panel B depicts on the coefficients in columns (4) and (6) in Table 3 and column (2) in Table 2. Panel C depicts the coefficients in columns (7) and (9) in Table 3 and column (3) in Table 2. Panel D depicts the coefficients in columns (10) and (12) in Table 3 and column (4) in Table 2.

also positive. Finally, Panel D shows that the accumulation of the intangible capital decreases the factor price distortion and obscures the negative pure age effects.

5.3. Quantitative effects of organizational and total intangible capital on sales

In this subsection, we quantify the effects of intangible capital on the TFPQ, markup, and distortion, respectively. In this subsection, we quantify the total effects of organizational capital and total intangible capital on sales through the TFPQ, markup, and distortion. For this aim, we simulate the sales by regarding each of the three factors as functions of the organizational capital or total intangible capital. In the case of organizational capital, we first calculate the TFPQ that is caused by the accumulation of organizational capital, $A(O_a)$, as

$$\ln A(O_a) = \ln A_1 + \hat{\beta}_{A,O} \sum_{a'=2}^{a} \left(\frac{1}{N_{a'}} \sum_{age_{it}=a'} \Delta \ln O_{it} \right) \tag{28}$$

where $\hat{\beta}_{A,O}$ is the estimated coefficient for the investment of the organizational capital in equation (27b) on the log difference in the TFPQ (column (5) in Table 3). We define $A(O_1)$ as A_1. We calculate the markup $\mu(O_a)$ and distortion $\tau(O_a)$ that are caused by the accumulation of organizational capital similarly (columns (8) and (11) in Table 3). Then we simulate the paths of sales, $\ln PQ[A(O_a), \mu(O_a), \tau(O_a)]$ and $\ln PQ[A(O_1), \mu(O_1), \tau(O_1)]$, where the latter is the hypothetical path of sales that would be realized if the organizational capital were not accumulated or have no effect on the parameters at all. We also calculate the path when the intangible capital would be fixed at initial level and not accumulated after entry. We, then, compare these paths of the log of sales to explore the changes in sales.

The simulated paths are shown in Figure 7. If organizational capital were fixed at the level of establishment, then the sales growth would be totally lost and the firm would shrink. Given that the rise in the TFPQ is crucial for firm growth, shown in Figure 5, the simulated path can be explained by the effects of organizational capital on TFPQ. While this effect is statistically insignificant in Table 3, it is potentially important channel to achieve the steady growth. Figure 7 also shows that the path of sales is similar when total intangible capital is replaced with the organization capital. In sum, the organizational capital plays a vital role in the firms growth.

[Insert Figure 7 here]

6. Conclusion

In this paper, we explore the role of intangible capital in the growth of a firm over time through the lens of a model with firm-specific TFPQ, markup, and factor price distortion. For this aim, we have constructed firm-level panel data of intangible capital consisting of software, organizational capital, and R&D stocks.

Using these data, we find that the accumulation of intangible capital plays a significant role in the growth of TFPQ, which, in turn, accounts for a major part of sales growth over firms' life cycles. We also find that the accumulation of the intangible capital mitigates the increase in markup with age, although its quantitative impact on sales is relatively small. Among the three types of intangible capital we examine: organizational capital, software, and R&D stocks, organizational capital accounts for a major part of the sales growth.

Our analysis sheds lights on the role of intangible capital on firm growth. Especially, our results indicate that intangible capital plays a substantial role in the growth of young firms mainly through the TFPQ. However, this analysis does not explore its exact mechanism nor does it explore the role of the selection of firms in sales growth due to the coverage of our data. These are left for future research. In addition, the observed negative association between intangible capital and markup after controlling for firm age might be surprising considering that some recent studies point out the positive association between intangible capital and market power observed for the U.S. and France (De Ridder, 2019; Crouzet and Eberly, 2019). This result may suggest that the effects of intangible capital on markup is non-linear, given that the accumulation of intangible capital is small in Japan relative to that in U.S. (e.g., Fukao et al., 2009). We need more pieces of evidence from other economies to explore this possibility.

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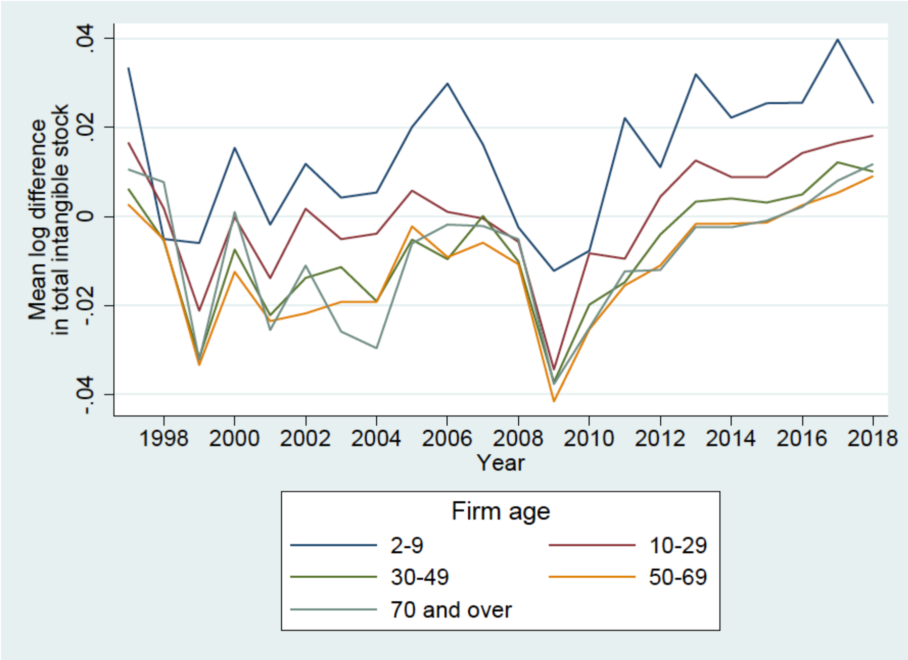
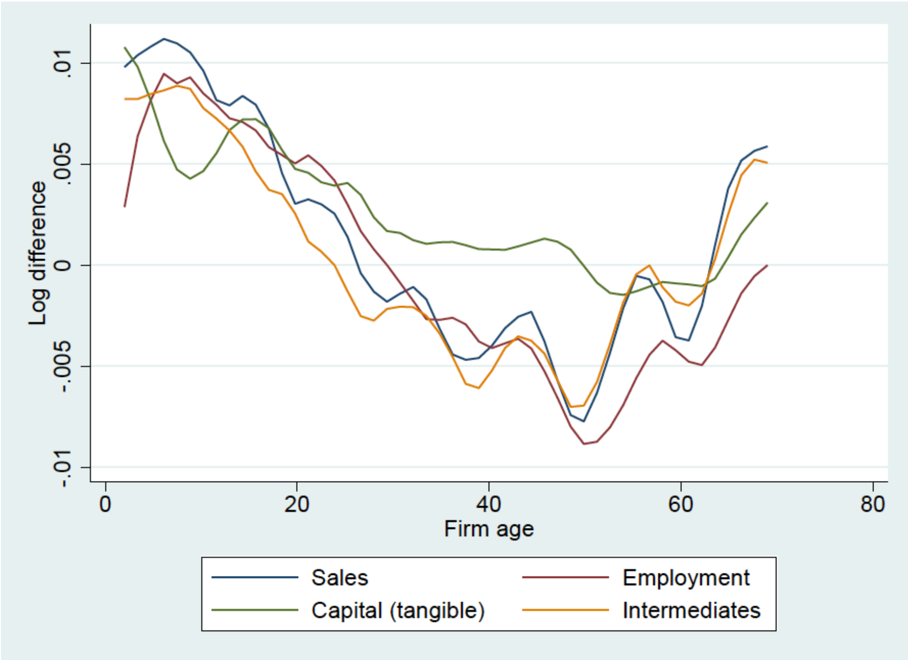
Figure 1: Investment rate of intangible capital by age groups



Source: Authors' calculation from the Basic Survey of Japanese Business Structure and Activities (METI).

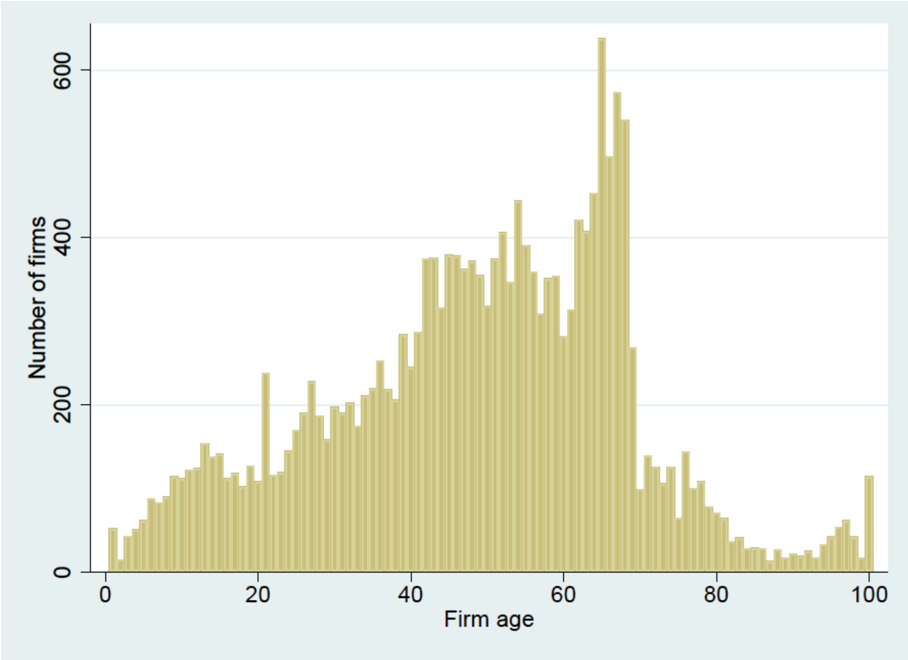
Figure 2: Age and growth rates in sales and inputs



Note: The lines are obtained by local polynomial smoothing method.

Source: Authors' calculation from the Basic Survey of Japanese Business Structure and Activities (METI).

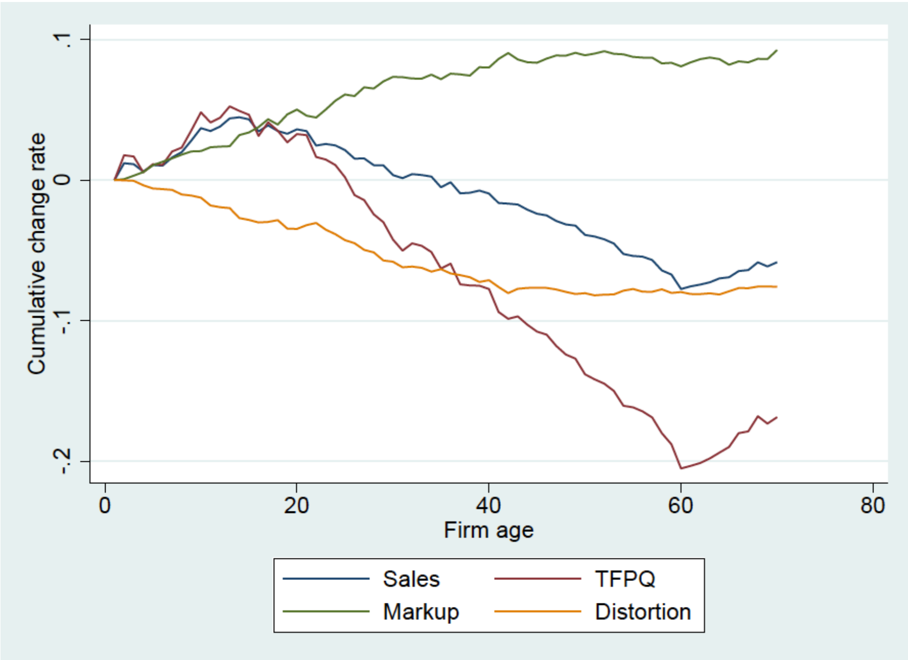
Figure 3: Age distribution in 2015



Note: Age over 100 is rounded as 100 in this figure.

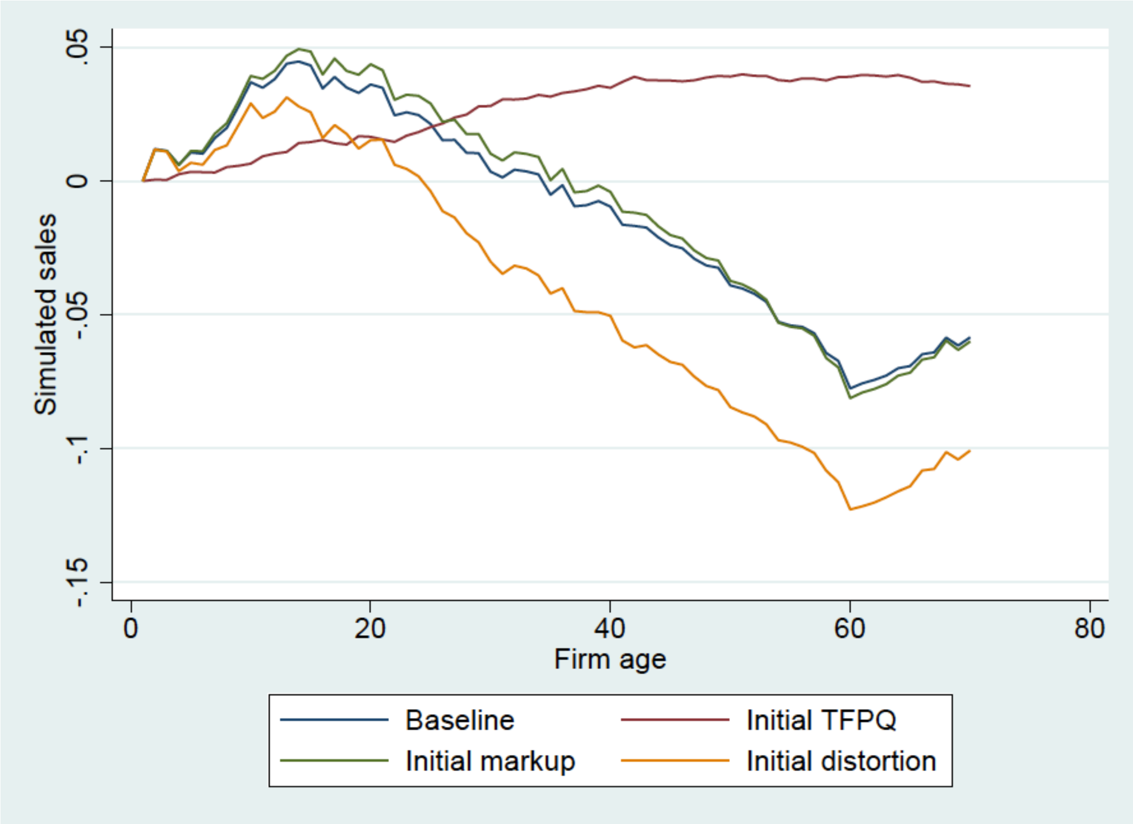
Source: Authors' calculation from the Basic Survey of Japanese Business Structure and Activities (METI).

Figure 4: Age and firm-level parameters of TFPQ, markup, and distortion



Source: Authors' calculation from the Basic Survey of Japanese Business Structure and Activities (METI).

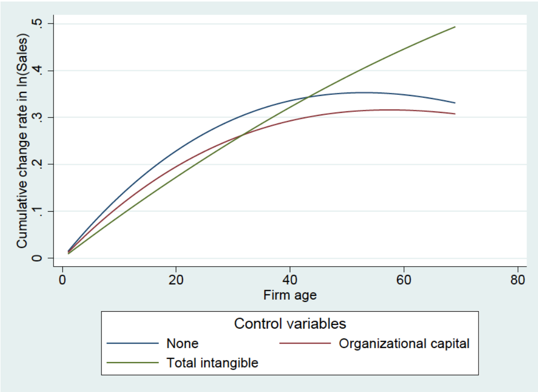
Figure 5: Hypothetical firm dynamics with initial parameters



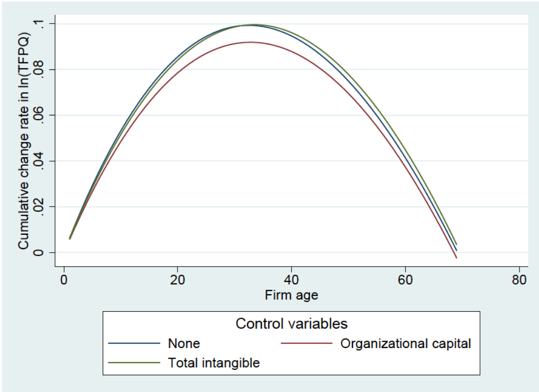
Source: Authors' calculation from the Basic Survey of Japanese Business Structure and Activities (METI).

Figure 6: Age and predicted values

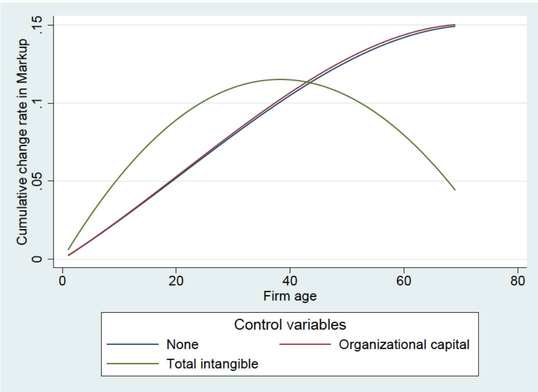
A. Sales



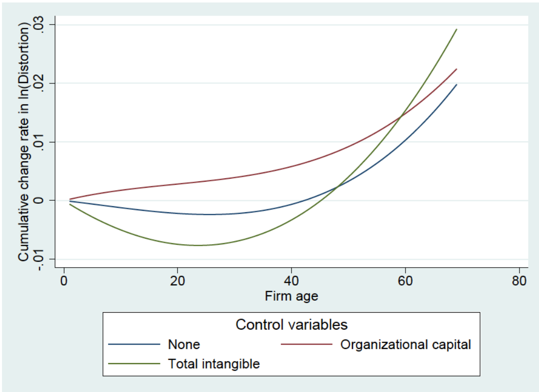
B. TFPQ



C. Markups

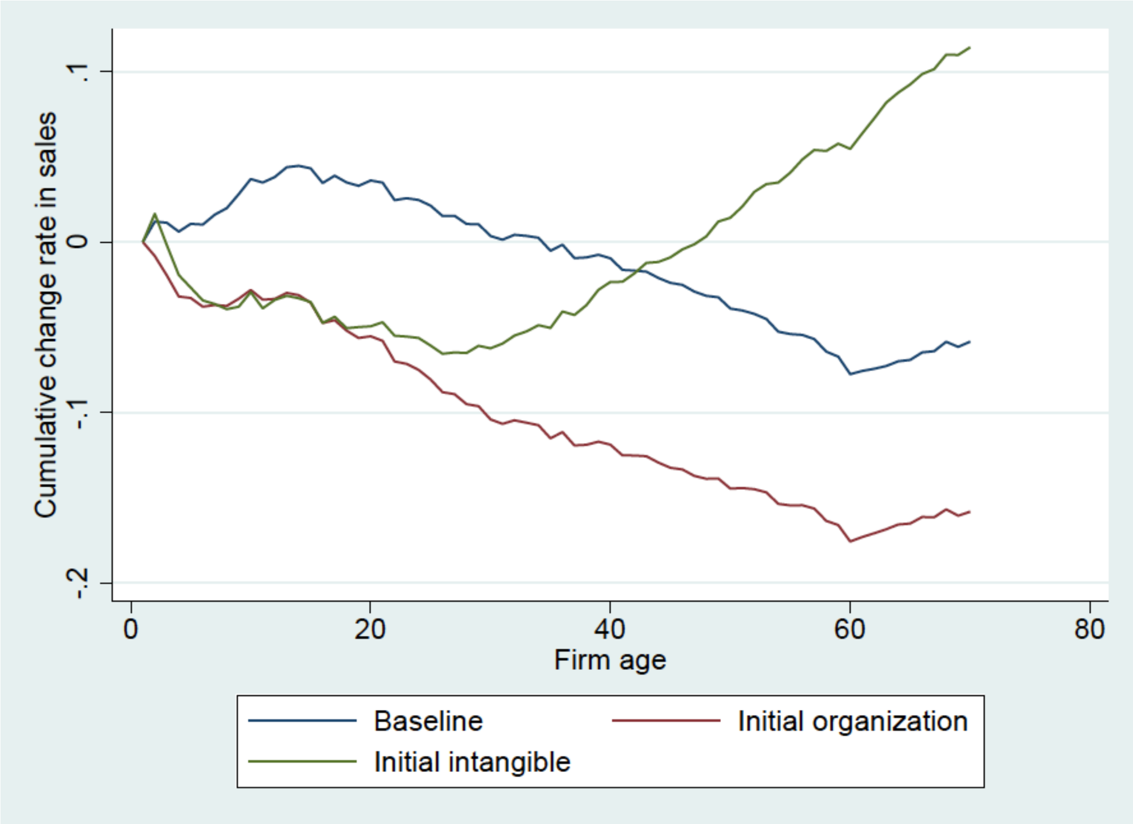


D. Factor price distortion



Source: Authors' calculation, based on the estimation results in Tables 2 and 3.

Figure 7: Hypothetical firm dynamics with initial intangible capital



Source: Authors' calculation, based on the estimation results in Table 3.

Table 1: Summary statistics

Variable	Mean	Median	SD	Max	Min
Sales	26,064	5,378	192,620	14,500,000	36
Tangible capital	6,096	1,035	79,548	11,900,000	1
Employment	443	149	1,836	133,321	50
Intermediates	18,648	3,108	163,635	14,200,000	6
Intangible capital	961	124	11,129	1,105,441	0
Software	115	18	1,275	172,720	0
Organization	368	86	2,044	147,430	0
R&D	478	0	8,858	923,462	0
Firm age	44	45	19	302	1
Markup	1.78	1.30	1.43	232.34	1.00
Δln(Sales)	0.00	0.00	0.13	0.54	-0.57
Δln(Tangible capital)	0.00	-0.02	0.16	1.06	-0.80
Δln(Employment)	0.00	0.00	0.09	0.53	-0.46
Δln(Intermediate)	0.00	0.00	0.24	1.81	-1.87
Δln(Intangible capital)	-0.01	0.00	0.14	1.83	-1.90
Δln(Software)	-0.06	-0.04	0.51	1.97	-2.10
Δln(Organization)	0.00	0.00	0.09	0.47	-0.49
Δln(R&D+1)	0.00	0.00	0.15	1.63	-0.22
Δln(TFPQ)	0.00	0.00	0.48	3.17	-4.09
ΔMarkup	0.00	0.00	0.54	10.03	-9.69
Δln(Distortion)	0.00	0.00	0.12	1.03	-1.01
αK	0.04	0.04	0.03	0.56	0.01
αL	0.24	0.24	0.15	1.23	0.04
αM	0.80	0.80	0.10	0.96	0.41
γ	1.07	1.02	0.12	2.01	0.76

Source: Authors' calculation from the Basic Survey of Japanese Business Structure and Activities (METI).

Table 2 Estimation results from an OLS

Dependent variable	(1) Δln(Sales)	(2) Δln(TFPQ)	(3) ΔMarkup	(4) Δln(Distortion)
Age	-0.000499	-0.000253	-0.00000471	0.0000365
	[0.0000552]***	[0.0000888]***	[0.0000901]	[0.0000206]*
Age squared	0.000242	0.000111	-0.0000849	0.0000074
	[0.0000607]***	[0.0000885]	[0.0000901]	[0.0000183]

Notes: ***, **, and * represent significance at the 1%, 5%, and 10% statistical levels, respectively. Parentheses contain the standard errors clustered by firms. Number of observations is 408,185. Industry-year fixed effect is included in all specifications.

Source: Authors' estimation from the Basic Survey of Japanese Business Structure and Activities (METI).

Table 3: Estimation results from GMM

Dependent variable	(1) Δln(Sales)	(2) Δln(Sales)	(3) Δln(Sales)	(4) Δln(TFPQ)	(5) Δln(TFPQ)	(6) Δln(TFPQ)
Age	-0.0000569	-0.000303	-0.000303	-0.000203	-0.000156	-0.000198
	[0.0000393]	[0.0000383]***	[0.0000388]***	[0.000121]*	[0.000107]	[0.000108]*
Age squared	-0.00000692	0.000136	0.000144	0.0000558	0.0000367	0.0000594
	[0.0000311]	[0.0000364]***	[0.0000372]***	[0.000109]	[0.000105]	[0.000105]
Δln(Intangible capital)	0.694			0.00474		
	[0.0486]***			[0.134]		
Δln(Software)		-0.00291			-0.0146	
		[0.00148]**			[0.00602]**	
Δln(Organization)		0.182	0.185		0.0462	0.0334
		[0.00956]***	[0.00944]***		[0.0317]	[0.0312]
Δln(R&D+1)		0.0163			-0.00553	
		[0.00391]***			[0.0150]	
No R&D in t-1 dummy		-0.0116			0.0108	
		[0.00592]*			[0.0253]	
No R&D in t and t-1 dummy		-0.00265			0.00383	
		[0.000531]***			[0.00178]**	

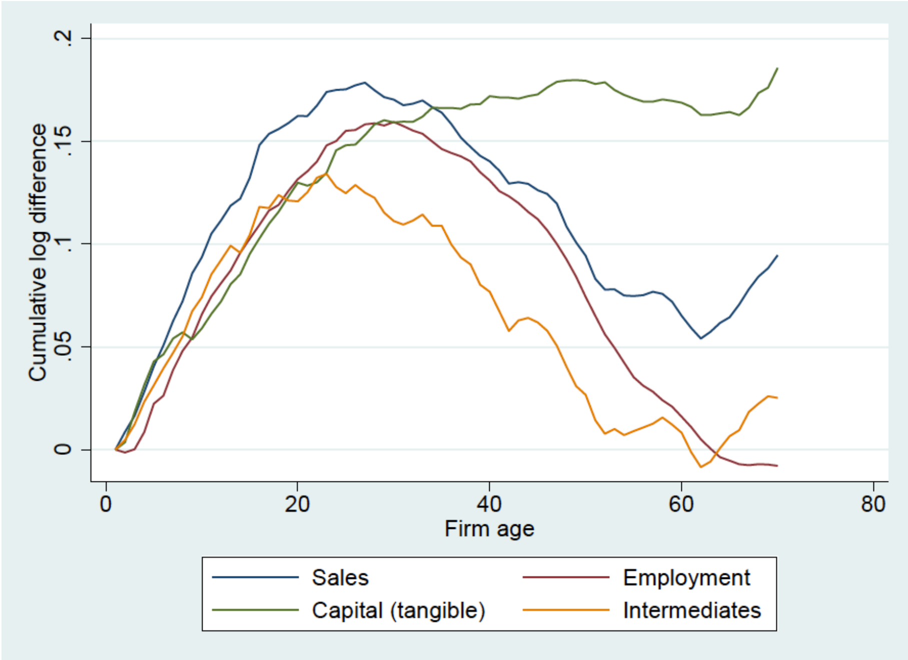
Dependent variable	(7) ΔMarkup	(8) ΔMarkup	(9) ΔMarkup	(10) Δln(Distortion)	(11) Δln(Distortion)	(12) Δln(Distortion)
Age	-0.000165	0.0000272	0.0000473	0.0000217	-0.00000583	-0.0000147
	[0.000106]	[0.0000928]	[0.0000935]	[0.0000288]	[0.0000264]	[0.0000260]
Age squared	0.0000154	-0.0000981	-0.00011	0.0000179	0.0000406	0.0000368
	[0.0000846]	[0.0000821]	[0.0000823]	[0.0000245]	[0.0000246]*	[0.0000240]
Δln(Intangible capital)	-0.452			0.0457		
	[0.125]***			[0.0319]		
Δln(Software)		0.00799			-0.00491	
		[0.00687]			[0.00156]***	
Δln(Organization)		-0.00737	-0.00685		-0.046	-0.0465
		[0.0351]	[0.0340]		[0.00796]***	[0.00780]***
Δln(R&D+1)		-0.0223			0.000965	
		[0.0173]			[0.00392]	
No R&D in t-1 dummy		0.0765			-0.00263	
		[0.0324]**			[0.00729]	
No R&D in t and t-1 dummy		-0.00141			0.00327	
		[0.00182]			[0.000491]***	

Notes: ***, **, and * represent significance at the 1%, 5%, and 10% statistical levels, respectively. Parentheses contain the standard errors clustered by firms. Number of observations is 267,609. Industry-year fixed effect is included in all specifications.

Source: Authors' estimation from the Basic Survey of Japanese Business Structure and Activities (METI).

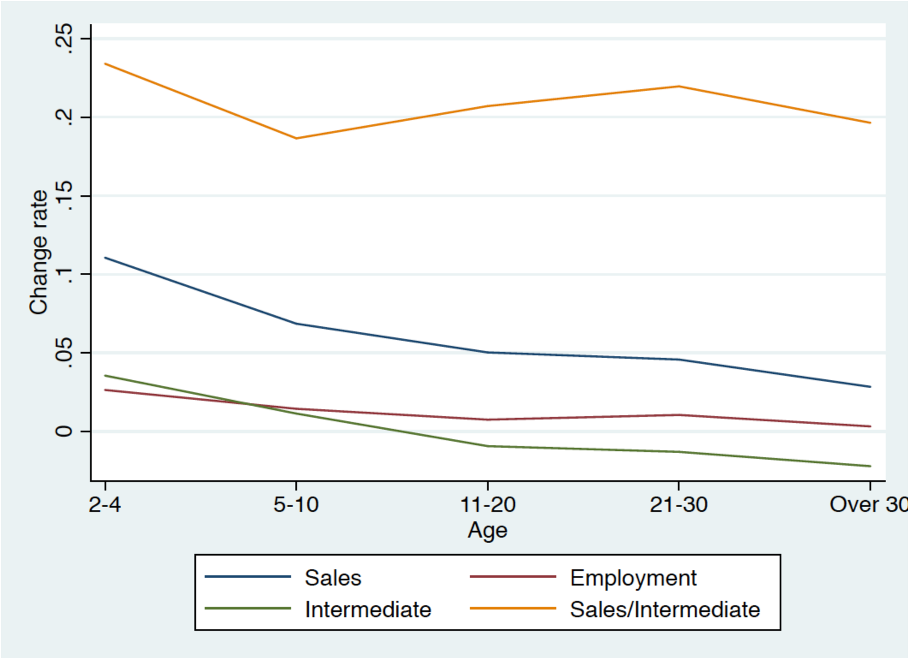
Appendix

Figure A1: Firm age and cumulative growth rates in sales and inputs



Source: Authors' calculation from the Basic Survey of Japanese Business Structure and Activities (METI).

Figure A2: Plant age and growth rates in sales and inputs



Notes: This figure shows the change rates in sales, employment, intermediate, and the ratio of sales to intermediates from 2014 to 2015. The sample covers the plants that had four or more employees in 2014 and survived until 2015.

Source: Authors' calculation from the Census of Manufacture (METI) and Economic Census for Business Activity (MIC and METI).

Table A1: Estimation results for intangible capital investment

Δln(Intangible capital)	(1)	(2)	(3)	(4)
Age	-0.0000915		-0.000589	
	[0.0000445]**		[0.0000558]***	
ln(Age)		-0.0116		-0.0212
		[0.00155]***		[0.00184]***
Lagged ln(Intangible capital)			-0.131	-0.131
			[0.00396]***	[0.00391]***
Lagged ln(Sales)			0.0894	0.0897
			[0.00262]***	[0.00260]***
Observations	403,443	403,443	323,674	323,674

Notes: ***, **, and * represent significance at the 1%, 5%, and 10% statistical levels, respectively. Parentheses contain the standard errors clustered by firms. Industry-year fixed effect is included in all specifications.

Source: Authors' estimation from the Basic Survey of Japanese Business Structure and Activities (METI).

Table A2: Estimation results from OLS

A. Δln(Sales)	(1)	(2)	(3)	(4)
Age	-0.000499	-0.000415	-0.0000589	-0.0000464
	[0.0000552]***	[0.0000457]***	[0.0000233]**	[0.0000232]**
Age squared	0.000242	0.000193	-0.000031	-0.000035
	[0.0000607]***	[0.0000494]***	[0.0000202]	[0.0000201]*
Δln(Intangible capital)		0.154		
		[0.00204]***		
Δln(Software)			0.00529	
			[0.000361]***	
Δln(Organization)			0.507	0.508
			[0.00360]***	[0.00359]***
Δln(R&D+1)			-0.000297	
			[0.00130]	
No R&D in t-1 dummy			-0.00377	
			[0.00343]	
No R&D in t and t-1 dummy			-0.00206	
			[0.000402]***	

B. Δln(TFPQ)	(5)	(6)	(7)	(8)
Age	-0.000253	-0.00018	0.000142	0.000142
	[0.0000888]***	[0.0000881]**	[0.0000931]	[0.0000940]
Age squared	0.000111	0.0000682	-0.000123	-0.000131
	[0.0000885]	[0.0000876]	[0.0000941]	[0.0000956]
Δln(Intangible capital)		0.133		
		[0.00660]***		
Δln(Software)			0.00841	
			[0.00163]***	
Δln(Organization)			0.442	0.443
			[0.0105]***	[0.0105]***
Δln(R&D+1)			-0.00503	
			[0.00579]	
No R&D in t-1 dummy			-0.0127	
			[0.0158]	
No R&D in t and t-1 dummy			0.00379	
			[0.00158]**	

C. ΔMarkup	(9)	(10)	(11)	(12)
Age	-0.00000471	0.00000314	0.0000499	0.0000514
	[0.0000901]	[0.0000904]	[0.0000925]	[0.0000925]
Age squared	-0.0000849	-0.0000894	-0.000117	-0.000119
	[0.0000901]	[0.0000905]	[0.0000928]	[0.0000930]
Δln(Intangible capital)		0.0143		
		[0.00763]*		
Δln(Software)			-0.000526	
			[0.00196]	
Δln(Organization)			0.0639	0.0629
			[0.0112]***	[0.0111]***
Δln(R&D+1)			-0.00707	
			[0.00677]	
No R&D in t-1 dummy			0.0244	
			[0.0218]	
No R&D in t and t-1 dummy			0.00024	
			[0.00165]	

D. Δln(Distortion)	(13)	(14)	(15)	(16)
Age	0.0000365	0.0000482	0.00012	0.000104
	[0.0000206]*	[0.0000204]**	[0.0000203]***	[0.0000206]***
Age squared	0.0000074	0.000000579	-0.0000321	-0.0000339
	[0.0000183]	[0.0000180]	[0.0000177]*	[0.0000183]*
Δln(Intangible capital)		0.0213		
		[0.00171]***		
Δln(Software)			0.000708	
			[0.000436]	
Δln(Organization)			0.076	0.0757
			[0.00259]***	[0.00258]***
Δln(R&D+1)			-0.00338	
			[0.00152]**	
No R&D in t-1 dummy			-0.000552	
			[0.00496]	
No R&D in t and t-1 dummy			0.00571	
			[0.000438]***	

Notes: ***, **, and * represent significance at the 1%, 5%, and 10% statistical levels, respectively. Parentheses contain the standard errors clustered by firms. Number of observations is 408,185. Industry-year fixed effect is included in all specifications.

Source: Authors' estimation from the Basic Survey of Japanese Business Structure and Activities (METI).