Three Essays on Innovation Activity, Investment in Intangible Assets, and Productivity

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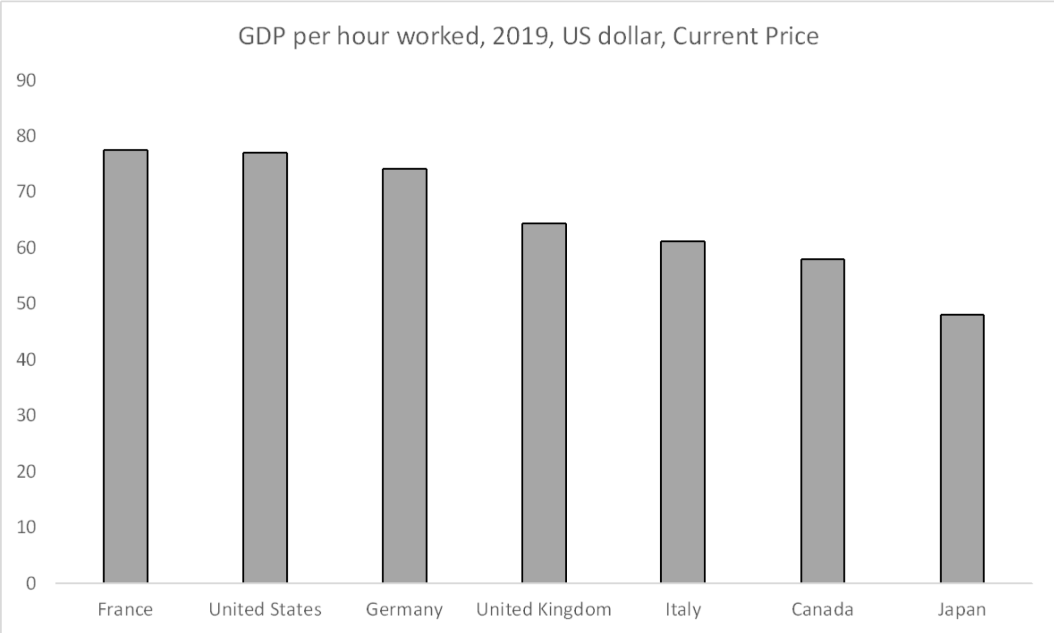
Chapter 1

Introduction

1.1 Purpose of the Dissertation and Economic Problems to be Analyzed

Japan has been experiencing a period of secular stagnation, known as the Two Lost Decades. The stagnation of labor productivity is considered to be the main cause — which is, in turn, attributed to the lack of capital accumulation and stagnant total factor productivity (TFP) growth (Fukao and Makino (2021)). According to OECD (2021), Japan's labor productivity is the lowest among G7 countries (Figure 1.1), which is directly related to stagnant real wage growth. As shown in Figure 1.2 and Figure 1.3, recently Japan has experienced a stagnation of capital accumulation. This stagnation of capital accumulation is puzzling because the capital-stock growth rate is even lower than the natural growth rate, which is unusual ; furthermore, the cause of this stagnation remains unclear. Additionally, as Gordon (2012) and Summers (2014) point out, the stagnation of TFP growth has become a common phenomenon among advanced economies in recent years. However, according to Jorgenson et al. (2015), the level of TFP in Japan is significantly lower than that in the United States. Therefore, there seems to be a room for Japan to catch up.



Source: OECD Productivity Statistics - © OECD 2021

Figure 1.1: Comparison of labor productivity among G7 countries, 2019

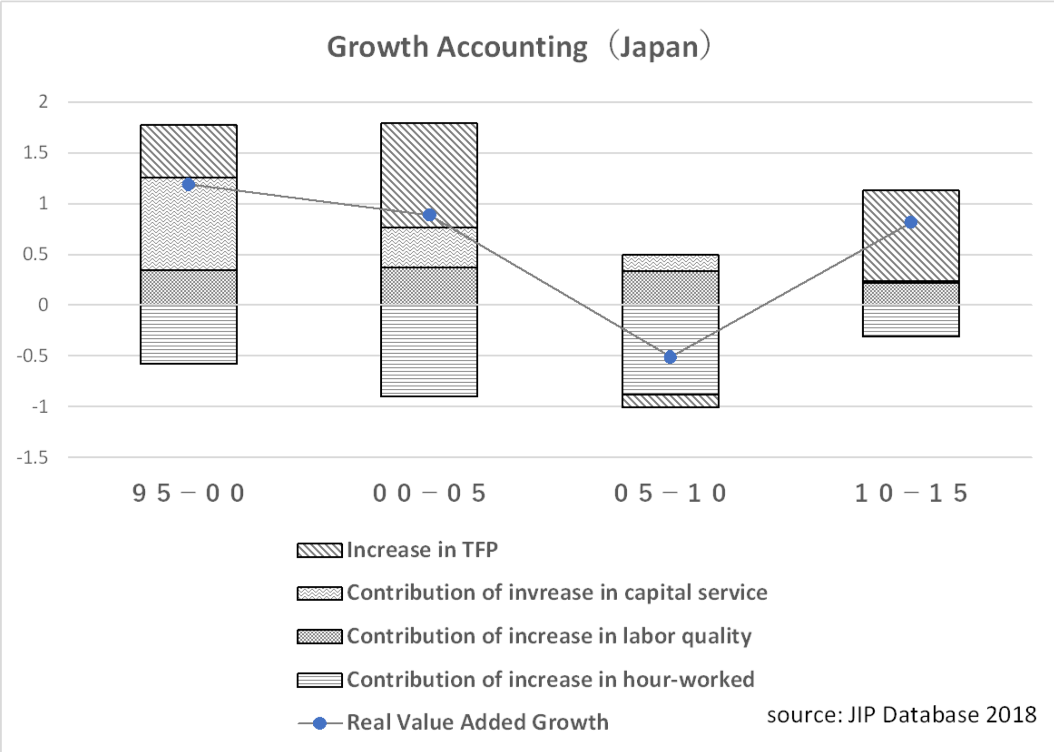


Figure 1.2: Growth accounting of the Japanese Economy

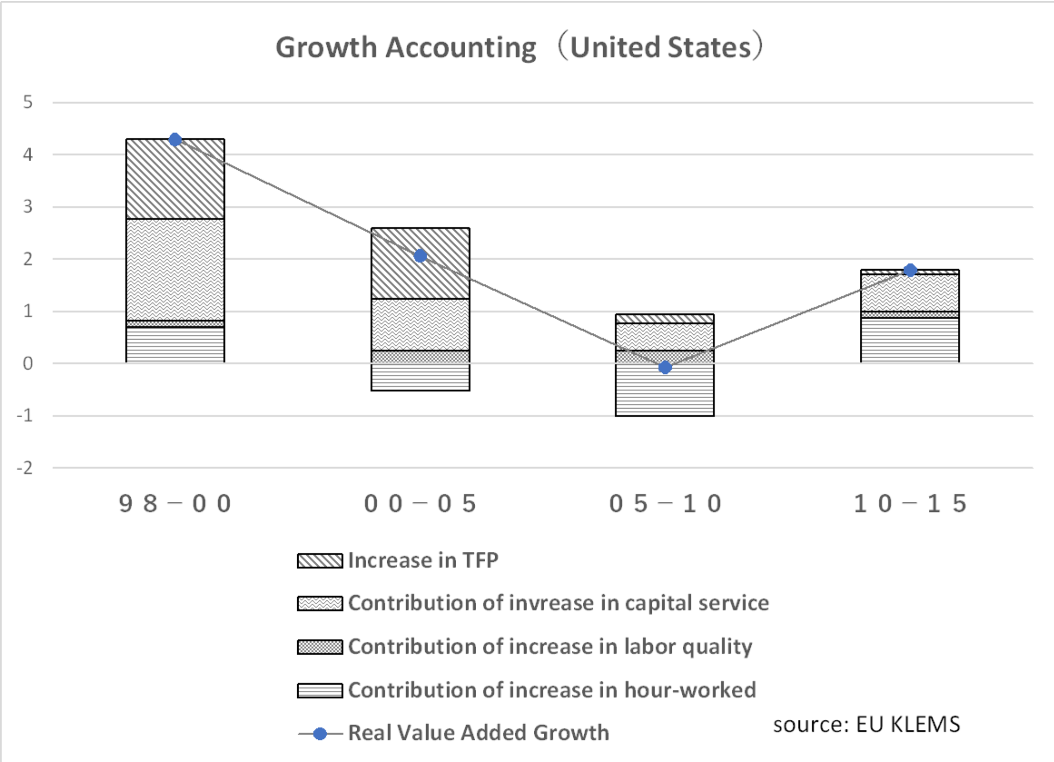


Figure 1.3: Growth accounting of the US Economy

We fear that the Two Lost Decades may turn into the Three Lost Decades. Many economists agree that during this period, the Japanese economy has suffered from an insufficient economic metabolism, a dual economy[1] (itself typified by Keiretsu), a delay in digitalization, an aging society, Japanese-style long-term employment practices, industry protection policies, and arcane regulations.

There is a view that Japan had almost caught up with Europe and the United States (US) during the period of “Japan as No.1,” i.e., around the time the economic bubble burst. According to Ito and Hoshi (2020), demand-side issues were the main cause of the Two Lost Decades. Ito and Hoshi (2020) divide this period into four phases: (1)

[1] In this context, the term “dual economy” refers to the disparity between firms of different sizes. Regarding the dual economy in the labor market, see Genda (2011).

the adjustment phase after the economic bubble burst; (2) a series of bank and securities company failures; (3) reforms by the Koizumi administration; and (4) the global financial crisis, the Great East Japan Earthquake, and political turmoil. They argue that the incomplete disposal of bad loans and the subsequent industrial protection policy were critical, leading to the survival of zombie firms and the deterioration of corporate metabolism. In particular, these factors resulted in a lack of investment and reduced consumption on the demand side.

At this point, it is necessary to examine Japan's potential growth rate[2]. Figure 1.4 shows that no matter how much the supply-demand gap is filled, the growth rate in 2000-2020 would remain at around 1% and secular stagnation could not be avoided. Therefore, although the secular stagnation is due partly to a lack of demand, the main cause must be on the production side.

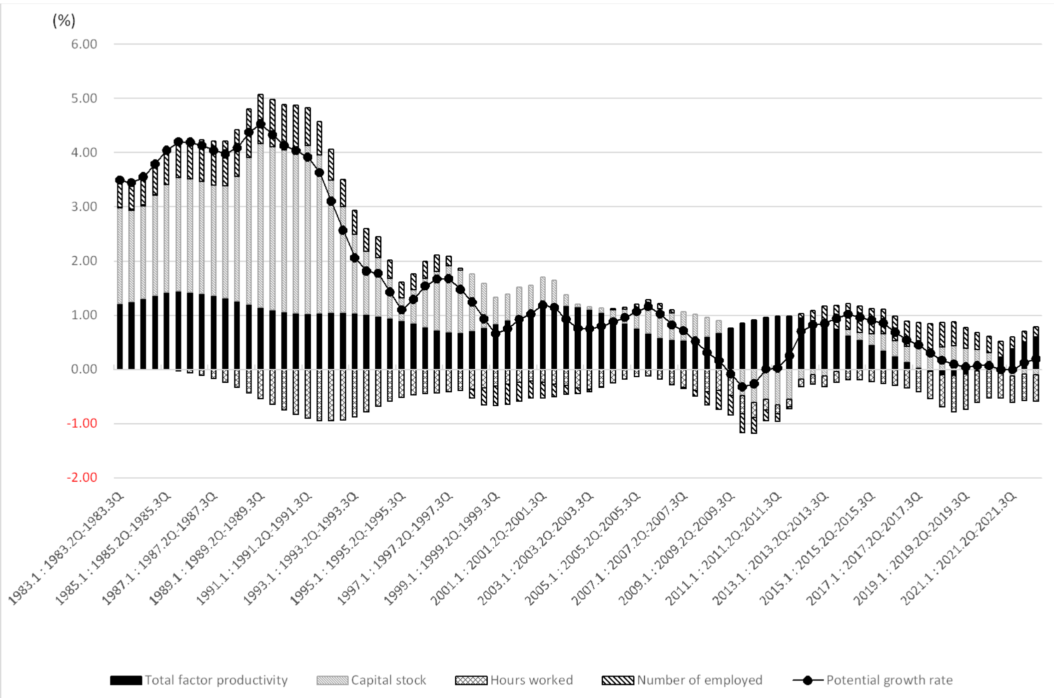


Figure 1.4: Japan's potential growth rate (Bank of Japan)

[2]The Bank of Japan notes that this potential GDP growth has a wide margin of errors (https : //www.boj.or.jp/research/brp/ron2017/data/ron170428a.pdf).

Regarding the supply side, the main innovators in the acquisition of new technology are large firms [3]. Japan has a dual economy problem, and the disparity between Keiretsu firms[4] (i.e., a group of firms with stable business or capital ties with each other) and Non-Keiretsu firms that do not have such connections is a concern. However, the environment surrounding the firms' relationship in the Keiretsu has changed because there was a prolonged period of yen appreciation before the Abenomics, during which firms began to make direct investments overseas and set up factories abroad. While the decrease in exports is related to aggregate demand, for companies with stable business and capital relationships, the relocation of factories overseas might have led to a decrease in technological spillover due to the hollowing-out of the industry. In fact, Belderbos et al. (2022) confirm that inter-firm R&D spillovers declined during this period. If parent companies and firms with stable business relationships disappear from a given location, small and medium enterprises (SMEs) will have to conduct innovation activities on their own. Consequently, it is necessary to determine whether SMEs' innovation activities depend on large firms' innovation activities.

Next, I examine the delay in investment in information and communication technology (ICT) capital goods and the delay in digitalization. As Fukao et al. (2016) have pointed out, Japan missed the ICT revolution. Why did Japan miss the ICT revolution? As we will see in Chapter 3, there are varieties of firms which made successful and unsuccessful responses to ICT revolution in Japan. I would like to examine where such differences originated from. A survey in 2013 investigated the degree to which CEOs in Japan and the U.S. consider ICT capital goods to be important.

[3]This can be verified in the Japanese National Innovation Survey, for instance.

[4]Aghion et al. (2021) cite Japan's Keiretsu society as one of the factors contributing to Japan's secular stagnation, especially due to the political pressure exerted on Keiretsu firms with regard to competition.

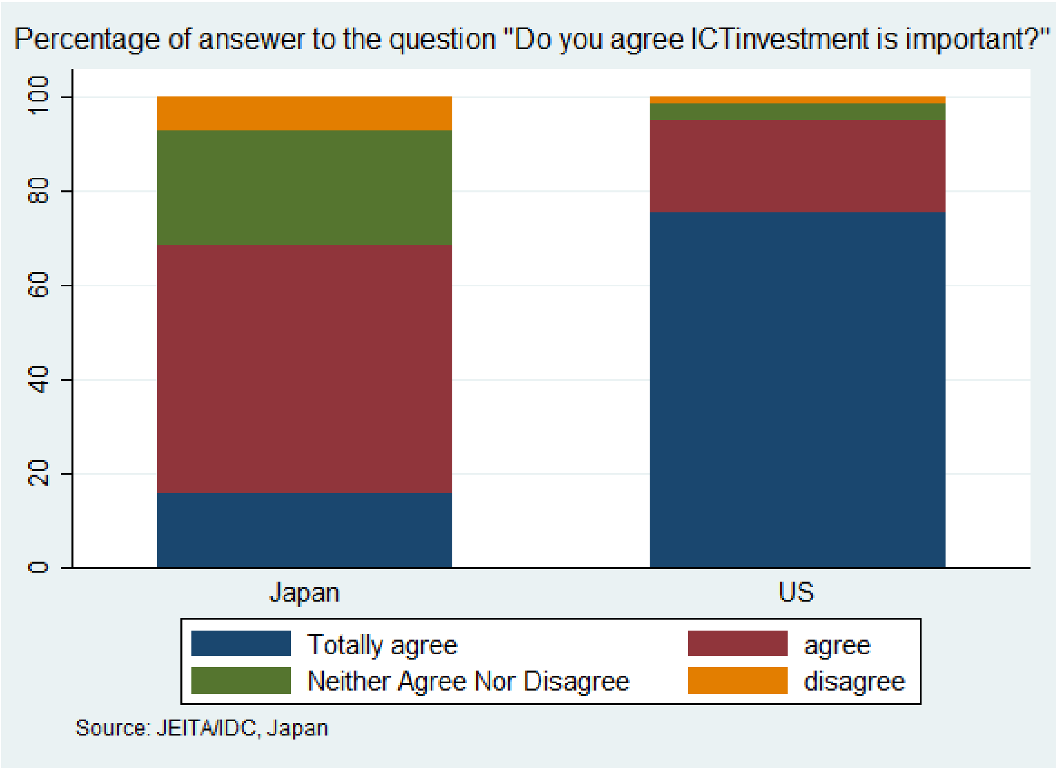


Figure 1.5: CEOs' answers regarding the importance of ICT capital goods

According to Figure 1.5, Japanese management does not realize the importance of ICT capital goods. In this dissertation, I argue that this is due to the difference in CEOs' ability, as companies with better educated CEOs are more likely to invest in ICT capital goods.

Next, I turn to human resources. Japan has a highly rigid labor market and the established culture of long-term employment practiced mainly by large firms. According to Fukao (2021), such culture is one of the factors that creates the dual economy that exhibits large disparity by firm size. Furthermore, because the locations of large companies are concentrated in Tokyo and other metropolitan areas where most individuals prefer to live (Kawaguchi and Kawada (2021)), when hiring new university graduates, large companies attract great many applicants including those graduating from the most prestigious and selective universities (such as the University of Tokyo). In other words, large firms have an upper hand in selecting workers. Under this circumstance, large firms have two hiring strategies: to individually examine the abilities of new graduates or to trust and use the prestige of the graduates' alma mater as a selection criterion without investigating individual abilities. Large firms must decide which strategy to adopt. Which choice is more likely to increase firms' future productivity? If a firm hires only on the basis of university prestige without examining the quality of the talent, will this hinder its productivity growth? I will analyze this question empirically, taking into account the reverse causality problem of talented graduates choosing firms with high productivity potential.

In this doctoral dissertation, the following three research questions will be explored: (1) the question of whether there is a positive relationship between SMEs' R&D intensity and that of its business and capital partners, (2) the question of whether managerial ability has any impact on the firms' ICT investment, and (3) the question of whether firm productivity increases when graduates from highly ranked universities join the firm. By addressing these questions, I would like to shed light on the reasons for the secular stagnation of the Japanese economy since the 1990s.

1.2 Structure of the Dissertation

In Chapter 2, I study the established culture of inter-firm relationships, known as Keiretsu, in Japan. I discuss the impact of partner companies' (i.e., those with which a company has business or capital relationships) R&D activities on firms' own R&D activities (*Chapter 2: Buyer and Supplier Relationships, Capital Relationships, and R&D Activities*). Next, I study the problems inside the firms in Chapter 3 and examine the relationship between CEOs' educational background and companies' software investments

(*Chapter 3: CEOs' Educational Background and Software Investments*). In Chapter 4, I consider the possibility that the secular stagnation is caused partly by the established practice of long-term employment. I present causal inferences regarding the effect of employees' educational background (measured by the quality of the university from which they graduated) on firms' subsequent productivity (as TFP) (*Chapter 4: The Impact of Hiring Elite University Graduates on Firms' Future Productivity: Evidence from Japanese Listed Firms*). Together, these three chapters investigate the causes of Japan's productivity stagnation and promote a better understanding of Japan's secular stagnation. In Chapter 5, I summarize the dissertation, describing the policy implications of each chapter and expected future research (*Chapter 5: Conclusion*).

1.3 Research Motivation

1.3.1 Buyer and Supplier Relationships, Capital Relationships, and R&D Activities

The share of SMEs' R&D in the total R&D in Japan is extremely low. As such, it is important to understand why this is the case.

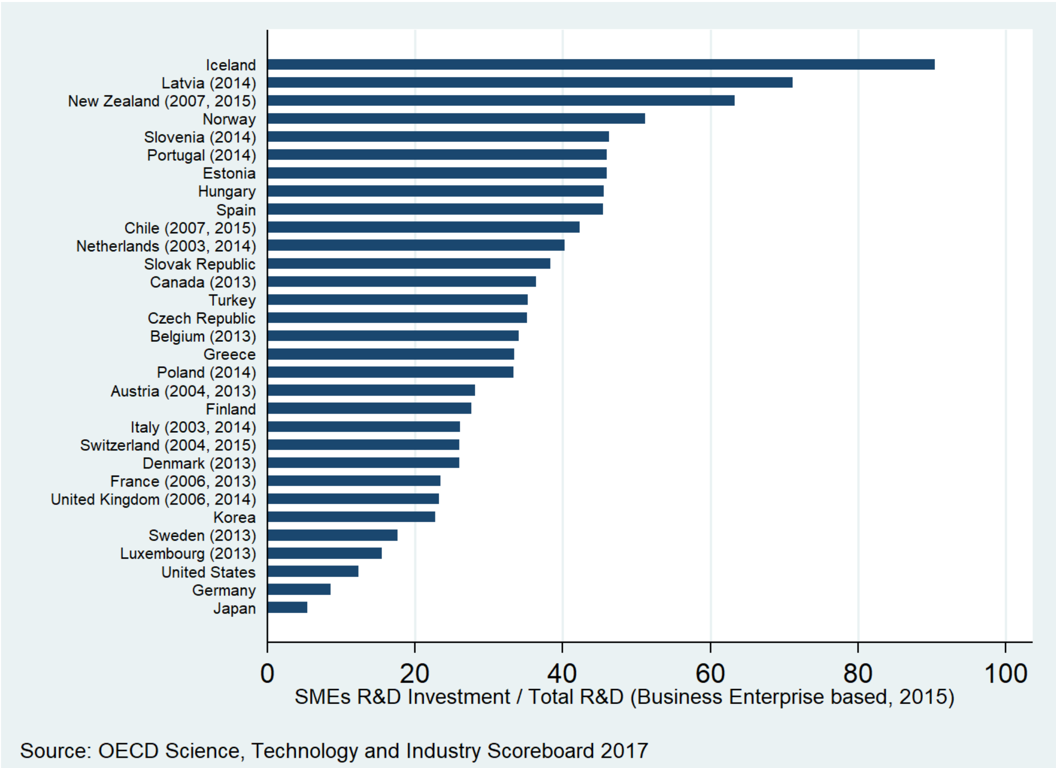
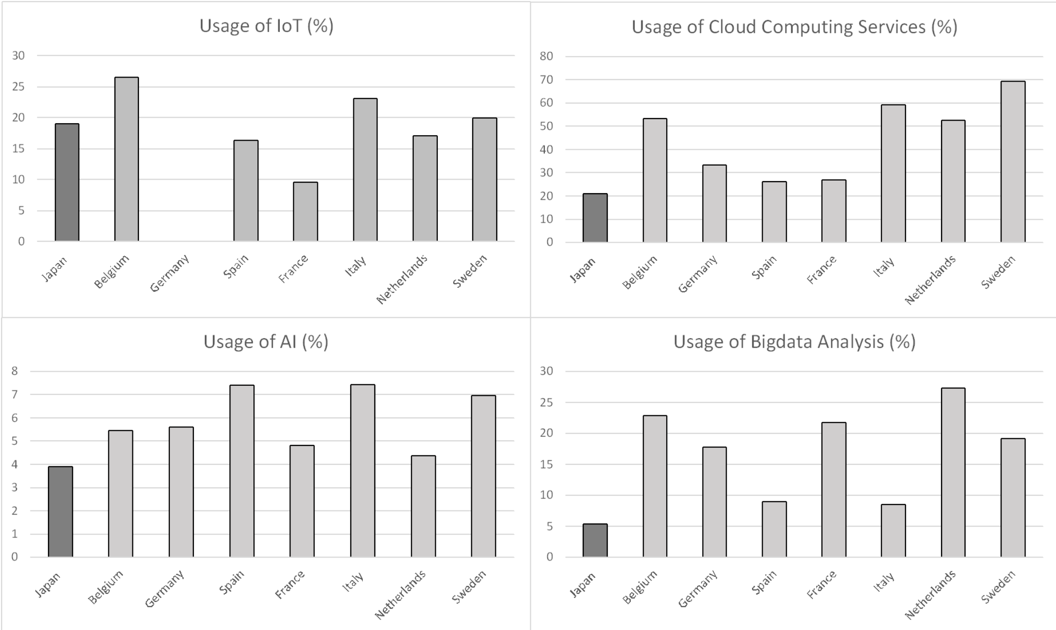


Figure 1.6: SMEs' R&D investment in total R&D (business enterprise-based, 2015)

According to Fukao et al. (2021), the TFP of Japanese listed companies in the manufacturing industry recovered rapidly after 1995, while TFP growth in the manufacturing industry as a whole stagnated, mainly due to the stagnant TFP growth of SME' factories. It is possible that the offshore relocation of large firms' factories led to the abandonment of previously stable transactions, which in turn reduced knowledge spillover (Ikeuchi et al. (2013)). Conversely, it is possible that firms with business and capital ties to R&D-intensive firms (including large firms) keep their own R&D at a lower level than other firms. Coauthors and I test the latter hypothesis in the present study. Specifically, we set the firm's R&D expenditures as the dependent variable and the average R&D expenditures of the partner firms (i.e., those with which the studied firm has business or capital relationships) as the independent variable, and obtained results consistent with the aforementioned hypothesis.

1.3.2 CEOs' Educational Background and Firms' Software Investments

Recently, the importance of digital technology, including the automation revolution and digital transformation (DX), has been emphasized; however, while the US was enjoying the ICT revolution in the 1990s, Japan was left behind (Fukao et al. (2016)). Much attention has been paid to whether this will happen again and whether Japan will be left behind in the current AI revolution (Fukao (2021)). In fact, the National Innovation Survey of 2020, conducted by the National Institute of Science and Technology Policy of the Ministry of Education, Culture, Sports, Science and Technology, surveyed the use of digitization. The data provided are internationally comparable, and the utilization of AI and big data was found to be low in Japan, compared with European countries (Figure 1.7). Furthermore, Morikawa (2016) conducted a pioneering survey on AI utilization trends in Japan and found that many firms were proactive in adopting AI.



Source:(Japan) NISTEP (EU) Eurostat

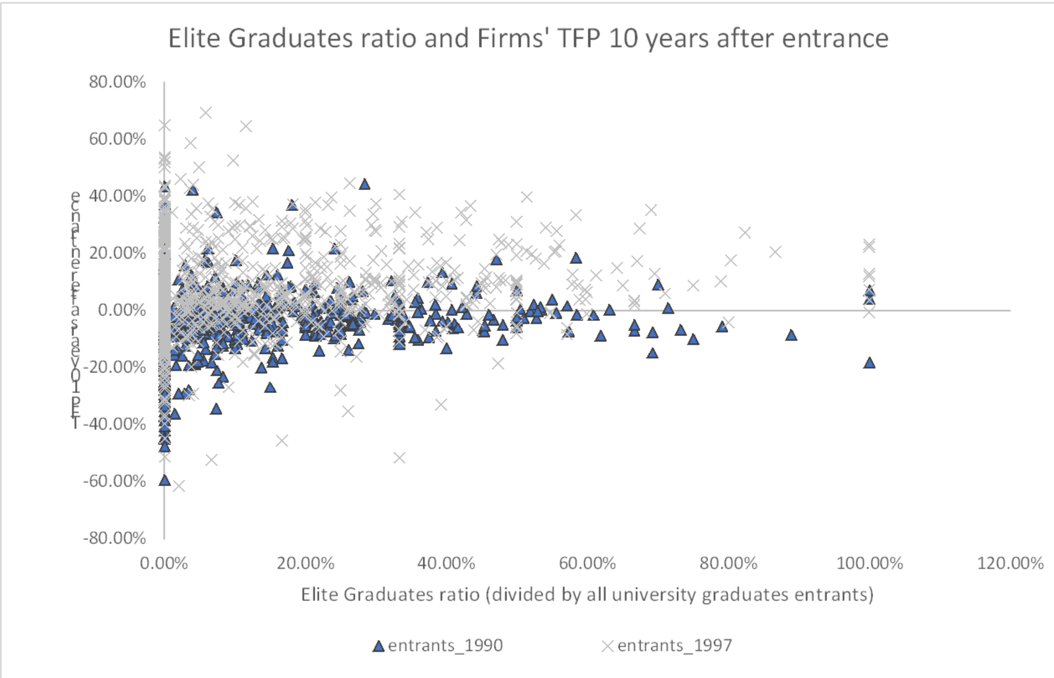
Figure 1.7: Usage of digitalization

Another problem is that AI is most often used for cost-reduction purposes, rather than for projects that could lead to radical innovations, such as improving existing goods and services or developing new ones (NISTEP (2021)). Thus, we must carefully analyze whether what happened in Japan during the Two Lost Decades (i.e., Japan being left behind during the ICT revolution) will happen again. To do so, first, we must examine why Japan was left behind in the first episode. I hypothesize that this happened because Japanese CEOs might not have fully understood how to best use the new goods (i.e., ICTs). The study sample consists of publicly listed firms. Further, I use CEOs' educational background (i.e., the Hensachi score[5] of the university from which CEOs graduated) as a proxy variable for CEOs' ability to understand the potential of new capital goods. The results are consistent with my proposed hypothesis.

[5] Hensachi score is a major indicator in Japan representing the selectiveness of universities.

1.3.3 The Impact of Hiring Elite University Graduates on Firms' Future Productivity: Evidence from Japanese Listed Firms

Can the differences in TFP levels across firms be explained by the differences in the educational quality of their employees? This is an issue that must be examined to determine whether there is justification for the current employment practices of large Japanese firms — e.g., large firms preferentially hire newly graduated students from the University of Tokyo and other elite national universities known as the “former imperial universities.”[6], [7].



Source: Shushoku saki Shirabe (Recruit works research), EALC database

Figure 1.8: Firms' elite graduates ratio and firms' TFP 10 years after recruitment

However, the question of whether firm-level TFP differences can be explained by differences in the educational quality of employees can be considered to have a two-way causal

[6] Higuchi (1994), who conducted a pioneering study on this subject,found that graduates from universities with more difficult entrance examinations are more likely to join large companies.

[7] The effect of university quality on wages was not confirmed by Nakamuro and Inui (2013), who also took university quality into account.

relationship: "Human resources with high-quality education are conducive to highly productive firms" and "Human resources with high-quality education are concentrated in highly productive firms." If the problem of endogeneity due to simultaneous bias is considered, usually a variable that is unrelated to the variable but related to the dependent variable can be used as an instrumental variable (IV) to identify causal relationships. However, in this case — especially since the dependent variable is TFP and the growth rate of TFP is calculated as a residual of growth accounting — it is not possible to identify a causal relationship between the dependent variable and the independent variable because it is difficult to find a variable that is not related to TFP. Therefore, in this study, I take this into account and examine the relationship between the quality of education of human resources in a firm and their firms' future TFP. Consequently, I found that firms with high productivity attract personnel with high-quality education; while a firm's productivity does not necessarily increase simply because personnel with high-quality education have joined the firm.

Chapter 2

Buyer and Supplier Relationships and Capital Relationships and R&D Activities

[1]

[1] This chapter is based on a paper published on RIETI (Yamaguchi et al. (2019)), coauthored by Ikeuchi Kenta, Fukao Kyoji, Kwon Hyeog Ug, and Kim Young Gak.

-Abstract-

Japanese SMEs' investment in R&D activities is much lower than the world average. In order to reveal the underlying causes of this phenomenon, focusing on Japanese industrial structure characteristics, we constructed a novel dataset on buyer and supplier relationships and capital relationships; this dataset comprised not only large firms but also small firms with less than 50 employees. Using this sample, we empirically tested our hypothesis that R&D investments by buyers, suppliers, and capital affiliates have a substitute effect on the R&D activities of small firms. Our findings support our hypothesis and further indicate that in the case of large firms, R&D investments by buyers, suppliers, and capital affiliates have the opposite effect, complementing firms' R&D investments. To date, no studies have considered the relationship between firms' buyer, supplier, and capital networks and firms' R&D activities. Thus, our study serves as a first step for further research on this topic.

2.1 Introduction

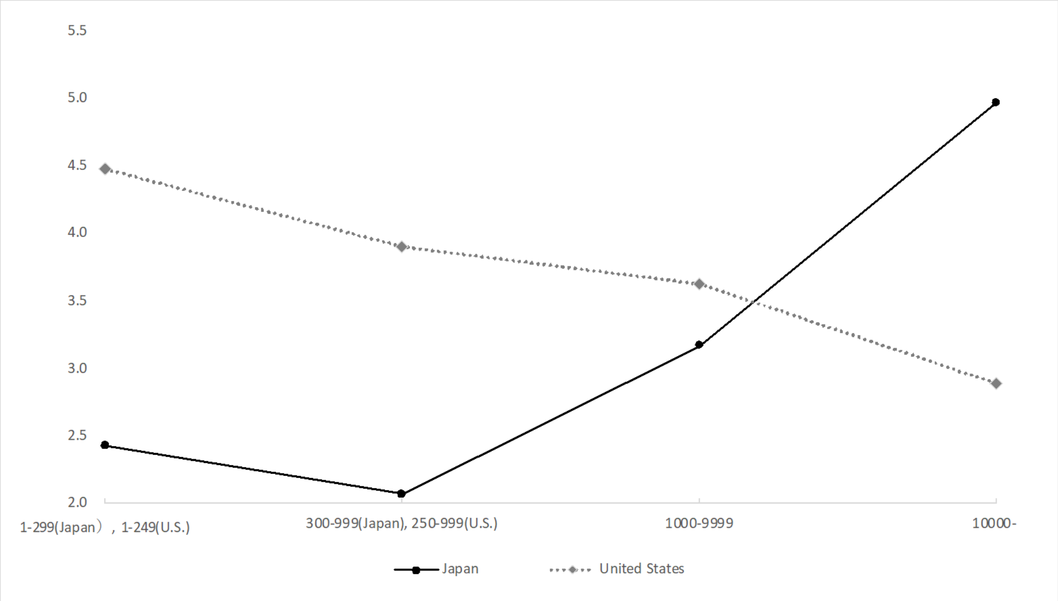
In developed countries, government policies that target economic growth encourage alternatives to capital accumulation and growth in the labor force. Japan is no exception, and developing a productivity-based growth policy is an urgent task for the Japanese government. Today, the productivity of SMEs and service-sector firms—two entities with a large presence in the Japanese economy—is stagnant (Inui et al. (2015), Kim et al. (2010a)). Although R&D activity is often mentioned as a key driver of productivity growth, the R&D share of SMEs in Japan was the lowest in an internationally comparable dataset created by the OECD (2017).

Table 2.1: R&D ratio of SMEs' R&D investment to total R&D investment

France	23.5%
United Kingdom	23.3%
Korea	22.7%
United States	12.4%
Germany	8.6%
Japan	5.4%

Source: OECD (2017)

Since we do not yet control for country GDP nor the total amount of products of each firm size cohort, it is fair to compare Japan's R&D intensity (R&D input divided by the total yield) to that of the US, which is the third lowest country in the OECD (2017) dataset.

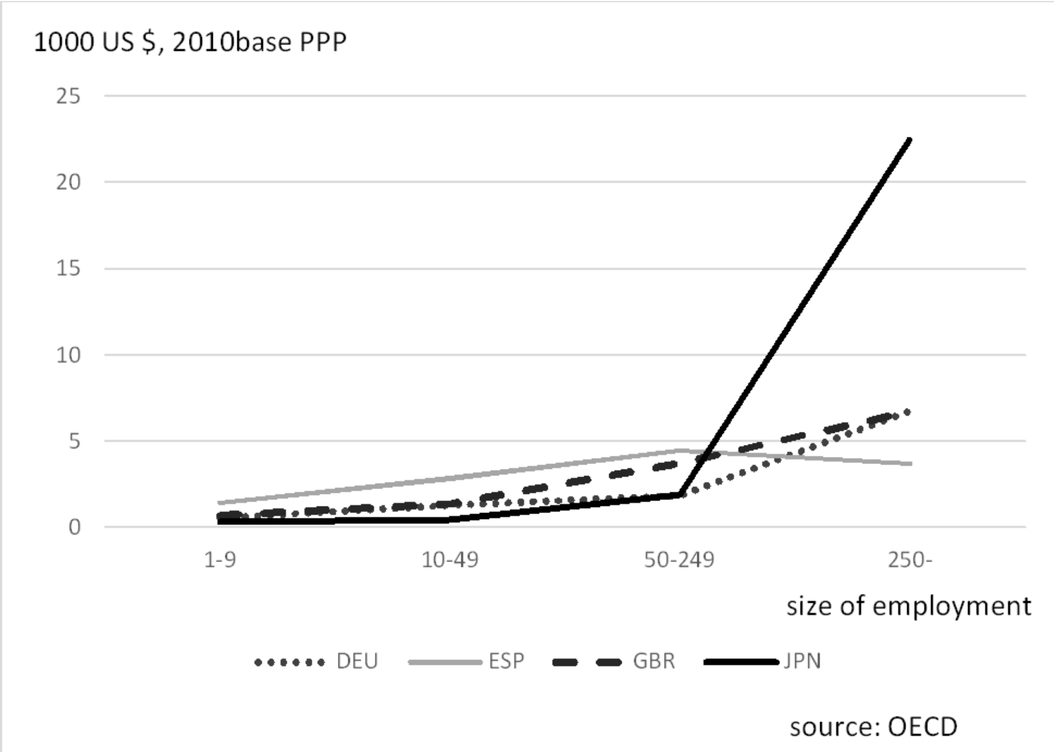


Source: (US) National Science Foundation, National Center for Science and Engineering Statistics, and the US Census Bureau, Business R&D: (Japan) Innovation Survey and Statistics Bureau, Survey of Research and Development

Figure 2.1: R&D intensity (R&D / sales) by firm size (%): 2015

In the US, large firms invest in R&D activities to a lesser extent, compared with SMEs; conversely, in Japan, large firms invest in R&D activities much more than SMEs.

Note that the composition of industries of the surveyed firms is different to the extent that it cannot be ignored. However, the Japanese structure (where large firms are the main R&D investors) is observed even when it is compared to Germany, Spain, and England.



Source: OECD
Vertical axis denotes Business and enterprise R&D expenditure (1,000US$ (2010, PPP)) per employee.

Figure 2.2: R&D intensity (R&D / employees) by firm size (%): 2013

Table 2.2: Sales composition of the R&D survey, by industry

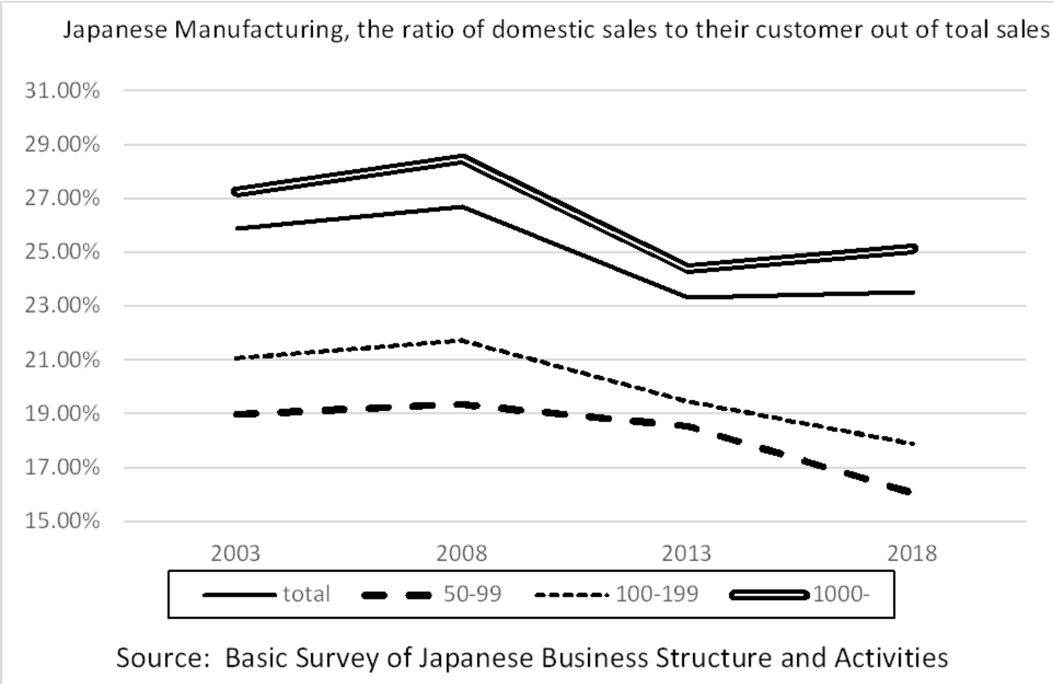
	Japan	US
Total (except finance and insurance)	100.00%	100.00%
Manufacturing industries	37.96%	64.52%
Utilities	2.70%	3.02%
Information	6.20%	13.29%
Transportation and warehousing	4.66%	1.68%

Source: Japan R&D survey, US R&D survey

The existing literature offers the following explanations. First, considering Schumpeter's hypothesis (according to which R&D activity is an incremental function of firm size), as mentioned in Cohen and Klepper (1996), SMEs may invest aggressively in R&D activities if an increase in productivity or in patents granted as an innovation outcome is a concave function of R&D activities as an innovation input because of the diminishing marginal productivity of the innovation outcome function. Second, there is also the possibility that SMEs are struggling with budget constraints. In fact, Bloch (2005) revealed that cash flow has a significantly positive impact on R&D activities in SMEs and an insignificant impact on large firms. Meanwhile, Goto et al. (1997) reports that, in Japan, cash flow is binding for large firms rather than SMEs; however, Goto et al. (1997) focuses on listed firms; however, it is uncertain whether the findings can be generalized to all SMEs. Okamuro (2005), who focuses on manufacturing SMEs and start-up firms, found no significant relationship between cash flow and R&D activities in start-up firms with binding budget constraints.

Therefore, as far as the Japanese economy is concerned, we do not have a clear understanding of the R&D activities of SMEs with stagnating productivity. We respond to this gap in the literature by examining SMEs' activities while simultaneously considering Japan's distinguishing industrial structures, namely, firm networks of buyers and suppliers and firm capital relationships, known in Japanese as Keiretsu. These relationships impact productivity growth and patent accumulation; therefore, a spillover effect may exist (Branstetter (2000), Ikeuchi et al. (2015)). This spillover may affect R&D activity itself (as an input of innovation activity) because it allows SMEs to access the knowledge of their partners (e.g., their buyers and suppliers or parent company) for free, thereby reducing the resources it needs to invest in R&D activities.

Our concerns are as follows: partly due to the long-term appreciation of the yen, large firms invest in foreign counties and the relationship between incumbent large firms and SMEs will become sparser. Hence, nobody can deny the possibility that the Keiretsu relationship will disappear eventually. If so, SMEs will have to conduct innovation activities on their own. That is why we must examine the contemporary economic landscape in Japan. Thus, we seek to determine why SMEs do not aggressively invest in innovation activities. Figure 2.3 shows that the ratio of domestic sales to total sales is declining in SMEs, which means the domestic relationship has been sparser.



Source: METI

Figure 2.3: Historical fluctuation of the ratio of domestic sales to total sales (Japan, Manufacture)

We conducted a statistical analysis on the hypothesis that as far as SMEs are concerned, the firms' partners R&D activities complements the firms' innovative activity and found the following main relationships: 1) the R&D activities of SMEs' parent companies can have a substitution (negative) effect on SMEs' R&D activities, 2) the R&D activities of the buyers and suppliers with whom SMEs have capital relationships can have a substitution (negative) effect on SMEs' R&D activities. These results imply that SMEs' R&D activities are strongly tied with firms' networks. To date, no studies have considered the relationship between firms' buyer, supplier, and capital networks and firms' R&D activities. Thus, our study serves as a first step for further research on this topic.

The next section presents a literature review on this topic. Section 3 describes our data and Section 4 presents and tests our model. Section 5 provides the results of our analysis. Section 6 concludes this paper.

2.2 Literature Review

As mentioned in Section 1, many studies were conducted based on Schumpeter's hypothesis, that is, firms' R&D activities is a positively increasing function of firm size and firm market power. These studies were based on the research of Schumpeter (1942), who insists that a monopoly is the origin of innovation. Regarding firm size, Cohen and Klepper (1996) finds that R&D activity increases with firm size, whereas the marginal productivity of innovation diminishes. Moreover, Cohen et al. (1987) reports that firm size and project size have a significantly positive effect on firms' R&D activity. Meanwhile, Arrow (1962) proposes a concept opposite to Schumpeter's hypothesis—that market competition promotes firm innovation activity (confirmed by Nickell (1996) and Okada (2005)). To reconcile the Schumpeter hypothesis and Arrow's view of the relationship between competition and innovation, Aghion et al. (2005) proposes an inverted-U relationship. While many studies have examined this relationship, they do not present a consensus[2].

Thus, a detailed discussion on the Schumpeter hypothesis (innovation, competition, and firm size) is required, as the studies discussed thus far might have omitted important aspects. We must, at the very least, take industrial characteristics into account on the basis of appropriate logic. For example, if scientists in a specific industry in a given year

[2]for example, Peroni and Ferreira (2012) and Hashmi (2013) do not report the clear results Aghion et al. (2005) expected.

find or invent something crucial to the industry, then firm R&D outcomes may be more efficient in that industry. Alternatively, a regulation may emerge in the industry that makes entrance into the industry costly, thereby affecting the scope of the monopolistic market that may potentially emerge after the realization of innovation. The first example corresponds to “Technological opportunity”(Klevorick et al. (1995)) and the latter case corresponds to “Appropriability”(Levin et al. (1987)). For Japan, Goto et al. (1997) controlled these effects and reported positive significant results.

Even if specific industries do provide a rich environment for firms, firms still need cash to employ good scientists and maintain laboratories. Furthermore, R&D projects are always uncertain and ambiguous elements of firm life for third parties, such as investors. This may mean that external financing (e.g., banking) may not function well, which forces firms to use cash to fund R&D projects. Bloch (2005) tested this liquidity constraint to SMEs’ R&D activities and reported that cash flow has a significant positive effect on SMEs’ R&D activities but does not have a significant effect on large firms. Similarly, Brown and Petersen (2011) reveals that younger firms use cash to deal with economic shocks; this is not observed in mature firms. In Japan, as Goto et al. (1997) and Okamuro (2005) report, the liquidity constraint is not always binding for SMEs or start-ups. Thus, to date, as far as Japan is considered there is no consistent explanation for the liquidity constraint’s impact on innovation activity.

As the discussion has revealed thus far, the traditional framework of the R&D equation provides a list of control variables such as firm size, market power, industrial characteristics, and liquidity constraints. Recent studies on this topic focus on geographical and business networks. These studies are typically interested in the relationship between firm innovation and universities—which seems similar to the concept of technological opportunity discussed earlier—and confirm that a firm’s geographical access to universities facilitates their innovation (Karlsson and Andersson (2009)). Moreover, Kwon and Inui (2013) focuses on networks within and between firms as well as Keiretsu relationships (which may be vertical or horizontal) and reveals that horizontal Keiretsu relationships promote firms' R&D activities, regardless of firm size. Multinational enterprises are another key area of concern in relation to this topic. Kwon and Park (2018) suggests that subsidiary firms take a passive approach to their R&D activities, whereas firms with parent companies that are not part of the G7 are aggressive in their R&D activities.

2.3 Data

This study uses microdata from the "Survey of Research and Development"[3], conducted by the Ministry of Internal Affairs and Communications (MIC), Japan, combined with firm-level data collected by Tokyo Shoko Research (TSR) which is the second largest credit rating company in Japan.

[3]Firms that answer "yes"to the question "do you conduct R&D activity?" over the last year and whose capital is more than 0.1 billion Yen are surveyed completely. Other thoroughly detailed inclusion and exclusion criteria are not clear; see the outline of this survey: https://www.stat.go.jp/english/data/kagaku/1530.html

Table 2.3: Sample distribution by size

Size (# of Employees)	2011	2012	2014	Total
0-9	57,930	140,788	145,049	343,767
10-49	57,623	82,850	82,052	222,525
50-99	10,256	12,966	12,837	36,059
100-299	8869	11,226	10,997	31,092
300-999	3,314	3,903	3,862	11,079
1000-9999	1,115	1,270	1,220	3,605
10000-	52	58	62	172
Total	139,159	253,061	256,079	648,299

Size (# of Employees)	2011	2012	2014	Total
0-9	41.63%	55.63%	56.64%	53.03%
10-49	41.41%	32.74%	32.04%	34.32%
50-99	7.37%	5.12%	5.01%	5.56%
100-299	6.37%	4.44%	4.29%	4.80%
300-999	2.38%	1.54%	1.51%	1.71%
1000-9999	0.80%	0.50%	0.48%	0.56%
10000-	0.04%	0.02%	0.02%	0.03%
Total	100.00%	100.00%	100.00%	100.00%

As Table 2.3 shows in its detailing of our sample distribution by firm size (number of employees), our dataset includes a large sample of small firms with less than 50 employees, whose data are sometimes difficult to capture in a standard economic survey. In the TSR dataset, data on the networks between firms are available, allowing us to specifically capture buyer-and-supplier networks and parent-and-subsidiary networks. Although the TSR dataset provides information on approximately one million firms per year, for accurate estimation, we do not use samples that cannot be connected to the Survey of R&D. Since said survey is strictly classified and other private firms, such as competitors, cannot access this information, there does not seem to be a meaningful incentive for firms to report false statistics[4].

2.4 Empirical Model

We hypothesize that the R&D activities of an SME's business partners (e.g., buyers, suppliers, parent companies, and subsidiaries) have a substitute effect on SME's R&D activities. In other words, the innovative activity of a firm's business partners can substitute or complement its own innovative activity. Let us consider, for example, SMEs with constrained resources for innovative activity and large business partners who provide technological knowledge (i.e., the spillover effect). These SMEs may innovate by borrowing the knowledge of their business partners, even without sufficient innovative activity on their own—indeed, this may allow these firms to survive. Such SMEs may also be able to make efficient business plans (e.g., their partners can guide their development instead of them having to research it themselves). We tested this hypothesis using the following equation

$$\ln(rdint + 1)_{it} = \sum_{r \in s,c,p,k} [\beta_{r,1} + \beta_{r,2} \ln(size_{it-1})] \ln(relrdint_{r,It-1}) + \boldsymbol{X_{it}\gamma} + u_{it} \quad (2.1)$$

where subscript i, t, s, c, p, and k stand for firm, time, suppliers, customers (buyers), parent firms, and children (subsidiaries). Firms' own R&D intensity (R&D expenditure / Sales * 100) is denoted as *rdint* and average R&D intensity of business partners as *relrdint*. *size* denotes firms' employment size.

[4]We may need to rigorously take into account the potential bias from surveys' design: the main part of the questionnaire is only answered by those who respond "Yes" to the question "Do you conduct R&D activity?"; however, if their response is "No" they do not have to answer the rest of the questionnaire.

We include control variables in $\boldsymbol{X_{it}}$, including cash flow, advertisement intensity, firm age, CEO age, year * industry (three digits) fixed effect, and firm-characteristic fixed effect for parents and children themselves (Yes = 1, No = 0). Cash flow and advertisement intensity were lagged in order to prevent perfect reverse causation.

We verified the model's robustness using a Probit model (firms active in the dependent variable of R&D takes 1 and 0 otherwise) instead of ordinary least squares (OLS).

2.5 Estimation Results

Table 2.4 shows the results of the OLS estimation of (2.1). The results mainly support our hypothesis that the R&D activities of SMEs' business partners have a substitute effect on SMEs' own R&D activities. In particular, we found that firms with less than 26 employees and a strong capital network enjoy a substitute effect from their partners' R&D activities. By contrast, the average R&D intensity of SMEs' children (subsidiaries) complement SMEs' own R&D activity.

Moreover, we confirm that the coefficient of large firms' (those with at least 300 employees) capital network's R&D activities is significantly positive. Meanwhile, if a firm's business network does not have a capital relationship with the firm, the coefficient becomes significantly negative.

In addition, since some firms do not report any R&D activities, we checked the robustness of our model using a Probit model (Table 2.5). The estimation results show that for small firms, the impact of partners' R&D activities on their own R&D activities were insignificant in some cases, such as when the partners are both their children and suppliers. Moreover, if their partners are their parent firms and/or suppliers or their children and/or customers, the partners' impact becomes significantly negative regardless of their size. If the partners are parent firms but not customers or suppliers, the partners have a negative impact; however, this is not the case in the OLS results. Meanwhile, if the partners are customers but do not have a capital relationship with the SME, they have a positive effect; this finding also opposes the OLS results.

The Probit estimation results for large firms show almost the same result except for the significance of the pair (children, supplier) and (independent, customer).

Table 2.4: OLS

Small Firm (# of Employees < 50)		Business Relation		
		Supplier	Customer	Other
	Parent	(-)***	(-)***	(-)***
Capital Relation	Child	(-)***	(-)***<26 (+)***>=26	(+)***
	Independent	(+)***<18 (-)***>=18	(+)***<8 (-)***>=8	-

Medium-sized Firm (50=<# of Employees<300)		Business Relation		
		Supplier	Customer	Other
	Parent	(-)***<72 (+)***>=72	(-)***<75 (+)***>=75	(-)***<83 (+)***>=83
Capital Relation	Child	(-)***<168 (+)***>=168	(+)***	(+)***
	Independent	(-)***	(-)***	-

Large Firm (# of Employees>=300)		Business Relation		
		Supplier	Customer	Other
	Parent	(+)***	(+)***	(+)***
Capital Relation	Child	(+)***	(+)***	(+)***
	Independent	(-)***	(-)***	-

* p<0.1, ** p<0.05, *** p<0.01

Table 2.5: Probit

Small Firm (# of Employees<50)		Business Relation Supplier	 Customer	 Other
	Parent	(-)***	(-)***<17 (+)***>=17	(-)***
Capital Relation	Child	(-)	(-)**	(-)***
	Independent	(+)***<9 (-)***>=9	(+)**	-

Medium-sized Firm (50=<# of Employees<300)		Business Relation Supplier	 Customer	 Other
	Parent	(-)***	(+)***	(-)***<66 (+)***>=66
Capital Relation	Child	(-)	(-)**<153 (+)**>=153	(-)***<69 (+)***>=69
	Independent	(-)***	(+)<60 (-)≧60	-

Large Firm (# of Employees>=300)		Business Relation Supplier	 Customer	 Other
	Parent	(-)***<344 (+)***>=344	(+)***	(+)***
Capital Relation	Child	(-)<381 (+)>=381	(+)**	(+)***
	Independent	(-)***	(-)	-

* p<0.1, ** p<0.05, *** p<0.01

Table 2.6: Estimation results: Impact of business partners' R&D activities on firms' own R&D activities

	[1]	[2]	[3]	[4]
	OLS	OLS	Probit	Probit
L.ln(Employee)	0.00961***	0.00785***	0.224***	0.219***
	(0.0001)	(0.0001)	(0.0033)	(0.0033)
L.ln(CF)	0.00389***	0.00356***	0.0202***	0.0193***
	(0.0001)	(0.0001)	(0.0041)	(0.0041)
ln(advertisement_intensity)	0.0001	0.000234***	0.201***	0.201***
	(0.0001)	(0.0001)	(0.0020)	(0.0020)
ln(firm_age)	-0.0003	0.0001	-0.0043	-0.0027
	(0.0002)	(0.0002)	(0.0061)	(0.0061)
ln(CEO_age)	0.00423***	0.00358***	0.110***	0.108***
	(0.0006)	(0.0006)	(0.0184)	(0.0184)
Child_themselves	0.00389***	0.00599***	0.254***	0.258***
	(0.0004)	(0.0003)	(0.0086)	(0.0087)
Parent_themselves	0.0191***	0.0173***	0.216***	0.213***
	(0.0004)	(0.0004)	(0.0094)	(0.0094)
L.ln(relrdint_supplier_parent)	0.112***	-1.160***	-0.180	-3.574***
	(0.0099)	(0.0376)	(0.2430)	(1.2430)
×L.ln(Employee)		0.272***		0.612***
		(0.0076)		(0.2030)
L.ln(relrdint_suplier_child)	4.247***	-19.57***	-2.285	-71.480
	(0.1770)	(0.7910)	(3.8540)	(49.7600)
×L.ln(Employee)		3.822***		12.0300
		(0.1270)		(8.7620)
L.ln(relrdint_suplier_independent)	-0.011	0.132***	-0.449	2.054***
	(0.0113)	(0.0278)	(0.4350)	(0.7430)
×L.ln(Employee)		-0.0464***		-0.953***
		(0.0090)		(0.2950)
L.ln(relrdint_customer_parent)	0.394***	-2.897***	2.348***	-3.099***
	(0.0156)	(0.0542)	(0.2940)	(1.1320)
×L.ln(Employee)		0.672***		1.108***
		(0.0106)		(0.2110)
L.ln(relrdint_customer_child)	0.915***	-4.202***	0.145	-72.15**
	(0.0778)	(0.1900)	(1.3480)	(29.5400)
×L.ln(Employee)		1.303***		14.35**
		(0.0448)		(5.6120)
L.ln(relrdint_customer_independent)	-0.117***	0.252***	0.248	1.246**
	(0.0106)	(0.0256)	(0.2540)	(0.6200)
×L.ln(Employee)		-0.128***		-0.3050
		(0.0084)		(0.1860)
L.ln(relrdint_nobusiness_parent)	1.312***	-5.637***	0.861***	-2.602***
	(0.0099)	(0.0417)	(0.1450)	(0.7920)
×L.ln(Employee)		1.276***		0.622***
		(0.0075)		(0.1430)
L.ln(relrdint_nobusiness_child)	4.349***	1.520***	6.305***	-33.42***
	(0.0345)	(0.1360)	(0.7790)	(6.1550)
×L.ln(Employee)		0.307***		7.902***
		(0.0205)		(1.1450)
Constant	-0.0223*	-0.0164	-2.854***	-2.841***
	(0.0122)	(0.0118)	(0.2680)	(0.2690)
industry(3 digit) * Year fixed effect	Yes	Yes	Yes	Yes
N	648,299	648,299	644,886	644,886

Table 2.6 shows the regression results, including the control variables, on which Table 2.4 and Table 2.5 are based. In Table 2.6, CF, advertisement_intensity denote cash flow and the amount of advertisement out of total sales, respectively. Note that although we set lagged values on RHS, the decision to construct networks ultimately depends on firms; accordingly, we need more detailed simultaneous equations to identify causality and eliminate any potential endogeneity bias. Further, we should take into account the possibility that the results are driven mainly by large firms. If these large firms make their R&D expenditure decisions based on their sales (if the fixed fraction of sales pays for their R&D), the fluctuation of sales can lead to a fluctuation in large firms' R&D. That is why we must verify the Probit model, where the dependent variable takes a value of 1 if the firm is active in R&D and 0 otherwise. The results appear stable in a comparison between the OLS and Probit models[5].

2.6 Conclusion

This study originated from the following question: "why do SMEs invest less in R&D, compared with large firms?" To answer this question, the present study focused on the R&D activities of SMEs' business and capital partners. We built a large dataset that includes information on firms' R&D activities and their business and capital networks. We revealed that for small firms, the R&D activities of their business and capital partners have a negative effect on their own R&D activity, which is contrary to the effect of partners' R&D activities on large firms' own R&D activities.

This suggests that innovation efficiency is higher for small firms that have relationships with R&D-active firms, compared with those without such relationships, perhaps because small firms' business and capital partners may support their R&D activities.

[5]The average R&D intensity of firms with less than 10 employees is 0.086% and the fraction of R&D-active firms with less than 10 employees is 2.2%, according to our dataset.

This possibility is consistent with existing studies on the spillover effect of innovation "output"—e.g., Ikeuchi et al. (2015); notably, we confirmed the same effect in innovation "input." Future research would do well to reveal the causality direction of R&D activity within a firm's network and to undertake a reasonable analysis of firms that do not have connections with R&D-active firms nor their own R&D activities.

Additionally, Since the counterparty may tend to be a larger firm when it is the R&D implementing firm, further investigation is necessary. Therefore, future research may want to control for the size of the counterparty's firm and then consider the impact of this on its own R&D activities..

Additional Tables

Table 2.7: Summary statistics of the data used

Variable	Observation	Mean	SD	Min	Max
ln(rd_intensity)	648,299	0.0053	0.09482	0	5.85149
L.ln(employee)	648,299	2.35164	1.38297	0	11.66678
L.ln(price_cost_margin)	648,290	0.01176	0.13944	-8.99739	6.50173
L.ln(cashrate)	648,299	0.97815	0.94348	0	13.58994
ln(advertise_intensity)	648,299	0.66834	1.34763	0	9.61356
ln(firm_age)	648,299	3.55367	0.6356	0	4.61512
ln(CEO_age)	648,299	4.05384	0.19358	2.36085	4.62628
existence_parents_dummy	648,299	0.16059	0.36715	0	1
existence_children_dummy	648,299	0.10965	0.31246	0	1
L.lnrelrdint_sup	648,299	0.00049	0.01075	0	4.06528
L.lnrelrdint_cus	648,299	0.00073	0.01035	0	2.39994
L.lnrelrdint_par	648,299	0.00075	0.01183	0	2.40659
L.lnrelrdint_chi	648,299	0.00001	0.00149	0	0.68157
L.lnrelrdint_sup1par1	648,299	0.00048	0.01147	0	6.1032
L.lnrelrdint_sup1chi1	648,299	0	0.00061	0	0.25908
L.lnrelrdint_sup1cap0	648,299	0.0005	0.00966	0	1.90241
L.lnrelrdint_cus1par1	648,299	0.00044	0.00734	0	1.97275
L.lnrelrdint_cus1chi1	648,299	0.00001	0.00139	0	0.68157
L.lnrelrdint_cus1cap0	648,299	0.00072	0.01024	0	2.39994
L.lnrelrdint_bus0par1	648,299	0.00034	0.01104	0	5.22145
L.lnrelrdint_bus0chi1	648,299	0.00004	0.0032	0	1.92634
L.lnrelrdint_bus0cap1	648,299	0.00021	0.00755	0	1.97275
L.lnrelrdint_bus0p1c0	648,299	0.00034	0.01104	0	5.22145
L.lnrelrdint_bus0p0c1	648,299	0.00001	0.0007	0	0.18222

Table 2.8: Average R&D intensity according to firms' network

	Observation	Mean
Total	648,299	0.017
Supplier1_R&D0	207,809	0.053
Customer1_R&D>0	264,843	0.041
Parents1_R&D>0	33,109	0.265
Children1_R&D>0	8,959	0.916
Capital1_Business1_R&D>0	26,886	0.318
Capital0_Business1_R&D>0	340,463	0.032
Capital1_Business0_R&D>0	16,903	0.542
Parent1_Supplier1_R&D>0	14,493	0.138
Parent1_Customer1_R&D>0	15,269	0.143
Children1_Supplier1_R&D>0	4,496	1.285
Children1_Customer1_R&D>0	4,160	1.414
Capital0_Supplier1_R&D>0	203,081	0.054
Capital0_Customer1R&D>0	259,399	0.039
Parent1_Business0_R&D>0	13,934	0.543
Children1_Business0_R&D>0	4,582	1.281

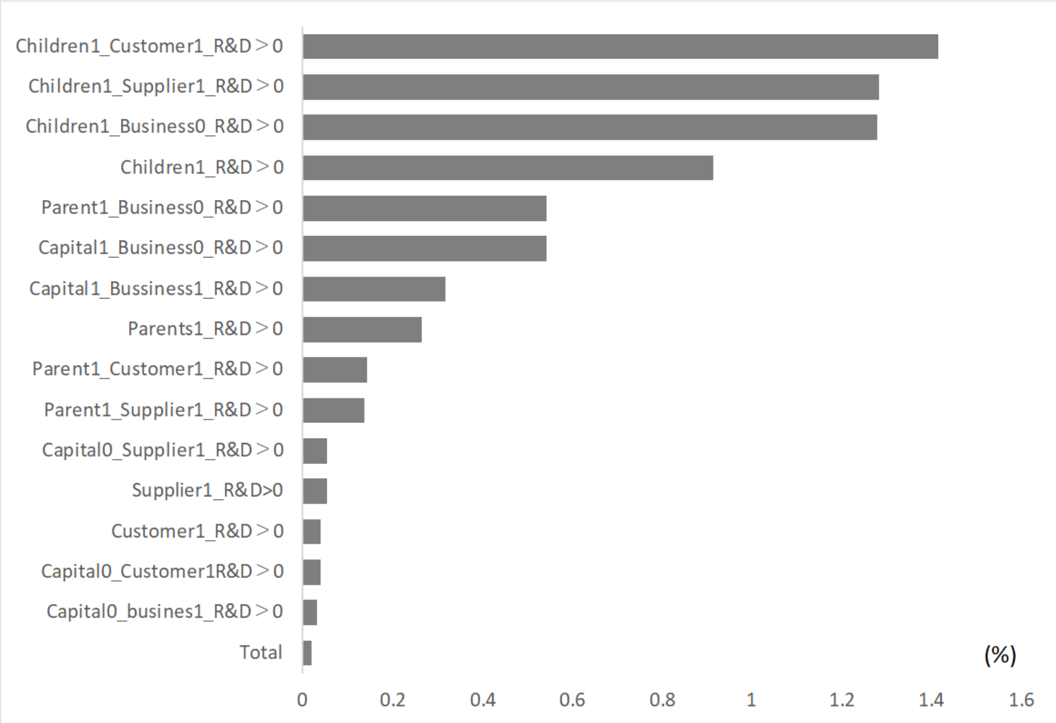


Figure 2.4: Average R&D intensity according to firms' network

Chapter 3

CEOs' Educational Background and Firms' Software Investments

[1]

[1]This article is based on a paper published by *Applied Economics Letters* (Yamaguchi (2021)).

-Abstract-

In the latter half of Japan's Two Lost Decades (1990–2010), Japanese firms failed to undergo a thorough ICT revolution. In this study, we investigate the most likely cause for this failure and find that CEOs in Japanese companies simply did not know how to utilize the novel equipment (i.e., ICT capital). We estimate the impact of CEOs' educational background(assessed based on their alma mater's prestige) on their firms' software investments by using a compiled dataset that included Japanese listed firms with panel fixed effects models and a generalized method of moments. We find significant evidence to support that an increase in CEOs' educational background score raises their firms' investment in software. We also revealed that CEOs' lack of knowledge regarding new equipment could be an obstacle to introducing new equipment and, consequently, could lead to a decrease in competitiveness.

3.1 Introduction

Japan's Two Lost Decades (1990-2010) were characterized by the stagnation of productivity (Hayashi and Prescott (2002), Kim et al. (2010b)). While the US underwent an ICT revolution that contributed to an increase in labor productivity (Jorgenson et al. (2008)), especially in the 2000s, Japan "was left behind in the ICT revolution" (Fukao et al. (2016))[2]. Fukao et al. (2016) highlights possible constraints that could have played a role in the Two Lost Decades, such as a shortage of ICT outsourcing suppliers, the relatively high cost of restructuring in the human resource system, and insufficient CEO education[3].

This study investigates the possibility that the insufficient education of firms' decision makers could have hindered the ICT revolution in Japan in the Two Lost Decades, as CEOs did not have sufficient knowledge regarding how to utilize the new ICT equipment.

In fact, the Japan Electronics & Information Technology Industries Association reported in 2013[4] that CEOs' understanding about the importance of ICT capital in Japan is much lower than that of CEOs in the US.

We build a model where CEOs' knowledge of how to utilize unfamiliar capital or equipment is a factor for introducing such capital. We also create a dataset of listed firms' investments in software, which we assume denotes investment in ICT capital. CEOs' educational level can be represented using information on their alma mater. In particular, CEOs' educational background was evaluated using Hensachi (a standard score and a major indicator in Japan representing the selectiveness of universities) information. We analyzed this relationship using first difference (FD) regression models and the generalized method of moments, ultimately revealing that an increase in CEOs' educational level

[2] Similar situation in Italy is investigated by Bugamelli and Pagano (2004)

[3] Inui and Kim (2018) conducted a study on a similar topic, where they captured the variety of investment in ICT by using information on foreign firms' management participation.

[4] https://home.jeita.or.jp/cgi-bin/page/detail.cgi?n=608&ca=1

significantly yields higher ICT capital intensity. This result implies that there was heterogeneity in Japanese listed firms' software intensity, which could be partially explained by their CEOs' educational level. Taking into account that smaller firms tend to be managed by relatively uneducated CEOs and that a large part of the Japanese economy consists of SMEs, we can speculate that the ICT investment landscape in Japan could be even worse.

The remainder of this paper is organized as follows. Section 2 presents the conceptual model to be tested and explains the data. We confirm the empirical strategy in Section 3, while the results are summarized in Section 4. Section 5 presents a discussion on the results. Section 6 presents our conclusions.

3.2 Model and Data

3.2.1 Model

When a completely new technology is introduced, it is common for individuals to be unfamiliar with its usage. Suppose that firms' decision makers are CEOs, and all of them know how to use their firms' capital (except the new technologies), labor, and materials. Furthermore, we assume that some of them know how to utilize new equipment (in this context, ICT capital, which is represented by software) but do not actually use it. We now examine the heterogeneity of knowledge among CEOs regarding how to utilize a new factor of the production function:

$$y = \left(k^{\frac{1}{\sigma}} + (\Omega z)^{\frac{1}{\sigma}} + \sum x^{\frac{1}{\sigma}}\right)^{\sigma}, \tag{3.1}$$

where $\sigma > 1$ is a parameter and y, k, Ω, z, and x are yields, capital (not ICT), CEO's knowledge, new equipment, and other inputs, respectively. Assuming that the firm is a price-taker, it will solve the following profit maximization problem:

$$\max \pi = y - rk - \omega z - \sum px, \tag{3.2}$$

where r, ω, and p are the factor market price of capital (not ICT), new equipment, and other inputs, respectively. The first-order conditions are expressed as follows:

$$\left(k^{\frac{1}{\sigma}} + (\Omega z)^{\frac{1}{\sigma}} + \sum x^{\frac{1}{\sigma}}\right)^{\sigma-1} k^{\frac{1}{\sigma}-1} = r \tag{3.3}$$

$$\left(k^{\frac{1}{\sigma}} + (\Omega z)^{\frac{1}{\sigma}} + \sum x^{\frac{1}{\sigma}}\right)^{\sigma-1} (\omega z)^{\frac{1}{\sigma}-1} = \omega. \tag{3.4}$$

Combining these two equations yields the following condition:

$$\frac{z}{k} = \left(\frac{\omega}{r}\right)^{\frac{\sigma}{1-\sigma}} \Omega^{-\frac{1}{1-\sigma}}, \tag{3.5}$$

which implies that the new equipment's usage intensity (= z over k) is a function of the CEO's knowledge.

3.2.2 Data

We analyze data from Japanese listed companies for the years 2004 and 2010, which mark the period right after the ICT bubble burst in the US and the last year of Japan's Two Lost Decades, respectively. We focus on this period because we assume the bottleneck of stagnation of investments in ICT is within Japan, assuming that there must be aggressive investors in ICT capital in Japan, expecting that we can observe the difference between aggressive and passive investors.

We build a dataset comprising new equipment (i.e., ICT capital), previous type of capital, and a CEO ability measure. We collect software asset information from intangible assets on firms' balance sheets[5,6]. Additionally, we collect tangible fixed asset information from the balance sheet and divide the nominal value of the software by the tangible fixed asset, which yields firms' software intensity. We assume that the software held by firms represents the total amount of ICT capital held by the firms. We also collect CEOs' educational background information[7], assuming that CEOs' educational background represents their knowledge on how to utilize new equipment. From this information, we can also assess the popularity of CEOs' alma mater (the popularity of universities they graduated from). Specifically, we use universities' Hensachi score (standard score, mean: 50, sigma: 10, normal distribution)[8], which denotes the difficulty of passing the entrance examinations of Japanese universities.

Table 3.1 provides the summary statistics on software intensity and Hensachi scores[9]. Tables 3.2 and 3.3 present data from firms' with high software intensity (top ranking 1–10).

[5]This study used a database provided by the Development Bank of Japan, containing data on financial information from listed companies

[6]The type of software is not observed. Typically, software can be classified as cheap ready-made or expensive order-made. Note that if large firms prefer order-made software and the CEOs of the large firms graduated from highly ranked universities, there can be a potential endogeneity bias, which we think can be alleviated by controlling for firm size.

[7]The Toyo Keizai company handbook series, which specializes in information on executive officers, provides data on CEOs' educational background, which enables us to identify from which university they graduated and when.

[8]We used universities' Hensachi data provided by Benesse Corporation, accessed in December 2017.

[9]The number of observations of Hensachi scores is much lower than that of observations of software intensity because a part of CEOs' data cannot be matched if the CEOs did not graduate university, or because the university did not exist in 2017, or if CEOs graduated from graduate schools, etc.

Table 3.1: Summary statistics

	N	mean	SD	max	min
Software intensity_2010 (%)	3141	51.496	515.725	24664.078	0.000
Software intensity_2004 (%)	3119	63.111	831.542	32108.334	0.000
D.Software intensity (%)	4680	10.117	677.670	32082.117	-11029.755
Hensachi_2004	2249	69.413	9.201	83.000	41.000
Hensachi_2010	1519	68.912	9.668	83.000	41.000
D.ln_Hensachi	1143	-0.008	0.127	0.585	-0.619

Table 3.2: Software-intensity ranking (Top 10) for 2004

2004 software_intensity (%)	firm_name (English)
8082.1	Pado
7561.1	Andor
7463.7	Japan Digital Contents
3493.8	Pia
2958.3	Database Communications
2232.0	E-system
2183.9	XNET
1762.9	Toyo Business Engineering
1660.8	Dawn
1323.5	C4 Technology

Table 3.3: Software-intensity ranking (Top 10), for 2010

2004 software_intensity (%)	firm_name (English)
24664.1	Aeria
66079	Pia
5325.8	Green Hospital Supply
4700.0	Asahi Holdings
4670.3	NTT Data IntraMart
4488.8	InfoMart
3779.5	Aplix
2718.2	Edion
2665.6	Business Trust
2476.7	Works Applications

Tables 3.2 and 3.3 show that the firms in the information industry tend to be highly ranked in terms of software intensity. In both years, business-to-business-type companies are highly ranked[10].

3.3 Empirical Strategy

In the previous section, we showed that software intensity is an increasing function of CEOs' knowledge on how to utilize new equipment/capital:(3.5). If we take the logarithm of both sides of (3.5), we obtain the following basic equation:

$$\ln\frac{z}{k} = \frac{\sigma}{1-\sigma}\ln\frac{\omega}{r} - \frac{1}{1-\sigma}\ln\Omega. \tag{3.6}$$

Subsequently, we assume that the firms are price-takers; thus, price ratio can be a constant term. Furthermore, we assume that the degree of utilization of Hensachi varies across

[10] Asashi Holdings is clearly noise due to partly unfavorable data handling.

firms. That is, if $\tilde{\Omega}$ is the measured Hensachi, then

$$\Omega_{it} = E_i \times \tilde{\Omega}_{it}. \tag{3.7}$$

Taking the logarithm of both sides of this equation, we have

$$\ln \Omega_{it} = \ln E_i + \ln \tilde{\Omega}_{it}. \tag{3.8}$$

We treat E_i, which is time-invariant, as a firm-fixed effect;

$$\eta = \ln E_i. \tag{3.9}$$

Thus, we obtain the following regression model.

$$\ln \left(\frac{z}{k}\right)_{it} = \tilde{\alpha} + \beta \ln \tilde{\Omega}_{it} + \eta_i + u_{it}, \tag{3.10}$$

where t = 2004 and 2010, while i denotes the firm. In order to eliminate the firms' fixed effects, we can apply the first-difference method, which tests the following equation:

$$\frac{\Delta \left(\frac{z}{k}\right)_{it}}{\left(\frac{z}{k}\right)_{it}} = \alpha + \beta \frac{\Delta \tilde{\Omega}_{it}}{\tilde{\Omega}_{it}} + u_{it}. \tag{3.11}$$

In practical terms, we essentially allow that the difference in software intensity depends on its lagged value, which can be interpreted as the ICT investment equation with the adjustment cost so that we assume the ad-hoc AR(1) model. Finally, we obtain the following benchmark equation:

$$\Delta \left(\frac{z}{k}\right)_{it} = \alpha + \beta_1 \left(\frac{z}{k}\right)_{it} + \beta_2 \frac{\Delta \tilde{\Omega}_{it}}{\tilde{\Omega}_{it}} + u_{it}. \tag{3.12}$$

Once we allow the difference in software intensity to be a function of its lagged level, we implicitly assume the following equation:

$$\left(\frac{z}{k}\right)_{it} = \bar{\alpha} + \gamma_1 \left(\frac{z}{k}\right)_{it-1} + \gamma_2 \tilde{\Omega}_{it} + \eta_i + v_{it}. \tag{3.13}$$

We will check the possibility using the methods of Arellano and Bond (1991).

3.4 Estimation Results

Table 3.4 shows the estimation results. We apply the FD method in columns (1)–(4) and the generalized method of moments in columns (5) and (6). The first column shows the result of the basic equation, (4.1), implying that a 10% increase in CEO's Hensachi raises a firm's software intensity significantly by 0.8%. If we add the industrial fixed effect (two digits), we obtain the second column, whose Hensachi's coefficient is doubled compared to the first column. If we further add firm characteristics such as size and CEO age, or change the industrial definition from the two-digit level to the three-digit level, we obtain a smaller coefficient compared to that in the second column but still larger than that in the first column. Finally, we checked the possibility where the true specification would be (3.13) in the fifth and sixth columns. All coefficients were positive and significant, when impacts of 10% increase in CEOs' Hensachi ranged from 0.8% to 1.3% [11,12]. The effects of firm size and CEO age are not significant, while the latter

[11] We can determine if the CEO graduated from the science and technology field. If we control the interaction term, which is a cross-term of the science and technology dummy and Hensachi, the coefficient of Hensachi is positive and stable, but no significant results were obtained. It is not clear if the science and technology dummy accelerates software intensity.

[12] We can also analyze an industry cross-term regression model where Hensachi is multiplied by industrial dummies. The regression results show that the cross-term of the petroleum manufacturing industry is positively significant. The cross-term of the electric equipment manufacturing industry is positive but not significant, whereas the cross-term of the machinery manufacturing industry is negative and insignificant.

attribute absorbs the effect of a change of CEO[13,14].

Table 3.4: Effects of CEO characteristics on software investment

D.Software_intensity = D.(Software asset / Tangible fixed asset)	(1) FD	(2) FD	(3) FD	(4) FD	(5) GMM	(6) GMM
D.ln_Hensachi	8.547**	12.91**	11.59**	10.62*	8.126*	8.147*
	(4.051)	(6.501)	(5.755)	(6.432)	(4.875)	(4.918)
L.Software_intensity	-0.0254	0.0921	0.854***	0.839***		
	(0.586)	(0.640)	(0.0412)	(0.0486)		
D.ln_Employee			-7.2091	-5.034		
			(6.693)	(7.123)		
D.CEO age			-0.178	-0.143		-0.0290
			(0.178)	(0.180)		(0.212)
L.D.Software_intensity					0.0557	0.0557
					(0.109)	(0.109)
Constant	3.496	0.492	-0.932	-0.660		
	(5.445)	(1.030)	(0.777)	(2.570)		
Two-digit industry FE	No	Yes	Yes	No	No	No
Three-digit industry FE	No	No	No	Yes	Yes	Yes
N	933	885	848	889	767	767

Robust standard errors in parentheses; * $p<0.1$, ** $p<0.05$, *** $p<0.01$, using robust standard error

3.5 Discussion

As the reason for Japan's delay in the ICT revolution remains nebulous, we researched whether the lag was generated by CEOs' insufficient education. To this end, we analyzed

[13]Because we use FD estimation, firm size and firm age are basically controlled

[14]The inclusion of CEOs' educational background at the department level (e.g., financial or technical education) into the model, as in the research of Malmendier and Tate (2005), did not yield any significant results

data from various Japanese listed firms. The estimation results show that a 10% decrease in CEOs' education reduces their investments in ICT by 0.8–1.3 %. This suggests that insufficient education among decision makers will hamper firms' investment in ICT. Taking into account that smaller firms tend to be managed by relatively uneducated CEOs[15] and that a large part of the Japanese economy consists of SMEs, we can speculate that ICT investment in Japan may be even lower.

Table 3.5 shows the change in different industries' average CEO Hensachi score throughout the study period. Except for the non-ferrous metal industry, the Hensachi score of the non-manufacturing sector decreased. Conversely, classical industries such as wood and wood products manufacturing or mining or petroleum and coal products manufacturing exhibited an increase in CEOs' Hensachi score.

Table 3.5: Average difference in CEOs' Hensachi score between 2004 and 2010, by industry

Industry	Difference	Industry	Difference
Security	5.67	Printing	-2.67
Mining	4.50	Transportation	-3.20
Wood and Wood Products	2.80	Accommodation	-3.50
Other Services	2.00	Building Services	-4.67
Petroleum and Coal Products	2.00	Non-ferrous Metal	-4.77

We also note that $< 20\%$ of CEOs graduated from the science and technology departments of their respective universities in the 2010 dataset. This trend may be problematic, as it denotes a lack of technicians. In this dataset, we could not find any significant results after controlling for the variable which denotes whether they graduated from science and technology field. These results suggest that society does not regard science and technology graduates to be valuable as CEOs. In that sense, we should be cautious regarding what

[15]This is confirmed by our dataset

CEOs' Hensachi score reflects. It seems more sensible to examine a given candidate's suitability[16] as a CEO rather than whether they have a science or technology background.

3.6 Conclusion

Over 2000–2010, there was only a partial ICT revolution in Japan. The most likely reason for the lack of ICT investment is that CEOs in Japanese companies simply did not know how to utilize the new ICT capital. Since we analyzed listed firms' data, we could not confirm whether our results are generalizable to the entire Japanese economy. However, there was a high degree of variability in software intensity among the listed firms, which can be partially explained by CEOs' educational background. This means that CEOs with insufficient education or knowledge of new equipment can be an obstacle for ICT introduction and, consequently, can lead to a decrease in competitiveness.

[16] For instance, "the suitability" means whether the CEOs experienced a chief of department of information-system.

Additional Tables

Table 3.6: Average software intensity, by industry (%)

Industry	Software_intensity_2004	Software_intensity_2010
Food	2.23	3.89
Textiles	1.14	3.3
Wood & Wood Products	1.43	9.56
Paper & Pulp	1.6	1.81
Printing	1.73	8.07
Chemicals	2.72	19.22
Petroleum	2.39	7.61
Stone, Clay, & Glass Pds.	1.15	1.61
Iron & Steel	1.29	2.8
Non-ferrous Metals	1.27	145.05
Fabricated Metal Products	1.59	27.16
Machinery	3.11	3.96
Electric Equipment	7.05	14.03
Transportation Equipment	2.21	3.34
Misc. Manufacturing	2.72	4.4
Agriculture	-	-
Mining	0.4	27.02
Construction	2.73	5.26
Electricity, Water, & Gas Supply	13.43	1.77
Communication & Cmp. Svcs.	257.95	252.6
Transportation	5.92	38.53
Warehousing	1.37	8.79
Other Transportation	5.87	15.02
Wholesale Trade	29.9	54.29
Retail Trade	11.27	33.73
Finance & Insurance	8.68	49.11
Real Estate	7.63	8.96
Services	88.07	58.63

Table 3.7: Average educational background (as Hensachi score), by industry

Industry	Hensachi_2004	Hensachi_2010
Food	70.15	70.85
Textiles	69.69	67.08
Wood & Wood Products	69.08	71.25
Paper & Pulp	70.83	69.79
Printing	69.53	67.36
Chemicals	68.96	69.99
Petroleum	72.71	74.22
Stone, Clay, & Glass Pds.	71.86	70.56
Iron & Steel	69.4	71.33
Non-ferrous Metals	76.93	72.78
Fabricated Metal Products	68.9	68.05
Machinery	67.98	67.98
Electric Equipment	67.54	68.46
Transportation Equipment	71.12	71.83
Misc. Manufacturing	68.52	69.38
Agriculture	66	66
Mining	71	75.75
Construction	68.1	67.2
Electricity, Water, & Gas Supply	73.43	70.24
Communication & Cmp. Svcs.	68.95	68.08
Transportation	75.67	74.36
Warehousing	76.45	71.75
Other Transportation	68.97	69.23
Wholesale Trade	71.11	69.62
Retail Trade	68.76	66.2
Finance & Insurance	73	75
Real Estate	70.48	69.38
Services	68.44	68.03

Table 3.8: CEO age and software intensity (%)

CEO age	Software_intensity_2004	Software_intensity_2010
<40	78.48	64.91
40=<age<50	63.36	154.98
50=<age<60	59.36	44.14
60=<age<70	10.07	26.42
70=<age<70	3.79	30.32
70=<age<80	1.51	3.23
80=<age	1.04	0.83

Table 3.9: Size and software intensity (%)

firm_size	Software_intensity_2004	Software_intensity_2010
<100	47.81	163.09
100=<# of employees<1000	9.18	33.96
1000=<# of employees<10000	7.23	14.74
10000=<# of employees	112.03	93.26

Chapter 4

The Impact of Hiring Elite University Graduates on Firms' Future Productivity: Evidence from Japanese Listed Firms

[1]

[1] This study is supported by the Service Sector Productivity in Japan project of Hitotsubashi University.

-Abstract-

According to endogenous growth theory, an increase in the educational level of employees will increase the productivity of firms. Further, a strong positive correlation between TFP and employees' educational level has been empirically observed. However, there remains some concern regarding the existence of reverse causality, in which high-quality university graduates join firms with high potential in anticipation that they will become good firms in the future. The usual solution to this problem is to use a variable unrelated to productivity but related to education level as an IV. However, when TFP is used as the dependent variable, there is no variable that is independent of TFP, since TFP is the residual of subtracting the growth of capital and labor, multiplied by their respective coefficients from the growth of production. Therefore, the conventional IV method is inappropriate. In this study, the endogeneity problem due to reverse causality was resolved by combining the control function approach and the IV method, as well as analyzing data on Japanese listed companies and data on the universities from which employees graduated. The results revealed that the positive correlation between TFP and education level is caused by the fact that high-quality university graduates are attracted to firms with high future TFP, although future TFP does not increase as a result of high-quality university graduates joining the firms.

4.1 Introduction

As shown by endogenous growth theory(Romer (1990)), there is a near consensus that technological progress is embedded in an increase in TFP[2] and is the main driver of economic growth.

According to endogenous growth theory, human capital accumulation through schooling is also important(Lucas Jr (1988)), while, empirically, there is a positive correlation between human capital accumulation through schooling and economic growth (Barro (2001), Ciccone and Papaioannou (2009)).

Hence, it is natural to think that there is a positive correlation between human capital accumulation through education and TFP growth. In fact, recent studies—such as that conducted by Liu and Bi (2019)—have investigated this education-TFP link using spatial data. Tsamadias et al. (2019) conduct a cross-country panel analysis using higher education as a proxy for human capital.

In the present study, we focus on the quality of education rather than the years of schooling. Following Hanushek and Kimko (2000), we use the impact of education on TFP at the firm level as a more accurate proxy of the quality of schooling. Further, we focus on the Japanese market at the firm level because a firm is a unit whose TFP growth is observable as the minimum economic activity unit. Hence, we capture the effect of education level on TFP growth at the minimum level for causal inference[3].

For this, we use the information on employees' alma mater to measure employees' education level at the firm level. In particular, we use the proportion of graduates from highly ranked universities among the total new university graduate entrants to represent the educational level at the firm level at time t. We utilize data from 1990 and 1997, which

[2] Mahadevan (2003) conducted a detailed literature review on this topic.

[3] A similar regression conducted by Fleisher et al. (2011) was based on different research motivations, whereas our study uses a more detailed assessment of the quality of education and account for reverse causation much more carefully.

signal the end of the bubble economy and the employment ice age (a time when university graduates had great difficulty in finding employment), respectively, in the Japanese economy. Using this dataset, we see a positive correlation between future TFP (10 years after the employees' recruitment) and employees' educational level at the firm level, as shown in Figure 4.1.

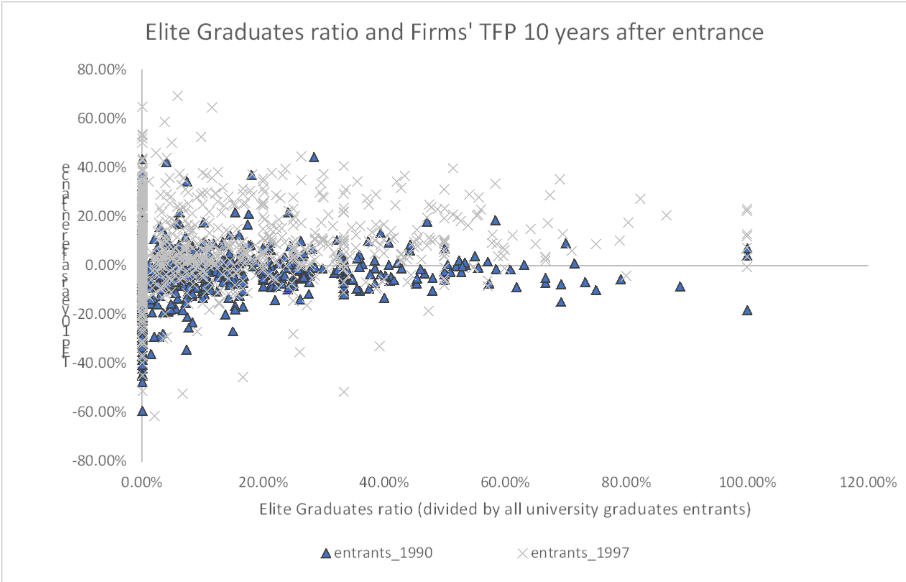


Figure 4.1: Educational level and future TFP at the firm level

Regarding causal inference, there is a concern in this positive correlation: reverse causation. There is a possibility that there is a positive correlation not because university graduates from highly ranked universities contribute to firms' productivity but because university graduates from highly ranked universities seek employment in promising companies because they know that these companies are promising. To deal with this reverse causality, applying the IV approach—which uses a variable that is orthogonal to TFP and has a correlation with firms' education level—is common. However, because TFP is calculated as a residual[4], we assume that no variables are orthogonal to TFP. Con-

[4]On this point, Hulten (2007) and Felipe (1999) criticize TFP as a measure of technological progress.

versely, we can make the reverse causation estimation, the dependent variable for which is education at the firm level. Using the information obtained from a reverse causation estimation, we show that we can obtain a consistent estimator of the effect of education on TFP.

As a result of the analysis, employees' educational level at the firm level has a significant negative effect on firms' future productivity. This means that university graduates from highly ranked universities may have harmed firms' productivity. These results are counterintuitive because, according to human capital theory, the productivity of firms with highly educated employees must be high. This study contributes to the literature because it is the first study in which the novel measure of firm-level education level is used. We utilize employees' alma mater (university) information, with which we can capture the quality of education. This provides more detailed information than employees' schooling years as an education measurement. Second, and more importantly, we conduct rigorous causal inference, especially using TFP as a dependent variable. When regressing some variables on TFP and when there is reverse causation, most studies use as an IV a variable that is supposed to be orthogonal to TFP. However, this approach is often criticized because TFP is derived from growth accounting and what exactly TFP represents is unclear. Therefore, it is fair to assume that there are no variables that are orthogonal to TFP. In this case, causal inference using traditional IV is not appropriate. We utilize a combination of the control function approach and IV methods to overcome this problem, which makes our study novel in the current TFP literature.

The rest of the paper is organized as follows: In Section 2, we provide the theoretical intuition behind the empirical analysis. In Section 3, we present the detailed information of the data used in this study. In Section 4, we present an econometric framework for causal inference. In Section 5, we show the empirical strategy, specifically, the validity of the IVs used in the analysis. In Section 6, we present the results of the analysis, and in Section 7, we present the conclusions drawn from the study.

4.2 Theoretical Intuition

In this section, we show that implementing an inappropriate recruiting policy in terms of resource allocation under different labor market conditions results in decreased productivity. We suppose that the firm's production function consists of skilled and unskilled labor. The form of the production function is assumed to be a Cobb-Douglas production function:

$$y = L_u^{\alpha} L_s^{(1-\alpha)}, \tag{4.1}$$

under the following budget constraint:

$$w_u L_u + w_s L_s = C \tag{4.2}$$

where y denotes production, C indicates the total budget, L_u represents unskilled labor, L_s represents skilled labor, and w_u and w_s represent the wages of unskilled laborers and skilled laborers, respectively. Now the firm products goods according to the solution of profit maximization problem (y* in Figure 4.2. Suppose the exogenous shocks raise the wage of skilled labor (w_s<w_s'). If the firm does not change the ratio of skilled labor to unskilled labor, the necessary production will be y" in Figure 4.2. Conversely, if the firm changes the employment policy appropriately, production will have to be y'* under the assumption of an ordinary production function in which the production function is continuous, always increasing, and strictly quasi-concave, $y'' < y'*$, under the same budget constraints b2 in Figure 4.2. Hence, the productivity of the firm sticking to the former rule is less than the optimal production.

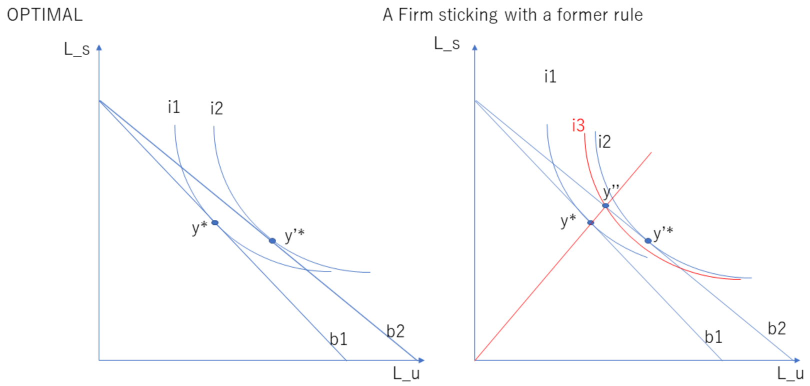


Figure 4.2: Theoretical intuition: Optimal firms vs firms sticking to a former rule

4.3 Data

We consider the effect of employees' educational level at the firm level on firms' future productivity. As stated in the introduction, there would be reverse causation because university graduates from highly ranked universities would want to go to promising firms. Hence, as explained in the econometric section, two equations must be tested. In particular, a simultaneous equations system that contains TFP data makes it harder for us to solve the endogeneity problem. As mentioned in the introduction, it is natural to assume that no variables are orthogonal to TFP. This system consists of two equations: One is the future TFP equation and the other is the equation of firms' employees' educational level. In this section, we also check the covariates that would appear in both equations. Note that some variables appear only in the TFP equation but do not appear in the equation of employees' education level. These variables will be the IVs to identify the effect of TFP on employees' educational level.

4.3.1 Employees' Educational Level

We would like to capture the heterogeneity of labor quality derived from the quality of the university. We utilize a dataset that shows where and how many university graduates were hired after they graduated from universities at the firm level[5]. Using this dataset, we prepare the measurement of labor quality at the firm level, i.e., the elite graduates ratio, as follows:

$$Elite\_Graduates\_ratio_{it} = \frac{\sum_{s \in S} new\_entrants_{its}}{\sum_{S} new\_entrants_{its}} \tag{4.3}$$

where s denotes a set of highly ranked universities[6] and S denotes all universities. Here, we measure the ratio of entrants from highly ranked universities to all university graduate entrants at the firm level as an indicator of firm-level labor quality. We assume that the higher the elite graduates ratio, the higher the labor quality at the firm level. Firm-level labor quality at a given time is based on the information of new entrants. This is a specific measure of labor quality and is unique in the existing literature. For the robustness check, we prepare the variable of the average Hensachi score of new entrants. This measure can also be interpreted as labor quality.

4.3.2 TFP

We utilize the TFP information provided by the EALC database[7]. In this database, TFP is calculated as the residual of growth accounting. However, we want to note that

[5] This study utilizes "Shu-Shoku-Saki Shirabe" a Japanese publication on recruitment research, of which only the hard copy is available. We utilize a dataset that creates digital data from a hard copy

[6] The universities considered highly ranked are the University of Tokyo, Kyoto University, Osaka University, Hokkaido University, Tohoku University, Nagoya University, Kyushu University, Tokyo Institute of Technology, Hitotsubashi University, Waseda University, and Keio University.

[7] This database is provided by the Japan Center for Economic Research, Center for Economic Institutions in Hitotsubashi University, the Center for China and Asian Studies at Nihon University, and the Center for Corporate Competitiveness at Seoul National University; it is published on https://www.jcer.or.jp/report/asia/detail3735.html. For more details, see Fukao et al. (2011).

the TFP growth rate is calculated as follows[8]:

$$\frac{\Delta TFP_{it}}{TFP_{it}} = \frac{\Delta Y_{it}}{Y_{it}} - \tilde{\alpha}_{it}\frac{\Delta K_{it}}{K_{it}} - \tilde{\beta}_{it}\frac{\Delta L_{it}}{L_{it}} - (1 - \tilde{\alpha}_{it} - \tilde{\beta}_{it})\frac{\Delta M_{it}}{M_{it}}. \tag{4.4}$$

From this equation, the TFP is based on residuals. Therefore, we do not know what TFP represents, although we often assume that TFP represents technology and knowledge. However, as we do not know exactly what TFP represents, we do not know the variable that is orthogonal to TFP. Moreover, we should assume that there are no variables that have nothing to do with TFP. In this study, we do not use any variable assumed to be orthogonal to TFP, although we assume that some variables have nothing to do with the elite graduates ratio. Hence, we consider the universe depicted in Figure 4.3. We assume that no variables are orthogonal to future TFP. Since we want to observe the long-term effect of new entrants' educational level on firms' future TFP, we take into consideration a 10-year lag for the future TFP measure (10 years since the entrance of university graduates).

[8]Once we obtain the TFP growth rate, we can calculate the level of productivity vertically and horizontally by setting the base year and base (average) firm, using the method of Good et al. (1997).

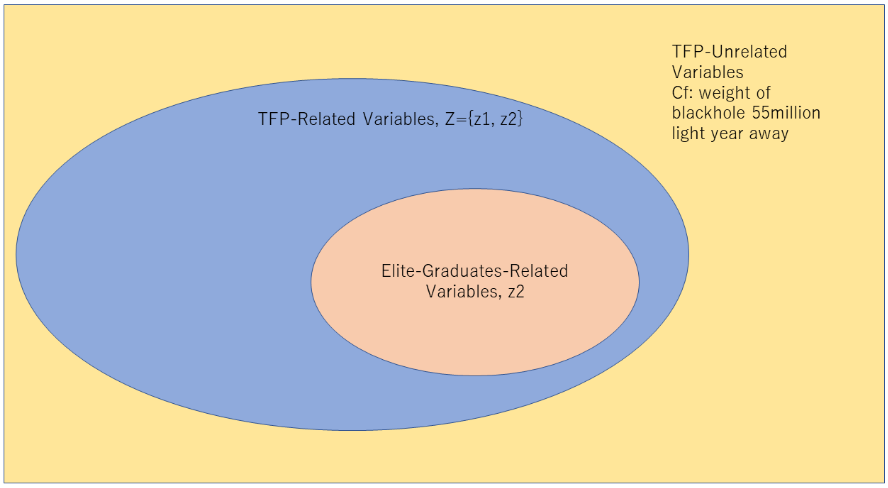


Figure 4.3: Image of the universe of variables, which is correlated with TFP and the elite graduates ratio

4.3.3 Covariates

Covariates appear in both equations, namely, the TFP equation and the equation of employees' educational level (i.e., the education equation). We control three variables coherently (from the main result to the robustness check specification), namely, debt-equity ratio (which represents firms' financial situation), firm size (the logged number of employees), and employees' average age. The dependent variable of the main regression is TFP(t+10). Therefore, the debt-equity ratio, firm size, and employees' average age are evaluated at time t+10. However, since a student at time t looks at a firm's state at time t, in the robustness check subsection, we control the initial (time t) value of the level of TFP and the logged number of employees.

Descriptive statistics can be reviewed in Table 4.1.

Table 4.1: Descriptive statistics

1990	Observation	mean	SD	min	max
TFP:t+10	1057	-0.04	0.10	-0.59	0.44
Elite_Graduates_ratio:t	1212	0.07	0.14	0.00	1.00
ln(debt_equity_ratio):t+10	1097	-0.63	1.72	-11.59	6.09
ln(Employee):+10	1215	6.88	1.16	3.14	11.09
employees' average age:t+10	1215	38.96	3.09	27.00	48.50
initial_TFP:t	1070	-0.09	0.11	-0.49	0.29
initial_ln(Employee):t	1217	7.03	1.15	3.22	12.49
1997					
TFP:t+10	1166	0.07	0.15	-0.61	0.69
Elite_Graduates_ratio:t	1192	0.11	0.17	0.00	1.00
ln(debt_equity_ratio):t+10	984	-1.27	1.63	-11.87	2.10
ln(Employee):+10	1190	6.82	1.13	1.95	11.12
employees' average age:t+10	1190	39.69	3.34	27.10	49.80
initial_TFP:t	1187	0.07	0.19	-0.87	0.90
initial_ln(Employee):t	1166	7.08	1.13	4.04	12.11

4.4 Econometric Framework

We would like to estimate the effect of employees' educational background on firm-level productivity, where education captures the heterogeneity of quality among the universities. In particular, we estimate the firm-level impact of firms hiring graduates from a highly ranked university (elite graduates). However, as mentioned in the introduction section, there would be a reverse causality of productivity on the elite graduates ratio because highly ranked university graduates would wish to be employed by promising firms. Therefore, to identify the causal relationship, we must use simultaneous equations to solve the endogeneity problem.

To solve the endogeneity arising from reverse causality, it is common to use variables that are orthogonal to the independent variable and correlated with the dependent variables. In our case, we seek variables that are orthogonal to future productivity and correlated to the elite graduates ratio.

Here, we define the set of TFP-related variables as $Z = [z_1 z_2]$, whereas the set of elite graduates-related variables is defined as z_2. Hence, z_1 is orthogonal to the elite graduates ratio. Of course, there are likely to be some variables orthogonal to TFP. However, as those variables would never be correlated with the elite graduates ratio, identifying those variables would not serve any useful purpose. We generally set the simultaneous equations as follows:

$$y_i = \beta x_i + u_i \tag{4.5}$$

$$x_i = \alpha y_i + v_i, \tag{4.6}$$

where we assume

$$E(u) = E(v) = 0 \tag{4.7}$$

$$u, v \sim i.i.d. \tag{4.8}$$

x and y are as follows:

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} -\beta & 1 \\ 1 & -\alpha \end{bmatrix}^{-1} \begin{bmatrix} u \\ v \end{bmatrix} = \frac{1}{\alpha\beta - 1} \begin{bmatrix} -\alpha & -1 \\ -1 & -\beta \end{bmatrix} \tag{4.9}$$

$$x = \frac{\alpha}{1-\alpha\beta} u + \frac{1}{1-\alpha\beta} v \tag{4.10}$$

$$y = \frac{1}{1-\alpha\beta} u + \frac{\beta}{1-\alpha\beta} v \tag{4.11}$$

Because u is correlated to x, and v is correlated to y, the OLS of each equation yields a biased estimator. However, if we know the true value of α, we can calculate the vector $\hat{v}$ accurately using the data. Now, we show that $\hat{v}$ is a candidate to be an IV for the estimation of equation (4.5). Note we assume $v \perp u$,

$$\hat{\beta}_{IV} = (v'x)^{-1} v'y = (v'x)^{-1} v'(\beta x + u) = \beta_{IV} + (v'x)^{-1} v'u \tag{4.12}$$

and suppose the following condition:

$$plim \frac{1}{n} v' x = Q_{vx} \tag{4.13}$$

and from orthogonality of u and v,

$$plim \frac{1}{n} v' u = 0 \tag{4.14}$$

then

$$plim \hat{\beta_{IV}} = \beta + Q_{vx} \times 0 = \beta. \tag{4.15}$$

Hence, as long as we know the true value of α, we can estimate β. However, because we often do not know the true parameter α, we need some variables that appear only in the y equation, which is z[9] [10].

$$y_i = \beta x_i + \gamma z_i + u_i \tag{4.16}$$

$$x_i = \alpha y_i + v_i \tag{4.17}$$

and also assuming that

$$E(u) = E(v) = 0 \tag{4.18}$$

$$u, v \sim i.i.d. \tag{4.19}$$

Now, we can use the control function approach[11] where we conduct the following regression:

$$y_i = \Omega z_i + \omega_i. \tag{4.20}$$

[9] This method can be interpreted as one method of Lewbel (2012)

[10] For a more general setting (see Appendix A), we develop a method of identification when there is perfect reverse causality.

[11] Wooldridge (2015) provides a clear understanding of the control function approach.

then obtain $\hat{\Omega}$ and insert it into the x_i equation as an independent variable, and regress to obtain the consistent estimator of α. Once we obtain the consistent estimator α, we can obtain $\hat{v_i}$ to be used as an IV in the y_i equation to obtain a consistent estimator of β:

$$x_i = \alpha y_i + \hat{\omega} + \tilde{v}_i \tag{4.21}$$

$$\hat{v} = y_i - \hat{\alpha} y_i \tag{4.22}$$

and setting

$$Z = [\hat{v}z], X = [xz] \tag{4.23}$$

$$\begin{bmatrix} \hat{\beta} \\ \\ \hat{\gamma} \end{bmatrix} = (Z'X)^{-1} Zy, \tag{4.24}$$

In our study, y corresponds to the TFP, whereas x corresponds to the employees' educational level. TFP has many correlated variables, however, some of those variables are unrelated to education. For the following setting, see Appendix A.

$$TFP = \beta\, elite\_graduates\_ratio + \gamma_1 z_1 + \gamma_2 z_2 + u \tag{4.25}$$

$$elite\_graduates\_ratio = \alpha\, TFP + \zeta z_1 + v. \tag{4.26}$$

Here, u and v must be orthogonal, while z_1 must include all variables that relate to the elite_graduates_ratio and TFP. In the next chapter, we show the variables corresponding to z_2, which can be interpreted as an IV for (4.26).

4.5 Empirical Strategy and Model

4.5.1 Empirical Strategy

Next, we consider the variables included in the TFP equation but excluded from the elite graduates ratio equation and can be interpreted as IVs for the elite graduates ratio as an endogenous variable. We considered two IVs candidates for the elite graduates ratio.

The first candidate is the ratio of account receivable to sales (account receivable ratio) at time t+10. This ratio should be an IV because it represents the firm's network at time t+10 (although credit transactions are generally not favored, it is considered to represent the state of trust between firms with dense networks). However, university graduates who would enter the firm at time t cannot know the firms' future networks. Hence, this could be a candidate to be considered as an IV for the elite graduates ratio. Figures 4.4 and 4.5 show that this candidate is appropriate as an IV because such variables are orthogonal to the elite students' ratio at time t+10 and correlated with TFP at time t+10.

The second one is other countries' firm-level TFP at time t+10 in the same industry as firm i, especially for countries that have ties with said firm[12]. These variables are likely candidates to be IVs for elite graduates because, for example, the number of Japanese university graduates who migrate to other countries is very small because of certain assumed constraints—e.g., the language barrier and limited information they have about foreign countries—even if the company they will serve has strong ties with foreign countries.

[12]The countries that have ties with firm i include those whose international trade relationships with firm i were the largest and second largest in 2016

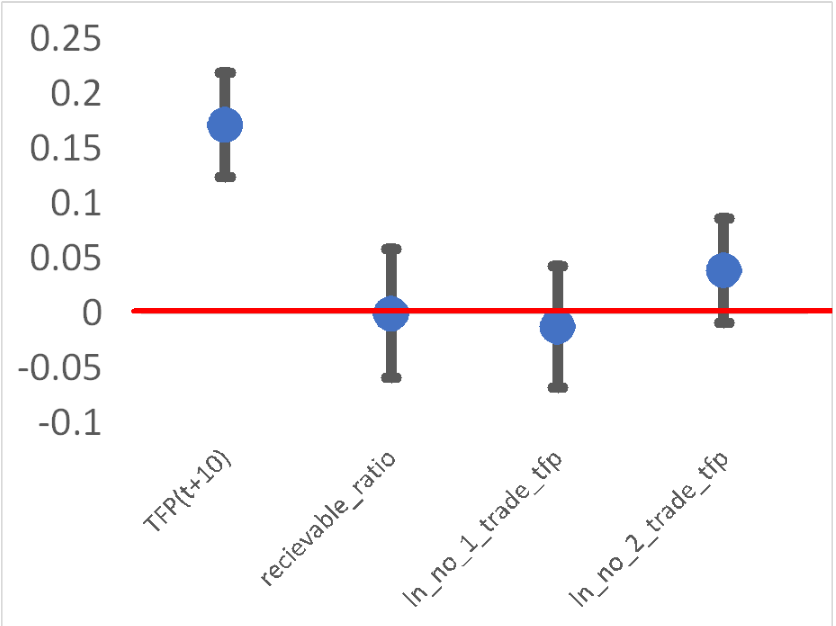


Figure 4.4: The coefficients of the regressed elite student ratio on x

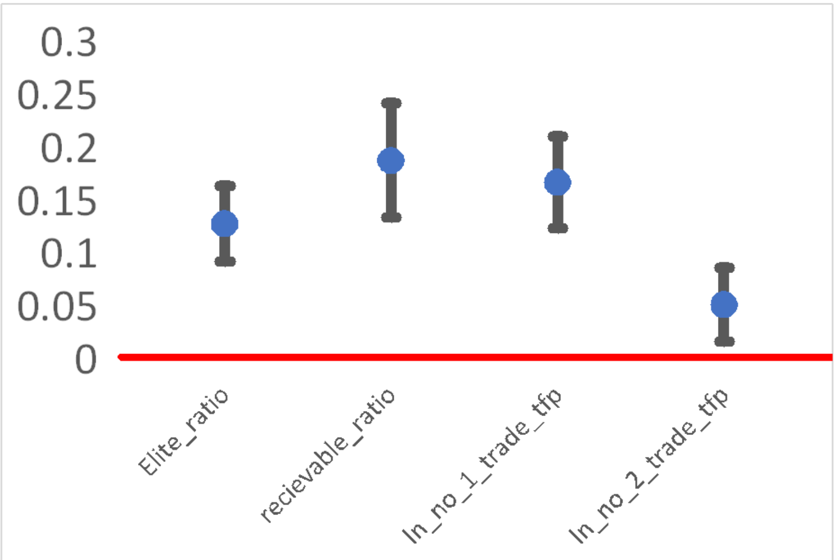


Figure 4.5: The coefficients of the regressed TFP(t+10) on x

We also control the year-time industry fixed effects. As described in the Data section, the logged value of the debt-equity ratio (ln_de ratio), employment size, and the average

age of firms' employees are to be controlled. The descriptive statistics of the candidate IVs are listed in Tables 4.2 and 4.3.

Table 4.2: Descriptive statistics of receivable_ratio

Year	N	Mean	SD	min	max
1990	1214	0.20	0.11	0.00	0.94
1997	1186	0.20	0.11	0.00	0.81

Table 4.3: Descriptive statistics of ln_no_1_trade and ln_no_2_trade

1990	N	mean	SD	min	max
ln_no_1_trade_tfp	393	4.54	0.21	3.48	4.86
ln_no_2_trade_tfp	282	4.37	0.37	3.48	4.86

1997	N	mean	SD	min	max
ln_no_1_trade_tfp	438	4.73	0.19	4.33	5.20
ln_no_2_trade_tfp	314	4.64	0.18	4.33	5.20

4.5.2 Model

First, we estimate the following equation via OLS.

$$TFP = z_1\Omega_1 + z_2\Omega_2 + \eta + \omega \tag{4.27}$$

where z_2 represents the IVs for the elite graduates equation (no_1_tfp(t+10), no_2_tfp(t+10), account_ receivable_sales_ratio(t+10)), and z_1 represents the control variables. η represents firms' fixed effects. This is the first stage of the control function approach for obtaining the residuals $\hat{\omega}$. Second, we estimate the following equation using the residuals of the first equation.

$$Elite\_graduates\_ratio = \alpha TFP + z_1\zeta + \gamma\hat{\omega} + \delta \times year + \tilde{v}. \tag{4.28}$$

where $\delta \times year$ represents the industry $\times$ year fixed effect.

We define $\hat{v} = \hat{\gamma}\hat{\omega} + \tilde{v}$ and use $\hat{v}$ as an instrument for the following equation:

$$TFP = \beta_1 Elite\_graduates\_ratio + z_1\beta_2 + z_2\beta_3 + \eta + \delta * year + u. \tag{4.29}$$

4.6 Results

4.6.1 Main Results

We show the results of the estimation. The main results are derived by using the receivable ratio as an IV because the sample size is much larger than that of the usage of industry TFP information of other countries (second candidates for IV).

We show the second-stage regression results. Here, the dependent variable was the elite graduates ratio[13].

[13] We obtain roughly the same results if we use the traditional IV method instead of the control function approach for the second stage.

Table 4.4: Second stage of main results

	(1)	(2)	(3)
	Elite_ratio	Elite_ratio	Elite_ratio
	OLS	OLS	OLS
TFP	0.222***	0.208***	0.197***
	(0.03)	(0.03)	(0.03)
vhat	-0.207**		
	(0.09)		
vhat2		-0.188**	
		(0.09)	
size		0.056***	0.056***
		(0.00)	(0.00)
ln_de_ratio		0.010***	0.008***
		(0.00)	(0.00)
vhat3			-0.178**
			(0.09)
employees' average age			0.006***
			(0.00)
_cons	0.086***	-0.290***	-0.518***
	(0.00)	(0.02)	(0.05)
industry * year	Yes	Yes	Yes
N	2212	1918	1918
r2	0.110	0.261	0.271

Robust standard errors in parentheses

* $p < 0.1, **p < 0.05, ***p < 0.01$

From (Table 4.4), we can confirm that the reverse causality (of future TFP as a causality of the elite graduates ratio) is positive and significant. This implies that highly educated graduates tend to be hired by promising firms. The corresponding third-stage results are as follows (the dependent variable is TFP):

Table 4.5: Third stage of the main results

	(1)	(2)	(3)
	TFP	TFP	TFP
	FE-IV	FE-IV	FE-IV
elite graduates ratio	-0.0715***	-0.0584**	-0.0553**
	(0.0246)	(0.0246)	(0.0245)
receivable ratio	-0.0640	-0.0151	-0.0144
	(0.0614)	(0.0602)	(0.0607)
size		0.0107	0.0102
		(0.0158)	(0.0158)
ln_de_ratio		-0.0108***	-0.0109***
		(0.00407)	(0.00407)
average employees' age			-0.000619
			(0.00213)
N	1570	1318	1318
r2	-0.0149	0.00860	0.00998

Robust standard errors in parentheses
$*p < 0.1, **p < 0.05, ***p < 0.01$

From the third stage of the main results (Table 4.5), the impact of the elite graduates ratio is negative and significant across all specifications[14]. As TFP is a logged value, a 10% increase in the elite graduates ratio reduces future TFP by 0.5-0.7%. We check the robustness in the next subsection.

4.6.2 Robustness Check Using the Other IVs: No 1 Trade TFP and No 2 Trade TFP

We check the findings' robustness using other IVs: the firm-level TFP in other countries at time t+10, considering the same industry as that of the analyzed firm, especially in countries that have strong ties with the firm. The results of the second-stage regression are shown in Table 4.6, and the reverse causation from TFP to education level is positive

[14] The exclusion of small firms with less than 50 employees does not change the results in terms of both level and significance.

and significant.

Table 4.6: Second stage of the robustness check (IV as other regions' TFP)

	(1) Elite graduates ratio OLS	(2) Elite graduates ratio OLS	(3) Elite graduates ratio OLS
TFP	0.358***	0.453***	0.443***
	(0.10)	(0.11)	(0.11)
vhat	-0.235		
	(0.21)		
vhat2		-0.346	
		(0.22)	
size		0.064***	0.062***
		(0.01)	(0.01)
ln_de_ratio		0.012**	0.010*
		(0.01)	(0.01)
vhat3			-0.334
			(0.22)
average employees' age			0.010
			(0.00)***
_cons	0.120***	-0.331***	-0.717***
	(0.01)	(0.04)	(0.11)
N	559	490	490
r2	0.088	0.289	0.306

Robust standard errors in parentheses
$*p < 0.1, **p < 0.05, ***p < 0.01$

The results of the third stage with other IVs shows that, in this case as well, the elite graduates ratio is negative and significant. Also, the magnitude of the coefficient of the elite graduates ratio does not change significantly.

Table 4.7: Third stage of the robustness check (other regions' TFP as the IV)

	(1)	(2)	(3)
	TFP	TFP	TFP
	FE-IV	FE-IV	FE-IV
elite graduates ratio	-0.0634*	-0.0810**	-0.0782*
	(0.0343)	(0.0410)	(0.0407)
ln_no_1_trade_tfp	-0.00882	0.00491	0.00473
	(0.0305)	(0.0331)	(0.0332)
ln_no_2_trade_tfp	-0.0239	-0.0197	-0.0207
	(0.0287)	(0.0282)	(0.0284)
size		0.0149	0.0143
		(0.0189)	(0.0194)
ln_de_ratio		-0.0135*	-0.0139*
		(0.00706)	(0.00759)
average employees' age			-0.00136
			(0.00450)
N	468	398	398
r2	-0.0280	-0.00891	-0.00593

Robust standard errors in parentheses
$*p < 0.1, **p < 0.05, ***p < 0.01$

4.6.3 Robustness Check Using Another Index of Education: Hensachi

There is some concern that the elite graduates ratio might not fully reflect the quality of universities. In particular, there is a possibility that the quality of universities considered highly ranked is time-variant[15]. Hence, we use other measurements that reflect the quality of universities using Hensachi. As Hensachi score is a major indicator in Japan representing the selectiveness of universities, it is supposed to reflect universities' quality. We calculated the average Hensachi score based on the same dataset. Table 4.8 shows that reverse causation is positive and significant.

[15]We also check this possibility using the ratio of graduates from the University of Tokyo to the total new entrants at the firm level. However, this does not yield any significant results.

Table 4.8: Second stage of the robustness check (Hensachi-based)

	(1)	(2)	(3)
	Hensachi	Hensachi	Hensachi
	OLS	OLS	OLS
TFP	4.763***	3.876***	3.774***
	(1.05)	(1.06)	(1.07)
vhat	-4.622		
	(2.62)*		
ln_de_ratio	0.258***	0.287***	0.275***
	(0.06)	(0.06)	(0.06)
vhat2		-4.620*	
		(2.68)	
size		0.789***	0.793***
		(0.09)	(0.09)
vhat3			-4.515*
			(2.69)
average employees' age			0.039
			(0.04)
ln_de_ratio			0.000
			(.)
_cons	58.784***	53.210***	51.644***
	(0.17)	(0.70)	(1.58)
N	1706	1702	1702
r2	0.161	0.195	0.196

Robust standard errors in parentheses
$*p < 0.1, **p < 0.05, ***p < 0.01$

The results of the third stage (Table 4.9) show that although the measure of the educational level changed, the effect of educational measures at the firm level (Hensachi) is negative and significant.

Table 4.9: Third stage of the robustness check (Hensachi-based)

	(1) TFP FE-IV	(2) TFP FE-IV	(3) TFP FE-IV
Hensachi	-0.00255***	-0.00205***	-0.00203***
	(0.000815)	(0.000772)	(0.000767)
receivable ratio	-0.0323	-0.0210	-0.0221
	(0.0632)	(0.0596)	(0.0595)
size		0.0186	0.0191
		(0.0171)	(0.0173)
ln_de_ratio		-0.00892**	-0.00886**
		(0.00398)	(0.00398)
average employees' age			0.000614
			(0.00221)
N	1112	1110	1110
r2	-0.00309	0.0182	0.0186

Robust standard errors in parentheses
$*p < 0.1, **p < 0.05, ***p < 0.01$

4.6.4 Robustness Check Including Variables at Time t

The next robustness check comprises a regression including variables at time t (1990 and 1997, the same year as students' graduation). We will see that even after testing this specification, the result will not change significantly. Table 4.10 shows the results of the second stage with variables at time t. This time also shows that reverse causation is positive and significant.

Table 4.10: Second stage of the robustness check (including variables at time t)

	(1) Elite graduates ratio OLS	(2) Elite graduates ratio OLS	(3) Elite graduates ratio OLS
TFP(t+10)	0.200***	0.228***	0.229***
	(0.04)	(0.04)	(0.04)
TFP(t=0)	-0.019	-0.007	-0.015
	(0.04)	(0.04)	(0.04)
ln_initial_empoyee	0.059***	0.071***	0.064***
	(0.00)	(0.01)	(0.01)
vhat	-0.179**		
	(0.08)		
vhat2		-0.206**	
		(0.10)	
size		-0.011	-0.004
		(0.01)	(0.01)
ln_de_ratio		0.006***	0.006***
		(0.00)	(0.00)
vhat3			-0.207**
			(0.10)
average employees' age			0.002*
			(0.00)
_cons	-0.333***	-0.333***	-0.421***
	(0.02)	(0.02)	(0.05)
N	2178	1890	1890
r2	0.266	0.286	0.287

Robust standard errors in parentheses

$*p < 0.1, **p < 0.05, ***p < 0.01$

Table 4.11 shows the results of the third stage of regression with variables in time t. The inclusion of the variables into the regression does not yield major differences.

Table 4.11: Third stage of the robustness check (inclusion of variables at time t)

	(1)	(2)	(3)
	TFP	TFP	TFP
	FE-IV	FE-IV	FE-IV
elite graduates ratio	-0.0590***	-0.0628**	-0.0633**
	(0.0226)	(0.0249)	(0.0254)
TFP(t=0)	0.193***	0.171**	0.171**
	(0.0544)	(0.0687)	(0.0688)
initial employees (log)	0.00869	0.00700	0.00775
	(0.0195)	(0.0232)	(0.0240)
receivable ratios	-0.0648	-0.00939	-0.00825
	(0.0626)	(0.0593)	(0.0595)
size		0.00584	0.00515
		(0.0172)	(0.0173)
ln_de_ratio		-0.00971**	-0.00982**
		(0.00388)	(0.00389)
average employees age			-0.000685
			(0.00226)
N	1564	1314	1314
r2	0.0244	0.0313	0.0312

Robust standard errors in parentheses
$*p < 0.1, **p < 0.05, ***p < 0.01$

4.6.5 Robustness Check Using TFP Data (t+20)

It is unclear as to whether setting a lag of 10 years is appropriate, as employees who are 32 or 33 years old may not be firm executives. Thus, we collect data with a 20-year lag instead[16]. Table 4.12 shows that the results of second-stage regression. TFP(t+20) remain significant and positive.

[16]However, noise or contamination will be greater than that of t + 10.

Table 4.12: Second stage of the robustness check (TFP(t+20) as the dependent variable)

	(1) Elite graduates ratio OLS	(2) Elite graduates ratio OLS	(3) Elite graduates ratio OLS
TFP(t+20)	0.138***	0.132***	0.140***
	(0.03)	(0.04)	(0.04)
vhat	-0.277**		
	(0.12)		
vhat2		-0.195	
		(0.13)	
size		0.051***	0.053***
		(0.00)	(0.00)
ln_de_ratio		0.016***	0.015***
		(0.00)	(0.00)
vhat3			-0.206*
			(0.12)
average employees' age			0.006***
			(0.00)
_cons	0.091***	-0.234***	-0.505***
	(0.01)	(0.02)	(0.07)
N	1922	1610	1610
r2	0.097	0.244	0.253

Robust standard errors in parentheses
$*p < 0.1, **p < 0.05, ***p < 0.01$

Table 4.13 shows the third stage of regression. The sign of the coefficient of the elite graduates ratio remains negative and significant, though the level increases slightly.

Table 4.13: Third stage of the robustness check (using TFP(t+20))

	(1) TFP FE-IV	(2) TFP FE-IV	(3) TFP FE-IV
elite graduates ratio	-0.0621***	-0.0410*	-0.0433*
	(0.0227)	(0.0228)	(0.0229)
receivable ratios	-0.0443	-0.0570	-0.0531
	(0.0507)	(0.0579)	(0.0578)
size		-0.00751	-0.00638
		(0.0139)	(0.0140)
ln_de_ratio		-0.00938**	-0.00954**
		(0.00372)	(0.00373)
average employees age			0.00148
			(0.00178)
N	1338	1094	1094
r2	0.00208	0.0146	0.0151

Robust standard errors in parentheses
$*p < 0.1, **p < 0.05, ***p < 0.01$

4.7 Conclusion

We investigate the impact of the quality of employees' alma mater on firms' future TFP as a unique education measure that accounts for the possibility of reverse causation from TFP to education. We estimate this impact using a relatively new method of simultaneous equations, employing a combination of a control function approach and an IV method. In particular, we assume that there are variables that are orthogonal to education and that there are no variables orthogonal to future TFP. Under this assumption, we use a three-stage regression model: on Stage 1), we regress the IVs (orthogonal to education but tied with future TFP) for the impact of education on future TFP using the control function approach; on Stage 2), we regress future TFP on education using estimated residuals obtained in the first stage; on Stage 3), we use the residuals obtained in the second stage as IVs to estimate the future TFP equation. The IVs for education are valid and the estimation results show that the quality of the university from which the employees graduated has a significant negative effect on firms' future TFP. These results are robust through many specifications and the use of different proxies of education. These results imply that hiring graduates from highly ranked universities may harm firms' productivity, which is counterintuitive according to human-capital theory. One explanation for explaining this may be that the proportion of elite university graduates working in firms differs from 1990 (which marks the end of the bubble economy) to 1997 (which is the middle of employment ice age—a time when university graduates found it hard to find employment). If the relative wages for elite university graduates had changed, compared with those of graduates from non-elite universities, the optimal hiring balance between elite university graduates and non-elite university graduates would have changed. If the firms had adhered to a single recruiting policy although the relative wage been changed, these firms' productivity would have decreased. Since we have only two-year panel data and do not have evidence that the relative wage had changed, this explanation remains purely speculative[17]. Future studies on the relationship between firm employees' educational level and productivity should aim to clarify this issue.

[17]We already controlled for time-invariant firms' fixed effect. However, we may be able to test this hypothesis if we could access data that represent firms' time-variant conservativeness. See also Appendix B to see the variance in the elite graduates ratio in the electronics industry.

Appendix A: Generalized Version of the Econometrics Framework

Our econometrics universe is as follows:

$$y_i = \beta x_i + \gamma_1 z_{1i} + \gamma_2 z_{2i} + u_i \tag{4.30}$$

$$x_i = \alpha y_i + \gamma_3 z_{1i} + v_i \tag{4.31}$$

And we assume the following:

$$E(u) = E(v) = 0 \tag{4.32}$$

$$u, v \sim i.i.d. \tag{4.33}$$

and further,

$$z_1, z_2 \perp u, v \tag{4.34}$$

After the control function approach, we can obtain a consistent parameter of α and γ_3, which is equivalent to obtaining v. We set $Z = [vz_1z_2]$ and $X = [xz_2z_3]$ and then conduct an IV estimation:

$$\begin{bmatrix} \beta \\ \gamma_1 \\ \gamma_2 \end{bmatrix} = (Z'X)^{-1}Z'y = \begin{bmatrix} \beta \\ \gamma_1 \\ \gamma_2 \end{bmatrix} + (Z'X)^{-1}Z'u \tag{4.35}$$

If we suppose that $\frac{1}{n}Z'X \to Q_{ZX}$, then:

$$\frac{1}{n}Z'u = \frac{1}{n}\begin{bmatrix} v'u \\ z_1'u \\ z_2'u \end{bmatrix} = 0 \tag{4.36}$$

Hence, the IV estimators of $\begin{bmatrix} \hat{\beta} \\ \hat{\gamma_1} \\ \hat{\gamma_2} \end{bmatrix}$ are consistent.

Appendix B: List of Firms Exhibiting Elite Graduates Ratio Changes within the Electronic Industry

Rank: Elite_ratio 1997 - Elite_ratio 1990

Firms exhibiting a decrease in the elite graduates ratio	decrease %	Firms exhibiting an increase in the elite graduates ratio	increase %
Teikoku Tsushin Kogyo Co., Ltd.	-75.00%	FANUC CORPORATION	62.47%
Yokogawa Electric Corporation	-45.16%	Pioneer Corporation	50.67%
Nippon Avionics Co., Ltd.	-34.78%	Murata Manufacturing Company, Ltd.	33.42%
Furukawa Battery Co., Ltd.	-33.33%	TOSHIBA CORPORATION	32.40%
TOGAMI ELECTRIC MFG.CO., LTD.	-14.29%	SANYO Electric Co., Ltd.	29.04%
Kyosan Electric Manufacturing Co., Ltd.	-11.94%	SHARP CORPORATION	26.18%
Nihon Kohden Corporation	-9.71%	Victor Company of Japan, Limited	26.12%
AIPHONE CO., LTD.	-9.09%	Fujitsu Limited	26.07%
Japan Aviation Electronics Industry, Limited	-8.97%	Oki Electric Industry Co., Ltd.	23.03%
Osaki Electric Co., Ltd.	-8.33%	Hitachi, Ltd.	22.62%
HOKURIKU ELECTRIC INDUSTRY CO., LTD.	-8.33%	Tamura Corporation	22.22%
CMK CORPORATION	-7.69%	TEAC Corporation	20.45%
Ikegami Tsushinki Co., Ltd.	-7.14%	KYOCERA Corporation	20.24%
Sumitomo Wiring Systems, Ltd.	-3.33%	Shin-kobe Electric Machinery Co., Ltd.	20.00%
Hamamatsu Photonics K.K.	-3.33%	MITSUBISHI ELECTRIC Corporation	19.84%

Chapter 5

Conclusion

To gain a comprehensive understanding of Japan's secular stagnation since the 1990s, this doctoral dissertation examined firms' R&D behavior, firms' utilization of ICT capital goods, and the impact of human resources on firm productivity.

Regarding firms' business and capital ties and R&D activities, discussed in Chapter 2, it was found that firms with business and capital ties with R&D-intensive firms kept their own R&D activities lower than those of the firms without such ties. We expect that SMEs that do not have connections with such R&D-intensive firms will be able to supplement their R&D human resources and R&D facilities (which may be insufficient) by establishing business and capital relationships with such firms. In this dissertation, I investigated the expansion of the knowledge spillover pool, which is one of the ways to increase TFP by acquiring knowledge other than through independent R&D. Conversely, the relationship between TFP and the increase in SMEs' absorptive capacity should be examined, while the extent to which human resources and facilities contribute to this absorptive capacity should also be examined in the future.

In Chapter 3, we discussed Japanese firms' failure to take advantage of the ICT revolution in the 1990s, based on the hypothesis that CEOs' insufficient knowledge of new capital goods, especially ICT capital goods, may lead to lower investment in ICT capital. Additionally, the relationship between educational background and software investment was investigated. Consequently, we found that if the Hensachi score of the university from which the CEOs graduated was higher, the software investment of the firm was higher than that of other firms. This suggests that ICT education for CEOs and executives in companies is important. Since only listed companies were included in this analysis, future studies should analyze not only listed firms but also SMEs. In addition, it will be necessary to examine the latest data to determine whether or not Japan is missing out on the Fourth Industrial Revolution. Furthermore, in the context of investment in intangibles, the complementary effects of intangibles (including investment in human resources) and other assets, such as the problem in the vintage of tangible assets, should be comprehensively examined. It is also important to analyze the background of the unbalanced and mismatched investments in intangible assets during this period, such as the reduction of investments in other human resources, even though software investments have been strong recently.

Chapter 4 examined whether firms' productivity increases when graduates of highly ranked universities join firms as new entrants. We examined the effect of the aforementioned human resources on productivity, taking into account reverse causality—i.e., the effect of attracting well-educated university graduates to promising firms. The results of the analysis showed that hiring university graduates from highly ranked universities did not increase productivity (i.e., TFP) but rather decreased it. Therefore, the positive correlation between firms' future productivity and the proportion of new entrants who graduated from highly ranked universities (in total new hires) is caused by the attraction of university graduates from highly ranked universities to firms with higher future productivity. This indicates that simply hiring graduates from highly ranked universities does not necessarily lead to higher productivity, suggesting that a well-balanced recruitment process is more important than simply attracting highly skilled personnel. However, future research should examine what types of firms simply attract highly ranked university graduates and what types of firms have a more balanced recruitment process.

In these three chapters, I have analyzed Japan's economic stagnation since the 1990s from three perspectives: R&D investment, ICT investment, and the relationship between human resources and TFP. Each of these issues has its own future research agenda, but I hope that they will be clarified and that a more comprehensive understanding of the Two (or Three) Lost Decades will be obtained.

Bibliography

Aghion, Philippe, Nick Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt (2005) "Competition and innovation: An inverted-U relationship," *The Quarterly Journal of Economics*, Vol. 120, No. 2, pp. 701–728.

Aghion, Philippe, Antonin Céline, and Bunel Simon (2021) *The Power of Creative Destruction: Economic Upheaval and the Wealth of Nations*: Belknap Press: An Imprint of Harvard.

Arellano, Manuel and Stephen Bond (1991) "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations," *The Review of Economic Studies*, Vol. 58, No. 2, pp. 277–297.

Arrow, Kenneth (1962) "Economic Welfare and the Allocation of Resources for Invention,"Technical report, National Bureau of Economic Research.

Barro, Robert J (2001) "Human capital and growth," *American Economic Review*, Vol. 91, No. 2, pp. 12–17.

Belderbos, RenÃ, Kenta Ikeuchi, Kyoji Fukao, Young Gak Kim, and Hyeog Ug Kwon (2022) "What Do R&D Spillovers from Universities and Firms Contribute to Productivity? Plant level productivity and technological and geographic proximity in Japan,"Technical report, Research Institute of Economy, Trade and Industry (RIETI).

Bloch, Carter (2005) "R&D investment and internal finance: The cash flow effect," *Economics of Innovation and New Technology*, Vol. 14, No. 3, pp. 213–223.

Branstetter, Lee (2000) "Vertical keiretsu and knowledge spillovers in Japanese manufacturing: An empirical assessment," *Journal of the Japanese and International Economies*, Vol. 14, No. 2, pp. 73–104.

Brown, James R and Bruce C Petersen (2011) "Cash holdings and R&D smoothing," *Journal of Corporate Finance*, Vol. 17, No. 3, pp. 694–709.

Bugamelli, Matteo and Patrizio Pagano (2004) "Barriers to Investment in ICT," *Applied Economics*, Vol. 36, No. 20, pp. 2275–2286.

Ciccone, Antonio and Elias Papaioannou (2009) "Human Capital, the Structure of Production, and Growth," *The Review of Economics and Statistics*, Vol. 91, No. 1, pp. 66-82, February, DOI: 10.1162/rest.91.1.66.

Cohen, Wesley M and Steven Klepper (1996) "A reprise of size and R & D," *The Economic Journal*, Vol. 106, No. 437, pp. 925–951.

Cohen, Wesley M, Richard C Levin, and David C Mowery (1987) "Firm Size and R&D Intensity: A Re-examination," *Journal of Industrial Economics*, Vol. 35, No. 4, pp. 543–65.

Felipe, Jesus (1999) "Total factor productivity growth in East Asia: A critical survey," *The Journal of Development Studies*, Vol. 35, No. 4, pp. 1–41.

Fleisher, Belton M, Yifan Hu, Haizheng Li, and Seonghoon Kim (2011) "Economic transition, higher education and worker productivity in China," *Journal of Development Economics*, Vol. 94, No. 1, pp. 86–94.

Fukao, Kyoji (2021) *Productivity of Service Sector and Japanese Economy*, Chap. 12, The way to improve productivity of Service Sector (in Japanese), pp. 387-413: University of Tokyo Press.

Fukao, Kyoji and Tatsuji Makino (2021) *Productivity of Service Sector and Japanese Economy*, Chap. 2, Origin of labor productivity growth in the service sector (in Japanese), pp. p83-p110: University of Tokyo Press.

Fukao, Kyoji, Tomohiko Inui, Keiko Ito, Young Gak Kim, and Tangjun Yuan (2011) "An international comparison of the TFP levels and the productivity convergence of Japanese, Korean, Taiwanese and Chinese listed firms," *Journal of Chinese Economic and Business Studies*, Vol. 9, No. 2, pp. 127–150.

Fukao, Kyoji, Kenta Ikeuchi, YoungGak Kim, and Hyeog Ug Kwon (2016) "Why was Japan left behind in the ICT revolution?" *Telecommunications Policy*, Vol. 40, No. 5, pp. 432–449.

Fukao, Kyoji, YoungGak Kim, and Hyeog Ug Kwon (2021) "Sources of Growth and Stagnation in the Japanese Economy: An Analysis Based on Data for Listed Firms Spanning More Than Five Decades,"Technical report, RIETI.

Genda, Yuji (2011) "Dual Economy, revisited," *Nihon Roudou Kenkyu Zasshi*, Vol. 609, pp. 2–5.

Good, David H, M Ishaq Nadiri, and Robin C Sickles (1997) "Index number and factor demand approaches to the estimation of productivity," *Handbook of Applied Econometrics*, Vol. 2, pp. 14–80.

Gordon, Robert J (2012) "Is US economic growth over? Faltering innovation confronts the six headwinds,"Technical report, National Bureau of Economic Research.

Goto, Akira, Tadahisa Koga, and Suzuki Kazuyuki (1997) “The Determinants of R&D Investment in the Japanese Manufacturing Industries: Small Firms and Large Firms (Japanese),”Technical report, National Institute of Science and Technology (NISTEP).

Hanushek, Eric A and Dennis D Kimko (2000) “Schooling, labor-force quality, and the growth of nations,” *American Economic Review*, Vol. 90, No. 5, pp. 1184–1208.

Hashmi, Aamir Rafique (2013) “Competition and innovation: The inverted-U relationship revisited,” *Review of Economics and Statistics*, Vol. 95, No. 5, pp. 1653–1668.

Hayashi, Fumio and Edward C Prescott (2002) “The 1990s in Japan: A lost decade,” *Review of Economic Dynamics*, Vol. 5, No. 1, pp. 206–235.

Higuchi, Yoshio (1994) *Distribution of Wealth and Income in Japan*, Chap. 8, University Education and Income Distribution, p. 245 278: University of Tokyo Press.

Hulten, Charles R (2007) *New Developments in Productivity Analysis*, Chap. 1.Total Factor Productivity: A Short Biography, pp. 1-54: University of Chicago Press.

Ikeuchi, Kenta, Yong Gak Kim, Hyeog Ug Kwon, and Kyoji Fukao (2013) “Productivity Dynamics and R&D Spillovers in the Japanese Manufacturing Industry : An Empirical Analysis Based on Micro-level Data (in Japanese),” *Keizai Kenkyu*.

Ikeuchi, Kenta, Rene Belderbos, Kyoji Fukao, Young Gak Kim, and Hyeog Ug Kwon (2015) “Buyers, suppliers, and R&D spillovers,” *RIETI Discussion papers*, Vol. 15-E-047.

Inui, Tomohiko and YoungGak Kim (2018) “Why Do Japanese Firms Lag Behind in Introducing and Expanding IT Technologies? (Japanese),”Technical report, Research Institute of Economy, Trade and Industry (RIETI).

Inui, Tomohiko Kim, Kim YoungGak, Hyeog Ug KWON, and Kyoji Fukao (2015) "Productivity Dynamics and Japan's Economic Growth: An empirical analysis based on the Financial Statements Statistics of Corporations by Industry (Japanese)," *Keizai Kenkyu*, Vol. 66, No. 4, pp. 289-300.

Ito, Takatoshi and Takeo Hoshi (2020) *The Japanese Economy*: MIT press.

Jorgenson, Dale W, Mun S Ho, and Kevin J Stiroh (2008) "A retrospective look at the US productivity growth resurgence," *Journal of Economic Perspectives*, Vol. 22, No. 1, pp. 3–24.

Jorgenson, Dale W, Koji Nomura, and Jon D Samuels (2015) "A Half Century of Trans-Pacific Competition: Price level indices and productivity gaps for Japanese and US industries,"Technical report, RIETI Discussion Paper, 15-E-054.

Karlsson, Charlie and Martin Andersson (2009) "The location of industry R&D and the location of university R&D: How are they related?" in *New Directions in Regional Economic Development*: Springer, pp. 267–290.

Kawaguchi, Daiji and Keisuke Kawada (2021) *Productivity of Service Sector and Japanese Economy*, Chap. 4, Improvement of Productivity of SMEs human resource (in Japanese), pp. 145- 173: University of Tokyo Press.

Kim, YoungGak, Kyoji Fukao, and Tatsuji Makino (2010a) "The Structural Causes of Japan's" Two Lost Decades"(Japanese),"Technical report, Research Institute of Economy, Trade and Industry (RIETI).

——— (2010b) "The Structural Causes of Japan's" Two Lost Decades"(Japanese),"Technical report, Research Institute of Economy, Trade and Industry (RIETI).

Klevorick, Alvin K, Richard C Levin, Richard R Nelson, and Sidney G Winter (1995) "On the sources and significance of interindustry differences in technological opportunities," *Research Policy*, Vol. 24, No. 2, pp. 185–205.

Kwon, Hyeog Ug and Tomohiko Inui (2013) "What determines R&D intensity? Evidence from Japanese manufacturing firms," *SOGANG ECONOMIC PAPERS*, Vol. 42, No. 1, pp. 43–69.

Kwon, Hyeog Ug and Jungsoo Park (2018) "R&D, foreign ownership, and corporate groups: Evidence from Japanese firms," *Research Policy*, Vol. 47, No. 2, pp. 428–439.

Levin, Richard C, Alvin K Klevorick, Richard R Nelson, Sidney G Winter, Richard Gilbert, and Zvi Griliches (1987) "Appropriating the returns from industrial research and development," *Brookings Papers on Economic Activity*, Vol. 1987, No. 3, pp. 783–831.

Lewbel, Arthur (2012) "Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models," *Journal of Business & Economic Statistics*, Vol. 30, No. 1, pp. 67–80.

Liu, Jie and Chao Bi (2019) "Effects of higher education levels on total factor productivity growth," *Sustainability*, Vol. 11, No. 6, p. 1790.

Lucas Jr, Robert E (1988) "On the mechanics of economic development," *Journal of Monetary Economics*, Vol. 22, No. 1, pp. 3–42.

Mahadevan, Renuka (2003) "To measure or not to measure total factor productivity growth?" *Oxford Development Studies*, Vol. 31, No. 3, pp. 365–378.

Malmendier, Ulrike and Geoffrey Tate (2005) "CEO overconfidence and corporate investment," *The Journal of Finance*, Vol. 60, No. 6, pp. 2661–2700.

Morikawa, Masayuki (2016) “The Effects of Artificial Intelligence and Robotics on Businesses,” *RIETI Discussion Paper 16-J-005*, Vol. 16, pp. 1–18.

Nakamuro, Makiko and Tomohiko Inui (2013) “The returns to college quality in Japan: Does your college choice affect your earnings?”Technical report, ESRI Discussion Paper Series.

Nickell, Stephen J (1996) “Competition and corporate performance,” *Journal of Political Economy*, Vol. 104, No. 4, pp. 724–746.

NISTEP (2021) “Report on the Japanese National Innovation Survey 2020 (J-NIS 2020),”Technical report, National Institute of Science and Technology Policy.

OECD (2017) *OECD Science, Technology and Industry Scoreboard 2017-The Digital Transformation*: OECD Publishing.

——— (2021) *Cross-country comparisons of labour productivity levels.*

Okada, Yosuke (2005) “Competition and productivity in Japanese manufacturing industries,” *Journal of the Japanese and International Economies*, Vol. 19, No. 4, pp. 586–616.

Okamuro, Hiroyuki (2005) “Determinants of R&D Investment by Start-up Firms (Japanese),”Technical report, Research Institute of Economy, Trade and Industry (RIETI).

Peroni, Chiara and Ivete S Gomes Ferreira (2012) “Competition and innovation in Luxembourg,” *Journal of Industry, Competition and Trade*, Vol. 12, No. 1, pp. 93–117.

Romer, Paul M (1990) “Endogenous technological change,” *Journal of Political Economy*, Vol. 98, No. 5, Part 2, pp. S71–S102.

Schumpeter, Joseph Alois (1942) *Socialism, capitalism and democracy*: Harper and Brothers.

Summers, Lawrence H (2014) “US Economic Prospects: Secular Stagnation, Hysteresis, and the Zero Lower Bound,” *Business Economics*, Vol. 49, No. 2, pp. 65–73.

Tsamadias, Constantinos, Panagiotis Pegkas, Emmanuel Mamatzakis, and Christos Staikouras (2019) “Does R&D, human capital and FDI matter for TFP in OECD countries?” *Economics of Innovation and New Technology*, Vol. 28, No. 4, pp. 386–406.

Wooldridge, Jeffrey M (2015) “Control Function Methods in Applied Econometrics,” *Journal of Human Resources*, Vol. 50, No. 2, pp. 420–445.

Yamaguchi, Akira (2021) “CEOs’ educational background and investments in software,” *Applied Economics Letters*, pp. 1–4.

Yamaguchi, Akira, Kenta Ikeuchi, Kyoji Fukao, KWON Hyeog Ug, and KIM Young Gak (2019) “Effects of Buyer and Supplier Relationships and Capital Relationships on R&D Activities (Japanese),”Technical report, RIETI.