RIETI Discussion Paper Series 25-E-023

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https://www.rieti.go.jp/en/

RIETI Discussion Paper Series 25-E-023

March 2025

CEO Age and Technology Adoption: Network effects in e-commerce propagation in Japan[1]

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Abstract

This study examines how CEO age influences the speed of technology adoption, focusing on e-commerce diffusion during COVID-19. Using unique survey data linked to credit scores and trading networks, we find firms are more likely to adopt e-commerce when their trading partners do, with adoption elasticity rising from 0.27 in 2020 to 0.37 in 2021. However, firms led by older CEOs respond more slowly, with elasticity decreasing by 0.13 to 0.21 for CEOs 10 years above the average. These findings highlight the role of leadership demographics in technology diffusion and firms' adaptability in digital transformation.

Keywords: Network Externality, Demographics, B2B E-commerce, Japan

JEL classification: D10, E10, J10, O11

[1]This study is conducted as a part of the Project "Household heterogeneity: individuals, families and macroeconomy" undertaken at the Research Institute of Economy, Trade and Industry (RIETI). This project is based on a joint research collaboration between Tokyo Shoko Research, LTD. (TSR) and the Center for Research and Education on Policy Evaluation (CREPE) at the University of Tokyo. The draft of this paper was presented at the RIETI DP seminar for the paper. We thank participants of the RIETI DP Seminar for their helpful comments.
∗We acknowledge financial support by the Japan Society for the Promotion of Science (JSPS), 22H00057. Takashi Fujisawa, Kazuha Ogawa, and Kanta Ogawa provided excellent research assistance.

1 Introduction

The adoption of technology is crucial for firm growth, but its productivity-enhancing potential often depends on coordination among transacting firms. Business-to-business (B2B) transaction technology is a prime example: while the technology itself may have been available for some time, its effective utilization requires widespread adoption of the common technology by trading partners. The presence of network externalities often stands as a prerequisite for technology diffusion, and the transition to economy-wide adoption typically unfolds gradually over time.

The onset of the COVID-19 pandemic accelerated firms' reliance on electronic transactions to reduce physical contact and mitigate infection risk. However, adoption decisions vary across firms. A business partner's decision to adopt the technology depends on their existing trading networks, which are exogenous to a decision-making firm. Therefore, this shock presents a unique opportunity to study the role of network externalities in the adoption of online B2B commerce.

In this paper, we leverage the COVID-19 crisis to investigate how such a shock triggers coordinated technology adoption and what factors determine heterogeneous adoption patterns observed across firms with different characteristics. Our analysis draws on unique survey data covering firms' technology adoption decisions before and after the pandemic, combined with rich information on the firms' characteristics and their managerial profiles.

More precisely, our study uses data from a special survey conducted by Tokyo Shoko Research Ltd. (TSR) and the Center for Research and Education in Program Evaluation (CREPE) at the University of Tokyo, with the sample of firms located in Japan. The survey specifically inquires about the proportion of electronic transactions within firms' B2B activities during 2019, 2020 and 2021. This dataset is linked to each firm's credit file provided by TSR, enabling us to extract information about various firm characteristics, including managerial demographics such as age, education, and experience, as well as firms' size in employment and capital, and credit scores. We also exploit the unique strength of the TSR data in its detailed record of firms' trading networks before the pandemic, which serves as a critical input for our analysis.

In our estimation, we use the pre-pandemic networks, conditional on various firm characteristics such as industry and size, as an exogenous source of variation in the likelihood of technology adoption. Our findings indicate that firms are more likely to engage in electronic transactions when their business partners adopt such technology. Moreover, we observe substantial heterogeneity in firms' responses, driven by both firm-level and managerial characteristics. In particular, managers' age gradient shows a significant impact on adoption outcomes following the onset of the COVID-19. Firms led by younger managers are more likely to adapt to shifts in business practices among their trading partners. Specifically, a firm whose manager is ten years older than average is 15.5% less likely to adopt the technology, immediately after the shock. This result is robust and similar differences are observed in alternative models, for example, when we control for firm size and age, CEO's education levels, and firm's credit scores. We also find that the negative effect of CEO age persists over time, remaining between 13.0% and 20.6% during the two years following the outbreak of COVID-19.

Our research is related to two strands of literature. First, we make empirical contribution to the literature on network effects in technology adoption. This empirical research builds on theoretical studies that explore the possibility of multiple equilibria arising from network externalities (Murphy et al. 1989, Matsuyama 1995). When private returns to technology adoption depend on the adoption behavior of others, coordination failures can result in inefficiently low adoption rates, hindering economic growth (Rosenstein-Rodan 1943, Katz and Shapiro 1985, 1986).

Recent empirical studies examining technology adoption in the presence of network externalities include Björkegren (2018), who analyzes how individuals' social networks influence the spread of mobile phones in developing countries, using subscriber data from Rwanda. Similarly, Crouzet et al. (2023) exploit India's 2016 demonetization as a natural experiment, leveraging geographic variation in the banks' cash transaction services. They find that the unexpected reduction in cash transactions persistently increased the adoption of electronic payments. Higgins (2024) studies the large-scale rollout of debit cards to low-income households in Mexico as a network externality shock affecting both consumers and retailers, prompting significant changes in payment technology usage.[1]

Second, our paper is related to the literature investigating the economic consequences of demographic aging. Population aging has raised concerns about its potential to slow down growth worldwide, contributing to secular stagnation (Carvalho et al., 2016; Eggertsson et al., 2019). Empirical studies have investigated the link between aging demographics and economic activities at national and local levels. For example, Feyrer (2007) finds a positive relationship between the share of workers in their 40s and productivity growth, drawing on data from OECD and low-income countries. Maestas et al. (2023) use U.S. state-level data to demonstrate that a 10% increase in the share of the population aged 60 and above lowers average income by 5.5%.[2]

Age also plays a crucial role in business formation and entrepreneurial innovations, as highlighted by several studies. Liang et al. (2018) construct a structural model in which creativity and business skills evolve independently with age, illustrating that older

[1] See also Ryan and Tucker (2012) and Ackerberg and Gowrisankaran (2006).

[2] Labor shortages due to demographic aging may stimulate investment in labor-saving technology. Acemoglu and Restrepo (2017, 2022) argue that demographic aging is associated with increased adoption of automation technologies, helping to mitigate the negative effects of labor scarcity.

societies exhibit lower rates of entrepreneurship. Acemoglu et al. (2022) demonstrate that firms engaged in radical innovations tend to hire younger managers. Additionally, Hopenhayn et al. (2022) show how demographic shifts affect firm dynamics, including declining entry rates, increasing market concentration, and falling labor shares. Our study adds to this literature by showing that managerial age can slow technology diffusion: firms led by older managers adopt technology more slowly when faced with trading partners' adoption of e-commerce during the COVID-19 pandemic. This is another mechanism how the demographic aging can slow economic growth when the age distribution of managers correlates with the age structure of the population.

The rest of the paper is organized as follows. Section 2 describes the data we use in the analysis and section 3 presents our empirical model. We discuss our numerical results in section 4 and section 5 concludes.

2 Data

2.1 TSR-CREPE Survey: B2B Electronic Commerce Data

The main data used in this study are from the online firm survey conducted by TSR and CREPE of the University of Tokyo. In 2022, we conducted the follow-up survey to our initial survey in 2020, collecting information on the adoption of business-to-business (B2B) electronic commerce (e-commerce) transactions. We sent invitations to TSR email magazine subscribers from March 14 to 23, 2022. About 2,000 firms responded to the survey, of which 1,608 firms are matched to the TSR credit file.

The survey asks the share of B2B online transactions as a percentage of total transactions for each firm at four points in time: December 2019 (before COVID-19), April 2020 (during the emergency declaration), December 2020, and December 2021. We focus on B2B transactions adopted by Japanese firms, which include e-commerce through their own or a partner company's digital portal but exclude transactions conducted solely via email.

Japan is the world's fourth largest e-commerce market, following China, the United States, and the United Kingdom. According to Japan's Ministry of Economy, Trade and Industry's 2023 e-Commerce Market Survey, about one-third of B2B transactions occur through e-commerce. Our sample indicates a significant increase in the diffusion rate, rising from 8.7% before COVID-19 in December 2019 to 12.4% in April-May 2020, followed by a moderate rise to 14.0% in December 2021, as shown in Figure 1.

By industry, Table A.1 shows the share of firms that had adopted online business as of December 2019 and the percentage of firms' trade conducted via online business platforms. Before the pandemic, e-commerce adoption was more common in the information, living-related services, and wholesale and retail industries. In terms of the share of online business trade, e-commerce was most prevalent in the information (21.5%), wholesale & retail (9.6%), and manufacturing (9.3%) sectors.

2.2 Descriptive Statistics

We obtain data on firms' basic and financial characteristics, including year of establishment, employment, capital, and credit score, from a proprietary credit data compiled by TSR. Table 1 presents descriptive statistics for our analysis sample covering CEOs (Panel A), firms (Panel B), and trading partners (Panel C). Columns 1, 2, and 3 show summary statistics for TSR's full sample (N=743,590), the matched sample with our survey (N=1,608), and the regression analysis sample with non-missing observations of all variables (N=1,099).

In our sample, the average CEO age is 59, and nearly half of CEOs have a college degree. Compared to TSR's full sample, where the college graduation rate is about 20%, CEOs in our survey sample are relatively more educated and may be more familiar with e-commerce.[3] On average, CEOs have 12 years of business experience, measured as the duration since assuming their role as of December 2019.

Figure 2 illustrates the distribution of CEOs' ages as of December 2019. While most CEOs are between 50 and 70 years old, the sample also includes relatively young managers under 40.

Panel B of Table 1 shows that firms in the sample are relatively more established with an average of 51 years of business operations which employ about 70 employees. In comparison, firms in the TSR full sample are slightly newer and smaller, averaging 44 years of operations and 31 employees. In terms of capital, the median size is JPY 20 million, which is twice as large as the median size in the full sample. Regarding the B2B e-commerce adoption, 34% of firms in our analysis sample adopted online e-commerce with the average online trade share of 8.7% before the COVID-19 (in December 2019). B2B adoption continued to spread over time since December 2019, initially by 3.8% shortly after the pandemic in April 2020, 4.4% by December 2020, and 5.2% by December 2021.

Furthermore, Table 2 describes the main determinants of firm's initial adoption status of e-commerce. Columns 1-2 show the correlation between CEO and firm characteristics and the probability of e-commerce adoption before the COVID-19, while columns 3-4 show the estimates for the intensity of e-commerce adoption as of December 2019. Firm's demographic characteristics (CEO's age) and the size of firms are significantly associated with the e-commerce adoption. An increase in CEO's age by 10 is associated with the reduction in e-commerce adoption rate by 3.1%. E-commerce transactions are

[3]Table A.2 also shows that college graduation rate is higher for large firms (65%) than **small** firms (39%).

more prevalent among large firms. At the intensive margin, the negative coefficient for CEO age and firm age also suggest that the intensity of e-commerce use is relatively lower for firms with older CEOs and longer business operations. While existing studies report the positive association of human capital and technology adoption (Nelson and Phelps (1966); Doms and Dunne (1997); Foster and Rosenzweig (2010)), in the current context, educational background of CEO is not associated with the adoption of online trade.

2.3 Firm Production Linkage

The TSR dataset also provides a list of its suppliers and customers for each firm, thus enabling us to construct the production network of supplier-customer linkages (Carvalho et al. (2021)). From this information, we create each firm's trading partner characteristics, such as the number of partners, partner firms' average CEO age, partner firms' average age, employment, and capital size.

In our analysis sample, Panel C of Table 1 shows an average of 11.8 partners, indicating significantly stronger interfirm linkages compared to the full sample. The median value of partner average employment is 990, compared to 360 in the full sample; and the median value of partner average capital is JPY 5,950 million, compared to JPY 792 million in the full sample. This suggests that firms in our survey sample tend to trade with larger firms.

Figure A.1 shows the correlation between a firm's CEO age (x-axis) and the average CEO age of its partners (y-axis), showing a positive relationship. This suggests a possibility of assortative matching, where firms select trading partners with similar characteristics, particularly age of CEOs. In a robustness check of our regression analysis, we account for the average CEO age of partners to estimate the influence of a firm's CEO age on its e-commerce adoption decision in response to partners' e-commerce adoption.

Finally, to analyze the propagation of B2B e-commerce in trading network, we compute trading partner's e-commerce adoption rate as follows. As e-commerce adoption status can be observed only in our survey sample (not observable in full TSR sample), we first calculate the average e-commerce adoption rate for prefecture-industry-firm size group g. Next, for firm i in prefecture-industry-firm size group g, we identify all trading firms j which belong to different groups g'. Then, we compute the weighted jackknife mean (WJKM) of B2B adoption using each group's number of employees as the weight. On average, trading partners' e-commerce adoption rate increased by 5.2% from December 2019 to December 2021.

3 Empirical Model

We estimate the effect of business partners' adoption to B2B e-commerce on a firm's own adoption. Specifically, we examine how this exposure affects the adoption of B2B e-commerce by firm i between 2019 and period t using the following model:

$$Y_{it} - Y_{i2019} = \beta(\bar{Y}_{it} - \bar{Y}_{i2019}) + X_{i2019}\delta + FE_{ind} + FE_{pref} + FE_{size} + u_{it}, \tag{1}$$

where Y_{it} is the percentage of B2B trade that completes on internet transaction by firm i in time period t. For time period t, we use April-May in 2020, December 2020, and December 2021. The dependent variable is the percentage change from the baseline year 2019, given by $Y_{it} - Y_{i2019}$. The exposure variable is defined as $\bar{Y}_{it} = N(T_{2019}(i))^{-1} \sum_{j \in T_{2019}(i)} (\bar{Y}_{G(j),t})$, where $T_{2019}(i)$ is the set of firms that transact with firm i in 2019, and $N(T_{2019}(i))$ is the number of firms in this set. The term $G(j)$ represents the group defined by industry (16 industries) $\times$ prefecture $\times$ firm-size (small, medium, and large), to which the business partner j belongs. The expression captures the average adoption rate of a firm's business counterparts. However, instead of using the actual adoption behavior of individual business partners, we use the group mean of adoption rates, aggregated by industry, prefecture, and firm-size.[4]

Thus, the first term on the right-hand side of (1) captures the increase in the adoption rate of a firm i's pre-COVID business partners. The low probability that the business partner j is included in the analysis sample is the primary reason why we utilize the group average of the adoption. Additionally, the usage of the group average of the adoption helps to circumvent the reverse causality, where a firm's own B2B adoption could affect its partners' adoption, a reflection problem highlighted by Manski (1993).

The vector X_{i2019} includes the number of business partners, own firm age, the average firm age of partner firms, the natural log of the number of workers, and the natural log of the stated capital. Since B2B e-commerce adoption during COVID-19 may vary across industries, prefectures, and firm sizes, the model includes the corresponding fixed effects. In this first difference specification, these fixed effects capture heterogeneity in the impact of COVID-19 across industries, geographic locations, and firm sizes.

The parameter β captures the causal impact of business counterparts' B2B e-commerce adoption on firm i's adoption. This causal impact arises from the complementarity of network technology adoption. The OLS estimator of β provides a consistent estimate of the causal impact if the error term u_{it} is exogenous to business

[4]Firm size is categorized by the definition of the Small and Medium Enterprise (SME) Agency. The official cutoff for the SME size varies by industry: 50 employees for retail, 100 for wholesale and service industries, and 300 for manufacturing, construction, and other industries.

partners' adoption, conditional on observed firm characteristics and fixed effects for industry, prefecture, and firm size.

Variation in network exposure arises from two sources: heterogeneity in pre-COVID trade network, and the heterogeneous adoption of B2B e-commerce across industry$\times$prefecture$\times$firm-size groups. If the product of these two sources of variation is orthogonal to unobserved determinants of B2B e-commerce adoption conditional on observed characteristics and the set of fixed effects, then the exogeneity assumption is satisfied.

A key threat to our identification strategy is the endogeneity of the network formation. Firms inclined to adopt B2B e-commerce may already be embedded in transaction networks with firms that also tend to adopt it. To address this concern, we leverage plausibly exogenous technology adoption among business partners, driven by the spread of COVID-19.

Firms that are similar in terms of industry, location, and the firm size, are different in their trade partners. For example, two medium-sized auto parts manufacturers in Aichi Prefecture may be different in trading partners' locations: one may ship products to a large assembler located in Kanagawa Prefecture, while the other ships it to a large assembler in Hiroshima Prefecture. If the assembler in Kanagawa adopts B2B e-commerce due to a more severe COVID-19 outbreak, while the assembler in Hiroshima does not, then the auto parts manufacturer transacting with the Kanagawa firm is more likely to adopt B2B e-commerce due to network effect. The constructed shift-share variable is designed to capture such exogenous and heterogeneous exposure to B2B e-commerce adoption across firms.

4 Results

4.1 Baseline Results

Table 3 reports the estimated coefficients of equation (1) for each time period. The initial share of online trade (as of December 2019) is controlled for in all regressions. A negative estimate indicates that firms with lower initial B2B trade adoption before COVID-19 adopted online trade more rapidly.

The peer effect β (the first row) is positive and increases over time. The estimated elasticity of own B2B adoption to the peer's adoption was 0.269 by the end of 2020 (one year after the COVID-19 outbreak) and strengthened to 0.365 by the end of 2021. This implies that when the B2B adoption rate among partner firms increases by 10 percentage points, the firm's adoption rate rises by 3.65 percentage points. For reference, the average adoption rate as of December 2019 was 8.7 percent (Table A.1).

The interaction term with CEO's age (second row) sheds light on how CEO aging affects the speed of B2B adoption.[5] The coefficient is negative and significant, indicating that older CEOs were less responsive to shifting business practices and adopting electronic transactions in firm-to-firm transactions. Firms led by CEOs 10 years older than the average exhibited significantly lower (or negative) adoption elasticity in the short term, with the point estimates of -0.155 by end-April 2020 and -0.206 by December 2020. The negative effect remained significant but diminished slightly to -0.130 by December 2021. These results imply that younger CEOs adapted to B2B trade more quickly after the pandemic, whereas firms with older CEOS adopted new technology more gradually over the subsequent two years after the onset of the pandemic.

Several potential mechanisms may explain why firms led by older CEOs exhibited lower adoption elasticity to new technology. First, older CEOs may face physical and health constraints that reduce their cognitive ability to make new investment decisions. While Oshio et al. (2024) highlight the substantial work capacity of elderly Japanese workers beyond retirement age, their adaptability to new technologies, such as e-commerce, may still lag behind younger cohorts due to fewer learning opportunities. Second, older business owners may be less willing to invest in new technologies as they approach retirement. A shorter planning horizon due to aging could reduce incentives to adopt innovative business practices and invest in new technologies. Identifying the key mechanisms behind these findings is an important direction for future research.

4.2 Robustness Checks

Interactive Fixed Effects: While the baseline model controls for the average differences in B2B e-commerce adoption across geographic locations, industries, and firm sizes, firms within the same prefecture may be influenced by unobserved industry- or size-specific common shocks. Similarly, the B2B adoption of firms that belong to the same industry or firm size category may depend on location-specific shocks. As a robustness check, we allow the effect of trading partners' B2B adoption on a firm's own adoption to vary depending on the combination of prefecture, industry, and firm size by including interaction terms of three fixed effects. The interactive fixed-effect model (Bai (2009)) also controls for the heterogeneous exposure of firms to COVID-19 across these dimensions.

As shown in Appendix Table A.3, the estimates under the interactive fixed-effects model closely align with those in Table 3, confirming the robustness of our baseline results.

CEO Business Experience: Recent literature points that CEO's industry experience is often associated with the adoption and utilization of e-commerce and remote

[5] See Tomiura and Kumanomido (2023) for an analysis on remote work adoption in Japan.

work technologies during COVID-19 (Lashitew (2023)). Thus, our findings on CEO age may reflect both a demographic aging effect and an effect of CEO's years of experience in corporate management on e-commerce adoption. The latter could affect firm's adaptability to unexpected shocks.

To disentangle these effects, we re-estimate the model, incorporating CEO's business experience and its interaction term with trading partners' e-commerce adoption. As reported in Appendix Table A.4, manager experience has only an insignificant impact on B2B adoption, leaving our baseline results unchanged.

Other Determinants of Technology Diffusion: Besides CEO's age and experience, we consider two additional determinants of e-commerce adoption identified in Table 2, namely, (a) firm size and (b) firm's financial strength (the credit score), and the results are reported in Appendix Table A.5. On firm size, we categorize firms into small, medium, and large firms per Japan's SME Basic Act, as explained in section 3. Firms' financial strength is measured by a credit score, which is a composite index of firm performance assigned by TSR, ranging from 0 to 100. A higher score indicates stronger creditworthiness and better management quality.

The size of organization could be one of the key determinants of technology diffusion. Prior research finds a positive relationship between production scale and new technology adoption (Wozniak (1987)). However, the organizational hierarchy in large firms could create barriers to new technology adoption. In some contexts, the slow adoption of new technology has been attributed to misaligned incentives within firms (Atkin et al. (2017)). Such barriers may be more pronounced within larger firms, where the decision-making process is more decentralized, leading to higher adjustment costs in changing corporate business practices. In contrast, smaller firms, where top management has direct control, may exhibit greater flexibility in adopting new technologies new technologies.

Furthermore, financial constraints can also limit a firm's ability to undertake innovative activities and upgrade existing facilities (Gorodnichenko and Schnitzer (2013); Zhang (2023)). If the adoption of B2B trade necessitates significant upgrades and investments in new information and communication technology (ICT), credit-constrained firms may lag behind.

We extend the baseline specification by incorporating additional interaction terms between B2B adoption and firm size dummies (small and large), as well as the credit score, as reported in Table A.5. Even after accounting for these additional determinants of e-commerce adoption, our main finding regarding the negative aging effect remains consistent across all periods. The results suggest that firm size is the only significant factor influencing e-commerce adoption. Specifically, we found a positive interaction term between the small-firm dummy and peer adoption growth. This indicates high adaptability of small firms in changing their traditional business practices to new e-commerce trade, with CEOs playing a more pronounced role in this process. In contrast, the interaction term with the credit score is statistically insignificant in our context.

5 Conclusion

Our study investigates how firms' network externalities influence technology diffusion, focusing on the adoption of B2B e-commerce among Japanese firms during the COVID-19 pandemic. Using unique survey data, we analyze firms' technology adoption decisions in response to their trading partners' actions, linking them to firm and managerial characteristics.

Our findings demonstrate that firms are more likely to adopt e-commerce when their trading partners do, highlighting strong network externality effects and the importance of network-driven technology diffusion. The elasticity of firms' e-commerce adoption to that of their partners increased from 0.27 in 2020 to 0.37 in 2021, indicating a strengthening of this effect over time.

We also find substantial heterogeneity in adoption patterns based on managerial characteristics, particularly CEO age. Firms led by older CEOs consistently exhibit lower adoption elasticity, suggesting that aging leadership can hinder the swift diffusion of technology in response to external shocks. These results underscore the critical role of leadership demographics in shaping firms' ability to adapt to evolving business environments and practices.

The results carry important implications for corporate management. Firms with aging leadership may face challenges in responding to technological advancements. To address this challenge, strategies such as diversifying leadership teams to include younger or more tech-savvy executives, fostering a culture of innovation across all organizational levels, and decentralizing decision-making processes could enhance firms' agility and responsiveness. Implementing these measures may help mitigate the adverse effects of aging leadership on technology adoption.

At a broader level, the study suggests that the aging of corporate leadership could have macroeconomic consequences, particularly in economies with rapidly aging populations. Slower technology adoption among firms led by older CEOs may delay productivity gains and impede the diffusion of innovations across industries, potentially dampening economic growth. Given the role of network externalities in technology diffusion, delayed adoption of one firm can have cascading effects on its trading partners, further amplifying the impact at the macroeconomic level. These findings underscore the importance of addressing demographic challenges associated with aging leadership to sustain technological progress and economic dynamism.

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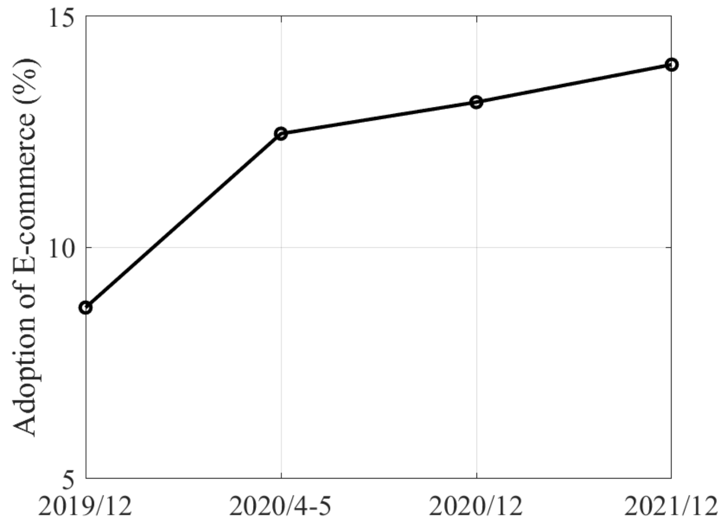

Figure 1: Adoption of E-commerce in B2B Transactions

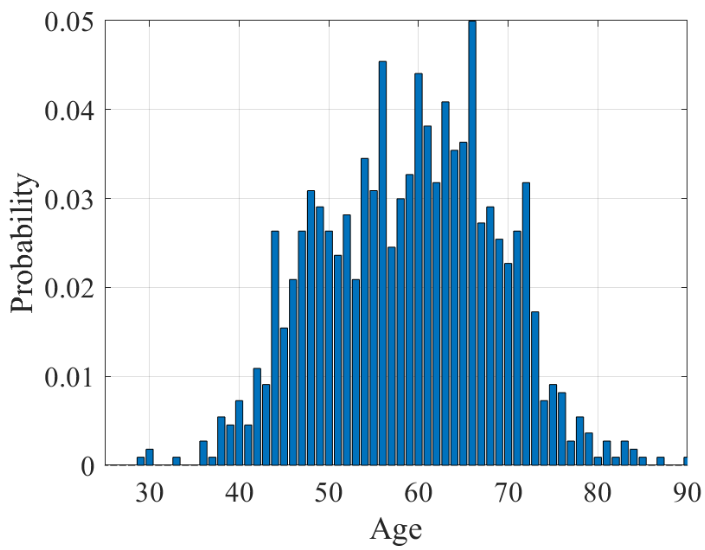

Figure 2: Age of CEO as of December 2019

Table 1: Descriptive Statistics

	(1) Full Sample			(2) Survey Matched Sample			(3) Analysis Sample		
	Mean	S.D.	Median	Mean	S.D.	Median	Mean	S.D.	Median
Panel A: CEO characteristics									
Manager age	60.6	11.6	61	60.1	10	61	59	9.74	60
Manager college graduate	.195	.396	0	.464	.499	0	.495	.5	0
Manager business experience	12.2	10.9	9	12.2	10.9	9	12.9	10.5	10
Panel B: Firm characteristics									
Firm age	43.9	22.4	43	50.3	25	50	50.8	25	51
Employment	31.2	420	6	80.6	212	31	69	206	28
Capital (billion Yen)	.163	10.7	.01	.201	1.48	.0225	.109	.782	.02
Credit score	47.8	5.86	47	54	6.43	54	53.9	6.42	53
Online trade 2019/12 > 0				.397	.489	0	.338	.473	0
Share online trade 2019/12				9.21	20.2	0	8.68	19.5	0
Δ% B2B E-Com 2020/4-5				3.73	13.9	0	3.75	14.4	0
Δ% B2B E-Com 2020/12				4.46	14.3	0	4.44	14.6	0
Δ% B2B E-Com 2021/12				5.22	15.7	0	5.24	15.7	0
Panel C: Trading partner characteristics									
Number of partners	5.44	4.98	4	11.6	6.98	11	11.8	6.72	11
Partner avg manager age	60.4	6.3	60.8	60.8	4	60.9	60.7	3.83	60.9
Partner avg firm age	60	17.6	60.3	61.9	13.4	62.8	62.2	12.6	62.7
Partner avg employment	1701	5034	360	2162	3536	1027	2136	3685	990
Partner avg capital (billion Yen)	15.8	85.6	.793	21.5	56.8	6.38	18.4	34.8	5.95
Δ% WJKM B2B E-Com 2020/4-5				6.68	4.88	5.92	6.46	4.45	5.83
Δ% WJKM B2B E-Com 2020/12				7.48	5.18	6.65	7.24	4.77	6.49
Δ% WJKM B2B E-Com 2021/12				8.04	5.63	7.1	7.8	5.22	7.01
N	743590			1608			1099		

Table 2: Manager Characteristics by Implementation Status

	(1)	(2)	(3)	(4)
	Online trade 2019/12 > 0		Share online trade 2019/12	
Manager age	-0.00313**	-0.00313**	-0.111*	-0.101
	(0.00146)	(0.00147)	(0.0647)	(0.0636)
Manager college graduate	-0.00474	-0.00483	-0.0611	0.168
	(0.0294)	(0.0296)	(1.194)	(1.212)
Firm age	-0.000747	-0.000727	-0.0422	-0.0378
	(0.000629)	(0.000645)	(0.0257)	(0.0258)
Credit score	-0.00476*	-0.00458*	-0.151	-0.141
	(0.00257)	(0.00274)	(0.100)	(0.108)
Number of partners	0.00285	0.00291	0.0133	0.0116
	(0.00228)	(0.00230)	(0.0913)	(0.0904)
Large	0.133	0.139	3.588	5.183
	(0.0815)	(0.0926)	(3.715)	(4.045)
Small	-0.0892***	-0.0936**	-0.998	-0.685
	(0.0341)	(0.0417)	(1.503)	(1.840)
Capital (log)		-0.000212		-1.055
		(0.0158)		(0.821)
Employment (log)		-0.00323		0.668
		(0.0188)		(0.809)
Constant	0.806***	0.808***	25.51***	32.32***
	(0.160)	(0.188)	(7.040)	(9.106)
N	1099	1099	1099	1099
R^2	0.0164	0.0164	0.00952	0.0119

Standard errors in parentheses

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

Table 3: Peer Effect of Technology Adoption: CEO Age

	(1)	(2)	(3)
	Δ% B2B 2020/4-5	Δ% B2B 2020/12	Δ% B2B 2021/12
Δ% WJKM B2B E-Com	0.110	0.269***	0.365***
	(0.142)	(0.0823)	(0.0681)
Δ% WJKM B2B E-Com × Manager age	-0.0155*	-0.0206**	-0.0130**
	(0.00762)	(0.00731)	(0.00574)
Manager age	0.0863	0.120	0.106
	(0.0504)	(0.0747)	(0.0772)
Share online trade 2019/12	-0.0302***	-0.0234**	-0.0322
	(0.00864)	(0.0108)	(0.0225)
N	1099	1099	1099
R^2	0.0821	0.0977	0.110
Prefecture FE	YES	YES	YES
Industry FE	YES	YES	YES
Firm size FE	YES	YES	YES

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

Note: Standard errors robust against prefecture and industry-level clustering are reported in parentheses. All regressions control for own and partners' firm age, log of the number of workers and the stated capital, and the number of partners. Variables in the interaction terms are demeaned when used in the regression.

Appendix A Online Appendix

Table A.1: Initial E-commerce Adoption by Industry (as of December 2019)

	Online trade>0	Share of online trade (%)
Agriculture, forestry, fisheries	0.4	11.0
Metal mining	0	0
Construction	0.25	4.9
Manufacturing	0.34	9.3
Electricity, gas, heat, water	0.20	4.0
Information and communications	0.62	21.5
Transport, postal-activities	0.21	4.6
Wholesale and retail trade	0.38	9.6
Real estate, rental, leasing	0.21	1.9
Scientific-research	0.29	7.6
Accommodations, eating, drinking	0.29	8.1
Living-related services	0.63	11.3
Medical, health-care, welfare	0.20	0.2
Compound-services	0.28	6.4
Total	0.34	8.7
N	1099	1099

Table A.2: CEO Age and Education by Firm Size

	Large	Medium	Small
Manager age	59.59	58.66	59.69
	(8.86)	(9.69)	(9.93)
Manager college graduate	0.649	0.529	0.386
	(0.484)	(0.499)	(0.488)
N	37	767	295

Table A.3: Robustness Check: Interactive Fixed Effect Model Results

	(1)	(2)	(3)
	Δ% B2B 2020/4-5	Δ% B2B 2020/12	Δ% B2B 2021/12
Δ% WJKM B2B E-Com	0.108	0.263**	0.356***
	(0.144)	(0.0885)	(0.0851)
Δ% WJKM B2B E-Com × Manager age	-0.0151*	-0.0203**	-0.0129*
	(0.00807)	(0.00814)	(0.00662)
Manager age	0.0864	0.120	0.107
	(0.0540)	(0.0778)	(0.0792)
Share online trade 2019/12	-0.0312***	-0.0243*	-0.0331
	(0.00968)	(0.0121)	(0.0227)
N	1099	1099	1099
R^2	0.0835	0.0990	0.112
Prefecture×Industry FE	YES	YES	YES
Industry×Firm size FE	YES	YES	YES
Firm size×Prefecture FE	YES	YES	YES

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

Note: Standard errors robust against prefecture and industry-level clustering are reported in parentheses. All regressions control for own and partners' firm age, log of the number of workers and the stated capital, and the number of partners. Variables in the interaction terms are demeaned when used in the regression.

Table A.4: CEO Age and Experience

	(1)	(2)	(3)
	Δ% B2B 2020/4-5	Δ% B2B 2020/12	Δ% B2B 2021/12
Δ% WJKM B2B E-Com	0.109	0.268***	0.364***
	(0.147)	(0.0836)	(0.0695)
Δ% WJKM B2B E-Com $\times$ Manager age	-0.0128*	-0.0195**	-0.0124*
	(0.00605)	(0.00690)	(0.00574)
Δ% WJKM B2B E-Com $\times$ Manager experience	-0.00490	-0.00191	-0.00120
	(0.00591)	(0.00374)	(0.00457)
Manager age	0.0669	0.0859	0.0613
	(0.0539)	(0.0654)	(0.0933)
Manager experience	0.0356	0.00977	0.0216
	(0.0699)	(0.0532)	(0.0546)
Share online trade 2019/12	-0.0306*	-0.0227	-0.0306
	(0.0151)	(0.0143)	(0.0226)
N	1099	1099	1099
R^2	0.0822	0.0967	0.110
Prefecture FE	YES	YES	YES
Industry FE	YES	YES	YES
Firm size FE	YES	YES	YES

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

Note: Standard errors robust against prefecture and industry-level clustering are reported in parentheses. All regressions control for own and partners' firm age, log of the number of workers and the stated capital, and the number of partners. Variables in the interaction terms are demeaned when used in the regression.

Table A.5: Robustness Checks: Firm Size and Financial Strength

	(1)	(2)	(3)
	Δ% B2B 2020/4-5	Δ% B2B 2020/12	Δ% B2B 2021/12
Δ% WJKM B2B E-Com	-0.0497	0.113	0.183*
	(0.165)	(0.113)	(0.0980)
Manager age	0.0989	0.137	0.126
	(0.0582)	(0.0837)	(0.102)
Manager age × Δ% WJKM B2B E-Com	-0.0176*	-0.0228**	-0.0161*
	(0.00877)	(0.00932)	(0.00932)
Manager experience	0.0138	0.0123	0.0183
	(0.0544)	(0.0621)	(0.0648)
Firm age	-0.0136	-0.0272	-0.0379*
	(0.0181)	(0.0195)	(0.0199)
Large	-2.821	-0.401	3.394
	(4.329)	(4.736)	(2.928)
Small	-1.572	-2.075	-2.894
	(1.623)	(1.305)	(1.843)
Large × Δ% WJKM B2B E-Com	0.460	0.158	-0.0386
	(0.615)	(0.494)	(0.328)
Small × Δ% WJKM B2B E-Com	0.447**	0.491**	0.557*
	(0.205)	(0.202)	(0.301)
Manager college graduate	-1.079	-1.058	-1.057
	(1.152)	(1.042)	(0.750)
Credit score	0.0783	-0.0332	-0.0649
	(0.111)	(0.0887)	(0.108)
Credit score × Δ% WJKM B2B E-Com	-0.0108	-0.00528	-0.00763
	(0.0200)	(0.0140)	(0.0129)
Partner average manager age	-0.0999	-0.162	-0.108
	(0.129)	(0.126)	(0.152)
Share online trade 2019/12	-0.0317**	-0.0262*	-0.0349
	(0.0143)	(0.0143)	(0.0255)
N	1099	1099	1099
R^2	0.0881	0.105	0.119
Prefecture FE	YES	YES	YES
Industry FE	YES	YES	YES
Firm size FE	YES	YES	YES

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

Note: Standard errors robust against prefecture and industry-level clustering are reported in parentheses. All regressions control for own and partners' firm age, log of the number of workers and the stated capital, and the number of partners. Variables in the interaction terms are demeaned when used in the regression.

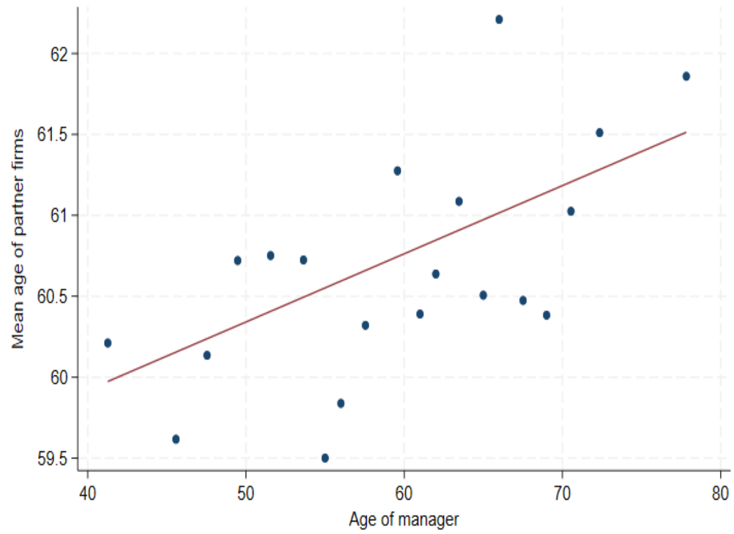

Figure A.1: Correlation between CEO Age and Partner CEO Age