Demographic Influences on Technology Adoption: Network Effects in E-commerce Diffusion*

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Abstract

Population aging is often accompanied by the aging of corporate leadership. This study investigates how CEO age affects the pace of technology adoption, focusing on the diffusion of e-commerce during the COVID-19 pandemic. Leveraging unique survey data linked to firm-level credit files that include trading networks, we show that 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 exhibit slower responses: elasticity declines by about 30% when CEOs are ten years older than the average. These results underscore the importance of leadership demographics for technology diffusion and highlight their implications for firms' adaptability in digital transformation.

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1 Introduction

As populations age in developed economies, economists debate the consequences for long-run growth. Some argue that aging can spur automation and offset potential slowdowns (Acemoglu and Restrepo, 2017a, 2022), while others contend it hampers growth because older workers adopt new technologies more slowly, creating skill mismatches and reducing adaptability (Maestas et al., 2023). Aging also reshapes corporate leadership, and concerns have been raised that older CEOs may be less responsive to rapidly changing business environments (Morris, 2024). Yet little is known about how CEO age affects technology adoption, an example of firm's adoption to changing environment. This paper examines this question in the context of business-to-business (B2B) e-commerce adoption.

The rapid adoption of e-commerce during the COVID-19 pandemic provides an ideal setting to analyze how firms' technology adoption varies with the age of corporate leadership. The spread of COVID-19 accelerated reliance on electronic transactions to reduce physical contact and mitigate infection risk, but adoption decisions critically depend on whether trading partners also adopt. Consequently, firms' exposure to the new technology differs substantially according to their existing trading networks, which are exogenous to the focal firm's decision. This setting thus generates exogenous variation in firms' exposure to e-commerce, allowing us to study both the role of network externalities in online B2B commerce and how adoption behavior varies with CEO age.

In this paper, we exploit firm-level panel data that includes information on firm characteristics, trading relationships, and managerial attributes, supplemented with unique survey data capturing firms' technology adoption decisions before and after the pandemic. This data set enables us to construct firm-specific measures of exposure to trading partners' B2B commerce adoption. We use the exogenous shock of the COVID-19 pandemic to examine how this disruption triggered technology adoption along the supply chain, and to explore the firm-level factors that drive heterogeneity in adoption patterns.

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 exploit pre-pandemic trading networks—conditional on firm characteristics such as industry, size, and location—as an exogenous source of variation in the likelihood of technology adoption. We find that firms are more likely to engage in electronic transactions when their business partners adopt such technologies. At the same time, we observe substantial heterogeneity in responses, shaped by both firm-level and managerial characteristics. In particular, CEO age plays a significant role in shaping adoption outcomes after the onset of COVID-19: firms led by younger CEOs respond more readily to shifts in business practices among their trading partners. This result is robust across alternative specifications, including models that account for heterogeneous responses by firm size and credit scores. Moreover, the negative effect of CEO age persists over time. Two years after the initial shock, firms led by CEOs ten years older than the average remain roughly 30% less responsive to their partners' adoption of new technology compared to firms with average-aged CEOs.

Our research relates to three strands of literature. First, it contributes to the literature investigating the economic consequences of demographic aging. Population aging has raised concerns about its potential to slow growth worldwide, contributing to secular stagnation (Carvalho et al., 2016; Eggertsson et al., 2019). Empirical studies have examined the link between demographic aging and economic outcomes at both national and local levels. For example, Feyrer (2007) documents a positive relationship between the share of workers in their 40s—arguably the prime age in production—and productivity growth, using data from OECD and low-income countries. Maestas et al. (2023) show with U.S. state-level data that a 10% increase in the share of the population aged 60 and above reduces average income by 5.5%.[1]

Second, we contribute to the literature on CEO characteristics and corporate behavior. Bertrand and Schoar (2003) demonstrate that CEOs' personal traits significantly influence firm policies and outcomes. Serfling (2014) finds that older CEOs are more likely to pursue conservative corporate policies, such as reducing firm risk-taking and limiting investment in innovation. Belenzon et al. (2019) report that firms with older CEOs tend to exhibit lower investment and slower growth. Other studies explore the role of age in entrepreneurship and innovation. Liang et al. (2018) develop a structural model showing that creativity and business skills evolve with age, implying that older societies exhibit lower rates of entrepreneurship. Acemoglu et al. (2022) document that firms engaged in radical innovation tend to hire younger managers. Hopenhayn et al. (2022) show how demographic shifts affect firm dynamics, including declining entry rates, rising market concentration, and falling labor shares. Collectively, this literature suggests that CEO aging may reduce corporate innovation activity. Our study extends

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

this line of work by showing that managerial age can also slow technology diffusion: specifically, firms led by older managers were slower to adopt e-commerce in response to their trading partners' adoption during the COVID-19 pandemic. This highlights a novel channel through which demographic aging may hinder economic growth, especially when the age distribution of managers mirrors broader population trends.

Third, we contribute to the empirical literature on network effects in technology adoption. This research builds on theoretical studies showing how network externalities can generate multiple equilibria (Murphy et al., 1989; Matsuyama, 1995). When private returns to adoption depend on the adoption decisions of others, coordination failures may lead to inefficiently low adoption rates, hindering growth (Rosenstein-Rodan, 1943; Katz and Shapiro, 1985, 1986). Recent empirical studies include Björkegren (2018), who analyzes how individuals' social networks shaped the diffusion of mobile phones in Rwanda. Similarly, Crouzet et al. (2023) exploit India's 2016 demonetization as a natural experiment, leveraging geographic variation in banks' cash transaction services, and show that the shock persistently increased electronic payments. Higgins (2024) study the large-scale rollout of debit cards to low-income households in Mexico as a network externality shock affecting both consumers and retailers, which substantially increased adoption of electronic payment technologies.[2] Our study bridges two strands of literature –demographic aging and network externality in technology diffusion– by showing that firms' responsiveness to peer adoption depends critically on CEO age. Exploiting firm-level heterogeneity in leadership demographics, we examine whether aging has weakened externalities in the diffusion of network-driven technologies, such as B2B e-commerce during the COVID-19 pandemic.

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 jointly 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.

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

The survey collects information on 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 state of emergency), December 2020, and December 2021. B2B online transactions are defined as commercial transactions conducted through a firm's own or a partner company's digital portal, excluding those carried out solely via email.

Our sample shows a notable increase in the diffusion rate of B2B online transactions during the pandemic. On average, B2B e-commerce transactions rose from 8.7% in December 2019 (before COVID-19) to 12.4% in April–May 2020, followed by a moderate increase to 14.0% by December 2021, as illustrated in Figure 1. This trend aligns with the findings from Japan's 2023 e-Commerce Market Survey conducted by the Ministry of Economy, Trade and Industry, which reports a growing share of e-commerce in total B2B transactions during the COVID-19 pandemic. Japan is currently the world's fourth-largest e-commerce market, after China, the United States, and the United Kingdom.

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

To enrich the survey, we link firms to TSR's proprietary detailed credit data, which provides information on basic characteristics such as establishment year, employment, capital, and credit score. Table 1 presents descriptive statistics for our analysis sample covering the variables related to CEOs, firms, and trading partners. Columns (1)-(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).

CEO characteristics (Panel A) In our analysis sample (column (3)), the average CEO is 59 years old, and nearly half of the CEOs hold a college degree. While the average age is comparable to that in the full TSR sample reported in column (1), the college graduation rate is about 30 percentage points higher—approximately 50% in our sample compared to 20% in the TSR full sample. This suggests that CEOs in our survey sample are generally more educated and may be more familiar with e-commerce.On average, CEOs have 13 years of business experience, measured as tenure since assuming their current 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.

Firm characteristics (Panel B) Column (3) show that the average firm age is 51 years, with 69 employees and capital of 100 million yen. Compared with the full TSR sample, firms in our sample are older and substantially larger in terms of employment (more than double the number of workers), but operate with smaller amounts of capital. The credit score, a unique feature of this dataset, is an index assigned by TSR investigators to assess a firm's credibility on a scale from 0 to 100. A higher score indicates stronger creditworthiness and better management quality and a score below 50 indicates heightened credit risk. The average credit score in our analysis sample is 54, compared to 48 in the full TSR sample, suggesting that the survey firms are generally more financially sound than those in the full sample. This pattern is consistent with their higher CEO educational attainment, which further suggests that our survey firms are more resilient and better positioned than the average TSR firm. Regarding the B2B e-commerce adoption, 34% of firms in our analysis sample had already adopted B2B e-commerce, with an average online trade share of 8.7% before the COVID-19. B2B adoption spread further during the pandemic, initially by 3.8 percentage points (ppt) shortly after the pandemic in April 2020, 4.4 ppt by December 2020, and 5.2 ppt by December 2021.

Trading partner characteristics (Panel C) Finally, the TSR dataset also provides information on each firm's suppliers and customers, allowing us to construct production networks based on supplier–customer linkages (Carvalho et al., 2021). Using this information, we generate firm-level measures of trading partner characteristics, such as the number of partners, the average CEO age of partner firms, and their average firm age, employment size, and capital.

Column (3) of Table 1 shows that firms in our analysis sample have an average of 11.8 trading partners, compared to 5.4 in the full sample, indicating significantly stronger interfirm linkages than those in the full sample. We then calculate the average firm characteristics of trading partners in terms of CEO age, firm age, the number of employees, and capital. According to Column (3), the median number of employees at partner firms is 990, compared to 360 in the full sample; and the median capital size of partner firms is JPY 5,950 million, compared to JPY 792 million in the full sample. These figures are much larger than the average employment and capital reported in Panel B, which suggests that firms in our survey sample tend to be more interconnected and trade with substantially large business partners. Moreover, partner firms have a median employment size of 990, whereas its mean is much larger at 2,136. Similarly, the median capital is 6 billion yen, while its mean reaches 18 billion. The fact that the mean far exceeds median indicates a skewed firm size distribution, reflecting the presence of a few firm extremely large trading partners.

Finally, to analyze the propagation of B2B e-commerce in trading networks, 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 of B2B adoption using each group's average number of employees as the weight. On average, trading partners' e-commerce adoption rate increased by 7.8 percentage point from December 2019 to December 2021 as shown in column (3) of Table 1.

2.3 Determinants of Initial E-commerce Adoption

To better understand the CEO and firm characteristics associated with the initial adoption of e-commerce, Table 2 reports regression coefficients from models regressing a firm's initial e-commerce adoption status on CEO and firm attributes. Columns 1 and 2 present the correlations between CEO and firm characteristics and the probability of adopting e-commerce before the COVID-19 pandemic, while Columns 3 and 4 show the estimates for the intensity of e-commerce use as of December 2019. The probit specifications (Columns 1–2) report marginal effects at the mean, indicating how much changes in characteristics affect the probability of any adoption, whereas the Tobit specifications (Columns 3–4) account for censoring and measure the effect of the same characteristics on the percentage share of e-commerce trade among adopters.

CEO age is negatively associated with e-commerce adoption in statistically significant ways. A 10-year increase in CEO age is associated with a 3 percentage point decrease in the probability of adoption, relative to an average rate of 33.8% (Table 1), and is also linked to lower intensity of e-commerce use. This implies that firms led by older CEOs not only had a lower probability of being adopters but also conducted a smaller share of their transactions online, suggesting that managerial demographics systematically shaped pre-COVID digital engagement.

Despite prior studies reporting a positive relationship between human capital and technology adoption (Nelson and Phelps (1966); Doms and Dunne (1997); Foster and Rosenzweig (2010)), in our setting, whether CEO has college degree is not significantly associated with the adoption of online trade.

One might be concerned that the negative association between CEO age and the tendency to adopt e-commerce simply reflects a negative relationship between firm age and adoption. However, we find no statistically significant association between firm age and the likelihood of adoption, suggesting that our results are not driven by firm age.

Firms with higher credit scores tend to use e-commerce less intensively—a somewhat counterintuitive finding that may reflect the greater reliance of more creditworthy, established firms on traditional transaction modes prior to the pandemic. By contrast, firms with a larger number of trading partners are more likely to adopt e-commerce, although this association is not statistically significant.

On firm size, we adopt the definition of the Small and Medium Enterprise (SME) Agency. Under Japan's Basic Act on Small and Medium-sized Enterprises, SMEs are defined as firms with capital of ¥300 million or less or 300 or fewer employees in manufacturing, construction, and transportation; ¥100 million or less or 100 or fewer employees in wholesale; ¥50 million or less or 50 or fewer employees in retail; and ¥50 million or less or 100 or fewer employees in services. In addition, "small enterprises"—a subset of SMEs—are defined as firms with five or fewer employees in commerce and service sectors, and 20 or fewer in manufacturing and other sectors. Probit result indicates that e-commerce transactions are less prevalent among smaller firms, suggesting that organizational scale matters on firms' initial readiness to adopt online trade.

As noted above, our survey-matched sample consists of relatively older and larger firms, led by better-educated managers than those in the full TSR sample. These differences imply that our estimates may be most informative for incumbents with capable leadership and established trading networks. We take the sample characteristics into account when interpreting the results in the next section.

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:

$$\begin{aligned} Y_{it} - Y_{i2019} = {} & \beta(\bar{Y}_{it} - \bar{Y}_{i2019}) \\ & + \gamma(\bar{Y}_{it} - \bar{Y}_{i2019}) \cdot (CEOAge - \overline{CEOAge}) \\ & + \delta CEOAge + \zeta Y_{i2019} + X_{i2019}\eta \\ & + FE_{ind} + FE_{pref} + FE_{size} + u_{it}, \end{aligned} \tag{1}$$

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.

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

We then interact the peer variable, $\bar{Y}_{it} - \bar{Y}_{i2019}$, with the mean deviation of CEO age, $CEOAge - \overline{CEOAge}$, to capture how the strength of the peer effect depends on CEO age. The mean deviation of CEO age is used so that the main effect, β, measures the peer effect at the average CEO age. The coefficient of the interaction term, γ, indicates how the peer effect varies with CEO age. We also include the linear term of CEO age.

The 2019 B2B e-commerce penetration rate, Y_{i2019}, captures the possibility that firms with initially high usage had less room to increase adoption. The vector X_{i2019} includes the firm's age, average partner firm age, and the natural logs of employee count and stated capital, and the number of business partners — all potential determinants of e-commerce uptake during the COVID-19 period. To account for differential impacts across industries, regions, and firm sizes, the model includes fixed effects for industry, prefecture, and size. In this first-difference specification, these fixed effects capture heterogeneity in the pandemic's impact across these dimensions.

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 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 networks, 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.

Our model addresses potential endogeneity in network formation: firms predisposed to adopt B2B e-commerce may already be embedded in networks with similarly inclined firms. To mitigate this concern, we exploit plausibly exogenous variation in partner firms' e-commerce adoption within the same industry, location, and firm size. Even among firms sharing these attributes, substantial heterogeneity exists in their customer composition. For instance, two medium-sized auto parts manufacturers in Aichi may serve assemblers in different prefectures—Kanagawa and Hiroshima—exposing them to distinct adoption patterns shaped by local COVID-19 conditions. If the Kanagawa assembler adopts B2B e-commerce due to a severe outbreak while the Hiroshima assembler does not, the Aichi firm linked to the former faces greater network pressure to adopt. Our shift-share variable captures such variation in exposure to trading partners' adoption behavior.

4 Results

4.1 Baseline Results

Table 3 reports the estimated coefficients from equation (1) for each time period. The peer effect coefficient, β (reported in the first row), is positive and increases over time. The estimated elasticity of a firm's own B2B e-commerce share with respect to its trading partners' share was not statistically significant in April–May 2020, but rose to 0.269 by December 2020 (one year after the COVID-19 outbreak) and further to 0.365 by December 2021; both estimates are statistically significant. This implies that a 10 percentage point increase in the average share of e-commerce among a firm's trading partners is associated with a 3.65 percentage point increase in the firm's own e-commerce share as of December 2021. For reference, the average e-commerce adoption rate in December 2019 was 8.7% (Table 1).

The interaction term with demeaned CEO age, reported in the second row, sheds light on how CEO aging affects responsiveness to changes in B2B e-commerce share.[3] The coefficient is negative and statistically significant, indicating that older CEOs were less responsive to shifting business practices and slower to adopt electronic transactions in firm-to-firm trade. Firms led by CEOs who are 10 years older than the average exhibited significantly lower adoption elasticities in the short term, with point estimates of -0.155 by April–May 2020 and -0.206 by December 2020. The negative effect remained statistically significant, though slightly attenuated, at -0.130 by December 2021. These results imply that firms with older CEOs adopted new technologies more slowly. More specifically, a firm led by a CEO who is 10 years older than the average has an estimated elasticity of 0.235, compared to 0.365 for a firm with an average-aged CEO—representing approximately 30% lower responsiveness in December 2021.

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 deci-

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

sions. 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 (Serfling, 2014; Belenzon et al., 2019). Identifying the key mechanisms behind these findings is an important direction for future research.

It is worth noting that 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.

4.2 Robustness Checks

4.2.1 Interactive Fixed Effects

The baseline model controls for the average differences in B2B e-commerce adoption across geographic locations, industries, and firm sizes by including separate fixed effects for each. However, firms often face shocks that operate simultaneously across these dimensions. For example, 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 also controls for the heterogeneous exposure of firms to COVID-19 across these dimensions (Bai, 2009).

As shown in Appendix Table A.2, the estimates under the interactive fixed-effects model closely align with those in Table 3. This indicates that our findings are not an artifact of omitted shocks at the intersection of geography, industry, and firm size, confirming the robustness of our baseline results.

4.2.2 Other Determinants of Technology Diffusion

Besides CEO's age, we consider two additional determinants of the magnitude of the peer effect identified in Table 2, namely, (a) firm size and (b) firm's financial strength (the credit score). 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 4.

Firm size: The size of organization has long been debated as one of the key determinants of technology diffusion and innovation (Cohen and Klepper, 1996; Akcigit and Kerr, 2018). Larger organizations typically enjoy scale economies, enabling them to spread the fixed costs and spend more resources to acquire information to be early adopter of new technology (Wozniak, 1987). Yet, organizational economics emphasizes that size also brings complexity: hierarchical structures, multiple decision layers, and entrenched routines could create barriers for new technology adoption. Atkin et al. (2017) provides evidence from Pakistan that misaligned incentives within large firms prevented them from adopting a productivity-enhancing technology, even when it was profitable. Such barriers tend to be more pronounced within larger firms, where decentralized decision-making raises adjustment costs and delays changes in corporate business practices. In contrast, smaller firms often operate with flatter hierarchies and more direct managerial oversight, allowing them to respond quickly in response to shocks or partners' demand for business practices adopting new technologies.

Our results align with this latter view. Table 4 shows a positive and significant interaction between the small-firm dummy and partners' e-commerce adoption. This indicates that small firms are particularly responsive to network pressures, adapting their business practices to match their partners' digital transformation. In contrast, the interaction term for large firms is statistically insignificant, suggesting that organizational frictions outweigh potential resource advantages in this context. The evidence therefore underscores that adaptability, rather than scale alone, is decisive for technology diffusion during COVID-19 in Japan.

Financial strength: Financial strength is another channel through which firm characteristics may condition technology adoption. Theory suggests that credit constraints can hinder a firm's ability to invest in new technologies and innovation, particularly when adoption entails upgrading existing systems or retraining workers (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.

Stronger credit ratings should, in principle, allow firms to overcome liquidity barriers, making them more likely to adopt when trading partners do. However, our estimates reveal that the interaction between credit score and partner adoption is statistically insignificant. One interpretation is that the cost of adopting basic B2B e-commerce systems was relatively low, allowing even financially weaker firms to participate. Another explanation is that extraordinary pandemic conditions—characterized by both urgency to maintain operations and broad government support programs—reduced the salience of financial constraints. In such circumstances, survival imperatives may have driven adoption even among firms that would otherwise be constrained.

Taken together, even after accounting for these additional determinants of e-commerce adoption, our main finding regarding the negative aging effect remains robust across all periods. The heterogeneity analysis in Table 4 shows that smaller firms are more responsive to peer's e-commerce adoption, whereas larger firms adjust more slowly in Japan. Firms' financial constraint does not emerge as a binding determinant for e-commerce adoption.

Finally, as noted in the data section, proper interpretation of the estimated elasticity requires acknowledging that our survey sample combines trait that can pull in opposite directions –CEOs with higher educational attainment (potentially amplifying responsiveness) and larger or more creditworthy firms (potentially dampening the effect) compared with the full TSR sample. Accordingly, the peer effect we report should be understood as the net outcome of these offsetting forces, conditional on observables and fixed effects, rather than as a population-wide average for all Japanese firms.

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' behavior and link these responses to firm and managerial characteristics.

Our findings demonstrate that firms are significantly 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 uncover 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.

By contrast, smaller firms appear more adaptable in shifting from traditional business practices to new e-commerce trade when nudged by their partners. While our results do not point to financial constraint as a major barrier, they suggest that measures aimed at enhancing managerial adaptability and trade network linkages may help smaller firms take advantage of digital opportunities.

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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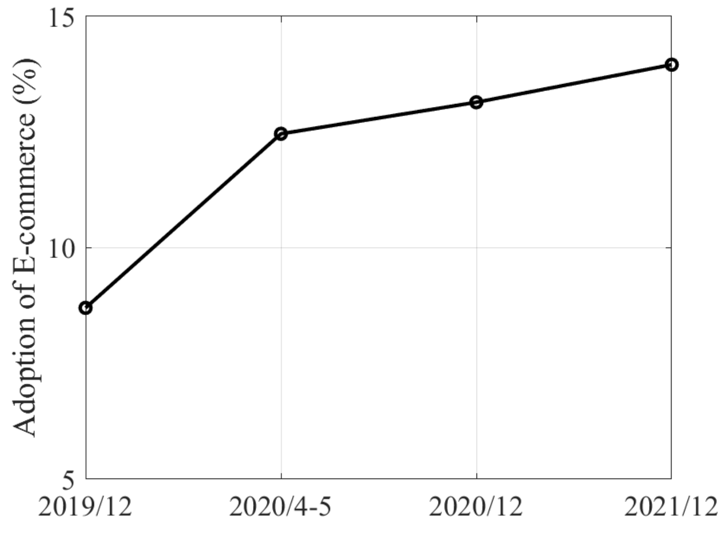

Figure 1: Adoption of E-commerce in B2B Transactions

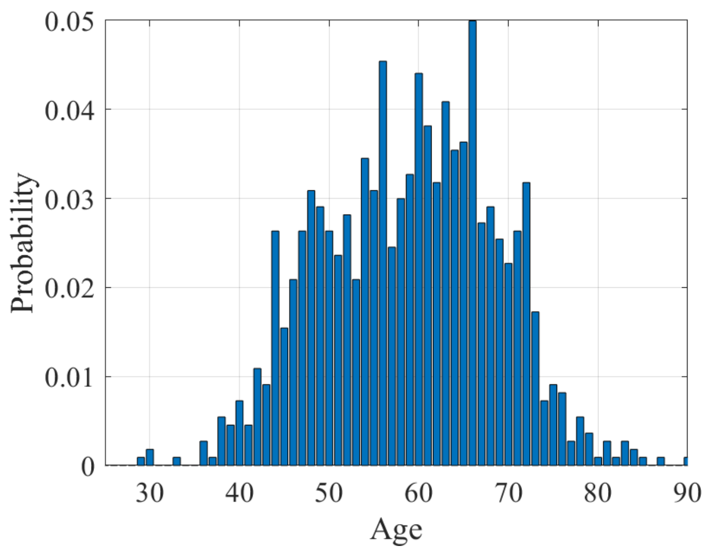

Figure 2: Age of CEO as of December 2019

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									
CEO age	60.6	11.6	61	60.1	10	61	59	9.74	60
CEO college graduate	.195	.396	0	.464	.499	0	.495	.5	0
CEO 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 CEO 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% Business Partner B2B E-Com 2020/4-5				6.68	4.88	5.92	6.46	4.45	5.83
Δ% Business Partner B2B E-Com 2020/12				7.48	5.18	6.65	7.24	4.77	6.49
Δ% Business Partner B2B E-Com 2021/12				8.04	5.63	7.1	7.8	5.22	7.01
N	743590			1608			1099		

Table 2: Regression of e-commerce adoption on CEO and firm characteristics

	(1)	(2)	(3)	(4)
	1(Online trade > 0)		Share of e-commerce	
CEO age	-0.003**	-0.003**	-0.359**	-0.345**
	(0.001)	(0.001)	(0.171)	(0.170)
CEO college graduate	-0.006	-0.006	-0.681	-0.325
	(0.030)	(0.030)	(3.232)	(3.265)
Firm age	-0.001	-0.001	-0.111	-0.103
	(0.001)	(0.001)	(0.069)	(0.070)
Credit score	-0.005*	-0.005	-0.500*	-0.470
	(0.003)	(0.003)	(0.280)	(0.301)
Number of partners	0.003	0.003	0.212	0.219
	(0.002)	(0.002)	(0.246)	(0.247)
Large	0.128*	0.135	11.811	14.763
	(0.077)	(0.089)	(7.854)	(9.210)
Small	-0.090**	-0.095**	-6.550	-6.388
	(0.036)	(0.043)	(4.146)	(4.935)
Capital (log)		-0.001		-1.719
		(0.016)		(1.993)
Employment (log)		-0.003		0.852
		(0.019)		(2.136)
Constant			11.879	24.009
			(15.183)	(20.184)
Observations	1099	1099	1099	1099
R^2	0.0128	0.0128	0.00328	0.00348
Mean.dep	0.338	0.338	8.681	8.681

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

Note: Standard errors robust against heteroskedasticity are reported in parentheses. Columns (1) and (2) report the marginal effect of each covariate (at the mean value) from probit regressions. Columns (3) and (4) report tobit regression estimates. CEO age is centered around the mean.

Table 3: Peer Effect of Technology Adoption: CEO Age

	(1)	(2)	(3)
		Δ% B2B	
End Period	2020/4-5	2020/12	2021/12
Δ% Business Partner B2B E-Com	0.110	0.269***	0.365***
	(0.142)	(0.0823)	(0.0681)
Δ% Business Partner B2B E-Com × CEO age	-0.0155*	-0.0206**	-0.0130**
	(0.00762)	(0.00731)	(0.00574)
CEO 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

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

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. CEO age is centered around the mean.

Table 4: Robustness Checks: Firm Size and Financial Strength

	(1)	(2)	(3)
		Δ% B2B	
End Period	2020/4-5	2020/12	2021/12
Δ % Partner B2B E-Com	-0.0397	0.122	0.192*
	(0.156)	(0.109)	(0.102)
Δ % Partner B2B E-Com × CEO age	-0.0174*	-0.0225**	-0.0158*
	(0.00877)	(0.00891)	(0.00780)
Δ % Partner B2B E-Com × Large	0.428	0.125	-0.0722
	(0.599)	(0.482)	(0.319)
Δ % Partner B2B E-Com × Small	0.437*	0.479**	0.545*
	(0.203)	(0.201)	(0.298)
Δ % Partner B2B E-Com × Credit score	-0.0107	-0.00535	-0.00771
	(0.0196)	(0.0139)	(0.0129)
CEO age	0.102*	0.139	0.132
	(0.0560)	(0.0873)	(0.0907)
Credit score	0.0712	-0.0390	-0.0706
	(0.106)	(0.0863)	(0.107)
Share Online Trade 201912	-0.0313*	-0.0258*	-0.0344
	(0.0157)	(0.0132)	(0.0246)
N	1099	1099	1099
R^2	0.0869	0.104	0.118
Prefecture FE	YES	YES	YES
Industry FE	YES	YES	YES
Firm size FE	YES	YES	YES

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

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, the number of partners, and partners' average CEO age. CEO age and credit score are centered around the mean.

Appendix A Online Appendix

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

	Extensive margin Online trade>0	Intensive margin 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

Note: Share of online trade includes the firms that do not use online trade.

Table A.2: Robustness Check: Interactive Fixed Effect Model Results

	(1)	(2)	(3)
		Δ% B2B	
End Period	2020/4-5	2020/12	2021/12
Δ% Business Partner B2B E-Com	0.108	0.263**	0.356***
	(0.144)	(0.0885)	(0.0851)
Δ% Business Partner B2B E-Com × CEO age	-0.0151*	-0.0203**	-0.0129*
	(0.00807)	(0.00814)	(0.00662)
CEO 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

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

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. CEO age is centered around the mean.