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Technology Extension Services, Intangible Capital, and SME Productivity before and during the COVID-19 Pandemic

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Technology Extension Services, Intangible Capital, and SME Productivity Before and During the COVID-19 Pandemic[1]

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Abstract

This study investigates the impact of Technology Extension Services (TES) on the productivity of small and medium-sized enterprises (SMEs) in Japan, using an Endogenous Switching Regression model and firm-level panel data covering both the pre-pandemic (2016–2019) and pandemic (2020–2023) periods. Focusing on *Kohsetsushi*, Japan's extensive network of public support institutes for SMEs, the analysis finds that TES adoption significantly improves firm productivity across both periods, highlighting its role as a locally embedded innovation intermediary. Firms with higher levels of intangible capital benefited more, with complementary effects particularly pronounced during the pandemic—suggesting that absorptive capacity became critical under crisis conditions. Selection estimates reveal that more productive firms were more likely to adopt TES, although some equally capable firms opted out—consistent with comparative advantage shaping self-selection patterns. Geographic proximity to service providers constrained TES access in stable periods but became less critical during the pandemic due to the expansion of digital service delivery. These findings underscore how firm capabilities, external shocks, and spatial access jointly influence the effectiveness of public technology support programs.

Keywords: Technology Extension Services, Intangible Capital, Labor Productivity, COVID-19, Absorptive Capacity, Endogenous Switching Regression, Innovation Intermediary, *Kohsetsushi*

JEL classification: O32, L26, D24, J24, H43, C21

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1. Introduction

Small- and medium-sized enterprises (SMEs) are vital drivers of economic growth, accounting for the majority of firms, employment, and value added globally. However, they often face persistent productivity challenges, partly due to limited investment in intangible capital—such as digital technologies, intellectual property, and organizational competencies—which is essential for innovation and sustained performance (Jones & Jin, 2017; OECD, 2019). Unlike large firms that benefit from economies of scale, SMEs frequently encounter barriers in acquiring and leveraging such capital, underscoring the need for effective external support mechanisms (Cusmano, 2019).

A core difficulty for SMEs lies in their exposure to market and innovation system failures. The former occurs when firms cannot capture returns on innovation due to financing constraints or lack of complementary assets, while the latter stems from isolation from knowledge networks (Klerkx et al., 2012). Technology extension services (TES) aim to address these gaps by offering technical assistance, training, and networking, thereby facilitating knowledge diffusion and enhancing innovation capacity (Shapira et al., 2011; Fukugawa, 2024). This highlights the importance of examining whether and how TES help SMEs leverage their intangible capital for improved performance.

While prior research highlights the complementary nature of intangible capital components—such as R&D, ICT, and human capital—in driving firm performance (Bresnahan et al., 2002; Brynjolfsson & Hitt, 2003; Corrado et al., 2013; Mohnen et al., 2018), less attention has been paid to how intangible capital interacts with external knowledge services like TES. The extent to which TES effectiveness depends on firms' existing intangible capital remains an open empirical question.

TES outcomes may also differ by firm capabilities and broader contextual conditions. For example, the COVID-19 pandemic accelerated digitalization and disrupted knowledge diffusion channels, potentially altering how SMEs access and benefit from TES. In parallel, selection into TES may not be random: less productive firms might seek help to overcome deficits, while more capable firms may leverage TES to build on their strengths. Understanding whether these selection dynamics vary during stable versus crisis periods is crucial for identifying causal effects.

This study investigates the impact of TES on SME productivity, particularly in relation to firms' intangible capital investments, and how these relationships evolve amid external shocks. Using firm-level panel data, we address four research questions: (1) Does TES participation enhance SME productivity? (2) Is this effect contingent on firms' intangible capital, indicating differences in absorptive capacity? (3) Does the selection into TES differ between stable and crisis periods? (4) Has digitalization, accelerated by the pandemic, altered the importance of geographic proximity to TES providers? By answering these questions, the study advances understanding of how TES and intangible capital jointly shape SME innovation and productivity under changing economic conditions.

The remainder of the paper is organized as follows. Section 2 outlines the hypotheses. Section 3 describes the data, key variables, and empirical strategy. Section 4 presents the estimation results. Section 5 discusses implications. Section 6 concludes with a summary, limitations, and directions for future research.

2. Hypotheses

2.1 Technology Extension Services and Firm Productivity

The long-term improvement in the living standards measured by the growth of real GDP per capita hinges on total factor productivity (TFP) growth. Growth accounting explains that TFP grows as internal knowledge capital accumulates and external knowledge flows from spillover pools that comprise knowledge created by competitors, suppliers, customers, public research institutes, and universities. Since the seminal work by Mansfield et al. (1977), a number of econometric studies using the sample of various periods, regions and industries have established a stylized fact: TFP gains from external knowledge (i.e., the social rate of return to R&D) often exceed those from internal knowledge (i.e., the private rate of return to R&D). Although knowledge spillovers play a significant role in macroeconomic growth, small and medium-sized enterprises (SMEs) tend to encounter difficulty in tapping into external sources of knowledge due to a lack of social capital, search capabilities, and absorptive capacity. This makes spillover suboptimal at the aggregated level and the local business ecosystem less innovative, which causes innovation system failure (Klerkx et al., 2012). Innovation intermediaries help address this failure by enabling SMEs to learn from others, and many countries have established such institutions as part of regional innovation policy (Dodgson & Bessant, 1996; Shapira et al., 2011, Fukugawa 2024). Recent studies identified technology transfer and knowledge networking as main routes for innovation intermediaries to improve clients' performance, including productivity (Feser, 2023; Zhang & Liu, 2023) and empirical studies support this view. In the UK, the Manufacturing Advisory Service (MAS) improved firm performance through targeted support for lean production, though effects varied by region (Department for Business, Innovation and Skills, 2016). In the U.S., evaluations of the Manufacturing Extension Partnership (MEP) found robust average treatment effect on the treated (ATT), particularly among smaller firms with limited access to external expertise (Lipscomb et al., 2018). These findings suggest that TES can improve SME productivity by bridging internal capability gaps and

strengthening innovation system linkages. Synthesizing these theoretical and empirical insights, the following hypothesis is proposed:
H1: The ATT of TES on firm productivity is positive.

2.2 Absorptive Capacity as a Moderator of TES Effectiveness

The effectiveness of TES depends not only on the quality of services delivered but also on the firm's ability to internalize and apply external knowledge. This idea is captured by the concept of absorptive capacity, defined by Cohen and Levinthal (1990) as a firm's ability to recognize the value of external information, assimilate it, and apply it to commercial ends. Similarly, research on external knowledge utilization (Arora & Gambardella, 1994) highlights organizational routines that support the acquisition and integration of external technologies. These perspectives converge on the view that productivity gains from TES depend on a firm's internal capabilities. Critically, absorptive capacity is not innate; it is cultivated through prior investments in intangible capital—such as R&D, employee training, digital infrastructure, and managerial competence. These assets provide the cognitive and organizational foundation for interpreting and applying external inputs. Without them, TES interventions may have limited or short-lived effects. Empirical evidence supports this view. For example, Lipscomb et al. (2018) found that among U.S. MEP clients, productivity gains were more pronounced in technologically advanced sectors—those with higher absorptive capacity. This indicates that the benefits of TES are not evenly distributed but are conditioned by firms' internal capabilities.
H2: The ATT of TES is greater for firms with higher absorptive capacity, as reflected in their intangible capital, than for firms with lower absorptive capacity.

2.3 Selection into TES and Its Variation Across Stable and Crisis Periods

Firms' decisions to participate in TES are governed by a logic of comparative advantage: they self-select based on expected net productivity gains. This principle aligns with the Roy model (Roy, 1951), which posits that agents choose the option with the highest anticipated return. In the TES context, firms participate when the perceived benefits of external support outweigh their opportunity costs—shaped by internal capabilities and access to alternative knowledge sources. Lee's (1983) econometric framework extends the Roy model by formalizing how selection on unobserved characteristics can bias impact estimates. Firms may base their decision not only on observable traits—such as size or past performance—but also on latent attributes like managerial foresight or unmeasured productivity potential. These same unobserved factors may influence both the likelihood of participation and the resulting productivity, introducing endogeneity. Although prior evaluations of TES programs in the U.S. and U.K. show productivity gains, they often overlook this selection on unobservables. To address this, the present study adopts the Roy-Lee framework and distinguishes two types of selection: firms with high expected gains may self-select into TES (*positive selection into participation*), while others with strong internal capabilities may opt out because the marginal returns are lower (*positive selection into non-participation*). These selection patterns, however, may shift during periods of disruption. Disruptions such as the COVID-19 pandemic can shift firm behavior from strategic planning to short-term survival, weakening the usual link between TES participation and unobserved capabilities. Firms that would typically abstain may participate out of urgency, diluting positive selection into use. Conversely, non-participation may no longer reflect strong internal capacity, as weaker firms might opt out due to overwhelm or disconnection, weakening positive selection into non-use as well.

H3: The selection mechanism into TES differs between stable and crisis periods, exhibiting weaker positive selection during external shocks such as the COVID-19 pandemic.

2.4 Geographic Access to TES and the Role of Digital Transformation

Beyond internal capabilities, firms' access to TES is shaped by geographic proximity to service providers. Physical closeness has historically facilitated participation by reducing coordination costs, enabling face-to-face interaction, and increasing exposure to outreach. These benefits align with spatial transaction cost theory, which highlights how distance can hinder the delivery and uptake of external support. Although proximity encompasses multiple dimensions—cognitive, organizational, and institutional (Boschma, 2005)—spatial proximity has been particularly important in tacit-knowledge-intensive contexts such as TES. It encourages logistical ease, builds trust, and enables iterative learning through repeated personal contact, thereby reinforcing regional disparities in program access (Izushi, 2003). The COVID-19 pandemic, however, disrupted these spatial patterns. As in-person interactions declined, TES providers rapidly adopted digital formats, including remote consultations and online training. This pivot reduced the importance of physical proximity, broadened service reach, and normalized virtual participation across regions. Consequently, geographic constraints faced by firms located far from TES centers may have weakened.

H4: Firms located closer to TES providers are more likely to participate, but this geographic advantage weakens after the pandemic because of increased reliance on digital interactions.

3. Method

3.1 Data

This study uses an unbalanced panel dataset constructed from nationwide online surveys conducted between 2021 and 2024. The surveys captured both TES users and non-users in all industries, enabling firm-level comparisons based on engagement with *Kohsetsushi*. Collected data cover the period from 2016 to 2023.

Kohsetsushi are public technology centers established by local governments across Japan. They provide a wide range of technology transfer services, including technical consultation, training, joint research, patent licensing, and access to testing facilities and equipment. Initially founded in the late 19th century with a focus on agriculture, *Kohsetsushi* expanded into manufacturing during the 20th century (Fukugawa & Goto, 2016). Prior studies show that their services align with regional innovation systems (Fukugawa, 2016) and positively affect labor productivity (Fukugawa, 2024). Compared to TES providers such as MEP and MAS, *Kohsetsushi* represent the largest public extension system globally in terms of client base, staff, and budget (Shapira et al., 2007; Fukugawa, 2024). As of 2023, 64 centers operated across all 47 prefectures.

The survey was designed and supervised by the author and administered via a private consulting firm using an online panel of 726,000 registrants representing all major industries and regions. The final sample includes 1,026 managers and entrepreneurs in manufacturing and 1,036 firms in services. Due to budget constraints, the survey closed once the target response count was reached, without follow-up for non-respondents.

The analysis distinguishes between the pre-pandemic (2016–2019) and pandemic (2020–2023) periods. Although Japan reclassified COVID-19 in May 2023, many firms continued to act cautiously in long-term investments such as R&D and workforce training. Including 2023 as part of the pandemic period captures this lagged behavioral recovery and the continued uncertainty.

TES participation varies across industries, reflecting differences in technological opportunities. Firms in high-tech sectors are more likely to utilize TES, suggesting that industrial characteristics—rather than temporal trends—drive engagement. Meanwhile, firm performance is influenced by macro-level exogenous shocks. The impact of such disruptions varies by industry; for example, pandemic-related shocks to sectors like accommodation, airlines, food services, and tourism had spillover effects on associated manufacturing industries (Morikawa, 2023). To account for both sectoral heterogeneity and temporal variation in TES access and firm performance, the empirical models incorporate industry and time fixed effects. Following Lipscomb et al. (2018), the machinery and ICT sectors are defined as high-tech.

As the data were collected through a questionnaire survey, potential limitations such as sampling bias, non-response bias, and response bias must be acknowledged. The reliance on an online survey panel may introduce bias toward digitally literate firm managers, potentially skewing responses related to technology adoption and investment in computerized systems. While the use of multiple survey modes could have mitigated this issue, budget constraints restricted the methodology to online distribution. To assess representativeness, the distributions of respondents across regions and industries were compared with national census data. No statistically significant differences were detected, suggesting that the sample is broadly representative in terms of regional and sectoral composition. However, because the respondents were not randomly selected from the broader population, the dataset may still exhibit unobserved biases that could affect the generalizability of the results. Accordingly, the findings of this study should be interpreted with appropriate caution.

Some panel members may have opted not to participate due to limited engagement with TES, potentially introducing self-selection bias (Armstrong & Overton, 1977). To assess this concern, the sample was divided into early and late respondents—a standard technique based on the assumption that late respondents more closely resemble non-respondents. A t-test comparing TES usage across the two groups revealed no statistically significant differences, suggesting that non-response bias is likely minimal. Additionally, while there is a possibility that some respondents may have provided answers they believed were expected by the researchers, the risk of such response bias is limited, as the survey primarily relied on objective business records rather than subjective perceptions or attitudes.

Survivorship bias constitutes a potential limitation of the dataset, as firms that exited the market during the pandemic are not captured in the survey. However, non-response does not necessarily imply firm failure. Some firms may have remained operational but chose not to participate due to loss of interest or because they were too burdened by pandemic-related disruptions to allocate time to the survey. Consequently, the sample may overrepresent firms with greater managerial resources, organizational slack, or a stronger inclination toward institutional engagement. While robustness checks comparing early and late respondents indicate minimal differences in TES usage, the possibility of selection bias due to differential willingness to respond, rather than survival alone, must be acknowledged. These potential biases should be taken into account when interpreting the results.

3.2 Model

Although panel data often motivate the use of Difference-in-Differences (DID) approaches, this method assumes that once treated, a unit remains treated throughout the observation period. In contrast, TES adoption in this study is non-monotonic—firms may adopt in one year, discontinue in the next, and resume thereafter. This treatment variation over time violates the monotonic treatment assignment assumption of conventional DID models, rendering them inappropriate for this context. Fixed-effects models, another common panel data strategy, rely on within-transformation, which eliminates all time-invariant variables from the analysis. In this study, geographic distance serves as an instrumental variable, capturing exogenous variation in firms' exposure to support services. However, since distance does not vary over time within firms, it is eliminated under fixed-effects IV estimation. To address these limitations, this study employs the Endogenous Switching Regression (ESR) framework, which accommodates time-invariant instruments by modeling treatment selection and outcome equations jointly, without relying on within transformation. In addition, the ESR model is well suited for examining complementarity effects, as it estimates separate outcome equations for treated and untreated groups—effectively functioning as a fully interacted model. This structure facilitates the identification of heterogeneous treatment effects conditional on firm characteristics.

Firms decide whether to access TES based on observed and unobserved characteristics. The selection equation is specified as a binary choice model:

$D^* = \gamma Z + \eta$ (1)

where D^* is a latent variable representing the firm's inclination to use TES, Z includes firm-specific factors such as firm size, industry, and distance to the nearest service provider, γ is a vector of parameters to be estimated, and η is an error term assumed to follow a standard normal distribution. The observed participation decision is given by:

$D = 1$ if $D^* > 0$ (Firm accesses TES), and $D = 0$ otherwise.

Under the assumption of joint normality between the selection error η and the outcome equation errors ε_j, selection bias can be addressed using the expected value of the outcome error conditional on participation status. This results in selection correction terms derived from the inverse Mills ratios:

$\lambda_1 = \phi(\gamma Z) / \Phi(\gamma Z)$ for D=1, and $\lambda_0 = -\phi(\gamma Z) / (1 - \Phi(\gamma Z))$ for D=0,

where ϕ and Φ denote the standard normal probability density function and cumulative distribution function, respectively. These terms enter the structural equations for outcome estimation and appear explicitly in the parametric expressions for ATT and ATU.

Conditional on TES participation, a firm's productivity evolves according to separate equations:

For firms using TES (D = 1): $Y_1 = \beta_1 X_1 + \varepsilon_1$ (2)

For firms not using TES (D = 0): $Y_0 = \beta_0 X_0 + \varepsilon_0$ (3)

where Y_1 and Y_0 denote labor productivity for TES users and non-users, respectively, X_1 and X_0 include firm characteristics, year dummies, and industry dummies, β_1 and β_0 are the parameters to be estimated, and ε_1 and ε_0 are error terms. All second-stage regressors are lagged by one year. This ensures that firm decisions, like intangible investment or subsidy receipt, precede observed productivity outcomes, reducing simultaneity bias. The lag structure also reflects the realistic delay in the effects of such decisions. Results remain consistent with the contemporaneous model but gain robustness and plausibility. Instrumental variables in the selection equation are not lagged, as they are assumed to influence TES uptake contemporaneously. This approach strengthens the model's temporal logic and supports more credible causal inferences regarding productivity effects.

Since unobserved factors may affect both TES participation and firm productivity, the ESR model corrects for selection bias by allowing correlation between the error terms of the selection and outcome equations. Estimation is conducted via full-information maximum likelihood using the *movestay* command in Stata (Lokshin & Sajaia, 2004).

The error terms across the selection and outcome equations are assumed to follow a trivariate normal distribution with mean zero and the following covariance matrix:

$$Cov(\eta, \varepsilon 0, \varepsilon 1) = \begin{bmatrix} \sigma_{\eta}^2 & \rho 0 \sigma 0 & \rho 1 \sigma 1 \\ \rho 0 \sigma 0 & \sigma_0^2 & \cdot \\ \rho 1 \sigma 1 & \cdot & \sigma_1^2 \end{bmatrix} \quad (4)$$

where σ_{η}^2 is the variance of the selection equation's error term, typically normalized to one for identification. σ_0^2 and σ_1^2 are the variances of the productivity equations for TES non-users and users, respectively. The off-diagonal terms $\rho_0\sigma_0$ and $\rho_1\sigma_1$ represent the covariances between the selection equation and each outcome equation. The covariance between the two outcome equations is undefined (denoted by a dot) because TES participation is mutually exclusive (Maddala, 1983, p. 224).

The Average Treatment Effect on the Treated (ATT) quantifies the impact of TES on firms that actually adopted the services. It combines differences in structural outcomes and corrections for selection on unobservables. Conversely, the Average Treatment Effect on the Untreated (ATU) reflects the hypothetical gain for non-participating firms had they received the treatment.

$\text{ATT} = \text{E}(Y_1 \mid D = 1) - \text{E}(Y_0 \mid D = 1) \quad (5)$

Rewriting based on model parameters:

$\text{ATT} = (\beta_1 - \beta_0)X_1 + (\rho_1\sigma_1 - \rho_0\sigma_0)\ (\phi(\gamma Z) / \Phi(\gamma Z))\ (6).$

$\text{ATU} = \text{E}(Y_1 \mid D = 0) - \text{E}(Y_0 \mid D = 0) \quad (7)$

Rewriting based on model parameters:

$\text{ATU} = (\beta_1 - \beta_0)X_0 + (\rho_1\sigma_1 - \rho_0\sigma_0)\ (-\phi(\gamma Z) / (1 - \Phi(\gamma Z)))\ (8).$

These expressions isolate the structural treatment effect (β_1 - β_0) from the selection correction based on unobservables, completing the ESR model framework.

To assess complementarity between TES and intangible capital, the ESR model is specified as a fully interacted system, where the effect of intangible capital investment is estimated separately for TES users and non-users. In this framework, the coefficient on intangible capital in the outcome equation for TES participants captures the extent to which TES enhances the productivity effects of intangible investment. A positive and statistically significant coefficient indicates that TES users with greater intangible capital experience higher productivity gains, supporting the presence of complementarity.

To assess whether digitalization reduced geographic barriers to TES access, the analysis examines how the effect of time-distance to TES providers on participation varies across pre- and post-pandemic periods. If remote service delivery expanded as hypothesized, the negative effect of distance on TES engagement should decline in the post-pandemic period, indicating a weakening of spatial constraints.

To identify the causal effect of TES participation on firm productivity, the analysis employs two instrumental variables (IVs). The first IV is time-distance to the nearest *Kohsetsushi*, measured in minutes, which captures practical accessibility through the lens of transport infrastructure. This represents a methodological refinement over previous studies such as Lipscomb et al. (2018), who used straight-line (geographic) distance as a proxy for access. Unlike geographic distance, time-distance reflects actual travel costs and constraints, offering a more behaviorally relevant measure of firms' ability to engage with TES providers. Time-distance is assumed to influence participation decisions but not productivity outcomes directly, thus satisfying the exclusion restriction.

Together, these IVs help address selection on both observables and unobservables in TES participation. The validity of the instruments is evaluated using a Sargan test of overidentifying restrictions. The test fails to reject the null hypothesis, indicating that the instruments are statistically consistent with the assumptions of relevance and exogeneity, and supporting their use in identifying unbiased treatment effects.

3.3 Variables

The dependent variable is labor productivity, measured as real sales per worker. Nominal output is deflated using the GDP deflator for Japan (IMF, 2025), yielding a firm-level indicator of efficiency in converting labor input into output.

To adjust for differences in firm size and workforce structure—and to avoid inflating productivity measures for very small firms—the models include the natural logarithm of regular and nonregular employee counts in each stage of the ESR model. These control for scale effects in the selection equation and isolate TES impacts in the second-stage outcome equations.

Manager age is included in the first-stage selection equation, based on evidence that age influences openness to innovation. Kawaguchi et al. (2025) show that older managers may be less responsive to external technologies. To capture potential nonlinear effects, both age and age squared are included in the outcome equations.

TES participation is captured by a binary variable (*Kohsetsushi* client dummy), coded 1 if the firm used any technical support or advisory service from a *Kohsetsushi* center. This variable functions as the dependent variable in the first-stage selection model and defines the regime in the second stage.

STEM education is represented by a binary indicator coded 1 if the respondent holds a degree in science, technology, engineering, or mathematics. STEM-educated managers are more likely to understand and adopt technical assistance, enhancing both the probability of TES uptake and firm-level innovation capability.

Public subsidy receipt is coded 1 if the firm received government (municipal, local, and national) funding for technology upgrading. This variable proxies for underlying technological orientation and policy engagement, which may influence both productivity and TES participation.

Intangible capital is operationalized using three categories from Corrado et al. (2006): computerized information (ICT hardware, software, services), innovative properties (R&D, design, branding), and economic competencies (on- and off-the-job training). A composite index is created from eight binary indicators. Cronbach's alpha (0.858) confirms strong internal consistency, supporting aggregation. A factor analysis based on tetrachoric correlations and oblique rotation identified one factor with its eigenvalue greater than one. This dominant factor explains over 90% of the total variance, suggesting that firms investing in one area of intangible capital are likely to invest in others as well. The resulting continuous factor score is used as the main intangible capital variable. Given the highly concentrated distribution of the factor scores, alternative operationalizations were explored as robustness checks. Binary and three-category versions were also tested (positive vs. non-positive, and no/moderate/high investment), with consistent results across specifications. Detailed tables are omitted for brevity.

Table 1 summarizes descriptive statistics.

Table 1

Appendix Table 1 presents the number and proportion of TES users by region. A Chi-square test indicates statistically significant regional disparities in TES adoption. The West region has the highest share of TES users at 27.79%, while the North region has the lowest at 17.12%. The Metro region, despite having the highest absolute number of users, shows a moderate proportion at 20.20%. These results suggest that regional context plays a crucial role in shaping TES engagement. Policy efforts to expand access should be regionally customized to reflect local institutional, industrial, and infrastructural conditions.

Appendix Table 2 displays the distribution of TES users by technological category. A Chi-square test reveals significant differences across sectors. Mid-tech manufacturing firms exhibit a TES adoption rate of 23.37% (147/629), while high-tech firms show an even higher rate at 30.26% (59/195). In contrast, adoption is lower in low-tech and other manufacturing sectors, and almost negligible in non-manufacturing, where only 1 out of 143 firms reported using TES. These findings demonstrate that TES engagement is concentrated in technologically sophisticated industries, highlighting the need to enhance outreach to lower-tech sectors.

Appendix Table 3 compares TES adoption rates before and during the pandemic. The Chi-square test shows no statistically significant difference in adoption rates across the two periods. Specifically, 22.71% (202/889) of firms used TES before the pandemic, while 20.66% (189/915) did so during the pandemic. This indicates that, despite the operational disruptions caused by COVID-19, the overall propensity of firms to engage with TES remained relatively stable. The result suggests institutional continuity in TES provision and a persistent demand among firms even under crisis conditions.

Appendix Table 4 examines changes in firms' ICT-related activities before and during the pandemic. While no statistically significant differences are found in ICT hardware investments or software adoption, the use of ICT services shows a significant increase during the pandemic period. This pattern suggests that firms prioritized flexible, service-oriented solutions—such as cloud services and remote IT support—over fixed investments in hardware or standalone software. The results point to a shift in digitalization strategies during crises, favoring more adaptable and less capital-intensive approaches.

3.4 Robustness Tests

To assess the robustness of the main model, an alternative specification uses year-on-year productivity growth as the outcome. This approach captures dynamic effects of TES and intangible capital on performance improvements and helps mitigate unobserved time-invariant firm characteristics by differencing out persistent heterogeneity. Although the ESR framework does not include fixed effects, the growth specification reinforces the temporal interpretation of TES impacts. Initial productivity is included to account for conditional convergence—where higher-performing firms tend to grow more slowly—and to control for unobserved traits linked to both baseline productivity and growth potential. If the estimated effects of TES and its interaction with intangible capital remain stable in direction and significance across both the level and growth models, it increases confidence that the results are not driven by simultaneity or model-specific assumptions. This robustness check strengthens the study's core claims about the productivity effects of TES and intangible capital investment.

4. Results

4.1 Key Findings

This section presents findings from the ESR models, evaluating how access to TES affects labor productivity while accounting for selection bias. The main model uses one-year lagged values for second-stage explanatory variables to address simultaneity and reflect delayed effects of TES and firm characteristics. A robustness check uses year-on-year productivity growth as the outcome to control for time-invariant unobserved heterogeneity. Results are reported separately for pre-pandemic and pandemic periods. Table 2 presents coefficient estimates from the productivity-level models; Table 3 reports the corresponding ATT and ATU values. Tables 4 and 5 provide results for the productivity growth specification, while Table 6 consolidates key outcomes across both model types—summarizing variation in TES effects, complementarities with intangible capital, selection patterns, and geographic access differences by period. The followings report results aligned with each hypothesis, drawing on both specifications to provide an integrated assessment of TES effectiveness.

Tables 2 to 6

Hypothesis 1 posits that TES enhance firm-level productivity. Results from both the main and robustness specifications support this claim. In the main model, the ATT is positive and statistically significant across all three periods. The largest effects occur in the pre-pandemic years, when firms likely faced fewer constraints in integrating TES. During the pandemic, the impact remains significant, indicating the continued relevance of TES amid operational disruptions and accelerated digital transition. The robustness model shows differentiated outcomes. While the full-sample ATT is not significant, disaggregated estimates reveal positive and significant effects before and during the pandemic. This suggests that TES may not yield uniform short-term improvements, but can drive growth in periods of stability or under conditions of heightened pressure and readiness to implement support. The muted full-sample result may reflect transitional frictions, timing mismatches, or structural shifts during the crisis. Overall, TES participation improves productivity in level terms and contributes to growth when contextual factors are favorable. These findings underscore the importance of period-specific analysis and support the view that TES serve as an effective policy instrument when implementation conditions are aligned.

Hypothesis 2 proposes that TES are more effective when firms possess greater intangible capital, indicating a complementary relationship between internal capabilities and external support. The empirical results from both the main and robustness models offer context-dependent evidence supporting this claim. In both models, the interaction between TES and intangible capital is significantly positive in the full sample and the pandemic subsample, with stronger effects observed during the pandemic period. This suggests that crisis conditions heightened the importance of internal capabilities—such as digital infrastructure and organizational knowledge—in leveraging external assistance. In contrast, under stable conditions, firms may not have actively engaged or aligned their intangible resources with TES inputs, resulting in insignificant complementarities. These findings point to a conditional and dynamic form of complementarity. TES are more productive when firms have stronger intangible capital, but the effect is most visible either during crises—when capabilities are mobilized under pressure—or when measured over longer timeframes. Intangible capital thus functions as a latent enabler of TES effectiveness, requiring activation through urgency or sustained engagement.

The empirical results offer a mixed assessment of Hypothesis 3. In the pre-pandemic period, a significantly negative ρ_0 indicates positive selection into non-use: firms with higher unobserved productivity were more likely to abstain from TES, likely because the expected marginal benefit was low. In contrast, ρ_1 is statistically insignificant, suggesting that TES participation was not clearly associated with latent firm capability. This asymmetric pattern indicates that, while some capable firms opted out strategically, participation may have been influenced more by institutional access or policy design than by comparative advantage. These findings partially align with the theoretical expectation of strong selection mechanisms in stable periods, while also pointing to limitations in how TES reached high-potential firms. During the pandemic, the patterns shift. Positive selection into TES (ρ_1) becomes significant and robust across both model specifications, indicating that firms with higher unobserved productivity were more likely to adopt TES, and that these firms experienced greater performance benefits. This finding runs counter to the theoretical prediction that urgent, crisis-driven behavior would weaken the strategic sorting mechanism into participation. Instead, the data suggest that TES uptake during the pandemic remained selective—possibly reflecting the resilience of high-capability firms in navigating support programs or effective policy targeting. In contrast, the evidence on selection into non-participation (ρ_0) during the pandemic is mixed. In the productivity level model, ρ_0 is significantly negative, indicating that non-users had higher unobserved productivity — a pattern consistent with comparative advantage and positive selection into non-use. This suggests that even under crisis conditions, some capable firms strategically opted out of TES, possibly due to low marginal returns. However, in the growth model, ρ_0 is statistically insignificant, implying that non-users did not differ systematically from users in terms of short-term productivity gains. This divergence suggests that, while latent capability may still have shaped TES opt-out decisions in terms of long-run performance, crisis-induced volatility and short-term constraints weakened the sorting mechanism in dynamic productivity outcomes.

The finding that ATU exceeds ATT suggests that non-users, based on their observable characteristics — such as greater intangible capital, larger size, and stronger managerial human capital — had greater potential to benefit from TES than those who actually used it. However, the significantly negative selection coefficient for non-users (ρ_0<0) indicates that these firms were positively selected on unobservables under non-treatment. This implies that their decision not to use TES was not a mistake, but a reflection of higher opportunity costs or preference for alternative knowledge channels — such as internal R&D, in-house capability development, or direct collaboration with universities. In this sense, TES may have been less attractive or redundant to these capable firms, despite their structural complementarity with TES tools. Therefore, the high ATU should not be interpreted as evidence that all such firms ought to have been treated, but rather as a signal that TES was not designed to match their mode of learning or innovation organization.

Hypothesis 4 posits that greater distance from service centers reduces the likelihood of TES participation. The main and robustness models reveal a different pattern. In the main model, time distance has a negative but statistically insignificant effect across all periods. In contrast, the robustness model shows significantly negative effects on adoption in the full sample and the pre-pandemic subsample, indicating that firms located farther from TES hubs were less likely to participate under normal conditions. However, this effect is not significant during the pandemic period, suggesting that the adoption of digital tools and remote engagement strategies may have mitigated geographic barriers. Overall, the findings provide partial support for Hypothesis 4. Distance does constrain TES participation, but the digitalization of service delivery and firm engagement appears to have reduced the importance of spatial proximity. These results underscore the importance of supporting digital transformation on both the supply and demand sides to promote equitable access to TES.

4.2 Other Findings

The analysis reveals several important secondary findings. First, managers with a STEM background are significantly more likely to lead firms that adopt TES. In the main model, the STEM coefficient is positive and significant, especially in the pre-pandemic period, and remains positive during the pandemic. The robustness model confirms significantly positive effects of STEM background on adoption in all periods. These results suggest that STEM-educated managers are better equipped to recognize the value of technical assistance and engage with external support. Their technical literacy and institutional connectivity may have been especially important during the pandemic, when rapid adaptation was critical. These findings underscore managerial human capital as a key enabler of TES uptake and identify it as a potential target for policy interventions aimed at broadening access.

Second, public subsidies for technological upgrading do not exhibit a significant complementary effect with TES. This indicates that subsidies did not enhance the effectiveness of TES among small firms, even though such synergy was expected—particularly under financial constraints. The absence of coordination between financial and technical support may reflect a misalignment in policy design: the technological goals of subsidy programs may not correspond to the practical upgrading needs that TES addresses. In short, small firms that benefited from TES may have pursued innovation goals that differed from those targeted by public funding programs.

Finally, the main results show a nonlinear relationship between manager age and productivity among non-users of TES. An inverted U-shaped pattern is observed across all periods, with productivity peaking around age 60 in the full sample. The result aligns with existing literature. Hong et al. (2020), for example, find that CEO age correlates with voluntary firm exit after age 60. This suggests that while experience contributes to performance, older managers may face declining adaptability or reduced engagement in innovation. The effect is stable across periods, suggesting the persistence of such demographic constraints on productivity. These findings point to TES as a potential renewal mechanism for aging leadership, helping sustain productivity as strategic agility wanes.

5. Discussion

The results offer strong empirical support for the productivity-enhancing role of TES, particularly under conditions that demand rapid organizational adaptation. While this finding aligns with prior research, it has several policy and theoretical implications that extend beyond confirmation of program effectiveness. First, the demonstrated impact of TES across both crisis and stable periods reinforces its function as a multi-purpose policy instrument. Rather than viewing TES solely as short-term support, the findings suggest it should be integrated as part of a long-term industrial development strategy—focused on capability accumulation, knowledge transfer, and innovation system upgrading. Second, the findings emphasize the critical role of public intermediaries like *Kohsetsushi* in sustaining regional innovation infrastructure. TES enhances firms' absorptive capacity through services ranging from technical consultation to material analysis. However, its effectiveness depends not only on service content but also on institutional design. This is particularly urgent in light of recent institutional changes: some local governments have incorporated *Kohsetsushi*—a move found to reduce technology transfer efficiency (Fukugawa, 2025). Policymakers should carefully evaluate such structural reforms in light of their potential to erode the institutional distinctiveness that underpins TES success. Third, beyond the decision to use or not use TES, many small firms remain unaware of *Kohsetsushi* altogether, meaning they are effectively excluded from the decision-making process. This informational barrier precedes self-selection and reflects a more fundamental form of exclusion. If, as the results suggest, the productivity effects of TES are generally positive, then increasing the visibility and recognition of *Kohsetsushi* among small firms could have meaningful aggregate effects on national productivity, especially in Japan where SMEs comprise the backbone of the industrial structure. Addressing this knowledge gap through proactive outreach and awareness-building campaigns should be a core priority alongside funding and service provision. Finally, for SME managers, the implication is that TES should not be treated as peripheral or one-off assistance. The results support the view that proactive and strategic integration of TES into core operations—especially during organizational transitions—can yield sustained performance gains. Public communication and targeting strategies should emphasize TES as a developmental, not merely remedial, resource.

The results offer targeted support for Hypothesis 2, suggesting that TES is most effective when paired with sufficient internal capacity, particularly during crisis conditions. Rather than viewing absorptive capacity as a fixed trait, the findings emphasize its contextual and dynamic nature—activated under pressure or accumulated through experience. This has key implications for TES policy design. First, TES should not be treated as a standalone intervention but rather as a complement to pre-existing intangible assets, such as digital systems and organizational routines. This calls for the development of capability diagnostics or readiness assessments that help policymakers identify firms most likely to benefit from TES. Second, the limited synergy between TES and government subsidies highlights a coordination gap between technical and financial programs. Aligning these instruments more effectively—by targeting firms that have both internal readiness and external needs—could amplify their collective impact. Finally, these findings reinforce the importance of sequencing interventions: capability-building efforts, including digitalization and skill development, may need to precede or co-develop with technical assistance to maximize productivity outcomes.

Beyond identifying patterns of selection regarding Hypothesis 3, the results have several implications for innovation policy and TES design. First, the persistence of positive selection into TES during the pandemic—despite widespread uncertainty—suggests that well-capitalized and strategically minded firms remained able to recognize and act on support opportunities. This implies that TES programs may serve not only as crisis-response tools, but also as mechanisms for reinforcing capability-driven growth trajectories if targeted effectively. Second, the absence of positive selection into use during stable periods points to potential misalignment between TES offerings and the perceived needs of capable firms. While some high-performing firms opted out strategically, this may reflect a design gap rather than redundancy, highlighting the need for more adaptive service models or incentive structures. Third, the divergence between level and growth model results suggests that TES benefits may not manifest in short-term productivity shifts but instead contribute to longer-term capacity building. Finally, the observed differences in uptake across managerial profiles indicate that program visibility and framing matter. Customizing outreach strategies based on managerial background—such as emphasizing technical complementarities for STEM-led firms—could help broaden the reach of TES to untapped but capable segments of the business population.

The findings on time distance and TES access yield broader implications for the spatial design of innovation support systems. While the pandemic accelerated the adoption of digital delivery, enabling greater outreach to remote firms, the persistence of spatial effects highlights the enduring importance of geographic embeddedness. Proximity enables trust-building, contextual tailoring, and spontaneous knowledge exchange—features that digital channels cannot fully replicate. This suggests that digitalization is a necessary but insufficient condition for inclusion. Rather than replacing in-person mechanisms, it should be deployed as part of a hybrid engagement model that leverages both technological reach and localized relational infrastructure. For policy, these findings highlight a growing tension between the need for localized TES engagement and the fiscal realities facing local governments. Many municipalities, particularly in peripheral regions, face declining financial capacity and are increasingly consolidating administrative functions—often centralizing TES delivery into core urban centers. This trend toward functional integration and regional divestment risks further marginalizing remote firms, precisely when hybrid service models and inclusive access are most needed. To counteract this, national or prefectural-level intervention may be required to preserve regionally distributed TES infrastructure, including localized staffing, mobile support teams, and satellite facilities. The pandemic-era expansion of digital delivery offers a valuable blueprint, but without a deliberate reinvestment in physical proximity mechanisms, spatial inequality in innovation access will persist or deepen. These structural shifts underscore that digitalization alone is not a substitute for territorially embedded support ecosystems—and that a balanced, place-sensitive policy architecture is essential to maintain national innovation coherence.

6. Conclusion

This study evaluated the impact of TES on SME productivity using an ESR framework that addresses selection bias and firm heterogeneity. Drawing on panel survey data from 2016 to 2023, the analysis highlights how TES effectiveness varies with firm capabilities, managerial traits, and geographic access. Four key findings emerge. First, TES adoption significantly enhances productivity, regardless of the period analyzed. Second, firms with stronger intangible capital benefit more from TES, especially during the pandemic, when external support was most critical, reinforcing the role of absorptive capacity. Third, adoption is shaped by unobserved productivity, consistent with comparative advantage, particularly under crisis conditions. Fourth, geographic distance remains a barrier to access, even in a digitized environment, pointing to persistent spatial inequalities. These results carry important implications. Policymakers should maintain and adapt TES programs by aligning them with financial incentives and broader capability-building initiatives. Targeted outreach is needed for firms with latent potential—particularly those led by older or non-STEM-educated managers. Overcoming spatial barriers will require hybrid delivery models and regional infrastructure investment. Overall, TES is shown to be a versatile and impactful tool for strengthening SME productivity, especially when integrated with internal capability development and delivered inclusively. For managers, the findings underscore the value of building internal systems—such as training, digital readiness, and innovation processes—that can absorb and extend the benefits of TES.

Future research should explore sector-specific effects, long-term outcomes like innovation or resilience, and cross-national comparisons to assess how institutional and digital infrastructures shape TES effectiveness. More granular data on intangible capital and heterogeneous firm responses would further enrich the understanding of how external support drives SME growth in diverse contexts.

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Table 1. Descriptive Statistics

Variable	N	Mean	Std. dev.	Min	Max
Labor productivity (growth)	4,588	-0.051	1.303	-13.908	9.213
Labor productivity (level)	6,572	2.041	1.694	-5.066	19.910
Factor score of intangible capital	6,572	0.087	0.244	-0.048	1.043
Subsidy recipient dummy	6,572	0.084	0.277	0.000	1.000
Ln(regular workers)	6,572	1.437	1.504	0.000	5.707
Ln(nonregular workers)	6,572	0.557	1.084	0.000	7.496
STEM education dummy	6,572	0.251	0.434	0.000	1.000
Manager age	6,572	61.013	9.383	29.000	94.000
High-tech industry dummy	6,572	0.169	0.374	0.000	1.000
Regional means of *Kohsetsushi* client ratio	6,572	0.307	0.461	0.000	1.000
Ln(time distance to *Kohsetsushi*)	6,556	0.206	0.132	0.000	1.000
Kohsetsushi client dummy	1,625	3.832	0.727	0.000	6.043

Table 2. Estimated ESR Models Before and During the COVID-19 Pandemic: Productivity Level Models

	2016-2023	2016-2019	2020-2023
	(1)	(2)	(3)
	Model 1	Model 2	Model 3
TES non-users			
L_INTANGIBLE	0.273	0.060	0.298
	(0.202)	(0.354)	(0.254)
L_SUBSIDY	0.073	-0.688**	0.239
	(0.164)	(0.318)	(0.202)
L_LNREG	0.264***	0.232***	0.239***
	(0.059)	(0.088)	(0.072)
L_LNNONREG	-0.336***	-0.428***	-0.274***
	(0.073)	(0.108)	(0.084)
STEM	-0.232	-0.595**	-0.035
	(0.156)	(0.289)	(0.178)
L_AGE	0.295***	0.463***	0.228***
	(0.073)	(0.151)	(0.087)
L_AGE2	-0.002***	-0.004***	-0.002***
	(0.001)	(0.001)	(0.001)
_CONS	89.838	-493.267	202.762
	(91.163)	(341.338)	(167.318)
TES users			
L_INTANGIBLE	0.666***	0.014	0.752**
	(0.246)	(0.567)	(0.334)
L_SUBSIDY	0.268	0.627	0.230
	(0.195)	(0.461)	(0.263)

	2016-2023	2016-2019	2020-2023
L_LNREG	0.281***	0.036	0.261**
	(0.084)	(0.161)	(0.115)
L_LNNONREG	0.220**	0.125	0.221*
	(0.090)	(0.167)	(0.117)
STEM	0.677***	0.574	0.519*
	(0.230)	(0.505)	(0.292)
L_AGE	-0.069	0.001	-0.059
	(0.095)	(0.228)	(0.121)
L_AGE2	0.000	-0.000	0.000
	(0.001)	(0.002)	(0.001)
_CONS	57.513	-384.608	-103.838
	(119.708)	(536.096)	(253.819)
SELECT			
REGIONALMEAN	1.916***	2.730***	2.127***
	(0.322)	(0.511)	(0.446)
TIMEDISTANCE	-0.019	-0.007	-0.062
	(0.055)	(0.086)	(0.075)
INTANGIBLE	0.296***	0.080	0.348**
	(0.102)	(0.170)	(0.142)
SUBSIDY	0.420***	0.536***	0.418***
	(0.084)	(0.140)	(0.116)
LNREG	0.105***	0.067	0.136***
	(0.035)	(0.051)	(0.048)

	2016-2023	2016-2019	2020-2023
LNNONREG	0.099***	0.074	0.109**
	(0.038)	(0.049)	(0.049)
STEM	0.290***	0.410***	0.237*
	(0.095)	(0.150)	(0.124)
AGE	-0.010*	-0.017*	-0.012*
	(0.005)	(0.010)	(0.007)
_CONS	-22.367	53.201	-204.622*
	(55.566)	(185.172)	(112.429)
OBSERVATIONS	873.000	339.000	565.000

Level of significance: *** 1%, ** 5%, * 10%.
Standard errors in parentheses

Table 3. ATT and ATU Before and During the COVID-19 Pandemic: Productivity Level Models

Period	Estimator	Treated	Untreated	Difference	Significance
All Years (2016–2023)	ATT	3.008	0.336	2.672	***
	ATU	2.688	-0.146	2.834	***
Pre-pandemic (2016–2019)	ATT	3.067	-0.175	3.243	***
	ATU	3.137	2.084	1.053	***
Pandemic (2020–2023)	ATT	2.978	0.685	2.292	***
	ATU	2.628	0.029	2.599	***

Notes
Level of significance: *** 1%, ** 5%, * 10%.

Table 4. Estimated ESR Models Before and During the COVID-19 Pandemic: Productivity Growth Models

	2016-2023	2016-2019	2020-2023
	(1)	(2)	(3)
	Model 1	Model 2	Model 3
TES non-users			
LP	-0.369***	-0.299***	-0.562***
	(0.028)	(0.039)	(0.041)
L_INTANGIBLE	0.023	-0.454*	0.466*
	(0.187)	(0.244)	(0.250)
L_SUBSIDY	0.208	-0.124	0.325
	(0.164)	(0.215)	(0.209)
L_LNREG	0.130***	0.100	0.162**
	(0.047)	(0.063)	(0.066)
L_LNNONREG	-0.029	-0.067	-0.006
	(0.060)	(0.080)	(0.087)
STEM	-0.040	-0.169	0.039
	(0.112)	(0.151)	(0.154)
L_AGE	0.075	0.062	0.167*
	(0.062)	(0.084)	(0.086)
L_AGE2	-0.001	-0.001	-0.001**
	(0.001)	(0.001)	(0.001)
_CONS	90.669	-9.850	-84.022
	(63.958)	(140.067)	(177.608)
TES users			
LP	-0.361***	-0.390***	-0.300***
	(0.052)	(0.064)	(0.078)
L_INTANGIBLE	0.452*	0.429	0.644*
	(0.232)	(0.295)	(0.370)
L_SUBSIDY	-0.194	-0.115	-0.062
	(0.192)	(0.239)	(0.294)
L_LNREG	0.140*	0.117	0.296**
	(0.073)	(0.090)	(0.121)
L_LNNONREG	0.029	0.011	0.082
	(0.072)	(0.091)	(0.119)
STEM	0.194	0.346	-0.131
	(0.183)	(0.230)	(0.292)
L_AGE	0.038	0.151	-0.062
	(0.080)	(0.113)	(0.090)

	2016-2023	2016-2019	2020-2023
L_AGE2	-0.000	-0.002	0.000
	(0.001)	(0.001)	(0.001)
_CONS	-28.390	-42.860	322.461
	(95.386)	(196.382)	(315.043)
SELECT			
REGIONALMEAN	3.368***	3.221***	3.822***
	(0.471)	(0.560)	(0.741)
TIMEDISTANCE	-0.179**	-0.169*	0.017
	(0.080)	(0.091)	(0.126)
INTANGIBLE	0.566***	0.578***	0.371
	(0.141)	(0.175)	(0.231)
SUBSIDY	0.589***	0.551***	0.712***
	(0.119)	(0.149)	(0.205)
LNREG	0.199***	0.135**	0.297***
	(0.043)	(0.053)	(0.073)
LNNONREG	0.015	0.009	0.092
	(0.049)	(0.061)	(0.083)
STEM	0.348***	0.347***	0.357**
	(0.107)	(0.131)	(0.181)
AGE	-0.015***	-0.005	-0.032***
	(0.006)	(0.007)	(0.010)
_CONS	20.284	1.325	-94.529
	(62.394)	(120.356)	(218.127)
OBSERVATIONS	877.000	547.000	330.000

Level of significance: *** 1%, ** 5%, * 10%.
Standard errors in parentheses

Table 5. ATT and ATU Before and During the COVID-19 Pandemic: Productivity Growth Models

Period	Estimator	Treated	Untreated	Difference	Significance
All Years (2016–2023)	ATT	0.120	0.124	-0.004	
	ATU	-0.030	-0.643	0.613	***
Pre-pandemic (2016–2019)	ATT	0.065	-1.170	1.234	***
	ATU	0.084	-0.504	0.588	***
Pandemic (2020–2023)	ATT	0.483	0.332	0.152	***
	ATU	-0.156	-1.636	1.480	***

Level of significance: *** 1%, ** 5%, * 10%.

Table 6. Consolidated Summary: Productivity Level and Productivity Growth Models

Key factor	Hypothesis	2016-2023 Level	2016-2019 Level	2020-2023 Level	2016-2023 Growth	2016-2019 Growth	2020-2023 Growth
ATT (TES impact on productivity)	H1	2.672***	3.243***	2.292***	-0.004	1.234***	0.152***
ATU (TES impact on productivity for non-users)	.	2.834***	1.053***	2.599***	0.613***	0.588***	1.480***
Complementarity (TES × Intangible capital)	H2	0.666***	0.014	0.752**	0.452*	0.429	0.644*
Selection into TES (*ρ1*)	H3	0.856***	0.201	0.804***	0.331**	0.213	0.902***
Selection into not using TES (*ρ0*)	H3	-0.905***	-0.955***	-0.856***	0.005	-0.590***	0.131
Selection dynamics	H3	Comparative advantage	Positive selection into non-user	Comparative advantage	Positive selection into TES user	Positive selection into non-user	Positive selection into TES user
Effect of time distance on TES use (results from the first-stage selection model)	H4	-0.019	-0.007	-0.062	-0.179**	-0.169*	0.017

Level of significance: *** 1%, ** 5%, * 10%.

Appendix Table 1 Number of *Kohsetsushi* Users by Region

Region	Non-users	Users	Total
North	92	19	111
Metro	545	138	683
Central	363	84	447
West	343	132	475
Southwest	70	18	88
Total	1,413	391	1,804

Pearson $\chi^2(4) = 14.95$, $p = 0.005$

Appendix Table 2 Number of *Kohsetsushi* Users by Technological Intensity

Category	Non-users	Users	Total
Low-tech (Mfg)	244	80	324
Mid-tech (Mfg)	482	147	629
High-tech (Mfg)	136	59	195
Other Mfg	254	92	346
Non-Mfg	142	1	143
Total	1,258	379	1,637

Pearson $\chi^2(4) = 48.80$, $p < 0.001$

Appendix Table 3 Number of *Kohsetsushi* Users by Period

Period	Non-users	Users	Total
Pre-pandemic	687	202	889
Pandemic	726	189	915
Total	1,413	391	1,804

Pearson $\chi^2(1) = 1.13$, $p = 0.287$

Appendix Table 4 ICT investment by Period

ICT Variable	Pandemic = 0	Pandemic = 1	Pearson χ^2	p-value
ICT Hardware = 1	707 (20.7%)	701 (20.1%)	0.396	0.529
ICT Software = 1	341 (10.0%)	382 (10.9%)	1.710	0.191
ICT Service = 1	237 (6.9%)	293 (8.4%)	5.177	0.023