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The Productivity Effects of Cross-Border Data Flows: Evidence from Japanese firm-level data*

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Abstract

This paper examines the effect of initiating cross-border data flows on firm productivity, using original survey data from Japanese manufacturing and service firms collected in 2019 and 2021, merged with annual productivity measures over 2019–2022. The survey identifies new entrants into cross-border data transfers, enabling a difference-in-differences design that compares "switchers" to firms that either do not collect data or collect data only domestically. We estimate the average treatment effect on the treated using regression-adjustment, inverse probability weighting, and doubly robust AIPW DID estimators, controlling for exporter status, multinational affiliation, R&D intensity, and ICT cost intensity. The results show that firms with higher initial productivity are more likely to start transferring data internationally, which is consistent with self-selection patterns documented in the export- and FDI-related literature. Entry into cross-border data flows is associated with significant productivity gains, which become particularly pronounced in the year after entry. These findings provide rare firm-level evidence from Japan, while also offering broader insights for data-governance debates by highlighting the potential productivity costs of overly restrictive cross-border data regulations.

Keywords: Cross-border data flows; Firm productivity; Difference-in-differences; Firm-level survey data; Japan
JEL Classification: F14; F23; O33; L86;

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1. Introduction

The rapid expansion of the digital economy has transformed the way firms produce, exchange information, and innovate. Among the various channels of digital globalization, cross-border data flows have emerged as a critical enabler of economic activity, facilitating real-time communication, remote service provision, and integration into global value chains. For both manufacturing and service firms, the ability to transfer data internationally supports efficiency gains through better coordination, market access, and integration of advanced digital tools such as cloud computing and artificial intelligence. This study examines how engaging in cross-border data flows influences firm productivity.

In the evolving landscape of globalization, the trade in intermediate services has become increasingly prominent, complementing traditional goods trade. Baldwin et al. (2024) argue that the future of international trade lies largely in intermediate services, reflecting a structural shift toward intangible, knowledge-intensive cross-border exchanges. These services frequently require real-time data transfers and seamless digital connectivity. Key pathways for such trade include: (i) global gig work and crowdsourcing platforms such as Fiverr, Freelancer, and Upwork, which connect firms with freelance talent worldwide; (ii) business process outsourcing (BPO) operations, encompassing activities such as call centers, customer service, marketing, debt collection, and other back-office functions; and (iii) the establishment of shared service centers (SSCs) by multinational corporations, which consolidate human resources, accounting, legal, IT, and administrative functions for multiple subsidiaries.

Theoretical work on globalization and firm performance has been dominated by heterogeneous-firm models (Melitz, 2003), which predict that only more productive firms can afford the fixed costs of entering international markets. Relatedly, the "learning-by-exporting" literature shows that firms entering export markets can enhance productivity by absorbing advanced technologies, managerial know-how, and market knowledge from foreign buyers (Clerides, Lach, & Tybout, 1998; Bernard & Jensen, 1999). Similarly, research on foreign direct investment (FDI) highlights productivity gains from integrating into global production networks and benefiting from knowledge spillovers (Keller, 2004; Branstetter, 2006). While most of this literature has focused on goods trade and capital flows, cross-border data transfers can be viewed as a digital form of internationalization that operates through analogous mechanisms—requiring firms to overcome fixed entry costs (e.g., investment in IT systems, cybersecurity compliance, interoperability with foreign standards) and enabling them to capture learning benefits once connected to global digital networks.

Despite the growing policy relevance of digital connectivity, empirical studies on the economic effects of cross-border data flows remain relatively scarce. Freund and Weinhold (2004) found that internet penetration boosted bilateral trade in goods, suggesting that digital connectivity facilitates market access. More recent research has examined the role of data flows in enabling cross-border services trade and increasing productivity at the sectoral level (Bauer et al., 2016; Ferracane & van der Marel, 2018). However, most existing work relies on aggregate proxies such as internet bandwidth or modeled data traffic estimates, which do not reveal firm-level engagement in international data transfers. Firm-level evidence remains limited, despite calls by UNCTAD (2021) for more microdata-based research on the digital economy.

Two key gaps motivate this study. First, the mechanisms by which cross-border data flows affect firm performance remain insufficiently theorized relative to goods trade and FDI. It is unclear whether digital flows follow similar self-selection patterns, and to what extent their productivity effects operate through channels such as cost reduction, product quality enhancement, or innovation acceleration. Without firm-level evidence, it is difficult to assess whether engagement in cross-border data flows merely reflects pre-existing competitiveness or constitutes an independent driver of performance. Second, unlike international merchandise trade—which is comprehensively captured in customs statistics—there is no official statistical system that systematically records cross-border data transfers. As a result, prior research has been constrained to aggregate indicators, preventing precise identification of the firms involved, the timing of their entry into international data flows, and the associated performance changes. This data gap has been recognized as a major barrier to advancing empirical work in the field (UNCTAD, 2021).

This study addresses these gaps by using original firm-level survey data from Japanese manufacturing and service firms collected in 2019 and 2021. The surveys directly ask whether firms engage in cross-border data transfers, allowing us to identify new entrants into such activities between the two survey periods. Using a difference-in-differences (DID) framework, we estimate the causal effect of initiating cross-border data flows on firm productivity, while also examining the selection patterns into digital globalization.

Our analysis yields two main findings. First, firms with higher initial productivity are more likely to engage in cross-border data transfers, consistent with self-selection patterns observed in the exporting and FDI literature. Second, firms that begin transferring data internationally experience statistically significant productivity gains, suggesting that global data access enhances efficiency and innovation in a manner analogous to learning-by-exporting effects. These findings contribute to the literature by providing rare firm-level evidence on the productivity effects of cross-border data flows, using microdata from Japan. While the Japanese context offers a distinctive case, the results also carry broader implications for understanding how cross-border data flows affect firm performance in advanced economies more generally.

The remainder of this paper is organized as follows. Section 2 describes the data collection process and descriptive analyses. Section 3 outlines the empirical strategy for performing DID technique. Section 4 presents the estimation results of DID. Section 5 concludes the paper.

2. Data and Descriptive Analyses

We conducted two large-scale questionnaire surveys of Japanese firms in 2019 and 2021 to examine corporate activities related to cross-border data collection and their potential effects on productivity. The target population consisted of large and mid-sized firms—defined as those with at least 50 employees and capital of at least 30 million yen—in the manufacturing, wholesale, and information-related service industries. The 2019 survey was sent to 19,790 firms in April, yielding 4,227 responses (21.3%).[1] The 2021 survey was sent to 22,948 firms in February, yielding 6,722 responses (29.3%). These response rates are relatively high for academic firm surveys.[2]

The questionnaire defined "data collection" as the continuous and deliberate collection of raw digital information—such as customer purchase histories, machine maintenance records, or employee personal data—through daily business operations, excluding purchases of pre-prepared databases.[3] Respondents selected one of four options:

[1] The "Survey of Cross-border Data Flows of Firms" was conducted by the Tokyo Shoko Research Co., Ltd. (TSR) for our research project at the RIETI. We sent the questionnaire to all firms in the sectors covered by the METI's *Basic Survey of Japanese Business Structure and Activities* (BSJBSA, *Keizaisangyosho Kigyo katsudo kihon chosa* in Japanese).

[2] The "Survey of Globalization and Reduced Face-to-face Contacts during the COVID-19 Pandemic" was conducted by TSR for our research project at RIETI. We sent the questionnaire to all firms in the manufacturing and wholesale sectors covered by the METI's BSJBSA.

[3] Although an exact definition of "data" has not been established in this context, there have been several discussions on the conceptualization of a definition. For example, see (Gonzáles and Jouanjean, 2017).

1. *Continuous digital data collection in both Japan and overseas ("Domestic & Overseas")*

2. *Continuous digital data collection in Japan only ("Domestic")*

3. *Continuous digital data collection overseas only ("Overseas")*

4. *No continuous data collection in either Japan or overseas ("None").*

The distribution of firms responding to the data collection questions in each survey is presented in Table 1.[4] Given the small number of "Overseas only" cases, these were merged with "Domestic & Overseas" into a single "Overseas-involved" category for analysis. firms not engaged in continuous data collection comprised the largest group in both 2019 and 2021, followed by those engaged only in domestic data collection. Overseas-involved data collection was least common but grew notably between the two surveys. Overall, the share of firms engaged in any form of data collection rose from about 30% in 2019 to over 50% in 2021, with the share engaged in overseas-involved collection roughly doubling. This marked shift raises the question of which firms entered overseas data collection and how such entry relates to subsequent productivity changes.

[4] The detailed results of our surveys are summarized in (Tomiura et al, 2019; 2020) for the 2019 survey.

Table 1. Response distribution for questions regarding data collection activities

	2019		2021	
No dataflows	2891	71.8%	2967	44.7%
Domestic	691	17.2%	2096	31.6%
Dom&Overseas	443	11.0%	1574	23.7%
Total	4025	100.0%	6637	100.0%

To investigate this, we constructed a balanced panel of 2,108 firms that responded to both surveys. Table 2(a) cross-tabulates their data collection status in 2019 (rows) and 2021 (columns). Firms on the diagonal (52.2% of the sample) maintained the same status, while nearly one-third (21.1% + 11.1%) initiated some form of data collection. Importantly, 14.2% began overseas-involved collection, compared to 5.6% that exited it. Panels 2(b) and 2(c) indicate broadly similar patterns for manufacturing and non-manufacturing firms, although manufacturing shows a slightly higher share of overseas-involved collection.

Table 2. Distribution of data collection status changes from 2019 to 2021

(a) Total	2021			
2019	No dataflows	Domestic	Dom&Overseas	Total
No dataflows	862 (40.9%)	444 (21.1%)	234 (11.1%)	1540
Domestic	146 (6.9%)	136 (6.5%)	66 (3.1%)	348
Dom&Overseas	55 (2.6%)	64 (3.0%)	101 (4.8%)	220
Total	1063	644	396	2108 (100%)

(b) Manufacturing				
2019	No dataflows	Domestic	Dom&Overseas	Total
No dataflows	547 (39.7%)	285 (20.7%)	161 (11.7%)	993
Domestic	96 (7.0%)	92 (6.7%)	45 (3.3%)	233
Dom&Overseas	38 (2.8%)	39 (2.8%)	76 (5.5%)	153
Total	681	416	282	1379 (100%)

(c) Non-manufacturing				
2019	No dataflows	Domestic	Dom&Overseas	Total
No dataflows	315 (43.2%)	159 (21.8%)	73 (10.0%)	547
Domestic	50 (6.9%)	44 (6.0%)	21 (2.9%)	115
Dom&Overseas	17 (2.3%)	25 (3.4%)	25 (3.4%)	67
Total	382	228	119	729 (100%)

Table 3 reports the mean 2019 labor productivity (value added per employee, log-transformed) corresponding to each cell in Table 2. Firm-level data for labor productivity were obtained from METI's BSJBSA in 2019.[5] In both years, and across both manufacturing and non-manufacturing sectors, overseas-involved collectors consistently exhibit the highest productivity,

[5] The METI conducts this survey annually by imposing legal reporting obligation for all mid- or large-sized firms as defined above. Firms are required to report the previous year's information on a non-consolidated firm basis.

followed by domestic-only collectors, and then non-collectors. Moreover, among firms changing status, those that initiated overseas-involved collection between 2019 and 2021 display higher baseline productivity than those initiating domestic-only collection.

Table 3. Data collection status changes from 2019 to 2021 and productivity in 2019

(a) Total	2021			
2019	No dataflows	Domestic	Dom&Overseas	Total
No dataflows	1.706	1.747	1.847	1.739
Domestic	1.703	1.864	1.830	1.790
Dom&Overseas	1.878	1.933	1.986	1.944
Total	1.714	1.790	1.879	1.769

(b) Manufacturing	2021			
2019	No dataflows	Domestic	Dom&Overseas	Total
No dataflows	1.684	1.749	1.824	1.727
Domestic	1.685	1.830	1.786	1.761
Dom&Overseas	1.888	1.914	1.916	1.917
Total	1.731	1.803	1.910	1.752

(c) Non-manufacturing	2021			
2019	No dataflows	Domestic	Dom&Overseas	Total
No dataflows	1.744	1.745	1.897	1.765
Domestic	1.738	1.935	1.925	1.852
Dom&Overseas	1.854	1.963	2.201	2.025
Total	1.788	1.843	2.039	1.802

These descriptive patterns are consistent with heterogeneous-firm models of globalization, in which more productive firms are more likely to bear the fixed costs of engaging in internationally integrated activities such as cross-border data flows. However, descriptive statistics alone cannot establish whether initiating overseas data collection causally improves productivity. In the next section, we implement a DID approach to estimate the causal impact of switching into overseas-involved data collection on firm productivity from 2019 to 2022.

3. Empirical Analysis

To estimate the causal effect of initiating overseas-involved data collection on firm productivity, we employ a difference-in-differences (DID) research design with a single treatment timing. Since all treated firms begin overseas-involved data collection in the same year (2021), the empirical setting corresponds to a single-cohort DID design, and causal identification relies on within-firm changes relative to untreated firms under the parallel trends assumption. Our treatment group ("Switchers") consists of the 234 firms that reported no data collection in 2019 but overseas-involved collection ("Domestic & Overseas") in 2021, plus the 66 firms that reported domestic-only collection in 2019 but overseas-involved collection in 2021—a total of 300 treated firms. The control group comprises 1,500 firms that in both 2019 and 2021 either (i) did not collect data or (ii) collected data only domestically.

To ensure robustness to model misspecification, we implement three alternative DID estimators based on the framework of Sant'Anna and Zhao (2020): (i) regression adjustment DID (RA-DID), (ii) inverse probability weighting DID (IPW-DID), and (iii) augmented inverse probability weighting DID (AIPW-DID). These estimators differ in how they model the outcome process and the treatment assignment process, while identifying the same causal parameter—the average treatment effect on the treated (ATT).

RA-DID adjusts for observable differences between treated and control firms by modeling the untreated potential outcome as a function of covariates. IPW-DID instead reweights control firms using estimated propensity scores to construct a comparison group that is observationally similar to the treated firms. AIPW-DID combines both approaches and enjoys double robustness: consistency is guaranteed if either the outcome regression or the propensity score model is correctly specified. Given the presence of non-random self-selection into overseas-involved data collection based on exporting behavior, multinational activity, and innovation intensity, we adopt AIPW-DID as our preferred estimator, while reporting RA-DID and IPW-DID side by side for comparison.

We examine two alternative measures of firm performance, both constructed from firm-level data in METI's Basic Survey of Japanese Business Structure and Activities (BSJBSA). The first is labor productivity, calculated annually as the logarithm of value added per employee. The second is total factor productivity (TFP), estimated following the method of Levinsohn and Petrin (2003), which addresses simultaneity bias in production function estimation by using intermediate inputs as proxies for unobserved productivity shocks. Both measures are available for each year from 2019 through 2022, thereby covering the pre-treatment year (2019) and the post-treatment period from the initiation of overseas-involved data collection, as identified in the 2021 survey, through 2022.

Our baseline DID model is specified as follows:

$$y_{it} = \beta(Switcher_i \times Post_t) + \gamma' X_{it} + \delta_i + \theta_t + \varepsilon_{it},$$

where y_{it} denotes either log labor productivity or TFP for firm *i* in year *t*; $Switcher_i$ is a binary variable indicating treatment status; $Post_t$ is an indicator for the post-treatment period equal to one for 2021 and 2022; δ_i are firm fixed effects controlling for time-invariant heterogeneity; θ_t are year fixed effects controlling for macroeconomic shocks; X_{it} is a vector of control variables, and ε_{it} is an idiosyncratic error term. In our empirical implementation, the control variables include an exporter dummy, a multinational enterprise (MNE) dummy, R&D intensity, and information and communication cost intensity, each measured at the firm level. Standard errors are clustered at the firm level. The coefficient β captures the ATT, i.e., the causal impact of initiating overseas-involved data collection on productivity.

In the RA, IPW, and AIPW implementations, the causal parameter of interest remains the same—the ATT—while the adjustment for selection on observables differs across estimators. In particular, AIPW combines an outcome regression Formally, the AIPW estimator for the ATT combines an outcome regression $m_0(X_{it}, t)$ for the untreated potential outcome with a propensity score mode $e(X_i) = P(Switcher_i = 1|X_i)$, yielding a doubly robust DID estimator constructed as a weighted difference in residual outcome changes between treated and reweighted control firms.

Importantly, although these estimators differ in implementation, the underlying identification strategy remains that of a standard two-way fixed effects DID design, as all treated firms experience treatment initiation in the same year (2021). Accordingly, treatment effects are identified from within-firm changes relative to comparable untreated firms, conditional on observed covariates.

The parallel trends assumption is assessed using an event-study specification based on the dynamic ATT profiles obtained from RA-DID, IPW-DID, and AIPW-DID estimators. The year 2020 (one year prior to treatment) is taken as the reference period. If the estimated pre-treatment coefficient for 2019 (two years before treatment) is statistically indistinguishable from zero, this provides empirical support for the validity of the parallel trends assumption for our key outcome variables: labor productivity and Total Factor Productivity (TFP). This is visually confirmed in the diagnostic event-study plots in Figures 1 and 2, where treated and control firms exhibit nearly identical pre-treatment paths. In our data, the pre-treatment estimates for labor productivity are indeed close to zero and statistically insignificant (P=0.189)). A similar result was obtained for TFP, with pre-treatment estimates also being statistically insignificant (P=0.099). These findings collectively support the identifying assumption of the DID design for both productivity measures.

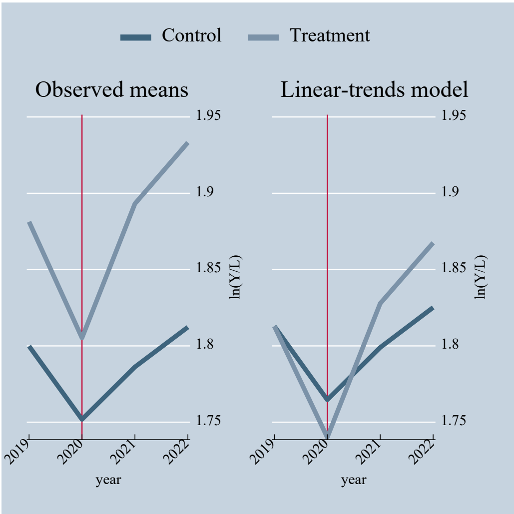

Figure 1. Parallel Trends Assumption Check (Labor productivity)

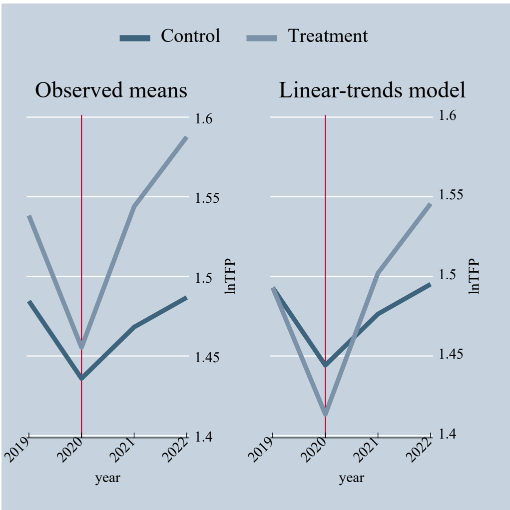

Figure 2. Parallel Trends Assumption Check (TFP)

4. Results

Table 4 reports the estimated ATT from the three DID estimators discussed in Section 3: regression-adjustment DID (RA-DID), inverse probability weighting DID (IPW-DID), and augmented inverse probability weighting DID (AIPW-DID). All specifications include the same set of firm-level controls— exporting, multinational status, R&D intensity, and ICT cost intensity—and standard errors are clustered at the firm level.

Across the three estimators, the ATT estimates are remarkably similar in magnitude. For log labor productivity, the overall ATT lies between 0.044 (RA-DID) and 0.047 (IPW-DID and AIPW-DID), implying an average productivity gain of about 4–5 percent among treated firms relative to controls over the post-treatment period (2021–2022). For TFP, the overall ATT is between 0.054 and 0.056, corresponding to an average TFP increase of roughly 5–6 percent. These effects are statistically significant at conventional levels, indicating that firms initiating overseas-involved data collection in 2021 experience economically meaningful improvements in both labor productivity and TFP compared with firms that either do not collect data or collect only domestically. The close agreement of RA, IPW, and AIPW estimates suggests that the main findings are not driven by a particular modeling choice for either the outcome or the treatment assignment process, while the doubly robust AIPW estimator can be regarded as our preferred specification.

The year-specific ATT estimates further illuminate the dynamics of the treatment effect.

For both labor productivity and TFP, the 2020 coefficients are negative but small and statistically insignificant, consistent with the absence of systematic pre-trends between treated and control firms. In contrast, the 2022 coefficients are positive and statistically significant across all three estimators. Under the AIPW specification, the 2022 ATT is 0.061 for log labor productivity and 0.076 for TFP, both significant at the 5–1 percent levels. The 2021 coefficients are positive but not statistically significant, suggesting that the productivity gains from overseas-involved data collection materialize more clearly in the second post-treatment year rather than immediately at the time of treatment initiation.

Figures 3 and 4 plot the dynamic treatment effects from the AIPW-based event-study estimates for labor productivity and TFP, respectively, using the same specification with the aforementioned firm-level controls. Each figure shows point estimates by relative time with 95% confidence intervals, where 2021 is the treatment year and 2019–2020 are pre-treatment years. The pre-treatment coefficients are close to zero and statistically insignificant, providing visual support for the parallel trends assumption. Post-treatment coefficients exhibit a moderate increase in 2021 and a larger, statistically significant rise in 2022, mirroring the patterns observed in Table 4. Taken together, the table and figures indicate that, conditional on exporter status, MNE status, R&D intensity, and ICT cost intensity, overseas-involved data collection is associated with a lagged but sustained improvement in firm productivity.

Table 4. ATT Estimates for Labor Productivity and TFP from RA, IPW, and AIPW-DID Regressions

Productivity	Year	RA-DID	IPW-DID	AIPW-DID
ln(Y/L)	2020	-0.0279	-0.0261	-0.0294
		[0.0216]	[0.0204]	[0.0218]
	2021	0.0309	0.0319	0.0322
		[0.0259]	[0.0259]	[0.0258]
	2022	0.0578**	0.0612**	0.0614**
		[0.0281]	[0.0283]	[0.0282]
	overall	0.044*	0.047**	0.047**
		[0.0233]	[0.0233]	[0.0233]
lnTFP	2020	-0.0339	-0.0308	-0.0355
		[0.0223]	[0.0203]	[0.0224]
	2021	0.035	0.0362	0.0365
		[0.0259]	[0.0258]	[0.0258]
	2022	0.0728**	0.0758***	0.0760***
		[0.0283]	[0.0285]	[0.0285]
	overall	0.054**	0.056**	0.056**
		[0.0232]	[0.0232]	[0.0232]

Note: Estimates are obtained from regression-adjustment DID (RA-DID), inverse probability weighting DID (IPW-DID), and augmented inverse probability weighting DID (AIPW-DID). Heteroskedasticity-robust standard errors clustered at the firm level are reported in brackets. All specifications include an exporter dummy, a multinational enterprise dummy, R&D intensity, and ICT cost intensity. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

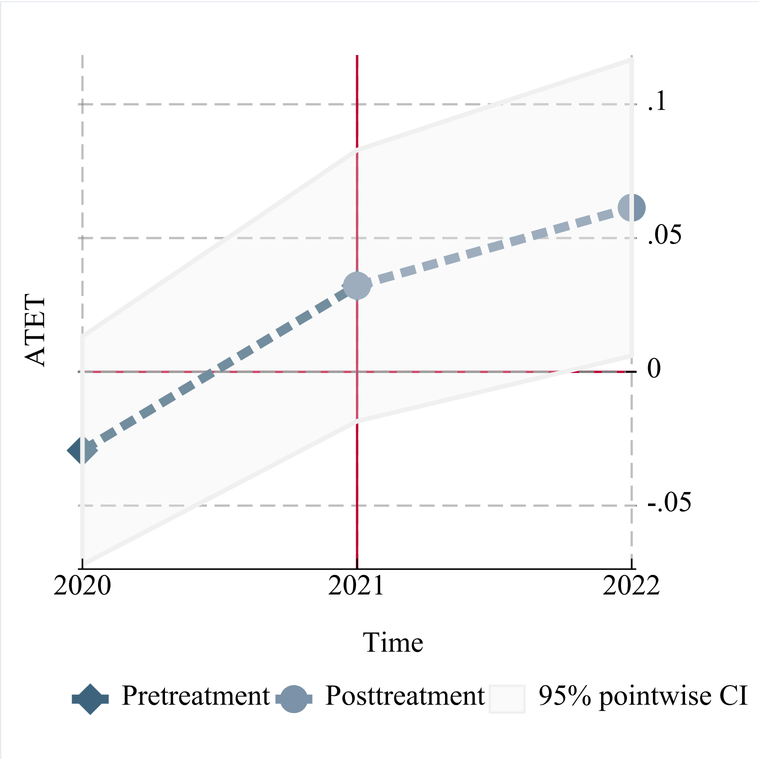

Figure 3. Dynamic Treatment Effects for Labor Productivity (AIPW-DID)

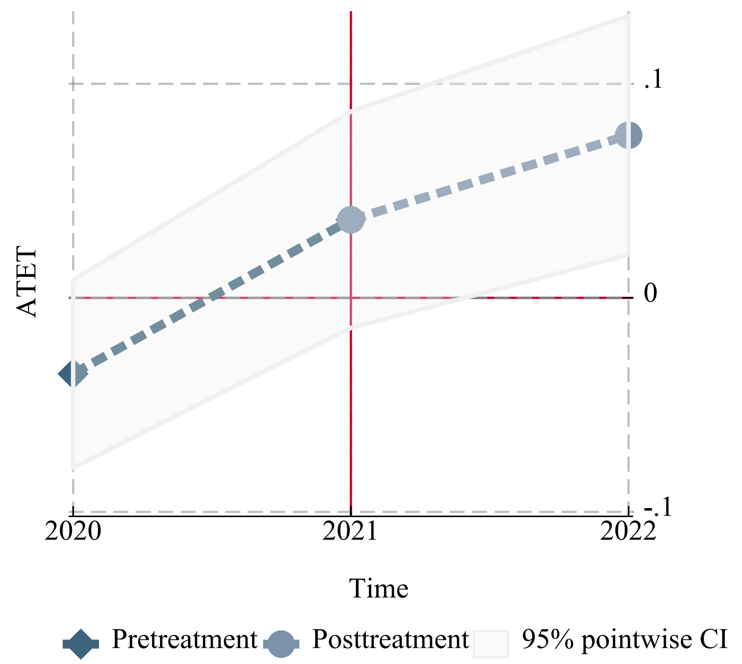

Figure 4. Dynamic Treatment Effects for TFP (AIPW-DID)

5. Conclusions

This paper provides firm-level evidence on the productivity effects of engaging in cross-border data flows, using original Japanese survey data merged with official productivity measures over 2019–2022. Implementing a DID identification strategy with firm and year fixed effects, and estimating the ATT via RA, IPW, and doubly robust AIPW DID estimators, we show that firms initiating overseas-involved data collection in 2021 realize statistically and economically significant improvements in both labor productivity and TFP relative to comparable firms that either do not collect data or collect only domestically. The close agreement of RA, IPW, and AIPW estimates, together with the absence of significant pre-treatment differences, supports the parallel trends assumption and strengthens the causal interpretation of our findings. Moreover, the dynamic event-study results indicate that productivity gains become particularly pronounced in the second post-treatment year (2022), suggesting a lagged but sustained effect rather than an immediate, one-off response to treatment.

Interpretively, these results are consistent with the "learning-by-exporting" and related literatures on the productivity effects of internationalization, in which engagement in cross-border activities—such as exporting or foreign direct investment—enhances firm performance through exposure to advanced technologies, managerial practices, and global knowledge networks (Clerides, Lach, & Tybout, 1998; Bernard & Jensen, 1999; Branstetter, 2006; De Loecker, 2013).

In the present context, initiating overseas-involved data collection can be viewed as a form of digital internationalization that facilitates similar learning channels: improving efficiency via better coordination with foreign partners, leveraging richer and more diverse data resources, and integrating into international digital ecosystems. From a policy perspective, the findings caution that stringent restrictions on cross-border data flows may entail unintended costs by limiting firms' ability to realize such productivity gains, underscoring the importance of balanced data-governance frameworks that safeguard privacy and security while preserving open and interoperable digital connectivity.

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