RIETI Discussion Paper Series 26-E-027

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

RIETI Discussion Paper Series 26-E-027
April 2026

Inter-Firm Network Dynamics of Production during the COVID-19 Pandemic*

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Abstract

This paper examines the dynamics of the Japanese production network during the COVID-19 pandemic. We utilize a panel dataset of approximately 1.8 million firms spanning from 2015 to 2023 and document that firms largely maintained existing inter-firm relationships during the early stages of the pandemic, often before severing ties in subsequent periods. Moreover, new link formation did not recover at a commensurate pace, resulting a net contraction of the production network. Furthermore, we identify a shift in the geographical distance between transacted firms. Firms increasingly dropped local partners but added distant partners. Notably, changes in network dynamics and geographical distance were driven by firms with high ICT intensity and those located in core prefectures.

Keywords: Production Networks, COVID-19, ICT
JEL classification: D22, D85, E32, L14, R12

*This study is conducted as a part of the Project "Innovation, Globalization and Employment" undertaken at the Research Institute of Economy, Trade and Industry (RIETI) and financially supported by JSPS KAKENHI Grant Number "20K20511". The draft of this paper was presented at the RIETI DP seminar for the paper. The authors would like to thank participants of the RIETI DP Seminar for their helpful comments.

1 Introduction

Production networks are central to the economy. While they facilitate specialisation and act as a transmission mechanism for microeconomic shocks, propagating idiosyncratic disturbances into aggregate fluctuations (Acemoglu et al., 2016a). However, the vast majority of this literature treats the production network as a static conduit—a fixed architecture through which shocks travel. Far less is understood about endogenous production networks: how their geographical distances change in response to aggregate crises (Acemoglu and Azar, 2020). This distinction is critical because the ability of an economy to recover depends not just on the transmission of shocks, but on the capacity of agents to form new relationships and bypass severed ones.

Meanwhile, the recent COVID-19 outbreak raises questions about how the pandemic affects the global and local economies in diverse ways. A series of literature navigated production networks to explore how COVID-19 shocks affected firm performances and how they propagated through the network of firms.[1] Nonetheless, we spot a gap in research investigating how the pandemic affects the creation and termination of production networks, which remains underexplored. This research aims to provide new evidence to fill this gap.

This paper investigates the endogenous dynamics of the Japanese inter-firm production network during the COVID-19 pandemic. We view the pandemic not merely as a contraction in supply and demand, but as a shock to the search and matching conditions within the inter-firm transactional network. Mobility restrictions and heightened uncertainty dramatically increased the transaction costs of identifying and vetting new trading partners. Using this framework, we ask two central questions: First, how did the extensive margin of link creation and destruction evolve during the COVID-19 pandemic? Second, which firm-level characteristics governed such dynamics? Specifically, we explore how location and digital capabilities determine the dynamics of inter-firm linkages during the pandemic.

To answer these questions, we exploit a firm-level dataset from Tokyo Shoko Research (TSR), covering approximately 1.8 million firms and their transactional linkages from 2015 to 2023.

[1] Recent studies focused on how COVID-19 shocks propagate through production networks. Baqaee and Farhi (2020) and Baqaee and Farhi (2021) have shown that a COVID-induced supply shock to a single sector can be amplified through production networks by incomplete substitutability between consumption and production sectors, with the degree of propagation amounting to 100%. Baqaee and Farhi (2022) added that this interaction could strengthen or weaken the effects of stimulus economic policies depending on network structure. In Japan, Yoshiyuki and Daisuke (2022) highlighted that COVID-19 spread through both large and small suppliers in the Japanese production network, unlike the external demand shocks observed during the Global Financial Crisis, which concentrated on large suppliers. While this line of research has thrived, to our knowledge, there is little research yet on how the pandemic has changed production networks.

This granular data allows us to observe the extensive margin of firm-to-firm trade, distinguishing between upstream (supplier) and downstream (buyer) adjustments. We employ an event-study framework to track network turnover relative to a pre-pandemic baseline, controlling for time-varying firm size and unobserved heterogeneity. Furthermore, we leverage rich data on firm characteristics—including ICT specialist intensity and precise geographic location—to explore the heterogeneity in network adjustment.

We document the impact of the COVID-19 pandemic on the termination and creation of buyer-supplier linkages. We first show that during the initial stages of the pandemic, the termination and creation of inter-firm relationships fell sharply below pre-shock levels. In later years, link termination increased, but link creation contracted persistently. We also document substantial firm-level heterogeneity: network turnover remained relatively stable among firms with a high intensity of ICT specialists and among those located in core prefectures. We posit that the initial aggregate decline in network reallocation was caused by mobility restrictions and economic uncertainty, which made searching for and vetting new partners prohibitive and compelled firms to maintain existing relationships. Furthermore, we conjecture that digital capacity and geographic market thickness mitigated these constraints. Digitally intensive and centrally located firms leveraged remote communication technologies and denser local pools of potential partners to bypass physical search frictions, enabling them to dynamically re-optimise their production networks despite the aggregate shock.

The distance between buyers and suppliers in the inter-firm relationship also changed during the COVID-19 pandemic. We observe a decline in the average geographic distance of terminated relationships by 2021–2022, alongside an immediate and persistent increase in the distance of newly created links. We find that the drop in link termination distance is concentrated among short-distance local linkages in non-core prefectures, whereas the rise in creation distance is driven by firms in densely populated core regions and high-ICT buyers. We posit that buyers leveraged their digital capabilities to create new partnerships in geographically distant regions to source materials or intermediate goods during the pandemic.

Our study follows the literature on the dynamics of production networks, which has evolved from using purely statistical methods to emphasising economic incentives. Early research by Atalay et al. (2011) used graph theory to describe network formation, assuming firms followed preferential and random attachment rules. Later, Oberfield (2018) placed greater emphasis on incentives, proposing that buyers optimally choose suppliers from an evolving pool. Empirical studies have further explored these dynamics: Bernard et al. (2019) showed that the introduction of high-speed rail lines in Japan reduced search costs and improved firm performance. Adding to this, Arkolakis et al. (2023) analysed Chilean firms, documenting that network formation depends on firm size and location, where densely populated areas have richer networks and distance mainly reduces the number of trade partners.

This paper contributes to the literature by examining the dynamics of the network—specifically regarding network structure and geographical distance. First, we add to the work on the propagation of shocks (Acemoglu et al., 2016b; Carvalho et al., 2021; Barrot and Sauvagnat, 2016) by treating the network as endogenous. We show that geographical distances are not static but undergo dynamic changes in response to aggregate shocks. In addition, we find the determinants of this change, contributing to the literature on search and matching frictions (Bernard et al., 2019). We provide evidence that ICT intensity and geographic density facilitate network rewiring, supporting the conjecture of information frictions as a primary barrier. Finally, our results provide evidence against a standard Schumpeterian cleansing theories, positing that cleansing was delayed and partial dependent on firm's ability to overcome search costs.

The rest of the paper is organised as follows. Section 2 describes the data. Section 3 presents stylised facts regarding the creation and destruction of inter-firm linkages during the COVID-19 pandemic. Section 4 investigates the dynamics of these linkages, controlling for firm characteristics, and explores heterogeneity driven by productivity, digital capabilities, and geographic location. Section 5 concludes.

2 Data

This study utilises firm-level data from Tokyo Shoko Research (TSR), a prominent Japanese credit rating agency. TSR compiles comprehensive information on Japanese companies, including detailed financial data and inter-firm transaction relationships. The database is updated annually, and our analysis uses data spanning 2015 to 2023.

From the TSR database, we constructed two distinct datasets. The first is a firm-year dataset that tracks approximately 1.8 million non-financial firms annually, with the median firm observed for 7 years. For each firm and each year, we recorded the number of transaction links, separating existing links into those that carried into the next year and those that were dropped. We also measure the number of newly added links between the current and the following year. To ensure that our estimates capture changes in firm behaviour rather than mechanical changes in sample composition due to firm entry and exit, we restrict our sample to firms that operate continuously between consecutive periods. This focus on continuing firms allows us to exclude links added or dropped solely due to firm attrition. We also recorded firm characteristics, including the number of employees and firm age. The second is a link-level dataset that examines the specific link between a buyer and a seller each year. For every link, we recorded information about both companies involved, including their total number of buyers or suppliers, number of employees, and firm age.

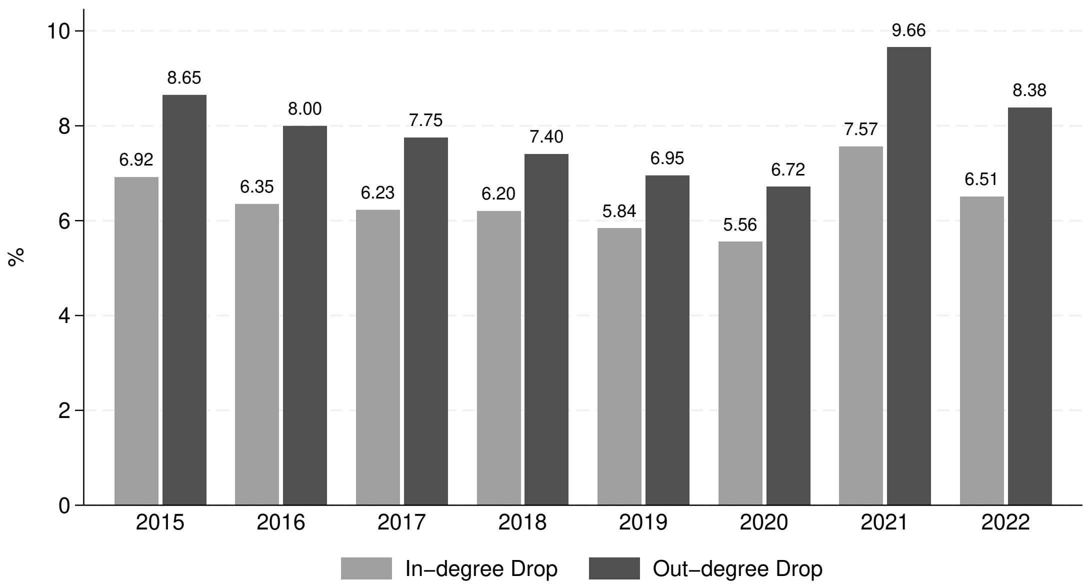
3 Summary Statistics

We begin by documenting several stylised facts that characterise the evolution of the inter-firm production network over the 2015–2023 period. Figure 1 plots the average of inter-firm link termination and creation rate over time. We define the link termination rate for each firm as the number of linkages dissolved between year t and $t+1$, normalised by the total number of linkages existing at time t. Similarly, the link creation rate represents the number of new linkages established between year t and $t+1$, again normalised by the total number of linkages at time t.The horizontal axis indicates the base year t. For each period, the light grey bars depict the average rate for in-degree (supplier) links, while the dark grey bars show the average rate for out-degree (buyer) links. This visualization allows for a clear comparison of the entry and exit dynamics of firm networks.

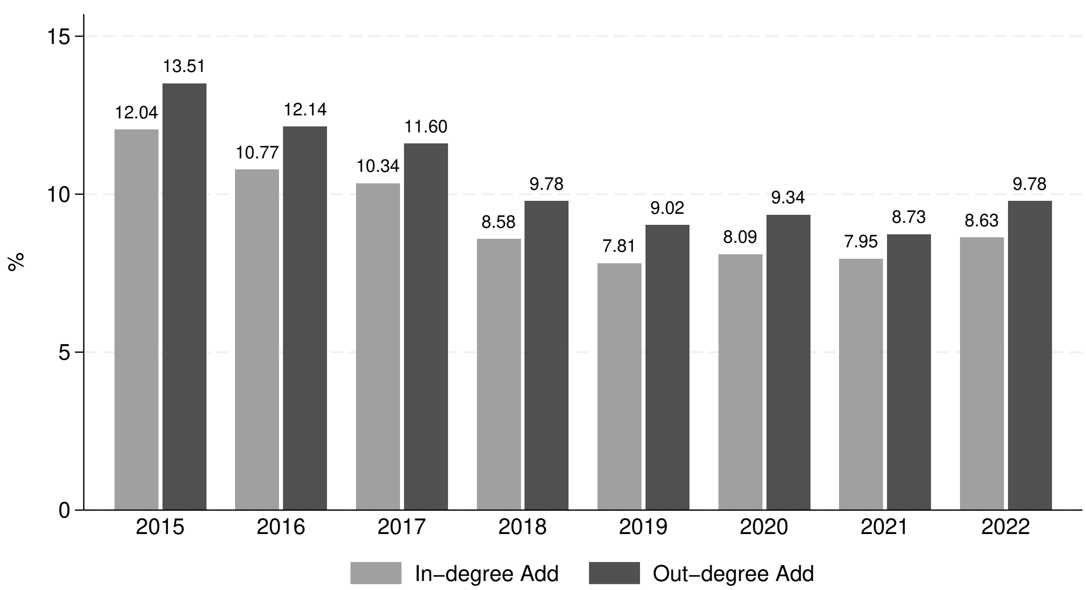
Stylised Fact 1: *Link termination and link creation rates decline during the early stage of the COVID-19 pandemic. Later on, link termination increased in 2022, but link creation did not increase at a commensurate pace.*

Between 2015 and 2018, both the creation and termination of firm linkages edged downward. For link termination, the in-degree rate fell from 6.92% between 2015-2016 to 6.20% between 2018-2019, while the out-degree rate dropped from 8.65% to 7.40%. Similarly, link creation rates saw a steady decline. The in-degree addition rate decreased from 12.04% to 8.58%, and the out-degree addition rate fell from 13.51% to 9.78%.

During the early stage of the pandemic between 2020-2021, these rates continued to fall. Link termination reached its lowest point, with in-degree at 5.56% and out-degree at 6.72% between 2020 and 2021. By 2022, the number of link terminations increased sharply. The in-degree termination rate rose to 7.57% between 2021 and 2022, and the out-degree rate climbed to 9.66%. However, link creation did not experience a recovery as strong as link termination. Between 2021 and 2022, the in-degree creation rate was 7.95%, and the out-degree rate was 8.73%. Between 2022 and 2023, these figures remained relatively low at



((a)) Link Termination



((b)) Link Creation

Notes: The figure plots average inter-firm link termination and creation rates. Link termination (creation) rate is defined as the number of linkages dissolved (established) between year t and $t+1$ normalized by the total number of linkages at time t. Light and dark grey bars represent in-degree (supplier) and out-degree (buyer) relation.

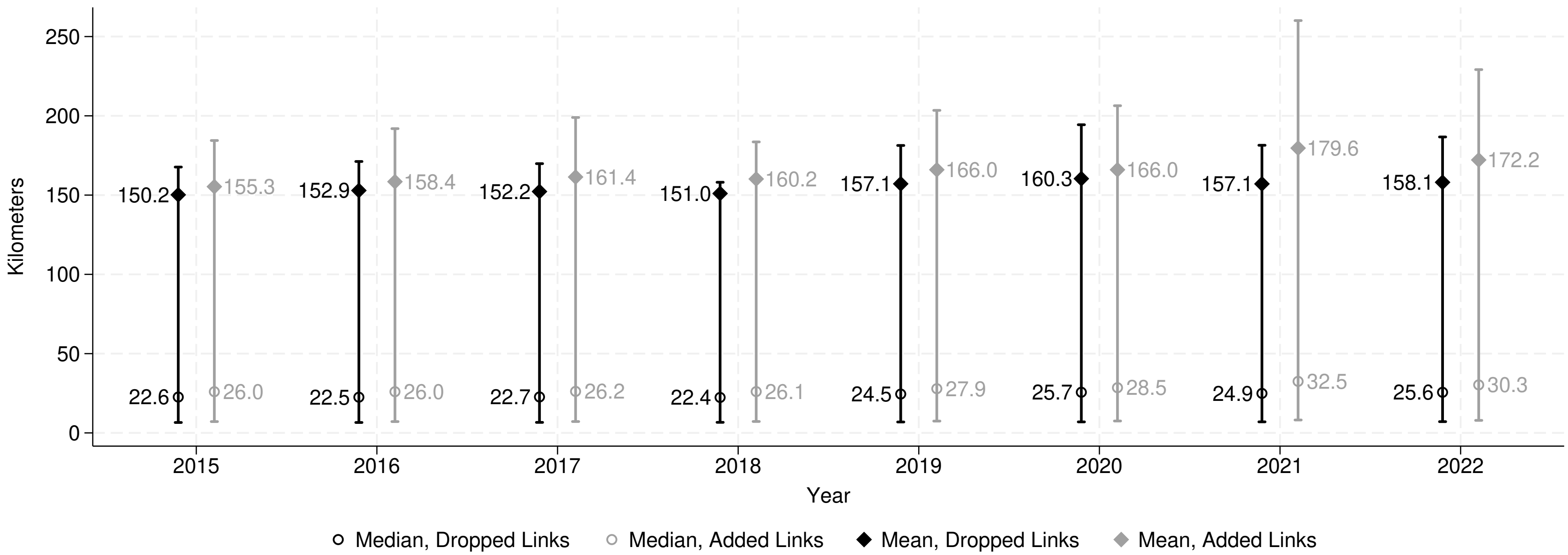
Figure 1: Terminations and Creation of Inter-firm Transaction Network

8.63% and 9.78%, respectively. While firms were quick to cut ties that were no longer viable, they remained more cautious about establishing new inter-firm linkages compared to the pre-pandemic era.

Stylised Fact 2: *The distribution of geographical distance between inter-firm linkages concentrates on close relationship. Firms created longer-linkages since the COVID pandemic.*

As Figure 2 illustrates the geographical distance (in kilometers) for terminated (Dropped, black) and created (Added, grey) transaction links from 2015 to 2023. The horizontal axis indicates the transition year between t and $t+1$, where the adjustment in the network occurred. Solid diamonds represent the mean distance, while hollow circles represent the median. Vertical bars show the inter-quartile range, providing a measure of the data's distribution and the spread of distances for the middle 50% of the links in each category. A consistent gap exists between the mean and median distances across the entire period. While the median distance remains stable between 22 and 31 kilometers, the mean distances are significantly higher, ranging from 150 to nearly 180 kilometers. This disparity indicates a right-skewed distribution of geographical distances. Because the median is low, the majority of links are likely concentrated within local proximity. This aligns with Bernard, Moxnes, and Saito (2019), who document that geographical promixity is a primary determinant of matching with the majority of links occurring within local commuting zones. On the other hand, the much higher mean is driven by a relatively small number of long-distance links that increase the average without shifting the typical transaction distance for the majority of firms. Furthermore, the mean distance of added links is generally higher than that of dropped links across most years, which implies that newly established partnerships tend to cover more distance than those that were terminated.

Importantly, the mean distance for created links reached its highest points in the sample, reaching 179.6 km for created links between 2021 and 2022 and 172.2 km between 2022 and 2023. During this same interval, the median distance for added links remained relatively low at 32.5 km and 30.3 km, respectively. This suggests that the increase in average distance during the later stage of the pandemic was not a broad shift across the entire network, but rather the result of a specific subset of links forming at much greater distances. These results point to heterogeneity in the distance at which links are created.



This figure illustrates the evolution of the geographical distance (in kilometers) between transaction partners for links that were newly formed (Added, grey series) and those that were terminated (Dropped, black series). The horizontal axis represents the year t in which the adjustment occurred between t and $t+1$. The solid diamonds represent the mean distance, while the hollow circles represent the median distance. Vertical bars indicate the inter-quartile range.

Figure 2: Geographical Distance of Network Turnover

4 Empirical Results

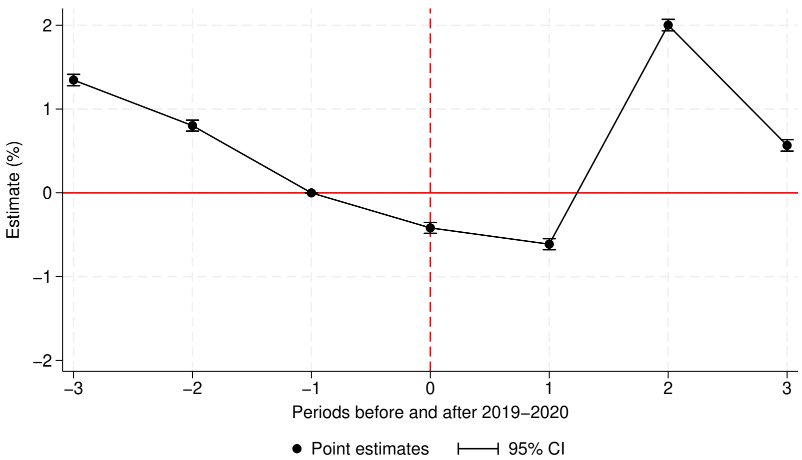
4.1 Network Turnover

In this section, we quantify the impact of the COVID-19 pandemic on the dynamics of the production network. We estimate a dynamic panel model of the turnover of inter-firm transactional linkages at the firm level, using an event-study framework to capture the development of added and dropped links relative to the pre-pandemic base period. For firm i in relative period k, we estimate the following regression:

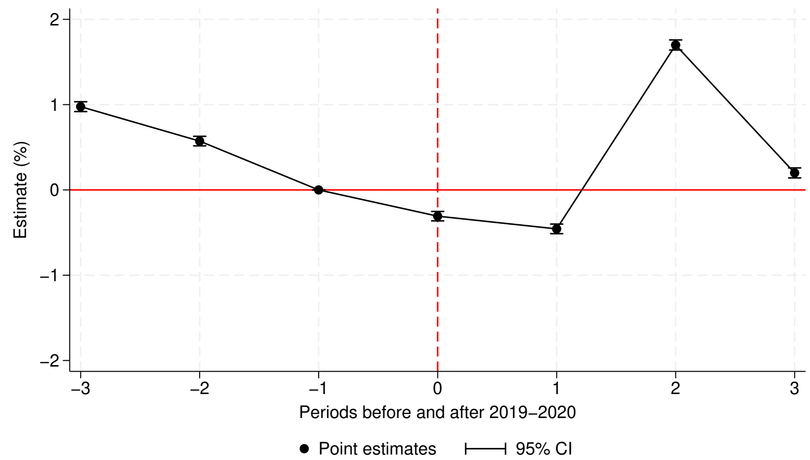
$$\ln(NumberOfLinks_{i,t}) = \alpha + \sum_{k \neq -1} \beta_k \mathbf{1}(Period_t = k) + \gamma \mathbf{X}_{i,t} + \delta_i + \epsilon_{i,t}$$

where the dependent variable, $NumberOfLinks_{i,t}$, represents the flow of transactional partners added or dropped by firm i between year t and $t+1$. We index time relative to the pandemic shock such that $k = 0$ corresponds to the 2019–2020 period (the immediate impact of the pandemic), while $k = -1$ corresponds to the 2018–2019 period. The summation allows us to trace the dynamics of network adjustment over time relative to the omitted reference period ($k = -1$). We estimate this equation separately for four distinct margins of adjustment: buyers dropped, suppliers dropped, new buyers added, and new suppliers added. The coefficients of interest are the vector β_k, which captures period-specific deviations in network churn relative to the 2018-2019 period. A negative β_k indicates that, conditional on controls, firms engaged in significantly less network reallocation during that period compared to the base period.

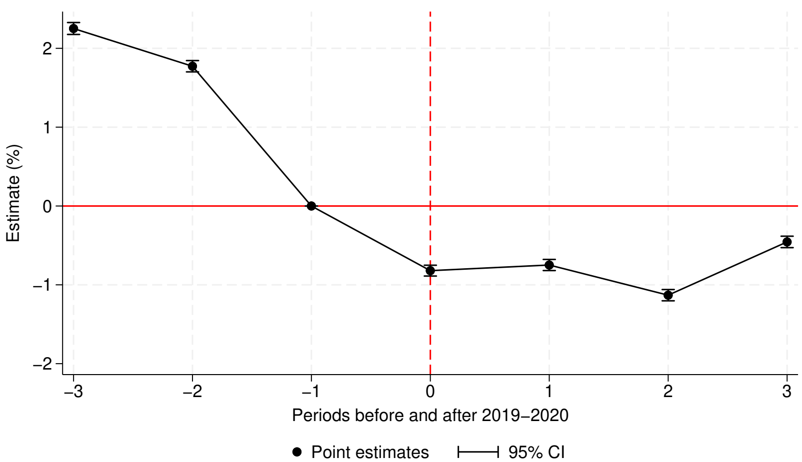
Our specification includes a set of controls ($\mathbf{X}_{i,t}$) and fixed effects. We control for time-varying firm size using the log of employment and for the firm's existing network capacity using the log of the mean number of buyers or suppliers at time t. These controls isolate the adding and dropping of inter-firm linkages from mechanical effects driven by changes in firm scale. Finally, we include firm fixed effects (δ_i) to absorb time-invariant unobserved heterogeneity such as managerial quality or risk appetite, allowing us to exploit within-firm variation to examine how transaction networks evolved during the pandemic relative to each firm's historical level.



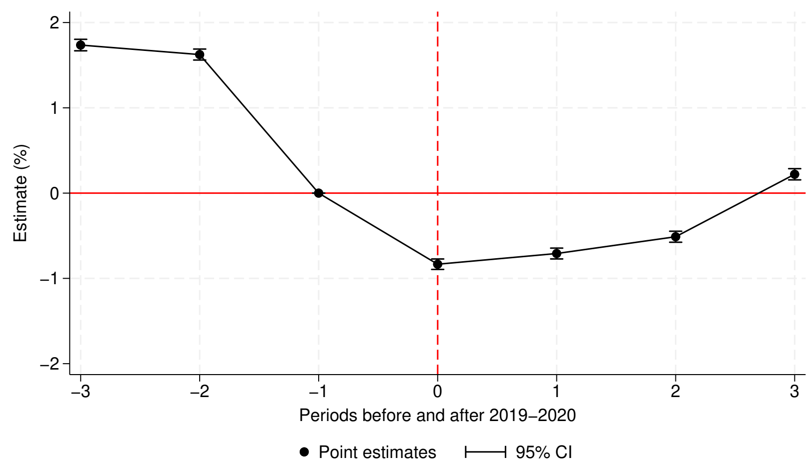
((a)) Buyers dropped



((b)) Suppliers dropped



((c)) Buyers added



((d)) Suppliers added

Notes: This figure plots the estimated coefficients β_k from the dynamic panel regression described in Equation (1). The dependent variable is the natural logarithm of the number of (a) buyers dropped, (b) suppliers dropped, (c) buyers added, and (d) suppliers added by firm i in period k. The coefficients capture the within-firm deviation in network turnover relative to the pre-pandemic base period of 2018–2019 ($k = -1$). The specification controls for firm fixed effects, time-varying firm size (measured by log employment), and existing buyers or suppliers. The vertical dashed line at $k = 0$ marks the 2019–2020 period, corresponding to the immediate impact of the pandemic. The shaded region indicates the 95% confidence interval.

Figure 3: Dynamics of inter-firm transaction network

Figure 3 plots the percentage change in link destruction (Panels A and B) and link creation (Panels C and D) relative to the 2018–2019 baseline. While the estimates show a slight downward trend prior to the pandemic, there is no evidence to suggest this pattern would have persisted in the absence of the COVID-19 shock. We therefore adopt a conservative empirical strategy, evaluating the impact of the pandemic by comparing outcomes directly to the immediate pre-shock baseline.

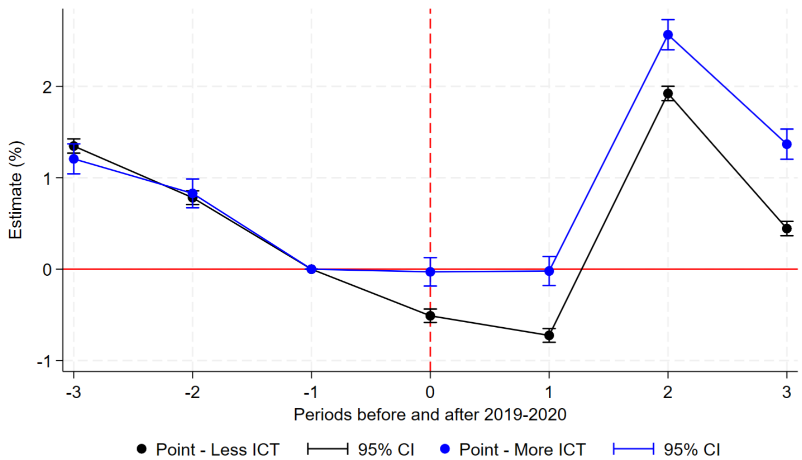
Panels A and B illustrate that the termination of buyer-supplier relationships fell below the base-period level during the initial stages of the pandemic ($k = 0$ and $k = 1$). Because these specifications include firm fixed effects, the results suggest that the patterns documented in Section 3 are driven by within-firm adjustments rather than by changes in the sample composition. First, this decline coincides with a period of high mobility restrictions and significant uncertainty. Because of these restrictions and high compliance, firms could not easily verify the financial health or survival of their partners. Consequently, the cost of searching for new partners became very high. Second, during the early stage of the pandemic, the business impact and duration of COVID-19 were uncertain. It was therefore difficult for firms to evaluate whether a partner's financial deterioration was transitory or permanent. In economic terms, the value of maintaining an existing relationship outweighed the risk of switching, even if the current partner was not the most suitable. From $k = 2$ onwards, link termination rose above the baseline before stabilising. This shift coincided with the lifting of mobility restrictions and increased vaccination rates. We conjecture that, as mobility improved, the cost of validating the health of business partners fell, allowing firms to re-evaluate their connections. The subsequent rise in link destruction likely reflects firms terminating relationships that no longer provided sufficient value once the immediate crisis subsided.

Panels C and D present the results for the addition of new inter-firm relationships. Between 2019 and 2021 ($k = 0$ and $k = 1$), link creation declined sharply. Notably, this contraction was more persistent and larger in magnitude than the changes in link destruction. At the onset of the pandemic ($k = 0$), the number of new relationships fell by roughly double the decline seen in dropped relationships. While the number of link destruction increased by the 2021–2022 period ($k = 2$), link creation remained suppressed. By the 2022–2023 period, we observe that the estimate of buyer creations remains negative, while supplier creations rebounded above the base period.

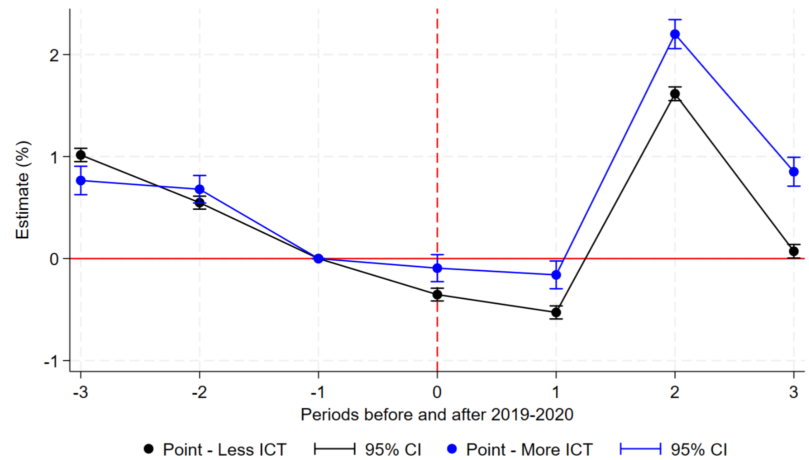
Heterogeneity by Digital Capacity

We investigate firm-level heterogeneity. Our central hypothesis is that digital technologies mitigate the information frictions associated with finding and switching business partners, thereby facilitating the reconfiguration of buyer-supplier linkages. To operationalise this idea, we follow Calvino et al. (2018) and measure a sector's digital capacity using ICT Specialist Intensity, defined as the share of sectoral employment dedicated to developing and maintaining ICT systems.[2] This metric serves as a natural proxy for the human capital required to integrate digital technologies directly into the firm's production function. Building on the OECD taxonomy, we construct a binary indicator, $HighICT_s$, which takes the value of one if industry s ranks in the top half of the ICT-intensity distribution, and zero otherwise.

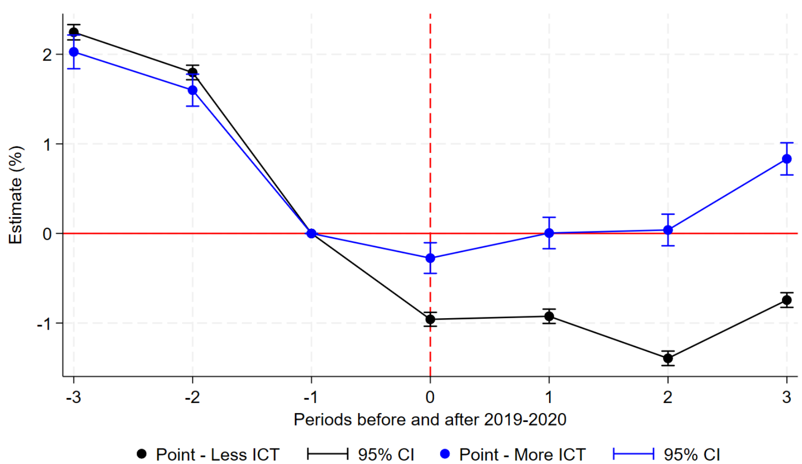
[2] Specifically, this includes ISCO-08 codes 133, 251, 252, and 351.



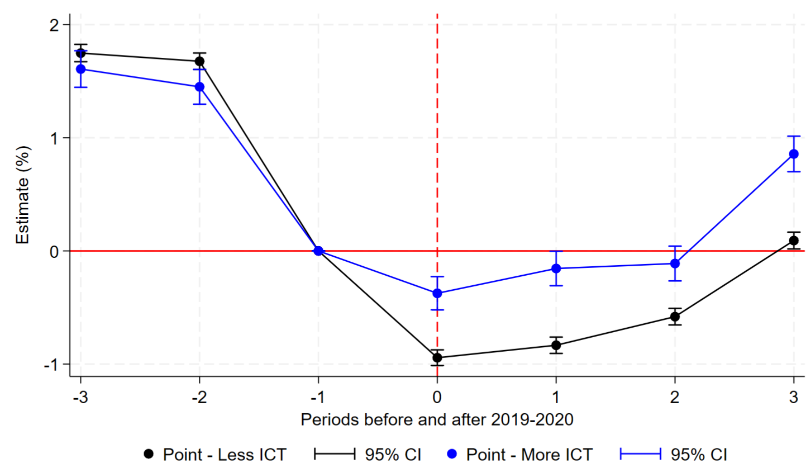
((a)) Buyers dropped



((b)) Suppliers dropped



((c)) Buyers added



((d)) Suppliers added

Notes: This figure plots the estimated coefficients β_k from the dynamic panel regression described in Equation (1), comparing between firms a relatively low number of ICT specialists (in black) and a relatively high number of ICT specialists (in blue). The dependent variable is the natural logarithm of the number of (a) buyers dropped, (b) suppliers dropped, (c) buyers added, and (d) suppliers added by firm i in period k. The coefficients capture the within-firm deviation in network turnover relative to the pre-pandemic base period of 2018–2019 ($k = -1$). The specification controls for firm fixed effects, time-varying firm size (measured by log employment), and existing buyers or suppliers. The vertical dashed line at $k = 0$ marks the 2019–2020 period, corresponding to the immediate impact of the pandemic. The shaded region indicates the 95% confidence interval.

Figure 4: Dynamics of inter-firm transaction network by ICT intensity

Figure 4 presents event-study estimates from our dynamic panel regression, documenting the evolution of link termination and link creation before and after the COVID-19 pandemic shock. The horizontal axis denotes event time k, normalised such that the 2018–2019 pre-pandemic period serves as the baseline ($k = -1$), with the vertical dashed line at $k = 0$ marking the onset of the crisis. The vertical axis measures the estimated percentage deviation in the number of relationships terminated (Panels A and B) or created (Panels C and D) relative to this baseline, conditional on firm fixed effects and time-varying controls. Within each panel, the plotted coefficients capture these within-firm adjustments for two distinct groups: the blue series represents firms with a high intensity of ICT specialists, while the black series represents firms with lower ICT capacity.

Following the onset of the shock, low-ICT firms experienced a contraction in both the termination and creation of inter-firm relationships. In contrast, link creation and destruction among high-ICT firms remained relatively stable. During the initial periods of the pandemic ($k = 0$ and $k = 1$), our estimates indicate that high-ICT firms maintained a 0.4 percent higher buyer creation and a 0.3 percent higher supplier creation relative to their low-ICT counterparts. This divergence persists into the recovery phase ($k = 3$). While link creation among high-ICT firms accelerated, the network expansion of low-ICT firms remained depressed. We conjecture that high-ICT firms were able to leverage remote communication technologies to bypass the physical search frictions imposed by mobility restrictions. This technological advantage allowed them to continuously re-optimise their production networks by evaluating a broader set of local and distant partners. Consequently, digitally intensive firms were able to dynamically adjust their network during the COVID-19 pandemic.

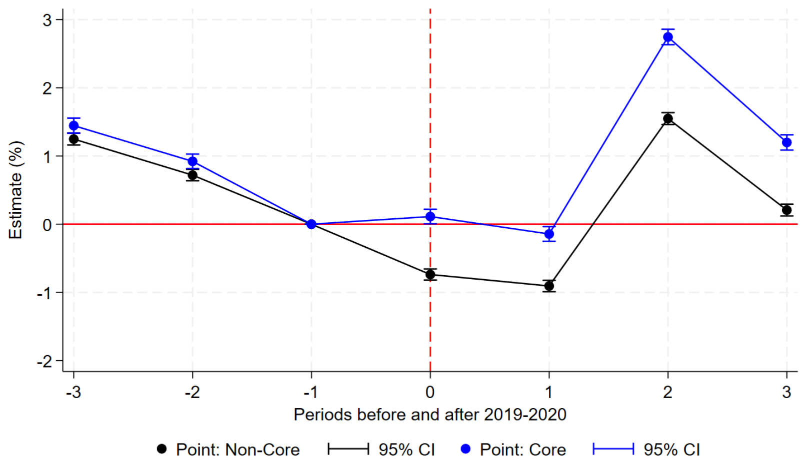
Heterogeneity by Locations

Figure 5 documents the evolution of inter-firm networks for firms located in core metropolitan areas compared to those in peripheral regions.[3] At the onset of the pandemic shock ($k = 0$), non-core firms experienced a contraction in network turnover. Relative to the pre-shock baseline, these non-core firms reduced the termination and creation of buyer relationships by 0.7 percent and 0.9 percent, respectively. In contrast, network activity among core firms remained stable. This divergence persisted into $k = 2$ and $k = 3$. By $k = 3$, buyer creation among non-core firms remained 1.1 percent below the pre-pandemic baseline. Core firms, conversely, increased both buyer and supplier creation above baseline levels during this same period. We interpret these heterogeneous responses through the lens of local market thickness. Geographic proximity and market density shape network dynamics by lowering the

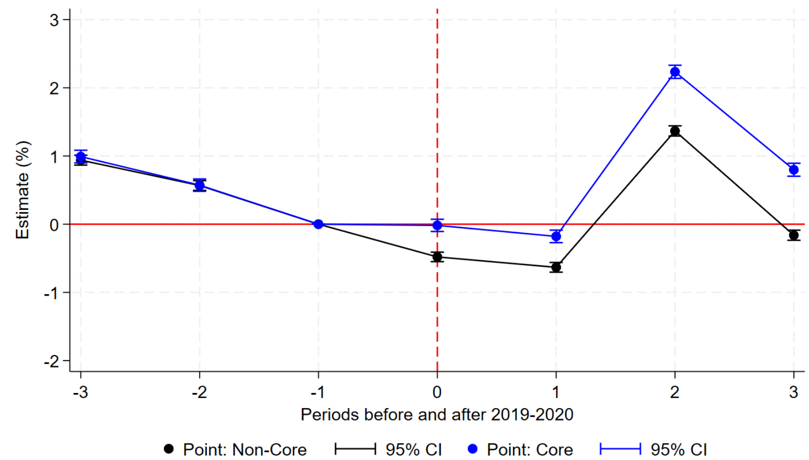
[3] Core areas include Tokyo, Kanagawa, Saitama, Chiba, Aichi, Osaka, and Kyoto.

search and vetting costs associated with finding new partners. Core prefectures offer a denser pool of potential partners, which facilitates network adjustments even during the COVID-19 pandemic. Consistent with Bernard et al. (2019) and Acemoglu and Azar (2020), firms in thick markets sever inefficient relationships because the probability of finding a replacement is high. Firms in peripheral regions, however, face fewer outside options, compelling them to retain suboptimal matches when search costs increase. Consequently, the post-pandemic reallocation of resources was more dynamic in core areas.[4]

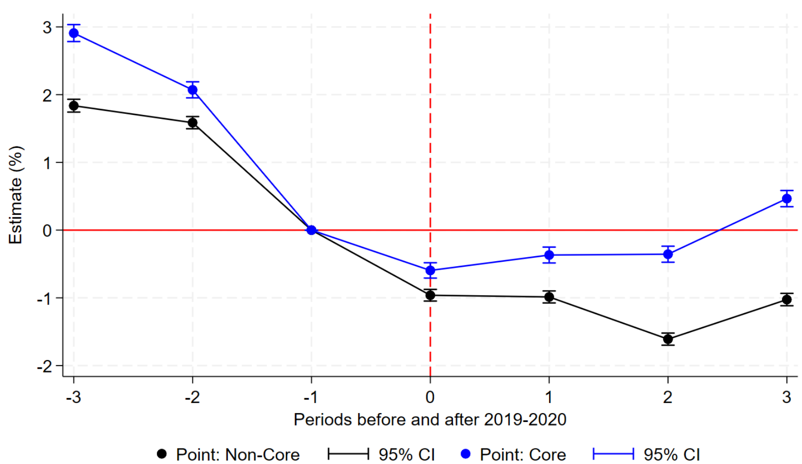
[4]A natural concern is that core prefectures may simply have a higher concentration of ICT-intensive firms, confounding the effect of geography with digital capacity. To address this, we partition the sample into four mutually exclusive groups based on location (core versus non-core) and ICT intensity (high versus low). The divergence in network turnover between core and non-core regions remains consistent within both the high- and low-ICT subsamples. This suggests that geographic location exerts an independent effect on network dynamics. See Figure A1.1 in the Appendix for these results.



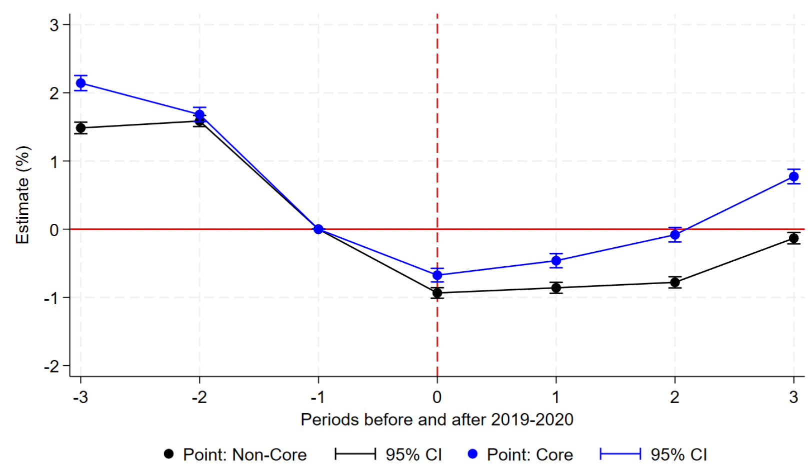
((a)) Buyers dropped



((b)) Suppliers dropped



((c)) Buyers added



((d)) Suppliers added

Notes: This figure plots the estimated coefficients β_k from the dynamic panel regression described in Equation (1), comparing between firms in non-core prefectures (in black) and those in core prefectures (in blue). Core areas include Tokyo, Kanagawa, Saitama, Chiba, Aichi, Osaka, and Kyoto. The dependent variable is the natural logarithm of the number of (a) buyers dropped, (b) suppliers dropped, (c) buyers added, and (d) suppliers added by firm i in period k. The coefficients capture the within-firm deviation in network turnover relative to the pre-pandemic base period of 2018–2019 ($k = -1$). The specification controls for firm fixed effects, time-varying firm size (measured by log employment), and existing buyers or suppliers. The vertical dashed line at $k = 0$ marks the 2019–2020 period, corresponding to the immediate impact of the pandemic. The shaded region indicates the 95% confidence interval.

Figure 5: Dynamics of inter-firm transaction network by locations

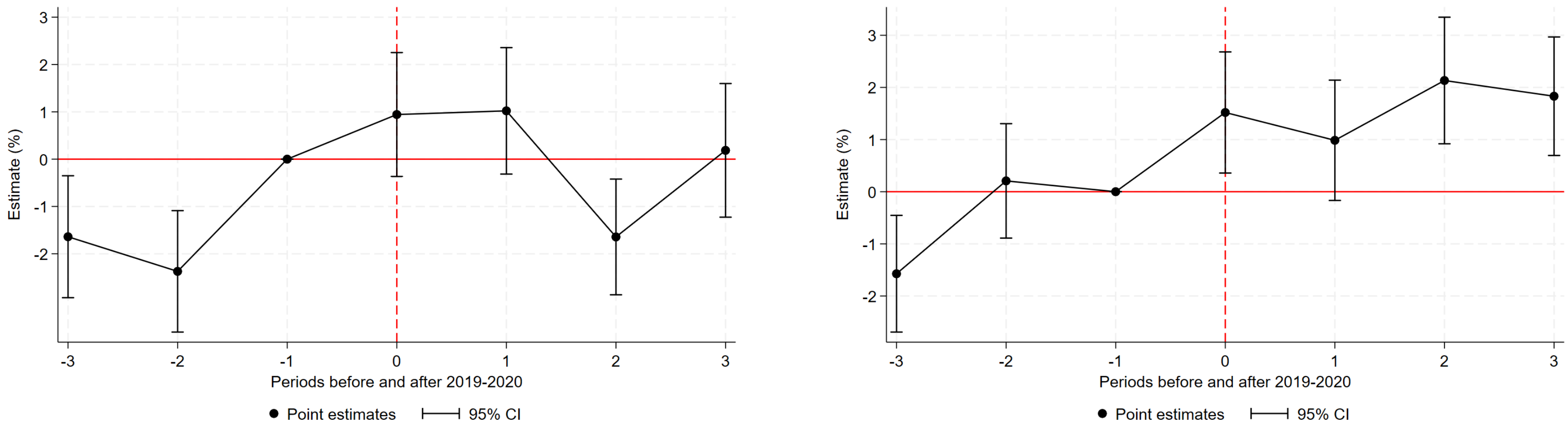
4.2 Geographical Distance

In this section, we examine the geographic distance between firms that established or terminated transactional linkages during the COVID-19 pandemic. We employ a dynamic panel model to track the geographic characteristics of relationship turnover. We adopt an event-study framework to capture changes in the distance of terminated and created links relative to the pre-pandemic reference period. For the link between buyer i and supplier j in year t, we estimate the following regression:

$$\ln(Distance_{ijt}) = \alpha + \sum_{\tau \neq 2018} \beta_\tau \mathbf{1}(Year_t = \tau) + \gamma \mathbf{X}_{it} + \gamma \mathbf{X}_{jt} + \delta_i + \delta_j + \epsilon_{itj}.$$

The dependent variable, $\ln(Distance_{ijt})$, represents the natural logarithm of the geographical distance (in kilometres) between buyer i and supplier j. We estimate this equation separately for two extensive margins. First, for relationship destruction, we measure the distance between partners in links terminated between t and $t+1$. Second, for relationship creation, we measure the distance between partners in links formed between t and $t+1$. The coefficients of interest are the vector β_τ. These capture year-specific deviations in distance relative to the omitted base year (2018). A positive β_τ indicates that, conditional on controls, firms interacted with more distant partners during that year compared to the pre-pandemic norm.

Identifying shifts in network preferences requires accounting for firm characteristics that dictate network geography. For instance, larger firms typically trade over longer distances. To isolate the time-varying shock of the pandemic, our specification includes controls for buyer ($\mathbf{X}_{it}$) and supplier ($\mathbf{X}_{jt}$) characteristics. First, we control for time-varying firm size using the log of employment. This ensures that observed increases in distance are not driven by firms expanding their catchment areas due to growth. Second, we control for network structure using the log of the number of suppliers for buyer i and the log of the number of buyers for supplier j. These controls allow us to compare firms with similar network complexities. Finally, we include buyer and supplier fixed effects (δ_i and δ_j) in all specifications. These absorb time-invariant unobserved heterogeneity, such as specific locations, industry sectors, and business models.



((a)) Dropped links

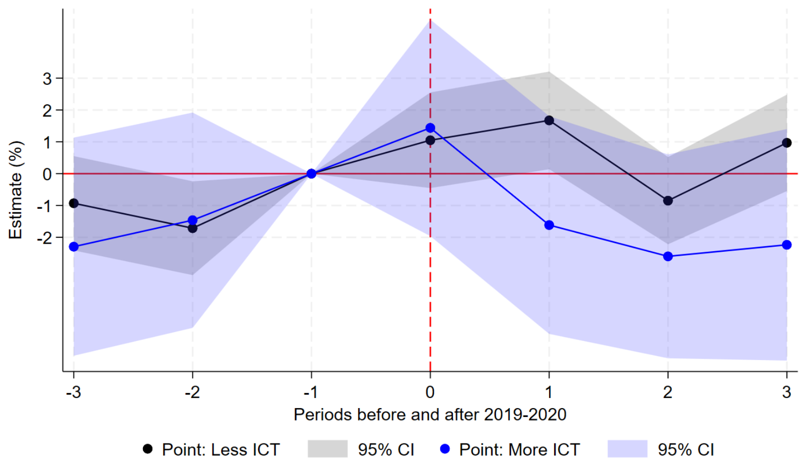
((b)) Added links

Notes: This figure plots the estimated coefficients β_k from the dynamic panel regression described in Equation (2). The dependent variable is the natural logarithm of the distance of (a) links dropped and (b) links added by firm i in period k. The coefficients capture the within-firm deviation in the average of log distance relative to the pre-pandemic base period of 2018–2019 ($k = -1$). The specification controls for firm fixed effects, time-varying firm size (measured by log employment), and existing buyers or suppliers. The vertical dashed line at $k = 0$ marks the 2019–2020 period, corresponding to the immediate impact of the pandemic. The shaded region indicates the 95% confidence interval.

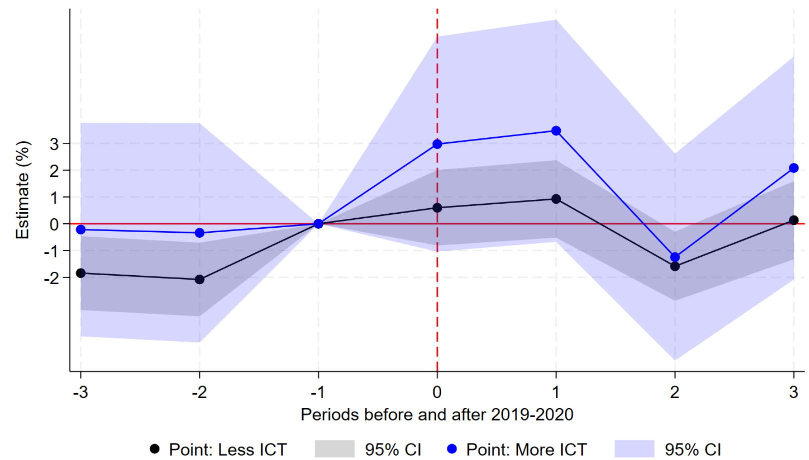
Figure 6: Geographical distance of inter-firm transaction during COVID-19

Figure 6 presents event-study estimates from our dynamic panel regression. The horizontal axis denotes event time k, with the 2018–2019 pre-pandemic period serving as the normalised baseline at $k = -1$. The graphs illustrate the estimated percentage deviation in the average geographic distance of terminated relationships (Panel A) and created relationships (Panel B) relative to the baseline. These plotted coefficients capture within-firm spatial adjustments, conditional on firm fixed effects, time-varying firm size, and the number of existing partners.

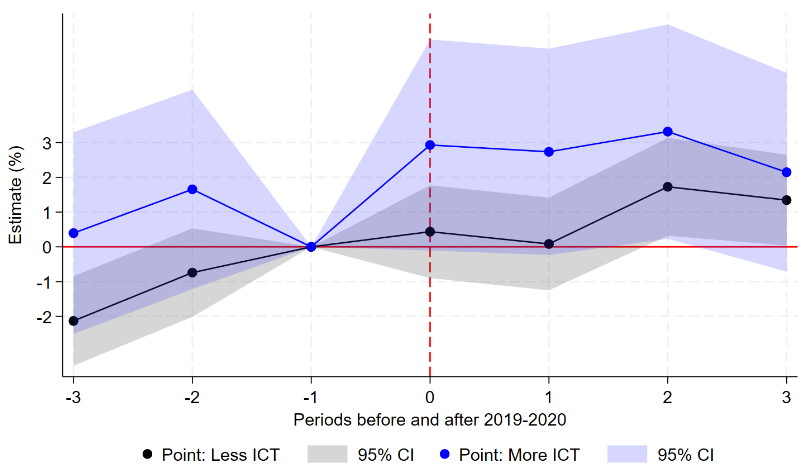
Panel A of Figure 6 illustrates that during the initial stages of the pandemic ($k = 0$ and $k = 1$), the average geographic distance of terminated links remained statistically indistinguishable from the pre-shock baseline. However, at $k = 2$—a period coinciding with the aggregate rise in network turnover—we observe a statistically significant decline. Specifically, the average distance of severed relationships fell by 1.6 percent relative to the reference period. In contrast, Panel B documents an increase in the distance of newly formed networks. The average distance of created links increased immediately at the onset of the shock ($k = 0$) and remained positive and statistically significant through 2021–2023 ($k = 2$ and $k = 3$).



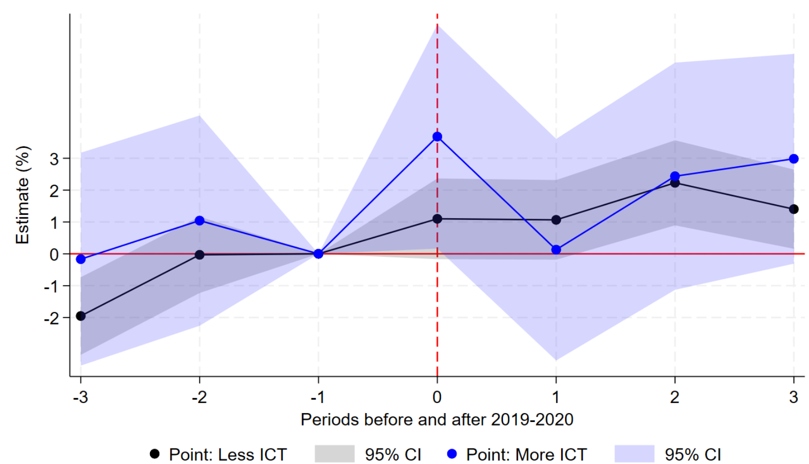
((a)) Dropped links by buyer's ICT intensity



((b)) Dropped links by supplier's ICT intensity



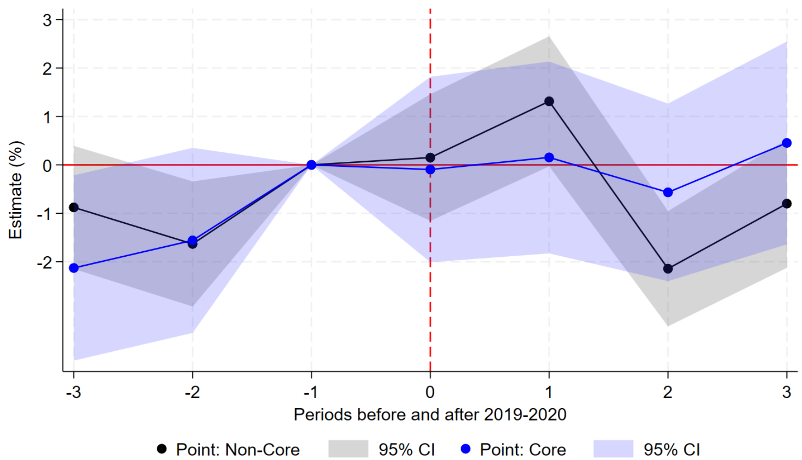
((c)) Added links by buyer's ICT intensity



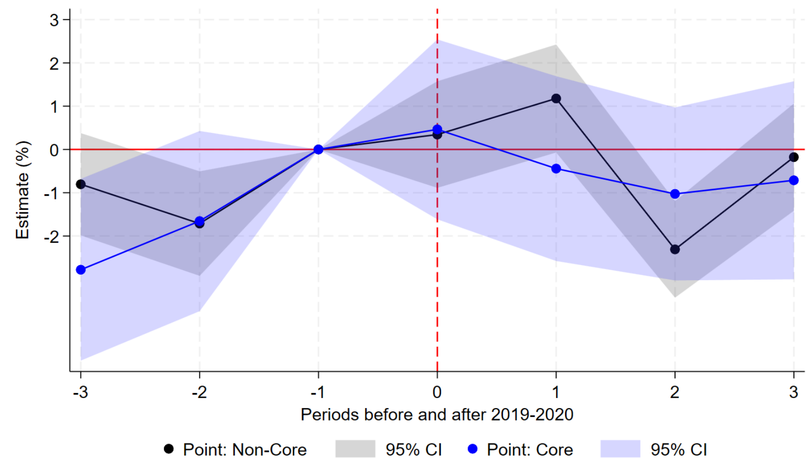
((d)) Added links by supplier's ICT intensity

Notes: This figure plots the estimated coefficients β_k from the dynamic panel regression described in Equation (2), comparing between firms a relatively low number of ICT specialists (in black) and a relatively high number of ICT specialists (in blue). The dependent variable is the natural logarithm of the distance of (a) links dropped and (b) links added by firm i in period k. The coefficients capture the within-firm deviation in the average of log distance relative to the pre-pandemic base period of 2018–2019 ($k = -1$). The specification controls for firm fixed effects, time-varying firm size (measured by log employment), and existing buyers or suppliers. The vertical dashed line at $k = 0$ marks the 2019–2020 period, corresponding to the immediate impact of the pandemic. The shaded region indicates the 95% confidence interval.

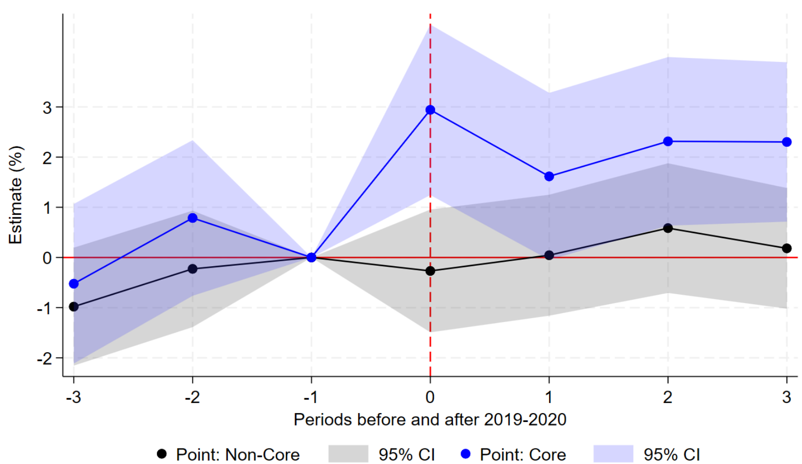
Figure 7: Geographical distance of inter-firm transaction during COVID-19 by ICT intensity



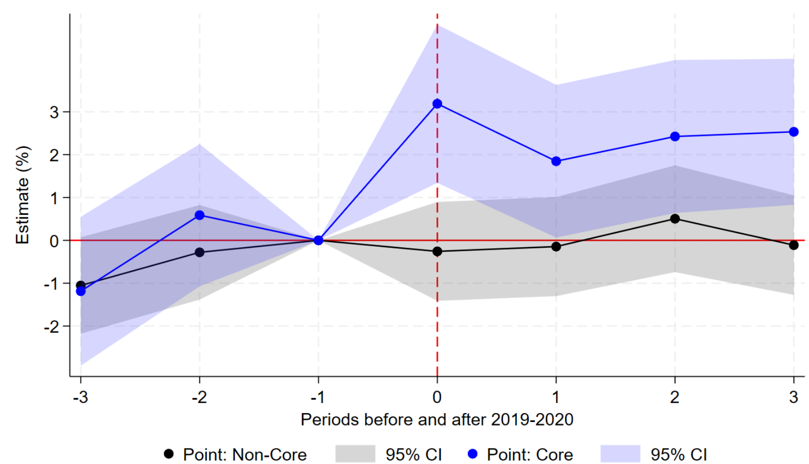
((a)) Dropped links by buyer's location



((b)) Dropped links by supplier's location



((c)) Added links by buyer's location



((d)) Added links by supplier's location

Notes: This figure plots the estimated coefficients β_k from the dynamic panel regression described in Equation (2), comparing between firms in non-core prefectures (in black) and those in core prefectures (in blue). Core areas include Tokyo, Kanagawa, Saitama, Chiba, Aichi, Osaka, and Kyoto. The dependent variable is the natural logarithm of the distance of (a) links dropped and (b) links added by firm i in period k. The coefficients capture the within-firm deviation in the average of log distance relative to the pre-pandemic base period of 2018–2019 ($k = -1$). The specification controls for firm fixed effects, time-varying firm size (measured by log employment), and existing buyers or suppliers. The vertical dashed line at $k = 0$ marks the 2019–2020 period, corresponding to the immediate impact of the pandemic. The shaded region indicates the 95% confidence interval.

Figure 8: Geographical distance of inter-firm transaction during COVID-19 by locations

To explore the economic mechanisms underlying these phenomena, we investigate the heterogeneity in link distance across various firm characteristics. We first categorise firms by the ICT intensity of buyers and suppliers and distinguish transaction linkages by geographic location (Figure 7), specifically comparing firms in core versus non-core regions (Figure 8).

Our results indicate that the decline in the average distance of terminated relationships during the 2021–2022 period ($k = 2$) is driven by links where either the buyer or the supplier is located in a non-core prefecture. This suggests that relationship terminations during this period were concentrated among local linkages. Conversely, the increase in the average distance of newly created relationships during the pandemic is primarily driven by firms located in core prefectures and by buyers with high ICT intensity. We posit that because mobility restrictions were more stringent in densely populated core areas, firms in these regions sought to diversify their supply chains by forming partnerships with more distant firms, thereby avoiding the localised pandemic shocks. This pattern is particularly pronounced for high-ICT-intensity buyers, who likely utilised digital capabilities to source intermediate goods from geographically distant areas where the COVID-19 pandemic was less severe.

5 Conclusion

The paper examines the dynamics of buyer-supplier networks during the COVID-19 pandemic. We first establish that during the initial phase of the crisis, the destruction and creation of inter-firm linkages fell sharply below their pre-shock baseline. In subsequent years, while link destruction increased, link creation remained depressed. We also document that network turnover remained relatively stable for firms with a high intensity of ICT specialists and for those located in core prefectures. We posit that the initial slowdown in network dynamics was driven by mobility restrictions and economic uncertainty, which made the search and vetting of new partners prohibitively costly and forced firms to maintain existing ties. We further conjecture that digital capacity and local market thickness mitigated these constraints. Digitally intensive and centrally located firms were able to leverage remote technologies and thicker pools of potential partners to bypass physical search frictions, allowing them to dynamically re-optimise their production networks despite the aggregate shock.

For geographic distance of link termination and creation between buyers and suppliers, we observe a decline in the average geographic distance of terminated relationships by the 2021–2022 period, alongside an immediate and persistent increase in the distance of newly created linkages. We show that the drop in the distance of terminated links is concentrated among short-distance local connections in non-core prefectures, whereas the increase in the distance of newly created links is driven by firms in densely populated core regions and high-ICT buyers. We posit that these patterns reflect buyers leveraging their digital capabilities to overcome physical frictions, establishing new, relatively more distant partnerships to reliably source materials and intermediate goods during the crisis.

A1 The dynamics of inter-firm relationships during the pandemic

Table A1.1 shows how firms changed their inter-firm transactional relationships during the pandemic. The coefficients of interest has been discussed in Section 4 of the main body. The estimated coefficients on the control variables generally align with theoretical priors regarding firm scale and network capacity. Across all specifications, we find that larger firms, as proxied by the log of employment, exhibit a higher propensity to add links and a lower propensity to drop links. One plausible interpretation is that larger firms possess the resources to maintain relationships during shocks while simultaneously expanding their extensive margin. The coefficients on the lagged network degree controls are also highly significant, confirming that the topology of the firm's network is a strong predictor of future network turnover.

	Dependent Variable: Number of Links			
	(1) Dropped Buyers	(2) Dropped Suppliers	(3) Added Buyers	(4) Added Suppliers
Time Effects (Base: 2018–2019)				
2015–2016	0.025***	0.019***	0.031***	0.024***
	(0.000)	(0.000)	(0.000)	(0.000)
2016–2017	0.013***	0.010***	0.023***	0.017***
	(0.000)	(0.000)	(0.000)	(0.000)
2017–2018	0.008***	0.006***	0.018***	0.016***
	(0.000)	(0.000)	(0.000)	(0.000)
2019–2020 (Pandemic Onset)	-0.004***	-0.003***	-0.008***	-0.008***
	(0.000)	(0.000)	(0.000)	(0.000)
2020–2021	-0.006***	-0.005***	-0.007***	-0.007***
	(0.000)	(0.000)	(0.000)	(0.000)
2021–2022	0.020***	0.017***	-0.011***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.000)
2022–2023	0.006***	0.002***	-0.005***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm Characteristics				
Log Employment	-0.010***	-0.004***	0.021***	0.036***
	(0.001)	(0.001)	(0.001)	(0.001)
Log Mean Degree	0.314***	0.272***	-0.278***	-0.270***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-0.164***	-0.148***	0.316***	0.276***
	(0.001)	(0.001)	(0.002)	(0.002)
Observations	8,824,070	8,824,070	8,824,070	8,824,070
Adj. R^2	0.37	0.51	0.38	0.48
Firm FE	Yes	Yes	Yes	Yes
Clustering	Firm	Firm	Firm	Firm

Notes: The dependent variable is the number of buyers/suppliers dropped (Columns 1–2) or added (Columns 3–4) between year t and $t+1$. Time fixed effects refer to the 2018–2019 period. "Log Mean Degree" corresponds to the mean number of buyers (in Columns 1 and 3) or suppliers (in Columns 2 and 4) associated with the counterparty. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table A1.1: Dynamics of Network Turnover

Heterogeneity across firms with different ICT intensity and locations

Tables A1.2 and A1.3 document the detailed estimation results on how firms with heterogeneous characteristics changed their inter-firm transactional relationships during the pandemic, namely, comparisons between high and low ICT capabilities and between firms in core and non-core prefectures. Figure A1.1 illustrates the heterogeneous dynamics across both ICT capabilities and location dimensions.

	Dependent Variable: Log Number of Links							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dropped Buyers		Dropped Suppliers		Added Buyers		Added Suppliers	
Time Effects (Base: 2018-2019):								
Between 2015 and 2016	0.0233***	0.0278***	0.0181***	0.0208***	0.0292***	0.0325***	0.0248***	0.0227***
	(0.0005)	(0.0006)	(0.0004)	(0.0005)	(0.0005)	(0.0007)	(0.0005)	(0.0006)
Between 2016 and 2017	0.0125***	0.0145***	0.0094***	0.0099***	0.0184***	0.0291***	0.0148***	0.0214***
	(0.0004)	(0.0006)	(0.0004)	(0.0005)	(0.0005)	(0.0006)	(0.0004)	(0.0006)
Between 2017 and 2018	0.0072***	0.0092***	0.0057***	0.0057***	0.0159***	0.0207***	0.0159***	0.0168***
	(0.0004)	(0.0005)	(0.0004)	(0.0005)	(0.0005)	(0.0006)	(0.0004)	(0.0005)
Between 2019 and 2020	-0.0074***	0.0011**	-0.0048***	-0.0002	-0.0096***	-0.0060***	-0.0093***	-0.0067***
	(0.0004)	(0.0005)	(0.0004)	(0.0005)	(0.0004)	(0.0006)	(0.0004)	(0.0005)
Between 2020 and 2021	-0.0091***	-0.0014***	-0.0063***	-0.0018***	-0.0099***	-0.0037***	-0.0086***	-0.0046***
	(0.0004)	(0.0005)	(0.0004)	(0.0005)	(0.0005)	(0.0006)	(0.0004)	(0.0005)
Between 2021 and 2022	0.0155***	0.0275***	0.0137***	0.0223***	-0.0161***	-0.0036***	-0.0078***	-0.0008
	(0.0004)	(0.0006)	(0.0004)	(0.0005)	(0.0005)	(0.0006)	(0.0004)	(0.0005)
Between 2022 and 2023	0.0021***	0.0120***	-0.0016***	0.0080***	-0.0103***	0.0047***	-0.0013***	0.0077***
	(0.0004)	(0.0006)	(0.0004)	(0.0005)	(0.0005)	(0.0006)	(0.0004)	(0.0005)
Firm Characteristics:								
Log of mean number of buyers	0.3453***	0.2693***			-0.2724***	-0.2884***		
	(0.0011)	(0.0012)			(0.0011)	(0.0014)		
Log of mean number of suppliers			0.2946***	0.2386***			-0.2745***	-0.2638***
			(0.0009)	(0.0010)			(0.0010)	(0.0013)
Log of employment	-0.0131***	-0.0052***	-0.0069***	-0.0003	0.0120***	0.0316***	0.0278***	0.0462***
	(0.0008)	(0.0010)	(0.0007)	(0.0009)	(0.0009)	(0.0014)	(0.0008)	(0.0013)
Observations	5462011	3360132	5462011	3360132	5462011	3360132	5462011	3360132
Adj. R-sq	0.35	0.41	0.47	0.56	0.35	0.43	0.43	0.55
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Subgroup	Non-core	Core	Non-core	Core	Non-core	Core	Non-core	Core

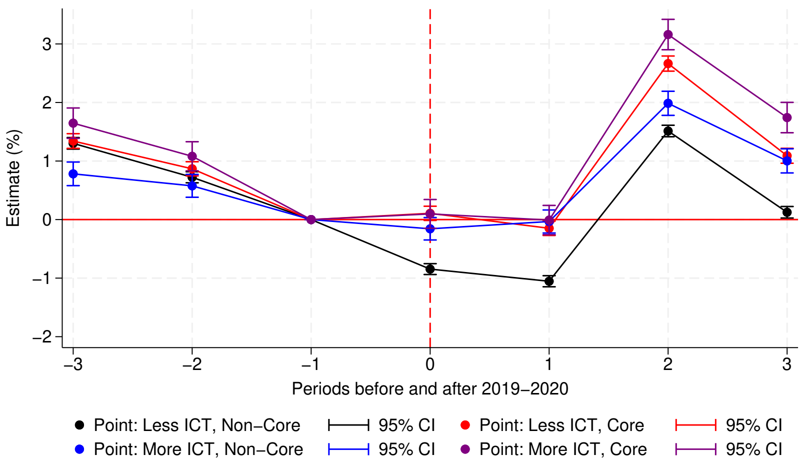
Notes: The dependent variable is the number of buyers/suppliers dropped (Columns 1-4) or added (Columns 5-8) between year t and t+1. Time fixed effects refer to the 2018-2019 period. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table A1.2: Network Dynamics by Locations of Firms

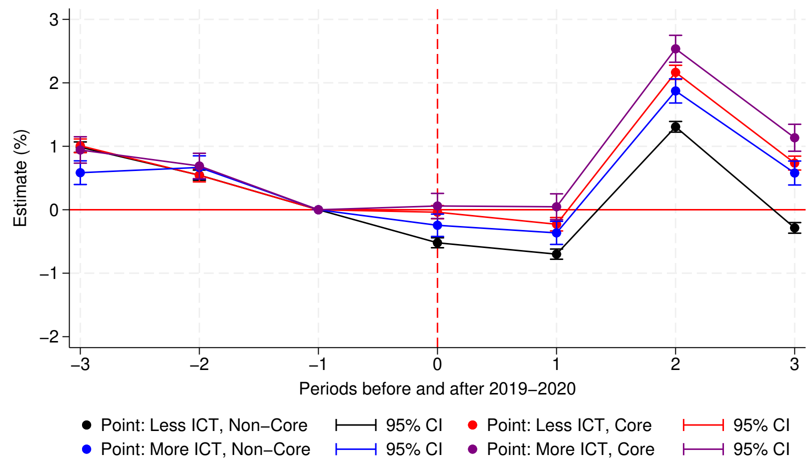
	Dependent Variable: Log Number of Links							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dropped Buyers		Dropped Suppliers		Added Buyers		Added Suppliers	
Time Effects (Base: 2018-2019):								
Between 2015 and 2016	0.0255***	0.0209***	0.0197***	0.0148***	0.0310***	0.0233***	0.0238***	0.0216***
	(0.0004)	(0.0009)	(0.0004)	(0.0007)	(0.0005)	(0.0010)	(0.0004)	(0.0009)
Between 2016 and 2017	0.0135***	0.0121***	0.0102***	0.0077***	0.0225***	0.0203***	0.0175***	0.0161***
	(0.0004)	(0.0008)	(0.0003)	(0.0007)	(0.0004)	(0.0010)	(0.0004)	(0.0008)
Between 2017 and 2018	0.0078***	0.0083***	0.0055***	0.0068***	0.0180***	0.0160***	0.0168***	0.0145***
	(0.0004)	(0.0008)	(0.0003)	(0.0007)	(0.0004)	(0.0009)	(0.0004)	(0.0008)
Between 2019 and 2020	-0.0051***	-0.0003	-0.0035***	-0.0009	-0.0096***	-0.0028***	-0.0094***	-0.0037***
	(0.0004)	(0.0008)	(0.0003)	(0.0007)	(0.0004)	(0.0009)	(0.0004)	(0.0008)
Between 2020 and 2021	-0.0072***	-0.0002	-0.0053***	-0.0016**	-0.0092***	0.0000	-0.0083***	-0.0016**
	(0.0004)	(0.0008)	(0.0003)	(0.0007)	(0.0004)	(0.0009)	(0.0004)	(0.0008)
Between 2021 and 2022	0.0192***	0.0256***	0.0162***	0.0220***	-0.0139***	0.0004	-0.0058***	-0.0011
	(0.0004)	(0.0008)	(0.0003)	(0.0007)	(0.0004)	(0.0009)	(0.0004)	(0.0008)
Between 2022 and 2023	0.0044***	0.0137***	0.0007**	0.0085***	-0.0074***	0.0083***	0.0009**	0.0086***
	(0.0004)	(0.0008)	(0.0003)	(0.0007)	(0.0004)	(0.0009)	(0.0004)	(0.0008)
Firm Characteristics:								
Log of mean number of buyers	0.3320***	0.2563***			-0.2742***	-0.3059***		
	(0.0009)	(0.0019)			(0.0010)	(0.0023)		
Log of mean number of suppliers			0.2799***	0.2584***			-0.2740***	-0.2570***
			(0.0008)	(0.0017)			(0.0008)	(0.0021)
Log of employment	-0.0125***	-0.0035**	-0.0059***	-0.0011	0.0144***	0.0335***	0.0306***	0.0408***
	(0.0007)	(0.0015)	(0.0006)	(0.0012)	(0.0008)	(0.0019)	(0.0008)	(0.0019)
Observations	6849462	1527499	6849462	1527499	6849462	1527499	6849462	1527499
Adj. R-sq	0.38	0.38	0.49	0.60	0.39	0.38	0.46	0.59
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Subgroup	Less ICT	More ICT	Less ICT	More ICT	Less ICT	More ICT	Less ICT	More ICT

Notes: The dependent variable is the number of buyers/suppliers dropped (Columns 1-4) or added (Columns 5-8) between year t and t+1. Time fixed effects refer to the 2018-2019 period. Standard errors are clustered at the firm level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

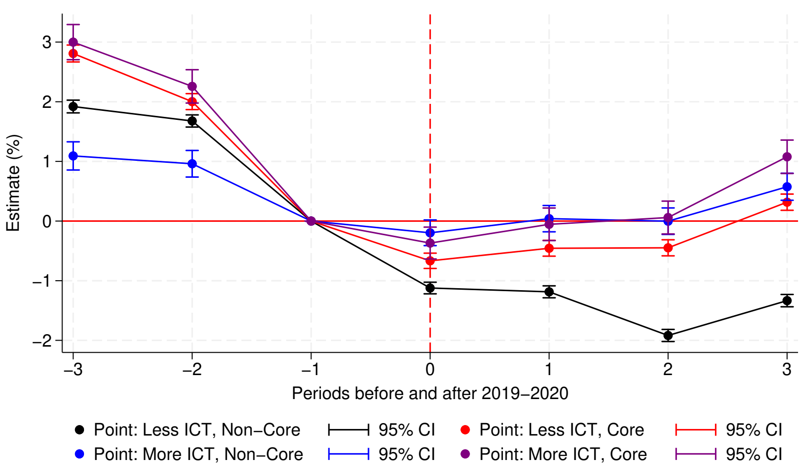
Table A1.3: Dynamics of Network Distance: Extensive Margin



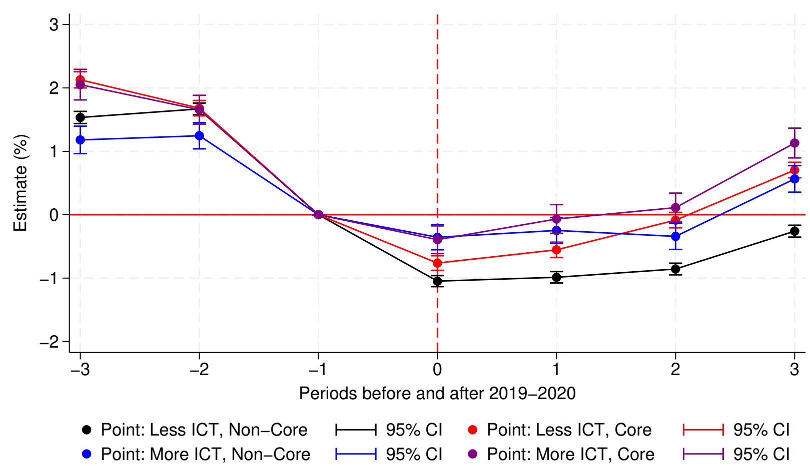
((a)) Buyers dropped



((b)) Suppliers dropped



((c)) Buyers added



((d)) Suppliers added

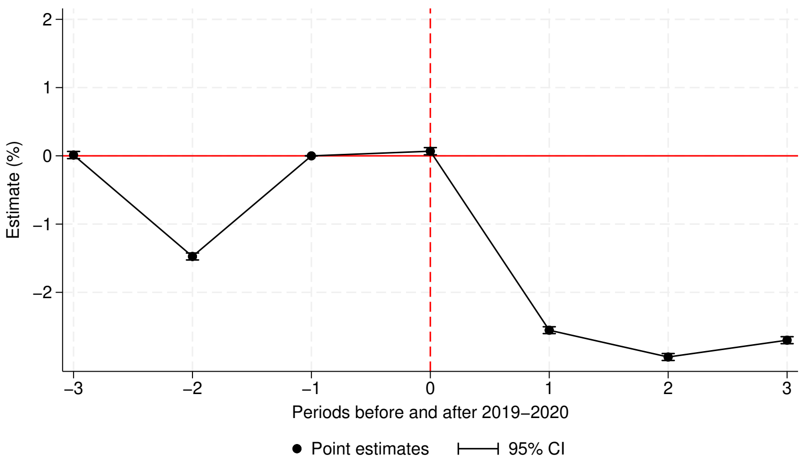
Notes: This figure plots the estimated coefficients β_k from the dynamic panel regression described in Equation (1), comparing between firms with a relatively low number of ICT specialists and located in non-core areas (in black), a relatively low number of ICT specialists and located in core areas (in red), a high number of ICT specialists and located in non-core areas (in blue), and a high number of ICT specialists and located in core areas (in purple). The dependent variable is the natural logarithm of the number of (a) buyers dropped, (b) suppliers dropped, (c) buyers added, and (d) suppliers added by firm i in period k. The coefficients capture the within-firm deviation in network turnover relative to the pre-pandemic base period of 2018–2019 ($k = -1$). The specification controls for firm fixed effects, time-varying firm size (measured by log employment), and existing buyers or suppliers. The vertical dashed line at $k = 0$ marks the 2019–2020 period, corresponding to the immediate impact of the pandemic. The shaded region indicates the 95% confidence interval.

Figure A1.1: Dynamics of inter-firm transaction network for firms across ICT intensity and locations

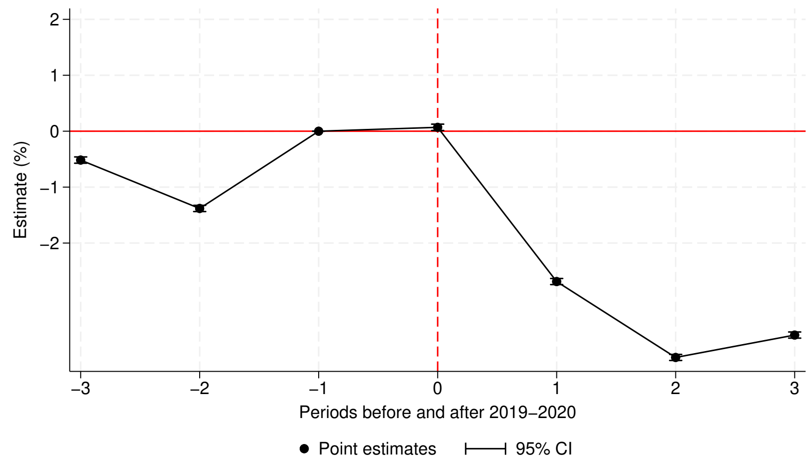
Dynamics of link termination due to firm exits and link creation due to firm entry

In this appendix, we study the dynamics of link termination due to firm exits and link creation due to firm entry during the pandemic. The event study estimates presented in Figure A1.2 indicate a divergence between the destruction and creation margins of inter-firm trade relative to the 2018–2019 reference period ($k = -1$). Panels (a) and (b) display statistically significant negative coefficients starting from $k = 0$, implying that the destruction of trade links due to partner exit decreased during the pandemic compared to pre-pandemic levels. In contrast, Panels (c) and (d) show positive deviations in periods $k = 0$ and $k = 1$, indicating a transient increase in the formation of new trade relationships with both buyers and suppliers. Collectively, these results suggest that while the extensive margin of separation due to firm exit contracted, the extensive margin of entry expanded significantly during the shock.

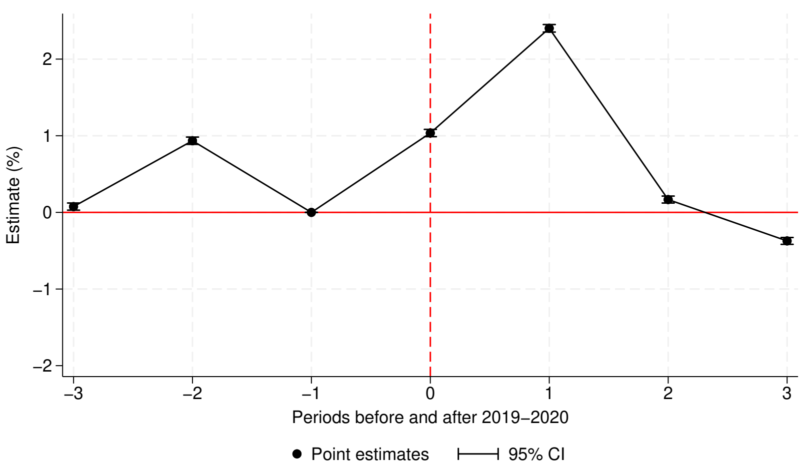
The decline in network destruction due to partner exit is consistent with the findings of Saito and Wongkaew (2023), who observed that aggregate exit rates stabilised during the pandemic. This phenomenon is likely attributable to policy interventions—such as liquidity support—which mitigated firm failures that typically accompany aggregate negative shocks. On the other hand, the simultaneous increase in network creation (Panels c and d), despite the survival of incumbent partners, suggests a mechanism of strategic diversification. Amid heightened uncertainty and operational frictions among incumbent partners, firms likely sought to establish transactional links to ensure supply chain resilience, thereby expanding their networks.



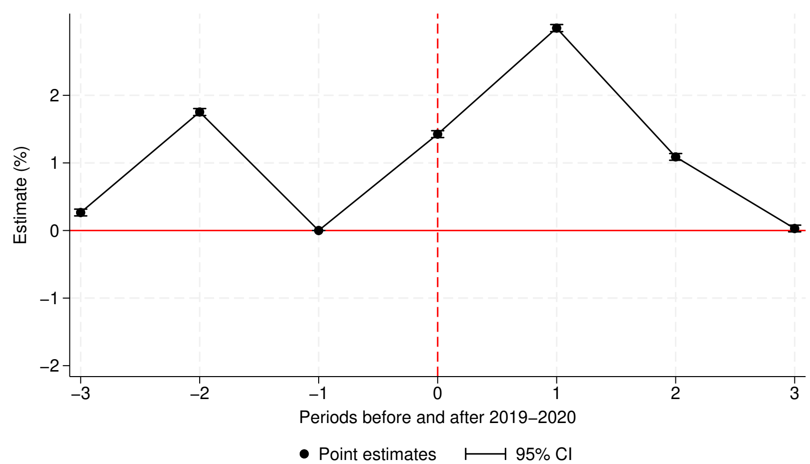
((a)) Buyers dropped



((b)) Suppliers dropped



((c)) Buyers added



((d)) Suppliers added

Notes: This figure plots the estimated coefficients β_k from the dynamic panel regression described in Equation (1). The dependent variable is the natural logarithm of the number of (a) buyers dropped due to partner exit, (b) suppliers dropped due to partner exit, (c) newly-entered buyers added, and (d) newly-entered suppliers added by firm i in period k. The coefficients capture the within-firm deviation in network turnover relative to the pre-pandemic baseline of 2018–2019 ($k = -1$). The specification controls for firm fixed effects, time-varying firm size (measured by log employment), and existing buyers or suppliers. The vertical dashed line at $k = 0$ marks the 2019–2020 period, corresponding to the immediate impact of the pandemic. The shaded region indicates the 95% confidence interval.

Figure A1.2: Dynamics of inter-firm transaction network against exit or entry firms

A2 Heterogeneity in the change in distance

The estimated coefficients on firm characteristics align with standard gravity models. Larger firms, measured by log employment, and those with more trade partners consistently add links over greater distances. This positive association confirms that larger firms possess the productivity buffers necessary to overcome spatial search frictions, allowing them to operate over a broader geographic scope than their smaller counterparts as Bernard et al. (2019) suggest. These controls ensure that the observed increase in distance during the pandemic reflects a true shift in search behaviour rather than a composition effect driven by firm size.

	Dependent Variable: Log Distance	
	(1) Dropped	(2) Added
Time Effects (Base: 2018–2019)		
2015–2016	-0.032***	-0.018***
	(0.007)	(0.006)
2016–2017	-0.016**	-0.016***
	(0.007)	(0.006)
2017–2018	-0.024***	0.002
	(0.007)	(0.006)
2019–2020 (Pandemic Onset)	0.009	0.015**
	(0.007)	(0.006)
2020–2021	0.010	0.010*
	(0.007)	(0.006)
2021–2022	-0.016***	0.021***
	(0.007)	(0.006)
2022–2023	0.002	0.018***
	(0.007)	(0.006)
Firm Characteristics		
Log Employment of Buyers	-0.008	0.036***
	(0.007)	(0.007)
Log Employment of Suppliers	0.013	0.036***
	(0.009)	(0.006)
Log Mean In-Degree of Buyer	0.038***	0.044***
	(0.010)	(0.006)
Log Mean Out-Degree of Supplier	0.066***	0.064***
	(0.007)	(0.004)
Constant	3.300***	3.125***
	(0.056)	(0.040)
Observations	1,404,397	1,777,321
Adj. R^2	0.50	0.51
Buyers and Suppliers FE	Yes	Yes
Clustering at Buyers and Suppliers Level	Yes	Yes

Notes: The dependent variable is the log of the distance between partners that was dropped (Column 1) or added (Column 2) between year t and $t+1$. Time fixed effects refer to the 2018–2019 period. "Log Mean Degree" corresponds to the mean number partners associated with the counterparty. *** p<0.01, ** p<0.05, * p<0.1.

Table A2.1: Change in Distance of Terminated and Created Transactional Linkages

	Dependent Variable: Log Distance							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dropped Links		Added Links		Dropped Links		Added Links	
Time Effects (Base: 2018-2019):								
Between 2015 and 2016	-0.028***	-0.005	-0.012**	-0.005	-0.023***	-0.010	-0.014**	-0.003
	(0.007)	(0.009)	(0.006)	(0.008)	(0.006)	(0.010)	(0.006)	(0.009)
Between 2016 and 2017	-0.009	-0.021**	-0.010	-0.005	-0.008	-0.028***	-0.011*	-0.012
	(0.006)	(0.010)	(0.006)	(0.008)	(0.006)	(0.011)	(0.006)	(0.009)
Between 2017 and 2018	-0.016**	-0.016	-0.002	0.008	-0.017***	-0.017	-0.003	0.006
	(0.007)	(0.010)	(0.006)	(0.008)	(0.006)	(0.011)	(0.006)	(0.008)
Between 2019 and 2020	0.002	-0.001	-0.003	0.029***	0.003	0.005	-0.003	0.032***
	(0.007)	(0.010)	(0.006)	(0.009)	(0.006)	(0.011)	(0.006)	(0.009)
Between 2020 and 2021	0.013*	0.002	0.000	0.016*	0.012*	-0.004	-0.001	0.018**
	(0.007)	(0.010)	(0.006)	(0.008)	(0.006)	(0.011)	(0.006)	(0.009)
Between 2021 and 2022	-0.021***	-0.006	0.006	0.023***	-0.023***	-0.010	0.005	0.024***
	(0.006)	(0.009)	(0.007)	(0.009)	(0.006)	(0.010)	(0.006)	(0.009)
Between 2022 and 2023	-0.008	0.005	0.002	0.023***	-0.002	-0.007	-0.001	0.025***
	(0.007)	(0.011)	(0.006)	(0.008)	(0.006)	(0.012)	(0.006)	(0.009)
Constant	2.868***	3.580***	2.985***	3.556***	3.022***	3.438***	3.052***	3.504***
	(0.050)	(0.085)	(0.042)	(0.051)	(0.051)	(0.083)	(0.041)	(0.050)
Network Variables:								
Log of number of buyers' suppliers	0.059***	0.045***	0.042***	0.031***	0.069***	0.038**	0.049***	0.025***
	(0.010)	(0.016)	(0.006)	(0.009)	(0.010)	(0.016)	(0.007)	(0.009)
Log of number of supplier's employment	0.059***	0.056***	0.061***	0.033***	0.058***	0.065***	0.055***	0.041***
	(0.007)	(0.011)	(0.005)	(0.006)	(0.007)	(0.012)	(0.004)	(0.007)
Log of buyer's employment	0.005	-0.012	0.038***	0.002	0.000	-0.016*	0.031***	0.001
	(0.009)	(0.007)	(0.009)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)
Log of supplier's employment	0.017**	-0.000	0.020***	0.019**	0.019**	0.003	0.032***	0.013*
	(0.008)	(0.011)	(0.007)	(0.008)	(0.009)	(0.009)	(0.008)	(0.007)
Observations	722,573	594,651	897,408	773,019	779,071	555,150	930,013	748,240
Adj. R-squared	0.68	0.58	0.69	0.58	0.71	0.53	0.70	0.55
Buyers and Suppliers FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firms	Firms	Firms	Firms	Firms	Firms	Firms	Firms
Buyer's Subgroup	Non-core	Core	Non-core	Core				
Supplier's Subgroup					Non-core	Core	Non-core	Core

Notes: The dependent variable is the log distance. Time fixed effects refer to the deviation from the 2018-2019 period. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table A2.2: Dynamics of Network Distance by Location

	Dependent Variable: Log Distance							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dropped Links		Added Links		Dropped Links		Added Links	
Time Effects (Base: 2018-2019):								
Between 2015 and 2016	-0.022***	-0.024	-0.030***	0.018	-0.020***	-0.022	-0.024***	0.009
	(0.007)	(0.017)	(0.007)	(0.015)	(0.007)	(0.021)	(0.006)	(0.018)
Between 2016 and 2017	-0.009	-0.023	-0.021***	0.004	-0.018***	-0.002	-0.020***	-0.002
	(0.008)	(0.017)	(0.007)	(0.015)	(0.007)	(0.020)	(0.006)	(0.017)
Between 2017 and 2018	-0.017**	-0.015	-0.007	0.017	-0.021***	-0.003	-0.000	0.010
	(0.008)	(0.017)	(0.006)	(0.015)	(0.007)	(0.021)	(0.006)	(0.017)
Between 2019 and 2020	0.010	0.014	0.004	0.029*	0.006	0.030	0.011*	0.037**
	(0.008)	(0.017)	(0.006)	(0.015)	(0.007)	(0.020)	(0.006)	(0.018)
Between 2020 and 2021	0.017**	-0.016	0.001	0.027*	0.009	0.035	0.011*	0.001
	(0.008)	(0.017)	(0.007)	(0.015)	(0.007)	(0.021)	(0.006)	(0.018)
Between 2021 and 2022	-0.008	-0.026	0.017**	0.033**	-0.016**	-0.012	0.022***	0.024
	(0.007)	(0.016)	(0.007)	(0.016)	(0.007)	(0.020)	(0.007)	(0.018)
Between 2022 and 2023	0.010	-0.022	0.013**	0.021	0.001	0.021	0.014**	0.030*
	(0.008)	(0.019)	(0.007)	(0.015)	(0.007)	(0.021)	(0.006)	(0.017)
Constant	3.213***	3.281***	3.235***	3.017***	3.205***	3.477***	3.092***	3.391***
	(0.063)	(0.150)	(0.044)	(0.103)	(0.060)	(0.158)	(0.047)	(0.097)
Network Variables:								
Log of number of buyer's suppliers	0.054***	0.009	0.027***	0.077***	0.043***	0.024	0.037***	0.065***
	(0.011)	(0.029)	(0.007)	(0.016)	(0.010)	(0.030)	(0.007)	(0.016)
Log of number of supplier's buyers	0.058***	0.102***	0.062***	0.074***	0.063***	0.092***	0.061***	0.086***
	(0.008)	(0.018)	(0.005)	(0.011)	(0.007)	(0.023)	(0.005)	(0.013)
Log of buyer's employment	0.007	0.007	0.043***	0.007	-0.010	-0.009	0.046***	0.002
	(0.010)	(0.012)	(0.009)	(0.014)	(0.009)	(0.013)	(0.008)	(0.013)
Log of supplier's employment	0.009	0.006	0.028***	0.032**	0.024**	0.011	0.029***	0.004
	(0.011)	(0.017)	(0.007)	(0.013)	(0.010)	(0.016)	(0.009)	(0.014)
Observations	1,003,661	249,851	1,259,035	322,012	1,072,193	206,615	1,341,578	272,441
Adj. R-squared	0.53	0.50	0.52	0.52	0.53	0.48	0.53	0.50
Buyers and Suppliers FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firms	Firms	Firms	Firms	Firms	Firms	Firms	Firms
Buyer's Subgroup	Non-digital	Digital	Non-digital	Digital				
Supplier's Subgroup					Non-digital	Digital	Non-digital	Digital

Notes: Time fixed effects refer to the deviation from the 2018-2019 period. Columns 1-4 split the sample by the Buyer's ICT specialisation, while columns 5-8 split the sample by the Supplier's ICT specialisation. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table A2.3: Dynamics of Network Turnover by ICT Specialisation

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