The Impact of Tariff Trade Barriers on the Operating Performance of U.S. Firms: The Role of Supply Structure and Complexity

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Abstract

Multinational corporations (MNCs) have benefited tremendously from free trade in the past few decades in the form of cost reductions, resource advantages, and market expansion. However, the dynamism of international relations and a global recession have rekindled the debate over frictionless trade. In this study, we examine how trade friction, created by tariff trade barriers, affects the operational performance of domestic firms. We also investigate how different supply chain characteristics and strategies can moderate the impact of such trade friction.

Motivated by the 2018 U.S.-China trade war, we conducted a difference-in-difference analysis to examine the impact of trade tariffs on various firm performance indicators of U.S. firms. We find that U.S. firms with direct supply chain partners (i.e., first-tier suppliers) in China have worse performance in terms of inventory (days of supply) and profitability (ROA). We further show that the negative impact on firms' profitability is more severe when firms have a lower degree of vertical integration and when firms have a higher degree of horizonal, spatial, and cooperative supply base complexity. We discuss the implications for international operations management, supply chain networks, and supply risk management, and provide suggestions to supply chain practitioners and trade policy makers.

Keywords: Supply chain management, international, trade war, policy, difference-in-difference

Introduction

Since the 1980s, various favorable trade agreements established by various governments have enticed many multinational corporations (MNCs) to offshore their operations to Asia, creating complex global supply chains for industrial and consumer products. In the context of stable, open trade, and a low-trade barrier global environment, research shows that, through these cross-border transactions, firms can reduce cost and develop knowledge (Pitelis & Teece, 2010), and improve efficiency of physical resources and increase business opportunities (Teece, 1986).

But there is also the flip side of global sourcing. Transaction costs economics (TCE) suggests that global sourcing increases transaction and coordination costs that MNCs need to bear (Lampel & Giachetti, 2013); these costs can be significant (Grover & Malhotra, 2003). Also, complex global supply chains can make a firm vulnerable to dynamic changes in trade policies. The recent emerged nationalism has triggered governments to impose new trade restrictions to de-globalize (Witt, 2019). These new restrictions create major supply chain disruptions (Kouvelis et al., 2011), forcing firms to rethink their global operational strategies (Charpin et al., 2020; Darby et al., 2020). While researchers have examined various aspects of supply chain risks (e.g., Kleindorfer & Saad, 2005; Tang & Tomlin, 2008), empirical research investigating the impact of geopolitical tensions and trade conflicts on firms' operational performance remains nascent (Charpin et al., 2020).

In this paper, we examine the impact of trade tariffs on firms' performance by using the recent U.S.-China trade war declared by former President Trump as the backdrop. Since 2018, over 1,300 categories and $50 billion of products imported from China were affected in the first wave of 25% tariff increases (Office of the United States Trade Representative, 2018). Later on, the scope was increased to $300 billion over 3,805 categories. To retaliate, China imposed tariff increases for $75 billion of U.S. products.

The intent of increasing import tariffs was to reduce the trade deficit between the United States and China, but U.S. firms have major concerns. The American Chamber of Commerce found that 42% of its members experienced higher production costs, and over 50% of its members believed that their product sales would decline (Bray, 2019). Huang et al. (2019) found a negative stock market reaction toward higher import tariffs for firms importing from China. These observations prompted us to examine our first research question (RQ1): *How would the U.S.-China trade war affect the operating performance of the U.S. firms sourcing from China?* We measure the operating performance in terms of inventory (days of supply) (Wiengarten et al., 2017; Darby et al., 2020) and profitability (ROA) (Swift et al., 2019).

Grover & Malhotra (2003) conceptualize transaction cost as the sum of *transaction risk* and *coordination cost*. Supply diversification is a major source of coordination cost in supply chain management. The use of supply diversification as a risk mitigation strategy is controversial. On the one hand, diversification can increase supply flexibility: alternative supply sources are available when failures happen to a supply source (Hendricks et al., 2009; Tang & Tomblin, 2008). On the other hand, diversification can also increase coordination difficulties and reduce responsiveness to cope with uncertainty (Choi & Krause, 2006). This view is in line with the fact that Japanese firms have significantly reduced their supply network complexity after the disruption caused by the 2011 earthquake in eastern Japan (Son et al., 2021). We therefore also examine the extent to which a firm's degree of vertical integration (Hendricks et al., 2009; Steven et al., 2014) and supply base complexity (Dong et al., 2020; Lu & Shang, 2017) would moderate or accentuate the impact of the increased trade tariffs on a firm's performance. Specifically, we examine our second research question (RQ2): *How would a U.S. firm's supply structure and complexity affect its capability in responding to the trade war?*

To examine our research questions, we conducted a quasi-natural experiment to understand the *treatment effect* of the U.S.-China trade war on U.S. firms' operating performance. By focusing on U.S. industries that are affected by the tariffs imposed in 2018, we compared the performance changes for those *sample firms* with direct suppliers from China against those of *control firms* with no direct suppliers in China. We used secondary data collected from COMPUSTAT (financial data), Bloomberg's SPLC, and the FactSet Reverse and COMPUSTAT Segment (supply chain relationship data) databases, and adopted the propensity score matching (PSM) technique to develop the matched pairs. The matching procedures ensure that the sample and control firms are highly similar in terms of firm properties and supply network characteristics (e.g., second-tier suppliers).

Our difference-in-difference (DID) regression analysis reveals that the sample firms suffer from a more serious loss in operating efficiency (inventory – days of supply) and profitability (ROA) than the comparable control firms. We further show that the negative impact on firms' profitability is more severe for firms with a lower degree of vertical integration, and for firms with a higher degree of horizonal, spatial, and cooperative supply base complexity (Choi & Krause, 2006; Dong et al., 2020). Overall, we find that supply base complexity exacerbates the negative impact of the U.S.-China trade war. We also discuss the implications of our results in the context of international operations management, supply chain networks, and supply risk management, and provide suggestions to supply chain practitioners and trade policy makers.

Literature Review

Transaction Cost Economics (TCE) and Global Sourcing

TCE conceptualizes a firm's "make or buy" decisions: low transaction cost is a key driver for a firm's outsourcing (or "buy") decision (Coase, 1937). Relative to the century before, the international transaction costs in the first decade of the 21st century were much lower owing to technological advancement (Müller & Seuring, 2007) and stable trade (Oh et al., 2011). Besides transaction costs, the pursuit of competitive advantage was another reason for global sourcing (Kotabe & Murray, 2004). Global sourcing helps firms to differentiate products by exploiting unique resources (Teece, 1986); increase firms' bargaining power over their suppliers (Lampel & Giachetti, 2013); and reduce costs (Jiang et al., 2007; Lampel & Giachetti, 2013).

TCE also highlights the challenges of global sourcing from the perspective of transaction risk and coordination costs (Clemons et al., 1993; Grover & Malhotra, 2003). Transaction risk causes disturbances to the global supply chain (Williamson, 2008) and affects operational continuity and efficiency (Grover & Malhotra, 2003). Coordination costs are associated with efforts to facilitate information exchanges, production rationalization, and process standardization (Clemons et al., 1993; Lampel & Giachetti, 2013). Using the TCE framework, OM scholars have developed two streams of literature (supply chain risk management and supply base complexity), which we describe next.

Political Tension and Supply Chain Risk

Supply chain risks are defined as "the likelihood and impact of unexpected macro or micro level events or conditions that adversely influence any part of a supply chain leading to operational, tactical, or strategic level failures or irregularities" (Ho et al., 2015). The adverse influence includes increased operational costs and reduced competitive advantages (Kwak et al., 2018; Tang, 2006). Global supply chains are more risky than domestic ones as the former involve more cross-regional links that are prone to disruptions caused by macroeconomic and political changes (Manuj & Mentzer, 2008). Thus, managing global supply chain risks requires cross-country coordination and collaboration to ensure operational continuity and firm efficiency (Tang, 2006).

The supply chain risk literature focused on risk identification, assessment, mitigation, and control at both macro- and micro-level types is vast (Ho et al., 2015). Most OM researchers examined the impact of natural disasters: Hendricks et al. (2020) examined market reactions to the supply chain disruptions caused by the 2011 Great East Japan Earthquake; and Shen et al. (2020) investigated the impact of the Covid-19 pandemic on firm performance. Compared with investigations of natural disasters, the research that examines the impact of man-made crisis (e.g., trade wars) on a firm's performance is nascent (Darby et al., 2020). Charpin et al. (2020) find that the foreign subunits of MNCs need to earn legitimacy to mitigate political uncertainty and risk. In the Brexit context, Hendry et al. (2019), Roscoe et al. (2020), and Moradlou et al. (2021) find that geopolitical tensions cause significant supply chain disruptions, entailing resilient and robust supply chain designs. These qualitative studies provide valuable information, yet empirical investigations are scarce (Charpin et al., 2020). Hence, our study fills a research gap by examining the impact of the US-China trade war.

Supply Base Complexity

While firms have little control over political tensions and trade wars, they can mitigate these risks through supply base diversification (e.g., Robinson, 2020; Schmitt et al., 2015; Shih, 2020; Tomlin & Wang, 2011). The merits of supply base diversification are illustrated by Nokia's multiple-sourcing strategy. By increasing the firm's supply flexibility, supply base diversification alleviated the disruption caused by fire in the Philips semiconductor factory in 2000 (Tang, 2006).

Choi & Krause (2006) argue that diversifying the supply base can lead to "supply base complexity" in three dimensions: (1) multiplicity—the number of suppliers, (2) diversity—the differentiations among the suppliers, and (3) interrelatedness—the interrelationship among suppliers (Dong et al., 2020; Lu & Shang, 2017; Sharma et al., 2020). The complexity can increase transactional uncertainty in the supply chain, requiring extra coordination efforts (Bode & Wagner, 2015). Research shows that supply base complexity hinders a firm's use of its supply base's R&D development (Dong et al., 2020). It also creates delivery delays (Milgate, 2001; Vachon & Klassen, 2002), production disruptions (Bozarth et al., 2009), and quality problems (Steven et al., 2014). Supply base complexity creates major difficulties for a firm to manage materials and information flows (Brandon-Jones et al., 2015) and to coordinate among suppliers (e.g., Giri & Sarker, 2017; Qi et al., 2004; Tang, 2006; Xiao et al., 2007). Hence, a firm with a higher supply base complexity may be less resilient (Choi & Krause, 2006). Hendricks et al. (2009) find that firms with a higher geographical diversification suffer a higher market value loss from supply disruptions. These findings inspired us to establish a hypothesis suggesting that firms with higher supply base complexity are likely to suffer more due to the increased trade tariffs.

Trade War

The U.S.-China trade war has prompted economists to examine its impact: Li et al. (2018) estimated that the GDP and manufacturing employment for the world will be negatively affected; Itakura (2020) estimated that the GDP of China and the United States will be reduced by 1.41% and 1.35%, respectively; and Mao and Görg (2020) estimated that the EU, Canada, and Mexico will face a burden of up to $1 billion. In the finance research literature, Burggraf et al. (2020) found that tweets related to the U.S.-China trade war reduced the S&P 500's returns and increased market volatility. Huang et al. (2019) showed that U.S. firms with more supply and market connections with China suffer from a stronger negative market reaction to the trade war.

Not much is known about the impact of increased trade tariffs associated with the U.S.-China trade war on the firms' operational performance (Plehn et al., 2010). Most OM analytical models focus on examining how trade barriers affect a firm's global procurement strategy (Wang et al., 2011) and supply chain design (Hsu & Zhu, 2011). Lu and Van Mieghem (2009) and Dong and Kouvelis (2020) found that import tariffs can make a firm reconfigure its global supply chain network. Grossman and Helpman (2020) found that import tariffs can lead to the renegotiation of buyer-supplier dyads or a buyer's search for new suppliers. Nagurney et al. (2019) revealed that, while some firms may benefit from trade barriers, the consumer welfare may be compromised. Using data from the Korean automobile industry, Choi et al. (2012) found that import tariffs can affect a firm's postponement strategy. He et al. (2019) found that trade barriers can increase the global and local environmental costs of agricultural production. By conducting in-depth interviews, Roscoe et al. (2020) explored how firms implemented different strategies in response to supply chain disruptions caused by Brexit. The above OM literature has provided grounds for us to develop our hypotheses to explore how the increased trade tariffs affect firm performance.

Hypothesis Development

Trade Tariffs and the Performance of U.S. Firms Sourcing from China

Trade tariffs have been viewed as a supply chain disruptor (e.g., Grossman & Helpman, 2020; Handfield et al., 2020; Roscoe et al., 2020) that can affect a firm's inventory performance (days of supply) negatively. The increased import tariffs increase the costs of transacting with Chinese suppliers (Roscoe et al., 2020). While U.S. firms can source beyond China, it is time-consuming and costly (Burnson, 2019). Also, the increased tariffs created incentives for firms to stock up before the increased tariffs took effect (Darby et al., 2020; Wu, 2018), piling up inventory in warehouses throughout the United States in 2018 (Naidu & Baertlein, 2018).

Because the import tariffs have a direct impact on the trade operations between two countries (the United States and China), our modeling framework is based on the general equilibrium models of Tintelnot et al. (2018) and Huang et al. (2019) that involve one domestic country and one foreign country. Specifically, in our study, our *sample firms* are U.S. firms with direct first-tier suppliers in China, and the trade tariffs will affect these firms directly (Huang et al., 2019). In contrast, as a benchmark, our *control firms* are U.S. firms with no direct suppliers in China. Because tariff increases are less likely to affect inventory for our control firms, we propose the following:

H1: The tariff increases associated with the U.S.-China trade war will increase the inventory (days of supply) for U.S. firms with direct suppliers from China.

OM researchers have examined the role of tariffs from the cost perspective (e.g., Choi et al., 2012; Wang et al., 2011) and the sales performance perspective (Dong & Kouvelis, 2020). From the cost perspective, our sample firms will incur higher purchasing costs than our control firms. A report from Moody's revealed that U.S. importers absorbed 90% of the additional costs resulting from the tariff levies (Lee, 2021). In the event that the sample firms hold more inventory (due to advance purchases), these firms bear additional inventory holding, goods-in-transit, and transportation costs. Therefore, the overall cost efficiency would be negatively affected. Our argument was echoed by a survey of over 200,000 firms, which indicates that 40% of U.S. firms reported that the trade war had increased their operating costs (Sim, 2020).

Some sample firms might choose to transfer the increased cost to their downstream customers by increasing the product prices, but such a strategy would reduce sales. For example, data show that a 20% tariff imposed by the U.S. government on foreign washing machines drove U.S. washing machine prices up by 13%, while reducing demand by 3% (Tankersley, 2019). On the other hand, our control firms with no direct connection to Chinese firms are much less affected by the tariffs. Therefore, our sample firms with direct suppliers from China are likely to bear additional costs, leading to lower profitability (ROA). Thus, we propose the following hypothesis:

H2: The tariff increases associated with the U.S.–China trade war will decrease the ROA for U.S. firms with direct suppliers from China.

The Role of Supply Structure and Complexity

In addition to the direct impact of trade tariff increases on inventory and ROA as stated in hypotheses H1 and H2, we investigate to what extent this impact is affected by a firm's degree of vertical integration. This exploration is based on Tang's (2006) argument that supply chain risk management requires extraordinary coordination efforts among the supply chain partners and Choi & Krause's (2006) suggestion that a complex supply structures reduce firms' responsiveness in coping with supply disruption. More broadly, our exploration fits in the two components of transaction costs, namely transaction risk (i.e., the operational uncertainty due to the trade war) and coordination costs (supply complexity). Specifically, we first examine the role of firm's make or buy structure (Steven et al., 2014) and the three dimensions of supply base complexity, namely multiplicity, diversity, and interrelatedness (Choi & Krause, 2006; Dong et al., 2020).

In general, firms with a higher degree of vertical integration bear lower transaction costs (Mahoney, 1992), and face a lesser impact should a trade war break out. However, firms with a low degree of vertical integration can focus on core competency and exploit low-cost production opportunities (Stevenson, 2018). However, as these firms outsource their operational tasks, they have less control over their supplies (Hendricks et al., 2009), more vulnerability to disruptions (Kleindorfer & Saad, 2005; Hendricks et al., 2009), more supply chain complexity, and higher coordination costs (Steven et al., 2014). Therefore, we argue that the negative impact of the trade war will be more severe for firms with a low degree of vertical integration:

H3: The negative impact of tariff increases on U.S. firm performance is more severe for firms with a lower degree of vertical integration.

We also examine the extent to which the trade war's impact is affected by a firm's horizontal (supply base) complexity (measured in terms of the number of suppliers) (Choi & Krause, 2006). Firms with a lower degree of horizontal complexity can foster close, trusting relationships (Heese, 2015); information sharing, collaborative planning, forecasting, and replenishment (Hollman et al., 2015; Hsu et al., 2008); closer coordination; and more resilience to disruptions (Treleven & Schweikhart, 1988). In contrast, research suggests that a large supply base can reduce supplier responsiveness, hindering a firm's ability to coordinate supply resources in case of supply chain disruptions (Choi & Krause, 2006). Therefore, the negative impact of the trade war will be more severe for firms with a higher degree of horizontal complexity. We postulate the following:

H4: The negative impact of tariff increases on U.S. firms' performance is more severe for firms with a higher degree of horizontal (supply base) complexity.

In addition to horizontal complexity, firms have different degrees of spatial (supply base) diversity. A spatially diversified supply base can increase a firm's sourcing flexibility: it can shift its supply to a different sourcing location to cope with supply chain disruptions and uncertainties caused by the trade war. However, firms with a higher degree of spatial complexity find it difficult to maintain close relationships and coordinate with suppliers (Choi & Krause, 2006) due to different management styles, cultures, and operational practices of suppliers in different locations (Dong et al., 2020; Sousa & Bradley, 2008). Consequently, the negative impact of the trade war will be more severe for firms with a higher degree of spatial complexity. We thus postulate the following:

H5: The impact of tariff increases on U.S. firms' performance is more negative when the firms have a higher spatial (supply base) complexity.

Besides supply complexity (degree of horizontal and spatial complexity), the relationships among suppliers can create cooperative complexity (Lu & Shang, 2017). When suppliers are substitutes (e.g., backup suppliers), supplier dependency is weak and suppliers operate independently. Hence, the focal firm can act as a bridge controlling the information flow and thus enjoy a more powerful status when interdependency among suppliers is absent or weak (Dong et al., 2020).

When suppliers are complements (e.g., the output of one supplier will be used as input for the other supplier), their operations are interdependent; disruption that occurs at one supplier can affect the operations for the other supplier. Hence, when suppliers are complements, material, information, and financial flow exchanges among suppliers will take place, leading to a supplier-supplier relationship embedded in a buyer-supplier-supplier triad (Wu & Choi, 2005; Wu et al., 2010). In this case, when interdependency among suppliers is present and strong, the focal firm has little information advantage over suppliers, especially when the relationships across suppliers are beyond the purview of the firm (Choi & Krause, 2006) and not so visible (Lu & Shang, 2017). When dealing with a disruption in this environment, the focal firm would incur extra cost to develop intersupplier cooperation and coordination. We thus postulate the following:

H6: The impact of tariff increases on U.S. firms' performance is more negative when the firms have a greater cooperative (supply base) complexity.

Figure 1 shows the theoretical framework of this study.

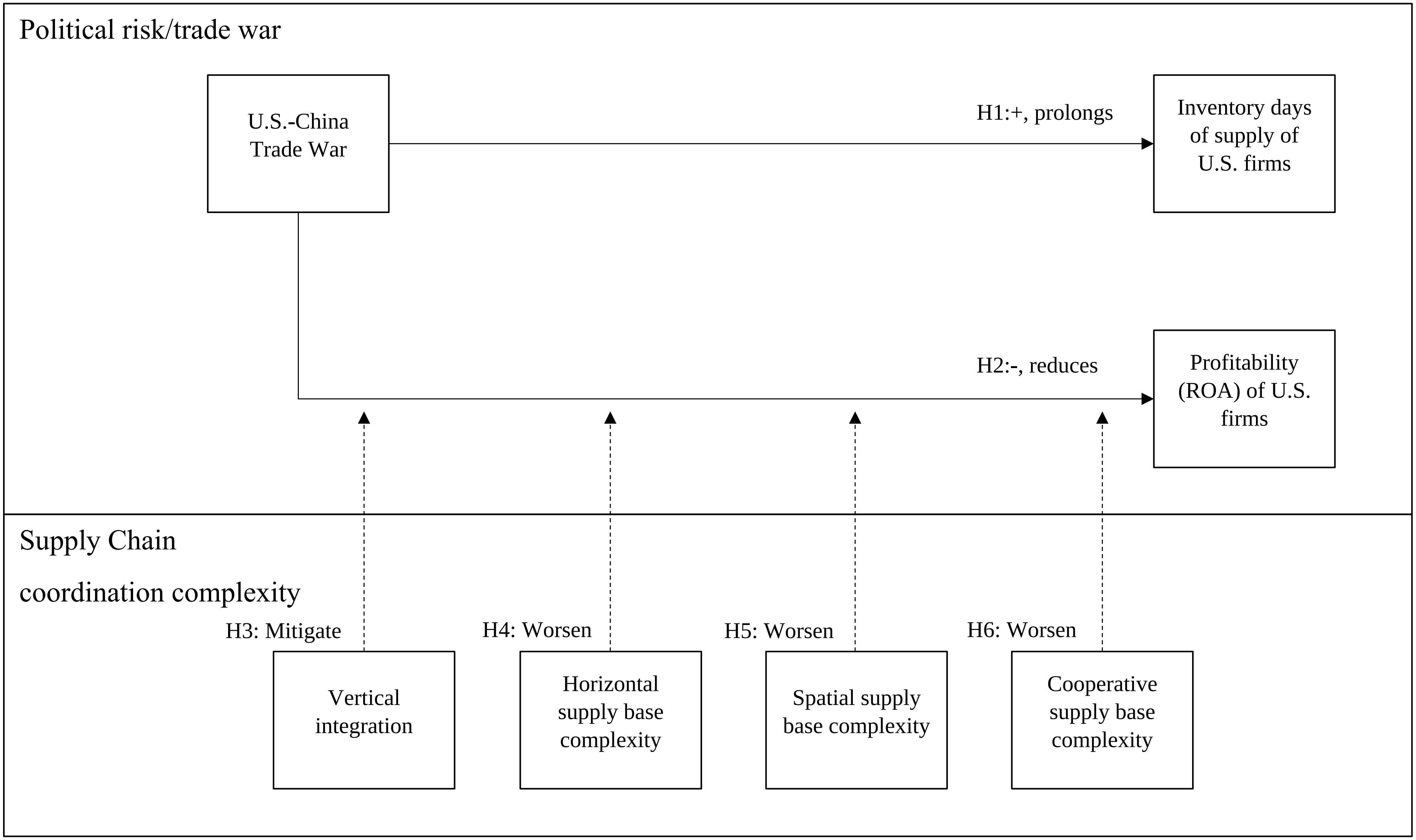

Figure 1. Theoretical framework

Method

Data Collection

Company lists

We sampled U.S. firms in industries affected by the U.S.-China trade war tariff increases as follows. The Office of the United States Trade Representative (USTR) announced three trade action industry lists in 2018 and one in 2019. We used the three lists announced in 2018 because the impact of tariff increase can be captured in the following years. However, we did not use the fourth list announced in 2019 that took effect on September 1, 2019, for two reasons. First, it was just three and half months before the Phase One “ceasefire” trade deal. Second, the fourth list is based on the 2019 announcement, which may cause unobservable variations caused by the year that are different from 2018. By focusing on the three trade action industry lists announced in 2018, we identified 2,473 U.S.-listed firms (from COMPUSTAT) in the affected industry based on the USTR lists. Note that the USTR uses the Harmonized Tariff Schedule of the United States (HTSUS) industry classification code, which was translated to Standard Industrial Classification (SIC) codes as per the translation table provided by the United States International Trade Commission (USITC). Appendix Table A1 summarizes the details and web links of the three lists used in this study.

Because the intent of these tariff actions was to protect the U.S. economy, we focus on the publicly listed U.S. firms that have business activities in the United States. To screen out those listed in the United States with no business activity in the United States, we checked to ensure that each sample firm had a headquarters; property, plant, and equipment (PP&E); segment sales; or identified customers in the United States. We verified each sample firm by using the data collected from the COMPUSTAT Segment, Bloomberg SPLC, FactSet Fundamentals, and FactSet Reverse databases. We eliminated the firms that did not fulfill the above criteria in the year 2017 (prior to the year the trade war started). After the screening process, we obtained 1,631 qualified U.S.-listed firms in our initial pool.

Supply chain data.

For each of the 1,631 firms in our initial pool, we collected the supply chain data from Bloomberg's SPLC database, which has been widely adopted by recent supply chain studies on product recall (Steven et al., 2014), inventory strategy (Elking et al., 2017), firm innovation (Sharma et al., 2020), and supply base innovation (Dong et al., 2020). We used each focal firm's name and CUSIP code (obtained from COMPUSTAT) to search in the database to locate its customers and suppliers. We then collected the firm's customer and supplier identifiers (e.g., name and ticker) and locations. The customer data were used to check whether a firm has business activities in the United States.

Because we hypothesized that the firms with *direct* Chinese suppliers would be most affected by tariff increases, we focused on the first-tier suppliers of these U.S. firms. However, firms that have no first-tier Chinese suppliers may still have second-tier Chinese suppliers; ignoring them may cause bias in the later matching process. Therefore, we further collected the focal firm's second-tier Chinese suppliers by searching for the first-tier suppliers' suppliers in the database. The supply data were used to identify whether a firm has supply connections in China.

Although Bloomberg SPLC is a legitimate database and widely used by researchers, we cannot guarantee that its supplier and customer data are exhaustive. Using a single database (i.e., Bloomberg) to identify a firm's supply chain partners may miss some suppliers and customers because some not-so-visible connections were missed in the database's data collection process. Therefore, we used extra databases to supplement and validate the Bloomberg data. First, we used the FactSet Reverse database to replicate the supply chain data collection process. FactSet Reverse collects supply chain data from various sources such as SEC 10-K annual filings, investor presentations, press releases, and corporate actions (FactSet, 2014) to cover a wide range of supply chain information. This database was used in recent supply chain management literature such as Chae et al. (2020) and Modi and Cantor (2020). We added the supplier and customer connections that were not identified in the Bloomberg database. Second, to make sure that our sample firms truly have supply relationships with China and that our control firms truly have none, we checked whether the firms have a segmental cost of goods sold made in China by using the COMPUSTAT Segment database. A firm has a value of cost of goods sold in a specific location reflects actual purchasing activities in that location. This step helped revealing the complete supply chain activity data.

Through the above process, we found 1,206 firms (out of the 1,631 U.S.-listed firms) with available supplier and customer data spanning 106 three-digit SIC industries. We then collected the accounting data associated with these firms from the COMPUSTAT database. Although the study period of our later analysis is from 2015 to 2020, some firms may not have six years of accounting data. So, firms' accounting data had to be available at least in 2017, 2018, and 2019. We filtered out an additional 220 firms without complete accounting data in these years, leaving us with 986 firms for identifying the *sample* and *control* matching pairs later in our process.

Data Analysis

Quasi-experiment research design

Attempting a direct comparison between the firms' performances before and after the tariff increases in 2018 is problematic because the counterfactual outcomes are unobservable and cannot be calculated (Caliendo & Kopeinig, 2008). Therefore, we adopted a sample-control matching approach to design a quasi-natural experiment that accounts for the unobservable outcomes (Heckman et al., 1998). The *sample firms* were U.S.-listed firms that had direct first-tier suppliers in (mainland) China identified in the Bloomberg SPLC and FactSet Reverse databases. These firms should have had a segmental cost of goods sold in China. The *control firms* were U.S.-listed firms that had no direct suppliers in China identified, and these control firms should have had no segmental cost of goods sold in China. This process generated 268 sample firms and 718 potential control firms for our analysis.

Propensity score matching

Heterogeneity between sample and control firms may also confound the impact of the tariff increases. For example, if the sample firm is significantly smaller than the control firm, any additional negative impact captured in a sample firm would likely originate from its lack of resources to cope with the change in the trade environment. Therefore, we applied a widely used matching approach, propensity score matching (PSM), to ensure that the sample and control firms were highly similar (Fan et al., 2021; Levine & Toffel, 2010). In a nutshell, the PSM approach aims to calculate the probability (i.e., propensity score) of having direct Chinese suppliers for our sample and control firms. We then used the nearest neighborhood approach to match each sample with the control with the closest probability. We used the below estimation model to generate the equation for propensity score calculation:

$$CNsupplier_{i,t} = F\left(X_{i,t-1\&-2\&-3}, Industry_j\right). \quad (1)$$

Here, $F(.)$ is the probit function, and $CNsupplier_{it}$ indicates whether a firm *i* has suppliers in China or not in year *t*, where *t* equals 2018, the announcement year of the used tariff lists. Also, $X_{i,t-1\&-2\&-3}$ is a vector of the average of one-, two-, and three-year lagged levels of a series of matching covariates. Three-year average independent variables help mitigate the impacts of outliers in the estimation (Pagell et al., 2019), and $Industry_j$ is a set of 106 industry dummies.

Selection of matching covariates.

We included firm size and return on assets (ROA) in *X*, as well as a control for industry because previous literature has identified them as three major sources of heterogeneity that would confound the quasi-experimental results (Barber & Lyon, 1996; Corbett et al., 2005; Swift et al., 2019). Firm size is measured by the natural logarithm of the total assets ($Log\ Total\ Assets_{t-1\&-2\&-3}$). Return on assets is measured by the firm's operating ROA ($ROA_{t-1\&-2\&-3}$). Industry dummies ($Industry_j$) can also control outsourcing status to China, because some industries may rely heavily on Chinese suppliers while others may not. We also included a dummy variable ($2nd\text{-}tier\ CN\ supplier_t$) to indicate whether a firm had any second-tier Chinese suppliers. Although we focused on *direct* first-tier Chinese suppliers, firms with second-tier Chinese suppliers may also be affected by the trade war. Thus, we tried to ensure the sample and control firms have no statistical difference in terms of second-tier Chinese suppliers.

In addition, we included a series of determinants of having Chinese suppliers in *X*, including inventory efficiency, production efficiency, capital intensity, research and development (R&D) expenditure, and R&D efficiency. Inventory efficiency ($Inventory\ Efficiency_{t-1\&-2\&-3}$) is the ratio of sales to average inventory, and production efficiency ($Production\ Efficiency_{t-1\&-2\&-3}$) is the ratio of sales to property, plant, and equipment. They indicate a firm's overall operating efficiency. Firms with a higher operating efficiency may have reduced slack in production resources, so they are more likely to have Chinese suppliers to help them mitigate the effect of supply chain disruptions (Modi & Mishra, 2011; Wiengarten et al., 2017). Capital intensity (*Capital Intensity* $_{t-}$

$_{1\&-2\&-3}$) was calculated by a firm's capital expenditure normalized by sales. It represents the capital expenditure in various operating activities. Firms may outsource activities to Chinese suppliers to reduce or defer their capital expenditure (Raddats et al., 2016). R&D expenditure (*Log R&D* $_{t-1\&-2\&-3}$) represents a firm's investment in innovation, and we applied a natural logarithm transformation to it to correct for skewness. Lower R&D expenditure may indicate that a firm is more likely to outsource its own R&D and depend on its suppliers' R&D (Kim & Zhu, 2018). R&D efficiency (*R&D efficiency* $_{t-1\&-2\&-3}$) is the ratio of sales to R&D expense, which represents the efficiency of a firm using R&D activities to generate sales. Firms with higher R&D efficiency may concentrate more on innovating their core products/processes if they outsource their non-core activities to Chinese firms (Jiang et al., 2006). We summarized the measurements and references of these matching covariates in Appendix A2.

Table 1 shows that larger, capital-intensive, production-efficient, R&D-oriented while less profitable firms tend to have direct Chinese suppliers. In addition, firms' having second-tier Chinese suppliers can also be associated with whether the firms have direct Chinese suppliers. Based on these salient factors, we calculated the propensity score for each sample and control firm based on the estimation coefficients in Table 1. The Pseudo-R-squared equals 38.50%, which suggests an excellent fit of our model (Levine & Toffel, 2010; McFadden, 2021). The range of VIF is between 1.05 to 1.51, indicating that multicollinearity is not a serious concern.

Table 1: *Estimated Coefficients of Probit Model for PSM*

Coefficients	Estimate	Std. error	VIF
Intercept	–3.7800	[0.2496]***	
Log Total Assets $_{t\text{-}1\&\text{-}2\&\text{-}3}$	0.2264	[0.0273]***	1.51
ROA $_{t\text{-}1\&\text{-}2\&\text{-}3}$	–0.2398	[0.0659]***	1.32
Second-tier CN supplier $_t$ (dummy)	1.0654	[0.1492]***	1.31
Inventory efficiency $_{t\text{-}1\&\text{-}2\&\text{-}3}$	–0.0033	[0.0032]	1.05
Production efficiency $_{t\text{-}1\&\text{-}2\&\text{-}3}$	0.0008	[0.0005]*	1.05
Capital intensity $_{t\text{-}1\&\text{-}2\&\text{-}3}$	0.0697	[0.0359]*	1.22
Log R&D $_{t\text{-}1\&\text{-}2\&\text{-}3}$	0.0335	[0.0079]***	1.14
R&D efficiency $_{t\text{-}1\&\text{-}2\&\text{-}3}$	–0.0002	[0.0013]	1.15
n	986		
Chi-squared	444.2	***	
Pseudo-R-squared (McFadden)	38.50%		

Notes. $*p < 0.10$; $**p < 0.05$; $***p < 0.01$. Dependent variable: having first-tier CN supplier (dummy). Additional controls include 106 industry dummies. Variables subscripted *t-1&-2&-3* are averages of one-, two- and three-year lags.

When calculating the propensity score, we drew a boxplot for each variable and carefully checked whether extreme values existed that could affect the validity of the propensity score. As a result, we removed 25 samples because they had extreme values in the variables including ROA, production efficiency, capital intensity, and inventory days. We then matched each sample firm with a control firm (1) with the closest propensity score, and (2) from the same industry (3-digit SIC code). We avoided the scenario in which one control firm was matched to multiple sample firms, which might cause a double-counting issue. If two samples were found matched to the same control, we kept the one with the closest propensity score. Twenty-eight firms were discarded in this step. Ultimately, we successfully obtained 215 sample-control pairs.

Table 2 provides a description of the significant factors in our probit model for the propensity score calculation of 215 sample firms and their matched control firms. We also show the results of tests for difference in the table. The statistics of sample and control firms show that they are highly similar; only two metrics differ at the marginal level (10%). This matching result is acceptable compared with the previous studies using PSM (e.g., Levine & Toffel, 2010; Ye et al., 2020). We also added the covariates as the control variables in the second-stage hypothesis-testing analyses to further account for the variations between sample and control firms.

Table 2: *Statistics of Sample and Control Firms, and Results of Paired* t-*Test*

		Total assets (millions)	ROA	Second-tier CN supplier (dummy)	Production efficiency	Capital intensity	R&D expense (millions)
Sample firms	Mean	18,957.96	0.08	0.85	15.97	0.07	578.44
	SD	46,326.29	0.27	0.36	92.15	0.29	1,597.04
	Max	338,587.67	0.36	1.00	1,277.08	4.19	12,655.33
	Min	1.08	–3.45	0.00	0.10	0.00	0.00
Control firms	Mean	12,758.75	0.03	0.79	12.82	0.09	340.98
	SD	53,236.16	0.37	0.41	50.83	0.30	1,769.13
	Max	328,472.33	0.39	1.00	734.38	3.12	11,904.67
	Min	1.77	–3.35	0.00	0.00	0.00	0.00
Difference	p-value	n.s.	< 0.1	n.s.	n.s.	n.s.	< 0.1

Note. n = 215. Variables are averages value of 2015, 2106, and 2017.

Difference-in-difference regression analysis for the trade war impacts

After 215 matched pairs were constructed, we created a panel data set to test our hypotheses. This panel data set included 2,485 firm-year observations generated from 430 firms (i.e., 215 sample firms and their 215 matched control firms) between 2015 and 2020. This research time window was constructed based on the year (2018) when the tariff increases associated with the U.S.-China trade war was announced. We used three years (2015, 2016, and 2017) before 2018 as the benchmark. We then examined the impacts of trade war in the years 2018, 2019, and 2020. We performed a DID estimation to compare the differences in inventory days (H1) and ROA (H2) between the sample and control observations using the following model:

$$FP_{it} = \beta \cdot Post_t \cdot CNsupplier_i + \gamma X_{it} + \alpha_i + \delta_t + \varepsilon_{it}, \tag{2}$$

where the dependent variable FP_{it} refers to the firm's performance (i.e., inventory days or ROA) of firm i in the year t. $Post_t$ equals 1 if the year t corresponds to the year on or after the 2018 announcement of tariff increases (i.e., 2018, 2019, and 2020); otherwise, it equals 0. $CNsupplier_i$ equals 1 if firm *i* has first-tier Chinese suppliers, and equals 0 otherwise. Thus, the interaction term $Post_t \cdot CNsupplier_i$ equals 1 for the observations on or after 2018 of firm i who had first-tier Chinese suppliers before the trade war, and β should capture the change in the firm's performance after the tariff list is announced. We included the vector X_{it} to control for the firm-level characteristics controlled in the selection model, namely, total assets (natural logarithm transformed), capital intensity, inventory efficiency, production efficiency, log of R&D expenditure, and R&D efficiency to increase the validity of our results. The measurements of these control variables were the same as we use in PSM (see Appendix A2). Total assets were used to control for firm size, because larger firms may be affected by supply chain disruption easily as they seem to be more often involved in complex supply chains (Revilla & Saenz, 2017). Capital intensity includes a firm's capital investment in production and information technology, which may improve firm's financial and inventory performance (Steven et al., 2014). Inventory efficiency and production efficiency were included to control for the firm's operating efficiency. Efficient firms may have fewer slacks available to respond to supply chain disruptions (Wiengarten et al., 2017). R&D expenditure is included because the firm's investment on innovativeness is related to the firm's economic growth (Zahra et al., 2000). R&D efficiency indicates a firm's investment efficiency in research and development, which may affect its profitability (Cho & Pucik, 2005). We also included the supply complexity metrics in X_{it}, including vertical integration, horizontal complexity, spatial complexity, and cooperative complexity. The measurements of these variables will be described in the next section. We also included the firm's number of second-tier suppliers per first-tier suppliers (vertical complexity) to control for the indirect supply chain effect. In addition, we controlled for the firm fixed effect— α_i— and the year fixed effect: δ_t. ε_{it} is the error term. $Post_t$ and $CNsupplier_i$ are omitted in the model because we have controlled for the firm and year fixed effects (Levine & Toffel, 2010). In the above specified model, we expected to capture a positive coefficient in β in the inventory days model and a negative coefficient in the ROA model. These can capture the abnormal negative impacts experienced by the sample firms amidst trade war and examine H1 and H2.

Subsample difference-in-difference analysis for supply structure

The intent of hypotheses H3–H6 is to examine whether firms with a more complex supply structure suffer more from the tariff increases caused by the trade war. These hypotheses can be examined in two methods. First, we can insert an interaction term between the supply structure factors and the $Post_t \cdot CNsupplier_i$ and examine the significance in the coefficient. However, this treatment would create a three-way interaction term among supply structure factors, $\mathrm{Post_t}$ and $\mathrm{CNsupplier_i}$. These increase the difficulty of the interpretation of the coefficient and thus the marginal effects. Another method is to divide the subsamples according to the high and low levels of the supply structure factors, namely, *vertical integration* and *horizontal, spatial*, and *cooperative complexity*.

The subsample analysis approach is arguably more appropriate for indicating the "strength" of moderators across various scenarios (Arnold, 1982; Su et al., 2015; Ye et al., 2020). In H3 to H6, we hypothesized that the level of outsourcing activities and complexity accentuate the impacts of the trade war on a U.S. firm with Chinese suppliers. So, we intend to test the "strength" of the moderators. In addition, the coefficients in the divided group can be easily interpreted, which facilitates the calculation of the marginal effects for managerial implications. This approach is consistent with the previous OM literature using a DID regression technique (e.g., Gu et al., 2017; Soysal et al., 2019; Ye et al., 2020).

Therefore, we used the subsample analysis to examine H3 to H6. Specifically, for each hypothesis testing, we divided the sample firms into two groups (i.e., low-level group and high-level group) based on the yearly industry median of the moderators (i.e., vertical integration, horizontal complexity, spatial complexity, and cooperative complexity). We then reran the regression by using each of the groups to examine H3 to H6. As a robustness check, we also followed Levine & Toffel (2010) to create interaction terms to verify our conclusions (see robustness check section). We used ROA as the dependent variable for these analyses because this indicator was widely used as the bottom-line firm performance metric (e.g., Lo et al., 2014; Swift et al., 2019). The data of supply structure factors were taken at year 2017. They were measured in the following ways:

Vertical integration was measured according to a method developed by Frésard et al. (2020).[1] Hendricks et al. (2009) had applied an industry-level measure, vertical relatedness, based on the "Use Table" of the input-output (IO) table provided by the Bureau of Economic Analysis (BEA), but the authors stated that "it would be ideal to use firm-specific data to compute the vertical relatedness at the firm level" (p. 239). Recently, Frésard et al. (2020) developed a firm-level vertical integration measure built on the IO table and calculated using a textual analysis of an individual firm's business description from its 10-K disclosure. The measurement was based on the assumption that a firm's product vocabularies are vertically related to the same firm's other product vocabularies. The vertical integration score is higher when the product vocabulary in the

[1] The variable can be obtained from http://faculty.marshall.usc.edu/Gerard-Hoberg/FresardHobergPhillipsDataSite/index.html.

description spans vertically related markets (Frésard et al., 2020). The validity of the variable was verified by its significant statistical correlation with firms mentioned using the words "vertical integration" and "vertically integrated" in their 10-K report (Frésard et al., 2020). A higher value of vertical integration indicated that the firm was offering products that were more vertically related.

Horizontal complexity was measured by the firm's number of first-tier suppliers (Bode & Wagner, 2015; Dong et al., 2020). This measurement reflects the multiplicity of the firm's supply base (Choi & Krause, 2006; Sharma et al., 2020). We excluded the U.S. and Chinese suppliers in this measurement to better reflect the sense of backup suppliers that would be less directly affected by the U.S.-China trade war.

Spatial complexity is the geographical spread of a firm's suppliers (Bode & Wagner, 2015). We followed Lu and Shang (2017) to measure spatial complexity as the number of countries or regions where a firm's suppliers were located. This measurement reflects the diversity of the supply base (Sharma et al., 2020). We excluded U.S. and Chinese suppliers to capture the firm's international supply network. This measure assumes that widespread supply bases should increase the difficulty of coordinating production and create more policy uncertainties (Lu & Shang, 2017; Vachon & Klassen, 2002).

Cooperative complexity was measured by the level of connection among the firm's first-tier suppliers (Dong et al., 2020; Lu & Shang, 2017). Specifically, we counted the number of actual links among first-tier suppliers. This number was then divided by the maximum number of possible links among first-tier suppliers to control for the network size. This measurement reflects the interrelatedness of the supply base (Krause & Choi, 2006).

Table 3. *Correlation table of variables in DID analysis.*

	1	2	3	4	5	6	7	8	9	10	11
1. Post*CNsupplier											
2. log Total Assets	0.25***										
3. Capital Intensity	-0.03	0.01									
4. Inventory Efficiency	-0.01	0.12***	0.09***								
5. Production Efficiency	-0.02	-0.18***	-0.04*	0.05**							
6. Log R&D	0.13***	0.21***	-0.08***	-0.02	-0.14***						
7. R&D Efficiency	0.02	0.09***	-0.38***	0.03	0.01	0					
8. Vertical Complexity	-0.13***	-0.04*	0.04**	0.02	0.01	-0.03*	-0.05***				
9. Vertical Integration	-0.02	0.11***	-0.06***	-0.1***	-0.06***	-0.06***	0.02	-0.07***			
10. Horizontal Complexity	0.04*	0.36***	0.01	0.15***	0.01	0.17	0.01	-0.01	-0.04***		
11. Spatial Complexity	0.04**	0.46***	0.01	0.16***	-0.02	0.18	0.01	0.03	-0.02	0.76***	
12. Cooperative Complexity	-0.06***	-0.06***	-0.01	0.01	0	-0.01	0.01	0.17***	-0.02	-0.06***	-0.06***

Note. $*p<0.10$; $**p<0.05$; $***p<0.01$. n=2485

Analysis of Results

Table 4: *Results of DID Analysis*

	Inventory days		ROA	
Coefficients	Estimate	Std. error	Estimate	Std. error
Post*CN supplier	8.0331	[3.1389]**	–0.0389	[0.0162]**
Log total assets	–4.2715	[0.5734]***	0.0703	[0.0030]***
Capital intensity	–3.7736	[4.0110]	–0.0808	[0.0208]***
Inventory efficiency	–1.7510	[0.0918]***	0.0004	[0.0005]
Production efficiency	–0.0388	[0.0168]**	0.0001	[0.0001]
Log R&D	1.0410	[0.1701]***	–0.0008	[0.0009]
R&D efficiency	0.3785	[0.1084]***	0.0026	[0.0006]***
Vertical complexity	–0.0580	[0.0307]*	–0.0005	[0.0002]***
Vertical integration	–587.5539	[81.6706]***	0.4723	[0.4226]
Horizontal complexity	0.0467	[0.0647]	–0.0002	[0.0003]
Spatial complexity	–0.7037	[0.3491]**	–0.0083	[0.0018]***
Cooperative complexity	–22.9997	[15.1911]	0.0209	[0.0786]
n	2485		2485	
R-squared	20.54%		23.17%	
Adj. R-squared	19.99%		22.64%	
F-statistic	53.15	***	61.99	***

Note. ∗p < 0.10; ∗∗p < 0.05; ∗∗∗p < 0.01. Firm and year fixed effects were controlled.

Table 3 presents the correlation of the indicators while Table 4 presents the results for examining H1 and H2 by considering the coefficients of interaction term $Post_t \cdot CNsupplier_i$. The inventory days model shows that the interaction term $Post_t \cdot CNsupplier_i$ is significantly positive (b = 8.0331, p < 0.05), indicating that the inventory days measure increased by 8.03 days (8.3% according to the same mean) in sample firms during the trade war. Thus, H1 is supported. The results suggest that the tariff induced a sense of policy uncertainty for U.S. firms with Chinese suppliers. These firms might have responded by initiating relocations and advance purchasing to mitigate the uncertainty. However, these responses undermined inventory turnover. The increased number of inventory days echoed the increase of the United States' trade deficit, which reached a

10-year high at $621 billion in 2018 (Dmitrieva, 2019), which indicates that U.S. firms with Chinese suppliers were in a buying binge triggered by uncertainty about future tariff increases (Naidu & Baertlein, 2018).

The ROA model of Table 4 shows that the interaction term $Post_t \cdot CNsupplier_i$ is significantly negative (b = –0.0389, p < 0.05), indicating a decrease in ROA of about 3.89% for the sample firms during the trade war. Thus, H2 is supported. This result suggests that the tariffs were undermining U.S. firms' profitability. The deterioration appeared after the tariff went into effect, and firms were unable to recover even 2 years after the tariff was imposed.

Tables 5 to 8 present the results of our subsample DID analysis for comparing the levels of vertical integration, horizontal complexity, spatial complexity, and cooperative complexity, respectively. In Table 5, the coefficient of interaction term $Post_t \cdot CNsupplier_i$ in groups with low levels is significantly negative (b = –0.0742, p < 0.05), indicating that the ROA performance of firms with Chinese suppliers that have a low level of vertical integration was 7.42% lower compared to firms without Chinese suppliers. However, the coefficient of interaction term $Post_t \cdot CNsupplier_i$ in groups with high levels is not statistically significant (p > 0.1), indicating that firms with a high level of vertical integration did not experience a decline in ROA during the trade war. These contrasting results support H3.

Table 6 presents the results of horizontal complexity. The interaction term $Post_t \cdot CNsupplier_i$ in the high-level group is significantly negative (b = –0.0392, p < 0.05), which indicates that the ROA performance of firms with Chinese suppliers having a high level of horizontal complexity was 3.92% lower compared to firms without Chinese suppliers. However, the coefficient of interaction term $Post_t \cdot CNsupplier_i$ in the low-level group is not statistically significant (p > 0.1), which indicates that firms with fewer direct suppliers suffered little from the trade war. Thus, H4 is supported.

The result of spatial complexity is presented in Table 7. The interaction term $Post_t \cdot CNsupplier_i$ in the high-level group is significantly negative (b = –0.0637, p < 0.05), which indicates that the ROA performance of firms with Chinese suppliers having a high level of spatial complexity was 6.37% lower compared to firms without Chinese suppliers. However, the coefficient of interaction term $Post_t \cdot CNsupplier_i$ in the low-level group is not statistically significant (p > 0.1), which indicates that firms with fewer sourcing locations suffered little from the trade war. Thus, H5 is supported.

Table 8 shows the result of cooperative complexity. The interaction term $Post_t \cdot CNsupplier_i$ in the high-level group is significantly negative (b = –0.0825, p < 0.01), which indicates that the ROA performance of firms with Chinese suppliers having a high level of cooperative complexity was 8.25% lower compared to firms without Chinese suppliers. However, the coefficient of interaction term $Post_t \cdot CNsupplier_i$ in the low-level group is not statistically significant (p > 0.1), which indicates that firms with supplier-supplier connections in the supply base suffered little from the trade war. Thus, H6 is supported.

In summary, the results in H5 to H8 consistently demonstrate the burden of having a complex supply structure amid the trade war. Besides the comparison above, the marginal treatment effects on ROA with a low level of vertical integration (–7.42%), high level of horizontal complexity (–3.92%), high level of spatial complexity (–6.37%) and high level of cooperative complexity (–8.25%) are all larger than the average treatment effects shown in Table 4 (–3.89%).

Table 5: *The Moderating Effect of Vertical Integration on ROA*

	High-level group		Low-level group	
Coefficients	Estimate	Std. error	Estimate	Std. error
Post*CN supplier	–0.0073	[0.0155]	–0.0742	[0.0295]**
Log total assets	0.0575	[0.0033]***	0.0851	[0.0049]***
Capital intensity	–0.1067	[0.0319]***	–0.0670	[0.0296]**
Inventory efficiency	0.0001	[0.0005]	0.0005	[0.0008]
Production efficiency	0.0051	[0.0006]***	0.0001	[0.0001]
Log R&D	–0.0021	[0.0009]**	0.0006	[0.0015]
R&D efficiency	0.0020	[0.0005]***	0.0056	[0.0022]**
Vertical complexity	–0.0010	[0.0001]***	–0.0003	[0.0003]
Vertical integration	0.6687	[0.3706]*	–0.3998	[1.0146]
Horizontal complexity	0.0002	[0.0005]	–0.0003	[0.0005]
Spatial complexity	–0.0073	[0.0020]***	–0.0103	[0.0030]***
Cooperative complexity	–0.0326	[0.0702]	0.0763	[0.1565]
n	1335		1150	
R-squared	29.95%		24.00%	
Adj. R-squared	29.05%		22.86%	
F-statistic	46.93	***	29.79	***

Note. ∗p < 0.10; ∗∗p < 0.05; ∗∗∗p < 0.01. Firm and year fixed effects were controlled.

Table 6: *The Moderating Effect of Horizontal Complexity on ROA*

	High-level group		Low-level group	
Coefficients	Estimate	Std. error	Estimate	Std. error
Post*CN supplier	–0.0392	[0.0198]**	–0.0298	[0.0272]
Log total assets	0.0616	[0.0037]***	0.0792	[0.0052]***
Capital intensity	–0.0232	[0.0318]	–0.0628	[0.0268]**
Inventory efficiency	0.0003	[0.0006]	0.0006	[0.0007]
Production efficiency	0.0001	[0.0002]	0.0000	[0.0001]
Log R&D	0.0009	[0.0011]	–0.0024	[0.0014]*
R&D efficiency	0.0423	[0.0046]***	0.0020	[0.0006]***
Vertical complexity	–0.0002	[0.0002]	–0.0012	[0.0003]***
Vertical integration	0.3896	[0.5328]	0.9066	[0.6611]
Horizontal complexity	–0.0002	[0.0004]	–0.0005	[0.0005]
Spatial complexity	–0.0072	[0.0022]***	–0.0075	[0.0032]**
Cooperative complexity	–0.0508	[0.0981]	0.1405	[0.1239]
n	1736		749	
R-squared	23.34%		33.05%	
Adj. R-squared	22.58%		31.49%	
F-statistic	43.59	***	30.07	***

Note. ∗p < 0.10; ∗∗p < 0.05; ∗∗∗p < 0.01. Firm and year fixed effects were controlled.

Table 7: *The Moderating Effect of Spatial Complexity on ROA*

	High-level group		Low-level group	
Coefficients	Estimate	Std. error	Estimate	Std. error
Post*CN supplier	–0.0637	[0.0254]**	–0.0240	[0.0196]
Log total assets	0.0768	[0.0049]***	0.0662	[0.0037]***
Capital intensity	–0.0228	[0.0354]	–0.0775	[0.0242]***
Inventory efficiency	0.0002	[0.0007]	0.0005	[0.0006]
Production efficiency	0.0001	[0.0002]	0.0000	[0.0001]
Log R&D	0.0015	[0.0013]	–0.0028	[0.0012]**
R&D efficiency	0.0325	[0.0052]***	0.0023	[0.0005]***
Vertical complexity	–0.0003	[0.0003]	–0.0007	[0.0002]***
Vertical integration	0.2424	[0.6652]	0.8231	[0.5097]
Horizontal complexity	–0.0004	[0.0005]	–0.0002	[0.0004]
Spatial complexity	–0.0073	[0.0027]***	–0.0076	[0.0024]***
Cooperative complexity	–0.0275	[0.1761]	0.0075	[0.0768]
n	1258		1227	
R-squared	23.90%		29.04%	
Adj. R-squared	22.86%		28.04%	
F-statistic	32.45	***	41.23	***

Note. ∗p < 0.10; ∗∗p < 0.05; ∗∗∗p < 0.01. Firm and year fixed effects were controlled.

Table 8: *The Moderating Effect of Cooperative Complexity on ROA*

	High-level group		Low-level group	
Coefficients	Estimate	Std. error	Estimate	Std. error
Post*CN supplier	–0.0825	[0.0235]***	0.0154	[0.0214]
Log total assets	0.0699	[0.0043]***	0.0684	[0.0042]***
Capital intensity	–0.0212	[0.0351]	–0.0812	[0.0253]***
Inventory efficiency	0.0000	[0.0007]	0.0006	[0.0007]
Production efficiency	0.0001	[0.0001]	–0.0001	[0.0003]
Log R&D	0.0001	[0.0013]	–0.0009	[0.0012]
R&D efficiency	0.0425	[0.0074]***	0.0023	[0.0005]***
Vertical complexity	0.0000	[0.0002]	–0.0011	[0.0002]***
Vertical integration	0.0607	[0.6369]	0.9241	[0.5446]*
Horizontal complexity	–0.0001	[0.0005]	–0.0004	[0.0004]
Spatial complexity	–0.0067	[0.0026]**	–0.0090	[0.0024]***
Cooperative complexity	0.0264	[0.1122]	0.0397	[0.1071]
n	1378		1107	
R-squared	22.15%		30.78%	
Adj. R-squared	21.18%		29.70%	
F-statistic	32.24	***	40.35	***

Note. ∗p < 0.10; ∗∗p < 0.05; ∗∗∗p < 0.01. Firm and year fixed effects were controlled.

Robustness Checks

We conducted several additional tests with alternative specifications, measurement, and grouping approach to check the robustness of our findings. We plotted the mean ROA and inventory days performance in Figure 2 and conducted a common trend analysis to check the parallel assumption for DID analysis. We also plotted the results of placebo test based on firms with “false” Chinese suppliers in 2018 under the tariff changes in Figure 3. For moderating factors, we dropped the samples between 45th to 55th percentile to achieve great separation. We also applied subgroup dummies to create a three-way interaction term to confirm our moderating effects in Table 11. Overall, these tests provide consistent evidence on our main results. We discussed the detailed procedures as below.

Parallel assumption for DID analysis

The assumption for DID analysis to capture any treatment effect is parallel performance, which requires that there be a common trend in dependent variables (i.e., inventory days and ROA) between the sample and control groups before the announcement year of the tariff list. We first followed Song et al. (2020) to visualize the dependent variables for the sample and control groups in Figures 2a and 2b. The average inventory days and ROA for the sample and control firms indicate a consistent difference between the two groups before the tariff lists were announced.

We also performed an additional common trend analysis using the following relative time model (Angrist and Pischke, 2008; Song et al., 2020):

$$P_{it} = \beta \cdot CNsupplier_i + \sum_{t=2015}^{2020} \kappa_t \cdot CNsupplier_i \cdot D_{it} + \gamma X_{it} + \alpha_i + \delta_t + \varepsilon_{it}, \quad (3)$$

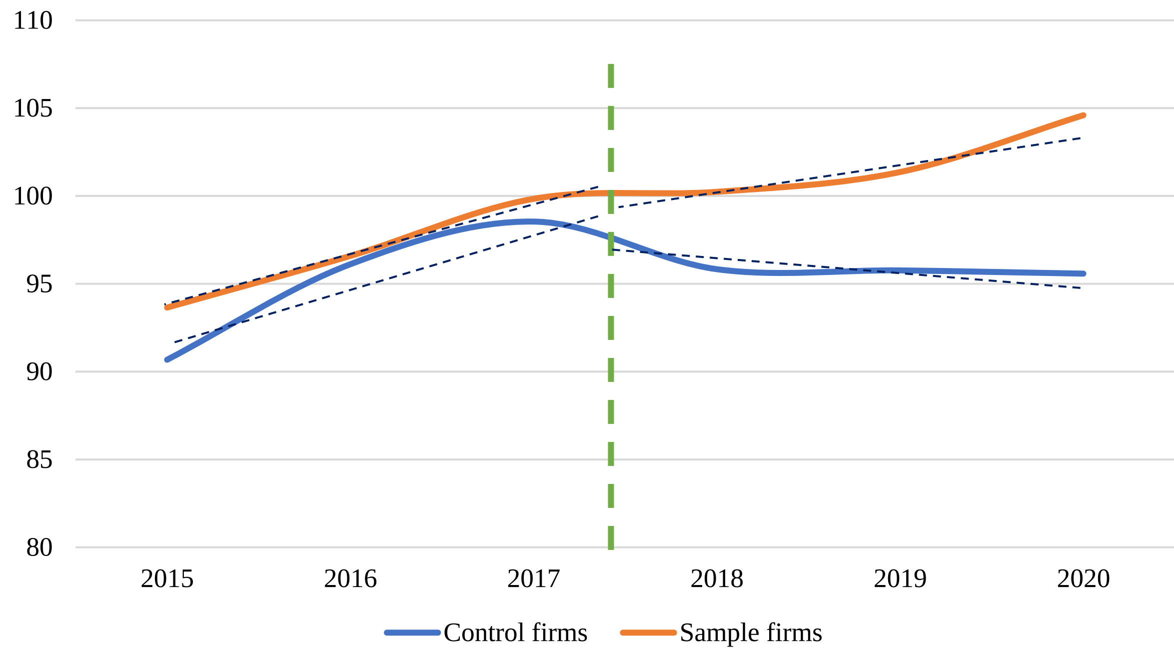

Figure 2a. Inventory days time trends for sample and control firms

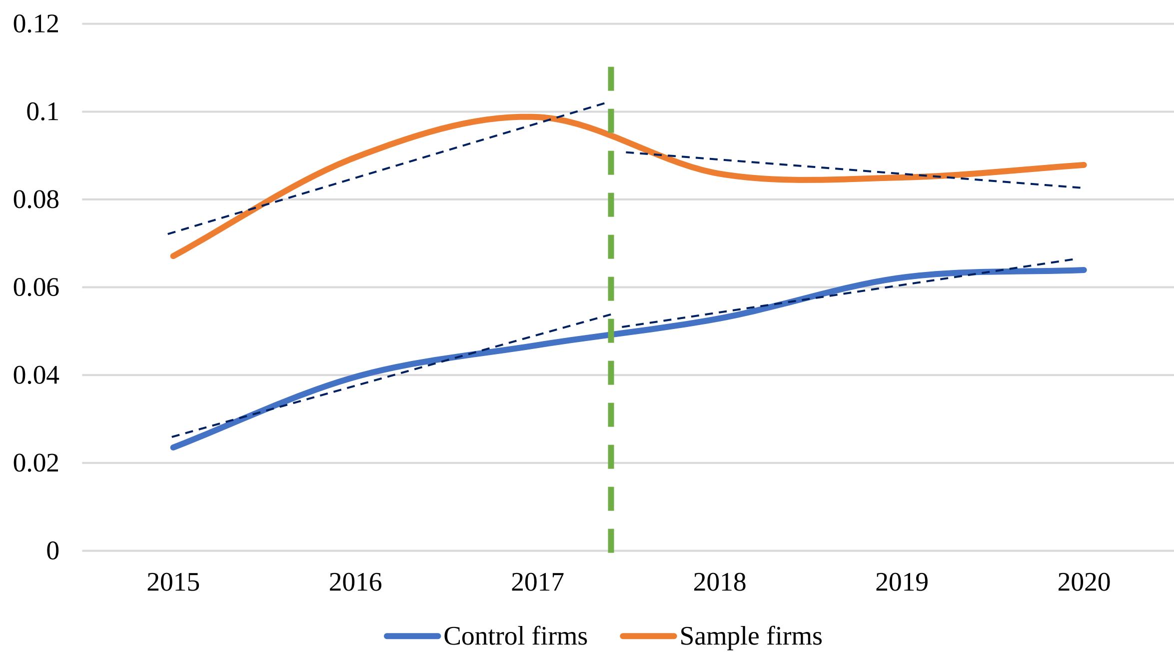

Figure 2b. ROA time trends for sample and control firms

where D_{it} are dummy variables that indicate years from 2015 to 2020, the study period in our main analysis. Other variables are the same as our main analysis in Formula 2. Table 9 presents κ_t for each year. There is no significant difference between sample firms and control firms regarding the inventory days and ROA in the 2-year period before the tariff lists were announced (i.e., 2016 and 2017). The differences appear 1 year after the tariff lists were announced (i.e., 2019 and 2020). The results largely support the parallel assumption in our analysis.

Table 9: *Results of Common Trend Analysis*

Year	Inventory days		ROA	
2015	0.11	[4.78]**	–0.057	[0.027]**
2016	6.72	[4.80]	–0.023	[0.027]
2017	7.80	[4.75]	–0.005	[0.027]
2018	7.13	[4.76]	–0.025	[0.027]
2019	9.34	[4.66]**	–0.045	[0.026]*
2020	1.12	[5.23]**	–0.058	[0.029]**

Note. ∗p < 0.10; ∗∗p < 0.05; ∗∗∗p < 0.01. Standard errors are in parentheses.

Placebo test

We further conducted a placebo test to test the robustness of our results, as follows. We randomly faked 268 firms with “false” Chinese suppliers in 2018 and repeated the PSM-DID analysis. If the firms with “true” Chinese suppliers in our study can increase inventory days and decrease ROA, we expect the $Post_t \cdot CNsupplier_i$ in Formula 2 for the faked firms to be insignificant. We repeated the process 1000 times and plotted the t-values in Figure 3a and 3b. The result shows that most of the “false” t-values are between –1.6 and 1.6, indicating that most of the coefficients of $Post_t \cdot CNsupplier_i$ in our placebo test are not statistically significant. Thus, the results did not refute our conclusions. Thus, our analysis results are not captured by chance.

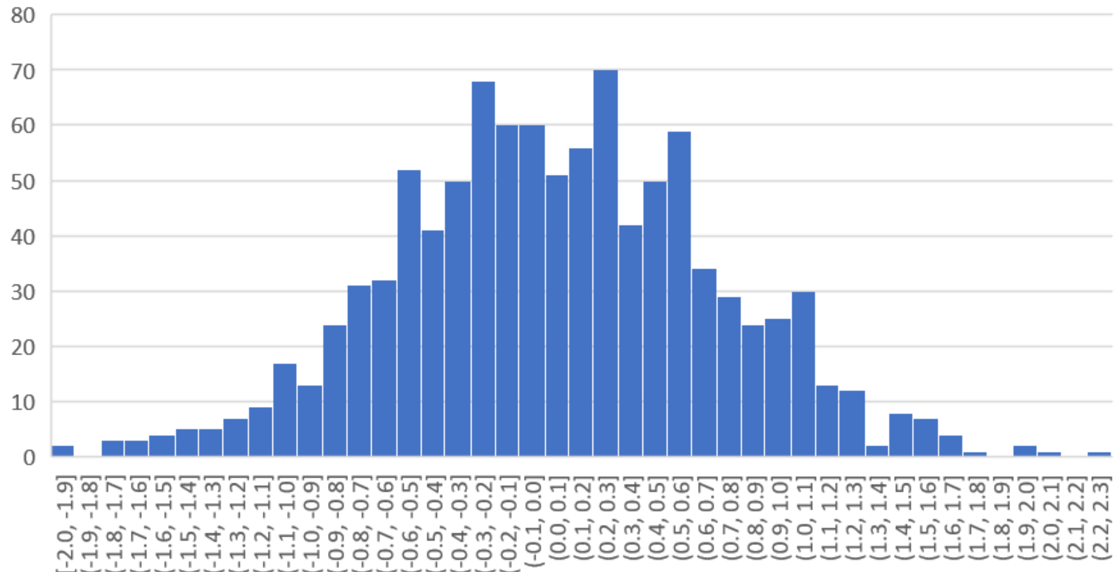

Figure 3a. Distribution of t-value for inventory days

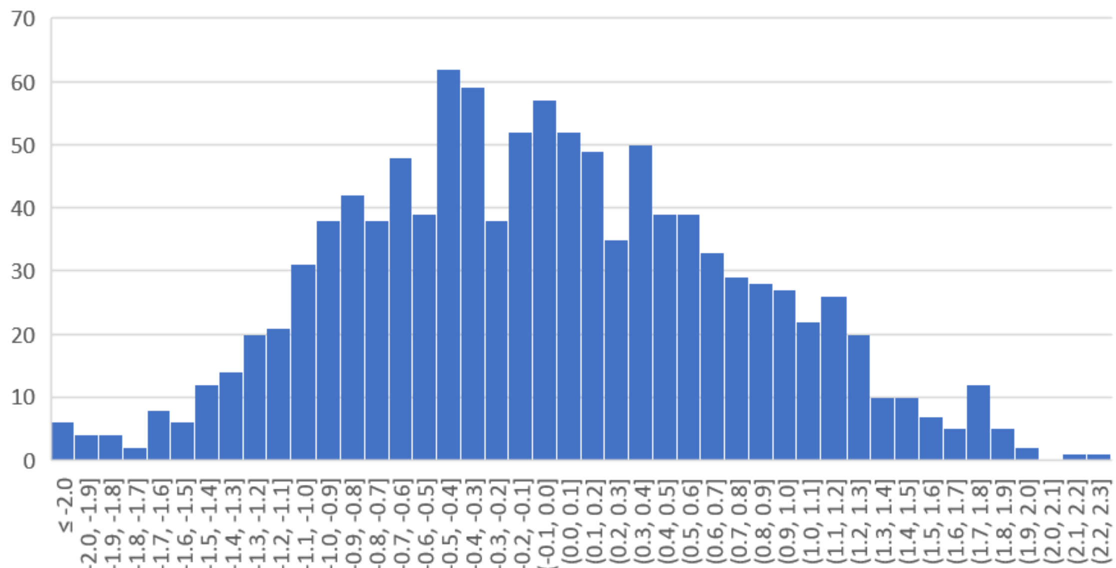

Figure 3b. Distribution of t-value for ROA

Table 10. *The results of DID analysis on different samples.*

	Sample without US PP&E				Sample without involving with other trade wars			
	Inventory Days		ROA		Inventory Days		ROA	
Coefficients	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Post*CNsupplier	7.5150	[3.8983]*	-0.0515	[0.0222]**	11.1474	[3.7737]***	-0.0418	[0.0205]**
log Total Assets	-4.6507	[0.6822]***	0.0781	[0.0039]***	-3.5664	[0.6984]***	0.0852	[0.0038]***
Capital Intensity	5.0586	[4.7164]	-0.0681	[0.0269]**	4.0090	[4.6386]	-0.0702	[0.0252]***
Inventory Efficiency	-1.8248	[0.1125]***	0.0007	[0.0006]	-1.9191	[0.1167]***	0.0006	[0.0006]
Production Efficiency	-0.0344	[0.0175]**	0.0001	[0.0001]	-0.0287	[0.0180]	0.0001	[0.0001]
Log R&D	1.3258	[0.2248]***	-0.0025	[0.0013]**	0.9400	[0.2207]***	-0.0039	[0.0012]***
R&D Efficiency	0.4611	[0.1143]***	0.0024	[0.0007]***	0.4664	[0.1128]***	0.0025	[0.0006]***
Vertical Complexity	-0.0337	[0.0356]	-0.0006	[0.0002]***	-0.0412	[0.0342]	-0.0006	[0.0002]***
Vertical Integration	-498.9141	[103.0398]***	0.1394	[0.5876]	-549.2126	[100.6378]***	0.1906	[0.5465]
Horizontal Complexity	0.0333	[0.0743]	-0.0004	[0.0004]	-0.1794	[0.2178]	0.0025	[0.0012]**
Spatial Complexity	-1.0393	[0.4272]**	-0.0089	[0.0024]***	0.2181	[0.6481]	-0.0130	[0.0035]***
Cooperative Complexity	-29.4430	[18.5420]	0.0657	[0.1057]	-31.8787	[15.7598]**	0.0003	[0.0856]
n	1723		1723		1793		1793	
R-Squared:	21.86%		23.82%		18.63%		26.83%	
Adj. R-Squared:	21.08%		23.06%		17.85%		26.13%	
F-statistic:	39.74	***	44.44	***	33.86	***	54.24	***

Note. ∗p<0.10; ∗∗p<0.05; ∗∗∗p<0.01. Firm and year fixed effect were controlled.

Variations in samples

In addition, we fine-tuned our sample to conduct a DID regression analysis. First, U.S. firms with U.S. PP&E in our sample may not be affected by the tariff changes as they may purchase raw materials that are not on the tariff lists and produce finished goods in their US plants. We therefore excluded those samples and redid the analysis. Second, the tariffs between the United States and other countries could also affect the results. Therefore, we eliminated the samples of U.S. firms with suppliers in other countries engaged in a trade war with the United States during our study period. The analysis of the results is largely identical to those of our main results. We present the results in Table 10.

Additional tests for subsample DID analysis

Dividing the samples into subgroups may not achieve clear separation between firms with higher versus lower integration and complexity levels because some firms' integration and complexity levels may be close to the median levels. We therefore dropped the samples between 45th to 55th percentile for integration and complexity levels to achieve great separation (Su et al., 2015). We reran the analysis based on the subsamples below 45th percentile (low-level groups) and above 55th percentile (high-level groups), and the results are identical as those of our main analysis. The results are presented in Appendix B Table B1 (Vertical Integration), B2 (Horizontal Complexity), B3 (Spatial Complexity) and B4 (Cooperative Complexity).

The difficulty of interpreting coefficients of three-way interaction terms motivated us to use subsample analysis to examine H3 to H6. To further cross-examine the robustness of our subsample analysis results, we followed Levine and Toffel (2010) to apply the interaction terms and the below estimation model:

$$FP_{it} = \beta \cdot Post_t \cdot CNsupplier_i \cdot HighGroup_i + \kappa \cdot Post_t \cdot CNsupplier_i \cdot LowGroup_i + \gamma X_{it} + \alpha_i + \delta_t + \varepsilon_{it} \quad (4)$$

where $HighGroup_i$ are dummy variables that indicate firm i belongs to high-level group, $LowGroup_i$ are dummy variables that indicate firm *i* belongs to low-level group. Other variables are the same as our main analysis in formula 2. So β and κ should capture the changes in firm's performance in high- and low-level groups after the tariff lists were announced. Model 1, 2, 3, and 4 in Table 11 show the results of vertical integration, horizontal complexity, spatial complexity, and cooperative complexity respectively. Post*CNsupplier*Low Vertical Integration, Post*CNsupplier*High Horizontal Complexity, Post*CNsupplier*High Spatial Complexity, and Post*CNsupplier*High Cooperative Complexity are significantly negative ($p < 0.01$), which are identical to those of our main analysis.

In addition, using horizontal complexity to test H4 may ignore the effects of second tier suppliers in a supply chain. We therefore applied subsample DID analysis on vertical complexity to replace horizontal complexity. In Table 12, the interaction term $Post_t \cdot CNsupplier_i$ in high-level group is significantly negative (b = -0.0463, p < 0.05), indicating that firms with Chinese suppliers having a high level of vertical complexity reduce the ROA performance by 4.63% compared to firms without Chinese suppliers. However, the coefficient of interaction term $Post_t \cdot CNsupplier_i$ in low-level group is not statistically significant (p > 0.1), indicating that firms with fewer direct and indirect suppliers suffered little from the trade war. Thus, H4 is still supported.

Table 11. *The moderating effects on ROA*

	Model 1 Vertical Integration		Model 2 Horizontal Complexity		Model 3 Spatial Complexity		Model 4 Cooperative Complexity	
Post*CNsupplier*High Vertical Integration	-0.0282	[0.0192]	-	-	-	-	-	-
Post*CNsupplier*Low Vertical Integration	-0.0525	[0.0200]***	-	-	-	-	-	-
Post*CNsupplier*High Horizontal Complexity	-	-	-0.0494	[0.0179]***	-	-	-	-
Post*CNsupplier*Low Horizontal Complexity	-	-	-0.0142	[0.0229]	-	-	-	-
Post*CNsupplier*High Spatial Complexity	-	-	-	-	-0.0817	[0.0198]***	-	-
Post*CNsupplier*Low Spatial Complexity	-	-	-	-	-0.0106	[0.0193]	-	-
Post*CNsupplier*High Cooperative Complexity	-	-	-	-	-	-	-0.0746	[0.0192]***
Post*CNsupplier*Low Cooperative Complexity	-	-	-	-	-	-	0.0017	[0.0199]
log Total Assets	0.0707	[0.0029]***	0.0706	[0.0030]***	0.0673	[0.0029]***	0.0714	[0.0030]***
Capital Intensity	-0.0821	[0.0207]***	-0.0808	[0.0207]***	-0.0799	[0.0208]***	-0.082	[0.0207]***
Inventory Efficiency	0.0004	[0.0005]	0.0004	[0.0005]	0.0003	[0.0005]	0.0005	[0.0005]
Production Efficiency	0.0001	[0.0001]	0.0001	[0.0001]	0.0001	[0.0001]	0.0001	[0.0001]
Log R&D	-0.0009	[0.0009]	-0.0007	[0.0009]	-0.001	[0.0009]	-0.0008	[0.0009]
R&D Efficiency	0.0026	[0.0006]***	0.0026	[0.0006]***	0.0026	[0.0006]***	0.0026	[0.0006]***
Vertical Complexity	-0.0005	[0.0002]***	-0.0005	[0.0002]***	-0.0006	[0.0002]***	-0.0005	[0.0002]***
Vertical Integration	-	-	0.4718	[0.4223]	0.4797	[0.4235]	0.401	[0.4221]
Horizontal Complexity	-0.0002	[0.0003]	-	-	-0.0013	[0.0002]***	-0.0003	[0.0003]
Spatial Complexity	-0.0083	[0.0018]***	-0.0092	[0.0013]***	-	-	-0.0083	[0.0018]***
Cooperative Complexity	0.0206	[0.0786]	0.0196	[0.0786]	0.0305	[0.0787]	-	-
n	2485		2485		2485		2485	
R-Squared	23.17%		23.22%		22.84%		23.54%	
Adj. R-Squared	22.64%		22.69%		22.31%		23.02%	
F-statistic	61.99	***	62.18	***	60.87	***	63.30	***

Note. ∗p<0.10; ∗∗p<0.05; ∗∗∗p<0.01. Firm and year fixed effect were controlled.

Table 12: *The moderating effect of vertical complexity on ROA*

	High value group		Low value group	
Coefficients	Estimate	Std. Error	Estimate	Std. Error
Post*CNsupplier	-0.0463	[0.0206]**	-0.0303	[0.0265]
log Total Assets	0.0646	[0.0038]***	0.0833	[0.0051]***
Capital Intensity	-0.0754	[0.0239]***	-0.0284	[0.0485]
Inventory Efficiency	0.0005	[0.0008]	0.0005	[0.0006]
Production Efficiency	0.0001	[0.0001]	0.0000	[0.0003]
Log R&D	0.0001	[0.0011]	-0.0017	[0.0014]
R&D Efficiency	0.0022	[0.0006]***	0.0070	[0.0019]***
Vertical Complexity	-0.0004	[0.0002]**	-0.0008	[0.0003]**
Vertical Integration	0.6486	[0.5813]	-0.0634	[0.6284]
Horizontal Complexity	-0.0001	[0.0004]	-0.0028	[0.0011]***
Spatial Complexity	-0.0074	[0.0022]***	-0.0056	[0.0034]
Cooperative Complexity	0.0220	[0.0890]	-0.0748	[0.1780]
n	1600		885	
R-Squared:	20.34%		30.33%	
Adj. R-Squared:	19.48%		28.96%	
F-statistic:	33.66	***	31.45	***

Note. ∗p<0.10; ∗∗p<0.05; ∗∗∗p<0.01. Firm and year fixed effect were controlled.

Conclusion and Discussion

We have examined the impact of import tariff increases caused by the U.S.-China trade war on MNCs' performance and explored the extent to which supply structure and complexity affected a firm's performance. We tested our hypotheses using operational performance data obtained between 2015 and 2020 to capture the effect before and after the new tariffs were instituted in the recent U.S.-China trade war. Our analysis, which adopted a quasi-experimental design with DID regression analysis, revealed that the trade war led to higher inventory (days of supply) and lower profitability (ROA) for U.S. firms with direct suppliers in China. In addition, we find that firms with a lower degree of vertical integration or a more horizontally, vertically, spatially, and cooperatively complex supply base would suffer even more.

Theoretical Contributions

This study is motivated by the transaction cost framework, where transaction cost = transaction risk + coordination costs (Grover & Malhotra, 2003). However, arguing that the transaction risk and coordination costs interact in global trade, we proposed that transaction cost = transaction risk * coordination costs. Through this interaction, our findings contribute to the supply chain risk management literature.

Most empirical and analytical OM studies have implicitly assumed the stability of the policy environment (Dong & Kouvelis, 2020). In line with Dong and Kouvelis (2020), Tokar and Swink (2019), and Fugate et al. (2019), this study echoed Charpin et al. (2020) and Darby et al. (2020) and explored the impact of political risks on a firm's operations at the global level. Using tariff levy as the source of uncertainty and risk, this study revealed how tariff increases could affect firms that were actively involved in international trade. Our findings confirmed that imposing trade tariffs affects domestic industries negatively in terms of inventory and ROA, especially when firms have relied heavily on the sourcing from China. Thus, trade war, as an adverse international event, increases transaction costs for firms in terms of disrupted operations and undermined profitability.

Recent OM research has examined the relationship between a firm's supply chain structure and financial performance (Lu & Shang, 2017), firm innovation (Sharma et al., 2020), and the impact of supply-base innovation on financial performance (Dong et al., 2020). We entered this discourse by studying how a complex supply chain can be a burden for MNCs when the international environment destabilizes. Conventional wisdom suggests that diversifying the sourcing base can mitigate the impact of bilateral trade relation deterioration. However, our findings challenge this view and suggests that firms with distributed supply bases suffered more from the tariff increases due to the U.S.-China trade war.

This study also contributes to the literature on manufacturing diversification. Previous research showed that international diversification can enable a firm to create an inverted U-shaped performance (e.g., Hitt et al., 1997; Lampel & Giachetti, 2013; Narasimhan & Kim, 2002; Palich et al., 2000), and increase the firm's flexibility to cope with supply disruption (e.g., Hendricks et al., 2009). However, our empirical evidence shows that sourcing diversification can become a burden for firms in responding to political risk events. This finding is in line with the view that supply chain risk management should coordinate and collaborate with supply chain partners to maintain operational continuity and profitability (Tang, 2006). A diversified supply structure reduces responsiveness because of the difficulty of coordination (Choi & Krause, 2006). Our empirical result is consistent with Henricks et al.'s (2009) finding that geographically diverse firms suffer more from supply chain disruption. These arguments are consistent with TCE's explanation of the constraints on international diversification expansion. TCE suggests that diversification increases transaction costs in terms of organizational complexity and the need for coordination (Lampel & Giachetti, 2013). Hence, our study advances the understanding of TCE by proposing that vulnerability to policy risks can plausibly explain the disadvantages of international diversification.

Vertical integration (make-decision) has been considered a strategy to improve administrative, advertising, and R&D efficiency (D'Aveni & Ravenscraft, 1994) and to facilitate coordination and real-time adaptation (Forbes & Lederman, 2010). Our study adds nuances to the literature by highlighting the merits of vertical integration for firms. Vertical integration increases a firm's resilience. When the trade war led to substantially increased transaction costs in the international environment, we found that vertically integrated firms were more likely to have suffered less from the increased transaction costs.

Practical Implications

This study reveals practical implications for supply chain managers by quantifying the impact of the U.S.-China trade war on firms' operational performances. In line with the survey conducted by the trade organizations (e.g., the American Chamber of Commerce in China), our results confirmed the firms' concerns over the U.S.-China trade war. Consistent with the prediction stated in Dong & Kouvelis (2020), we showed that U.S. firms' performances were undermined by the trade war. Specifically, we showed that a 1% tariff increase for Chinese products will immediately reduce the ROA by 3.89% and will prolong inventory days by 8.03 days for U.S. firms with direct Chinese suppliers.

Managers should understand that protectionism may not necessarily protect domestic industries. Our evidence illustrates that these tariffs undermined the competitiveness of U.S. firms. This finding echoes the case that the United States' tariff on foreign washing machines was backfiring on Whirlpool, which had lobbied for the tariff. In 2013 and 2018, Whirlpool filed complaints about the dumping of Samsung and LG washing machines, and the U.S. government-imposed tariffs on the imported washers and on related materials such as steel and aluminium, resulting in an increased price for raw materials and a declining demand for domestic washers (Rampell, 2018). Whirlpool's share price tumbled by 15% in the 6 months after the tariff became effective in 2018 (Tangel & Zumbrun, 2018). In the era of the global supply chain, therefore, the costs of lobbying for tariff protection may not generate the benefits one would hope for.

The abnormal increase in inventory reflects U.S. firms' advance purchase behavior due to trade policy uncertainty induced by the trade war. The U.S. trade deficit increase with China that expanded in 2018 echoes our findings. In 2019, despite a reduction in the U.S. trade deficit with China, the deficit with other countries increased. This suggests that, rather than moving production back to the United States, U.S. firms preferred to shift production to other countries with lower labor costs, such as Vietnam and Mexico (Zumbrun & Davis, 2020). Thus, in a globalized supply market, applying tariffs to a single country cannot stimulate reshoring to domestic manufacturing sectors. Instead, it can undermine the operations and profit for these firms. The U.S. government may find it more effective to focus on providing assistance to facilitate firms' relocation rather than on imposing tariffs.

This study also provides an empirical evaluation as to the effectiveness of trade barrier policy in the global supply chain era. Recently, we have observed a re-emergence of mercantilism, with governments emphasizing the trade gap and protectionism. Mercantilism considers international interactions as zero-sum games. According to this approach, a country should work to achieve as large a trade surplus as possible to benefit the country's economy. However, our study suggests that protectionism has lost its power to protect the domestic economy in the global supply chain era. Because the supply chain of influential MNCs relies significantly on global trade, any disruption would have a serious impact on these firms' operations and, in turn, on the domestic economy. Our views are bolstered by the case that major carmakers (such as Tesla) have filed lawsuits against the U.S. government over its tax imposed on Chinese products. As Volvo Cars indicated in their filed legal documents, "Volvo Cars strongly believes the way to reach economic growth is to reduce tariffs and harmonize international trade" (BBC, 2020).

Limitations

This study has several limitations that future research should address. First, despite the fact that the Bloomberg SPLC, FactSet Reverse, and COMPUSTAT Segment databases have been widely used in previous OM studies, the exhaustive identification of supply chain relationships was not guaranteed. It is possible that the three databases did not identify some minor and invisible relationships, which this study omitted. Therefore, our findings focused more on U.S. firms' key supply chain relationships with China. Second, the post-treatment window of this study (3 years) is relatively short given the data availability. In addition, this study focused only on the U.S.-China trade war that occurred between the two most prominent and dependent economic entities. The results may not apply to trade wars between two economic entities that depend less on each other. Furthermore, this study focused on two operating performance facets, inventory and profitability. However, other metrics such as responsiveness, resilience, and adaptability can be essential and worth exploring in future research.

This study also focused on the first-tier suppliers and customers that were directly connected with our sample firms. Our PSM approach controlled the confounding effects of second-tier suppliers. As a result of controlling these measures, however, we lost the opportunity to investigate the indirect effects of the less visible second-tier suppliers on the firms. Finally, we used the number of connections and number of countries to measure the firms' supply chain structure based on the available data. The use of relational values has substantially reduced our sample size because of the missing variable data in the Bloomberg SPLC and FactSet Reverse databases. Therefore, future research may apply multiple methods (e.g., case studies and longitudinal survey) and use data collected from multiple sources to increase data availability, triangulate this study's findings, and explore the boundary conditions.

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Appendix A

Table A1: *List of U.S.–China Trade War Industries*

List	Effective date	Value of Chinese goods	List of industries
1	July 6, 2018	U.S. $34 billion	https://ustr.gov/sites/default/files/enforcement/301Investigations/FRN301.pdf
2	August 23, 2018	U.S. $16 billion	https://ustr.gov/sites/default/files/2018-13248.pdf
3	September 23, 2018	U.S. $200 billion	https://ustr.gov/sites/default/files/enforcement/301Investigations/2018-0026%20China%20FRN%207-10-2018_0.pdf

Appendix A2

Variable	Measurement	in PSM process	in DID regression	Reference
ROA	Ratio of operating income to total assets	Yes	DV	Corbett et al., 2005
Inventory days	(Average inventory/cost of goods sold)*365	—	DV	Wiengarten et al., 2017
First-tier CN supplier	Dummy coded 1 if the firm has first-tier Chinese suppliers	DV	—	—
Second-tier CN supplier	Dummy coded 1 if the firm has second-tier Chinese suppliers	Yes	—	—
Log total assets	Natural logarithm of total assets	Yes	Yes	Wiengarten et al., 2020
Capital intensity	Capital expenditure normalized by sales	Yes	Yes	Steven et al., 2014
Inventory efficiency	Ratio of sales to average inventory	Yes	Yes	Modi & Mishra, 2011
Production efficiency	Ratio of sales to property, plant, and equipment	Yes	Yes	Modi & Mishra, 2011
Log R&D	Natural logarithm of research and development expense	Yes	Yes	Marino et al., 2016
R&D efficiency	Ratio of sales to research and development expense	Yes	Yes	Lo et al., 2014;
Vertical integration	Vertical integration level: text analysis of the product vocabulary in the firm's business description spans vertically related markets	—	Yes	Frésard et al., 2020
Horizontal complexity	Number of first-tier suppliers	—	Yes	Bode & Wagner, 2015; Dong et al., 2020
Spatial complexity	Number of countries or regions where a firm's suppliers were located	—	Yes	Lu & Shang, 2017
Cooperative complexity	Actual number of connections between first-tier suppliers over all possible connections	—	Yes	Lu & Shang, 2017; Dong et al., 2020

Appendix B. Subsample DID analysis based on the subsamples below 45th percentile (low level groups) and above 55th percentile (high level groups).

Table B1. *The moderating effect of vertical integration on ROA*

	High-level group		Low-level group	
Coefficients	Estimate	Std. Error	Estimate	Std. Error
Post*CNsupplier	-0.0042	[0.0162]	-0.0731	[0.0321]**
log Total Assets	0.0586	[0.0034]***	0.0882	[0.0054]***
Capital Intensity	-0.1033	[0.0326]***	-0.0641	[0.0307]**
Inventory Efficiency	0.0001	[0.0005]	0.0007	[0.0009]
Production Efficiency	0.0055	[0.0007]***	0.0001	[0.0001]
Log R&D	-0.0020	[0.0010]**	0.0024	[0.0017]
R&D Efficiency	0.0020	[0.0005]***	0.0054	[0.0023]**
Vertical Complexity	-0.0010	[0.0001]***	-0.0002	[0.0004]
Vertical Integration	0.6814	[0.3845]*	-1.0571	[1.1143]
Horizontal Complexity	0.0002	[0.0006]	-0.0005	[0.0005]
Spatial Complexity	-0.0076	[0.0021]***	-0.0115	[0.0033]***
Cooperative Complexity	-0.0247	[0.0719]	0.0592	[0.1639]
n	1276		1034	
R-Squared:	30.31%		23.96%	
Adj. R-Squared:	29.37%		22.68%	
F-statistic:	45.59	***	26.67	***

Note. ∗p<0.10; ∗∗p<0.05; ∗∗∗p<0.01. Firm and year fixed effect were controlled.

Table B2. *The moderating effect of horizontal complexity on ROA*

	High-level group		Low-level group	
Coefficients	Estimate	Std. Error	Estimate	Std. Error
Post*CNsupplier	-0.0428	[0.0250]*	-0.0258	[0.0293]
log Total Assets	0.0652	[0.0046]***	0.0842	[0.0056]***
Capital Intensity	-0.0255	[0.0360]	-0.0592	[0.0277]**
Inventory Efficiency	0.0004	[0.0008]	0.0004	[0.0007]
Production Efficiency	0.0001	[0.0002]	0.0000	[0.0001]
Log R&D	0.0015	[0.0014]	-0.0042	[0.0016]***
R&D Efficiency	0.0364	[0.0053]***	0.0020	[0.0006]***
Vertical Complexity	-0.0001	[0.0003]	-0.0013	[0.0003]***
Vertical Integration	0.1501	[0.6555]	0.5935	[0.7154]
Horizontal Complexity	-0.0001	[0.0005]	-0.0005	[0.0005]
Spatial Complexity	-0.0080	[0.0027]***	-0.0082	[0.0034]**
Cooperative Complexity	-0.1182	[0.1617]	0.1577	[0.1289]
n	1331		689	
R-Squared:	20.88%		34.04%	
Adj. R-Squared:	19.86%		32.37%	
F-statistic:	28.87	***	28.85	***

Note. ∗p<0.10; ∗∗p<0.05; ∗∗∗p<0.01. Firm and year fixed effect were controlled.

Table B3. *The moderating effect of spatial complexity on ROA*

	High-level group		Low-level group	
Coefficients	Estimate	Std. Error	Estimate	Std. Error
Post*CNsupplier	-0.0569	[0.0242]**	-0.0257	[0.0202]
log Total Assets	0.0777	[0.0045]***	0.0602	[0.0039]***
Capital Intensity	-0.0275	[0.0352]	-0.0717	[0.0234]***
Inventory Efficiency	-0.0002	[0.0007]	0.0008	[0.0006]
Production Efficiency	0.0002	[0.0002]	0.0000	[0.0001]
Log R&D	0.0016	[0.0013]	-0.0021	[0.0012]*
R&D Efficiency	0.0358	[0.0051]***	0.0024	[0.0005]***
Vertical Complexity	0.0000	[0.0003]	-0.0009	[0.0002]***
Vertical Integration	0.2622	[0.6401]	0.7053	[0.5270]
Horizontal Complexity	-0.0004	[0.0005]	-0.0002	[0.0004]
Spatial Complexity	-0.0076	[0.0026]***	-0.0071	[0.0025]***
Cooperative Complexity	-0.0297	[0.1480]	0.0252	[0.0795]
n	1131		1065	
R-Squared:	25.72%		28.55%	
Adj. R-Squared:	24.80%		27.39%	
F-statistic:	39.48	***	34.85	***

Note. ∗p<0.10; ∗∗p<0.05; ∗∗∗p<0.01. Firm and year fixed effect were controlled.

Table B4. *The moderating effect of cooperative complexity on ROA*

	High-level group		Low-level group	
Coefficients	Estimate	Std. Error	Estimate	Std. Error
Post*CNsupplier	-0.0847	[0.0237]***	0.0125	[0.0216]
log Total Assets	0.0703	[0.0044]***	0.0710	[0.0043]***
Capital Intensity	-0.0216	[0.0352]	-0.0828	[0.0253]***
Inventory Efficiency	0.0001	[0.0007]	0.0008	[0.0007]
Production Efficiency	0.0001	[0.0001]	-0.0001	[0.0003]
Log R&D	0.0001	[0.0013]	-0.0015	[0.0012]
R&D Efficiency	0.0424	[0.0075]***	0.0023	[0.0005]***
Vertical Complexity	0.0000	[0.0002]	-0.0011	[0.0002]***
Vertical Integration	0.0704	[0.6395]	0.8790	[0.5457]
Horizontal Complexity	0.0000	[0.0005]	-0.0005	[0.0004]
Spatial Complexity	-0.0070	[0.0027]***	-0.0088	[0.0025]***
Cooperative Complexity	0.0273	[0.1127]	0.0364	[0.1072]
n	1366		1095	
R-Squared:	22.20%		31.37%	
Adj. R-Squared:	21.22%		30.28%	
F-statistic:	32.05	***	41.02	***

Note. ∗p<0.10; ∗∗p<0.05; ∗∗∗p<0.01. Firm and year fixed effect were controlled.