Impact of the U.S.-China Trade War on the Operating Performance of U.S. Firms: The Role of Outsourcing and Supply Base Complexity

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Abstract

Multinational corporations 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, paired with the global recession, has 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 various 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 performance indicators of U.S. firms. We found that U.S. firms with direct supply partners (i.e., first-tier suppliers) in China had a worse performance in terms of inventory (i.e., days of supply) and profitability (return-on-assets). We further found that the negative impact on firms' profitability was more severe for firms with a higher degree of outsourcing, and horizontal and spatial 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 policymakers.

Keywords: Geopolitical risk, trade war, outsourcing, supply base complexity, difference-in-difference

1. Background

In the context of stable, open trade and a low trade barrier global environment, many multinational corporations (MNCs) have offshored production to Asia, creating complex global supply chains for industrial and consumer products. Through cross-border transactions, firms can reduce cost and develop knowledge (Pitelis & Teece, 2010), improve the efficiency of physical resources, and increase business opportunities (Teece, 1986). However, the flip side of global sourcing, as suggested by transaction costs economics (TCE), is that it increases the transaction and coordination costs that MNCs are forced to bear (Lampel & Giachetti, 2013). Additionally, complex global supply chains can make a firm vulnerable to dynamic changes in trade policies. Nowadays, increased transaction risks and coordination are major sources of operational costs (Grover & Malhotra, 2003; Yuan et al., 2020).

The recently emerging nationalism has forced governments to impose new trade restrictions for de-globalization (Witt, 2019), creating massive uncertainty in the global supply chain (Kouvelis et al., 2011) and forcing firms to rethink their global operational strategies (Charpin et al., 2020; Darby et al., 2020). These changes are challenging the presumption in most supply chain management studies of a stable, open global environment with low trade barriers (Dong & Kouvelis, 2020), motivating us to investigate how global trade environment changes may affect firms' supply chain management.

Although researchers have examined various aspects of supply chain risks (e.g., Kleindorfer & Saad, 2005; Tang & Tomlin, 2008), the understanding of the impacts of geopolitical tensions and trade conflicts on firms' operating performance remains limited (Charpin et al., 2020). Firms facing significant geopolitical risk must reconsider their operational strategy and resources and adapt accordingly (Charpin et al., 2020; Darby et al., 2020). In this study, we aim to provide an increased understanding of and implications for these decisions.

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

The intent of the import tariff increases 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% 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 our first research question (RQ1): How would the U.S.-China trade war affect the operating performance of U.S. firms sourcing from China? We examined the performance metrics of inventory days (Wiengarten et al., 2017) and profitability (Swift et al., 2019) by considering trade wars as supply chain disruptors (Roscoe et al., 2020) and cost burdens (Dong & Kouvelis, 2019).

Previous literature provides limited implications for global supply network design induced by geopolitical risk and tension. Diversifying supply was widely suggested for firms to cope with trade war because of the increased flexibility. Alternative supply sources are available when failures happen at a supply source (Hendricks et al., 2009; Tang & Tomblin, 2008). However, the use of supply diversification as a risk mitigation strategy is controversial. Grover and Malhotra (2003) conceptualized transaction cost as the sum of *transaction risk* and *coordination cost*.

Supply diversification is a major source of coordination costs in supply chain management. The increased need for coordination can reduce responsiveness to cope with uncertainty (Choi & Krause, 2006). This view is in line with Japanese firms' significant reduction in their supply network complexity after the disruption caused by the 2011 earthquake in eastern Japan (Son et al., 2021). We therefore propose our second research question (RQ2): How would a U.S. firm's supply diversification affect its capability to respond to the trade war? Specifically, we used the extent of outsourcing (Hendricks et al., 2009; Steven et al., 2014) and supply base complexity (Dong et al., 2020; Lu & Shang, 2017) as the indicators of supply diversification. We examined whether these factors would moderate or accentuate the impact of the increased trade tariffs on a firm's performance.

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

Our difference-in-difference (DID) regression analysis revealed that the treatment firms suffered a more serious loss in inventory efficiency (inventory days of supply) and profitability (return-on-assets, ROA) than did the control firms. We further found that the negative impact on firms' profitability is more severe for firms with a higher degree of outsourcing and horizontal and spatial supply base complexity. Overall, we found that supply diversification exacerbated the negative impact of the trade war.

The results contribute to the literature on supply chain risk management by constructing a link between geopolitical uncertainty and operating performance. In addition, we contribute to the supply management literature by examining the role of supply diversification amidst uncertainty caused by geopolitical tensions and trade barriers. This provides important implications for firms to develop resilient global supply networks under such an environment of uncertainty. We also discuss the implications of our results in the context of international operations management, supply chain networks, and supply risk management, and provide practical references to supply chain practitioners and policymakers.

2. Literature Review

2.1 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 previous century, 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). Aside from 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), increasing firms' bargaining power with their suppliers (Lampel & Giachetti, 2013), and reducing costs (Jiang et al., 2007; Lampel & Giachetti, 2013).

TCE also highlights the challenges of global sourcing from transaction risk and coordination costs perspectives (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), while 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, operations management (OM) scholars have developed two streams of literature—supply chain risk management and supply diversification—which we describe next.

2.2 Geopolitical Tension and Supply Chain Risk

Supply chain risk is "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, p.5035). This adverse influence includes increased operational costs and reduced competitive advantages (Kwak et al., 2018; Tang, 2006). Global supply chains are riskier than domestic ones because the former involves more cross-regional links that are prone to disruptions by macroeconomic and political changes (Manuj & Mentzer, 2008). Thus, the management of global supply chain risks requires cross-country coordination and collaboration to ensure operational continuity and firm efficiency (Tang, 2006).

The current 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 examine 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 on the impact of man-made crises (e.g., trade wars) on firms' performance is nascent (Darby et al., 2020). Charpin et al. (2020) found that the foreign subunits of MNCs must earn legitimacy to mitigate political uncertainty and risk. In the context of Brexit, Hendry et al. (2019), Roscoe et al. (2020), and Moradlou et al. (2021) found that geopolitical tensions cause significant supply chain disruptions, requiring resilient and robust supply chain designs. These qualitative studies provide valuable information, yet empirical investigations are scarce (Charpin et al., 2020). Thus, our study fills a research gap by examining the impact of the U.S.-China trade war.

2.3 Supply Diversification: Outsourcing and Supply Base Complexity

Although firms have little control over geopolitical tension and trade wars, the literature suggests that they can mitigate these risks through supply diversification (Robinson, 2020; Schmitt et al., 2015; Shih, 2020; Tomlin & Wang, 2011). The merits of supply diversification are illustrated by Nokia's multiple-sourcing strategy: by increasing its supply flexibility, supply diversification alleviated the disruption caused by the fire in its Philips semiconductor factory in 2000 (Tang, 2006). However, diversifying supply can induce complexity and create coordination difficulties for a firm's supply chain management. In this study, we used outsourcing (Steven et al., 2014) and supply base complexity (Choi & Krause, 2006) as two indicators of a firm's supply diversification.

Firms that depend more on outsourcing are generally less vertically integrated (Broedner et al., 2009). They are more heavily involved in activities of buying from other firms, thus more parties are involved, and operations are diversified (Steven et al., 2014). Firms can utilize external expertise and capacity for production through outsourcing, but their transaction costs may increase (Grover & Malhotra, 2003). Furthermore, they may encounter complexity in supplier searches, negotiation, monitoring, and coordination, all of which require extra resources, human capital, and time.

Aside from *whether* firms outsource, *how* firms outsource can also affect the need for coordination. Choi and Krause (2006) argued that diversifying the supply base can lead to "supply base complexity" in two dimensions that are visible to and can be directly controlled by the buyer (Lu & Shang, 2017): (1) multiplicity (the number of first-tier suppliers) and (2) diversity (the differentiations among the first-tier suppliers). This complexity can increase transactional uncertainty in the supply chain, requiring extra coordination efforts (Bode & Wagner, 2015). Research shows that such supply base complexity can hinder a firm's use of its supply base's research & development (R&D) development (Dong et al., 2020). It can also cause 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 in managing its materials and information flow (Brandon-Jones et al., 2015) and coordinating among suppliers (Giri & Sarker, 2017; Qi et al., 2004; Tang, 2006; Xiao et al., 2007).

In some contexts, a firm with increased supply diversification may be less resilient (Choi & Krause, 2006). For example, Hendricks et al. (2009) found that firms with higher geographical diversification suffer higher market value loss from supply disruptions than those with lower geographical diversification. These findings inspired us to hypothesize that firms with a greater extent of outsourcing and supply base complexity are likely to suffer more because of increased trade tariffs.

2.4 Trade War

The U.S.-China trade war has prompted economists to examine its impact. Li et al. (2018) estimated that the world's Gross Domestic Product (GDP) and manufacturing employment 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) found that U.S. firms with more supply and market connections with China suffered from a stronger negative market reaction to the trade war.

Little is known about the impact of increased trade tariffs (e.g., the ones associated with the U.S.-China trade war) on firms' operational performance (Plehn et al., 2010). Most OM analytical models examine 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 cause a firm to 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, 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, and 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 aforementioned OM literature provide grounds for us to develop our hypotheses to explore how the increased trade tariffs affect firms' performance.

Because the import tariffs directly affect trade operations between the 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. In our study, our treatment firms are U.S. firms with direct first-tier suppliers in China—the trade tariffs will affect these firms directly (Huang et al., 2019)—while our control firms are U.S. firms with no direct suppliers in China.

3. Hypothesis Development

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

Trade tariffs are supply chain disruptors (Grossman & Helpman, 2020; Handfield et al., 2020; Roscoe et al., 2020) that can negatively affect a firm's inventory performance (i.e., days of supply). Two main reasons underlie these impacts. First, geopolitical events are a significant risk factor and often disrupt firms' supply chains (Roscoe et al., 2020). Tariff levies destabilize the supply of goods and raw materials from China to the United States, increasing the cost associated with transacting with Chinese suppliers, thus forcing U.S. firms to renegotiate with their Chinese suppliers on prices and delivery schedules because of the new trade barrier. A recent survey echoes these difficulties: 66% of respondents with global manufacturing networks experienced significant disruptions in their business because of the U.S.–China trade war, which intensified operational challenges (Burnson, 2019).

Second, Darby et al. (2020) found that firms tend to increase their inventory level in response to policy uncertainty, providing a buffer for possible supply disruptions. Therefore, supply chain disruptions caused by the tariff levies may lead firms to make advance purchases to remedy policy uncertainty and increase their overall inventory level. Reports show that the tariff drove U.S. firms to pile up inventory (Wu, 2018), causing record-high levels of warehouse stock throughout the States in 2018 (Naidu & Baertlein, 2018). In contrast, tariffs for Chinese products are less likely to affect inventory days for U.S. firms with no direct Chinese supply chain connections. We thus postulated the following:

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

OM researchers have examined the role of tariffs from the cost perspective (Choi et al., 2012; Wang et al., 2011) and the sales performance perspective (Dong & Kouvelis, 2020). From a cost perspective, our treatment firms incurred 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). If the treatment firms hold more inventory (owing to advance purchases), they will bear additional inventory holding, goods-in-transit, and transportation costs, which negatively affects their overall cost efficiency. Our argument is echoed by a survey of over 200,000 firms wherein 40% of U.S. firms reported that the trade war increased their operating costs (Sim, 2020).

Some treatment firms may choose to transfer these increased costs to their downstream customers by increasing 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% and reduced demand by 3% (Tankersley, 2019). By contrast, our control firms with no direct connection to Chinese firms were much less affected by the tariffs. Therefore, our treatment firms with direct suppliers from China are likely to bear additional costs, leading to lower profitability (ROA). We thus postulate the following:

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.

3.2 The Role of Outsourcing and Supply Base Complexity

In addition to the direct impact of trade tariff increases on firm performance, we investigated the extent to which this impact is affected by a firm's supply diversification. Specifically, we first examined the role of a firm's "make or buy" structure (Steven et al., 2014) and then the two dimensions of supply base complexity—horizontal and spatial complexity (Choi & Krause, 2006; Lu & Shang, 2017). We discussed their moderating effects on the trade war's impact on firms' overall profitability (i.e., ROA).

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 and Krause's (2006) suggestion that complexity in the supply chain reduces firms' responsiveness in coping with supply disruption. This exploration is also in line with Hendrick et al.'s (2009) finding that a geographically diversified firm would suffer more from supply chain disruption. More broadly, our exploration is in line with the two components of transaction costs—transaction risk (i.e., the operational uncertainty resulting from the trade war) and coordination costs from supply diversification.

Firms that outsource their operational tasks have less flexibility and ability to control their supplies (Hendricks et al., 2009). Outsourcing may also cause agency problems that suppliers may act upon opportunistically, increasing the buyer's governance efforts (Williamson, 2008). These disadvantages increase the complexity for supply chain management, resulting in higher coordination costs for the buyer firm (Steven et al., 2014).

Scholars have argued that outsourcing can make supply chains vulnerable in uncertain environments (Kleindorfer & Saad, 2005). Empirical evidence also shows that firms that depend heavily on outsourcing suffer significantly from losses because of supply chain disruptions

(Hendricks et al., 2009). Interest alignment and information asymmetry are major issues in outsourcing (Steven et al., 2014). Suppliers may take advantage of a buyer's urgent need to increase product prices aggressively. In addition, coordination between firms, particularly in a cross-regional setting, is often more difficult than that within a firm.

Outsourcing is "the extent to which the vertical range of manufacturing is reduced" (Broedner et al., 2009, p.127). Thus, firms can conduct vertical integration to reduce their dependency on outsourcing. Vertical integration may be a favorable strategy in the case of trade wars. In fact, empirical evidence shows that, under tariff uncertainty, an industry tends to be more vertically integrated (Alfaro et al., 2016) and thus bear lower transaction costs (Mahoney, 1992) associated with coordination efforts in the global supply chain context resulting from reduced agency problems and lower information asymmetry across organizational boundaries (Hendricks et al., 2009). We thus postulate the following:

H3: The negative impact of tariff increases on U.S. firms' profitability is more severe for firms with a higher degree of outsourcing (lower degree of vertical integration).

Firms with the same level of outsourcing may have supply bases comprising different structures, resulting in variations in supply base complexity. We first examined the extent to which the trade war's impact is affected by a firm's horizontal (i.e., supply base) complexity, measured in terms of the number of suppliers (Choi & Krause, 2006). The literature suggests that a large supply base can reduce supplier responsiveness, hindering a firm's ability to coordinate supply resources during supply chain disruptions (Choi & Krause, 2006). A lower number of suppliers facilitates the development of long-term buyer–supplier relationships, which enhances information sharing, trust, collaborative planning, forecasting, and replenishment (Hollman et al., 2015; Hsu et al., 2008). A few key suppliers with close relationships can ensure close coordination and fast recovery during supply chain disruption. Thus, it is easier for the supply base to reconfigure its capacity and stabilize materials and supplies amidst the trade war. These arguments are in line with Treleven and Schweikhart's (1988) finding that single sourcing (or a few key suppliers) can enhance supplier responsiveness.

In addition, firms with a few major suppliers are likely to develop long-term trust and close mutual relationships. By focusing on a few major suppliers, firms can consolidate their purchases and take advantage of the economies of scale. The large order also forces these suppliers to more heavily depend on the buyer firms (Heese, 2015) and thus decrease opportunistic behaviors. We thus postulate the following:

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

In addition to horizontal complexity, firms maintain varying degrees of spatial (i.e., supply base) diversity. The increased number of sourcing locations is associated with increased spatial complexity of the supply base, which can weaken a firm's capability to coordinate production (Dong et al., 2020). The difficulties result from the varying management styles, cultures, languages, operational practices, and institutional environments of suppliers in different locations (Sousa & Bradley, 2008). Choi and Krause (2006) stated that the more differentiation among suppliers, the more difficulty exists for firms to maintain a close relationship with them, which in turn reduces suppliers' responsiveness. In the context of the U.S.-China trade war, spatially diversified firms may switch orders from key Chinese suppliers to many smaller suppliers in other places. However, these firms must renegotiate contract terms and reevaluate production processes to determine whether these alternative suppliers have the capability and capacity for the transferred orders. These tasks may require tremendous effort on the part of the firms because of the informational, cultural, and operational variations in practice caused by cross-regional suppliers. We thus postulate the following:

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

Figure 1 shows the theoretical framework of this study.

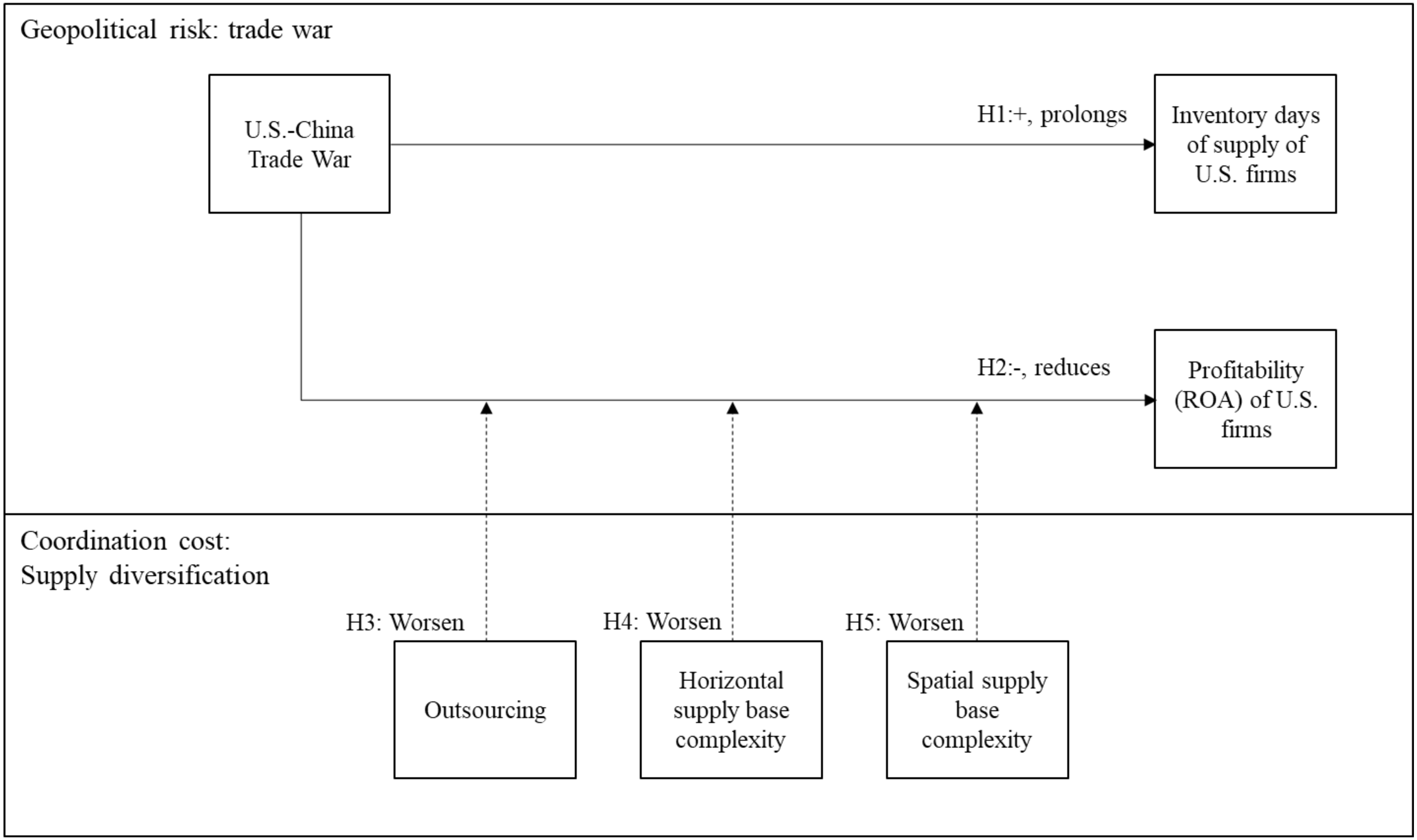


Figure 1. Theoretical Framework

4. Method

4.1 Databases

We compiled secondary data from the Compustat, Bloomberg SPLC, FactSet Revere, and Fresard-Hoberg-Philips databases to test the hypotheses. We collected financial data at firm and segment levels from the Compustat database. We collected longitudinal supply chain data from Bloomberg's SPLC database, which is widely adopted in recent research into supply chains, including 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). Although Bloomberg SPLC is a comprehensive database widely used by researchers, we cannot guarantee that its supplier and customer data are exhaustive. Using a single database (i.e., Bloomberg SPLC) to identify a firm's supply chain partners may omit some suppliers and customers owing to the oversight of some less visible connections. Therefore, we used an extra database, FactSet Revere, to supplement and validate the Bloomberg SPLC data. FactSet Revere collects panel 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 has also been used in recent supply chain research (see Chae et al., 2020; Modi & Cantor, 2020). Finally, we collected vertical integration data from the Fresard-Hoberg-Philips database.

4.2. Data Collection Process

Table 1 summarizes the data collection process, which is based on the U.S.–China trade war that started in 2018. A major objective of the tariff actions in the trade war was to protect the U.S. economy. Therefore, we focused on publicly listed U.S. firms that have business activities in the United States (Huang et al., 2019). Our data collection started with 5,667 U.S.-listed firms from 2017 to 2019 obtained from Compustat. This is because we need at least 1 year of data prior to (i.e., 2017) and 1 year of data after (i.e., 2019) the trade war to examine the effect.

Given our focus is on industrial supply chain management, we removed firms in service industries with little or no physical products, including finance, insurance, and real estate (Standard Industrial Classification, SIC 6000-6799; 1,273 firms); transportation, communications, power, gas, and sanitary services (SIC 4000-4999; 563 firms); services (SIC 7000-8999; 846 firms); and public administration and the non-classifiable industry (SIC 9100-9999; 49 firms). In total, we removed 2,731 firms, leaving 2,936 firms. We further removed firms with no inventory data (903 firms) and employee data (90 firms), leaving 1,943 firms.

We focused on the impact of the trade war on U.S. firms, thus removing 411 firms that are not headquartered in the United States (i.e., U.S.-listed foreign firms), leaving 1,532 firms. In addition, even U.S.-headquartered firms could have little substantial operations in the States (particularly in the manufacturing sectors). To confirm that the U.S.-headquartered firms have substantial operations in the States, we set the criterion that the firm must have U.S. operational assets (i.e., property, plant, and equipment [PP&E]) or sales activities. Specifically, we discarded 10 firms with no U.S. PP&E, segment sales, or customers in 2017, leaving 1,522 firms.

We then collected the supply chain data for these 1,522 firms. We first used each firm's name and CUSIP code (obtained from Compustat) to search in the Bloomberg SPLC database to locate its customers and suppliers. The firms' customer and supplier identifiers (e.g., name and ticker) and locations were then obtained. We collected 157,121 longitudinal supply chain data (80,206 suppliers and 76,915 customers) for 1,198 (out of 1,522) firms from Bloomberg SPLC. We then searched the firm names in the FactSet Revere database. We were able to collect 83,996 longitudinal supply chain data (25,737 suppliers and 58,259 customers) for 1,181 firms (out of 1,522).

The aforementioned figures show that Bloomberg SPLC has stronger coverage in terms of the numbers of customers and suppliers (157,121 in Bloomberg SPLC vs. 83,996 in FactSet Revere) reported per firm. Nevertheless, the two databases are quite consistent at 93.6% (1,121 overlapped firms over 1,198) in terms of firm coverage. Out of the 1,522 firms, we only removed 261 firms (17.1%) with no supply chain data in neither Bloomberg SPLC nor FactSet Revere, leaving 1,261 firms. The 17.1% sample loss owing to missing supply chain data is comparable with the 20.9% indicated in previous studies (e.g., Adhikary et al., 2020).

Because we hypothesized that the firms with direct Chinese suppliers would be most affected by tariff increases, we focused on first-tier suppliers of these U.S. firms. However, firms that have no first-tier Chinese supplier may still have second-tier Chinese suppliers, and ignoring these may cause bias in the later matching process. Therefore, we collected information on the focal firms' second-tier Chinese suppliers by searching for the first-tier suppliers' suppliers in the database.

Last, we collected the vertical integration data for the 1,261 firms from the Fresard-Hoberg-Philips database. We removed 204 firms with no vertical integration data from the database, leaving 1,057 firms as the final dataset.

Appendix Table A1 presents the industry distribution of these firms. We found no significant difference ($p > 0.1$) between the initial sample pool of 2,936 firms and the final dataset of 1,057 firms by industries. We also found no significant difference ($p > 0.1$) by industry ratios between the initial pool of 2,936 firms and the 376 firms we obtained after the matching procedures for hypothesis testing (discussed in Section 4.3), indicating no serious sample selection bias. We provided detailed descriptions of each data collection step in Appendix A2.

[Table 1 about here]

4.3 Data Analysis

4.3.1 Natural experiment research design

Attempting a direct comparison between the firms' performances before and after the tariff increases in 2018 can be problematic because the counterfactual outcomes are unobservable and cannot be calculated (Caliendo & Kopeinig, 2008). Therefore, we adopted a treatment-control matching approach to design a natural experiment that accounts for unobservable outcomes (Heckman et al., 1998). The treatment firms are U.S.-listed firms that have direct first-tier suppliers in mainland China identified in the Bloomberg SPLC or FactSet Revere databases. The control firms are U.S.-listed firms that have no direct suppliers from China.

From the 1,057 sample firms, we found 298 treatment firms and 759 potential control firms for our analysis. We further used Compustat's segment data on cost of goods sold (COGS) from different regions to verify the accuracy of the Bloomberg SPLC and FactSet Revere databases in identifying Chinese suppliers. Specifically, we found that all treatment firms reported COGS from China, while all control firms reported no COGS from China, confirming our assumption that the control firms did not source directly from China.

4.3.2 Propensity score matching

Heterogeneity between treatment and control firms may also confound the impact of the trade war. For example, if a treatment firm has significantly fewer operating assets than the control firm, any additional negative impact captured in a treatment firm could be owing to its lack of resources to cope with the change in the trade environment, rather than direct sourcing from China. Therefore, we applied a widely used matching approach, propensity score matching (PSM), to ensure that the treatment and control firms are highly similar (Fan et al., 2021; Levine & Toffel, 2010). The PSM approach aims to calculate the probability (i.e., propensity score) of having direct Chinese suppliers for our treatment and control firms. We then used the nearest neighborhood approach to match each treatment firm to a control firm with the closest propensity in the same industry (two-digit SIC code). We used the following estimation model to generate the equation for the 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* is 2018, the announcement year of the trade war. Additionally, $X_{i,t-1\&-2\&-3}$ is a vector of the average of 1-, 2-, and 3-year lagged levels (i.e., years 2015, 2016, and 2017) of a series of matching covariates. Three-year average independent variables help mitigate the impacts of outliers in the estimation (Pagell et al., 2019). Following Levine and Toffel (2010), if only 2 of the 3 years' data were available (i.e., 2015 and 2017 or 2016 and 2017), we used those two values and took the average. If a firm's data were not available for both 2015 and 2016, we used 2017 data only. Most of the firms (94.89%) have 3-year data. Finally, $Industry_j$ is a set of 39 industry dummies.

4.3.3 Selection of matching covariates

We summarized the measurements and references of the matching covariates in Appendix A3. Specifically, we controlled for firm size and industry because previous scholars identified them as two major sources of heterogeneity that would confound the experimental results (Barber & Lyon, 1996; Corbett et al., 2005; Swift et al., 2019). Firm size is measured by the total assets (*Total Assets* $_{t\text{-}1\&\text{-}2\&\text{-}3}$). Industry dummies (*Industry*$_j$) can also control outsourcing status to China because some industries rely more heavily on Chinese suppliers than others. We also included a variable (*2nd-tier CN supplier* $_{t\text{-}1\&\text{-}2\&\text{-}3}$) to indicate a firm's percentage of its second-tier Chinese suppliers to the total number of second-tier suppliers. One may argue that if a trade war has an impact on first-tier Chinese suppliers, part of the impact could come from second-tier Chinese suppliers. Thus, as we focused on the impacts through first-tier Chinese suppliers, we attempted to ensure that the treatment and control firms have no statistical difference in terms of impact from second-tier Chinese suppliers.

In addition, we included a series of potential determinants of having Chinese suppliers, including inventory efficiency, fixed assets turnover, capital expenditure, and R&D expenditure. Inventory efficiency (*Inventory efficiency* $_{t\text{-}1\&\text{-}2\&\text{-}3}$) is the ratio of sales to average inventory, and fixed assets turnover (*Fixed assets turnover* $_{t\text{-}1\&\text{-}2\&\text{-}3}$) is the ratio of sales to PP&E. These ratios indicate a firm's overall operating efficiency. A firm with a higher operating efficiency may have reduced slack in production resources and thus is more likely to have Chinese suppliers to help it to mitigate the effects of supply chain disruptions (Modi & Mishra, 2011; Wiengarten et al., 2017). Capital expenditure (*Capital expenditure* $_{t\text{-}1\&\text{-}2\&\text{-}3}$) is calculated by a firm's capital expenditure normalized by sales and represents the capital expenditure in various operating activities; a firm may outsource activities to Chinese suppliers to reduce or defer this capital expenditure (Raddats et al., 2016). R&D expenditure (*R&D expenditure* $_{t\text{-}1\&\text{-}2\&\text{-}3}$) is the annual value of R&D expenditure. A firm with higher R&D expenditure may concentrate more heavily on innovating its core products or processes and outsource its non-core activities to Chinese firms (Jiang et al., 2006).

We followed Levine and Toffel (2010) and performed natural logarithm transformation to the continuous independent variables, which aims at mitigating the skewness of variables and increasing the predicting power of the selection model.

Table 2 demonstrates that larger firms tend to have direct Chinese suppliers. We also find that firms with more second-tier Chinese suppliers, lower inventory efficiency, higher fixed assets turnover, and higher R&D expenditure tend to have direct Chinese suppliers. We calculated the propensity score for each treatment and control firm based on the estimation coefficients in Table 2. The Pseudo-R-squared equals 24.69%, suggesting a very good fit for our model (Levine & Toffel, 2010; McFadden, 2021). The range of variance inflation factor is between 1.00 and 1.28, indicating that multicollinearity is not a serious concern.

[Table 2 about here]

After calculating the propensity score, we matched each treatment firm with a control firm with (1) the closest propensity score, and (2) from the same industry (two-digit SIC code). We avoided the scenario in which one control firm is matched to multiple treatment firms, which may cause a double-counting issue. We had more treatment firms than control firms in two industries. Thus, we removed the treatment firms that could not be matched with any control firms. From the 298 treatment firms, we discarded seven in this step, leaving 291 treatment-control pairs.

We further improved our matching quality by setting a matching caliper of 0.1 (Levine & Toffel, 2010). We removed 103 treatment-control pairs with a difference in propensity score outside the caliper, leaving 188 pairs. We conducted paired t-tests on all the independent variables (except industry dummies) used in the probit model. The test results indicated no significant difference between treatment and control firms on these variables ($p > 0.1$) after PSM. Thus, we concluded that the statistics of treatment and control firms are highly similar. We present the descriptive statistics of the treatment and control firms in Table 3. We also added the covariates as the control variables in the second-stage hypothesis-testing analyses to further control for the variations in these variables.

[Table 3 about here]

4.3.4 DID regression analysis for trade war impacts

We created a 5-year panel dataset with the 188 pairs (376 firms) from 2015–2019. This research time window was constructed based on the year the tariff was significantly increased (i.e., 2018). We used 3 years (i.e., 2015, 2016, and 2017) before the trade war as the benchmark and then subsequently examined the impacts of the trade war in 2018 and 2019. Our event window cutoff was 2019 for two reasons: (1) the U.S. and Chinese governments signed the Phase One trade deal on January 15, 2020, suggesting a cease-fire, and (2) the 2020 COVID-19 global pandemic seriously affected the global supply chain.

Ideally, we would have 1,880 (376 x 5) firm-year observations. However, we deleted 32 observations owing to missing data in 2015 or 2016. We also followed previous literature (e.g., Corbett et al., 2005; Lo et al., 2014; Swift et al., 2019) with the DID approach to trim by 0.5% of extreme values of dependent variables (i.e., inventory days and ROA) at each end, further removing 38 observations. Finally, the DID analysis dataset included 1,810 observations (i.e., 1,880 - [32 + 38]).

We performed a DID estimation to compare the differences in inventory days (H1) and ROA (H2) between the treatment and control observations before and after the trade war using the following model:

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

where the dependent variable FP_{it} refers to the firm 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 and 2019); 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 treatment firm's performance after tariff increases compared with the control firm's performance.

We included the vector X_{it} to control for the firm-level characteristics controlled in the selection model—total assets, capital expenditure, inventory efficiency, fixed assets turnover, and R&D expenditure—to increase the validity of our results. The measurements of these control variables were the same as those used in PSM (see Appendix A3). Larger firms (i.e., firms with more total assets) may be more affected by the trade war because they seem to be more often involved in complex global supply chains (Revilla & Saenz, 2017). Capital expenditure includes a firm's capital investment in production and information technology, which may improve a firm's financial and inventory performance (Steven et al., 2014). Inventory efficiency and fixed assets turnover were included to control for firms' operating efficiency; efficient firms may have fewer slacks available to respond to supply chain disruptions (Wiengarten et al., 2017). R&D expenditure indicates a firm's focus on R&D, which may affect its profitability (Cho & Pucik, 2005). We also included the supply complexity metrics in X_{it}, including outsourcing, horizontal complexity, and spatial complexity. The measurements of these variables will be described in the next section. 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 $CNsupplier_i$ were omitted in the model because we have controlled for the firm and year fixed effects (Levine & Toffel, 2010). In the previously specified model, we expected to capture a positive coefficient β in the inventory days model and a negative coefficient β in the ROA model; these can capture the abnormal negative impacts experienced by the treatment firms amidst the trade war and examine H1 and H2.

4.3.5 Difference-in-difference-in-difference (DDD) analysis for moderating effects

For H3 to H5, we implemented triple-difference designs (Powell & Seabury, 2018) to examine whether firms with higher supply diversification suffered more from the tariff increases caused by the trade war. Specifically, we used outsourcing, horizontal complexity, and spatial complexity to generate the additional differences. We then created interaction terms $Post_t \cdot CNsupplier_i \cdot (Outsourcing_i)$, $Post_t \cdot CNsupplier_i \cdot (HorizontalComplexity_i)$, and $Post_t \cdot CNsupplier_i \cdot (SpatialComplexity_i)$ and examined the significance in the coefficients. We used ROA as the dependent variable for these analyses because this indicator is widely used as the bottom-line firm performance metric (e.g., Lo et al., 2014; Swift et al., 2019).

Outsourcing was indicated by the (low) level of vertical integration and measured according to the method developed by Frésard et al. (2020).[1] Because a vertically integrated firm is generally less dependent on external firms for supply. For example, since the 2000s, Tiffany & Co. has conducted vertical integration by purchasing diamond mines (Butler, 2004). Thus, Tiffany was able to reduce the outsourcing of raw diamonds and increase supply control through insourcing.

Hendricks et al. (2009) 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, but

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

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 it using a textual analysis of an individual firm's business description from its 10-K disclosure. The measurement assumes that a firm's product vocabularies are vertically related to its other product vocabularies. The vertical integration score is higher when the product vocabulary in the 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 reports (Frésard et al., 2020). A lower value of vertical integration indicated that the firm offered products that were less vertically related (i.e., more outsourcing). We thus reversed the scale of vertical integration to indicate a firm's level of outsourcing (i.e., higher value indicates more outsourcing).

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).

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. Firms with widespread supply bases across countries should increase the difficulty of coordinating production, creating higher uncertainty and complexity (Lu & Shang, 2017; Vachon & Klassen, 2002).

4.4 Analysis of Results

Table 4 presents the descriptive statistics and correlation of the indicators, while Table 5 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 = 8.2062, $p < 0.01$), indicating that the average treatment firms' inventory days are 8.21 days longer than the control firms during the trade war compared with the pre-trade-war period. Thus, H1 is supported. The increased number of inventory days is echoed by the increase in the United States' trade deficit with China, which reached a 10-year high of $621 billion in 2018 (Dmitrieva, 2019), indicating 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 5 shows that the interaction term $Post_t \cdot CNsupplier_i$ is significantly negative (b = -0.0129, $p < 0.05$), indicating that the average treatment firms' ROA is 1.29% lower than that of the control firms during the trade war compared with the pre-trade-war time. Thus, H2 is supported.

Table 6 presents the results of our triple difference analysis for the moderating effects of outsourcing, horizontal complexity, and spatial complexity, respectively. In Model 1, the coefficient of interaction term $Post_t \cdot CNsupplier_i \cdot Outsourcing_i$ is significantly negative (b = -0.0078, $p < 0.05$). We defined a high outsourcing level as when the firm has the outsourcing value at one standard deviation above the mean (2.71=1.27+1.44). Therefore, the results indicate that, among the treatment firms in the trade war, firms with a high outsourcing level had an average ROA that was 1.00% lower than that of firms with a mean outsourcing level. H3 is supported.

Model 2 presents the results of horizontal complexity. The interaction term $Post_t \cdot CNsupplier_i \cdot HorizontalComplexity_i$ is significantly negative (b = -0.0006, $p < 0.05$). We defined a high horizontal complexity level as when the firm has horizontal complexity value at one standard deviation above the mean (85.00=60.68+24.32). Therefore, the results indicate that, among the treatment firms in the trade war, firms with a high horizontal complexity level had an average ROA that was 3.64% lower than that of firms with a mean horizontal complexity level. H4 is supported.

Model 3 presents the results of the spatial complexity. The interaction term $Post_t \cdot CNsupplier_i \cdot SpatialComplexity_i$ is significantly negative (*b* = -0.0037, $p < 0.05$). We defined a high spatial complexity level as when a firm has the spatial complexity value at one standard deviation above the mean (9.41=5.14+4.27). The results indicate that, among the treatment firms in the trade war, firms with a high horizontal complexity level had an average ROA that was 1.90% lower than that of firms with a mean horizontal complexity level. H5 is supported.

[Table 4, 5 and 6 about here]

4.5 Parallel Assumption Check for DID Analysis

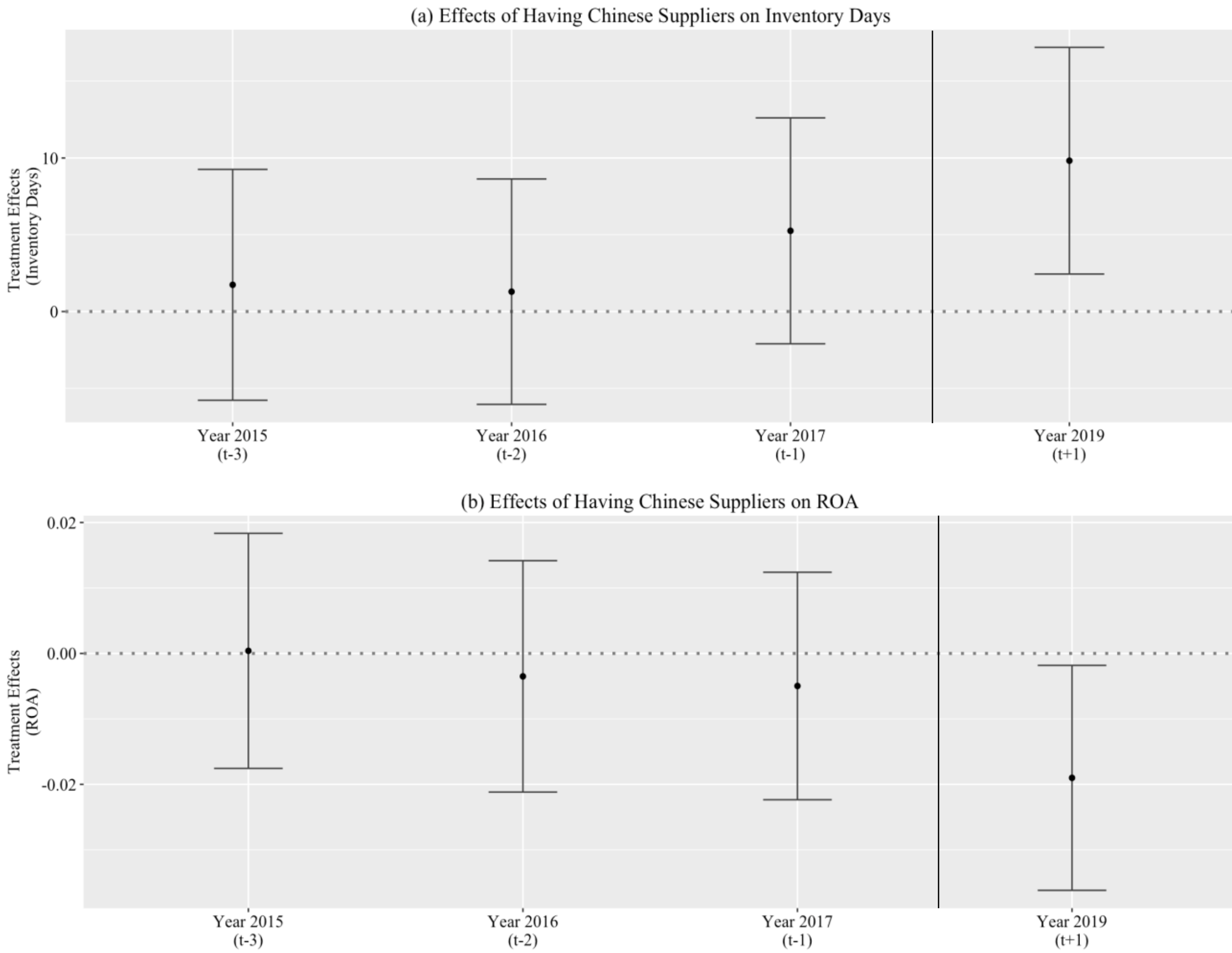
The assumption for DID analysis to capture any treatment effect is parallel performance trends, which requires the presence of common trends in dependent variables (i.e., inventory days and ROA) between the treatment and control groups before the announcement year of the tariff list. We first performed a common trend analysis using the following relative time model (Angrist and Pischke, 2008; Song et al., 2020):

$$FP_{it} = \sum_{t=2015}^{2019} \kappa_t \cdot CNsupplier_i \cdot D_t + \gamma X_{it} + \alpha_i + \delta_t + \varepsilon_{it}, \qquad (3)$$

where D_t are dummy variables that indicate the years from 2015–2019, the study period in our main analysis. We excluded the interaction between the treatment indicator and the dummy variable for 2018 (i.e., $CNsupplier_i \cdot D_{2018}$) because it is the reference group (Dhanorkar, 2019; Zou et al., 2020). The other variables are the same as in our main analysis in equation 2. We presented the analysis results in Table 7 and plotted the estimated coefficients and confidence intervals of $\kappa_t$in Figure 2.

Table 7 shows that the coefficients for the years 2015–2017 are nonsignificant in both inventory days and ROA models ($p > 0.1$), which suggests that the differences between the treatment and control groups in the 3-year pretreatment period are not significant. This result is illustrated in panel (a) and (b) of Figure 2, which shows that the limits of the 95% confidence interval for 2015, 2016, and 2017 have included zero. The results support the parallel-trends assumption of our analysis.

Table 7 also shows the coefficient for the year 2019 is significantly positive in inventory days model (9.8236, $p < 0.01$) and negative in ROA model (-0.0190, $p < 0.05$). Figure (a) and (b) also illustrate that the differences appear 1 year after the tariff lists were announced (i.e., 2019). This conclusion is consistent with the one we obtained from the primary analysis (Table 5).



Note. The values of estimated coefficients and standard errors [in parenthesis] are shown under the year label, ∗p<0.10.

Figure 2. The Effects Across Periods of Trade War

4.6 Placebo Test

We further conducted a placebo test to test the robustness of our results, as follows. We randomly faked the 298 treatment firms with "false" Chinese suppliers in 2018 and repeated the whole PSM-DID analysis. If the firms with "true" Chinese suppliers in our study can increase inventory days and decrease ROA, we expected the $Post_t \cdot CNsupplier_i$ in equation 2 for the faked firms to be nonsignificant. We repeated this process 1,000 times and plotted the t-values in

Figure 3a and 3b for the inventory days and ROA model, respectively. The result showed that 98.7% and 96.9% of the "false" p-values are not significant (with t-values between –1.65 and 1.65) for inventory days and ROA model, respectively. They also showed that most of the coefficients of false $Post_t \cdot CNsupplier_i$ in our placebo test were not statistically significant. Thus, the results did not refute our conclusions, and our analysis results were not captured by chance.

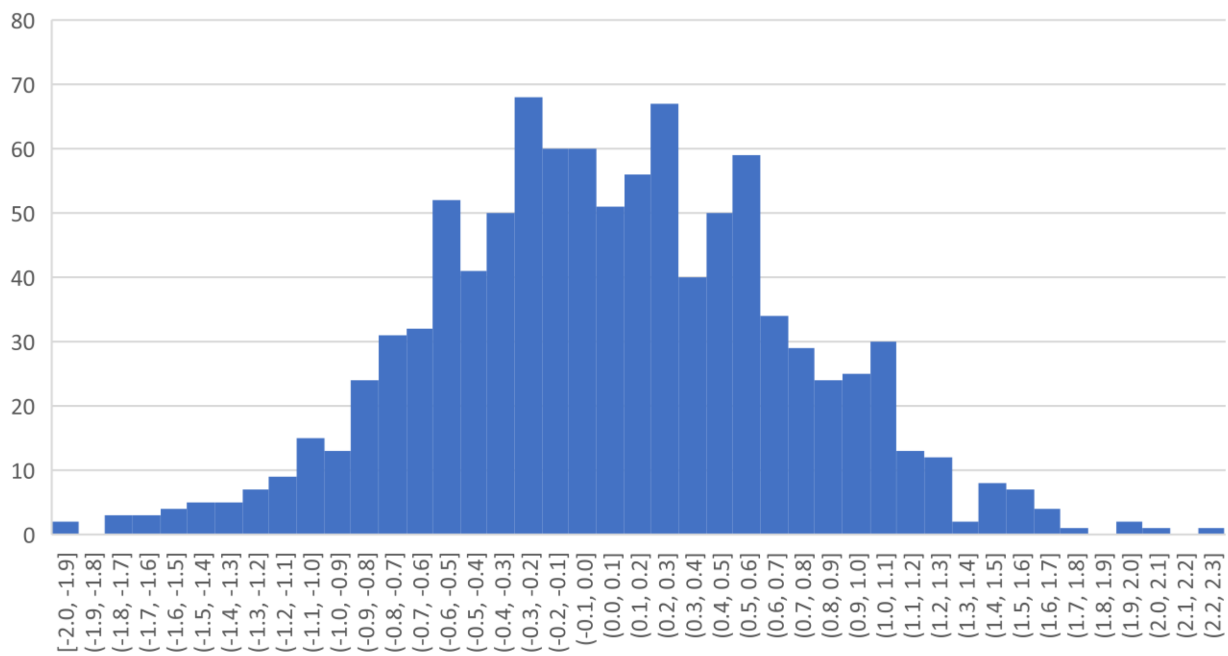


Figure 3a. Distribution of t-value for Inventory Days Model for Placebo Tests

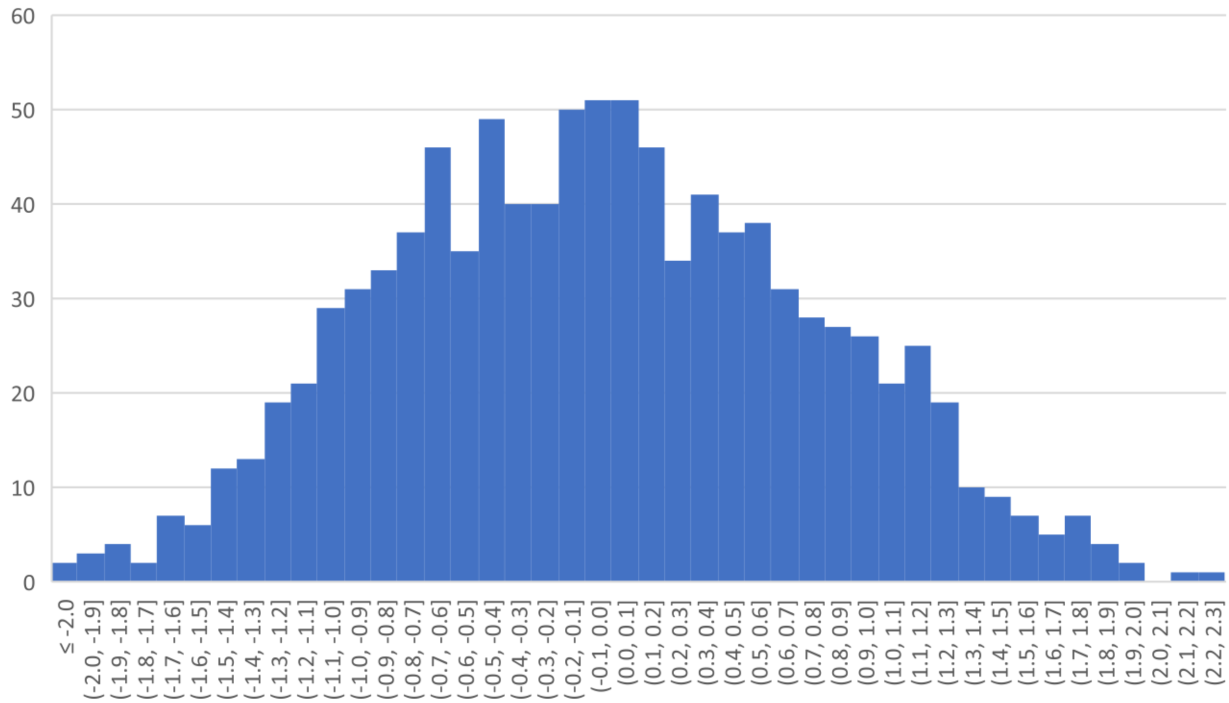


Figure 3b. Distribution of t-value for ROA Model for Placebo Tests

4.7 Other Robustness Checks and Further Analyses

To further ensure the robustness and increase the empirical value of our findings, we conducted several additional tests (Appendix B). First, some U.S. firms may use overseas facilities to process Chinese supply to bypass the tariff, which may confound our results. We thus selected U.S. firms that had only domestic operations (i.e., PP&E only in the U.S. but not overseas) and reran the analysis. The results (Table B1) show that the effects remained significant in both inventory days ($p < 0.01$) and ROA ($p < 0.1$) models, resulting in similar findings to those in Table 5.

Second, the current design considers only relations between U.S. buyers (treatments) and Chinese suppliers. However, these U.S. treatment firms may also have more customers in China and may suffer more because of retaliation tariff measures imposed by the Chinese government. We first examined whether this factor would confound the treatment effects (H1 and H2). We included and controlled the ratio of number of Chinese customers to total customers in the PSM, then reran the analysis. The results (Table B2) show that the trade war's impacts on inventory days and ROA remained significant ($p < 0.05$). Thus, the Chinese customer factor did not falsify conclusions we drew from our primary analysis (Table 5).

In addition, we examined whether the variation of Chinese customers among the treatment firms could cause a different result. We used the number of Chinese customers over total number of customers of the firms and conducted a DDD analysis. The results (Table B3) show that the treatment firms with more Chinese customers did not have a difference in terms of inventory and ROA compared with the treatment firms with less Chinese customers. Therefore, Chinese customer connections did not have a significant impact on our H1 and H2 results.

Our current identification of treatment firm was based on whether firms have direct Chinese suppliers. However, those treatment firms may have variation in the extent of relying on Chinese suppliers. We added control variables of the numbers of suppliers in China in our DID model and reran the analysis. The results (Table B4) show that the trade war's impacts on inventory days and ROA remained significant ($p < 0.01$). Thus, this additional control factor did not falsify our conclusions.

Some treatment firms may also source from other countries in trade wars with the United States. To examine whether this factor amplifies the negative impacts from the U.S.-China trade war, we implemented a DDD design to further examine whether firms involved in other trade war locations performed differently during the U.S.-China trade war. Specifically, we used whether a treatment firm has other trade war locations, defined as whether they have direct suppliers from other countries with a trade war with the United States, to generate the additional difference (1 = having direct suppliers in other trade-war countries, 0 = otherwise). We then created the interaction term $Post_t \cdot CNsupplier_i \cdot 1(\mathrm{OtherTradeWar}_i)$ and examined the significance of the coefficient in Appendix Table B5. Our results show that firms with suppliers in another trade-war country have longer inventory days ($p < 0.05$) and lower ROA ($p < 0.1$) compared to firms without other trade war locations.

High-tech sectors might rely more on a more dynamic, responsive, and reliable supply chain and thus suffer more from the trade war (SCMP, 2021). We thus examined the trade war's impacts on the high-tech industries. We followed Modi and Mishra (2011) to define the firms with SIC codes of 3511–3599, 3612–3699, and 3812–3873 as high-tech sectors. The analysis results (Table B6) show that high-tech firms suffer more in inventory days (6.93 days longer) than other firms. The high-tech firms also have a 1.74% lower ROA than other firms as a result of the trade war. In addition, our current sample construction is based on all listed U.S. firms (except the industries with little or no physical products). However, the Office of the United States Trade Representative announced three trade action industry lists in 2018. We examined whether there is a difference between firms within and outside the trade-action lists. The analysis results (Table B7) show that there is no significant difference between the firms in these two groups, indicating that the negative impact of the trade war is not limited to the trade-action industries.

Our primary analysis used the continuous form of moderators to examine H3 to H5. However, previous researchers (e.g., Levine & Toggel, 2010) also used the dichotomized moderators for the moderation analysis. We followed the literature to compare the additional differences between "high outsourcing" and "low outsourcing" groups for H3, "high horizontal complexity" and "low horizontal complexity" groups for H4, and "high spatial complexity" and "low spatial complexity" groups for H5. We assigned each treatment firm to one of those two groups based on the yearly industry median of the moderators (Levine & Toffel, 2010) and then created binary variables coded as "1" for the high-level groups and "0" for the low-level groups. We reran the analysis and presented the results in Table B8. The coefficients of all three interaction terms were significantly negative ($p<0.01$), which is consistent with the conclusions we obtained from the primary analysis (Table 6). In addition, we further conducted the analyses by assigning the high or low groups based on the yearly industry mean. We also followed Su et al. (2015) and dropped the treatments between the 45th and 55th percentile to achieve great separation. The results are similar to those in Table B8.

5. Conclusion and Discussion

We have examined the impact of import tariff increases caused by the U.S.-China trade war on U.S. firms' performance and explored the extent to which supply diversification affected a firm's performance. We tested our hypotheses using operational performance data obtained between 2015 and 2019 to capture the effect before and after the new tariffs were instituted in the recent trade war. Our analysis, in which we adopted a PSM natural 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 found that firms with a higher degree of outsourcing or a more horizontally and spatially complex supply base would suffer more than those with a lower degree of the same.

5.1 Theoretical Contributions

This study was 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 researchers 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), we examine the interfaces between public policy and supply chain management. We also echo Charpin et al. (2020) and Darby et al. (2020) to explore the impact of political risks on a firm's global operations. Using trade war as a proxy of uncertainty and risk, this study reveals how tariff increases could negatively affect firms both overseas and in the home country. Our findings confirm that imposing trade tariffs affects domestic industries negatively in terms of inventory and ROA, especially when firms have relied heavily on sourcing from overseas. Thus, a trade war, as an adverse international event, increases transaction costs for firms, disrupting operations and undermining profitability.

Recent OM researchers have examined the relationship between a firm's supply base complexity and its 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 diversified supply chain can be a burden for MNCs when the international trade environment destabilizes. Conventional wisdom suggests that diversifying a firm's sourcing base can mitigate the impact of bilateral trade relations deterioration. However, our findings challenge this view and suggest that firms with diversified supply bases suffer more from the tariff increases because of the U.S.-China trade war.

In addition, the results in Table 6 show that the direct effects of horizontal and spatial complexity on two firm performance indicators are not significant. This is in line with the debates over the relationship between supply base complexity and firm performance. On the one hand, increasing supply base complexity can increase sourcing flexibility (e.g., Hendricks et al., 2009; Tang & Tomblin, 2008). This is because firms can have alternative suppliers in different areas when a supplier fails. From the risk-diversification view, supply base divergence should increase firm performance. On the other hand, if the suppliers in a firm's supply base are inter-connected with each other (e.g., a supplier is buying from another supplier), the substitution advantages from having more suppliers can be undermined (Choi & Krause, 2006). In addition, the increased supply base complexity requires additional managerial resources for coordination, which increases transaction costs (e.g., Choi & Krause, 2006). From a transaction-cost perspective, supply base complexity could hinder firm performance. Thus, the nonsignificant direct effect results of the two supply base complexity variables might indicate that the flexibility advantage is offset by the transaction-cost problem.

This study also contributes to the literature on manufacturing diversification. Previous researchers showed that international diversification results in an inverted U-shaped performance outcome (e.g., Hitt et al., 1997; Lampel & Giachetti, 2013; Narasimhan & Kim, 2002; Palich et al., 2000) and increase its 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 geopolitical risk events. This finding is in line with the view that firms should maintain a simple supply chain configuration to better maintain continuity and profitability in case of uncertainty (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 also consistent with TCE's explanation on the constraints of international expansion and diversification. The TCE suggests that diversification increases transaction costs in terms of organizational complexity and the need for coordination (Lampel & Giachetti, 2013). Thus, in our study we advance 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 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 (i.e., increasing a firm's resilience). When the trade war led to substantially increased transaction costs in the international environment, we found that vertically integrated firms are likely to suffer less from the increased transaction costs.

5.2 Practical Implications

This study revealed practical implications for supply chain managers by quantifying the impact of the U.S.–China trade war on firms' operational performance. In line with the survey conducted by the trade organizations (e.g., the American Chamber of Commerce in China), our results confirm the firms' concerns over the U.S.–China trade war. Consistent with the prediction stated by Dong and Kouvelis (2020), we show that U.S. firms' performances were negatively affected by the trade war.

Policy makers should understand that protectionism may not necessarily protect domestic industries. Our evidence illustrates that these tariffs negatively affect the competitiveness of U.S. firms. This finding echoes how the United States' tariff on foreign imports backfired 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 related materials such as steel and aluminium, resulting in an increase in the price of 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, lobbying for tariff protection may not generate the benefits one would hope for.

The abnormal increase in inventory reflects U.S. firms' advance purchase behaviors 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. Rather, it can undermine the operations and profit for these firms. The U.S. government may find it more effective to focus on facilitating firms' relocation rather than 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 its 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 its filed legal documents, "Volvo Cars strongly believes the way to reach economic growth is to reduce tariffs and harmonize international trade" (BBC, 2020).

5.3 Limitations

This study has several limitations that future researchers should address. First, though the Bloomberg SPLC, FactSet Revere, 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 failed to 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 2 years in this study (i.e., 2018 & 2019) is relatively short. Third, this study was focused only on the U.S.–China trade war that occurred between the two most prominent and dependent economic entities, and thus the results may not apply to trade wars between two economic entities that depend less on each other. Fourth, this study was focused on two operating performance facets, including inventory and profitability; however, other metrics such as responsiveness, resilience, and adaptability can be essential and are worth exploring in future research.

Additionally, this study was focused on the first-tier suppliers who were directly connected with our treatment 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. Further, we used the number of connections and number of countries to measure the firms' supply base complexity based on the data available. The use of relational values reduced our sample size because of the missing variable data in the Bloomberg SPLC and FactSet Reverse databases. Future researchers may apply multiple methods (e.g., case studies and longitudinal surveys) and use data collected from multiple sources, triangulate this study's findings, and explore the boundary conditions.

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Table 1: Data collection steps

Panel A: Data development for selection model				
	Data screening steps	**Number of firms reduction**	**Number of firms**	**Database used**
1	Started with firms with available data at least one year before (i.e., 2017) and one year after (i.e., 2019) the trade war in 2018 (i.e., 2017-19)		5,667	Compustat
2	Remove firms in service industries with little or no physical products	2,731	2,936	Compustat
3	Remove firms without inventory and employee data	993	1,943	Compustat
4	Remove firms not headquartered in the U.S.	411	1,532	Compustat
5	Remove US-headquartered firms with no substantial operations in the U.S.	10	1,522	Compustat, Bloomberg SPLC, FactSet Revere
6	Remove firms with no data sources in Bloomberg SPLC or FactSet Revere databases	261	1,261	Bloomberg SPLC, FactSet Revere
7	Remove firms with no vertical integration data in the Fresard-Hoberg-Philips database.	204	1,057 (including 298 treatment and 759 control firms)	Fresard-Hoberg-Philips database

Panel B: Matching procedures				
	Data Screening Steps	**Number of treatment-control pairs removed**	**Number of treatment firms remained**	**Number of control firms remained**
8	Started with 298 matched pairs in step 7 in Panel A		298	759
9	Remove firms that cannot be matched with any control firms	7	291	291
10	Remove pairs with a caliper of higher than 0.1	103	188	188

Panel C: Data development for DID analysis				
	Data Screening Steps	**Number of observations removed**	**Number of observations remained**	**Number of firms remained**
			1880	376
11	Remove observations with missing data in 2015 or 2016, and their corresponding treatment or control firms.	16 x 2	1848	376
12	Remove extreme values for dependent variables (i.e., inventory days or ROA) and their corresponding treatment or control firms.	19 x 2	1810	376

Table 2: Estimated coefficients of probit model for PSM

Independent variables	Estimate	Std. Error	VIF
Intercept	-6.7493	[0.6077]***	
Log Total assets $_{t\text{-}1\&\text{-}2\&\text{-}3}$	0.2584	[0.0265]***	1.12
Log Second-tier CN supplier $_{t\text{-}1\&\text{-}2\&\text{-}3}$	9.6455	[1.0862]***	1.04
Log Inventory efficiency $_{t\text{-}1\&\text{-}2\&\text{-}3}$	-0.1188	[0.0647]*	1.11
Log Fixed assets turnover $_{t\text{-}1\&\text{-}2\&\text{-}3}$	0.1610	[0.0580]***	1.28
Log capital expenditure $_{t\text{-}1\&\text{-}2\&\text{-}3}$	-0.0135	[0.3770]	1.23
Log R&D expenditure $_{t\text{-}1\&\text{-}2\&\text{-}3}$	0.0193	[0.0055]***	1.08
n	1,057		
Chi-squared	310.46	***	
Pseudo-R-squared (McFadden)	24.69%		

Note. ∗p < 0.10; ∗∗p < 0.05; ∗∗∗p < 0.01. Dependent variable: having first-tier CN supplier. Additional controls include 39 industry dummies. Variables subscripted t-1&-2&-3 are averages of one-, two- and three- year lags.

Table 3: Statistics of treatment and control firms after PSM

		Total assets (millions)	Second-tier CN supplier %	Inventory efficiency	Fixed assets turnover	capital intensity	R&D expenditure (millions)
Treatment firms	Mean	11,624.10	3.67%	16.50	19.87	0.06	367.83
	SD	19,633.72	11.07%	40.83	109.95	0.16	1,314.91
	Max	111,820.00	100.00%	411.45	1,497.00	1.79	14,236.00
	Min	7.46	0.00%	2.20	0.15	<0.01	<0.01
Control firms	Mean	4,913.17	3.05%	12.17	15.76	0.06	113.52
	SD	6,962.63	6.74%	15.39	69.90	0.12	310.45
	Max	44,876.00	50.00%	102.88	948.65	1.07	2,899.00
	Min	6.29	0.00%	1.30	0.13	<0.01	<0.01
Difference	*p*	0.11	0.46	0.16	0.91	0.91	0.86

Table 4. Correlation of variables in DID analysis

	Mean	SD	1	2	3	4	5	6	7	8	9
1. Post*CN supplier	0.20	0.40									
2. Log total assets	21.76	1.66	0.11***								
3. Log second-tier CN supplier	0.05	0.08	-0.11***	-0.12***							
4. Log inventory efficiency	2.28	0.69	0.03	0.13***	-0.06**						
5. Log fixed assets turnover	2.06	0.95	-0.04	-0.32***	0.05*	0.08***					
6. Log capital expenditure	0.05	0.13	-0.02	0.08***	0.02	0.10***	-0.38***				
7. Log R&D expenditure	12.55	8.47	<0.01	0.09***	0.01	-0.06**	-0.16***	-0.03			
8. Outsourcing	1.44	1.27	-0.01	0.05**	0.04*	-0.17***	-0.14***	-0.07***	0.11***		
9. Horizontal complexity	24.32	60.68	0.03	0.27***	0.002	0.12***	0.14***	-0.03	-0.11***	-0.08***	
10. Spatial complexity	4.27	5.14	0.01	0.45***	0.01	0.11***	0.04	-0.01	-0.07***	-0.05**	0.79***

Note. ∗p<0.10; ∗∗p<0.05; ∗∗∗p<0.01 . n=1,810

Table 5: Results of DID analysis

	Inventory days		ROA	
Independent variables	Estimate	Std. Error	Estimate	Std. Error
Post*CN supplier	8.2062	[2.6570]***	-0.0129	[0.0063]**
Log total assets	1.2446	[0.5993]**	0.0247	[0.0015]***
Log second-tier CN supplier	-12.7929	[11.3151]	0.0235	[0.0270]
Log inventory efficiency	-51.5488	[1.2425]***	0.0078	[0.0030]***
Log fixed assets turnover	-0.6898	[1.0267]	-0.0016	[0.0025]
Log capital expenditure	-8.0828	[6.7456]	-0.1465	[0.0163]***
Log R&D expenditure	0.5413	[0.1014]***	-0.0007	[0.0002]***
Outsourcing	-7.6220	[0.6811]***	0.0028	[0.0016]*
Horizontal complexity	-0.0334	[0.0232]	-0.00003	[0.0001]
Spatial complexity	-0.4799	[0.2980]	-0.0017	[0.0007]**
n	1,810		1,810	
R-squared	52.05%		19.59%	
Adj. R-squared	51.68%		18.96%	
F-statistic	194.86	***	43.73	***

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

Table 6: The results of triple difference analysis on moderators

	Model 1		Model 2		Model 3	
Independent variables	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Post*CN supplier*Outsourcing	-0.0078	[0.0039]**				
Post*CN supplier*Horizontal complexity			-0.0006	[0.0002]**		
Post*CN supplier*Spatial complexity					-0.0037	[0.0016]**
Log total assets	0.0252	[0.0019]***	0.0328	[0.0022]***	0.0326	[0.0022]***
Log second-tier CN supplier	0.0430	[0.0338]	0.0637	[0.0396]	0.0630	[0.0396]
Log inventory efficiency	0.0159	[0.0037]***	0.0205	[0.0044]***	0.0204	[0.0044]***
Log fixed assets turnover	0.0027	[0.0032]	0.0138	[0.0037]***	0.0135	[0.0037]***
Log capital expenditure	-0.1714	[0.0201]***	-0.1492	[0.0236]***	-0.1495	[0.0236]***
Log R&D expenditure	-0.0009	[0.0003]***	-0.0003	[0.0004]	-0.0003	[0.0004]
Outsourcing	0.0049	[0.0022]**	0.0033	[0.0024]	0.0035	[0.0024]
Horizontal complexity	-0.0001	[0.0001]	-0.0001	[0.0001]	-0.0001	[0.0001]
Spatial complexity	-0.0013	[0.0009]	-0.0017	[0.0011]	-0.0014	[0.0012]
n	1,810		1,810		1,810	
R-squared	15.59%		16.28%		16.24%	
Adj. R-squared	14.93%		15.62%		15.59%	
F-statistic	33.15	***	34.89	***	34.80	***

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

Table 7: Results of DID analysis on years

	Inventory days		ROA	
Independent variables	Estimate	Std. Error	Estimate	Std. Error
Year2015*CN supplier	1.7396	[3.8362]	0.0004	[0.0092]
Year2016*CN supplier	1.2931	[3.7448]	-0.0035	[0.0090]
Year2017*CN supplier	5.2557	[3.7534]	-0.0050	[0.0089]
Year2019*CN supplier	9.8236	[3.7659]***	-0.0190	[0.0088]**
Log total assets	1.2198	[0.6008]**	0.0247	[0.0015]***
Log second-tier CN supplier	-13.0125	[11.3365]	0.0237	[0.0270]
Log inventory efficiency	-51.5692	[1.2451]***	0.0078	[0.0030]***
Log fixed assets turnover	-0.7138	[1.0284]	-0.0016	[0.0025]
Log capital expenditure	-8.2701	[6.7614]	-0.1463	[0.0163]***
Log R&D expenditure	0.5423	[0.1016]***	-0.0007	[0.0002]***
Outsourcing	-7.6046	[0.6818]***	0.0028	[0.0016]*
Horizontal complexity	-0.0311	[0.0233]	-0.00003	[0.0001]
Spatial complexity	-0.4900	[0.3034]	-0.0017	[0.0007]**
n	1,810		1,810	
R-squared	52.04%		19.63%	
Adj. R-squared	51.58%		18.87%	
F-statistic	149.56	***	33.67	***

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

Appendix Table A1: Industry distribution (two digit SIC)

SIC code	Initial set of firms		Final dataset for PSM				After matching	
	Firms	**%**	**Treatments**	**Controls**	**Total**	**%**	**Firms**	**%**
01	8	0.3%	1	1	2	0.2%	2	0.5%
02	3	0.1%	0	1	1	0.1%	0	0.0%
07	4	0.1%	0	0	0	0.0%	0	0.0%
08	1	0.0%	0	0	0	0.0%	0	0.0%
10	114	3.9%	0	6	6	0.6%	0	0.0%
12	15	0.5%	1	8	9	0.9%	2	0.5%
13	178	6.1%	6	42	48	4.5%	8	2.1%
14	19	0.6%	1	6	7	0.7%	2	0.5%
15	23	0.8%	0	1	1	0.1%	0	0.0%
16	20	0.7%	1	3	4	0.4%	0	0.0%
17	8	0.3%	0	4	4	0.4%	0	0.0%
20	104	3.5%	9	37	46	4.4%	12	3.2%
21	5	0.2%	0	1	1	0.1%	0	0.0%
22	8	0.3%	0	4	4	0.4%	0	0.0%
23	28	1.0%	10	5	15	1.4%	4	1.1%
24	17	0.6%	0	8	8	0.8%	0	0.0%
25	22	0.7%	2	14	16	1.5%	4	1.1%
26	27	0.9%	5	10	15	1.4%	4	1.1%
27	25	0.9%	2	10	12	1.1%	2	0.5%
28	845	28.8%	36	118	154	14.6%	40	10.6%
29	34	1.2%	4	9	13	1.2%	2	0.5%
30	29	1.0%	5	8	13	1.2%	0	0.0%
31	10	0.3%	4	5	9	0.9%	4	1.1%
32	24	0.8%	3	3	6	0.6%	4	1.1%
33	50	1.7%	6	16	22	2.1%	8	2.1%
34	55	1.9%	5	21	26	2.5%	10	2.7%
35	183	6.2%	30	61	91	8.6%	50	13.3%
36	295	10.0%	65	79	144	13.6%	74	19.7%
37	111	3.8%	23	31	54	5.1%	28	7.4%
38	279	9.5%	21	86	107	10.1%	38	10.1%
39	27	0.9%	6	6	12	1.1%	4	1.1%
50	76	2.6%	16	31	47	4.4%	28	7.4%
51	61	2.1%	4	22	26	2.5%	6	1.6%
52	8	0.3%	3	1	4	0.4%	0	0.0%
53	17	0.6%	5	8	13	1.2%	6	1.6%
54	15	0.5%	1	8	9	0.9%	2	0.5%
55	22	0.7%	3	14	17	1.6%	6	1.6%
56	31	1.1%	6	20	26	2.5%	10	2.7%
57	12	0.4%	2	6	8	0.8%	2	0.5%
58	54	1.8%	4	24	28	2.6%	6	1.6%
59	69	2.4%	8	21	29	2.7%	8	2.1%
Total	2936	100%	298	759	1057	100.0%	376	100.0%

Appendix A2: Description of data collection steps:

1. Our data collection started with 5,667 U.S. listed firms that were active from 2017 to 2019 collected from Compustat. This is because we needed at least one year of data prior to (i.e., 2017) and one year of data after (i.e., 2019) the 2018 trade war for analysis. Our research window cut off at 2019 because the impacts of COVID-19 were severe in 2020.

2. Given our focus on supply chain management, we removed firms in service industries with little or no physical products, including Finance, Insurance, and Real Estate (SIC 6000–6799; 1,273 firms), Transportation, Communications, Electric, Gas, and Sanitary Services (SIC 4000–4999; 563 firms), Services (SIC 7000–8999; 846 firms), and Public Administration and Non-classifiable industry (SIC 9100–9999; 49 firms). In total, we removed 2,731 firms, leaving 2,936 firms.

3. We removed firms with no inventory data (903 firms) or employee data (90 firms), leaving 1,943 firms.

4. We removed 411 firms not headquartered in the U.S., leaving 1,532 firms.

5. We removed 10 firms with no substantial operations in the U.S., leaving 1,522 firms. (Among the 1,532 firms, 542 firms specifically reported Property, Plant & Equipment (PP&E) data within the U.S., 1,518 firms reported segment sales in the U.S., and 1,233 firms reported US customers; 10 firms with none of these data were removed as they appear to have no substantial operations in the U.S.)

6. We removed 261 firms with no data in the Bloomberg SPLC or FactSet Revere databases, leaving 1,261 firms. To prepare the supply chain database for this study, we first searched the names of the 1,522 U.S. firms (from Step 5 in Table 1) in the Bloomberg SPLC database. We collected 157,121 supply chain data (80,206 suppliers and 76,915 customers) from 1,198 firms. We then searched the firm names in FactSet Revere database. We collected 83,996 supply chain data (25,737 suppliers and 58,259 customers) from 1,181 firms. We then compared the supplier and customer names for each of the 1,198 firms in Bloomberg SPLC with the 1,181 firms in FactSet Revere. We found 1,121 firms that appear in both databases. The figures show that Bloomberg SPLC has much stronger coverage in terms of the numbers of customers and suppliers (157,121 in Bloomberg SPLC vs. 83,996 in FactSet Revere) reported per firm. That's why we used Bloomberg SPLC as the primary source and FactSet Revere as a supplementary source. Nevertheless, the two databases are quite consistent in terms of firm coverage at 93.6% (1,121 overlaps out of 1,198 firms). We added 1,378 suppliers and 1,299 customers in 60 firms (i.e., 1,181-1,121) from FactSet Revere that were not included in the Bloomberg SPLC database at all. In addition, in another 80 firms we added additional suppliers and customers data (29 suppliers and 1,031 customers) from the FactSet Revere database (the 80 firms also appear in Bloomberg SPLC but there are some additional suppliers and customers data in FactSet Revere). Therefore, the use of FactSet data enabled us to increase the supply chain data for 140 firms (i.e., 60 + 80), or 11.7% (140/1198) of the data collected from Bloomberg. For these 140 firms, 10.05 suppliers and 17.83 customers per firm were added.

7. We removed 204 firms with no vertical integration data in the Fresard-Hoberg-Philips database, leaving 1,057 firms

8. The 1,057 firms, including 298 treatment firms and 759 control firms, were matched.

9. Among the 298 treatment firms, 7 firms that could not be matched with any control firms were removed, leaving 291 matched pairs. In two industries, there were more treatment firms than control firms. Specifically, in SIC 23 there were 10 treatment firms while there were only 5 control firms (removing 5); in SIC 52, there were 3 treatment firms while there was only 1 control firm (removing 2).

10. We removed 103 pairs with a propensity score difference outside the matching caliper of 0.1 (Levine & Toffel, 2010), leaving us with 188 matched pairs (376 firms) for analysis.

11. We then used these 376 firms to create a panel dataset from 2015 to 2019. Ideally, we would have 1,880 firm-year observations (i.e., 376 firms x 5 years). However, although we ensured that all firms have available data one year before (i.e., 2017) and one year after (i.e., 2019) the trade war in 2018 (i.e., 2017–2019 as explained in Step 1), firms could still have missing data in 2015 or 2016. We have 16 missing observations in 2015 or 2016. In addition, since we need treatment–control matched pairs for analysis, we need to delete the

corresponding control observation if the treatment observation is missing, and vice versa. Accordingly, we deleted 32 observations (instead of 16), leaving 1,848 firm-year observations (i.e., 1,880 – 16 x 2 = 1,848).

12. We then followed the previous literature (e.g., Corbett et al., 2005; Lo et al., 2014; Swift et al., 2019) with the difference-in-difference approach to trim by 0.5% extreme values of dependent variables (i.e., inventory days and ROA) at each end. We further remove 19 observations and their corresponding control or treatment firms (a total of 38), leaving 1,810 observations (i.e., 1,848 – 19 x 2 = 1,810 observations).

Appendix Table A3: The measurements and references of the matching covariates.

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	Ratio of second-tier Chinese suppliers to total second-tier suppliers	Yes	—	—
Total assets	Annual value of total assets	Yes	Yes	Wiengarten et al., 2020
capital expenditure	Capital expenditure normalized by sales	Yes	Yes	Steven et al., 2014
Inventory efficiency	Ratio of sales to average inventory	Yes	Yes	Modi & Mishra, 2011
Fixed assets turnover	Ratio of sales to property, plant, and equipment	Yes	Yes	Modi & Mishra, 2011
R&D expenditure	Annual value of research and development expense	Yes	Yes	Marino et al., 2016
Outsourcing	Reversed vertical integration level: text analysis of product vocabulary in 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 firm's suppliers were located	—	Yes	Lu & Shang, 2017

Table B1: Results of DID analysis (firms with only U.S. operations)

	Inventory days		ROA	
Independent variables	Estimate	Std. Error	Estimate	Std. Error
Post*CN supplier	30.1997	[9.3572]***	-0.0709	[0.0370]*
Log total assets	8.2169	[1.7437]***	0.0683	[0.0069]***
Log second-tier CN supplier	-24.4554	[38.7367]	0.3561	[0.1533]**
Log inventory efficiency	-59.8757	[3.4102]***	0.0602	[0.0135]***
Log fixed assets turnover	1.1058	[3.6514]	0.0931	[0.0145]***
Log capital expenditure	-1.5165	[16.4388]	-0.0517	[0.0651]
Log R&D expenditure	0.6535	[0.3857]*	-0.0026	[0.0015]*
Outsourcing	-6.7497	[3.5367]*	-0.0365	[0.0140]***
Horizontal complexity	-0.0650	[0.0922]	-0.0002	[0.0004]
Spatial complexity	-1.1384	[1.2196]	-0.0048	[0.0048]
n	312		312	
R-squared	54.13%		41.56%	
Adj. R-squared	51.96%		38.80%	
F-statistic	35.04	***	21.12	***

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

Table B2: Results of DID analysis (Chinese customers controlled in PSM)

	Inventory days		ROA	
Independent variables	Estimate	Std. Error	Estimate	Std. Error
Post*CN supplier	6.2502	[3.0325]**	-0.0181	[0.0091]**
Log total assets	0.3050	[0.6840]	0.0334	[0.0020]***
Log second-tier CN supplier	-27.5463	[13.1145]**	0.0252	[0.0392]
Log CN customer percent	-8.7679	[12.9052]	-0.0137	[0.0385]
Log inventory efficiency	-54.7153	[1.4286]***	0.0157	[0.0043]***
Log fixed assets turnover	-1.6241	[1.2759]	0.0115	[0.0038]***
Log capital expenditure	-11.1468	[8.6858]	-0.1610	[0.0259]***
Log R&D expenditure	0.6782	[0.1171]***	-0.0006	[0.0003]*
Outsourcing	-7.5790	[0.7789]***	0.0053	[0.0023]**
Horizontal complexity	-0.0019	[0.0277]	0.00001	[0.0001]
Spatial complexity	-0.7726	[0.3375]**	-0.0030	[0.0010]***
n	1,840		1,840	
R-squared	47.76%		17.72%	
Adj. R-squared	47.33%		17.05%	
F-statistic	151.60	***	35.72	***

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

Table B3: Results of triple difference analysis on firms with Chinese customers

	Inventory days		ROA	
Independent variables	Estimate	Std. Error	Estimate	Std. Error
Post*CN supplier*CN customer percent	0.1199	[24.6116]	-0.1037	[0.0735]
Log total assets	0.4001	[0.6832]	0.0331	[0.0020]***
Log second-tier CN supplier	-27.0858	[13.1435]**	0.0211	[0.0392]
Log CN customer percent	-8.3346	[14.1379]	0.0092	[0.0422]
Log inventory efficiency	-54.6961	[1.4307]***	0.0158	[0.0043]***
Log fixed assets turnover	-1.5599	[1.2780]	0.0115	[0.0038]***
Log capital expenditure	-11.1574	[8.6965]	-0.1606	[0.0260]***
Log R&D expenditure	0.6783	[0.1172]***	-0.0006	[0.0003]*
Outsourcing	-7.5460	[0.7802]***	0.0054	[0.0023]**
Horizontal complexity	-0.0020	[0.0278]	0.000004	[0.0001]
Spatial complexity	-0.7348	[0.3376]**	-0.0031	[0.0010]***
n	1,840		1,840	
R-squared	47.64%		17.63%	
Adj. R-squared	47.21%		16.95%	
F-statistic	150.86	***	35.49	***

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

Table B4: Results of DID analysis (controlled the number of suppliers in other trade war locations and Chinese suppliers)

	Inventory days		ROA	
Coefficients	Estimate	Std.error	Estimate	Std.error
Post*CN supplier	9.3650	[2.6939]***	-0.0140	[0.0064]**
Log total assets	2.4346	[0.7039]***	0.0243	[0.0017]***
Log second-tier CN supplier	-13.4552	[11.3389]	0.0279	[0.0271]
Log inventory efficiency	-51.7576	[1.2464]***	0.0072	[0.0030]**
Log fixed assets turnover	-0.0856	[1.0505]	-0.0021	[0.0026]
Log capital expenditure	-8.9603	[6.7535]	-0.1445	[0.0163]***
Log R&D expense	0.4558	[0.1035]***	-0.0007	[0.0002]***
Log Number of suppliers in other countries had trade war with the U.S.	-3.9779	[1.4476]***	-0.0054	[0.0035]
Log Number of CN supplier	-0.4066	[1.3991]	0.0051	[0.0033]
Outsourcing	-7.8904	[0.6852]***	0.0030	[0.0016]*
Horizontal complexity	-0.0430	[0.0233]*	-0.00003	[0.0001]
Spatial complexity	0.1544	[0.3398]	-0.0015	[0.0008]*
n	1,810		1,810	
R-squared	52.45%		19.72%	
Ajd. R-squared	52.03%		19.00%	
F-statistic	164.84	***	36.70	***

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

Table B5: Results of triple difference analysis on other trade war locations

	Inventory days		ROA	
	Estimate	Std. Error	Estimate	Std. Error
Post*CN supplier*Other Trade War	6.2407	[2.7535]**	-0.0112	[0.0065]*
Log total assets	1.1746	[0.6044]*	0.0248	[0.0015]***
Log second-tier CN supplier	-11.3530	[11.3282]	0.0210	[0.0270]
Log inventory efficiency	-51.5882	[1.2441]***	0.0078	[0.0030]***
Log fixed assets turnover	-0.6766	[1.0280]	-0.0016	[0.0025]
Log capital expenditure	-7.7415	[6.7535]	-0.1466	[0.0163]***
Log R&D expense	0.5512	[0.1016]***	-0.0007	[0.0002]***
Outsourcing	-7.5969	[0.6818]***	0.0028	[0.0016]*
Horizontal complexity	-0.0327	[0.0232]	-0.00003	[0.0001]
Spatial complexity	-0.4774	[0.2987]	-0.0017	[0.0007]**
n	1,810		1,810	
R-squared	51.93%		19.54%	
Adj. R-squared	51.56%		18.91%	
F-statistic	193.95	***	43.58	***

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

Table B6: Results of triple difference analysis for high-tech firms

	Inventory days		ROA	
Independent variables	Estimate	Std. Error	Estimate	Std. Error
Post*CN supplier*High-Tech industries	6.9262	[3.2828]**	-0.0174	[0.0078]**
Log total assets	1.3481	[0.5991]**	0.0245	[0.0015]***
Log second-tier CN supplier	-12.6620	[11.3329]	0.0238	[0.0270]
Log inventory efficiency	-51.4146	[1.2460]***	0.0074	[0.0030]**
Log fixed assets turnover	-0.7328	[1.0295]	-0.0014	[0.0025]
Log capital expenditure	-8.1211	[6.7561]	-0.1458	[0.0163]***
Log R&D expenditure	0.4987	[0.1037]***	-0.0006	[0.0002]**
Outsourcing	-7.5464	[0.6822]***	0.0026	[0.0016]
Horizontal complexity	-0.0330	[0.0232]	-0.00003	[0.0001]
Spatial complexity	-0.4407	[0.2981]	-0.0017	[0.0007]**
n	1,810		1,810	
R-squared	51.92%		19.63%	
Adj. R-squared	51.54%		19.00%	
F-statistic	193.81	***	43.83	***

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

Table B7: Results of triple difference analysis on firms in trade war list industries

Independent variables	Inventory days		ROA	
	Estimate	Std. Error	Estimate	Std. Error
Post*CN supplier*On trade war list	3.4749	[2.7881]	0.0011	[0.0066]
Log total assets	1.3269	[0.6001]**	0.0244	[0.0015]***
Log second-tier CN supplier	-12.3627	[11.3422]	0.0215	[0.0270]
Log inventory efficiency	-51.4766	[1.2468]***	0.0077	[0.0030]***
Log fixed assets turnover	-0.6251	[1.0287]	-0.0018	[0.0025]
Log capital expenditure	-8.0089	[6.7616]	-0.1464	[0.0163]***
Log R&D expenditure	0.5204	[0.1032]***	-0.0007	[0.0002]***
Outsourcing	-7.6164	[0.6830]***	0.0028	[0.0016]*
Horizontal complexity	-0.0323	[0.0233]	-0.00003	[0.0001]
Spatial complexity	-0.4494	[0.2986]	-0.0017	[0.0007]**
n	1,810		1,810	
R-squared	51.84%		19.40%	
Adj. R-squared	51.46%		18.78%	
F-statistic	193.20	***	43.21	***

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

Table B8: The results of triple difference analysis on moderators

	Model 1		Model 2		Model 3	
Independent variables	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Post*CN supplier*High outsourcing	-0.0289	[0.0098]***				
Post*CN supplier*High horizontal complexity			-0.0314	[0.0117]***		
Post*CN supplier*High spatial complexity					-0.0277	[0.0103]***
Log total assets	0.0251	[0.0018]***	0.0334	[0.0022]***	0.0333	[0.0022]***
Log second-tier CN supplier	0.0395	[0.0336]	0.0586	[0.0394]	0.0575	[0.0394]
Log inventory efficiency	0.0171	[0.0037]***	0.0213	[0.0043]***	0.0213	[0.0043]***
Log fixed assets turnover	0.0030	[0.0031]	0.0135	[0.0036]***	0.0134	[0.0036]***
Log capital expenditure	-0.1739	[0.0200]***	-0.1527	[0.0234]***	-0.1526	[0.0234]***
Log R&D expenditure	-0.0008	[0.0003]***	-0.0003	[0.0004]	-0.0003	[0.0004]
Outsourcing	0.0019	[0.0021]	0.0033	[0.0024]	0.0034	[0.0024]
Horizontal complexity	-0.0001	[0.0001]	-0.0001	[0.0001]	-0.0001	[0.0001]
Spatial complexity	-0.0014	[0.0009]	-0.0020	[0.0011]*	-0.0020	[0.0011]*
n	1,810		1,810		1,810	
R-squared	16.22%		16.58%		16.58%	
Adj. R-squared	15.57%		15.93%		15.93%	
F-statistic	35.06	***	35.98	***	35.99	***

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