Institute for International Economic Policy Working Paper Series
Elliott School of International Affairs
The George Washington University

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IIEP-WP-2021-19

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June 2021

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The Impact of COVID-19 on Supply Chain Credit Risk

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Global supply chains expose firms to multi-regional risks, but also provide benefits by creating a buffer against local shocks. The COVID-19 pandemic and its differential impact on different parts of the world provide an opportunity for insight into supply chain credit risk, and how operational and structural characteristics of global supply chains affect this risk. In this paper, we examine supply chain credit risk during different phases of the COVID-19 pandemic by focusing on Credit Default Swap (CDS) spreads and US-China supply chain links. CDS spreads reflect both the probability of default and expected loss given default, and are available with daily frequency, which allows the assessment of supply chain partners' credit risk in a timely manner. We find that CDS spreads for firms with China supply chain partners increase with the economic shutdown in China during the pandemic, and the spreads go down when the economic activity resumed with the re-opening in China. We consider Swift, Even Flow (SEF) and Social Network Theories (SNT) within our context. Supporting SEF theory, we find that the impact of pandemic-related disruptions to even flow of goods and materials reflected in supply chain credit risk is mitigated for firms with lower inventory turnover and those with better ability to work with longer lead times and operating cycles. Examining supply chain structural characteristics through SNT reveals that spatial and horizontal complexity, as well as network centrality (degree, closeness, betweenness, information) mitigate the impact of supply chain vulnerabilities on supply chain credit risk.

Key words: Supply Chains, Credit Risk, CDS, COVID-19, pandemic
History: First version: May 8, 2020. This version: June 13, 2021

1. Introduction

Supply chain risk management (SCRM) is a core issue in operations management (Ho et al. 2015, Tang 2006, Tang and Musa 2011, Sodhi et al. 2012), and the importance of SCRM has become a central topic during the current COVID-19 pandemic, particularly within the context of global supply chains. A critical question in assessing global supply chains is the extent to which supply chain connections in distinct regions of the world either expose firms to increased risk or provide a buffer against local shocks. While global supply chains allow firms to outsource production in a more cost-effective manner, they also expose firms to developments in the local economies where supply chain partners are located. The recent COVID-19 pandemic and its shock to global supply chains provide a particularly relevant setting for exploring these effects. The COVID-19 pandemic adversely affected production for downstream firms, and financial flows for upstream firms, creating major vulnerabilities for firms connected within a production network. These vulnerabilities put firms at risk by reducing their ability to continue operations and make payments, increasing their default risk.

We contribute to supply chain risk management (SCRM) by examining the credit risk of firms through their global supply chain linkages during the COVID-19 pandemic. Similar to Ağca et al. (2020) and Lee et al. (2019), we use credit default swaps (CDS) to examine credit risk. While other studies (Hendricks and Singhal 2003, 2005, Hendricks et al. 2020 etc.) show shareholder value losses due to supply chain disruptions, we focus on credit risk, which is particularly important for firms in managing their own cost of borrowing as well as assessing the creditworthiness and financial health of their supply chain partners.

As discussed in Sodhi et al. (2012) and Ho et al. (2015), SCRM has four components: risk identification, assessment, mitigation, and responsiveness. CDS spreads are useful in the risk identification and assessment of SCRM as they reflect both the probability of default and expected loss given default. CDS is like an insurance contract that provides protection to the CDS buyer if the underlying entity of the contract defaults. The CDS buyer pays the CDS seller periodic premiums (CDS spreads) over a certain maturity, and if the underlying entity defaults, the CDS seller pays the CDS buyer the amount that is not recovered due to default (loss given default, or LGD). Figure 1 shows how a CDS contract is structured. [1]. Furthermore, CDS trade more frequently than bonds, adjusts quicker than credit ratings, and are found to be more efficient than stocks and bonds in reflecting firm-specific information (Blanco et al. 2005, Stulz 2010, Lee et al. 2019). Thus, CDS spreads are useful measures for SCRM in identifying and assessing risks arising from supply chain vulnerabilities.[2]

We first examine CDS spreads in response to both disruption and resumption of supply chain activity during different phases of the COVID-19 pandemic.[3] We find that CDS spreads for firms with China supply chain partners increased with the economic shutdown in China during the pandemic, and the spreads declined when the economic activity resumed with the re-opening in China. We then look at factors that are pivotal in magnifying or reducing firms' supply chain vulnerabilities as reflected in CDS spreads. We interpret these factors from the perspectives of the

[1] We also provide an example on CDS contract in Appendix Figure A1.

[2] Section 3.1 provides a detailed overview of CDS.

[3] Our framework is similar to studies that focus on disasters for supply chain disruption such as Hendricks et al. (2020), Carvalho et al. (2021), which focus on Great East Japan Earthquake in 2011 as a cause for disruptions.

theory of Swift, Even Flow (SEF) and Social Network Theory (SNT). Supporting SEF theory, we find that the impact of pandemic-related disruptions to even flow of goods and materials reflected in supply chain credit risk are mitigated for firms with lower inventory turnover and better ability to work with longer lead times and operating cycles. Examining supply chain structural characteristics through SNT theory shows that spatial and horizontal complexity, as well as network centrality (degree, closeness, betweenness, information) are important factors that ameliorate the impact of supply chain vulnerabilities on supply chain credit risk.

Our study explores CDS spreads as they provide timely information to identify and assess supply chain credit risk. We study how operational characteristics mitigate or amplify supply chain credit risk within the context of Swift, Even Flow theory, as disruptions to and resumptions of operations during the pandemic affect the even flow of goods and materials (Schmenner and Swink 1998, Schmenner 2001, Frohlich and Westbrook 2001, Devaraj et al. 2007, Germain et al. 2008, Wong et al. 2011). We examine supply chain structural characteristics according to Social Network Theory (Choi et al. 2001, Choi and Hong 2002, Cassiman and Veugelers 2002, Vachon and Klassen 2002, Wu and Choi 2005, Choi and Krause 2006, Craighead et al. 2007, Choi and Wu 2009, Kim et al. 2011, Bellamy et al. 2014, Lu and Shang 2017) in order to understand which structural factors ameliorate or magnify supply chain credit risk. We specifically explore structural complexity by considering spatial and horizontal complexity (Bode and Wagner 2015, Choi and Hong 2002, Vachon and Klassen 2002, Choi and Krause 2006, Craighead et al. 2007, Lu and Shang 2017), and study network centrality by focusing on degree centrality (Cassiman and Veugelers 2002, Craighead et al. 2007, Kim et al. 2011), closeness centrality (Kim et al. 2011, Lee et al. 1997, Chen et al. 2000), betweenness centrality (Burt 1992, Burt et al. 1998, Wu and Choi 2005, Choi and Wu 2009, Kim et al. 2011), and information centrality (Bellamy et al. 2014, Stephenson and Zelen 1989, Choi and Krause 2006).

We look at U.S. firms' supply chain relationships to China. There are several reasons for focusing on China. First, China is a major production center of the world, providing the bulk of the components, raw or processed materials, and subsystems to companies globally.[4] Furthermore, among U.S. trade partners, China is the largest importer to the U.S., providing 18% of total imports in 2019.[5] Thus, COVID-19 related economic disruptions in China have significant potential consequences for U.S. firms. Secondly, China experienced different phases of COVID-19 earlier than the rest of the world, namely both the spread of the pandemic and the resulting economic shutdown

[4] "How China can rebuild global supply chain resilience after COVID-19?" World Economic Forum Report, March 23, 2020. See https://www.weforum.org/agenda/2020/03/coronavirus-and-global-supply-chains/

[5] Data is obtained from the U.S. Census Data on Foreign Trade in 2019. See https://www.census.gov/foreign-trade/statistics/highlights/top/top1912yr.html

orders, as well as the reopening of the economy when COVID-19 was more in control. This provides a useful setting to understand global supply chain risks during different pandemic phases. In robustness, we also consider other global supply chain relations of firms in addition to those with China.

Our research advances SCRM in identifying the risks arising from global supply chain partners and assessing the potential impact of this risk on firms' stability and financial health. The rest of the paper is as follows. Section 2 is on theory and hypotheses development. Section 3 introduces CDS and the COVID-19 timeline. Section 4 is on variables and empirical methods. Section 5 presents the main empirical results, the operations management attributes and supply chain network attributes as interaction variables, as well as the placebo test result. Section 6 examines several alternative specifications and robustness test. Section 7 is a discussion on results and managerial implications. Section 8 concludes.

2. Theoretical Background and Hypotheses Development

2.1. Theoretical Framework

We examine CDS spreads within the context of the COVID-19 pandemic, and by focusing on US firms with supply chain connections to China. We contribute to SCRM literature as CDS spreads are useful for two pillars of SCRM: (i) identifying risks (default risk); and (ii) assessing the impact of risk (expected loss given default, or LGD). In Section 3.1, we explain the details of how CDS contracts are structured and that CDS spreads contain information on both the risk of default and LGD. Thus, CDS spreads convey both arising or changing default risks and the losses that are expected from these risks. This information is valuable for supply chain managers in understanding risks in the supply chain networks, which is important for mitigating supply chain risk. We build on two theories within this perspective: Swift, Even Flow (SEF), and Social Network Theory (SNT).

2.1.1. Swift, Even Flow (SEF)

Understanding the influence of process variability in a supply chain system is central to inventory control and is manifested in the Theory of Swift, Even Flow (Schmenner and Swink 1998, Schmenner 2001, Devaraj et al. 2007, Schmenner 2012). According to Schmenner and Swink (1998), the Theory of Swift, Even Flow holds that the more swift and even the flow of materials through a process, the more productive that process is.

As discussed in Chen et al. (2013) and the references therein, flow variability is caused by the way the work is released to the system and the movement between stations. These factors may result in inconsistency in the throughput time, process yield, and product quality which makes the performance of the production process unpredictable and induces process risk.

Other things equal, the theory also urges the process to reduce the clock time spent through an even flow of materials. Throughput time is particularly useful as a mechanism to isolate where flows have become retarded or blocked. Supply chain productivity for any process rises with the speed by which materials flow through the process. One managerial lever is to eliminate supply chain disruptions, as materials in the supply chain can move swiftly only if there are no bottlenecks or other impediments to flow in the way.

The Theory of Swift, Even Flow has implications on operational and financial performance. Supply chains are most productive when there is an even flow of materials. Disruptions in such goods affect productivity and financial health. Schmenner (2001) explain that historically, those companies that have exemplified swift, even flow should have done better than companies that were not concerned with the variability of their production processes. Germain et al. (2001) suggest that the more consistent the flow of materials, the more productive processes should be. This productivity thus implies improved financial performance. Several studies find that information integration in the supply chain enables materials to flow more swiftly and evenly and brings forth improved operational performance (Frohlich and Westbrook 2001, Devaraj et al. 2007, Wong et al. 2011). Cotteleer and Bendoly (2006) finds that the implementation of enterprise systems following swift and even process dynamics leads to improved operational performance. Germain et al. (2008) shows that supply chain process variability has an inverse relationship with financial performance, regardless of the demand environment. Schoenherr and Swink (2012) suggests that Theory of Swift, Even Flow of materials should be applied throughout, including the firm's internal operations.

The Theory of Swift, Even Flow, overall, is consistent with the deductive laws of variability and of bottlenecks, indicating the positive impact of even flow of materials on operational and financial performance. As COVID-19 affects both the variability of the global supply chain process as well as the throughput time, our research looks at the effects of COVID-19 supply chain disruptions on firm default risk, contributing to the theory of Swift, Even Flow comprehensively.

2.1.2. Social Network Theory (SNT)

Social network theory (SNT) in supply chains focuses on the position of a firm in a supply chain network and how supply chain links connect with each other. The studies that focus on SNT and examine structural characteristics of supply chain networks (Choi et al. 2001, Choi and Hong 2002, Craighead et al. 2007, Kim et al. 2011, Bellamy et al. 2014, Lu and Shang 2017) show that structural supply chain characteristics have important implications for firm financial and operational performance. In this study, we focus on two complexity and four network centrality measures, which encompasses major structural characteristics in SNT within the context of supply chains (Choi et al. 2001, Cassiman and Veugelers 2002, Choi and Hong 2002, Vachon and Klassen 2002, Wu and Choi 2005, Choi and Krause 2006, Craighead et al. 2007, Choi and Wu 2009, Kim et al. 2011, Bellamy et al. 2014, Lu and Shang 2017). Specifically, we consider spatial complexity and horizontal complexity as complexity measures, and degree centrality, closeness centrality, betweenness centrality, and information centrality as network centrality measures.

Structural complexity in supply chains is generally measured as spatial, horizontal, and vertical complexity.[6] Spatial complexity is examined in SNT within the perspective of supply chain network performance by Bode and Wagner (2015), Choi and Hong (2002), Lu and Shang (2017), and Vachon and Klassen (2002) among others. Spatial complexity is the geographical dispersion of the supply base. Craighead et al. (2007) considers spatial complexity as inversely related to supply chain density, which is the geographic spacing of nodes within a supply chain. While Craighead et al. (2007) and Bode and Wagner (2015) indicate that supply chain disruptions are more likely with increasing spatial complexity, Lu and Shang (2017) find that spatial complexity has a potentially significant positive effect on firm performance as benefits of this complexity in resource and knowledge sharing exceeds its costs when this complexity increases up to a certain level.

Horizontal complexity is the number of direct suppliers in each supply chain tier, or alternatively, the number of suppliers connected to a given buyer, which is also considered as the width of the supply chain (Choi and Hong 2002, Bode and Wagner 2015, Lu and Shang 2017), among others. Bode and Wagner (2015) suggest that horizontal complexity increases the likelihood of supply chain disruptions, whereas Lu and Shang (2017) find that certain levels of horizontal complexity have benefits of risk mitigation for the firm and improves firm performance.

Network centrality is another important structural supply chain characteristic explored within the context of SNT (Choi and Hong 2002, Craighead et al. 2007, Kim et al. 2011, Bellamy et al. 2014). Central nodes in a supply chain network are integrated with many others in the network, which increases the importance of these nodes in the financial and operating performance of supply chain partners. Major centrality measures considered in SNT within supply chains are degree centrality, closeness centrality, betweenness centrality, and information centrality (Kim et al. 2011, Bellamy et al. 2014).

Degree centrality is a measure of the links to which a certain node is connected. The larger the number of connections, the more central that node is within a supply chain. Nodes that have high network centrality benefit from higher information flow and better integration to many nodes (Cassiman and Veugelers 2002, Kim et al. 2011). Craighead et al. (2007) considers degree centrality as part of node criticality since nodes that are connected to many other nodes are more critical in integrating supply chain networks. Craighead et al. (2007) also state that supply chain disruption severity may be positively related to a high degree centrality. Thus, degree centrality has benefits in aggregating information from many channels and the ability to integrate to supply chains in

[6] While vertical complexity, which is the hierarchical level in the supply chain, is examined by several studies (Bode and Wagner 2015, Choi and Hong 2002, Choi and Krause 2006, Lu and Shang 2017), in general, vertical complexity is not found to be a significant determinant of firm performance (Lu and Shang 2017). Thus our study focuses on the two dimensions of structural complexity that are found to affect firm performance: spatial and horizontal complexity.

multiple ways, but also may adversely affect supply chain performance by propagating disruption risk to many other nodes in the supply chain.

Closeness centrality measures how close a specific node is to others within a supply chain. Nodes with high closeness centrality have the ability to act in a more timely manner to developments in supply chains since such nodes have a better ability to access information (Kim et al. 2011, Lee et al. 1997, Chen et al. 2000). There is also less distortion of information along the supply chains for nodes with high closeness centrality, which reduces operational costs and allows firms to act more efficiently (Lee et al. 1997, Kim et al. 2011),

Betweenness centrality measures the frequency a node is on the shortest path between all node pairs in a supply chain network. Nodes with high betweenness centrality have the ability to facilitate interactions and information flow in the supply chain (Freeman 1978, Kim et al. 2011). Such firms are pivotal in transmitting material and information within a network. These firms have a better ability to navigate in a supply chain due to their reach to information, better control over others, and multiple resource alternatives in a network (Burt 1992, Burt et al. 1998, Wu and Choi 2005, Choi and Wu 2009, Kim et al. 2011)

Information centrality captures access to information in a supply chain network and measures how many short paths connect a node to other nodes. The nodes that have high information centrality will have better supply chain network accessibility (Bellamy et al. 2014, Stephenson and Zelen 1989). These nodes are connected to others with shorter paths and therefore have the ability to reach information faster. This characteristic allows firms to be more adaptable to changing supply chain dynamics as they have a more timely reach to information due to their centrality in the supply chain.

2.2. Hypotheses

CDS spreads are a construct of the probability of default and the loss given default. CDS is like an insurance contract for default. Increasing CDS spreads indicate increasing default risk accompanied by high expected losses in case of default. Thus CDS spreads are useful in identifying and assessing supply chain risk, contributing to supply chain risk management.

When a firm is exposed to disruptions or major vulnerabilities in its supply chain network, the operational performance and financial health of the firm are affected. Deterioration in financial health increases the probability of default and the expected loss in case of default, which is reflected in CDS spreads as increasing risk premiums. During economic shutdowns in the first phase of the COVID-19 pandemic in China, US firms with supply chain links to China experienced vulnerabilities due to disruptions in the flow of goods downstream and financial payments upstream. These vulnerabilities should be reflected as increasing CDS spreads for firms that experience supply chain vulnerabilities since the default risk and expected loss in case of default increases for these firms. The impact of these vulnerabilities on supply chain credit risk should depend on the operational characteristics that affect the swift, even flow of goods and materials, and the supply chain network structural characteristics.

As vulnerabilities in supply chains go down, so does the associated default risk and expected loss for the firms that are in that product network. When the economy reopened in China in the second phase of the COVID-19 pandemic while the rest of the world was experiencing economic shutdowns, US firms with supply chain links to China should experience lower CDS spreads. Supply chain vulnerabilities arising from China are resolved in the second phase, with the re-establishment of operations along the supply chain network, reducing default risk and expected LGD for firms that were exposed to these risk in the first stage of the pandemic. Reducing credit risk with mitigating supply chain vulnerabilities should be closely related to the operational and supply chain network characteristics of firms that affect swift, even flow of goods, a well as the position of firm in a supply chain network.

2.2.1. Swift, Even Flow Hypotheses

During the COVID-19 pandemic, the supply chain impact of local vulnerabilities arising from economic shutdowns in China exposed firms to the disruption of material and goods flow. According to the Theory of Swift, Even Flow (Schmenner and Swink 1998, Devaraj et al. 2007), the supply chain process should thus become less productive, impairing the firm's operational performance. We examine several factors related to the variability of the supply chain process and the throughput time, two key measures in the Theory of Swift, Even Flow.

Inventory turnover is a common measure of inventory productivity (Alan et al. 2014). Besides inventory turnover, we also examine the level of inventory, defined as the inventory-to-asset ratio. Higher inventory turnover or lower inventory level indicates higher efficiency in capital utilization (Gaur and Kesavan 2015), less inventory as a buffer, thus weaker resilience when facing inventory shortages since the firm needs to frequently replenish their inventory. As a result, supply chain disruptions should result in larger flow variability for firms with high inventory turnover or low inventory level, and such firms' credit risks should be more adversely affected when their supply chains are disrupted by COVID-19. On the other hand, when economic activity resumed in China, the recovery of such firms may also adjust faster.

H1a: Increasing inventory turnover and decreasing inventory levels amplify the increase in CDS spread (increasing default risk and expected loss given default) with supply chain vulnerabilities.

H1b: Increasing inventory turnover and decreasing inventory levels amplify the decrease in CDS spread (decreasing default risk and expected loss given default) with reduced supply chain vulnerabilities.

Lead time is the latency between the time of a customer's placing an order and the time that customer receives the order (Rumyantsev and Netessine 2007). A longer lead time during the pandemic indicates lower risk since the disruption creates a relatively smaller slack for the existent long lead time. Furthermore, if disruptions resolve faster, the impact on supply chain partners may be more mitigated for firms with longer lead time as the impact on cash flows or flow of goods are not immediate. Besides lead time, we further examine the operating cycle, which refers to the cycle length for a company to purchase, sell goods, and receive cash from goods sold. This variable has two components: the days' sales in inventory (inversely proportional to inventory turnover) and the average collection period of cash. A longer operating cycle means a longer cash flow delay and makes firms react slower to environmental change. For example, when a firm with a short operating cycle experiences a shock, cash flow will be immediately affected. In contrast, there should be a more lagged impact on cash flow for a firm with a longer operating cycle. Therefore, as a cycle time variable, its mechanism is similar to the lead time.

The Theory of Swift, Even Flow urges the process to reduce the clock time spent in production. However, firms with higher lead-time and operating cycles have long been accustomed to the time lags and uncertainty in the supply chain relative to shorter lead-time, operating cycle firms. Therefore those two factors can moderate an increase in firms' CDS spreads when facing supply chain shocks. Similarly, when their supply chain partners recover, their own recovery may also be slow.

H2a: Increasing processing time (lead time and operating cycle) mitigates the increase in CDS spread (increasing default risk and expected loss given default) with supply chain vulnerabilities.

H2b: Increasing processing time (lead time and operating cycle) mitigates the decrease in CDS spread (decreasing default risk and decreasing loss given default) with reduced supply chain vulnerabilities.

2.2.2. Social Network Theory (SNT) Hypotheses

We focus on supply chain structural characteristics within the context of SNT. Two of the main supply chain network complexity measures are spatial and horizontal complexity, and the other four are network centrality variables: Degree centrality, closeness centrality, betweenness centrality, and information centrality (Kim et al. 2011, Bellamy et al. 2014, Stephenson and Zelen 1989).

Spatial complexity, which is the dispersion of the supply chain base, is critical in providing alternative resources and increasing shared information (Bode and Wagner 2015, Choi and Hong 2002, Lu and Shang 2017, Vachon and Klassen 2002). Spatial complexity also allows firms to hedge against local developments through access to a more dispersed supply chain base that will be less affected by local shocks. During the COVID-19 pandemic, the supply chain impact of local vulnerabilities arising from economic shutdowns in China in the first phase should be less amplified for firms with higher spatial complexity. Firms with a more dispersed supply chain base that extends beyond the US and China have more flexibility in adjusting to local vulnerabilities. Thus, US firms with China supply chain partners should observe less pronounced increases in CDS spreads if these firms have higher spatial complexity. Spatial complexity allows firms to have more flexibility in adjusting to local shocks, reducing the default risk and LGD arising from supply chain activities.

When economic activity resumed in China in the second phase of the pandemic, firms with a wider supply base that has already adjusted to economic closures in the first phase should be less affected by this change in the local economy. Thus, US firms with China supply chain partners, which have higher spatial complexity, should observe less pronounced decreases in CDS spreads in the second phase of the pandemic.

Horizontal complexity is a key structural characteristic of supply chain networks that is determined by the number of suppliers connected to a given buyer (Bode and Wagner 2015, Choi and Hong 2002, Lu and Shang 2017). Firms with higher horizontal complexity have a better ability to mitigate risks as there are more alternative resources to adjust in the supply chain. When economic activity severely slowed down in China in the first phase of the pandemic, US firms with China supply chain partners observed increasing risks arising from supply chain vulnerabilities. However, for those firms with higher horizontal complexity, there are other potential ways to adjust, helping them hedge against these vulnerabilities. Thus, increasing horizontal complexity should reduce default risk and LGD arising from supply chain vulnerabilities during the first phase of the pandemic for these firms. As a result, an increase in CDS spreads for US firms with China suppliers should be less pronounced for firms with higher horizontal complexity.

When China's economy reopened in the second phase, firms with high horizontal complexity should need fewer adjustments as these firms already had the ability to mitigate the risk through their access to many alternative resources. Thus, the change in default risk and LGD should be less pronounced for these firms, which should reflect in less pronounced decreases in CDS spreads.

H3a: Increasing supply chain network complexity (spatial and horizontal complexity) mitigates the increase in CDS spread (increasing default risk and expected loss given default) with supply chain vulnerabilities.

H3b: Increasing supply chain network complexity (spatial and horizontal complexity) mitigates the decrease in CDS spread (decreasing default risk and decreasing loss given default) with reduced supply chain vulnerabilities.

Network centrality is an important structural characteristic in SNT that has implications for the financial and operating performance of supply chain partners. One of the widely considered network centrality measures is degree centrality, which is the number of nodes that a particular node in the supply chain is connected to (Cassiman and Veugelers 2002, Kim et al. 2011, Craighead et al. 2007). As a firm becomes more central in a network within the context of degree centrality, the connections that the firm has with many other nodes expose these firms to more potential vulnerabilities, but also provides these firms ability to shift to alternative resources and gather information from many sources, which are critical in mitigating supply chain risks.

Closeness centrality focuses on how quickly a firm can reach others within the supply chain beyond the ones that they are directly connected with (Kim et al. 2011, Lee et al. 1997, Chen et al. 2000). Thus, firms with high closeness centrality have a better ability to adapt to supply chain vulnerabilities due to access to alternative resources and information through a shorter distance in the supply chain.

Betweenness centrality captures how frequently a given node is on the shortest path between all pair combinations in a supply chain network. Firms with high betweenness centrality have the ability to control the flow of material and information. Thus, these firms can affect supply chain interactions (Burt 1992, Burt et al. 1998, Kim et al. 2011, Choi and Wu 2009, Wu and Choi 2005). When there are supply chain vulnerabilities due to local developments, firms with high betweenness centrality have a better capability to adapt through adjusting the dynamics within the supply chain network.

Information centrality incorporates firm opportunities to access information within the framework of SNT. Information centrality is measured by determining the number of short paths that connect a given node to other nodes in a supply chain network. This measure is also employed within the context of supply network accessibility (Bellamy et al. 2014, Stephenson and Zelen 1989). Firms with many short links to other supply chain partners have the advantage of reaching and use the information at a faster speed and thus can adjust to changes in supply chain network dynamics better.

When US firms with China suppliers are faced with economic shutdowns in China due to the COVID-19 pandemic, firms with higher network centrality (degree, closeness, betweenness, and information centrality) have better capability to adapt to supply chain vulnerabilities. The ability to connect to more nodes (degree centrality), reach to other resources or information with a shorter supply chain distance (closeness centrality), control flow of material and information (betweenness centrality), and reach to information faster (information centrality) reduce supply chain vulnerabilities more efficiently by utilizing more resources and more information in a faster speed in the supply chain. Thus, supply chain risk should go down with higher network centrality. In this regard, during the economic shutdown period, the increase in the CDS spreads of US firms with China supply chain partners should be mitigated more for firms with higher network centrality.

These firms have a better ability to adapt to these changes due to their position in the supply chain network and thus should have a more attenuated increase in default risk and LGD.

For firms with high network centrality, the impact of resuming economic activity on supply chain credit risk should also be more muted. Firms with high network centrality (degree, closeness, betweenness, and information centrality) have the ability to adapt to disruptions more effectively, and therefore re-opening of the economy in China should have a more mitigated effect for these firms. In this regard, a decrease in CDS should be less pronounced for firms with higher network centrality due to more ameliorated changes in default risk and LGD for these firms.

H4a: Increasing network centrality (degree, closeness, betweenness, and information centrality) mitigates the increase in CDS spreads (increasing default risk and expected loss given default) arising from supply chain vulnerabilities.

H4b: Increasing network centrality (degree, closeness, betweenness, and information centrality) mitigates the decrease in CDS spread (decreasing default risk and expected loss given default) with reduced supply chain vulnerabilities.

3. Credit Default Swaps and COVID-19 Timeline

3.1. Credit Default Swaps

The CDS market is one of the largest derivatives markets, with an outstanding notional of $8 trillion as of June 2018 (Boyarchenko et al. 2020). CDS contracts are used not only by lenders and institutional investors but also by suppliers and customers with financial exposure to a given company for risk management purposes (Intercontinental Exchange Report, 2010)[7]. As discussed in this report, suppliers and customers with financial exposures to a given company use CDS for risk management purposes. When a company defaults, its supply chain partners are exposed to disruptions in financial flows and need to wait for bankruptcy procedures to resolve in order to receive an uncertain recovery amount. Buying CDS contracts protects these supply chain partners against default as they recover cash payments faster and in a predictable manner in case of default.

A CDS is a derivatives contract that protects the buyer of the contract against the default of a particular entity (reference entity). The buyer of the CDS makes periodic payments to the CDS seller on a notional principal until the maturity of CDS or until the default of the reference entity, whichever is earlier. In the event that the reference entity defaults, the seller pays the buyer the difference between the underlying notional and the recovery value of defaulted assets, which is referred to as loss given default. When corporations are reference entities, defaults are cash-settled in the CDS contracts. If the reference entity does not default until maturity, then the CDS seller

[7] Global Derivatives Markets Overview: Evolution, Standardization and Clearing, Intercontinental Exchange (ICE), March 2010, available at https://www.theice.com/publicdocs/globalmarketfacts/docs/factsheets/ICE_CDS_White_Paper.pdf.

does not pay anything to the CDS buyer. Thus, CDS is like an insurance policy against default, which gives CDS buyers protection against a default event. The most common maturity (tenor) of CDS contracts are 3, 5, and 10 years, with 5 year maturity being the most liquid. CDS spread payments are made quarterly.[8] Figure 1 shows how a CDS contract is structured. An example of CDS contract in provided in Appendix Figure A1.

[Insert Figure 1 near here]

As discussed in Stulz (2010) and Blanco et al. (2005), CDS market is efficient in assessing a company's credit risk as it is a liquid market, and CDS pricing is determined mainly by expected default loss rather than contractual characteristics such as bond covenants. Lee et al. (2018) further show that CDS markets are more efficient than bond and stock markets in incorporating firm-specific credit information, such that information flows from CDS spreads to stock and bond prices, and CDS spreads predict stock and bond prices. Lee et al. (2018) also find that CDS spreads anticipate rating changes around 90 days before the announcement of the changes. Thus, CDS spreads are useful in providing timelier and accurate information for identifying and assessing credit risk conditions, two pillars of the SCRM (Ho et al. 2015, Sodhi et al. 2012).

The CDS contract pricing for a given maturity primarily builds on: (i) probability of default; and (ii) the loss given default.[9] CDS spreads are determined such that risk-neutral expected present value of CDS spread payments is equal to the risk-neutral expected present value of LGD, i.e., $PV(E(LGD)) = PV(E(s))$ where PV represents the present value, and $E(.)$ calculates expected value using risk-neutral probabilities of default and s is the CDS spread. Thus, the CDS spreads typically increase with both the probability of default and the loss given default for a given maturity of the contract. In this regard, an increase in CDS spreads for a given maturity provides information on increasing default risk of the underlying entity and the expected loss if the entity defaults. CDS contracts specify all obligations and rights of counterparties as well as the definition of default event for reference entity. Major default events for corporate CDS contracts are bankruptcy, failure to pay a scheduled obligation, and debt restructuring.

[8] In addition to corporate single-name CDS contracts, CDS contracts on sovereign bonds are another popular version of these financial products. There are also CDS-based indices. The most popular are CDX.NA.IG and CDX. NA.HY in the U.S., which consists of 125 investment grade (IG) and 100 high yield (HY) CDS contracts, respectively. The most common CDX index outside the U.S. is iTraxx Europe, which consists of 100 investment-grade CDS contracts.

[9] Loss given default is (1-recovery rate), i.e., the portion that was not recovered due to default.

3.2. COVID-19 Timeline

The first reports related to COVID-19 started on December 31, 2019, concerning a new pneumonia outbreak in China's Hubei province. During January and February of 2020, China continued to report COVID-19 cases. On January 30, China announced an extension of the Lunar New Year holiday and business closure until February 10. Although some businesses in China were reported to open on February 10, most businesses did not resume production until the end of February, when COVID-19 has been under control in China. On February 29, China reported a 91.6% work resumption rate, showing businesses and factories largely resumed operations. For the U.S. side, the U.S. government declared a travel ban to China on January 31, effective as of February 2. On March 2, Washington State declared a state of emergency due to COVID-19 in the U.S., followed by seven more states (California, New York, New Jersey, Maryland, Oregon, Utah, and Kentucky) within a week. On March 11, the U.S. announced a travel ban to Europe, and the World Health Organization declared COVID-19 a pandemic. A timeline on major events is shown in Appendix Figure A2.

Our analysis time frame is based on these developments on disruptions of economies due to COVID-19. We consider the first time period as Phase 1 of China COVID-19 when the pandemic affected China and led to shutdowns and disruption in the economy before COVID-19 spread widely in other countries. We let this time period start on January 31 due to two major announcements: closure of Chinese businesses by extension of the Lunar year, which was further extended until the end of February for a large number of businesses and factories, and the U.S. travel ban on China. These two developments are crucial for firms with supply chain relations to China as Chinese production is stalled and coordination between the U.S. and China was impaired due to travel restrictions following these announcements. We consider Phase 2 to start on March 1, when businesses and factories largely resumed operations in China. This is also the period when COVID-19 spread globally. On March 2, the World Health Organization declared COVID-19 a pandemic. Also, between March 2 and March 9, eight states in the U.S. declared a state of emergency. On March 16, the first shelter in place order was announced in the U.S., and, on March 11, the U.S. announced a travel ban for Europe. Thus, disruptions in the U.S. economy and Europe started to be evident starting March 1. Contrary to the developments in the U.S. and Europe, the Chinese economy was functioning at a reasonable capacity at that time, and COVID-19 cases were relatively under control during this period. Thus in Phase 2, the Chinese economy opened up at a time when the U.S. and Europe were hit by the pandemic. During this period, the U.S. firms with supply chain relations to China were in a better position than those with only domestic supply chain partners or suppliers/customers that are in Europe during this time period. We conclude this period on April

6.[10]

As observed in Figure 2, Phase 1 corresponds to high CDS spreads for the U.S. firms with Chinese suppliers or customers, whereas Phase 2 indicates low spreads for these firms. Thus, when the Chinese economy shut down due to COVID-19 in Phase 1, disruptions in the supply chains reflected in CDS spreads, indicating increased credit risk distress for the U.S. firms. When the U.S. and European economies shut down at a period when the Chinese economy was operating (Phase 2), the U.S. companies with links to Chinese suppliers/customers have lower abnormal CDS spreads than those with suppliers/customers that are domestic or in other regions. After documenting this relation in this basic analysis, we next run panel estimations that allow us to explore COVID-19 driven supply chain credit risk in more detail.

[Insert Figure 2 near here]

4. Data and Variables

In this section, we present the data sources and the definition of variables used in our research. A list of variables with their definitions, data sources, and the related literature are in Table 1 Panel A. The final sample descriptive statistics are in Table 1 Panel B.

[Insert Table 1 near here]

Our data are primarily collected from 3 sources: Markit, FactSet Revere, and Compustat. Markit daily CDS data from January 1, 2020 to April 6, 2020 are used to define the abnormal CDS spreads as a measure of credit risk for U.S. firms. We construct a panel of U.S. public-listed firms by merging the CDS data with the FactSet Revere global supply chain data as of December 2019. We augment this panel data with data on firm attributes, including their operations management attributes, supply chain metrics, and industry characteristics. We exclude firms in the financial and utility sectors.

[10] This allows us to examine the COVID-19 impact on supply chain credit risk for three approximately equal periods: pre-COVID-19 period: January 1-30, 2020; China COVID-19 and economic shutdown period: January 31 - February 29, 2020; and US COVID-19 and economic shutdown period: March 1 - April 6, 2020, respectively. We also use alternative Phase 1 start and end dates for different phases, such as Wuhan lockdown on January 23, 2020, and Lombardy lockdown on February 23, 2020, which is consistent with other recent studies (Ding et al. 2020, Guerrieri et al. 2020). The results are comparable to those presented.

4.1. CDS Data and Credit Risk Measurement

We use the Markit dataset for our daily close CDS quotes for the U.S. public firms from January 1, 2020, to April 6, 2020. Specifically, we use 5-year spreads as they are the most liquid and constitute the majority of the CDS market (Jorion and Zhang 2007, Lee et al. 2019, Ağca et al. 2020). Table 1 Panel B shows sample statistics for the daily 5-year spreads by day. The average daily CDS spread is 220 basis points, with significant variation.

For the measure of credit risk, we construct abnormal CDS spread as the main dependent variable for our analyses, which represents the CDS spread after adjusting for the implied ratings. Let CDS_{it} denote the daily closing quote of the firm i's CDS spread at day t, and I_{it} the value of the equally weighted CDS index of the firms with the same implied rating.[11] The abnormal CDS spread is then calculated as $AS_{it} = S_{it} - I_{it}$, which is neutral to credit rating and sector factors. We refer to the abnormal CDS spread as AS for brevity. Table 1 Panel B presents the summary of abnormal CDS spread (AS) for all firms across the time horizon. The mean of the variable, by definition, is zero, with a considerable cross-sectional variation.

4.2. Data on Supply Chains

Our supply chain information is collected from FactSet Revere data. FactSet Revere uses multiple public data sources, including annual and quarterly filings (U.S. Securities and Exchange Commission forms 10-K, 8-K, and 10-Q), investor presentations, company websites, and press releases. According to FactSet, the set of data sources is kept unchanged over time to ensure consistency of the data collection process. FactSet analysts systematically monitor and collect firms' relationships logged by the verifiable start and end dates. There are several papers in operations management and finance literature that utilizes this dataset (Hertzel et al. 2018, Ağca et al. 2020, Wang et al. 2020, Gofman et al. 2020, Osadchiy et al. 2021).

A traditionally used supply chain dataset in the literature is the Compustat Segment dataset (Cohen and Frazzini 2008, Hendricks et al. 2009, Kim and Henderson 2015) among others. The Compustat Segment collects data on supply chains from annual and quarterly filings in compliance with SEC regulation SFAS 131 and SFAS 14, which request reporting customers that account for more than 10% of the revenues. Due to this reporting requirement, the Compustat Segment dataset coverage is tilted towards smaller suppliers and larger customers. FactSet includes a substantially broader set of customers and suppliers compared to the Compustat Segment. Panel A in Appendix

[11] We use Markit's implied rating, which is recomputed more frequently than the credit ratings provided by rating agencies. Markit's implied credit rating is derived based on single-name, 5-year, daily CDS spreads, and the associated CDS sector curve spreads. According to Markit, the sectors are materials, consumer goods, energy, financials, government, healthcare, industrials, technology, telecommunications, and utilities (see `https://www.markit.com/Product/File?CMSID=368ae091505d401a80660456ba504930` for more details).

Table A1 presents the statistics on the characteristics of these two datasets. In terms of the firm coverage, FactSet data covers 25,321 firms globally with their supply chain information, and the Compustat Segment only covers 4,737 firms. In terms of the supply chain distribution, firms in FactSet on average have 6.96 suppliers and 7.74 customers, compared to only 1.8 suppliers and 1.46 customers for firms in Compustat Segment. In addition, the Compustat Segment dataset covers few suppliers and customers outside of the U.S. due to the single source of U.S. firms' public filings. Thus, for studies that focus on global supply chains, such as ours, Factset is a well-suited dataset with broad coverage of global linkages.

We use the Factset supply chain data as of December of 2019, which is the last month before the emergence of the COVID-19 pandemic and right before our sample period starting in January 2020. Public firms in FactSet Revere can be identified by CUSIP 9-digit code, and their headquarter registrations can be identified by the first two digits of the ISIN code. We obtain a sample of 545 US firms with global supply chain exposure after merging Factset with the Markit CDS data.

Since we use the Compustat dataset for the U.S. firm fundamentals, we construct our sample as follows. First, we collect firm variables for the 2019 fiscal year from Compustat. Next, we merge the Compustat fundamental variables with the Markit CDS data, and then merge this data further with the FactSet Revere supply chain data, which provides the final dataset used in our analyses. Our final sample consists of 424 US firms with their supply chain links and 27,632 daily CDS spread observations over the period January 1, 2020 - April 6, 2020.

Panel B in Appendix Table A1 shows degree distribution of domestic and Chinese supply chain links for firms in our final sample. As it can be observed, firms in our sample have more domestic supply chain links than links to China. We next compare the attributes of the firms in our sample with the firms in Compustat. Table A2 in the Appendix provides key characteristics for our final dataset (Column 1) and for the Compustat dataset (Column 2). Comparing Columns (1) and (2), we observe that firms in our final sample have similar operations management attributes as those in the overall Compustat dataset. Specifically, the firms in our dataset are comparable to an average public firm in the U.S. based on the inventory (inventory-to-asset ratio), inventory turnover, lead time, and the operating cycle. Furthermore, since using the FactSet dataset allows us to consider more supply chain linkages, the supply chain structural characteristics in our sample incorporate higher network centrality in terms of degree centrality and information centrality, and it is comparable to Compustat data in terms of betweenness centrality and closeness centrality. Thus, firms in our sample are comparable to an average public firm in the U.S. in terms of operations management attributes and have richer supply chain network characteristics. A representative sample of 30 firms from our sample is presented in Appendix Table A3. Finally, the credit rating distribution of 424 firms in our sample is in Table A4. There are both above and below investment grade rated firms in the sample, encompassing a variety of credit ratings. There are more below-investment-grade firms (below BBB) in the sample. This is consistent with the notion that as default probability is higher for firms with lower credit ratings, CDS contracts serving as insurance against default are more likely to be used.

4.3. Variable Definition

As discussed in Section 2, we consider operational and supply chain structural attributes that may affect the CDS response to the pandemic shock in supply chains. We explore these variables within the context of Swift, Even Flow Theory, and Social Network Theory. First, in the baseline analysis, we explore how CDS spreads change in response to changing supply chain vulnerabilities and are useful to identify and assess supply chain default risk and loss given default. Then, we focus on the SEF and SNT. For SEF, we utilize the following operations management variables: inventory, inventory turnover, operating cycle, and lead time. For SNT, we study spatial complexity, horizontal complexity, degree centrality, closeness centrality, betweenness centrality, and information centrality. We utilize operations management and supply chain network variables to explore the factors that may magnify or mitigate supply chain credit risk during the COVID-19 pandemic as reflected in CDS spreads. Operations management variables are useful in understanding the implications of SEF, and supply chain network variables help in identifying how SNT affects the supply chain credit risk.

The main variables in the baseline estimations are the China supply chain relations of U.S. firms and event period indicators. We use two definitions for US-China supply chain links: an indicator variable that is equal to 1 if a U.S. firm has any supplier or customer in China (*If CN Supplier* and *If CN Customer*) and the natural logarithm of the number of links to suppliers or customers in China (*CN Supplier Links* and *CN Customer Links*). We present baseline results with both sets of variables, and the extensions of baseline results using the number of supply chain links (in natural logarithm).[12]

We use indicator variables for different pandemic phases. The timeline and phase details are presented in Section 3. From late January to late February 2020, China experienced a pandemic shock when the rest of the world had not suffered from a surge of the confirmed cases, which is Phase 1 in our paper. After late February 2020, China's economy started to recover, while at the same time, the pandemic started to spread widely in other countries around the world, which is Phase 2 in our paper. Our definition of these two periods distinguishes China's epidemic situation from other countries to the greatest extent. This setting allows us to investigate the impact of

[12] The results on extensions of baseline results using indicator variables are comparable to those presented and are available upon request.

China's supply chain disruption and recovery on U.S. firms. The phase indicators are denoted as $Phase\ 1 = 1\{\text{If date is Jan 31st - Feb 29th, 2020}\}$ and $Phase\ 2 = 1\{\text{If date is March 1st - April 6th, 2020}\}$.

4.4. Empirical Model

We investigate the relationship between firm credit risk and supply chain linkages during the COVID-19 pandemic by focusing on US-China supply chains. We distinguish between U.S. companies that have Chinese supply chains and those that do not. We also study how U.S. firm credit risk changes at two different phases of COVID-19 – when the Chinese economy shut down in Phase 1 (January 31 - February 29, 2020) and later as the Chinese economy re-opened in Phase 2 (March 1 - April 6, 2020). Our approach is similar to Hendricks et al. (2020) and Carvalho et al. (2021) who examine the impact of the Great East Japanese Earthquake on supply chains. In our framework, COVID-19 represents the disaster, and we explore the effect of this disaster on supply chain credit risk. For baseline estimations, we first construct a model containing Phase 1 and Phase 2 independently. We then include these two periods together in the analysis. We control for firm fixed effects and industry-day fixed effects.[13] Our baseline models are as follows:

$$\begin{aligned} AS_{i,t} = \alpha + \beta \times Var\_CN\_Supplier\ (Customer)_i \times Phase\ 1(2)_t \\ + Firm_i + Industry_i \times Day_t + \epsilon_{i,t} \end{aligned} \tag{1a}$$

$$\begin{aligned} AS_{i,t} = \alpha + \beta_1 \times Var\_CN\_Supplier\ (Customer)_i \times Phase\ 1_t \\ + \beta_2 \times Var\_CN\_Supplier\ (Customer)_i \times Phase\ 2_t \\ + Firm_i + Industry_i \times Day_t + \epsilon_{i,t} \end{aligned} \tag{1b}$$

In the above equations, $Var\_CN\_Supplier\ (Customer)$ is either the indicator variable for supply chain links to China ($If\ CN\ Supplier\ (Customer)$) or the natural logarithm of the number of links to Chinese supply chain partners ($CN\ Supplier\ (Customer)\ Links$).

We consider extensions to the above baseline model in our analyses within the context of SEF and SNT to investigate operations management attributes and supply chain structural characteristics that may intensify or mitigate the supply chain-driven credit risk in the pandemic. In this regard, we interact inventory, inventory turnover, operating cycle, and lead time to understand the implications for the SEF, and interact horizontal and spatial complexity as well as four network centrality measures (degree, closeness, betweenness, and information centrality) to understand the role of SNT in supply chain risk propagation in the credit markets.

[13] We determine industries using 6-category industry classification based on the Fama-French industry groups, and those that are not included in these are in the Other category. We combine the Fama-French 12-industry into a 6-industry classification to ensure that there is a sufficient number of observations with both CDS and supply chain information for each industry. Appendix Table A5 shows the description of our industry classification and the representation of each industry in the sample.

5. Results

5.1. Supply Chain Relations, COVID-19, and CDS Spreads

We examine the relationship between abnormal CDS spreads and supply chain linkages during different phases of COVID-19. We differentiate between U.S. companies that have supply chain relations to China from those that do not. Within this framework, we explore abnormal CDS spreads to gauge credit risk in supply chains as CDS spreads reflect both the probability of default and the loss given default. We consider two phases of COVID-19: when the Chinese economy shut down in Phase 1 (January 31 - February 29, 2020), and the Chinese economy reopened in Phase 2, which is also when the U.S. economy is hit by COVID-19 (March 1 - April 6, 2020). We carry out these estimations as in equation eq. (1a) and eq. (1b). The results are in Table 2. Panel A and Panel B provide results for U.S. firms with China suppliers and China customers, respectively.

[Insert Table 2 near here]

As presented in Table 2 (Columns 1 and 2), when COVID-19 spread in China and businesses shut down, creating vulnerabilities in production in Phase 1, i.e., the first period of the pandemic, CDS spreads of the U.S. firms with Chinese supply chain partners go up. Thus, supply chain vulnerabilities in China increase default risk and the expected loss given default for companies with supply chain links to China. These findings hold for U.S. firms with Chinese suppliers as well as customers (Panels A and B of Table 2, respectively), and both by using an indicator for supply chain links to China and by using the number of supply chain links to China (in natural logarithm).

The results show that increasing supply chain vulnerabilities both upstream and downstream are reflected as increasing CDS spreads, which conveys raising default risks and expected losses given default in supply chains. Thus, CDS spreads are useful for two of the four pillars of SCRM (Ho et al. 2015, Sodhi et al. 2012): Identifying and assessing supply chain credit risk, which arise from supply chain vulnerabilities in our framework. Specifically, increasing abnormal CDS spreads identify increasing default risk from supply chain vulnerabilities, and the amount of increase in abnormal CDS spreads reflects the assessment of both the probability of default and the expected loss given default.

Resuming supply chain activity with China in Phase 2 should reduce abnormal CDS spreads for U.S. firms with China supply chain partners, since decreasing default risk and loss given default should lead to lower abnormal CDS spreads. The results in Table 2 (Columns 3 and 4) show a substantial reduction in CDS spreads in Phase 2 for U.S. firms with China suppliers and customers. As the pandemic hit globally in Phase 2 and supply chain links are disrupted in the rest of the world, re-establishing supply chain activity with China provides an advantage to firms with supply chain links to China, reducing the probability of default and loss given default for these firms.

We further consider both Phase 1 and Phase 2 together in Table 2, columns (5) and (6). Examining Column (5) of Table 2, Panel A indicates that during Phase 1, i.e., the period of supply chain disruptions in China, CDS spreads of US firms with China supply chain partners. When the economy reopens in China and supply chain activity resumes in Phase 2, CDS spreads of these firms go down. These findings support the baseline results discussed above.

The results are economically significant. As observed in columns (1) and (3) in Panel A, Table 2, US firms with supplier links to China observe 50 bps increase in abnormal CDS spreads in the first phase of the pandemic, and 70 bps decrease in abnormal CDS spreads when the economic activity resumes in China in phase 2 when the rest of the world is affected from COVID-19 pandemic. Considering that the average CDS spread is 220bps in our sample, these values correspond to around 22% increase in CDS spreads in Phase 1 and 32% decrease in CDS spreads in Phase 2. For firms with customer links to China, the increase in CDS spreads is around 33 bps (15% of sample spread) in Phase 1 and the decrease in CDS spreads is around 42 bps (19% of sample spread) in Phase 2 (columns (1) and (3) in Panel B, Table 2) . These results point out that regional shocks that create supply chain vulnerabilities and the resolution of these vulnerabilities have a substantial economic effect on supply chain partners as reflected in the credit risk observed in CDS spreads. Furthermore, the impact is larger for upstream relations than downstream relations.

Overall, the evidence points out that supply chain vulnerabilities, as well as the resolution of these vulnerabilities, change firms' default risk and expected loss given default, which are reflected in abnormal CDS spreads. CDS markets adjust quickly to supply chain dynamics during the pandemic as reflected in changing abnormal CDS spreads. Thus CDS spreads are useful for identifying and assessing credit risk in supply chains, two important pillars of SCRM. These two pillars allow firms to mitigate supply chain risk and develop responses accordingly (the next two pillars of SCRM (Ho et al. 2015, Sodhi et al. 2012)).

5.2. Operations Management Attributes

Establishing that CDS spreads reflect supply chain credit risk during the COVID-19 pandemic, we next explore which operations management attributes amplify or mitigate this risk in relation to the SEF theory. We consider inventory, inventory turnover, lead time, and operating cycle. We interact each of these variables with a firm's number of supplier (and customer) links to China (measured in natural logarithm).[14] Our estimation controls for the firm and industry-day effects. The results are in Table 3 for the U.S. firm linkages with China.

[14] We have similar results using indicator variables for China supply chain links, and they are available upon request.

[Insert Table 3 near here]

The results for U.S. firms with suppliers in China are in Panel A of Table 3. The findings show that there is an overall increase in CDS spreads during Phase 1 for U.S. firms with supplier links to China as Phase 1 corresponds to the period of the pandemic in China when there were production halts and supply chain vulnerabilities arose as a result. In the second phase of the pandemic, on the other hand, CDS spreads go down for U.S. firms with China suppliers when economic activity resumes in China and supply chain vulnerabilities alleviate. The results in Panel B on U.S. firms with China customers are mostly consistent with this evidence as well. These findings are in line with baseline findings discussed above, showing supply chain credit risk reflected in CDS spreads.

When we examine interaction variables for U.S. firms with China suppliers in Panel A of Table 3, we observe that the increase in CDS spreads is amplified for firms with high inventory turnover, and mitigated for firms that operate with high inventory levels. These findings indicate that firms with high inventory turnover are more sensitive to changes in the even flow of goods and materials, and firms with high inventory levels are able to buffer disruptions in the even flow of inventory more effectively. Thus, default risk and loss given default in Phase 1 of the pandemic increase for firms with high inventory turnovers, and reduce for firms with high inventory levels. When we examine Phase 2 of the pandemic, we observe that firms with high inventory turnover have more pronounced reductions in CDS spreads as the resumption of even flow of materials is more crucial for these firms. These effects are mitigated for firms with high levels of inventory since these firms have a better ability to adjust to changing supply change dynamics due to inventory levels. These results also hold for U.S. firms with China customers as presented in Panel B of Table 3.

Table 5 reports economic significance of these variables. As observed in the table, inventory turnover has a stronger economic effect on supply chain credit risk than inventory levels. Increasing inventory levels from median to 75th percentile mitigate changes in CDS spreads of US firms with China supply chain partners around 1 basis points both in the first and second phases. Inventory turnover, on the other hand, amplifies the changes in CDS spreads strongly, especially in the second phase. Increasing inventory turnover from median to 75th percentile corresponds to an amplification of 5 to 7 bps increase in CDS spreads in Phase 1. Resolving supply chain vulnerabilities in Phase 2 leads to a 26 to 36 bps greater decrease in CDS spreads for these firms. These findings indicate that firms with high inventory turnover are more sensitive to disruption of even flow of goods, and thus resolving these disruptions have a highly economically significant effect. Overall, these results support Hypotheses H1a and H1b within the context of swift, even flow such that higher inventory turnover and lower inventory levels amplify supply chain credit risk due to weaker resilience to supply chain vulnerabilities.

Examining operating cycle and lead time interactions for U.S. firms with suppliers in China in Panel A of Table 3 show that the increase in CDS spreads during Phase 1 is mitigated for firms with longer operating cycles and for those with longer lead times. Firms that operate with longer operating cycles have a better ability to deal with bottlenecks and therefore are able to adapt to supply chain vulnerabilities more effectively. When economic activity resumed in China in Phase 2, firms with longer operating cycles as well as those with longer lead times experience more mitigated decreases in CDS spreads. Since these firms have the ability to adapt more effectively in the first phase, there is less need to adjust in the second phase with the reduction of supply chain vulnerabilities. Examining results in Panel B for U.S. firms with China customers point out to comparable findings, where the impact of changing supply chain vulnerabilities on CDS spreads are mitigated for firms with longer operating cycles and lead times.

As reported in Table 5, the economic impact of these variables varies for Phase 1 and Phase 2. Increasing operating cycle from median to 75th percentile corresponds to around 4 to 5 bps less pronounced increase in CDS spreads in Phase 1, and 7 bps to 19 bps less pronounced decreases in CDS spreads when the economic activity resumes in China. The economic significance of lead time is weaker in Phase 1 and stronger in Phase 2. Increasing lead time by 26 days (median to 75th percentile) leads to around 1 basis points less pronounced increases in CDS spreads in Phase 1, but around 26 to 36 basis points less pronounced decreases in phase 2. These findings suggest that firms with longer lead times adapt to supply chain vulnerabilities more efficiently, and thus require smaller adjustments when supply chain vulnerabilities resolve. These findings support Hypotheses H2a and H2b. Firms with longer operating cycles and lead times have the ability to deal with bottlenecks more effectively and thus are able to adapt to supply chain vulnerabilities during the pandemic, moderating the impact of changing supply chain vulnerabilities on supply chain credit risk as reflected in the CDS spreads.

5.3. Supply Chain Network Attributes

We examine supply chain network attributes within the context of SNT to understand how these characteristics affect supply chain credit risk as reflected in CDS spreads. We interact the number of links to Chinese supply chain partners (in natural logarithm) with supply chain network characteristics.[15] The results are in Panels A and B of Table 4 for suppliers and customers, respectively.

[**Insert Table 4 near here**]

Examining the results in Panels A and B in Table 4, show that the evidence on supply chain credit risk during the COVID-19 pandemic supports our baseline findings: U.S. firms with suppliers

[15] We have similar results using indicator variables for China supply chain links, and they are available upon request.

or customers in China observe increasing credit risk in Phase 1 and decreasing credit risk in Phase 2 as reflected in CDS spreads.

To explore the impact of supply chain network attributes on supply chain credit risk, we first consider supply chain network complexity by focusing on spatial and horizontal complexity aspects. Spatial complexity is important for supply chains with global partners. In our study, this measure is particularly relevant as the COVID-19 pandemic first occurred in China (Phase 1), creating supply chain vulnerabilities in this region, and then the pandemic affected other regions in the world when China recovered (Phase 2). Examining the results on US firms with China suppliers and customers in Column 1, Panels A and B of Table 4, respectively, show that spatial complexity mitigates the impact of changing supply chain vulnerabilities on firm credit risk as reflected in CDS spreads. Since firms with high spatial complexity are more experienced in dealing with global challenges and have a more disperse supply chain base, they are able to adapt to regional supply chain vulnerabilities more effectively. The results in Column (1) of Table 4, Panel A and B both show that the increase in the CDS spreads is ameliorated with increasing spatial complexity during Phase 1 of the pandemic when China economy shutdown (coefficient is significant for China customers, and not significant for China suppliers although it is in the right direction). This finding supports hypothesis H3a showing that increasing spatial complexity mitigates the increase in supply chain credit risk as reflected in CDS spread when supply chain vulnerabilities increase. When China economy resumed in Phase 2, the decrease in CDS spreads is less pronounced as well, and the coefficient is highly statistically significant.

The economic significance of these results are in Table 5. Increasing spatial complexity from median to 75th percentile leads to around 1 bp less pronounced increase in CDS spreads in Phase 1 for US firms with China supply chain partners, and around 8 to 13 bps less pronounced decrease in Phase 2 when supply chain vulnerabilities resolve. Since firms with high spatial complexity have developed expertise to work with a dispersed supply chain base in different regions, they have the ability to adapt to changes in regional supply chain vulnerabilities. These firms can also reach alternative resources through their supply chain networks in other regions. Since firms with high spatial complexity adapt to changing supply chain vulnerabilities in different regions, resumption of supply chain activities in a given region does not lead to a major reduction in credit risk for such firms. This finding supports H3b as firms with higher spatial complexity have more mitigated decreases in supply chain credit risk as captured by CDS spreads when supply chain vulnerabilities ease.

[Insert Table 5 near here]

We next focus on horizontal complexity. Examining the results on horizontal complexity in Column (2), Panels A and B of Table 4 for US firms with China suppliers and customers, respectively, indicates that horizontal complexity mitigates the impact of changing supply chain vulnerabilities on firm credit risk as reflected in the CDS spreads both in Phase 1 and Phase 2 of the COVID-19 pandemic. Examining economic significance in Table 5 shows that increasing horizontal complexity from median to 75th percentile in the sample, results in around 1 bp less pronounced decrease in CDS spreads in Phase 1 for US firms with China supply chain partners, and around 4 to 6 bps less pronounced decrease in Phase 2 when supply chain vulnerabilities resolve. Horizontal complexity allows firms to reach alternative resources through a larger number of direct supply chain linkages. This adaptability mitigates the effects of supply chain vulnerabilities on credit risk as captured by CDS spreads during the economic shutdown in China. This finding supports hypothesis H4a showing that higher horizontal complexity is a mitigating factor of supply chain credit risk as reflected in CDS spreads during an increase of supply chain vulnerabilities. When China economy resumed in Phase 2, these firms have already adapted their supply chain operations and thus the reduction in CDS spreads is also mitigated for these firms. This evidence is consistent with hypothesis H4b, such that decreasing supply chain vulnerabilities lead to less pronounced decreases in supply chain credit risk for firms with high horizontal complexity.

Overall, our results on supply chain complexity show that both spatial complexity and horizontal complexity mitigate the impact of changing regional supply chain vulnerabilities on firm credit risk both upstream and downstream, as reflected in the CDS spreads.

Another important attribute of supply chain structural characteristics is supply chain network centrality. We examine supply chain network centrality by focusing on degree, closeness, betweenness, and information centrality measures. The results are in Columns (3)-(6), Panel A and B of Table 4 for US firms with China suppliers and customers, respectively. We find that all considered network centrality measures mitigate the impact of changing supply chain vulnerabilities on credit risk both upstream and downstream, as reflected in CDS spreads. Firms that are more central in supply chain networks have better ability to adapt to changes in supply chain dynamics by shifting to alternative resources through a number of connections (degree centrality), by reaching alternative resources faster (closeness centrality), by controlling the flow of material and information (betweenness centrality), and by accessing information more effectively (information centrality). Thus, in Phase 1 of the pandemic, US firms with China supply chain partners experience a less pronounced increase in CDS spreads if they have higher network centrality. These results are statistically significant for all centrality measures except information centrality for US firms with China suppliers, and closeness centrality for US firms with China customers. When China economy resumed in Phase 2, firms with high network centrality show a more mitigated decrease in credit risk as reflected in CDS spreads, since these firms have already adapted more effectively to changing supply chain dynamics in Phase 1. These results on Phase 2 are significant for all network centrality measures considered both upstream and downstream.

The economic significance reported in Table 5 shows that the impact of closeness centrality and information centrality is the largest in mitigating supply chain credit risk among all network centrality measures. The adjustment in Phase 2 is considerably less pronounced for firms with higher closeness and information centrality (firms at 75th percentile compared to median). Specifically, while all network centrality measures lead to around 1 bp less pronounced increases in CDS spreads in Phase 1 when these measures are increased from median to 75th percentile, in Phase 2, closeness and information centrality leads to between 14 to 29 bps less pronounced decreases in CDS spreads. These findings suggest that, while all network centrality measures mitigate supply chain credit risk as reflected in CDS spreads, with the ability to reach resources and information faster (closeness and information centrality, respectively) has the largest economic impact in mitigating supply chain credit risk arising from supply chain vulnerabilities caused by regional shocks. These findings support Hypotheses H5a and H5b, showing that network centrality mitigates the impact of changing supply chain vulnerabilities on the probability of default and loss given default, as reflected in CDS spreads.

Overall, network complexity and network centrality are critical supply chain structural characteristics that affect supply chain credit risk. The evidence on CDS spreads on the probability of default and expected loss given default points out that firms with higher spatial and horizontal complexity, as well as firms with high degree, betweenness, closeness, and information centrality, have better ability to adapt to changing supply chain vulnerabilities. Thus these firms have mitigated supply chain credit risk changes in response to changing supply chain vulnerabilities as observed during different phases of the pandemic.

5.4. Placebo Test

To explore whether supply chain credit risk is reflected in CDS spreads during the COVID-19 pandemic for US firms with supply chain links to China, we run a placebo test by randomly generating placebo supply chain links in China. Specifically, for a customer (supplier) firm comprising an actual link, we randomly identify a potential supplier (customer) that is present in our sample.

[Insert Table 6 near here]

The placebo result in Table 6 shows no significant effect of supply chain linkages on abnormal CDS spreads during the pandemic. This finding shows that supply chain credit risk reflected in CDS spreads is transmitted through active supply chain linkages.

6. Robustness and Alternative Specifications

In this section, we conduct several alternative specifications and robustness tests. Specifically, we use an alternative definition of abnormal CDS spread, use alternative dates for Phase 1 and Phase 2, substitute firm headquarter countries with countries where a firm has the largest sales, estimate using a balanced sample for the overall sample period, examine a subsample that is less exposed to trade disputes between US and China, and control for other global supply chains. All robustness and alternative specifications are shown in Table 7, and support baseline findings.

[Insert Table 7 near here]

6.1. Alternative Abnormal CDS Definition

In the analyses above, we construct the abnormal 5-year CDS spread by using the 5-year CDS spread after subtracting the average CDS spread of the firm portfolio with the same implied rating, similar to Jorion and Zhang (2007) and Ağca et al. (2020). There may exist underlying market level driven factors in credit markets that influence the risk premia, such as measurements of liquidity, the volatility of the secondary market, investor sentiments, and intermediary capital ratios. To take into account these factors, we use an alternative definition of adjusted abnormal CDS spread variable based on decomposition by regression:

$$AS_{i,t} = \alpha + \beta_1 r10_t + \beta_2 Term_t + \beta_3 VIX_t + \beta_4 S\&P500_t + \beta_5 \gamma_{it} + \beta_6 AggDef_t + \beta_7 ICR_t + \epsilon_{it} \quad (2)$$

where $r10_t$ stands for the U.S. 10-year Treasury bond yield; $Term_t$ indicates the gap between 10-year and 2-year T-bond yield, also called the term premium; VIX_t is a proxy for the volatility of the market; $S\&P500_t$ is the stock market index return; γ_{it} represents for illiquidity followed by Roll (1984); $AggDef_t$is the gap between Aaa and Baa bond yields, also known as the aggregate default premium in the market; Lastly, ICR_t stands for the intermediary capital ratio.[16]

Residuals from estimations of equation 2 are used as the alternative abnormal CDS spreads (AS). We use this redefined AS in the baseline model. The results are in Column (1) of Panels A and B, Table 7. The evidence continues to indicate that CDS spreads show increasing credit risk during the shutdown of the Chinese economy during Phase 1 of the pandemic and reduction in credit risk with the re-opening of the Chinese economy in Phase 2. Thus, our results are robust to an alternative definition of abnormal CDS spreads that consider other potential market-driven factors.

[16] He et al. (2017) show that the financial intermediary capital ratios significantly impact the cross-section asset return.

6.2. Alternative Definitions of Pandemic Phases

In our baseline settings, we use a timeline of January 31, 2020, the shutdown of the Chinese economy and the U.S. announcement of travel restrictions from China as the start of Phase 1, and March 1, 2020 as the start of Phase 2 since China's primary production has resumed by that time.

For robustness, we consider alternative dates for phases of economic shutdowns and re-openings due to COVID-19 in China. We consider the start of the Phase 1 period as January 23, 2020, the lockdown date of Wuhan, China. At the end of the first phase, we use the Lombardy lockdown date (February 23, 2020) as the pandemic started to spread globally by that time, even though the business operations have not yet resumed in China. The results are shown in Columns (2) of Panels A and B, Table 7. The results are comparable to those presented in the baseline.

6.3. Alternative Firm Location

In our analysis, we consider the country of a firm's headquarter as the main location of a firm in determining supply chain links to other regions. As an alternative method, we assign the location of firms based on the countries to which they have the largest sales using FactSet's geographical revenue exposure data. If a firm has the largest sales to a country different than its headquarter, we change the location of the firm from headquarter country to that country. There are 45 firms in our sample for which headquarter country is changed to the country of major sales, which is only 10.6% of the sample.

The results are presented in Column (3), Panels A and B of Table 7. The results are significant for US firms with Chinese suppliers and with Chinese customers (Panels A and B, respectively). Thus, our findings are robust to alternative firm location, showing that CDS spreads reflect changing supply chain credit risk arising from supply chain vulnerabilities using an alternative definition of firm location.

6.4. Balanced Sample

In our analysis, we explore CDS spreads before the pandemic and during Phase 1 and Phase 2 of the pandemic when China shut down economic activity and then resumed, respectively. During this period, some firms may disappear from the sample, creating a sample selection bias which may affect our findings. To address this issue, we consider a balanced sample of 398 firms that exist in the data during the overall sample period.

The results are presented in Column (4), Panels A and B of Table 7, and support the baseline findings. Thus, the evidence is not driven by the possibility of different firms being in different phases of the pandemic, which may create a selection bias. Changing supply chain vulnerabilities are reflected in CDS spreads, identifying and assessing supply chain credit risk in a robust manner as observed with the balanced sample.

6.5. Lower Trade Sanctions

In our analysis, we focus on the sample period around the COVID-19 pandemic in China, January 1, 2020 - April 6, 2020. Since there have been ongoing trade disputes since 2017 between the US and China with the imposition of tariffs on certain goods and materials,[17] our results may be affected from the implications of these trade sanctions on supply chain dynamics. To address this issue, we run our baseline estimations with a subsample of firms that are less exposed to these trade sanctions. Specifically, we exclude electronics and manufacturing industries, which are the most directly affected by trade sanctions.[18]

The results are presented in Column (5), Panels A and B of Table 7, and are in line with the baseline findings. Excluding firms that are in the industries that are highly affected from trade sanctions between the US and China continue to show that supply chain vulnerabilities during COVID 19 are reflected in CDS spreads.

6.6. Global Supply Chains

Our study focuses on supply chain linkages to China for the period January 1- April 6, 2020, for several reasons: (i) This setting is useful in examining the impact of COVID-19 driven supply chain disruptions and resumptions on credit risk as COVID-19 spread and resolved earlier in China than the rest of the world, thus providing a clear inference for different phases of the pandemic; (ii) China is an important supplier and customer for U.S. firms, constituting a major trade partner.

In this subsection, we further consider other global supply chain relations of U.S. firms to observe whether our findings are robust to these dynamics. We include the natural logarithm of total global supplier links and total global customer links (excluding China) for each U.S. firm as additional controls. The results are in Column (6), Panels A and B of Table 7. The evidence continues to show a strong effect of Chinese supply chain linkages on CDS spreads during the pandemic in support of the baseline. During the economic shutdown in China in Phase 1, CDS spreads increase, and when the Chinese economy re-opens in Phase 2, spreads decrease. Having other global supply chain relations do not eradicate the adverse effect of Chinese supply chain disruptions on CDS spreads of U.S. firms in Phase 1. When the pandemic spread more globally in Phase 2, having global supply chain links outside China increases the credit risk of U.S. firms, while having Chinese suppliers improves the credit risk due to the re-opening of the Chinese economy during this period. Overall, these results support our findings that CDS spreads reflect supply chain credit risk during the pandemic.

[17] For a detailed timeline on US-China trade disputes, refer to https://www.reuters.com/article/us-usa-trade-china-timeline/timeline-key-dates-in-the-u-s-china-trade-war-idUSKBN1ZE1AA

[18] According to U.S. Department of Commerce's entity list of Export Administration Regulations (EAR), (e.g., https://www.govinfo.gov/content/pkg/FR-2019-10-09/pdf/FR-2019-10-09.pdf), firms affected are mostly in electronics and manufacturing industries.

7. Discussion and Managerial Implications

The examination of CDS spreads in relation to supply chain vulnerabilities during the COVID-19 pandemic is valuable in understanding credit risk in supply chains. As COVID-19 affected China and the US at different time periods, it allows the analysis of the impact of changing supply chain vulnerabilities on supply chain credit risk by utilizing CDS spreads. Our findings point out that CDS spreads are useful on two pillars of SCRM: Identifying default risk and assessing the probability of default and the expected loss in the event of default. As CDS spreads reflect both of these information pieces, the changes in CDS spreads are a valuable gauge for changing credit risk conditions in the supply chains. This knowledge is useful for managers to mitigate and respond to supply chain credit risk.

Our results show that when the China economy shut down with the COVID-19 pandemic, CDS spreads of US firms with China supply chain partners increased, reflecting increasing default probabilities and the loss given default. When the economy resumed in the second phase, CDS spreads declined for these firms, showing that reducing credit risk in supply chains is reflected in lower CDS spreads. Thus, CDS spreads are helpful for managers in identifying and assessing credit risk so as to develop responses to address such challenges. Managers can further utilize the information of changing CDS spreads if they are in the same sector as those that are experiencing CDS increases or they are exposed to similar regional shocks. This information is valuable for managers in understanding the implications of supply chain credit risk on firms with similar characteristics or those experiencing similar shocks. Furthermore, the findings hold both upstream and downstream. Thus, CDS spreads are useful to identify and assess supply chain credit risk arising from both suppliers and customers.

We next explore how certain operations management characteristics can mitigate or amplify supply chain credit risk within the context of swift, even flow. Firms that operate with higher inventory turnover are more sensitive to disruptions in the even flow of goods and material, and those with higher inventory have the ability to buffer disruptions for a given period of time. Our results show that firms with high inventory turnover are exposed to amplified supply chain credit risk during the COVID-19 pandemic, and those with high levels of inventory have more mitigated supply chain credit risk. Thus, managers who work with low inventory levels or with high inventory turnover should pay attention to changing supply chain credit risk conditions as reflected in CDS spreads, since the probability of not being able to replace inventory has a more pronounced effect on the credit risk of these firms.

Our findings show that firms with a longer operating cycle and longer lead time have more mitigated supply chain credit risk changes during changing supply chain vulnerabilities. This evidence suggests that firms that operate with a higher likelihood of disruptions in even flow of goods and materials, such as those with longer operating cycle and lead time, develop abilities to deal with supply chain vulnerabilities that arise due to regional shocks in global supply chains. Thus, managers who work with shorter operating cycles and lead times should pay more attention to developments in supply chain credit risk through changing CDS spreads, as they may be more vulnerable to disruptions in even flow of goods and materials.

We further focus on supply chain structural characteristics within the context of social network theory and examine these attributes in relation to supply chain credit risk during COVID-19 for US firms with China supply chain partners. The position of a firm in a supply chain network can amplify or mitigate the impact of supply chain vulnerabilities on supply chain credit risk. We find that firms with high spatial complexity as well as those with high horizontal complexity experience mitigated changes in credit risk as reflected in CDS spreads in response to changing supply chain vulnerabilities. Firms with high spatial complexity are more globally dispersed and have more likelihood of facing shocks from different regions. Thus, such firms develop abilities to manage such uncertainties. These firms also have the ability to utilize resources from alternative regions in response to particular regional shocks. When the COVID-19 pandemic affected China and the US at different time periods, firms with higher spatial complexity has a better ability to adapt to these shocks more effectively. Thus, managers working with spatially dispersed supply chains may be able to reach resources from other regions that are not affected by regional local shocks, mitigating their supply chain credit risk. Firms with high horizontal complexity are connected to many supply chain partners and therefore can utilize alternative resources when faced with shocks affecting certain supply chains. Managers that work with high spatial or horizontal supply chain networks therefore should look into alternative resources to adapt during supply chain vulnerabilities in order to mitigate credit risk. Managers of firms with lower horizontal and spatial supply chain complexity, on the other hand, should pay particular attention to identify and assess credit risk in supply chains reflected in CDS spreads in a timely manner to develop a response as the impact is larger for such firms.

Another important supply chain structural attribute is network centrality. We focus on four centrality measures: Degree, closeness, betweenness, and information centrality. We find that all these centralities mitigate the impact of supply chain vulnerabilities on firm credit risk as reflected in CDS spreads. Firms with high network centrality are able to find more alternative resources through a larger number of connections (degree centrality), reach resources faster (closeness centrality), have a better ability to control the flow of material and information(betweenness centrality), and access information more effectively (information centrality). These findings show that managers should pay attention to the position of their firms in the supply chain since the centrality of a firm in the product network affect supply chain credit risk. Firms with lower network centrality will be more exposed to supply chain vulnerabilities due to more limited ability to adapt, and therefore should pay special attention to CDS spreads to identify and assess the probability of default and expected loss given default in order to mitigate or respond to supply chain credit risk. Alternatively, managers of firms with supply chain links that have a higher likelihood of shocks or disruptions should consider positioning the firm in the supply chain so as to increase their network centrality if that is attainable.

Overall, our findings show that CDS spreads reflect supply chain credit risk, and are valuable for managers to identify default risk and assess the default probability and expected loss given default. In terms of operations management attributes, firms with more inventory buffer and less inventory turnover, as well as firms with longer operating cycles and lead times, have better ability to mitigate supply chain credit risk when faced with variability in even flow of goods due to changing supply chain vulnerabilities as observed during COVID-19. In terms of supply chain structural characteristics, firms that operate with more spatial complexity and horizontal complexity, as well as those that are more central in supply chain networks, have better ability to reach alternative resources during supply chain vulnerabilities and thus can mitigate their supply chain credit risk.

8. Conclusion

This paper contributes to the literature on supply chain credit risk by utilizing the setting of COVID-19 pandemic for US firms with supply chain partners in China. We examine how CDS spreads reflect supply chain credit risk. We then look at the role of operations management and supply chain structural attributes in amplifying or mitigating this risk.

By exploring two phases of the pandemic, namely the period of COVID-19 spread and the period of re-opening of the economy in China while the rest of the world is affected by the pandemic, we find CDS spreads increase with increasing supply chain vulnerabilities, and decrease with decreasing supply chain vulnerabilities. Thus, CDS spreads reflect supply chain credit risk, and they are useful in identifying default risk and assessing the probability of default and the expected loss given default, given that CDS spreads are determined by these two factors.

When we examine operations management attributes within the context of swift, even flow, we find that higher inventory and lower inventory turnover, longer operations cycle and longer lead time mitigate supply chain credit risk when faced with the variability of even flow of goods due to changing supply chain vulnerabilities.

Our findings on supply chain network characteristics within the context of social network theory point out that firms that are more central in supply chain networks (degree, closeness, betweenness, and information centrality) are able to adapt to supply chain vulnerabilities better and thus have more mitigated supply chain credit risk as reflected in CDS spreads.

Overall, we examine the impact of COVID-19 disruptions on supply chain credit risk by utilizing CDS spreads, and by exploring different operations management and supply chain structural factors. We find that CDS spreads reflect supply chain credit risk. The disruptions in the swift, even flow of goods and material affect supply chain credit risk during the pandemic, and this effect is more amplified for firms with high inventory turnover and is mitigated for those with higher inventory buffer, longer operating cycle, and longer lead time. Finally, supporting social network analysis, we find that supply chain network centrality is an important factor mitigating supply chain credit risk. All these factors provide managerial insights for identifying and assessing supply chain credit risk, so that managers can develop responses to mitigate or address supply chain vulnerabilities that may affect their companies within the context of the flow of goods and materials as well as the position of their firms in supply chain networks.

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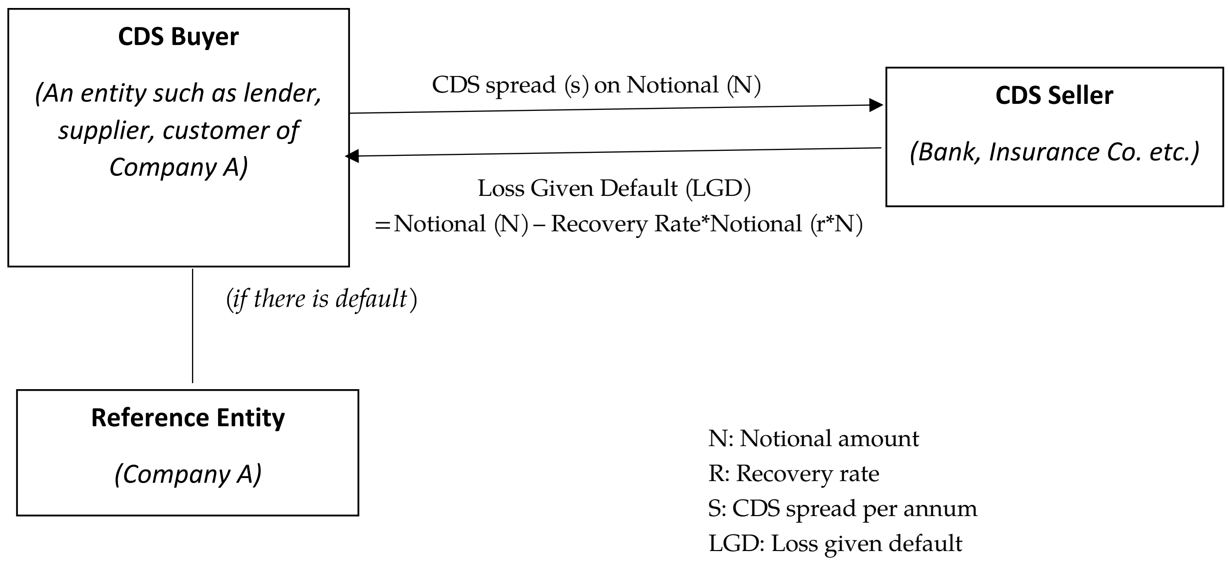
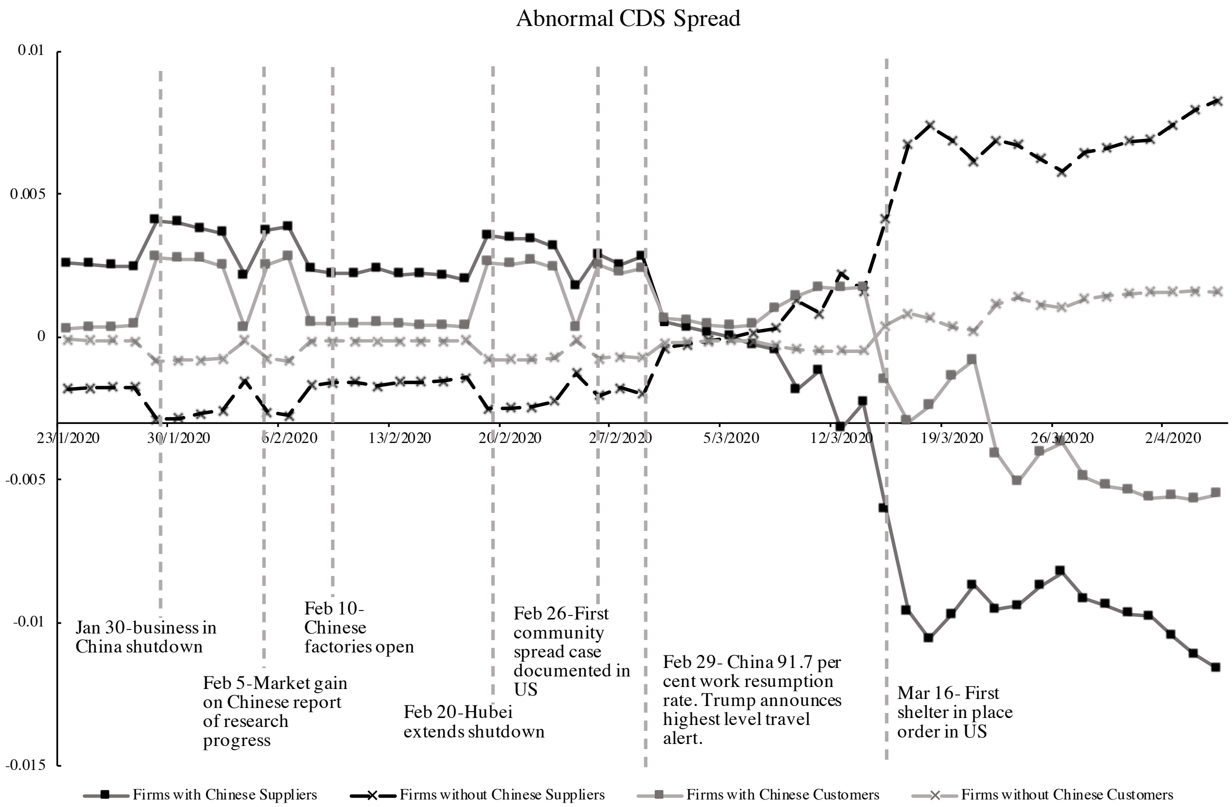
Figure 1 CDS Contract Structure



Note: This figure shows how a CDS contract is constructed.

Figure 2 Abnormal CDS Spread and Major Events



Note: This figure plots the equal-weighted abnormal CDS spreads (AS) for firms with Chinese suppliers, firms without Chinese suppliers, firms with Chinese customers, and firms without Chinese customers, as well as the important COVID-19 events along the timeline.

Table 1: Variable Definition and Summary Statistics

Note: Panel A provides definitions and sources of the variables, including CDS and supply chain variables, operations management variables, and supply chain network variables. Panel B presents descriptive statistics. The sample period is January 1-April 6, 2020. In Panel B, for each variable, the number of observations, mean, standard deviation, 25th, median, and 75th percentiles are reported.

Panel A: Variable Definitions and Data Source

Variable	Definitin	Data Source	Citation
CDS & Supply Chain Variables			
Abnormal CDS Spread	5-year CDS spread minus average spread within an implied rating		Jorion and Zhang, 2007 Jorion and Zhang, 2009 Agca et al., 2020
If CN Supplier	Indicator =1 If a US firm have at least one customer located in China	FactSet Revere	-
If CN Customer	Indicator =1 If a US firm have at least one customer located in China	FactSet Revere	-
CN Supplier Links	Number of China supplier links (in natural logarithm)	FactSet Revere	-
CN Customer Links	Number of China customer links (in natural logarithm)	FactSet Revere	-
Operations Management Variables			
Inventory	Inventory/Total Assets	Compustat	Gaur et al., 2005
Inventory Turnover	Cost of Good Sold (COGS)/Inventory	Compustat	Alan and Gaur, 2014
Lead Time	Days Accounts Payable=365/(4×COGS/Accounts Payable)	Compustat	Rumyantsev et al., 2007
Operating Cycle	365×(Inventory/Cost of Good Sold+Accounts Receivable/Sales)	Compustat	Byers et al., 1997
Supply Chain Network Variables			
Spatial Complexity	Number of countries that suppliers are based	FactSet Revere	Lu and Shang, 2017
Horizontal Complexity	Number of suppliers connected to a customer	FactSet Revere	Lu and Shang, 2017
Degree Centrality	The number of direct ties to a firm within a supply chain network: $C_D(n_i) = \sum_j x_{ij} / (g-1)$, where x_{ij} is the binary variable equal to 1 if there is a link between n_i and n_j, normalized by the g nodes directly adjacent to n_i	FactSet Revere	Kim et al., 2011
Closeness Centrality	Average farness (inverse distance) to all other nodes: $C_c(n_i) = \left[\sum_{j=1}^{g} d(n_i, n_j)\right]^{-1}$, where $\sum_{j=1}^{g} d(n_i, n_j)$ is the total distance between n_i and all other nodes	FactSet Revere	Kim et al., 2011
Betweeness Centrality	The extent to which a vertex lies on paths between other vertices: $C_B(n_i) = \sum_{j<k} \frac{g_{jk}(n_i)}{g_{jk}} / [\frac{(g-1)(g-2)}{2}]$, where g_{jk} is the total number of geodesics linking the two nodes, and $g_{jk}(n_i)$ is the number of those geodesics that contain n_i, normalized to a value between 0 and 1	FactSet Revere	Kim et al., 2011
Information Centrality	Indicating the accessibility information importance of a node : $IC = \frac{n}{nc_{ii} + \sum_{j=1}^{n} c_{jj} - 2\sum_{j=1}^{n} c_{ij}}$, where $B = D - A + J$, $C = (c_{ij}) = B^{-1}$, where D is a matrix of the number of direct ties firm i has, A is the adjacency matrix of the network, and J is with all elements at unity	FactSet Revere	Bellamy et al., 2014

Panel B: Sample descriptive statistics

Variable	Obs	Mean	Median	Std.Dev	p25	p75
CDS Spread (bps)	26,674	220.19	80.38	795.90	45.97	163.70
Abnormal Spread (bps)	26,674	0.00	-3.18	692.73	-18.05	10.55
If CN Supplier	26,674	0.35	0.00	0.48	0.00	1.00
If CN Customer	24,587	0.19	0.00	0.39	0.00	0.00
CN Supplier Links	26,674	1.85	0.00	8.14	0.00	1.00
CN Customer Links	24,587	0.51	0.00	1.50	0.00	0.00
CN Supplier Links (log)	26,674	0.45	0.00	0.78	0.00	0.69
CN Customer Links (log)	24,587	0.22	0.00	0.50	0.00	0.00
Inventory	19,234	0.10	0.05	0.14	0.01	0.12
Inventory Turnover	17,258	13.55	5.89	22.78	3.23	13.41
Lead Time	19,574	65.64	52.58	56.61	31.43	78.44
Operating Cycle	19,097	134.25	110.88	96.43	72.92	162.69
Horizontal Complexity	25,115	31.54	12	62.69	4	30
Spatial Complexity	25,115	8.08	6	7.95	2	11
Degree Centrality	24,106	0.07	0.03	0.11	0.01	0.07
Closeness Centrality	24,292	0.07	0.04	0.12	0.01	0.10
Betweeness Centrality	24,106	0.01	0.00	0.05	0.00	0.01
Information Centrality	24,106	0.08	0.03	0.13	0.01	0.11

Table 2: Panel Estimations for the Credit Risk through Chinese Supply Chains.

Note: This table reports the panel estimations for the relation between US firms' abnormal CDS spreads (AS) and supply chain links to China. Variable definitions are in Table 1. The dependent variable is abnormal CDS spreads in bps. Panel A reports the results for US firms with suppliers in China. Panel B reports the results for US firms with customers in China. The results are reported using an indicator for suppliers/customers in China "If CN Suppliers (Customer)" and by using "CN Supplier (Customer) Links", measured by the natural logarithm of a firm's total number of supplier (customer) relationships to China. Firm and industry-day fixed effects are included and robust standard errors are reported.

Panel A: Suppliers in China

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
If CN Supplier	50.45***				16.23**	
×Phase 1	(7.965)				(7.495)	
CN Supplier Links		17.70***				8.18***
×Phase 1		(2.849)				(2.664)
If CN Supplier			-70.32***		-62.19***	
×Phase 2			(10.895)		(11.631)	
CN Supplier Links				-21.79***		-17.67***
×Phase 2				(3.988)		(4.237)
Firm+Ind×Day FE	YES	YES	YES	YES	YES	YES
Observations	26,674	26,674	26,674	26,674	26,674	26,674
R-squared	0.773	0.773	0.774	0.773	0.774	0.773

Panel B: Customers in China

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
If CN Customer	32.68***				13.58**	
×Phase 1	(5.614)				(5.328)	
CN Customer Links		23.65***				10.36***
×Phase 1		(3.684)				(3.462)
If CN Customer			-42.00***		-35.21***	
×Phase 2			(7.671)		(8.194)	
CN Customer Links				-30.57***		-25.38***
×Phase 2				(5.110)		(5.408)
Firm+Ind×Day FE	YES	YES	YES	YES	YES	YES
Observations	24,587	24,587	24,587	24,587	24,587	24,587
R-squared	0.797	0.797	0.797	0.797	0.797	0.797

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3: Operations Management Attributes.

Note: This table reports the results on the impact of operations management attributes on supply chain credit risk.

Panel A: Suppliers in China

	(1)	(2)	(3)	(4)
VARIABLES	Inventory	Inventory Turnover	Operating Cycle	Lead Time
Factor	7.764	-0.532***	0.165***	-0.0246
×Phase 1	(11.677)	(0.147)	(0.0228)	(0.147)
Factor	83.511**	-1.313***	0.287***	-1.643***
×Phase 2	(38.762)	(0.189)	(0.0403)	(0.242)
CN Supplier Links	10.127***	4.614**	19.65***	11.23
×Phase 1	(2.898)	(2.267)	(5.691)	(7.667)
CN Supplier Links	-17.106***	-10.71**	-34.75***	-96.99***
×Phase 2	(6.276)	(5.372)	(9.171)	(12.10)
Factor×Phase 1	-2.625**	0.917***	-0.0749***	-0.0213***
×CN Supplier Links	(1.207)	(0.257)	(0.0228)	(0.006)
Factor×Phase 2	22.581***	-3.391***	0.127***	0.999***
×CN Supplier Links	(5.923)	(0.148)	(0.0354)	(0.114)
Firm+Ind×Day FE	YES	YES	YES	YES
Observations	18,036	17,094	18,865	19,342
R-squared	0.780	0.700	0.719	0.784

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Panel B: Customers in China

	(1)	(2)	(3)	(4)
VARIABLES	Inventory	Inventory Turnover	Operating Cycle	Lead Time
Factor	-10.555	-0.373***	0.138***	-0.055
×Phase 1	(22.417)	(0.109)	(0.023)	(0.140)
Factor	-25.710	-0.714***	0.247***	-1.413***
×Phase 2	(26.983)	(0.164)	(0.032)	(0.209)
CN Customer Links	10.795**	3.451	21.229***	12.408
×Phase 1	(4.313)	(4.376)	(7.474)	(9.782)
CN Customer Links	-40.575***	-15.287**	-90.410***	-137.588***
×Phase 2	(6.812)	(6.303)	(11.676)	(14.808)
Factor×Phase 1	-18.065***	0.579**	-0.092***	-0.040***
×CN Customer Links	(5.794)	(0.281)	(0.033)	(0.015)
Factor×Phase 2	20.250***	-4.811***	0.365***	1.410***
×CN Customer Links	(5.181)	(0.538)	(0.048)	(0.146)
Firm+Ind×Day FE	YES	YES	YES	YES
Observations	18,036	16,128	17,899	18,376
R-squared	0.780	0.772	0.783	0.808

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4: Supply Chain Network Attributes.

Note: This table reports the results on the impact of supply chain network attributes on supply chain credit risk.

Panel A: Suppliers in China

VARIABLES	(1) Spatial Complexity	(2) Horizontal Complexity	(3) Degree Centrality	(4) Closeness Centrality	(5) Betweeness Centrality	(6) Information Centrality
Factor	-0.368	0.0809*	0.738**	-0.079	2.316	0.0118
×Phase 1	(0.436)	(0.0433)	(0.313)	(0.159)	(1.776)	(0.253)
Factor	-5.352***	-0.280***	-1.155**	-1.512***	-12.47***	-3.266***
×Phase 2	(0.673)	(0.0884)	(0.564)	(0.258)	(2.564)	(0.457)
CN Supplier Links	11.03*	10.91**	8.941*	7.168	7.767*	5.317
×Phase 1	(5.712)	(4.485)	(5.376)	(6.641)	(4.406)	(4.759)
CN Supplier Links	-31.53***	-38.53***	-56.55***	-80.352***	-45.65***	-51.69***
×Phase 2	(8.881)	(7.287)	(8.619)	(11.023)	(7.022)	(7.640)
Factor×Phase 1	-0.0774	-0.0633**	-0.357**	-0.020**	-1.122***	0.0142
×CN Supplier Links	(0.264)	(0.0275)	(0.176)	(0.008)	(0.278)	(0.128)
Factor×Phase 2	2.607***	0.349***	1.954***	1.905***	9.106***	2.725***
×CN Supplier Links	(0.413)	(0.0507)	(0.290)	(0.219)	(1.241)	(0.297)
Observations	24,968	24,968	23,970	23,970	23,970	23,970
R-squared	0.794	0.794	0.796	0.796	0.796	0.796

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Panel B: Customers in China

VARIABLES	(1) Spatial Complexity	(2) Horizontal Complexity	(3) Degree Centrality	(4) Closeness Centrality	(5) Betweeness Centrality	(6) Information Centrality
Factor	0.268	0.089**	0.610*	0.035	1.160	0.078
×Phase 1	(0.391)	(0.041)	(0.344)	(0.160)	(1.455)	(0.231)
Factor	-3.661***	-0.070	-0.596	-1.202***	-3.877**	-1.914***
×Phase 2	(0.587)	(0.061)	(0.491)	(0.248)	(1.875)	(0.365)
CN Customer Links	10.058	9.543*	8.214***	5.536	9.489**	5.124**
×Phase 1	(6.859)	(5.706)	(2.193)	(8.141)	(4.058)	(2.314)
CN Customer Links	-34.660***	-49.227***	-80.767***	-87.270***	-68.831***	-57.373***
×Phase 2	(10.624)	(9.140)	(10.897)	(13.501)	(9.047)	(9.899)
Factor×Phase 1	-0.184***	-0.049***	-0.306*	0.023	-0.848***	-0.088***
×CN Customer Links	(0.051)	(0.014)	(0.177)	(0.140)	(0.162)	(0.018)
Factor×Phase 2	1.647***	0.221***	1.969***	1.607***	6.800***	1.819***
×CN Customer Links	(0.585)	(0.073)	(0.360)	(0.271)	(1.055)	(0.338)
Observations	22,499	22,499	21,663	21,663	21,663	21,663
R-squared	0.798	0.797	0.799	0.799	0.799	0.799

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5: Economic Significance of Operations Management and Supply Chain Netowrk Arrtibutes

Note: This table reports the economic significance of operations management and supply chain network attributes for results presented in Tables 3 and 4. Significant results are reported in bold.

	Effect on Supply Chain Credit Risk	Change in variable, (75th-median)	Change in Abormal CDS Spread (in bps)			
			CN Supplier		CN Customer	
			Phase 1	Phase 2	Phase 1	Phase 2
OM Variables						
Inventory	Mitigate	0.08	**-0.20**	**1.74**	**-1.39**	**1.56**
Inventory Turnover	Amplify	7.52	**6.90**	**-25.50**	**4.35**	**-36.18**
Lead Time	Mitigate	25.86	**-0.55**	**25.83**	**-1.03**	**36.46**
Operating Cycle	Mitigate	51.81	**-3.88**	**6.58**	**-4.77**	**18.91**
Supply Chain Network Variables						
Spatial Complexity	Mitigate	5.00	-0.39	**13.04**	**-0.92**	**8.24**
Horizontal Complexity	Mitigate	18.00	**-1.14**	**6.28**	**-0.88**	**3.98**
Degree Centrality	Mitigate	3.92	**-1.40**	**7.66**	**-1.20**	**7.72**
Closeness Centrality	Mitigate	15.19	**-0.30**	**28.94**	0.35	**24.41**
Betweeness Centrality	Mitigate	0.51	**-0.57**	**4.62**	**-0.43**	**3.45**
Information Centrality	Mitigate	7.83	0.11	**21.35**	**-0.69**	**14.25**

	Change in variable, (75th-median) or 0 to 1	Change in Abormal CDS Spread			
		CN Supplier		CN Customer	
		Phase 1	Phase 2	Phase 1	Phase 2
Baseline Variables					
If CN Supplier	1.00	**50.45**	**-70.32**	-	-
CN Supplier Links	0.69	**34.81**	**-48.52**	-	-
If CN Customers	1.00	-	-	**32.68**	**-42.00**
CN Customer Links	0.42	-	-	**13.73**	**-17.64**

Table 6: Placebo Test

Note: This table reports the placebo test by randomly generating placebo supply chain links, substituting the real supply chain links. We use the indicators of whether firms are exposed to the placebo China supply chains. Firm and industry-day fixed effects are included and robust standard errors are reported.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
If CN Placebo Supplier	2.295		-4.401			
×Phase 1	(7.897)		(7.336)			
If CN Placebo Supplier		-9.985	-12.19			
×Phase 2		(10.86)	(11.55)			
If CN Placebo Customer				9.775		6.973
×Phase 1				(6.766)		(6.298)
If CN Placebo Customer					-8.556	-5.062
×Phase 2					(9.329)	(9.950)
Firm+Ind×Day FE	YES	YES	YES	YES	YES	YES
Observations	26,674	26,674	26,674	24,587	24,587	24,587
R-squared	0.761	0.761	0.761	0.783	0.783	0.783

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 7: Robustness and Alternative Specifications

Note: This table reports robustness tests and alternative specifications. The dependent variable is abnormal CDS spreads (bps).

Panel A: Suppliers in China

VARIABLES	(1) Alternative CDS Definition	(2) Alternative Phase Dates	(3) Alternative Firm Location	(4) Balanced Sample	(5) Lower Trade Sanction Sample	(6) Global Supply Chains
CN Supplier Links	15.95***	7.353**	6.12***	8.05***	11.41***	6.879***
×Phase 1	(2.691)	(2.873)	(2.136)	(2.801)	(3.217)	(2.520)
CN Supplier Links	-12.86***	-18.52***	-11.40***	-18.11***	-16.63***	-13.05***
×Phase 2	(3.393)	(4.256)	(3.413)	(4.348)	(4.918)	(3.889)
Other Global Supplier Links						-9.424
×Phase 1						(13.21)
Other Global Supplier Links						114.7***
×Phase 2						
Observations	26,674	25,502	26,674	26,027	21,974	26,674
R-squared	0.761	0.776	0.797	0.639	0.757	0.774

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Panel B: Customers in China

VARIABLES	(1) Alternative CDS Definition	(2) Alternative Phase Dates	(3) Alternative Firm Location	(4) Balanced Sample	(5) Lower Trade Sanction Sample	(6) Global Supply Chains
CN Customer Links	22.29***	8.886**	10.61***	10.42***	8.63**	8.359**
×Phase 1	(3.701)	(3.748)	(4.085)	(3.760)	(3.756)	(3.481)
CN Customer Links	-20.50***	-26.81***	-16.67***	-26.96***	-24.14***	-26.69***
×Phase 2	(4.658)	(5.437)	(5.259)	(5.492)	(5.726)	(5.428)
Other Global Customer Links						-11.31
×Phase 1						(6.909)
Other Global Customer Links						-8.285
×Phase 2						(12.12)
Observations	24,587	23,505	24,587	24,094	19,791	24,587
R-squared	0.783	0.799	0.797	0.652	0.781	0.797

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Appendix

Figure A1 Example of CDS contract.

Note: As an example, a supplier has $100 million trade credit outstanding to Teva Pharmaceuticals, and is concerned about increased credit risk given their exposure. Teva's CDS spread for 5-year CDS contract is 120 basis points (bps) per annum. The expected recovery rate if there is a default is 40% based on the International Swaps and Derivatives Association (ISDA) Standard CDS Converter Specification. In this case, to protect itself against the default of Teva, the supplier can buy a CDS contract. As CDS premiums are paid quarterly, the supplier will pay to the CDS seller 120 bps/4 = 30bps (0.3%) quarterly on the outstanding notional amount of $100 million, which is 0.003*$100million = $300,000 for the next 5 years. If Teva defaults, CDS seller will pay the CDS buyer (the supplier), Teva's loss given default (LGD) = Notional – Recovery Amount ($recoveryrate \times notional$), which is $\$100million – 0.4 \times \$100million = \$60million$. If Teva does not default, the CDS buyer (supplier) will not receive any payment from the CDS seller.

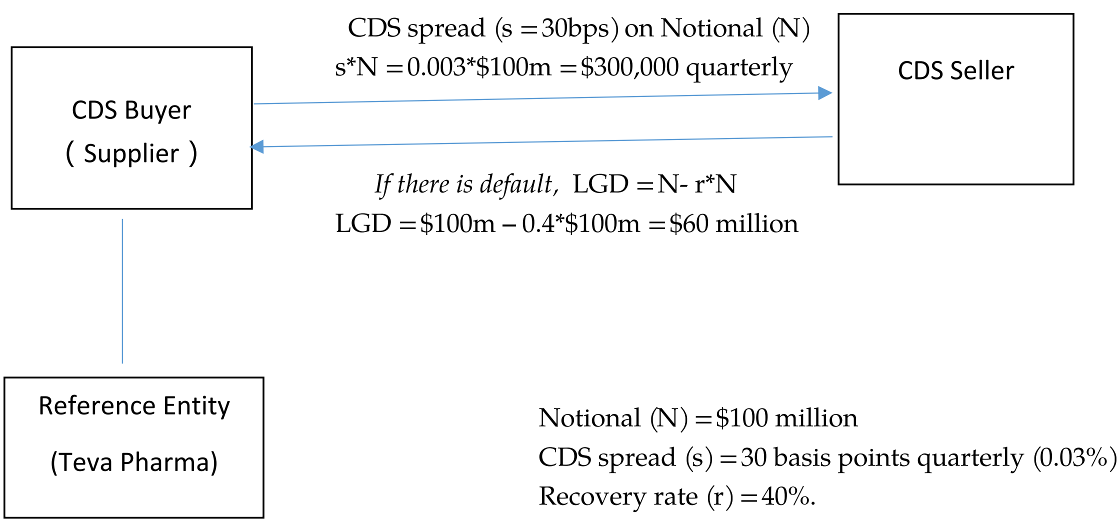
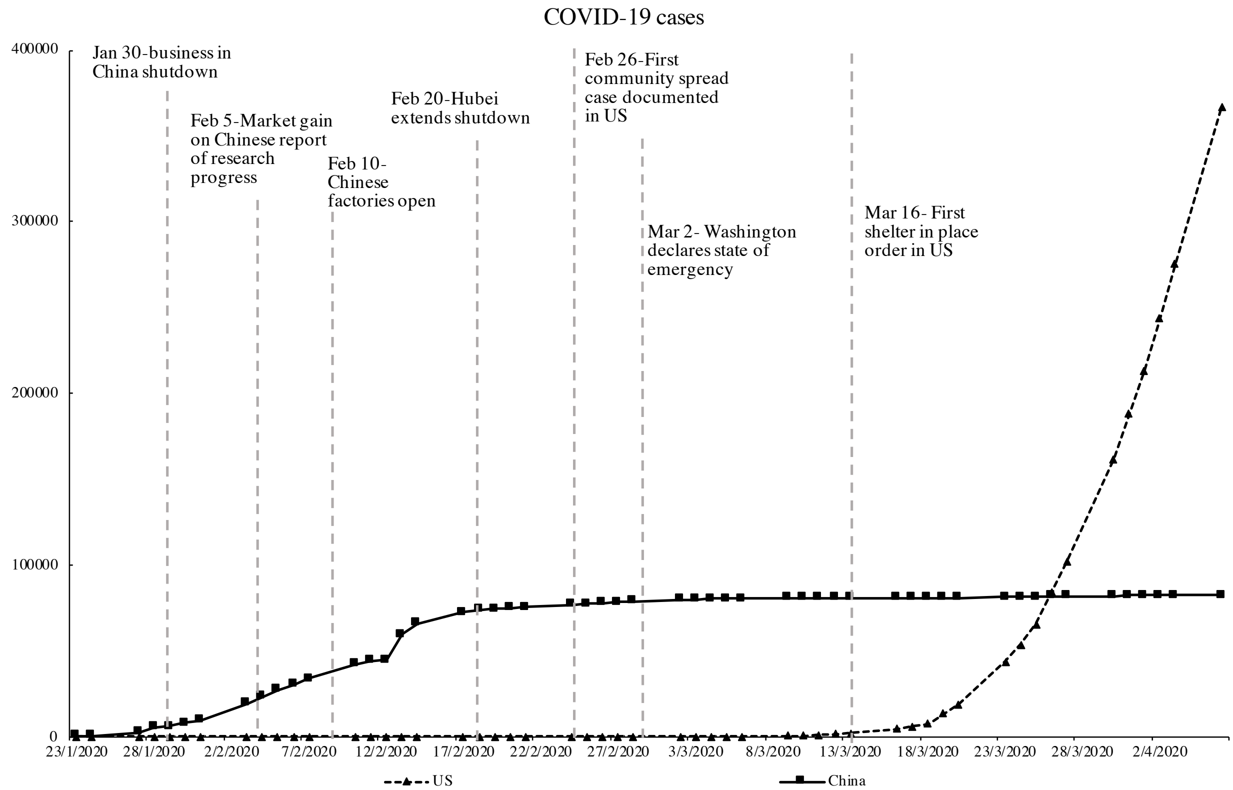


Figure A2 Confirmed COVID-19 cases and major events



Note: This figure plots the total confirmed cases in China and the U.S. with the important COVID-19 events along the timeline.

Table A1: Supply Chain Data Statistics.
Note: This table presents supply chain information in FactSet vs. Compustat Segment supply chain datasets.

Panel A. FactSet Supply Chain Data vs. Compustat Segment Supply Chain Data

A1. Supply Chain Data Firm Distribution

Number of firms Covered (FactSet Revere)	25321
Number of firms Covered (Compustat Segment)	4737
Number of firms with Non-US Suppliers (FactSet Revere)	16592
Number of firms with Non-US Suppliers (Compustat Segment)	70
Number of firms with Non-US Customers (FactSet Revere)	15395
Number of firms with Non-US Customers (Compustat Segment	347
Number of firms with China Suppliers (FactSet Revere)	2595
Number of firms with China Suppliers (Compustat Segment)	0
Number of firms with China Customers (FactSet Revere)	2498
Number of firms with China Customers (Compustat Segment)	0

A2. Supply Chain Data Degree Distribution

	Mean	Std Dev
Total		
Number of Suppliers (FactSet Revere)	6.96	20.77
Number of Customers (FactSet Revere)	7.74	16.5
Number of Suppliers (Compustat Segment)	1.8	2.18
Number of Customers (Compustat Segment)	1.47	1.13
US partners		
Number of Suppliers (FactSet Revere)	2.11	8.31
Number of Customers (FactSet Revere)	2.25	6.51
Number of Suppliers (Compustat Segment)	1.76	2.15
Number of Customers (Compustat Segment)	1.42	1.12
Non-US partners		
Number of Suppliers (FactSet Revere)	4.85	14.51
Number of Customers (FactSet Revere)	5.49	11.58
Number of Suppliers (Compustat Segment)	0.04	0.22
Number of Customers (Compustat Segment)	0.05	0.22
Chinese partners		
Number of Suppliers (FactSet Revere)	0.4	2.68
Number of Customers (FactSet Revere)	0.36	1.45
Number of Suppliers (Compustat Segment)	0	0
Number of Customers (Compustat Segment)	0	0

Panel B. Markit CDS-FactSet Supply Chain Merged Dataset (Final Sample) Degree Distribution

	Mean	Std Dev
US partners		
Number of Suppliers (Final Sample)	21.27	71.52
Number of Customers (Final Sample)	7.11	15.78
Chinese partners		
Number of Suppliers (Final Sample)	1.85	8.14
Number of Customers (Final Sample)	0.51	1.50

Table A2: Firm and Supply Chain Attributes Comparison between Final Sample and Compustat.
Note: This table compares key variables between the final sample used in this study and Compustat dataset.

Mean	Final DataSet (1)		Compustat (2)		T-test (1)-(2)
	Mean	StdDev	Mean	StdDev	
Inventory	0.10	0.14	0.10	0.13	-0.64
Inventory Turnover	13.55	22.78	14.40	28.94	-0.88
Lead Time	65.64	56.61	67.00	30.74	-1.08
Operating Cycle	134.25	96.43	135.00	83.97	-0.25
Spatial Complexity	8.08	7.95	6.97	10.94	3.06*
Horizontal Complexity	31.54	62.69	33.00	39.85	-0.95
Degree Centrality	0.07	0.11	0.05	0.19	2.53*
Closeness Centrality	0.07	0.12	0.06	0.22	1.60
Betweeness Centrality	0.01	0.05	0.01	0.08	1.42
Information Centrality	0.08	0.13	0.07	0.17	2.6*

Table A3: Representative Firms in the Final Sample.
Note: This table provides 30 representative firms from the final sample, which as both CDS and supply chain data. $\#CNDegree$ is the total number of China supply chain partners a firm has; $\#CNSuppliers$ is the total number of China suppliers a firm has; $\#CNCustomers$ is the total number of China customers a firm has.

Ticker	Company Name	SIC	# CN Degree	# CN Suppliers	#CN Customers	FF 12 Industry
GE	GENERAL ELECTRIC CO	9997	42	35	7	Other
AMZN	AMAZON.COM INC	5961	26	13	13	Wholesale, Retail, and Some Services
MSFT	MICROSOFT CORP	7372	21	10	11	Business Equipment
HPQ	HP INC	3570	20	12	8	Business Equipment
HON	HONEYWELL INTERNATIONAL INC	9997	19	14	5	Other
CAT	CATERPILLAR INC	3531	18	18	0	Manufacturing
PFE	PFIZER INC	2834	17	13	4	Healthcare, Medical Equipment, and Drugs
BA	BOEING CO	3721	15	8	7	Manufacturing
CSCO	CISCO SYSTEMS INC	3674	14	9	5	Business Equipment
INTC	INTEL CORP	3674	14	6	8	Business Equipment
IBM	INTL BUSINESS MACHINES CORP	7370	12	4	8	Business Equipment
KO	COCA-COLA CO	2086	12	12	0	Consumer NonDurables
JNJ	JOHNSON & JOHNSON	2834	10	8	2	Healthcare, Medical Equipment, and Drugs
PEP	PEPSICO INC	2080	9	9	0	Consumer NonDurables
DD	DUPONT DE NEMOURS INC	2860	9	7	2	Chemicals and Allied Products
QCOM	QUALCOMM INC	3674	9	4	5	Business Equipment
XOM	EXXON MOBIL CORP	2911	8	4	4	Oil, Gas, and Coal Extraction and Products
MRK	MERCK & CO	2834	7	4	3	Healthcare, Medical Equipment, and Drugs
NKE	NIKE INC	3021	5	3	2	Manufacturing
ABT	ABBOTT LABORATORIES	3845	5	2	3	Healthcare, Medical Equipment, and Drugs
T	AT&T INC	4812	4	3	1	Telephone and Television Transmission
MCD	MCDONALD'S CORP	2090	4	4	0	Consumer NonDurables
DOW	DOW INC	2821	4	2	2	Chemicals and Allied Products
YUM	YUM BRANDS INC	5812	4	4	0	Wholesale, Retail, and Some Services
MAR	MARRIOTT INTL INC	7011	3	2	1	Other
COST	COSTCO WHOLESALE CORP	5399	3	3	0	Wholesale, Retail, and Some Services
AVT	AVNET INC	5065	3	3	0	Wholesale, Retail, and Some Services
ARW	ARROW ELECTRONICS INC	5065	3	1	2	Wholesale, Retail, and Some Services
FDX	FEDEX CORP	4513	3	2	1	Other
DE	DEERE & CO	3523	3	3	0	Manufacturing

Table A4: Distribution of Credit Ratings
Note: This table reports credit rating distribution in our sample at the start of the sample period.

Implied Rating	Number of Firms	Percentage (%)
AAA	2	0.47
AA	27	6.37
A	59	13.92
BBB	102	24.06
BB	133	31.37
B	66	15.57
CCC	35	8.25

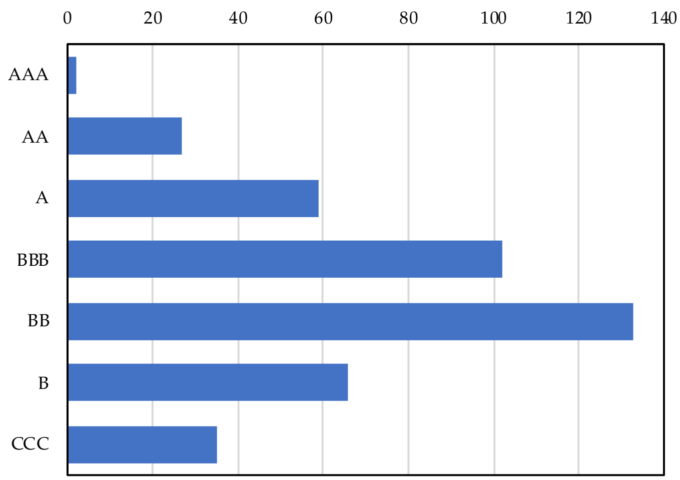


Table A5: Sample Industry Coverage.
Note: We utilize a 6-industry classification based on Fama French 12-industry, excluding financial, utility, and others. This table summarizes the definition of the industry classification method, and the firm distribution of the 6-industry classification in Panel A. Panel B & Panel C summarize the subsamples for the US firms exposed to China suppliers or customers respectively.

Panel A: 6-Industry Definition for Firms with CDS

6-Industry	**Fama French 12-industry**	**# of Firms with CDS**	**Percentage (%)**
Consumer Goods			
	Consumer Nondurables		
	Consumer Durables	46	10.85
Electronics			
	Computers, Software & Electronics		
	Telephone & Television	41	9.67
Healthcare, Medical Equip. & Drugs			
	Healthcare, Medical Equip. & Drugs	53	12.50
Manufacturing			
	Manufacturing	81	19.10
Oil, Gas. & Chemicals			
	Oil, Gas & Coal		
	Chemicals & Allied Products	59	13.92
Others			
	Others	144	33.96
Totals		424	100.00

Panel B: CDS-referenced Firms with China Suppliers

Industry	**# of Firms with CDS**	**Percentage (%)**
Consumer Goods	21	11.67
Electronics	16	9.17
Healthcare, Medical Equip. & Drugs	28	15.83
Manufacturing	40	22.50
Oil, Gas & Chemicals	28	15.83
Others	44	25.00
Total	177	100.00

Panel C: CDS-referenced Firms with China Customers

Industry	**# of Firms with CDS**	**Percentage (%)**
Consumer Goods	10	9.21
Electronics	7	6.58
Healthcare, Medical Equip. & Drugs	12	10.53
Manufacturing	34	30.26
Oil, Gas & Chemicals	10	9.21
Others	39	34.21
Total	112	100.00