Message in a Bottleneck:

Global Value Chain Disruptions and Manufacturing Output

in the United States

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ECONOMICS WORKING PAPER SERIES
Working Paper 2025–07–A

U.S. INTERNATIONAL TRADE COMMISSION
500 E Street SW
Washington, DC 20436

July 2025

The authors would like to thank the entire Office of Economics at the USITC for valuable feedback during the research seminar of July 2024. Special thanks to Karen Thome, David Riker, and Peter Herman for reviewing the paper and providing insightful comments and assistance.

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Abstract

In this paper, we examine the effect of container shipping disruptions on U.S. manufacturing output before and during the Covid-19 pandemic. We augment maritime trade with a global production network model where the reliability of container logistics is critical for the on-time and full delivery of inputs and output to foreign markets. Combining data on U.S. container reliability with input-output and trade data, we construct a novel supply chain disruption index that captures the upstream and downstream linkages of U.S. manufacturing integration into the global value chain. Our regression estimates suggest that a one-unit shock leads to a 38 basis point decrease of the manufacturing output through the upstream channel and a 355 basis point decrease through the downstream channel. The impulse response reveals that a one-unit shock would induce an additional four periods for the recovery of output during the Covid period compared to the pre-Covid period. Our estimates are robust to alternative measures of container disruptions.

Keywords: Global value chain, Covid-19, Input Output, Manufacturing, Maritime Transportation
JEL Codes: F14, O47, E23, R15, R41

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1 Introduction

Supply chain disruptions were among the challenges faced by industries and households during the Covid-19 pandemic. A recent surge of interest in studying the drivers of supply chain resilience has emerged. In this paper, we contribute to this line of research by investigating the impact of container shipping disruptions (container unreliability rate)[1] on U.S. manufacturing output.[2] In particular, we examine the effect of container disruptions through the upstream and downstream channels of U.S. manufacturing's integration into the global value chain.[3]

Our theoretical argument follows a production network model developed by Carvalho et al. (2021). We expand their framework by adding container shipping and international trade. In our model, the reliability rate of container shipping plays a key role in U.S. manufacturing industries' timely access to foreign inputs to meet their production goals to satisfy the demand for their output.

Our empirical strategy encompasses four main features. First, we construct a supply chain disruption index (SCDI) that distinguishes the upstream (upindex) and downstream (downindex) linkages of the U.S. manufacturing's integration into the global value chain (GVC).[4] The second feature is the organization of our empirical model into two main periods: the pre-Covid period from January 2012 to December 2019 and the Covid period from January 2020 to July 2022.[5]

The third feature of our methodology is the use of panel regression and impulse response techniques. We select these two econometric exercises for two main reasons: *(i)* we can quantify the impact of container shipping disruptions on U.S. manufacturing's output using the regression and the impulse response; *(ii)* the impulse response can predict the length of time that it would take for industrial production to recover following a one standard deviation shock of the SCDI. The fourth feature of our empirical strategy is the choice of our variables. In our econometric exercises, industrial production (IP) is the dependent variable, and the constructed container disruption index is the independent variable. We also follow Meier and Pinto (2024), Yao (2005), and Humphreys et al. (2001) and include

[1] According to, Sea-Intelligence (2021), the container reliability rate is defined as the monthly percentage of individual, distinct port calls, where the actual vessel arrival at the berth is made within a threshold on-time definition, relative to a vessel/service schedule published in advance.

[2] Industrial production (IP) is a proxy of output. IP is a monthly economic indicator published by the Federal Reserve Board that measures the real output of the manufacturing, mining, and electric and gas utilities industries.

[3] We define upstream channel as U.S. manufacturing importing inputs from other countries and downstream channel as U.S. manufacturing exporting its output to other countries.

[4] upindex measures the share of containerized import of intermediate inputs by U.S. manufacturing that is considered late based on an initial schedule. downindex measures the percentage of containerized export trade by U.S. manufacturing that is late. We use the container schedule reliability rate data from Sea Intelligence, the imports and exports data from U.S. Census Bureau (U.S. Trade online), and the input and output data from the Bureau of Economic Analysis. We then apply the import proportionality assumption.

[5] Our study starts in January 2012 and ends in July 2022 because it corresponds to the period of the container schedule reliability data that we received from Sea Intelligence. The choice of January 2020 as the start of Covid period is based on the early manifestation of the virus in China and the decision of Chinese's government to apply the first lockdown policies which have direct implications for container shipping of manufacturing goods to and from the U.S.

inventory (Invship) and employment (emp) as the control variables to account for supply and demand macroeconomic factors that may affect industrial production. Our panel data encompasses eighteen U.S. manufacturing industries organized at the three digits code of the North American Industry Classification System (NAICS).

Our regression results suggest that a one-unit[6] increase of the SCDI would cause a 38 basis point decrease in industrial production through the upstream channel and a 355 basis point decrease through the downstream channel. The impulse response exercise suggests U.S. manufacturing industrial production would take an additional four periods to recover during the Covid-19 pandemic compared to the pre-Covid period in response to a one-unit shock to the SCDI. Our estimates are robust to alternative measures of the supply chain disruptions such as average delays and average delay of late container vessels.[7]

The manufacturing sector accounts for 12% of U.S. total output, 60% of its total exports, and directly employs 8% of U.S. total workforce.[8] U.S. manufacturing is strongly integrated into the global value chain. Its imports of foreign inputs represent 18% of its total intermediate inputs.[9] The United States exports 6.5% of its total manufacturing output.[10] To trade with its partners, the U.S. manufacturing sector relies to a large extent on maritime transportation. Half of U.S. manufacturing imports and 36% of its exports are shipped through container logistics. Figure 1 illustrates the trends of the container schedule reliability rate and industrial production.[11] Both indicators decline strongly after the start of Covid-19 pandemic.

[6]The unit change of the disruption index can be also translated in terms of days of delay of container shipping. When we consider both the periods before and after the Covid-19, a one-unit change means around a delay of 2 days. If we focus only on the period before the Covid-19, a one-unit change of the SCDI is similar to 1.19 day. A one-unit change during the Covid-19 period would corresponds to a container delay of 4 days.

[7]The average delay is the number of days consider as delay among all container vessels' arrival including those that are late, on-time and early. The average delay of late vessel arrivals (*ald*) is the average number of days consider as delay across only those vessels that were recorded as being late.

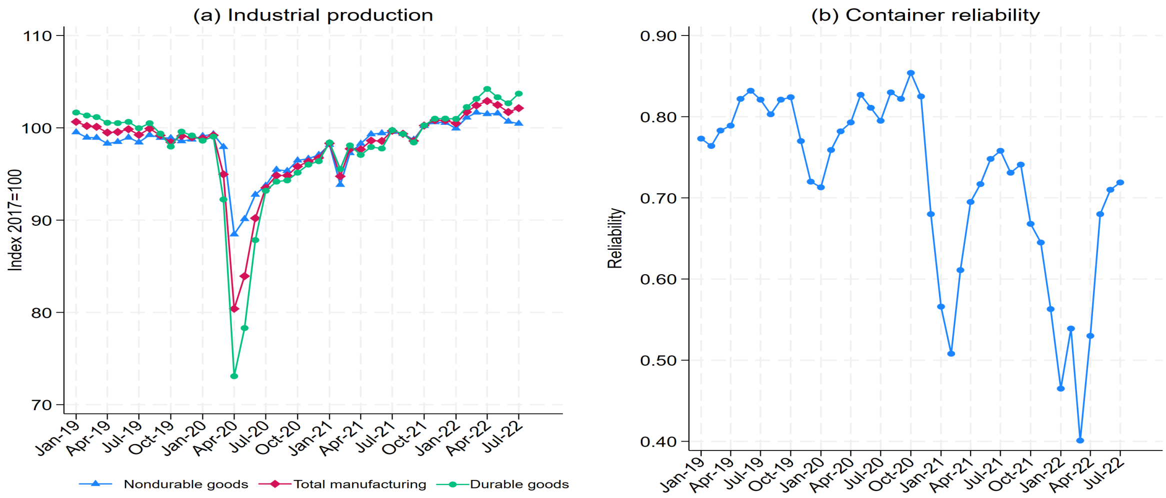
[8]NIST, U.S. Manufacturing Economy, November 2024.

[9]This number is calculated based on Bureau of Economic Analysis input-output import tables.

[10]US trade online, 2022.

[11]The Container schedule reliability rate measures the percentage of container vessels that arrive on-time. IP is a monthly measure of the real output of industrial establishments and covers sectors such as mining, manufacturing, and utilities. The container schedule reliability rate is published by Sea Intelligence and IP is published by the Federal Reserve Board with 2017 as the base year (value of 100).

Figure 1: U.S. Container logistics disruptions before and during Covid-19



Note: Panel(a) shows industrial production (IP) for the total manufacturing, the durable and nondurable industries. Durable industries produce goods that provide a stream of services or utility over time. Non-durable industries produce goods and services that tend to be consumed immediately. Panel (b) shows the container reliability (percentage of containerized vessels that arrive on-time at berth). Source of data panel (a): Board of Governors of the Federal Reserve System (US), Industrial Production: Total Index [INDPRO], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/INDPRO, July 1, 2023. Source of data for panel (b) Sea Intelligence, Global liner performance, Maritime Analysis Report, 2023.

There is a growing theoretical and empirical literature on supply chain disruptions and their economic impacts. Our study is the first paper that examines the impact of supply chain disruptions caused by the Covid-19 pandemic on U.S. manufacturing output by distinguishing the downstream and upstream of container shipping as transmission channels. We quantitatively estimate the industry-level output effects and their duration resulting from supply chain disruptions. Our study is connected to several strands of literature. First, our paper is linked to the literature on global production networks and shock propagation. This line of research suggests that globalization enhanced the trade of intermediate goods between countries and the propagation of shocks leading to fluctuations of the output (Zheng et al. (2025), Humphrey (2003), Johnson (2014), Boehm et al. (2019) and Meier and Pinto (2024)). Meier and Pinto (2024) is the closest paper to our study. Meier and Pinto (2024) use input-output linkages and construct an import exposure index to study the effects of international supply chain disruptions caused by COVID-19 on real economic activity in the United States. Their study focuses on the impact of China's lockdown and finds that industries with different exposure to intermediate products imported from China will respond differently. They also differ in some other aspects. For example, the timeline of their study goes from January 2019 to January 2021. Our study covers January 2012 to July 2022. Their index includes only upstream linkages because they focus more on imported products from China, while our index accounts for the upstream and downstream linkages. Our study focuses more on maritime transportation logistics and our supply chain disruption index integrates container logistics.

Second, our paper is linked to the literature on the resilience of maritime trade. The existing literature considers container shipping networks as the backbone of global trade and an important determinant of economic growth. Most of these studies are based on country-level or port-level data. However, relatively few studies focus on an industrial-level analysis of the relationship between container logistics disruptions and economic growth. A disruption to maritime trade originating from shocks such as pandemics, natural disasters, bad weather, worker strikes, and political instability can lead to economic downturns (Xu et al. (2020), Notteboom et al. (2010), Cariou and Notteboom (2022), Özer et al. (2021), Bernhofen et al. (2016), Jiang et al. (2021), Xu et al. (2024), Xu et al. (2022), Goel et al. (2021), Rashid Khan et al. (2018), Bridgman (2024), Xu et al. (2020), and Michail et al. (2021). Several related papers analyze the economic impact of container disruptions caused by the Covid-19 pandemic. Açık (2024) used the Global Supply Chain Pressure Index (GSCPI) to model the impact of events occurring in the global supply chain and the export and import container traffic at Turkish ports. Kilian et al. (2021) construct an index of the volume of container trade to and from North America to identify shocks to U.S. domestic demand and foreign demand for U.S. manufactured goods. Bai et al. (2024) build an index using spatial data on congestion in 50 ports to estimate the effects of container delays on economic variable such as output, inflation, and employment. Our study differs from these three papers because it integrates input-output linkages as the central element of the index and clearly disentangles the impact of container disruption through the upstream and downstream channels. By decomposing these two channels, our study sheds light on the mechanisms that could be causing the most impact when there are supply chain disruptions.

Third, our study contributes to the literature aiming to quantify the effect of supply chain disruptions (Tokui et al. (2017), Li et al. (2025), Açık (2024), Meier and Pinto (2024), Goel et al. (2021), and Carvalho et al. (2021). Carvalho et al. (2021) quantifies the role of input-output linkages as a mechanism for the transmission and amplification of supply chain disruption following the Great East Japan Earthquake of 2011. We use this paper as our reference paper because it is built on the premises of input-output linkages, it distinguishes upstream and downstream channels, and it measures the effect of supply chain disruptions on the output. However, our paper differs in many aspects: Our focus is on U.S. manufacturing, not on Japanese firms; our paper integrates container logistics and international trade of inputs. We construct a customized supply chain disruption index by combining input-output data, container reliability, and container data for the United States.

Fourth, our paper contributes to the literature on container schedule reliability (Nair et al. (2012), Okur and Tuna (2022), Zhang et al. (2022), and Notteboom (2006)). The container schedule reliability measure is a central element in our paper. Past studies on schedule reliability provide a characterization of its drivers. We innovate by combining the measures of schedule reliability for the United States with data on domestic and international production networks to construct a downstream and upstream supply chain disruptions index. Our index can be used to estimate the extent of the impact of container disruptions on several economic variables, such as the output.

The rest of the paper is organized as follows. We start by presenting in Section 2 the stylized facts about the timeline of the Covid-19 pandemic leading to the global container shipping disruptions. In Section 3, we describe the theoretical framework using a global production networks model. In Section 4, we discuss the data and the construction of our supply chain disruption index. In Section 5, we conduct the empirical analyses. Section 6 concludes.

2 Background: Covid-19 pandemic and container disruptions

In this section, we revisit the timeline of the Covid-19 pandemic into three waves. For each wave, we identify the various drivers that led to the deterioration of U.S. container shipping reliability.

2.1 January 2020 - March 2020: First supply Shock

In mid-December 2019, China noticed that some of its citizens began showing up in local hospitals with complaints of flu-like symptoms including high fever, cough and breathing difficulties. On 23 January 2020, China adopted a "zero Covid" policy by imposing a lockdown in regions that were affected to quarantine the center of an outbreak of Covid-19. This action lasted 76 days.[12] Many cities, districts, and counties across mainland China implemented similar policies in the days following. Meanwhile, the spread of the virus caused disruptions in China's production plants, port operations and hence its imports and exports.[13]

The first lockdown implemented by China shocked the global supply chain. Global container shipping experienced reduced shipping capacities of intermediates and final goods imported and exported from China. Seven out of the top ten container ports are located in China.[14]

2.2 April 2020 - June 2020: Demand shock

By the middle of March 2020, Covid-19 had spread globally. The rapid increase of Covid-19 infections led several countries to implement policies, including lockdowns, aiming to stop the spread

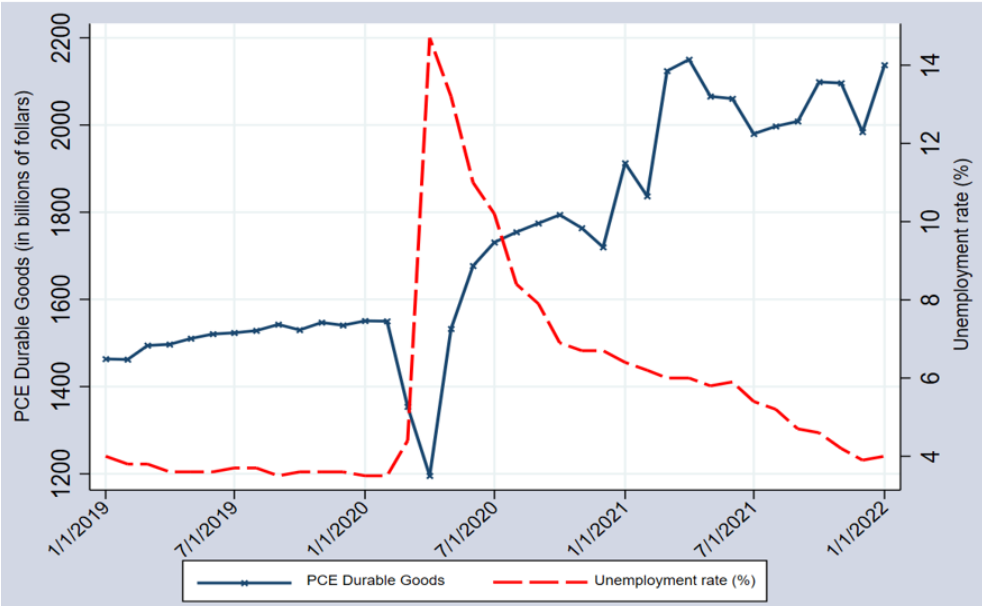
[12] AP News, Timeline: China's Covid-19 outbreak and lockdown of Wuhan, January 2021.

[13] China is an influential player in the global trade with 29.4% of global manufacturing (Thomas et al. (2020)) and 14% of world exports. Also, seven of the world's top ten container ports located in China - including Shanghai the largest container port in the world. See Figure A1.

[14] See figure A1.

of the virus.[15] In the United States, Covid-19 related job losses wiped out 113 straight months of job growth, with the nonfarm employment falling by 20.5 million jobs in April 2020, as shown in Figure 2.

Figure 2: U.S. Unemployment Rate and Personal Consumption Expenditure on Durable Goods



Notes: Personal consumption expenditures (PCE), commonly called consumer spending, measures the spending on goods and services by households in the U.S. PCE is published monthly by the Bureau of Economic Analysis (BEA) and accounts for about two-thirds of domestic spending and is a significant driver of gross domestic product (GDP). The unemployment rate represents the number of unemployed as a percentage of the labor force. It is released on a monthly basis. Source: U.S. Bureau of Economic Analysis, Personal Consumption Expenditures [PCE]; U.S. Bureau of Labor Statistics, Unemployment Rate [UNRATE], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/UNRATE, July 3, 2023.

In the United States, many states implemented restrictive measures (lockdowns, social distancing, mask mandates) during the period of mid-March 2020 to May 2020.[16] California and New York, the states with the largest container ports and traffic, had their lockdown polices in place until June of 2020. Figure 2 shows that the restrictions led to a fall in personal consumption during the first quarter of 2020, a decrease in labor availability across sectors, and a consumption shift toward durable manufacturing goods such as computer and electronics, furniture, exercise equipment, and home improvement items. The shift in consumption caused an exponential rise of U.S. imports' orders and a series of backlogs of unfilled orders and delays along the supply chains (Baschuk (2020)). U.S. manufacturing industries, fearing the risk of a global recession and idle inventory to build up, cut back their orders from China, pressing container carriers to reduce sailing capacities and to prioritize shorter routes. The shift of strategy from industries and carriers created a scattering and a misallocation of

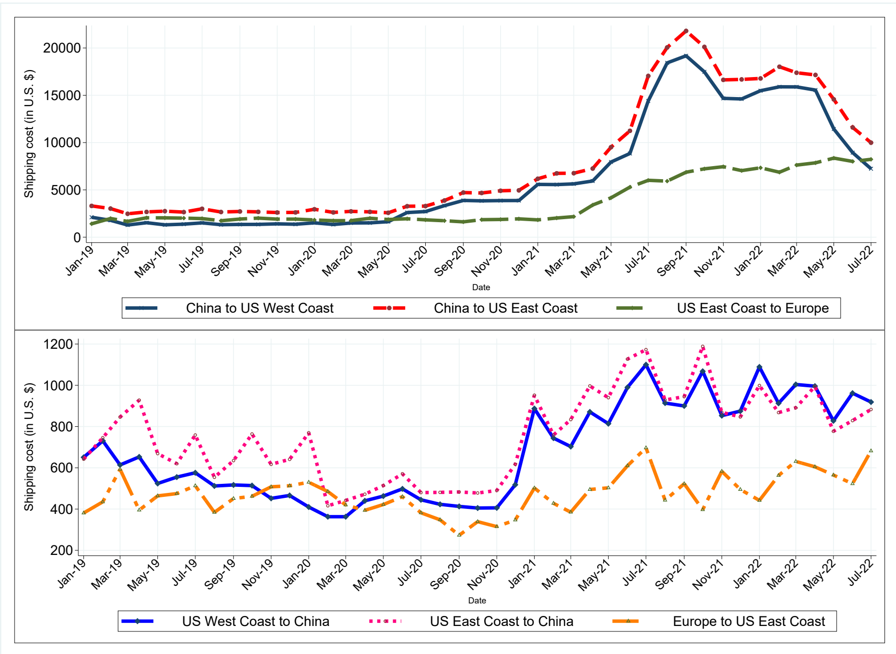
[15]BBC News, Coronavirus: The world in lockdown in maps and charts, April 2020.

[16]CNBC, Stay-at-home orders across the country, April 2020.
CNN, Covid-19 Pandemic Timeline Fast Facts, September 2024.

empty containers.[17] All these disturbances corresponded to a collapse in aggregate demand from both consumers and businesses.[18]

The reopening of China's production plants and ports in April 2020 combined with a demand surge in the United States for durable goods while other countries were still in lockdown created a strong need for empty containers to ship goods from Asia. In figure 3, the severe shortage of empty containers pushed freight rates up to unprecedented levels.[19] Meanwhile the reopening of the U.S. economy in late May 2020 revealed major challenges: a shortage of workers available to run port operations and an increase in imports from spending by households using their savings from the lockdown and stimulus funds from the government.[20]

Figure 3: Container freight rate



Notes: We used the Shanghai Containerized Freight Index (SCFI) because it is the most widely used index for sea freight rates worldwide. This index has been calculated weekly since 2009 and shows the most current freight prices for container transport. Source: Bloomberg L.P. (2023). Container freight rate accessed July 5, 20203. Retrieved from Bloomberg database.

2.3 July 2020 to July 2022: Second supply shock

A 43 percent drop in the container reliability rate characterized the second supply shock (figure 1). Shippers struggled to find resources such as container boxes, chassis, vessels, and warehouse spaces to effectively import their inputs or export their output. When shippers found the capacity, they had to

[17]WTO: COVID and Rising Shipping Rates: Facts, November 2021.

[18]Federal Reserve Board, Aggregate Demand and Aggregate Supply Effects of COVID-19: A Real-time Analysis, June 2020.

[19]UNCTAD, Shipping during COVID-19: Why container freight rates have surged? April 2021.

[20]U.S. Department of Treasury, About the CARES Act and the Consolidated Appropriations Act, December 2020.

overcome the hurdles of congestion at major ports.[21] In addition, the hinterland intermodal subsystems (trucking, warehousing, and rail) in the United States, particularly in the West Coast, could not keep up due to a shortage of truck drivers, and train and port workers. The arrival of backlogs orders from China overwhelmed the short-handed Los Angeles and Long Beach ports. Carriers and shippers diverted their shipments to the East Coast ports, mainly New York-New Jersey, Savannah, Virginia, and Houston ports.[22] Before long, these ports also became congested and created additional shortage of empty containers. To secure future shipments and ensure continuity in their production plans, shippers proactively started to pay high freight rate as shown in figure 3. The container freight rate for China to the U.S. West Coast and from China to the U.S. East Coast went up significantly as delays increased at U.S. ports (figure 3).

3 A model of global production networks with container shipping

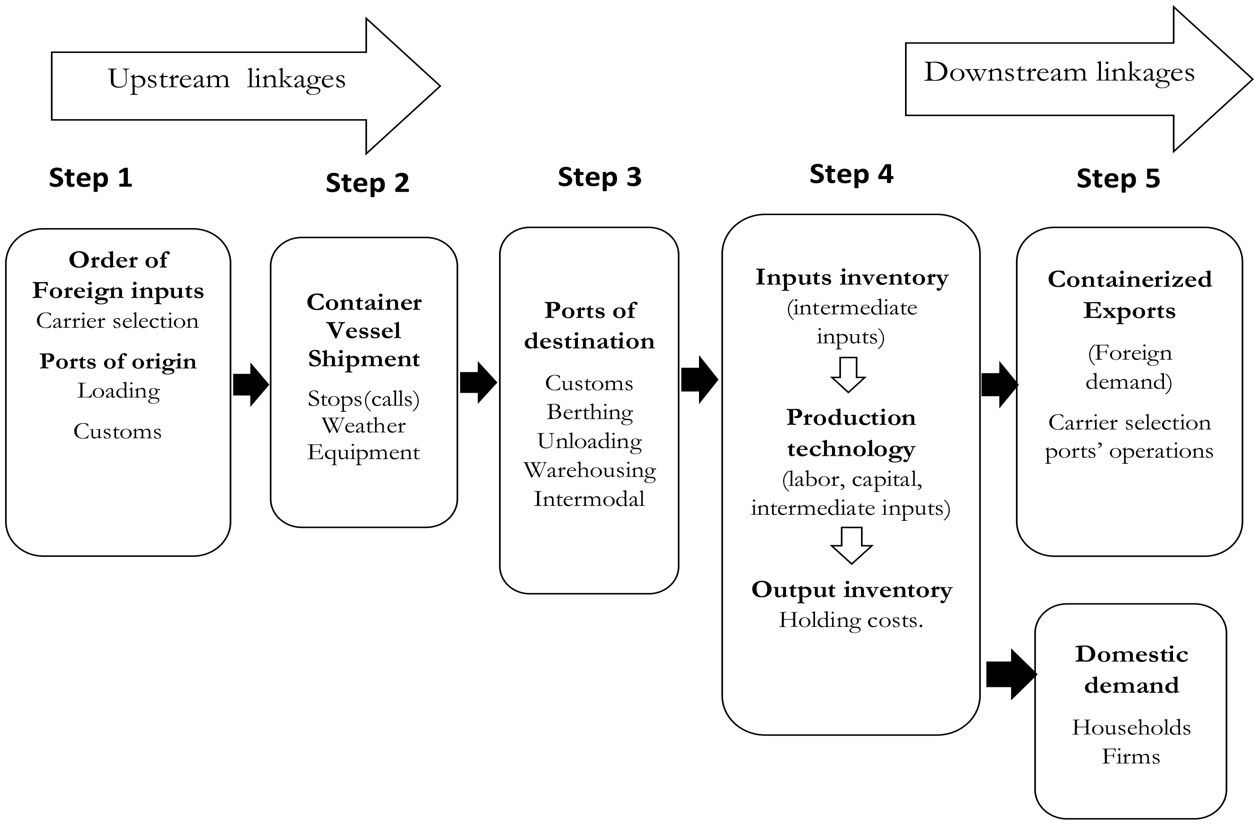
Our methodology follows the production networks model in Carvalho et al. (2021). We expand their reasoning by adding the international container shipping logistics and the global trade of goods (U.S. manufacturing's imports of intermediate inputs and exports of output to foreign markets). Then, we disentangle the mechanisms inherent to the upstream and downstream linkages through which an unreliability of the container shipping might affect U.S. manufacturing's output.

Figure 4 depicts our theoretical model. U.S. manufacturing industries go through various steps as they rely on the container logistics to import intermediate inputs (upstream) and to export their output (downstream). In our theoretical exercise, we identify the delivery effect, the productivity effect, and the input inventory effect as the drivers through which container disruptions affect output in the upstream channel. The delivery effect captures the change in the production schedule following a disruption in container shipping that affects the on-time arrival of inputs. The productivity effect captures the change in the efficiency in the use of labor and capital following a disruption in container logistics. The input inventory effect describes the change in inventory strategy as a result of the disruption to the container shipping network: the change in inventory strategy can target an increase in the stock of inputs to be carried (just-in-case) or a very low level of the stocks of inputs (just-in-time). The output inventory effect, the sales effect, and the competitiveness effect constitute the downstream channel's mechanisms. The output inventory captures the change in the output inventory stock following a disruption in container shipping. The sales effect describes the decrease in the sale revenue due to disruptions to the container logistics. The competitiveness effect shows the increase in

[21] Bureau of Transportation Statistics, U.S. Ports Work Through Daunting Challenges to Deliver the Goods, Jan 2022.
[22] SeaTrade Maritime News, Congestion shifts to US East Coast ports, July 2022.

U.S. export prices as a result of the rise in the freight rate following disruptions in container logistics.

Figure 4: Global stages of fabrication with container logistics networks



Notes: Upstream linkages reflect industries' reliance on container logistics networks in importing foreign inputs used in their production process. Downstream linkage dependency shows industries' reliance on container logistics networks for the export of their output to foreign markets.

Step 1 - Delivery effect: Industry i defines its production goal Y_{it} for the period t in equation (3.1). This production target requires a certain amount of labor, capital, and intermediate inputs. The intermediate inputs can be purchased domestically or abroad. The decision to rely to some extent on foreign inputs exposes industry i to potential supply chain disruptions such as the unreliability of the container shipping. For example, a shortage or strike of ports' workers, a slowdown of customs clearance process, an unplanned increase of the volume of container ships, and the low quality of the port of origin's infrastructure could delay the shipping and arrival of container vessels.

$$Y_{it} = f(Labor_{it},\ Capital_{it},\ Intermediate\ inputs_{it}) \tag{3.1}$$

Step 2 - Delivery effect: The goods are shipped through container vessels and are on their way to the port of destination. Several challenges could affect container shipping unreliability (UR_t): vessels not working properly, bad weather, number of stops on the route, attacks from pirates and terrorists, and congestion at choke points such as Suez and Panama Canals.

Step 3 - Delivery effect: The container vessel enters the queue at the port of destination. A shortage or a strike of port workers, difficulties to find storage space, and heavy seasonal container vessels traffic could cause the vessel to miss their arrival schedule. The container vessel is considered arrived when it reaches the berth. Its cargo can be unloaded and moved to the nearest container freight stations (CFS) of the carrier. The buyer can now take ownership of goods.

Step 4 - Productivity effect and Input Inventory effect: Industry i uses the hinterland intermodal subsystems (rail, trucking) to transport the imported intermediate goods from carrier's warehouse to its factory. The empty containers are returned to the carrier and can be used to export goods from the United States to other destinations. Equation (3.2) shows that the delivery of foreign inputs (M_{it}^f) is a function of the container unreliability rate.

$$M_{it}^f = g(UR_t) \qquad \textit{where} \quad g^{'}(UR_t) < 0 \tag{3.2}$$

Any factors causing container shipping to be unreliable will delay the on-time and in-full delivery of foreign inputs to industry i. Equation (3.2) implies that when the container unreliability rate increases, the on-time and in-full delivery of foreign intermediate inputs is challenged. The available level of intermediate inputs required to produce the targeted output (Y_{it}) could be insufficient. This situation would limit industry $i's$ ability to keep its labor and capital running optimally. It could also affect the commitment toward its customers. The delivery of foreign inputs M_{it}^f at $i's$ factory is added to the supply of domestic inputs (M_{it}^d) to form the total input delivery (M_{it}) in equation (3.3).

$$M_{it} = M_{it}^f + M_{it}^d = g(UR_{it}, \cdot) + M_{it}^d \tag{3.3}$$

Equation (3.4) details the flow of inputs: a portion of the inputs is used for production (X_{it}) and the other part will be the change or stock of input inventory(ΔIM_{it}). When industry i is running a just-in-time (JIT)[23] inventory strategy, ΔIM_{it} is kept at a low level or is negative. This strategy is used by industries to minimize holding costs and when the supply chain is reliable.

If industry i is implementing a just-in-case (JIC)[24] inventory approach, ΔIM_{it} will be positive and high because industry i is choosing to carry extra buffer stocks of inventory. This approach is used when the supply chain is unreliable or when there are uncertainties regarding future delivery of goods. However, the just-in-case approach comes also with high carrying inventory costs.

[23] Just-in-time prioritizes efficiency by producing goods only when needed with lower level of input inventory investment

[24] The just-in-case emphasizes a low risk management by maintaining higher inventory levels.

$$M_{it} = X_{it} + \Delta IM_{it} \tag{3.4}$$

Industry i puts together labor, capital, and the bundle of intermediate inputs X_{it} to produce its output (Y_{it}) using the production function in equation (3.1).

Step 5 - Output inventory effect, Sales effect, and Competitiveness effect: For each period, industry's i output (Y_{it}) supplies domestic demand (D^{d}_{it}) and foreign demand (D^{f}_{it}) as shown equation (3.5). The remaining part of Y_{it} will be the change or stock of output(ΔN_{it}).

$$Y_{it} = \Delta N_{it} + D^{d}_{it} + D^{f}_{it} \tag{3.5}$$

When sales grow faster than output production of final product, the stock of output inventory (ΔN_{it}) decreases. Otherwise, the output inventory stock increases. Industry i makes arrangements to export a portion of its output into foreign markets (D^{f}_{it}). This requires access to available container carriers, empty containers, and container vessels as illustrated in figure 4. Once industry i assembles all the logistics resources to export its output using the container shipping network, its cargo has to go through vessel loading and customs clearance procedures before its output can be exported. Because the same container carriers are usually conducting import and export shipment, a delay in the import of intermediate goods that causes the container unreliability rate to increase will also affect the availability of empty containers needed for the export of the output. Therefore, industry $i's$ exports of output depend on the container unreliability rate as it is expressed in (3.6).

$$D^{f}_{it} = \phi(UR_t, \cdot) \tag{3.6}$$

where $\phi^{'}(UR_t) < 0$. Equation (3.6) describes the sales effect through the downstream linkages channel. An increase in the container unreliability rate would delay and decrease the delivery of goods exported to foreign markets. This situation can also increase industry $i's$ output inventory holding costs (ΔN_{it}) if the domestic market cannot absorb the excess stocks of output that could not be exported due to an increase to the unreliability rate of the container shipping.

Our theoretical model presented above shows a characterization of the relationship between the reliability of container shipping, the primary factors of production (labor and capital), the intermediate inputs and output inventory management. Efficient inventory management can smooth disruptions to container logistics, which are characterized by an increase of the unreliability rate. Shocks that cannot be absorbed by inventory adjustments will have a negative effect on industry output. In the next section, we will demonstrate how disruptions of container shipping erode industry output through its upstream and downstream integration into the global value chain.

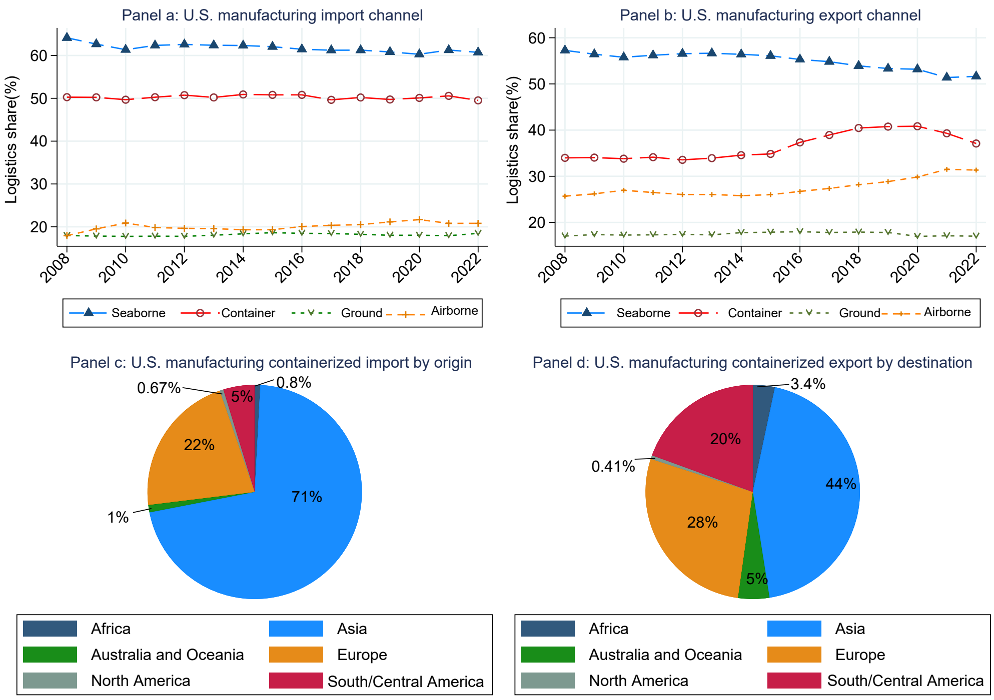
4 Data and construction of container disruption index

In this section, we present U.S. manufacturing's reliance on container shipping logistics and the construction of the container disruption index.

4.1 U.S. manufacturing's reliance on container logistics

Panels a and b of figure 5 show that around 50% of U.S. manufacturing's imported intermediate goods are shipped through containers. At the same time, 6.5% of U.S. manufacturing output is exported to foreign markets and 36% of these exports are shipped through container logistics.[25]

Figure 5: Container share of Manufacturing import and export



Notes: Ground refers to railroad and trucking logistics. Major trading partners in Asia include China, Japan, South Korea, Taiwan, Thailand. Major trading partners in Europe include Germany, United Kingdom, Italy, France, and Netherlands. Major trading partners in South and Central America include Chile, Colombia, Honduras, and Peru. Source: The Container ratio measure is author calculation based on 2019 data from the U.S. Census Bureau, "USA Trade Online," https://usatrade.census.gov, accessed on July 8, 2023.

When looking at the ports of origin (panel c of figure 5), Asia accounts for more than two-thirds of U.S. manufacturing's containerized imports, with China alone representing 35%. Europe represents 22% of U.S. containerized imports with Germany accounting for 5.32%. Panel d of figure 5, shows Asia

[25]Figure A4 shows the container dependence of import and exports for U.S. manufacturing industries across years.

as the destination of 44% of U.S. containerized exports. China (11%) and Japan (8%) are U.S. major importers through container shipping in Asia. Europe is the second importer of U.S. goods through containers with Netherlands and Belgium accounting respectively for 5% and 4% of U.S. containerized exports.

4.2 U.S. containerized ports

Table 1 shows the top ten U.S. container ports by their traffic volume estimated in the number of Twenty-Foot Equivalent Unit (TEU) received or shipped.[26] The top 10 ports handled a total of 36.5 million TEU, accounting for 86% of container traffic handled by all U.S. container ports. Half of the container traffic in the United States goes through three major coastal container hubs ports: Los Angeles, Long Beach, and New York-New Jersey. When one of these three hubs is congested, there could be implications for other ports as carriers try to find the nearest ports that can provide the fastest opportunity to discharge their cargo or reload their next shipment.

of Twenty-Foot Equivalent Unit (TEU) received or shipped

Table 1: Top 10 U.S. ports by volume of TEU in 2020

	Import		Export		Total containerized trade	
Ports	Import (10^3 TEU)	Import share (%)	Export (10^3 TEU)	Export share (%)	Total trade (10^3 TEU)	Share of total (%)
Los Angeles	5028	20.06	1376	12.07	6404	17.57
Long Beach	4228	16.87	1155	10.13	5383	14.77
New York	4186	16.7	1253	10.99	5439	14.92
Savannah	2365	9.44	1337	11.72	3702	10.16
Houston	1343	5.36	1185	10.39	2528	6.94
Virginia	1320	5.27	852	7.47	2172	5.96
Charleston	1084	4.33	737	6.46	1821	5
Oakland	1015	4.05	796	6.98	1811	4.97
Tacoma	710	2.84	414	3.63	1124	3.09
Seattle	618	2.47	358	3.14	976	2.68

Notes: The TEU describes the size of a shipping container and is used as standardized measures for the amount of volume being shipped. Alternatively, the forty-foot equivalent unit (FEU) is often used. Source: U.S. Army Corps of Engineers, Principal Ports of the United States, Waterborne tonnage for principal U.S. ports and all 50 states and U.S. territories, available at https://www.iwr.usace.army.mil/about/technical-centers/wcsc-waterborne-commerce-statistics-center/ as of May 20, 2023.

4.3 Description of the data

We start by presenting the container reliability measures defined by Sea-Intelligence (2021). Then, we describe the data and the steps leading to the construction of the SCDI.

4.3.1 Container reliability measures

Sea-Intelligence (2021) publishes three measures of container reliability: the container reliability rate, the average delays, and the average delay of late container vessel arrivals. The container reliability

[26]Figure A2 shows the geographical location of the top 25 U.S. containerized U.S. ports. TEU is a standard marine shipping container that measures 20 feet long, 8 feet wide and 8.6 feet tall.

measures are constructed with data that covers 324 distinct deep sea liner services, 349 distinct ports, benchmarks scores for 60 carriers, and 34 deep-sea trade lanes across 18 geographical regions.[27]

The following scenario explains the calculation of the three container reliability variables. Suppose that we have five vessels on a service arriving based on a certain number of days relative to a scheduled arrival: $[-4, +3, -1, +2, -1]$. Minus means a vessel arriving early and plus means that the container vessel arrives late.

The *reliability rate* (R_t) is the monthly percentage of individual, distinct port calls, where the actual container vessel arrival at the berth is made within a threshold of +/- one calendar day relative to a vessel schedule published in advance.

$$R_t = \frac{Number\ of\ vessels\ delayed_t}{Number\ of\ vessels\ delayed_t\ and\ vessels\ non-delayed_t} \times 100 \tag{4.1}$$

From the equation (4.1), we can derive the estimate of the container unreliability rate as follows.

$$UR_t = 100 - R_t \tag{4.2}$$

Using the scenario above, there are two vessels that arrived more than one day late [+3, +2]. Therefore, the reliability rate would be $R_t = (2/5) \times 100 = 40\%$ and the unreliability rate is $UR_t = 100 - 40\% = 60\%$

The average delay (ad_t) is the average number of days considered as delays across all vessel's arrivals including those that are early, late, and on-time to an initial scheduled. Using the case scenario (1) above, the average delays of all vessels would be $average\ delays_t = (-4+3-1+2-1)/5 = -0.2\ days$

The average delay of late vessels (ald_t) is the average number of days considered as delay across only the vessels that were recorded as being late. Using the case scenario above, there are two vessels considered as late. Hence, $average\ delay\ of\ late\ vessels = (2+3)/2 = 2.5\ days.$

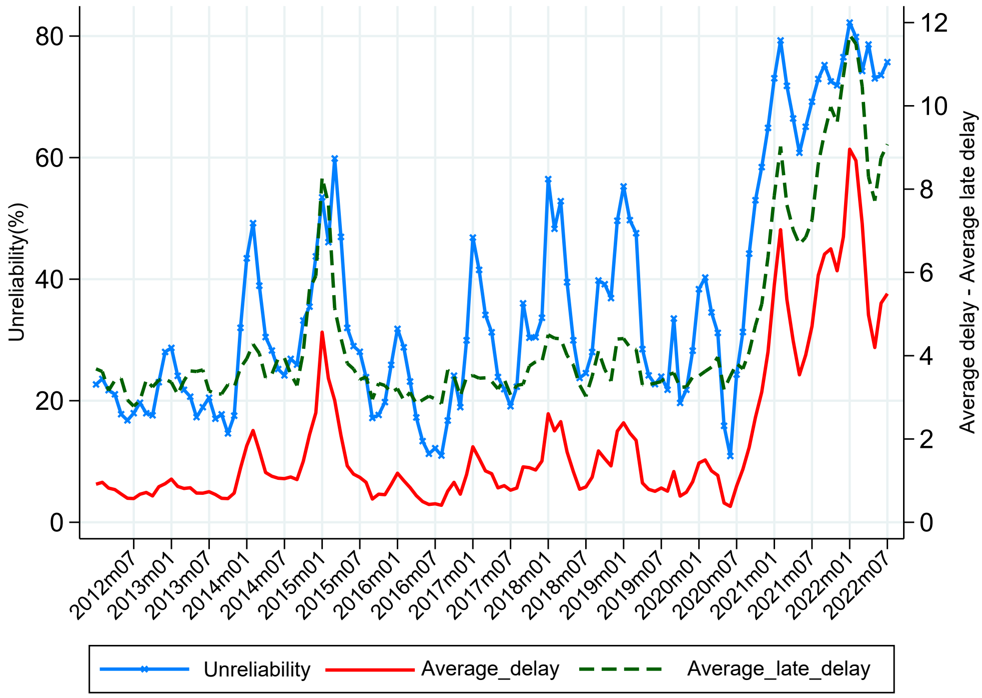
Figure 6 shows the trend of the three container reliability measures from Sea-Intelligence (2021). Before January 2020 there are cyclical short-term disruptions especially around the month of January due to shippers ordering ahead of lunar calendar. After January 2020, the Covid-19 period is characterized by a deep and persistent decline of the container reliability measures.

4.3.2 Input-output tables (IO tables)

We focus on the import of intermediates goods in the IO tables. These tables contain 72 industries and are produced annually by the Bureau of Economic Analysis (BEA). Our IO tables cover the period

[27] Sea-Intelligence (2021).

Figure 6: Container unreliability measures



Notes: Container reliability is expressed in percentage. Average delay and average late delays are estimated in days. Source: Sea Intelligence, Global liner performance database, accessed August 2023.

of 2012 to 2022. We use these data to construct the upstream channel of the container disruptions index.

4.3.3 U.S. trade data

We exploit the USA trade online (U.S. Census data portal) to extract U.S. manufacturing imports and exports and also its containerized shipping data. Industries are classified at the three digits level code of the North American Industry Classification System (NAICS). Then, we match the IO tables to the U.S. import and export data using a concordance table provided by the BEA.

4.4 Construction of the supply chain disruption index

We start by defining a general formulation of the containerized ratio (CR). Then, we describe the calculation of the containerized ratio of imported intermediate goods (CRIMP) and exports (CREXP).

4.4.1 Containerized ratio (CR):

The CR is the percentage of imports or exports of goods shipped using containers.

$$CR_{it} = \frac{TCT_{it}}{TT_{it}} \tag{4.3}$$

where TCT_{it} is the total containerized trade of industry i for the month t. TT_{it} is the total imports (foreign inputs) or exports of industry i at time t.

4.4.2 Containerized ratio of imported intermediate goods (CRIMP)

The goods imported into the United States include both intermediate and final goods. We use the trade data and import IO tables to calculate the CRIMP for each industry. In practice, we proceed in three steps to compute industry-specific containerized ratio of imports.

- Step 1: We use IO tables to calculate the share of each industry's usage of imported inputs.
- Step 2: We can calculate the containerized share of each industry using equation (4.3).
- Step 3: We combine the steps above to derive the containerized ratio of import in equation (4.4).

$$CRIMP_{it} = \sum_{j=1}^{J} \frac{imp_{ijt}}{imp_{it}} \cdot CRIMP_{jt} \tag{4.4}$$

where imp_{ijt} is the value of imported intermediate goods j by industry i at time t (from input output tables), $imp_{it} = \sum_{j=1}^{J} imp_{ijt}$ is the value of total imported intermediate goods by industry i at period t. For each industry j's $CRIMP_j$ is calculated by the following equation:

$$CRIMP_{jt} = \frac{CIMP_{jt}}{TIMP_{jt}} \tag{4.5}$$

where $CIMP_{jt}$ is the value of month t containerized imported goods by industry j; $TIMP_{jt}$ is the value of month t total imported goods by industry j. Equation (4.4) shows that inputs used by industry i come from various other industries j. A container disruption in any of industries j supplying inputs to industry i could therefore affect industry's i production plans.

4.4.3 Containerized ratio of exports (CREXP):

The $(CREXP)$ is calculated in equation (4.6).

$$CREXP_{it} = \frac{CEXP_{it}}{TEXP_{it}} \tag{4.6}$$

where $CEXP_{it}$ is the value at period t of the containerized exported goods by industry i; $TEXP_{it}$ is the value at period t of the total exported goods by industry i. The ratio of containerized trade within each industry provides insight into the reliance on the container shipping for international trade. Figure A4 shows the containerized ratios of import and export for the eighteen industries in our study. Across industries and time, there is a relative stability. However, there is a downward trend for containerized import and export of the industry prime metal since the start of the Covid-19 pandemic. The containerized ratio of exports of the industries wood product and food manufacturing has been increasing consistently since 2015.

4.4.4 Global value chain's dependence:

We define import dependence (imp_dep_{it}) and export dependence (exp_dep_{it}) in equations (4.7) and (4.8) using each industry's foreign inputs, exports, and industrial production. These two variables represent the intensity of dependence on respectively foreign intermediate inputs and foreign demand of U.S. manufacturing output.

$$imp\_dep_{it} = \frac{imp_{it}}{IP_{it}} \tag{4.7}$$

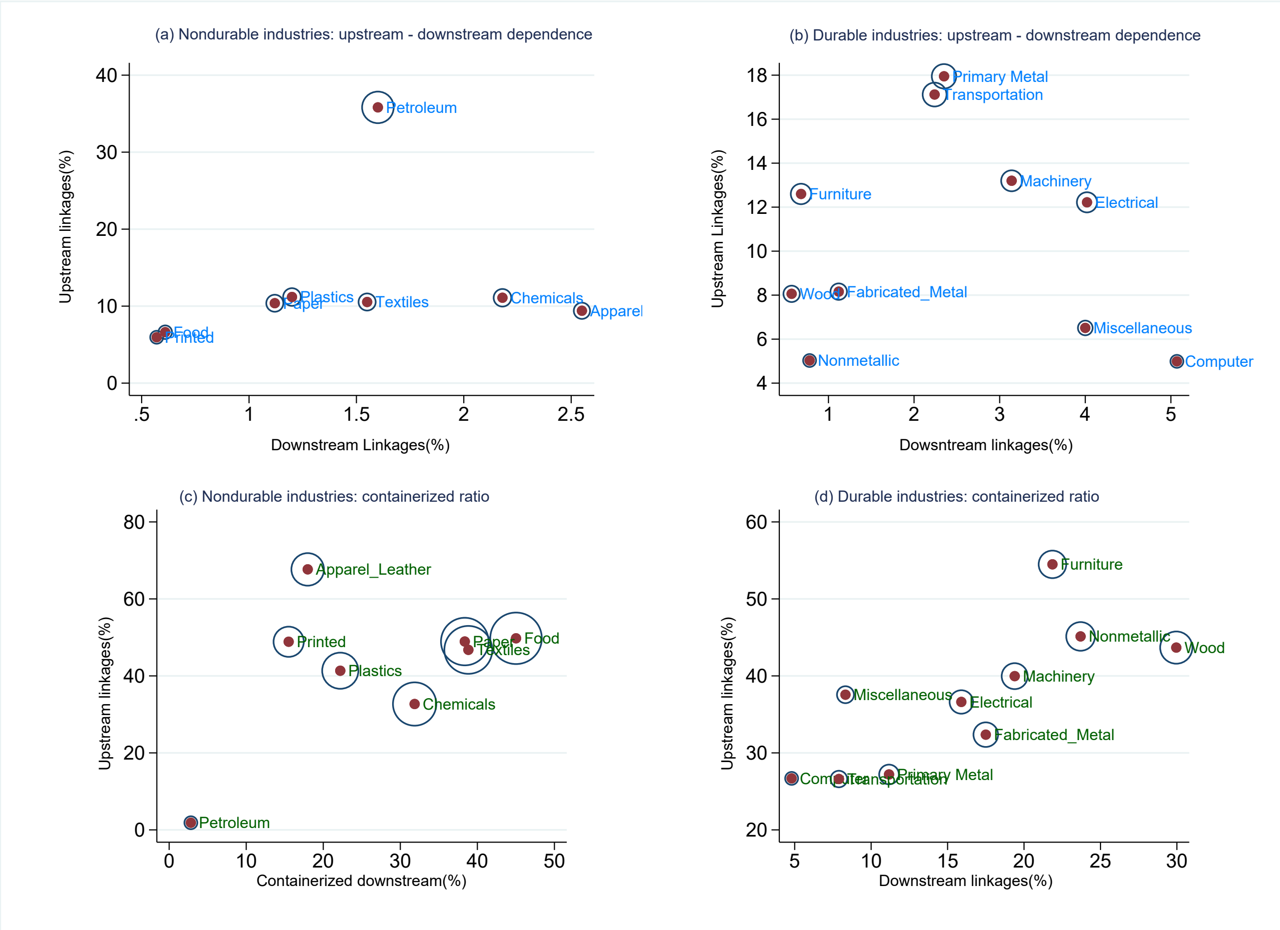
$$exp\_dep_{it} = \frac{TEXP_{it}}{IP_{it}} \tag{4.8}$$

Here, $imp_{it} = \sum_{j=1}^{J} imp_{ijt}$ is the value at time t of the sum of all the imported intermediate goods used by industry i. IP_{it} is industry i industrial production at time t. $TEXP_{it}$ is the value at period t of the total exported goods by industry i. IP_{it} is industry's i industrial production value at time t. Figure A3 shows the import dependence (imp_dep_{it}) and export dependence (exp_dep_{it}) for U.S. non-durable and durable industries. Over time, the import dependence is relatively constant except for a declining trend of petroleum reliance on foreign inputs since 2012. The same stable pattern can be seen for export dependence except for industries such as chemicals, petroleum, and printed products, which experienced an upward trend.

Figure 7 shows the average measure of U.S. manufacturing's global dependence and reliance on container logistics during the period of our study (January 2012 to July 2022).[28] Across industries, there is a large variation. In panel (a), non-durable industries have on average a modest reliance on foreign inputs(upstream) except petroleum. In panel (b), computer and miscellaneous are the durable industries with a strong export dependence (downstream). In panel (c), apparel shows a relatively strong CRIMP while food shows a high CREXP. In panel d, furniture and wood are the industries with both a high CRIMP and CREXP.

[28]Each circle and dot represents a particular industry. The size of a circle is proportional to an industry's import dependence in panels a and b and to CREXP in panels (c) and (d).

Figure 7: U.S. manufacturing dependence on global markets and container logistics



Notes: Panels (a) and (b) show U.S. industries' reliance on international market. Y-axis represents the *import dependence*. X-axis represents the final product *export dependence*. Panels (c) and (d) shows U.S. industries containerized ratio for seaborne logistics. Y-axis represents the inputs/intermediate products containerized ratio of import. X-axis represents the final product containerized ratio of export. Source: author's calculation using the average of 2012-2022 data from U.S. Census Bureau, "USA Trade Online," https://usatrade.census.gov, accessed on July 8, 2023.

We combine the container unreliability rate, the containerized ratio of import and export, and the import and export dependence to construct our container disruption index for upstream linkages *(upindex)* and downstream linkages *(downindex)*.

$$SC\ disruption\ index = unreliability\ rate \cdot CR \cdot trade\ dependence \tag{4.9}$$

So more specifically, we write the upstream and downstream disruption index as follow.

$$upindex = UR \cdot CRIMP \cdot\ imp\_dep \tag{4.10}$$

$$downindex = UR \cdot CREXP \cdot\ exp\_dep \tag{4.11}$$

When we replace the unreliability rate UR in equations (4.10) and (4.11) by the average delay and the average delay of late vessels, we obtain alternative estimates of container disruptions. We use these alternative measures in the robustness checks of our econometric regressions in tables 5 and 6.

5 Empirical analysis

5.1 Model specification

Our empirical analysis follows Acemoglu et al. (2016). Using the constructed container disruption index in section 4.4 (equations 4.10 and 4.11) as the independent variable and industrial production (IP) as the dependent variable, we follow Beck and Katz (1995) to estimate a panel autoregressive distributed lag model with a panel-corrected standard error (PCSE)[29] in equation (5.1). We select the PCSE to address any potential spuriousness that could arise from the relationship between our dependent and independent variables. Before we conduct the panel regression and the impulse response exercise, we performed a series of specification tests: the unit root test to ensure that our variables are stationary; the Hausman test to select between random and fixed effects; the optimal lag test to identify the appropriate lags to apply for our variables.[30] Our empirical strategy distinguishes two periods based on the Covid-19 timeline (section 2): the pre-Covid period (January 2012 - December 2019) has 1674 observations and the Covid period (January 2020 - July 2022) has 468 observations. Our analysis starts on January 2012 and ends in July 2022 to match the coverage of the container schedule reliability data that we received from Sea Intelligence. We estimate the following equation for both periods:

$$\begin{aligned} & Y_{it} = \beta_0 + \sum_{j=1}^{p} \beta_j Y_{i,t-j} + \theta \cdot Disruption\ Index_{it} + \phi X_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \\ & i = 1, 2, ..., n;\ t = 1, 2, ..., T. \end{aligned} \tag{5.1}$$

where Y_{it} is industrial production of industry i.[31] $Y_{i,t-j}$ represents the lags for industrial production. $Disruption\ Index_{it}$ is the vector of container disruption indices through the upstream channel ($upindex_{it}$) and through the downstream channel ($downindex_{it}$). The parameter θ represents the change in industrial production as a result of a one-unit increase of the disruption index.[32] We follow

[29] Models with panel-corrected standard error (PCSE) allow for the estimates of standard errors and variance based on the assumptions that disturbances are heteroskedastic and contemporaneously correlated across panels.

[30] Results of these tests are shown in tables A2, A3, A4, A5, and A6.

[31] Industrial production (IP) is an index that measures the real output of different industries such as the manufacturing, mining, and electric and gas utilities industries, etc.

[32] The unit change of the disruption index can be also translated in terms of days of delay of container vessels. When we consider both the periods before and after the Covid-19, a one-unit change means around a delay of 2 days. If we

the reasoning from Meier and Pinto (2024), Yao (2005), and Humphreys et al. (2001) to include inventory (Invship) and employment (emp) as the two main control variables.[33] Our regression results in tables A6 and A7 are not robust without the inclusion of the inventory and the employment as control variables. α_i and γ_t are respectively the industry fixed effect and the time fixed effect.

Table 2: Descriptive statistics

Pre-Covid Period

Variable	Observations	Mean	Std. dev.	Min	Max
IP	2,016	100.85	6.58	81.26	136.23
CRIMP	1,728	0.399	0.141	0.007	0.736
CREXP	2,016	0.223	0.124	0.014	0.624
imp_dep	1,728	0.113	0.084	0.030	0.679
exp_dep	1,728	0.019	0.013	0.0045	0.063
Unreliability_Rate	2,163	0.287	0.113	0.109	0.598
upindex	1,728	1.09	0.68	0.055	4.71
downindex	1,728	0.091	0.073	0.0032	0.43
Emp	1,824	6.36	4.79	1.06	17.38
Invship	2,016	1.48	0.42	0.66	2.79

Covid Period

Variable	Observations	Mean	Std. dev.	Min	Max
IP	546	95.77	7.62	70.46	112.35
CRIMP	558	0.377	0.134	0.022	0.703
CREXP	651	0.224	0.135	0.014	0.586
imp_dep	558	0.121	0.060	0.029	0.379
exp_dep	558	0.020	0.013	0.0043	0.053
Unreliability_Rate	525	0.667	0.143	0.243	0.822
upindex	558	2.52	1.61	0.084	7.28
downindex	558	0.20	0.15	0.004	0.65
Emp	494	6.35	4.96	.84	17.26
Invship	546	1.61	0.50	0.62	2.94

Notes: The Pre-Covid period covers January 2012-December 2019 while the Covid period covers June 2020-July 2022. The IP is published on a monthly basis by the Federal Reserve Board with 2017 as the base year for a value of 100. Employment is in thousands of persons.

5.2 Descriptive statistics

Table 2 shows the summary statistics of our variables for each period. We include eighteen U.S. manufacturing industries in the study. Table A1 lists these industries and their share in the total U.S. manufacturing output.[34] When comparing the descriptive statistics of the variables across the pre-Covid and the Covid periods, we do not observe a large change of the CRIMP, the CREXP, the imp_dep, and exp_dep. The value of our disruption indices (upindex and downindex) more than doubled in the Covid period compared to the pre-Covid period. Our supply chain disruption index is a combination of the unreliability rate, CRIMP, CREXP, import dependence and export dependence. The largest driver of the increase of our disruption index is the unreliability rate while other components of the index are stable across the two periods of our study. The unreliability rate declines by 43% during the Covid period. The inventory to shipment ratio (invship) increases by 9% during the Covid-19 pandemic period. This situation is consistent by U.S. manufacturing industries building up stocks of inputs inventory to cope with uncertainties in the supply chain.[35] Employment is flat during both periods, however the Covid period includes the lockdown and the recovery periods when

focus only on the period before the Covid-19, a one-unit change of the disruption index is similar to 1.19 day. A one-unit change during the Covid-19 period would corresponds to a container delay of 4 days.

[33]Inventory and employment are critical components to the supply chain process describes in our theoretical model (figure 4). They help us to control for drivers of the business cycle that could affect industrial production: inventories account for the supply side factors that could affect IP; employment accounts for the demand side factors that could also affect IP.

[34]These industries are classified at the three digits code level of the NAICS.

[35]McKinsey&Company, How the pandemic affected inventory, June 2024.

the economy reopened. Industrial production dropped by 5% during the Covid period compared to the pre-Covid period.

5.3 Baseline results: regression exercise

The results of our pre-Covid panel regression are shown in table 3. The coefficients of the disruption indices for upstream and downstream are both smaller in magnitude in magnitude compared to the Covid period in table 4. They are also not statistically significant. During the pre-Covid period, the supply chain was less unreliable with the container unreliability rate at 28% compared to 60% during the Covid period. Figure 6 shows that before January 2020 the supply chain was relatively resilient compared to the period after January 2020.[36]

Table 3: Industrial Production: Pre-Covid period

	(1) IP	(2) IP	(3) IP
Y_{it-1}	0.692***	0.690***	0.690***
	(0.0330)	(0.0330)	(0.0330)
Y_{it-1}	0.183***	0.183***	0.183***
	(0.0397)	(0.0397)	(0.0397)
Y_{it-3}	0.0758**	0.0767**	0.0754**
	(0.0329)	(0.0329)	(0.0329)
$upindex_{it}$	-0.216		-0.186
	(0.154)		(0.161)
$downindex_{it}$		-1.441	-1.029
		(1.241)	(1.308)
Emp_{it}	0.429***	0.429***	0.442***
	(0.0773)	(0.0763)	(0.0776)
$Invship_{it}$	-1.368**	-1.346**	-1.360**
	(0.617)	(0.618)	(0.618)
Observations	1674	1674	1674
Number of industries	18	18	18
Time fixed effect:	Yes	Yes	Yes
Industry fixed effect:	Yes	Yes	Yes

Notes: Standard errors in parentheses. * $p < .1$, ** $p < 0.05$, *** $p < 0.01$
Pre-Covid covers January 2012-December 2019

The negative sign of the coefficient of *Invship* in table 3 is expected and shows the pursuit of supply chain efficiency by industries: carrying higher level of inventory is costly in terms of opportunity costs, space in the warehouse, and insurance. One way to explain this result is the dominant just-in-time inventory strategy [37] during the pre-Covid period. Industries didn't find it necessary and efficient to carry extra weeks of inventory supply in their factories.

In contrast to the pre-Covid period, the impact of container disruptions during the Covid-19

[36]By supply chain resilience, we mean the ability of the container reliability rate to recover from disruptions, such as natural disasters, pandemics or other unexpected events. IBM, What is supply chain resilience? November 2024.
[37]Supplychaindive, Did the pandemic really kill just-in-time? Experts weigh in, November 2021.

Table 4: Industrial Production: Covid period

	(1) IPG	(2) IPG	(3) IPG
Y_{it-1}	0.884***	0.910***	0.883***
	(0.0746)	(0.0745)	(0.0751)
Y_{it-2}	-0.272***	-0.303***	-0.280***
	(0.0652)	(0.0658)	(0.0655)
Y_{it-3}	0.0455	0.0423	0.0431
	(0.0394)	(0.0415)	(0.0400)
$upindex_{it}$	-0.551***		-0.383**
	(0.192)		(0.185)
$downindex_{it}$		-5.146***	-3.556**
		(1.817)	(1.779)
Emp_{it}	2.354***	2.445***	2.449***
	(0.333)	(0.352)	(0.354)
$Invship_{it}$	-4.033**	-4.586***	-4.439**
	(1.732)	(1.740)	(1.799)
Observations	468	468	468
Number of industries	18	18	18
Time fixed effect:	Yes	Yes	Yes
Industry fixed effect:	Yes	Yes	Yes

Notes: Standard errors in parentheses. * $p < .1$, ** $p < 0.05$, *** $p < 0.01$
The Covid period covers June 2020-July 2022

period on U.S. manufacturing output is larger. Table 4 shows that the impact of the container disruptions is twice as large through the upstream channel and more than three times as large through the downstream channel. The magnitude and statistical significance of this impact implies that the worsening of container reliability played a role in the decline of U.S. manufacturing output.

The sign and magnitude of the coefficients of inventory and employment also reveal their importance for U.S. manufacturing output. We encounter an omission bias issue in our econometric exercise when we do not include employment and inventory as control variables (Tables A7 and A8). Our regression results are not robust, and the container disruptions do not have any impact on industrial production. The coefficient of employment is five time as large while the coefficient of inventory is three time as large compared to their pre-Covid levels. Many industries struggled[38] to secure labor and intermediate inputs to produce and satisfy domestic and foreign markets. Therefore, a small change to the employment and input inventory during the Covid period has a more pronounced impact on manufacturing industries. To reduce uncertainties created by supply chain disruptions, U.S. manufacturing industries shifted their inventory strategy to a just-in-case approach by building up heavy buffer stock and extra weeks of supply of material supplies.[39]

[38] Pitschner, Supply chain disruptions and labor shortages: COVID in perspective, Economic Letters, December 2022. Federal Reserve Bank Saint Louis, Labor Constraints Remain Greatest Challenge for Resurgent Manufacturing Sector, July 2022.

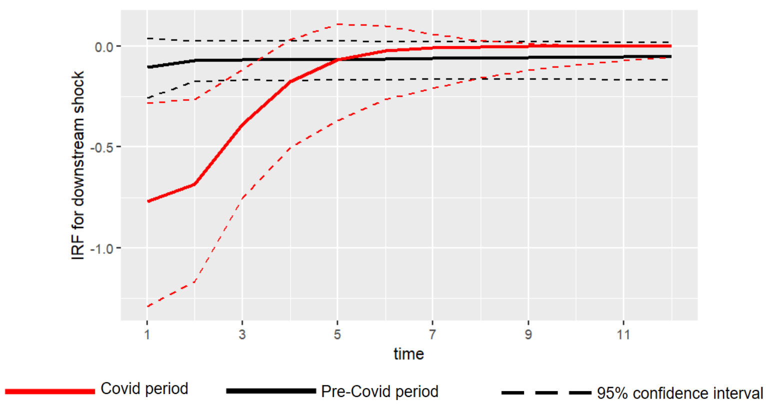
[39] CNBC, Lack of workers is further fueling supply chain woes, September 2021.

The regression results in tables 3 and 4 illustrate the process described by our theoretical model in figure 4: a reliable container shipping network would allow industries to receive their intermediate inputs in-full and on-time to keep up with their production schedule and to satisfy both their domestic and foreign demands. On contrary, a high container unreliability rate would create a shortage of inputs that cannot always be replaced in a short time frame by manufacturing industries. This situation could affect the productivity of other factors of production such as labor and capital: manpower and machines cannot be fully productive if there are not enough material supplies required for their optimal operation. Factories would operate under their capacity causing a decrease in their output goal.[40]

5.4 Impulse response function

We perform the impulse response exercise using the model specification in the equation 5.1.[41] The purpose of impulse response exercise in our study is to estimate the extent of U.S. manufacturing industrial production reaction following an increase of the container disruption index by one standard deviation. This exercise helps us to capture two important results: *(1)* the magnitude of the change of industrial production as a result of a one standard deviation change in our container disruption index; *(2)* the length of time that it would take industrial production to recover after a one standard deviation increase of our container disruption index.

Figure 8: Downstream Shock



Notes: Impulse response functions are derived from the model specification (equation 5.1) used in the regression in Table 3 and Table 4. Figures are based on reliability indicator. Black for before Covid, Thick red for after Covid. Dash line for 95% CI.

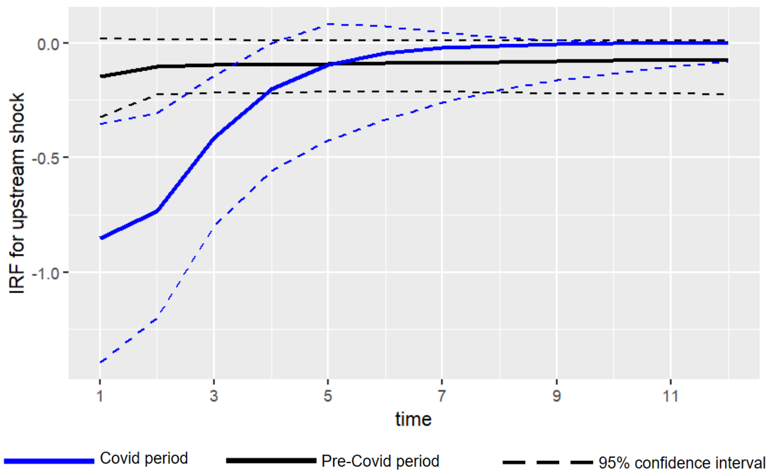
Figure 8 shows the impulse response of industrial production based on a one standard deviation shock to the container disruption index through the downstream channel. As shown by the straight black line representing the pre-Covid period, a supply chain shock does not have a significant impact on

[40] Rand, Supply Chain Disruptions: The Risks and Consequences, November 2021.

[41] Before we conduct the impulse response, we performed the same specification tests for the regression: Unit root, stationarity, appropriate lags. Tables A2, A3, A4, A5, and A6 recap the outcome of some of these tests.

the output of the manufacturing sector. The situation is different during the Covid period represented by the thick red line.

Figure 9: Upstream Shock



Notes: Impulse response functions are derived from the model specification (equation 5.1) used in the regression in Table 3 and Table 4. Figures are based on reliability indicator. Black for before Covid-19. Thick blue for during the Covid-19. Dash line for 95% CI.

An increase by one standard deviation of the container disruption through the downstream channel during the Covid-19 period has a strong and statistically significant impact based on the 95% confidence interval. This impact is persistent and significant with a recovery happening five periods after the increase in the disruption index. The impulse response function for the one standard deviation shock through the upstream channel is shown in Figure 9. A supply chain disruption from the upstream channel during the Covid-19 period has a bigger and longer lasting impact on the manufacturing output compared to the same shock before the Covid-19 pandemic. Figure 9 shows that the supply chain disruption before the Covid-19 periods has an impact that is weak follow by a quick recovery after two periods. However, the impact of the supply chain disruption though the upstream channel is strong during the Covid period and requires five periods to recover to its level before the increase of the disruption index. This result is consistent with the finding in Tables 3 and 4.

5.5 Robustness checks: alternative measures of container reliability

We follow the approach in section 4.4 to derive alternative disruption indices by replacing the container unreliability rate with average delays and average delay of late vessels.[42] Up_{ad} and $Down_{ad}$ are respectively the container disruptions indices for the upstream and downstream channels when we use average delays of all vessels. Up_{ald} and $Down_{ald}$ are respectively the container disruptions indices for the upstream and downstream channels when we use average delays of late vessels arrival.

[42]Section 4.3.1 explains these container reliability measures.

We also use the model specification in equation 5.1 where the main dependent variable is industrial production.

Table 5: Impact of average delay

	(Pre-Covid)	(Covid Period)	(Pre-Covid)	(Covid Period)	(Pre-Covid)	(Covid Period)
Y_{it-1}	0.693***	0.890***	0.692***	0.914***	0.692***	0.890***
	(0.0331)	(0.0741)	(0.0331)	(0.0744)	(0.0331)	(0.0745)
Y_{it-2}	0.182***	-0.280***	0.182***	-0.304***	0.182***	-0.285***
	(0.0398)	(0.0648)	(0.0398)	(0.0660)	(0.0398)	(0.0651)
Y_{it-3}	0.0771**	0.0445	0.0772**	0.0436	0.0769**	0.0434
	(0.0330)	(0.0398)	(0.0329)	(0.0416)	(0.0330)	(0.0403)
Up_{adit}	-0.952	-4.484***			-0.534	-3.158**
	(2.649)	(1.679)			(2.789)	(1.607)
$Down_{adit}$			-14.65	-41.33***	-13.22	-27.59*
			(21.44)	(15.68)	(22.64)	(15.05)
Emp_{it}	0.410***	2.370***	0.416***	2.412***	0.417***	2.435***
	(0.0757)	(0.337)	(0.0755)	(0.352)	(0.0758)	(0.353)
$Invship_{it}$	-1.358**	-4.107**	-1.358**	-4.585***	-1.359**	-4.481**
	(0.617)	(1.722)	(0.617)	(1.737)	(0.617)	(1.787)
Number of Observations	1674	468	1674	468	1674	468
Number of industries	18	18	18	18	18	18
Month fixed effect:	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect:	Yes	Yes	Yes	Yes	Yes	Yes

Tables 5 and 6 shows the results of the impact of container disruptions when the average delay and average delay of late arrivals are respectively the independent variables. The sign, magnitude, and statistical significance of the coefficients of the disruption indices are consistent with the findings in our baseline models (Tables 3 and 4) before and during the Covid periods. The consistency of the results is valid for the control variables. The results in tables 5 and 6 confirm the intuition that we explain in the theoretical section (figure 4): when the container reliability is severely challenged, there are sizable negative effects on U.S. manufacturing industries' output through both their upstream and downstream channels.

Table 6: Impact of Average delays of late arrivals

	(Pre-Covid)	(Covid Period)	(Pre-Covid)	(Covid Period)	(Pre-Covid)	(Covid Period)
Y_{it-1}	0.693***	0.882***	0.684***	0.901***	0.685***	0.875***
	(0.0331)	(0.0744)	(0.0330)	(0.0750)	(0.0330)	(0.0753)
Y_{it-2}	0.183***	-0.276***	0.185***	-0.296***	0.185***	-0.277***
	(0.0398)	(0.0644)	(0.0396)	(0.0658)	(0.0395)	(0.0647)
Y_{it-3}	0.0761**	0.0453	0.0770**	0.0411	0.0760**	0.0420
	(0.0330)	(0.0394)	(0.0327)	(0.0415)	(0.0328)	(0.0402)
Up_{aldit}	-1.755	-4.305***			-1.242	-2.876**
	(1.877)	(1.394)			(1.903)	(1.317)
$Down_{aldit}$			-37.44**	-42.41***	-35.67**	-30.37**
			(16.21)	(14.15)	(16.60)	(13.87)
Emp_{it}	0.424***	2.417***	0.469***	2.491***	0.478***	2.528***
	(0.0780)	(0.339)	(0.0767)	(0.362)	(0.0784)	(0.363)
$Invship_{it}$	-1.347**	-4.126**	-1.381**	-4.749***	-1.374**	-4.637**
	(0.617)	(1.724)	(0.619)	(1.752)	(0.619)	(1.805)
Number of Observations	1674	468	1674	468	1674	468
Number of industries	18	18	18	18	18	18
Month fixed effect:	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect:	Yes	Yes	Yes	Yes	Yes	Yes

6 Conclusion

In this study, we investigate the extent to which container logistics disruptions impact U.S. manufacturing output. To achieve this, we construct a supply chain disruption index based on measures of container unreliability from Sea Intelligence, industry-level containerized trade, and industry-level integration into foreign markets. For each of these measurements, we distinguish between downstream and upstream channels, representing the two primary pathways through which U.S. manufacturing industries are connected to the global value chain.

Using a global production networks model, we theoretically demonstrate that container disruptions through the upstream channel affect output via delivery, productivity, and input inventory effects. In the same way, container logistics disruptions through the downstream channel affect manufacturing output via output inventory, sales, and competitiveness effects.

Our econometric estimates using panel regression and impulse response show that an increase of the container unreliability rate (delays) would have a sizable negative and lasting impact on U.S. manufacturing output through both its downstream and upstream linkages. Our results are consistent when we use average delay and average delay of late container vessels as alternative measures of container disruptions. Our analysis also indicates that U.S. manufacturing industries shifted their inventory strategy since the start of the Covid-19 pandemic from a just-in-time towards a just-in-case approach to cope with uncertainties related to supply chain disruptions.

Our study is based on strong assumptions. We adopt a simplified representation of the relationship between schedule unreliability and industry-level output, operating through the channels of foreign inputs delivery and the shipment of exported final products. In reality, these relationships are likely more complex than depicted here. Nevertheless, our study represents a step towards understanding the interactions between domestic and global supply chain logistics and economic growth.

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2- Tables

Table A1: Industries' share of manufacturing gross output(%)

Industries	naics code	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Durable goods	**Durable goods**	**46.79**	**46.86**	**47.94**	**47.74**	**46.67**	**47.28**	**47.92**	**47.56**	**46.77**	**48.74**	**50.32**
Wood products	321	1.4	1.42	1.43	1.52	1.56	1.63	1.62	1.55	1.76	1.67	1.6
Nonmetallic mineral products	327	1.73	1.74	1.79	1.81	1.85	1.84	1.83	1.86	1.93	1.93	1.84
Primary metals	331	4.66	4.69	4.65	4.36	4.13	4.12	4.19	4.04	3.92	3.72	3.78
Fabricated metal products	332	5.95	5.87	5.95	5.77	5.61	5.6	5.74	5.75	5.66	5.58	5.36
Machinery	333	7.01	6.58	6.62	6.02	5.57	5.73	5.95	5.88	5.6	6.05	6.09
Computer and electronic products	334	6.14	6.01	5.99	6.05	6.16	6.33	6.54	6.62	7.13	7.47	7.7
Electrical equipment, appliances, and components	335	2.13	2.08	2.12	2.11	2.05	2.04	2.02	2.04	2.09	2.17	2.1
Transportation equipment	336	13.94	14.54	15.59	16.18	15.96	16.23	16.24	16.15	14.95	16.28	18.27
Furniture and related products	337	1.14	1.12	1.12	1.17	1.17	1.16	1.15	1.09	1.14	1.13	1.08
Miscellaneous manufacturing	339	2.7	2.79	2.68	2.7	2.54	2.55	2.6	2.55	2.6	2.83	2.83
Nondurable goods	**Nondurable goods**	**53.21**	**53.14**	**52.06**	**52.26**	**53.33**	**52.72**	**52.08**	**52.44**	**53.23**	**51.26**	**49.68**
Food and beverage and tobacco products	311	15.52	15.35	15.14	15.6	15.98	15.73	15.58	15.78	17.17	16.24	15.28
Textile mills and textile product mills	313	0.9	0.9	0.91	0.88	0.86	0.82	0.79	0.77	0.78	0.79	0.73
Apparel and leather and allied products	315	0.33	0.32	0.3	0.29	0.3	0.27	0.26	0.27	0.27	0.35	0.37
Paper products	322	3.1	3.01	2.96	2.92	2.86	2.85	2.78	2.81	2.9	2.81	2.51
Printing and related support activities	323	1.44	1.4	1.36	1.35	1.4	1.36	1.34	1.29	1.26	1.22	1.19
Petroleum and coal products	324	14.44	14.58	14.03	13.91	14.77	15.16	15.11	15.21	12.96	13.52	14.08
Chemical products	325	13.73	13.88	13.58	13.43	13.54	13.12	12.82	12.96	13.32	12.57	12.21
Plastics and rubber products	326	3.75	3.7	3.75	3.81	3.81	3.85	3.9	3.86	3.94	3.61	3.37

Notes: Sources: Bureau of Economic Analysis, accessed August 20203. Each share is calculated using an industry gross output divided by the total manufacturing gross output.

Table A2: Unit root test: Industrial production

				Fixed-N exact critical values		
		Statistic	p-value	1%	5%	10%
t	t-bar	-2.4062		-1.92	-1.81	-1.75
t	t-tilde-bar	-2.3436				
Z	z-t-tilde-bar	-4.6425	0.000			

Table A3: Unit root test: upstream index variable

				Fixed-N exact critical values		
		Statistic	p-value	1%	5%	10%
t	t-bar	-1.7965		-1.97	-1.84	-1.77
t	t-tilde-bar	-1.7798				
Z	z-t-tilde-bar	-1.4066	0.0798			

Table A4: Unit root test: downstream index variable

				Fixed-N exact critical values		
		Statistic	p-value	1%	5%	10%
t	t-bar	-2.217		-1.920	-1.810	-1.750
t	t-tilde-bar	-2.1754				
Z	z-t-tilde-bar	-3.711	0.0001			

Table A5: Hausman Test

	Coefficients			
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	fe	re	Difference	Std. err.
upindex	-.0841231	-.0779171	-.006206	.0109169
downindex	-.0752614	-.0761174	.000856	.0197615

b is Consistent under H0 and Ha; obtained from xtreg.

B is Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

$chi2(2) = (b - B)'[(V_b - V_B)^(-1)](b - B) = 5.68$

$Prob > chi2 = 0.0583$

Table A6: Optimal Lag Selection

lag	CD	J	J-pvalue	MBIC	MAIC	MQIC
1	1	367.9216	1.52e-21	-738.8858	79.92159	-219.4318
2	1	206.3127	3.88e-08	-623.7928	-9.68728	-234.2023
3	1	105.1643	.0065702	-448.2394	-38.83567	-188.5124
4	1	41.88827	.2305595	-234.8136	-30.11173	-104.9501

Table A7: Before Covid : Regression without emp and invship

	(1)	(2)	(3)
Y_{it-1}	0.724***	0.713***	0.723***
	(0.0333)	(0.0312)	(0.0333)
Y_{it-2}	0.188***	0.179***	0.189***
	(0.0405)	(0.0381)	(0.0405)
Y_{it-3}	0.0845**	0.101***	0.0855**
	(0.0334)	(0.0312)	(0.0334)
downindex_{it}		0.0240	-0.0179
		(0.0184)	(0.0198)
upindex_{it}	0.0223		0.0315
	(0.0211)		(0.0239)
Observations	1,674	1,953	1,674
R-squared	1.000	1.000	1.000
Number of ind	18	21	18

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A8: After Covid : Regression without emp and invship

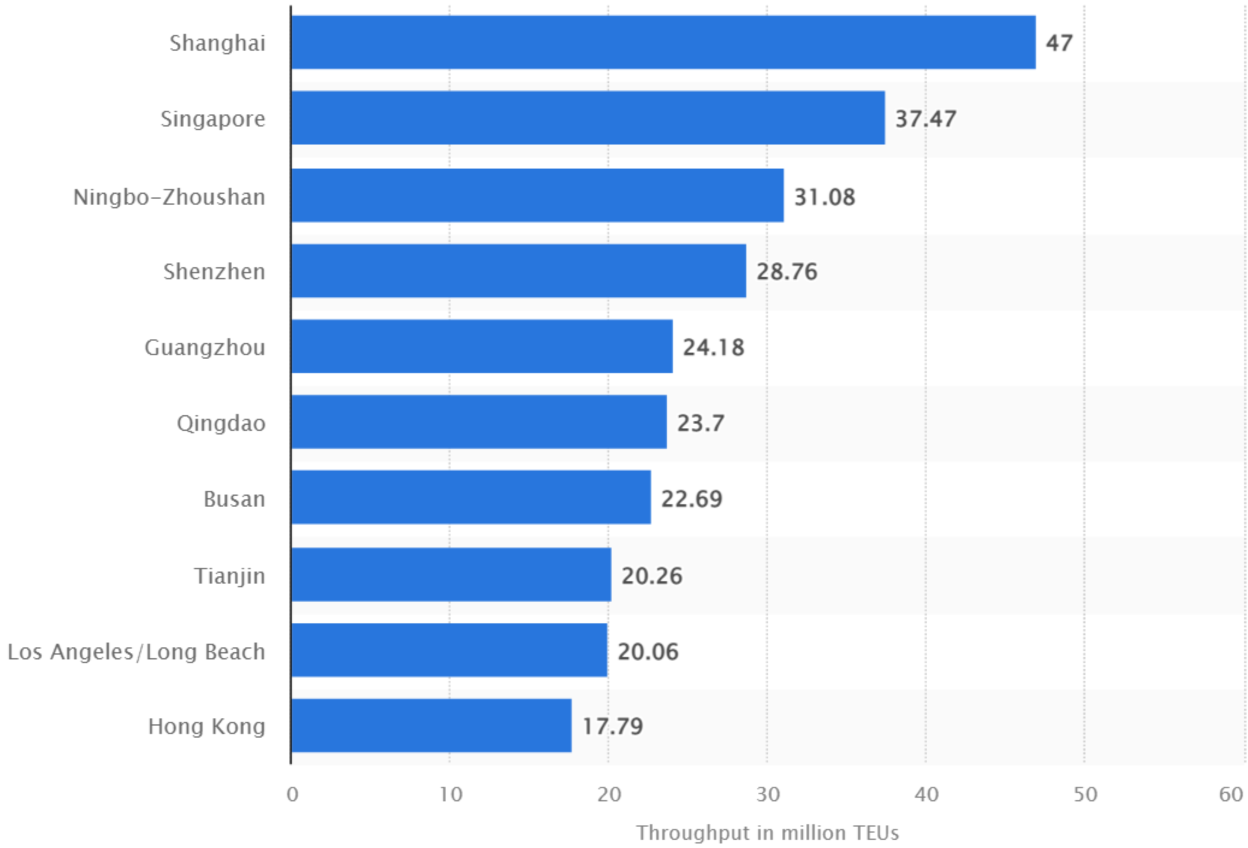
	(1)	(2)	(3)
Y_{it-1}	1.251***	1.183***	1.244***
	(0.112)	(0.104)	(0.111)
Y_{it-2}	-0.526***	-0.429***	-0.516***
	(0.170)	(0.154)	(0.169)
Y_{it-3}	0.262**	0.230**	0.256**
	(0.113)	(0.106)	(0.113)
upindex$_{it}$	0.0249		0.00886
	(0.0401)		(0.0527)
downindexit		0.0246	0.0274
		(0.0412)	(0.0476)
Observations	558	651	558
R-squared	0.999	0.999	0.999
Number of ind	18	21	18

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

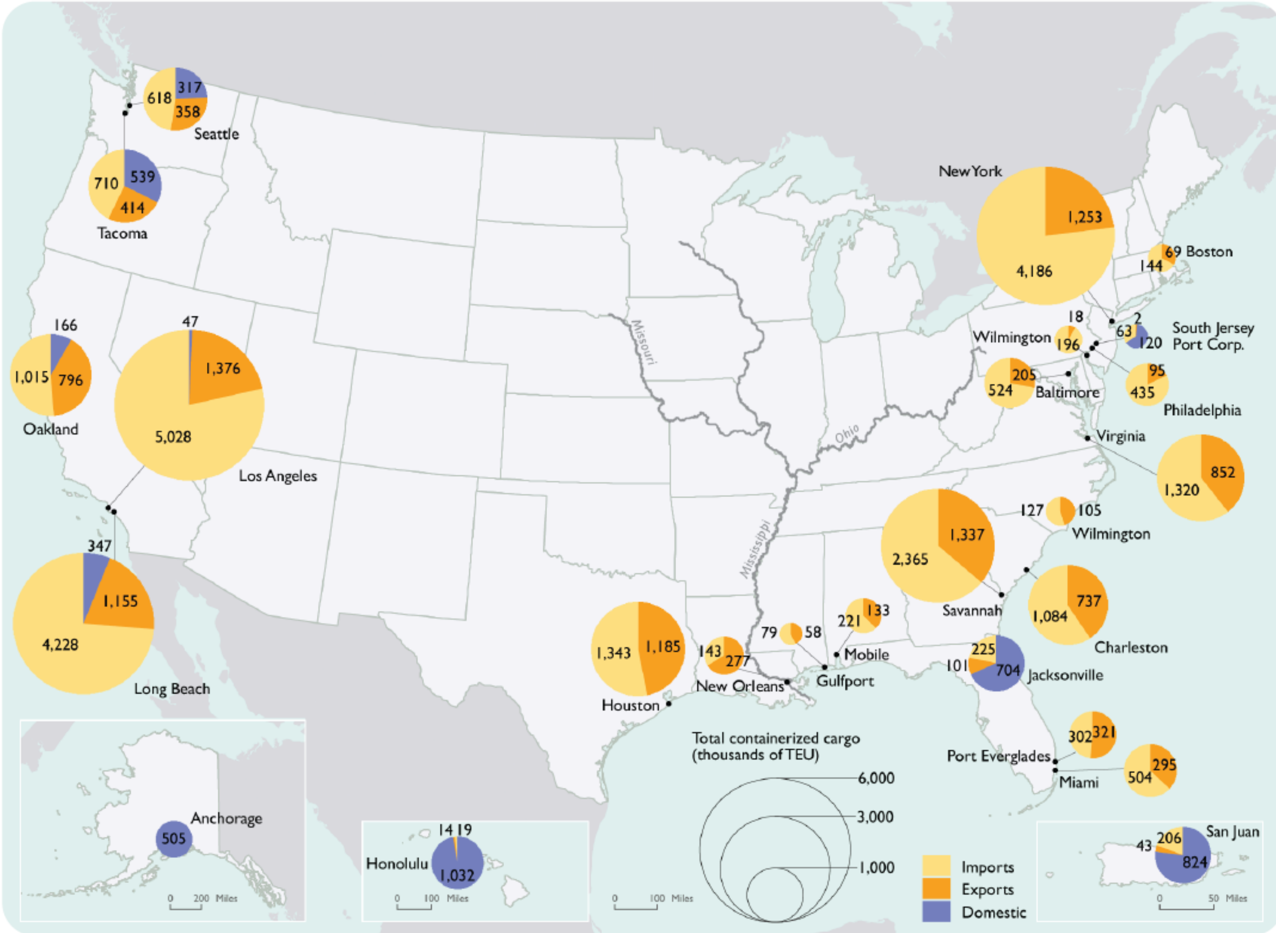
2- Figures

Figure A1: The largest container ports worldwide in 2021, based on throughput(in million TEUs)



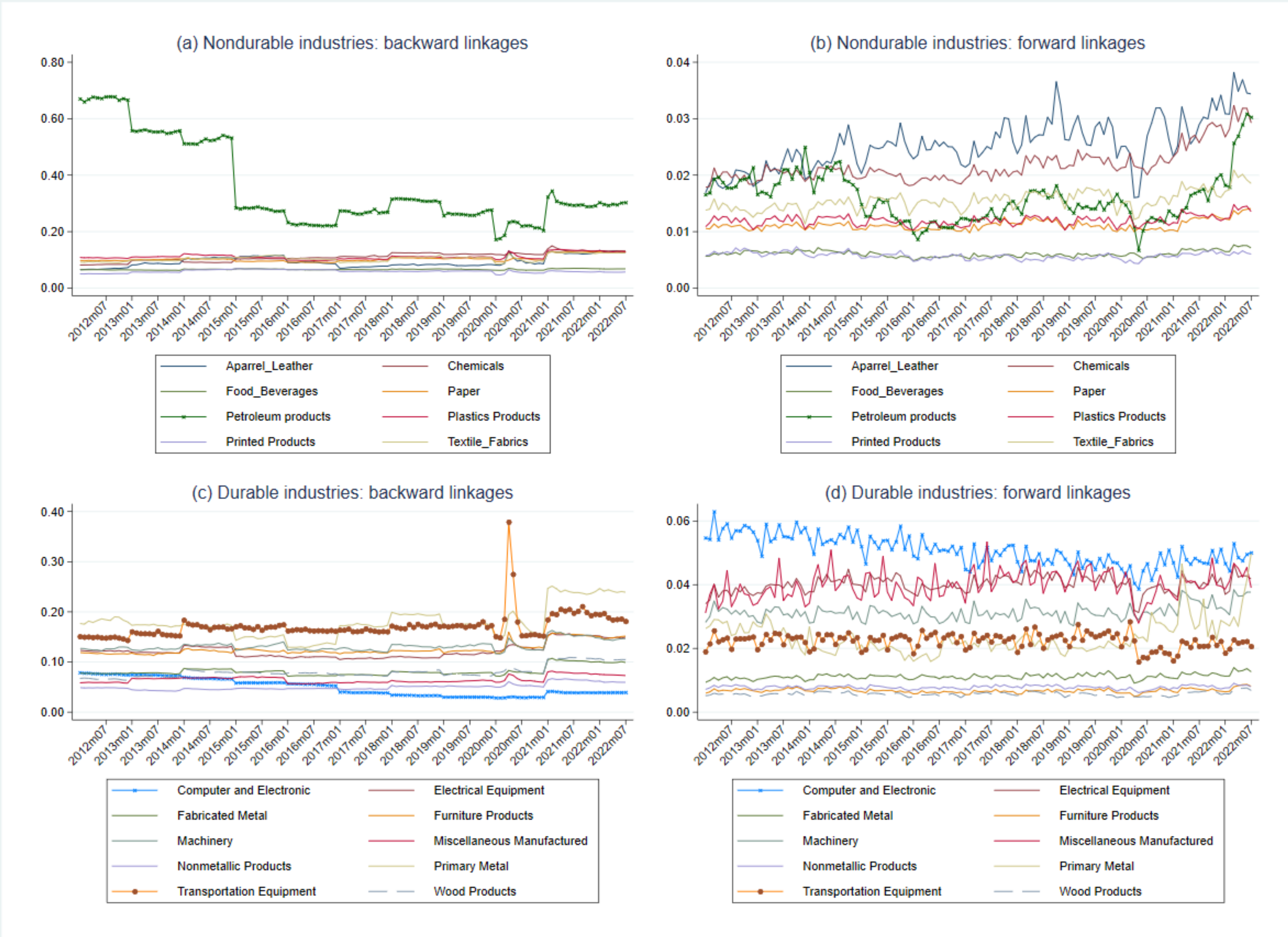
Source: Statista Research Department, Aug 30, 2023.

Figure A2: Top 25 U.S. container Ports locations



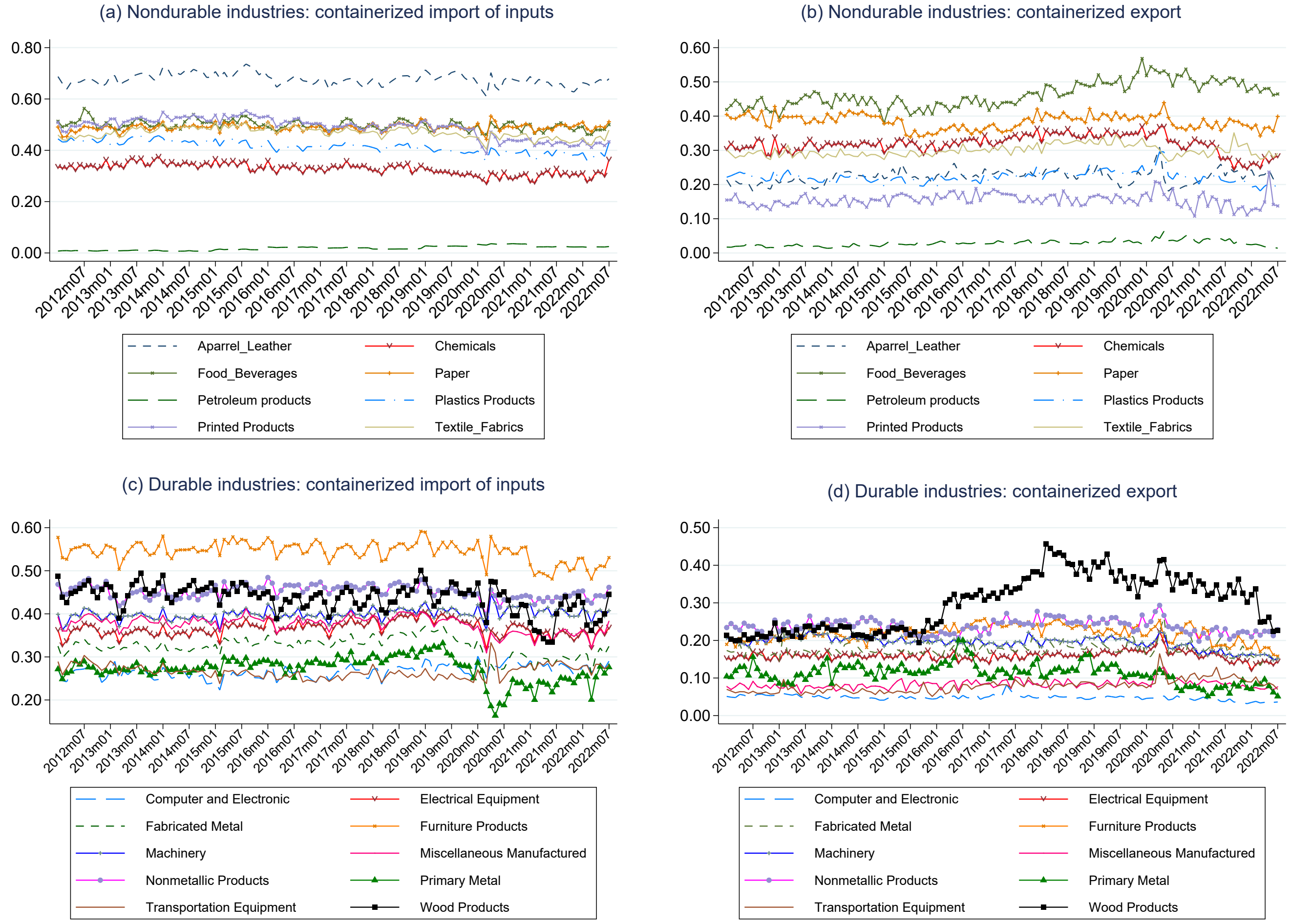
Notes: U.S. container ports activities are organized as the West Coast and the East Coast. The U.S. West Coast includes ports of Los Angeles, Long Beach, Oakland, Seattle, and Tacoma. U.S. East Coast include ports of New York-New Jersey, Savannah, Houston, Virginia, and Charleston.
Source: U.S Army Corps of Engineers, Navigation data center, personal communication, special tabulation, November 12, 2020 and as of November 2, 2021 and October November 2023.

Figure A3: Evolution of upstream and downstream linkages intensity by industries



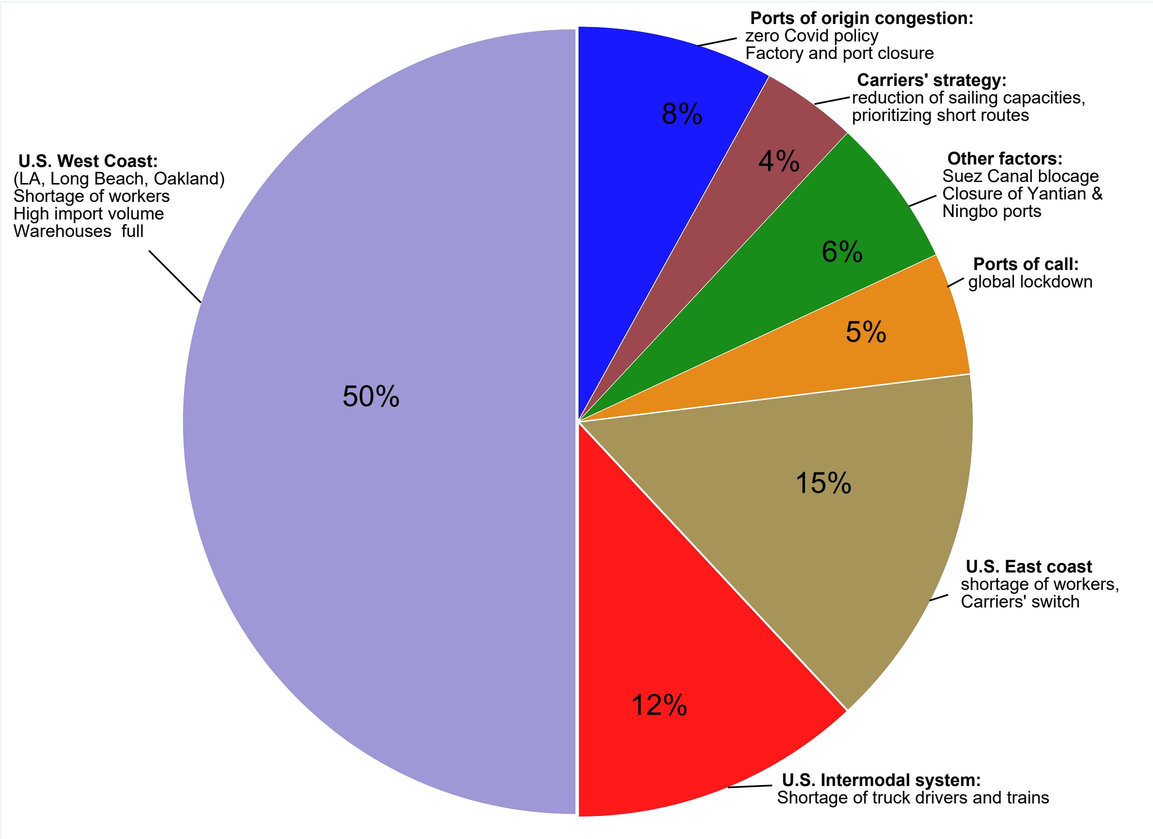
Notes: Upstream linkages describe the reliance of U.S. industries on foreign inputs. Downstream linkages refer to the reliance of U.S. industries on exports to sell their output. Durable industries produce goods that provide a stream of services or utility over time. Non-durable industries produce goods and services that tend to be consumed immediately. Source: Compile from U.S. Census Bureau, "USA Trade Online," https://usatrade.census.gov, accessed on July 8, 2023. Bureau of Economic Analysis input output tables accessed July 2023 U.S. Bureau of Economic Analysis, "Total Requirements, Industry-by-Industry - Sector", accessed Tuesday, July 1, 2023.

Figure A4: Evolution of containerized import and export by industries



Notes: Containerized import of inputs represent the share of input imported into the United StatesF through container logistics network. Containerized exports represent the share of exports by U.S. industries through container logistics network. Durable industries produce goods that provide a stream of services or utility over time. Non-durable industries produce goods and services that tend to be consumed immediately. Source: Compile from U.S. Census Bureau, "USA Trade Online," https://usatrade.census.gov, accessed on July 8, 2023. Bureau of Economic Analysis input output tables accessed July 2023 U.S. Bureau of Economic Analysis, "Total Requirements, Industry-by-Industry - Sector", accessed Tuesday, July 1, 2023.

Figure A5: Sources of container unreliability during Covid-19



Source: Author calculation based on Notteboom (2006). Data are from Sea Intelligence, Global liner performance, Maritime Analysis Report, July 2023.