# Demand Shock along the Supply Chain: The Bullwhip Effect of Covid-19 in Chinese Exports

Kaichong (Matt) Zhang [1]

Advisor: Felix L Friedt [2]

Department of Economics

Macalester College

April 28, 2021

[1] Macalester College; kzhang@macalester.edu

[2] Department of Economics, Macalester College; ffriedt@macalester.edu

I would like to express my special gratitude to my advisors, Professor Felix L Friedt and Professor Amy Damon, my Economics Honors Thesis committee members, Professor Liang Ding and Professor David Shuman, as well as my Honors Thesis classmates who gave me excellent supports and illuminating comments to my research project.

## Abstract

This study investigates the bullwhip effect of Covid-19 on global supply chains from the Chinese perspective. The bullwhip effect refers to the amplification of demand shock along the supply chain, and my baseline estimates show that a 1% increase in foreign new cases (a proxy for foreign demand shock) reduces exports of downstream products and that of upstream industries by 2.1% and 4.5% respectively. The estimates also suggest that whether industries are concentrated or not generates ambiguous effects on exports that vary from different empirical specifications. In addition, a heterogeneity analysis suggests that the bullwhip effect is stronger in regional supply chains among geographically proximate countries and countries that are closely connected in terms of the trade volume. Furthermore, a dynamic analysis shows that the outbreak of Covid-19 in foreign countries causes a lagged import substitution towards Chinese products that reverses the initially negative demand shock. Unlike the initial adverse effect, I find that the lagged import substitution does not amplify along the supply chain, but mostly affects downstream industries.

*Keywords:* Global Pandemic, Covid-19, International Trade, Bullwhip Effect, Supply Chains, Demand Shock

# 1 Introduction

The Covid-19 crisis began in December 2019 and has already infected more than 115 million people and caused more than 2 million deaths around the world. The public health crisis was accompanied by the global economic recession and the pandemic shock is as contagious economically as it is medically in the increasingly interconnected world (R. Baldwin, di Mauro, & Tomiura, 2020). A report from World Trade Organization predicted that the global trade in merchandise will decrease 9.2% in 2020 and the trade volume will remain below the pre-crisis level in 2021 (World Trade Organization, 2020). More importantly, the major trading nations, including US, China, Japan, Germany, Britain, France, and Italy, that account for 60% of world GDP, 65% of world manufacturing, and 41% of global manufacturing exports, are also the hardest-hit nations (R. Baldwin et al., 2020). As a result of the contagion of international production networks, the Covid shock leads to drastic welfare losses. China, for example, is expected to experience a welfare loss of about 30%, and such loss will spill over around the world through Global Value Chains (GVCs) (Eppinger, Felbermayr, Krebs, & Kukharskyy, 2020; Friedt & Zhang, 2020).

Many scholars explore the general mechanism of the Covid shock from either the demand side (the drop in aggregate demand and the "wait-and-see" purchase/investment delays) or the supply side (factory closures and supply-chain contagions) (see Balleer, Link, Menkhoff, and Zorn (2020); Bekaert, Engstrom, and Ermolov (2020); Hyun, Kim, and Shin (2020); Meier and Pinto (2020)). However, while previous works have shown that sudden shocks in demand can create a 'bullwhip effect' along the supply chain (Altomonte, Di Mauro, Ottaviano, Rungi, & Vicard, 2012; Zavacka, 2012), none of the Covid studies focus on this particular area.[3] This effect refers to the amplification of order volatility along the supply chain (Wang & Disney, 2016). It has been well studied by Altomonte et

[3] Although the bullwhip effect is briefly mentioned by some scholars like R. Baldwin et al. (2020) and Patrinley et al. (2020), they only suggest the possibility that the effect exists and can negatively affect the manufacturing sectors without delving into the details of the bullwhip effect.

al. (2012) and Zavacka (2012) in the context of the demand-driven 2008 Global Trade Collapse (GTC). They demonstrate the impact of the bullwhip effect along the supply chains and argue that the effect was mainly caused by the adjustment of production and inventory to new expectation. More specifically, the volatility of sales would increase from downstream to upstream industries, making upstream producers more likely to drop out of trade shortly after the GTC.

In this paper, I analyze the bullwhip effect of Covid-19 on global supply chains from the Chinese perspective. I first develop a simple theoretical framework to motivate my empirical analysis. The model demonstrates the mechanisms underlying the theorized bullwhip effect and explores how this effect is shaped by the degree of industry concentration. My primary empirical model uses Chinese new cases as a proxy for the Chinese domestic supply shock and uses foreign new cases to measure the foreign demand shock. The initial analysis provides baseline estimates showing that upstream industries tend to suffer more from an amplified demand shock compared to downstream ones. Moreover, concentrated industries tend to experience a weaker demand shock compared to non-concentrated ones. Statistically, a 1% increase in foreign new cases leads to 2.6% reduction in exports of downstream and non-concentrated industries, 4.7% reduction in exports if the industries are upstream, and only 0.2% reduction in exports if the industries are concentrated. The estimates are significant at 0.01 level and are robust against different fixed effects specifications, alternative measurements of the severity of the pandemic, and various sample restrictions.

Building on these baseline results, I conduct heterogeneity analyses that test the sensitivity of the estimated bullwhip effect along several dimensions. Restricting the sample to Asian countries, I find that the bullwhip effect is stronger among the regional supply chain network. Further restricting the sample to include only the top 30 Chinese trading partners according to trade data in 2019, I find that the demand shock upstream industries suffer is even stronger. Specifically, the estimates reveal that 1% increase in foreign new cases amplifies the reduction of upstream exports from 4.7% to 5.0% for Asian supply chains and to 5.7% for supply chains among Chinese major trading partners. These regression results suggest that the bullwhip effect is more prominent in supply chains in which countries are geographically proximate and are economically closely connected.

Lastly, as the conceptual model suggests that the bullwhip effect is dynamic in nature and upstream industries tend to suffer from a delayed instead of immediate demand shock that transmits along the supply chains, I examine the time lagged bullwhip effect by exploring the nuance of the demand shock month by month after the outbreak of Covid-19. The analysis, however, raises two important issues that are at odds with the stylized model: (1) the demand shock hits upstream and downstream industries at the same time within the first month after the outbreak of Covid-19; (2) while the lagged effects demonstrate a quick recovery in exports of Chinese downstream products and a reversal of the initial adverse demand shock, exports of upstream products are slower to recover and do not experience an amplified lagged positive demand shock.

The first deviation can be explained by the frequency of the observed trade data. Although the theorized bullwhip effect suggests the delayed demand shock on upstream industries, it does not specify the lag length. Given the advanced communication technology nowadays, it is possible that the amplified demand shock hits the most upstream industry within a month of the initial shock. In this case, such short postponement is unobservable in monthly trade data.

The second deviation is harder to reconcile with the theorized bullwhip effect. One potential explanation is that the lagged positive demand shock on exports of downstream industries represents the significant import substitution from heavily affected foreign countries, where factory closures stagnate the foreign production process and foreign raw material imports from Chinese upstream industries. In this case, foreign consumers' demand for final goods can only be fulfilled by Chinese downstream producers. As a result, the positive demand shock that hits downstream industries does not amplify along the proportion of the supply chains that involve foreign producers, which remain shut down, and leads to weak recovery of upstream exports 2 to 5 months after the initial outbreak.

This study contributes to several strands of the economic literature. My findings offer new insights on the pandemic effects on international trade and therefore advance the rapidly growing research on Covid-19. Bonadio, Huo, Levchenko, and Pandalai-Nayar (2020) and Antras, Redding, and Rossi-Hansberg (2020), for example, show that the lockdown of the major trading nations and the disruption of global trade can explain one third of the downturn of the global economy. Theoretically, the lockdown affects international trade through three channels: the demand shock, the supply shock, and the GVC contagion (R. Baldwin, 2020; Friedt & Zhang, 2020). First, firms are concerned about the factory closures, the collapse of demand, the supply chain disruption, and the uncertainty in the future (Hassan, Hollander, van Lent, & Tahoun, 2020). Second, households experience a drop in consumption shortly after the outbreak of Covid-19 as some of them become unemployed (Baker, Farrokhnia, Meyer, Pagel, & Yannelis, 2020). Third, the presence of the GVC contagion amplifies the initial supply shock and causes a ripple effect through international production networks and accounts for the majority of trade disruption (Friedt & Zhang, 2020). Balleer et al. (2020) and Bekaert et al. (2020) further suggest that while both shocks coexist, the demand shortage would dominate in the short run, namely the first quarter of 2020, and the supply shock will play a more important role in the long run.

My paper also extends the discussions of previous exogenous demand shocks on trade. The 2003 SARS outbreak, for example, is a pandemic shock that first hit China and then spread around the world, putting the international capital flow and international trade at risk (Lee & McKibbin, 2004). The 2008 GTC generates the worldwide demand shock as firms had less access to capital and consumers spent less on final goods (R. E. Baldwin, 2009; Bems, Johnson, & Yi, 2012). Particularly, investors' "wait-and-see" attitude strongly hurt the "postponeable goods[4]" that comprised a major portion of the global trade (R. Baldwin & Taglioni, 2009). Firms engaged in global manufacturing in 2008 had difficulty managing their inventory and therefore were at risk of the bullwhip effect (Altomonte et al., 2012; Leckcivilize, 2012). But both SARS and GTC are still different from the current Covid-19 crisis as there was no severe and widespread supply chain disruptions and GVC contagions in 2003 and 2008 and the impacted area of the SARS did not cover the major trading nations, like the United States and the European Union (Fernandes & Tang, 2020).

The rest of the paper is structured as follows. Section 2 presents a theoretical model building on the works by Altomonte et al. (2012) and Zavacka (2012). Section 3 introduces the data and discusses the relevant summary statistics. Section 4 provides the baseline estimates with robustness checks and geographic heterogeneity analysis. I also incorporate a dynamic analysis to explore the nuance of the lagged bullwhip effect and make a comparison between the theory and the empirical results. Section 6 concludes the paper and sheds lights upon the policy implications and the directions of future studies.

## 2 Theoretical Model

The bullwhip effect refers to the amplification of demand shock along the supply chain. The following theoretical model demonstrates two key features of the bullwhip effect. First, the more upstream the producers are, the greater the demand shock they suffer. The demand shock that hits the most downstream producers amplifies as it transmits along the supply chain to the most upstream ones. Second, diversification of output (or downstream industries) matters. Depending on the relationships among downstream products, upstream producers who have various downstream recipients can either reduce or further exacerbate their order volatility. The following model is built on the studies by Altomonte et al. (2012) and Zavacka (2012) who analyze the bullwhip effect resulting from 2008 GTC.

[4] This phrase is introduced by Richard Baldwin and Daria Taglioni and refers to products like new and updated equipment that are durable and that consumers don't have to buy immediately.

First, I assume that there are n+1 production stages along the supply chain. The most downstream final goods producers are at stage 0 and the most upstream raw material producers are at stage n. Second, I assume that producers adjust the amount of inventory according to the demand for their products yesterday. Specifically, they restock at the beginning of time t+1 to meet the demand for inventory at time t. After the inventory adjustment, producers at stage n will hold $\alpha D_{t-1}^{n}$ inventory at time t where $\alpha$ refers to the percentage of sales, or downstream demand, that is set to be the inventory.

For example, in the electronics supply chain, battery producers export batteries to cell phone producers and one battery is used to produce only one cell phone. If cell phone producers sell $x$ cell phones on the first day, their demand for inventory based on today's sales is $\alpha x$ cell phones. In other words, the cell phone producers expect to hold $\alpha\%$ of sales as inventory to prevent cell phones running out of stock. On the second day, the cell phone producers will restock batteries to produce cell phones. Given that cell phone producers hold $y$ cell phones as inventory on the first day, the number of restocking batteries can be calculated by the sales yesterday, $x$, plus the inventory adjustment (which is the difference between demanded inventory and held inventory), $\alpha x - y$. In summary, cell phone producers' inventory on the second day is adjusted to $\alpha$ percent of the sales, which is the demand for inventory, on the first day. The detailed setups of this example of the electronics supply chain are presented in Table 1, which extends the scenario to one more period.

In the rest of the Theoretical Model section, my explanation starts from the most fundamental Two Stage Model that only includes one upstream industry and one downstream industry. The basic logic and equation of the theorized bullwhip effect is developed from this model. Then, I expand the analysis to the more complex N-Stage Model in which the supply chain has n levels of producers. While the N-Stage Model offers a preliminary insight of the bullwhip effect, I make the model more realistic by considering the industry concentration. Concentration concerns the distribution of downstream recipients; if an industry is highly concentrated, it sells its products to only one downstream industry; if an industry is not concentrated, it exports its products to many downstream industries.

| Setups | Time | | |
|---|---|---|---|
| | Day 0 | Day 1 | Day 2 |
| Demand for product | $x_0$ | $x_1$ | $x_2$ |
| Held Inventory | y | $\alpha x_0$ | $\alpha x_1$ |
| Demand for Inventory | $\alpha x_0$ | $\alpha x_1$ | $\alpha x_2$ |
| Inventory Adjustment | | $\alpha x_0 - y$ | $\alpha x_1 - \alpha x_0$ |
| Restocking | | $x_0 + (\alpha x_0 - y)$ | $x_1 + (\alpha x_1 - \alpha x_0)$ |

Table 1
*Three-Period Setups of the Cell Phone Producers*

### 2.1 Two-Stage Model

In general, the demand for products at stage n equals to the purchase of the same products by producers at stage n-1. In the two-stage scenario, the demand for products at stage 1 is the same as the purchase by producers at stage 0, which is defined to be the sum of the realized demand and the inventory adjustment at stage 0 at time t.

$$D_t^1 = D_{t-1}^0 + (I_{t-1}^0 - Q_{t-1}^0) \tag{1}$$

In equation 1, $Q_{t-1}^0$ denotes the amount of inventory held by producers at stage 0 at time t-1. $I_{t-1}^0$ denotes the demand for inventory of producers at stage 0 at time t-1. $D_t^1$ and $D_{t-1}^0$ denote the demand for products at stage 1 at time t and at stage 0 at time t-1 respectively.[5] The inventory adjustment is $I_{t-1}^0 - Q_{t-1}^0$. This term can be interpreted as the action of producers at stage 0 at time t to restock or reduce inventory based on the expected demand set by consumer demand at time t-1. In the example of the electronics supply chain where battery producers are at stage 1 and cell phone producers are at stage

[5] The demanded products at stage 1 are raw materials for production while those at stage 0 are final goods selling to consumers.

0, if nothing happens, cell phone producers will demand the same amount of inventory and $I^0_{t-1} - Q^0_{t-1} = 0$ (there is no inventory adjustment). If cell phone producers have more inventory than they needed, that is if $I^0_{t-1} < Q^0_{t-1}$, they will decrease their order for products at stage 1. But if cell phone producers demand more inventory as their products are popular in the market, that is if $I^0_{t-1} > Q^0_{t-1}$, they will increase their order for products at stage 1.

Based on the second assumption that producers will set their inventory to $\alpha$ percent of the sales, the demand for inventory can be written as $I^0_{t-1} = \alpha D^0_{t-1}$. Building on the same assumption that the demand for inventory today is equal to the amount of inventory tomorrow, the inventory at time t-1 equals to the demand for inventory at time t-2 ($Q^0_{t-1} = I^0_{t-2} = \alpha D^0_{t-2}$. Then, we can rewrite equation 1 to:

$$\begin{aligned} D^1_t &= D^0_{t-1} + (I^0_{t-1} - Q^0_{t-1}) \\ &= D^0_{t-1} + \alpha D^0_{t-1} - \alpha D^0_{t-2} \end{aligned}$$

Simplifying the equation, we can get

$$D^1_t = (1+\alpha)D^0_{t-1} - \alpha D^0_{t-2} \tag{2}$$

While the bullwhip effect is not obviously presented in equation 2, it is more clear as I situate it in the context of negative demand shock where there is no seasonal change in demand for products at stage 0. In other words, if nothing happens, $D^0_{t-1} = D^0_{t-2}$. Consider a negative demand shock that can occur either at time t-1, reducing $D_{t-1}$ by $A\%$, or at time t-2, reducing $D_{t-2}$ by $B\%$.

**Scenario 1.** In the first scenario, the negative demand shock occurs only at time t-1. In this case, $D^0_{t-1}$ will be $(1-A)D^0_{t-1}$ where the term $(1-A)$ denotes the size of the shock. The demand for products at stage 1 at time t can be written as

$$\begin{aligned} D_t^1 &= (1-A)(1+\alpha)D_{t-1}^0 - \alpha D_{t-2}^0 \\ &= (1+\alpha)D_{t-1}^0 - (1+\alpha)AD_{t-1}^0 - \alpha D_{t-2}^0 \end{aligned}$$

The additional $-(1+\alpha)AD_{t-1}^0$ indicates that the negative demand shock at time t-1 will lead to a decrease in $D_t^1$. This is because producers at stage 0 at time t-1 suffer from the shock and need to reduce their inventory to meet the cutback of demand. More importantly, while producers at stage 0 at time t-1 only suffer $A\%$ decrease in demand, the reduction is amplified to $-(1+\alpha)A\%$ for producers at stage 1 at time t. This is equivalent to the definition of the bullwhip effect that the demand shock intensifies from downstream to upstream producers.

**Scenario 2.** In the second scenario, the negative demand shock occurs only at time t-2. In this case, $D_{t-2}^0$ will be $(1-B)D_{t-2}^0$ and the term $(1-B)$ denotes the size of the shock. The demand for products at stage 1 at time t can be written as

$$\begin{aligned} D_t^1 &= (1+\alpha)D_{t-1}^0 - (1-B)\alpha D_{t-2}^0 \\ &= (1+\alpha)D_{t-1}^0 - \alpha D_{t-2}^0 + B\alpha D_{t-2}^0 \end{aligned}$$

The additional $B\alpha D_{t-2}^0$ indicates that the negative demand shock at time t-2 will lead to an increase in $D_t^1$. This makes sense because the negative demand shock at time t-2 was transitory and producers at stage 0 at time t-1 will recover from the shock and need to restock their inventory to meet the relatively higher demand. Specifically, as the demand is higher at time t-1 than at time t-2, producers at stage 0 will purchase more inputs from the upstream producers to meet the increasing demand from t-2 to t-1. According to the second assumption, such restocking happens at time t and therefore the demand for products at stage 1 at time t ($D_t^1$) will increase.

The rest of the scenarios incorporate more dynamics of the demand shock that is persistent at both time t-1 and t-2. Specifically, the shock can be exacerbating, mitigating, and stationary[6] in both periods. The detailed mathematical proofs are shown in the Appendix A. In short, in the context of negative demand shock, equation 2 can effectively demonstrate the bullwhip effect.

### 2.2 N-Stage Model

Given that the bullwhip effect can be developed from equation 2 through the five scenarios, I will extend the model from two stages to n stages. Following the logic of equation 2, the demand of products at stage 2 at time t can be written as

$$
\begin{aligned}
D_t^2 &= D_{t-1}^1 + (I_{t-1}^1 - Q_{t-1}^1) \\
&= D_{t-1}^1 + \alpha D_{t-1}^1 - \alpha D_{t-2}^1 \\
&= [(1+\alpha)D_{t-2}^0 - \alpha D_{t-3}^0] + [\alpha(1+\alpha)D_{t-2}^0 - \alpha^2 D_{t-3}^0] - [\alpha(1+\alpha)D_{t-3}^0 - \alpha^2 D_{t-4}^0]
\end{aligned}
$$

Simplifying the equation, we can get

$$D_t^2 = (1+\alpha)^2 D_{t-2}^0 - 2\alpha(1+\alpha)D_{t-3}^0 + \alpha^2 D_{t-4}^0 \tag{3}$$

Equation 3 implies that only the shock occurring before t-1 can affect the demand of products at stage 2 at time t because the shock at stage 0 takes 2 period to transmit from stage 0 to stage 2. In other words, while downstream producers suffer from an immediate shock, upstream producers tend to suffer from a more delayed shock.

Generally, the demand of products at stage n at time t can be written as a function of the demand of products at stage 0 from time t-n to time t-2n

$$D_t^n = (1+\alpha)^n D_{t-n}^0 - n\alpha(1+\alpha)^{n-1} D_{t-n-1}^0 + ... + (-1)^n \alpha^n D_{t-2n}^0 \tag{4}$$

[6] An exacerbating shock means that the demand shock is greater at time t-1 than at time t-2; a mitigating shock means that the shock is greater at time t-2 than at time t-1; and a stationary shock means that the shocks are the same in both periods.

Equation 4 implies two key ideas. First, upstream producers suffer from a stronger shock and stronger post-shock fluctuation compared to downstream producers. Second, the shock will not hit upstream producers immediately and there is a time lag between the shock and the change in demand. These two ideas are shown by the partial derivative of $D_t^n$ with respect to $D_{t-n}^0$:

$$\frac{\partial D_t^n}{\partial D_{t-n}^0} = (1+\alpha)^n \tag{5}$$

This partial derivative suggests that one unit increase/decrease in the demand of products at stage 0, the most downstream producers, at time t-n is associated with $(1+\alpha)^n$ unit increase/decrease in the demand of products at stage n, the most upstream producer, at time t. The shock that hits producers at stage 0 takes n periods to transmit to producers at stage n. In other words, the initial change will magnify by $(1+\alpha)$ along every step in the supply chain, meaning that the more upstream along the supply chain, the more volatility firms suffer. This is equivalent to the definition of the bullwhip effect. In addition, while $\alpha$ represents the amount of inventory held by producers, the demand shock will be further amplified when $\alpha$ is greater, because producers have to have a more drastic inventory adjustment when facing the demand shock. In the example of the electronics supply chain, consider that there are n+1 stages from cell phone retailers at stage 0 to mining industries at stage n.[7] In the context of a negative demand shock that occurs at time t-n, consumers' cell phone purchases ($D_{t-n}^0$) will drop drastically. According to the N-Stage model, cell phone retailers will curtail their orders from cell phone assemblers at stage 1 in which the decrease in $D_{t-n+1}^1$ will be $1+\alpha$ greater than the decrease in $D_{t-n}^0$ as they need to downward adjust their inventory. Such amplification effect exists along the supply chain until the shock hits the mining industries at stage n at time t.

[7] Mining industries provide metals like gold, copper, aluminum, and silver to produce cell phones and circuits within them.

### 2.3 N-Stage Model with Concentration

While equation 5 explains the bullwhip effect in terms of the relationship between the upstreamness and the demand volatility, it does not fit well to the reality as it assumes that the supply chain does not bifurcate and each stage has a one to one relationship with its direct upstream producer and downstream consumer. For example, battery producers export batteries to both cell phones and camera producers. When an economic shock reduces consumers' real income, their demand for cameras might be lower but that for cell phones might be relatively higher because cell phones can take quality photos and can to some extent replace cameras.[8] In this case, the diversification of downstream industries mitigates the economic shock on battery producers as the higher purchases from cell phone producers can offset at least part of the decreasing purchase from camera producers. That is, an industry with less concentrated output is less likely to be fully exposed to the economic shock.

Mathematically, I assume that producers at stage n now export their product to two sub-supply chains[9] with exactly the same share of demand as inventory, $\alpha$. I also assume that producers at stage n export the same share of products to the two supply chains (50% of products at stage n will go to producers on either supply chain at stage n-1). The most downstream final goods producers in the two supply chain are now denoted x0 and y0. The relationship between $D_t^{x0}$ and $D_t^{y0}$ are simple linear, meaning that $D_t^{x0} = kD_t^{y0} + m$. The coefficient $k$ indicates the relationship between the two downstream final products. If $k$ is greater than 0, they are complements. If $k$ is less than 0, they are substitutes. The demand

[8] Here, I assume that cell phones and cameras are substitute goods.

[9] Note that these two sub-supply chains do not bifurcate, meaning that the only bifurcation in the supply chain presents between producers at stage n and producers at stage n-1.

of stage n producer can be written as

$$\begin{aligned} D_t^n &= (1+\alpha)^n D_{t-n}^{x0} - n\alpha(1+\alpha)^{n-1} D_{t-n-1}^{x0} + ... + (-1)^n \alpha^n D_{t-2n}^{x0} + \\ &\quad (1+\alpha)^n D_{t-n}^{y0} - n\alpha(1+\alpha)^{n-1} D_{t-n-1}^{y0} + ... + (-1)^n \alpha^n D_{t-2n}^{y0} \\ &= (1+\alpha)^n (kD_t^{y0} + m) - n\alpha(1+\alpha)^{n-1} D_{t-n-1}^{x0} + ... + (-1)^n \alpha^n D_{t-2n}^{x0} + \\ &\quad (1+\alpha)^n D_{t-n}^{y0} - n\alpha(1+\alpha)^{n-1} D_{t-n-1}^{y0} + ... + (-1)^n \alpha^n D_{t-2n}^{y0} \end{aligned} \tag{6}$$

The partial derivative of $D_t^n$ with respect to $D_{t-n}^{y0}$ is

$$\frac{\partial D_t^n}{\partial D_{t-n}^{y0}} = (1+k)(1+\alpha)^n \tag{7}$$

Based on equation 7, the change in $D_t^n$ caused by the change in $D_{t-n}^{y0}$, or the bullwhip amplification, depends on the value of $k$, namely the relationship between product at stage $x0$ and $y0$. If two products are substitutes ($k < 0$ and $1 + k < 1$) indicating that the increase in demand at stage x0 correlates with the decrease in demand at stage y0 and vice versa, one unit increase/decrease in $D_{t-n}^{y0}$ is associated with less than $(1+\alpha)^n$ increase/decrease in $D_t^n$. This applies to the cell phone and camera example I mention above. Intuitively, the upstream producers can reduce their risk of changing demand as they have more downstream industries that are mutually substitutable, and the bullwhip effects along these two supply chains offset each other.

But if two products are complements ($k > 0$ and $1 + k > 1$) indicating that the changes in demand at stage x0 and at stage y0 are positively correlated, one unit increase/decrease in $D_{t-n}^{y0}$ is associated with more than $(1+\alpha)^n$ increase/decrease in $D_t^n$. For example, the Covid shock reduces people's real income and consumption on electronic toys and corresponding remote controller, which are mutually complementary. In this case, the battery producers, which is the one step upstream industry of these two products, will suffer from a greater demand shock as the initial shock that hit the producers of complementary pairs (electronic toys and remote controller) aggravates.[10] Overall, the co-variation of the demand of two downstream products can either mitigate or magnify the fluctuation of the demand of the upstream raw material and therefore the bullwhip effects along the supply chain.

## 3 Data

In order to examine the bullwhip effect of Covid-19 on Chinese trade, I construct a new dataset that combines data on Chinese exports, Chinese Covid cases, global Covid cases, the upstreamness index, and the concentration index. The Chinese exports data is published by the General Administration of Customs of the People's Republic of China (GACC). It records the Chinese export trade value in US dollars at monthly frequency from January 2019 to September 2020 at the Chinese Province-Foreign Country-two digit Harmonized System (HS) commodity level. The full sample consists of 97 commodity classes exported from 31 Chinese provinces to 243 foreign countries. I then merge this trade data with Chinese Covid data published in the monthly reports of China's National Health Commission and global Covid data reported by the European Center for Disease Prevention and Control (ECDC). Both Chinese and foreign Covid data include the number of confirmed cases and deaths from January to September 2020 at the province/foreign country level (Note that the data from ECDC only includes the statistics for 212 countries). Combined, these case counts measure the severity of the pandemic on both the supply side (Chinese provinces) and the demand side (foreign countries) of the Chinese exports.

Notably, the original trade data is not balanced as the zero value trade are not recorded. In order to reduce the errors caused by the unbalanced and heterogeneous observations, I create two balanced sub-data by adding and removing some nonzero

[10] As electronic toys and corresponding remote controller are complement goods, the decrease in demand for one will lead to the decrease in demand for another, which further aggravate the initial demand shock and generate an even greater bullwhip effect along the supply chain.

trades.[11] The first one has 5 million observations and includes all the zero value trades of commodity k exporting from province p to foreign country j from 2019 to 2020 as long as at least one nonzero value trade exists.[12] The second one focuses on province-country-commodity pairs for which I observe positive Chinese exports in every sample period. This reduces the number of observations to 0.9 million. In this paper, I primarily focus on the second trade data and my baseline estimates are proved to be robust using the first trade data that includes more nonzero trades.[13]

The upstreamness index data comes from Antràs, Chor, Fally, and Hillberry (2012) who measure the upstreamness index of different industries in the United States and examine the applicability of the index to other countries. Due to the unavailability of Chinese upstreamness data, I assume that the inter-industrial connections are similar in different countries (i.e. the battery producers always export to the electronics producers and the tire producers always export to car makers) and therefore the upstreamness index from Antràs et al. (2012) can be applied to Chinese manufacturing sectors. The concentration index is derived from the Input-Output table published by the Eora Global Supply Chain Database in 2015 through the normalised Hirschman Herfindahl concentration index calculation provided by Zavacka (2012).[14] To merge the trade data with the upstreamness index and concentration index, I build two crosswalks between the industries and traded commodities. There are 57 matched commodities and 16 perfect

[11] In order to construct a balanced panel data, I create a template at the Chinese Province-Foreign Country-two digit Harmonized System (HS) commodity level that includes all the possible trades and merge it to the trade data to create zero trades.

[12] For example, if Beijing exports $694,156 of article of iron or steel to Bahrian in July 2019 and there is no trades of article of iron or steel from Beijing to Bahrian in the rest of the months from 2019 to 2020, I will still incorporate the zero value trades in these months.

[13] The coefficients of interest (the foreign new cases, the interaction term between upstreamness binary and foreign new cases, and the interaction term between concentration binary and foreign new cases) in Table A.5 are generally consistent with my baseline estimates in Table 4.

[14] The equation provided by Zavacka (2012) is $C_i = \frac{\sum_{j=1}^{N} s_{ij}^2 - \frac{1}{N}}{1-\frac{1}{N}}$ where $s_{ij}$ denotes the production share of industry $i$ contributes to industry $j$ relative to total production of industry i. The final normalization concentration index will vary between zero and one, with one indicating that the products of certain industry are only targeting one downstream industry.

matches. While the primary analyses are based on the data with only the 16 perfect matches, the empirical results with all 57 matched commodities[15] shown in Table A.4 are generally consistent with my baseline estimates presented in Table 4.

| Variables | Mean | Median | Std Deviation | Min | Max | N |
|---|---|---|---|---|---|---|
| Trade(2019)(mil) | 3.04 | 0.63 | 8.74 | 0.00 | 436 | 42381 |
| Trade(2020)(mil) | 2.98 | 0.57 | 9.18 | 0.00 | 558 | 42381 |
| Chinese new Covid cases | 338.40 | 11.00 | 3617.82 | 0.00 | 59754.00 | 42381 |
| Foreign new Covid cases | 52095.01 | 2975.00 | 224834.21 | 0.00 | 2604518.00 | 42381 |
| Upstreamness index | 2.46 | 2.49 | 0.89 | 1.06 | 3.96 | 16 |
| Concentration index | 0.27 | 0.26 | 0.15 | 0.03 | 0.53 | 16 |

Table 2
*Summary Statistics: Trade Value, New Covid Cases, and Upstreamness and Concentration Index*

### 3.1 Trade Value and Covid Cases

The outcome variable of interest is represented by the volume of Chinese exports, which measures the demand of foreign countries. Table 2 shows the summary statistics of the trade volume in 2019 and 2020, Chinese and foreign new Covid cases, and upstreamness and concentration index. Note that the statistics include 29 provinces and 62 foreign countries that have complete trade and Covid data and 16 commodities that have quality upstreamness and concentration index.

The mean and median trade value in 2019 are 2.01% and 10.53% higher than those in 2020, indicating the trade disruption generated by Covid-19. The standard deviation of Chinese new cases is significantly greater than the mean and the median. Combined with the fact that Hubei had approximately sixty thousands maximum monthly cases in February 2020, it is inferable that Chinese monthly new cases vary a lot by time and province and the pandemic is concentrated in several provinces like Hubei, Guangdong, and Heilongjiang in certain months. Also, the mean of Chinese new cases is much greater than the median, suggesting that the distribution of new cases is strongly right skewed.

[15] Two concordance tables are available upon request (email: chongematt@outlook.com).

The statistics of foreign new cases present the same patterns, that the standard deviation and the maximum value are far higher than the mean and the median, and the mean foreign new cases is also greater than the median ones. These imply that a small group of countries are hit harder by Covid-19 than others in certain months (the foreign new cases vary a lot by country overtime).

Figure 1 presents the change in trade value and Chinese and foreign new Covid cases in the first three quarters of 2020. As the shock on Chinese exports is mainly caused by the decrease in foreign demand, domestic supply, and the GVC contagion (Balleer et al., 2020; Bekaert et al., 2020; Friedt & Zhang, 2020), the severity of Chinese Covid cases can serve as the proxy for the supply shock and the severity of foreign Covid cases can be the proxy for the demand shock. The change in Chinese Covid cases seems to be inversely correlated with the change in trade volume before March (Chinese new cases form a reverse v-shape while the trade volume forms a v-shape). The change in foreign Covid cases also correlates to some degree with the trade volume. From February to July 2020, foreign new cases increases at an increasing rate while the trade volume increases at a decreasing rate. However, such correlation becomes much weaker after July, which is consistent with the study by Bekaert et al. (2020) that the demand shock tends to be dominant in the short run but less influential over time.

### 3.2 Trade Value and Upstreamness and Concentration Index

The other key variables of interest are the upstreamness and the concentration index. Table 2 offers a glimpse of the two indices. The most downstream commodity is ‘toys, games and sports requisite’ that mainly targets the consumers while the most upstream commodity industry is ‘cotton’ that is exported to other manufacturers as raw material. The most concentrated commodity is ‘salt, sulphur, earths and stone, plastering materials, lime, and cement’, which is purely raw material for limited scope of downstream productions, and the least concentrated commodity is ‘miscellaneous manufactured articles', which is defined to be so broad that might include a wide range of downstream receivers. The mean and median of the two indices are close to each other, implying that their distributions are relatively symmetric with approximately equal number of upstream and downstream/concentrated and non-concentrated commodities.

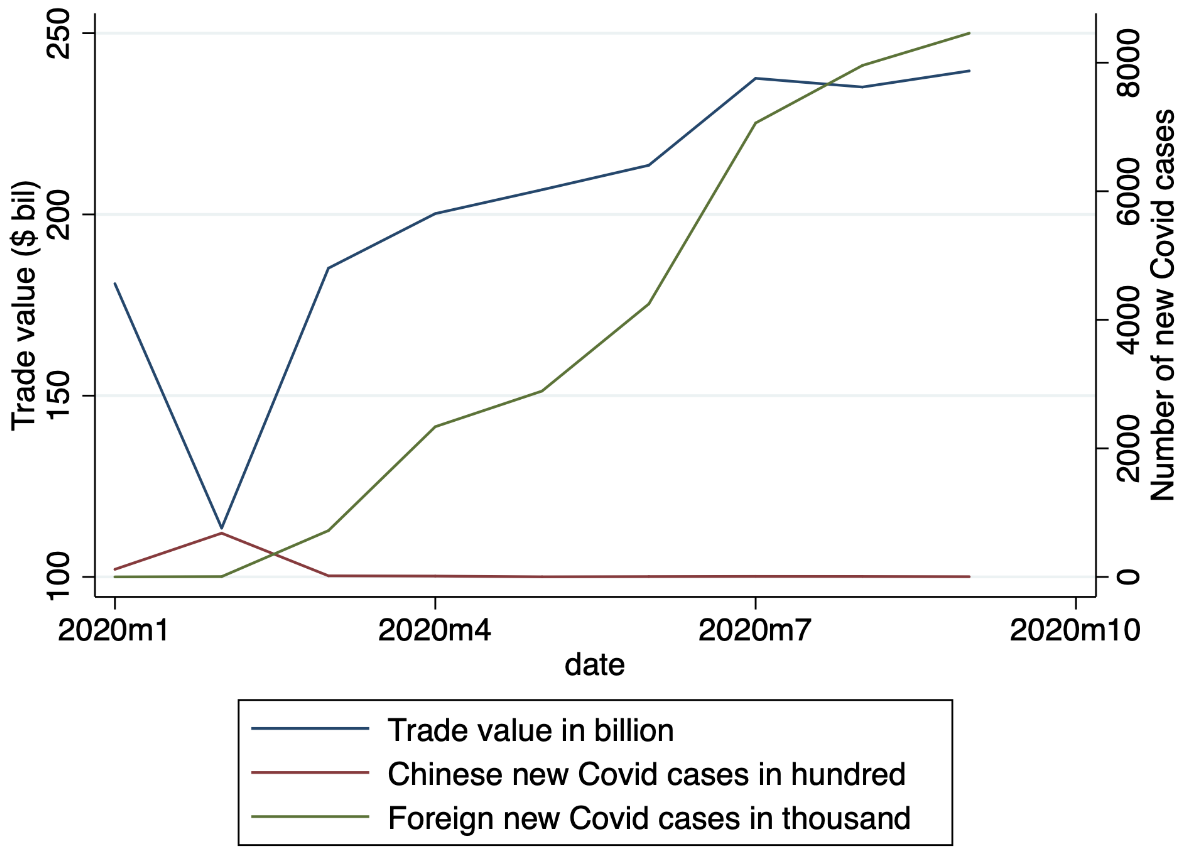
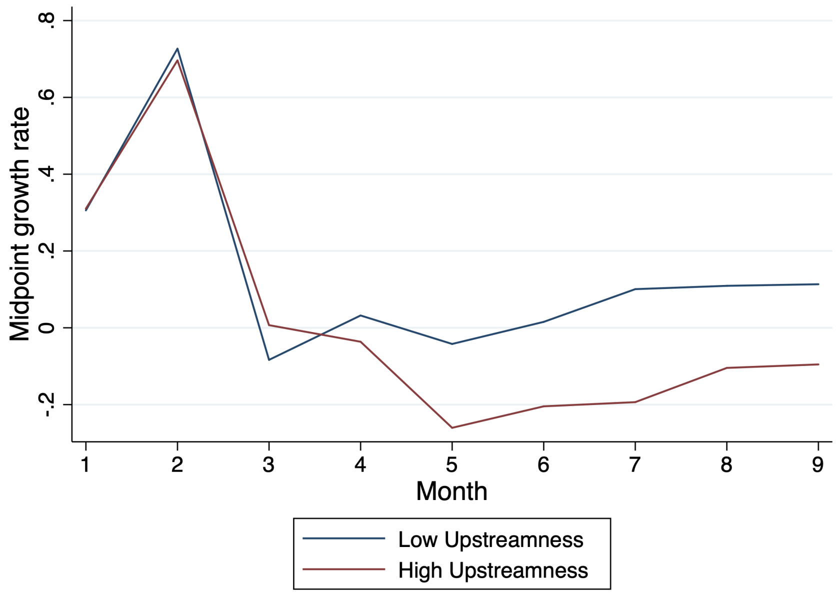



*Figure 1*. The relationship between trade value and new Covid cases

(a) Midpoint growth rate of trade value and upstreamness index




(b) Midpoint growth rate of trade value and concentration index

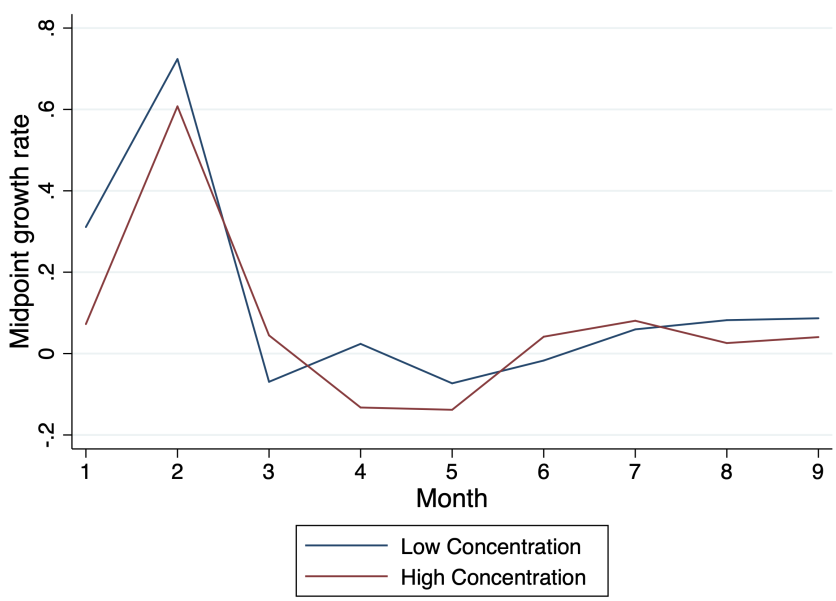



*Figure 2*. The relationship between trade value and upstreamness and concentration index

| Commodity | Upstreamness index | Concentration index | Exposure to Chinese Covid infection | Exposure to foreign Covid infection |
|---|---|---|---|---|
| Toys, games and sports requisites; parts and accessories thereof | 1.058 | 0.451 | 11777 | 6489197 |
| Beverages, spirits and vinegar | 1.266 | 0.242 | 70.55 | 7590 |
| Tobacco and manufactured tobacco substitutes | 1.581 | 0.276 | 50.45 | 6477 |
| Ceramic | 1.727 | 0.503 | 4194 | 1660892 |
| Ships, boats and floating structures | 1.818 | 0.226 | 144.4 | 126718 |
| Pharmaceutical products | 1.982 | 0.311 | 8928 | 1625681 |
| Railway or tramway locomotives, rolling stock, fixtures and fittings, and parts thereof; mechanical traffic signaling equipment of all kinds | 2.234 | 0.336 | 2425 | 449402 |
| Glass and glassware | 2.476 | 0.109 | 4038 | 1783320 |
| Sugars and sugar confectionery | 2.506 | 0.197 | 113.7 | 65900 |
| Dairy product; eggs; natural honey; edible products of animal | 2.554 | 0.262 | 460.4 | 4687 |
| Rubber and articles thereof | 2.741 | 0.0308 | 3833 | 2066729 |
| Plastics and articles thereof | 2.801 | 0.0390 | 24820 | 9262688 |
| Cereals | 3.109 | 0.157 | 3.049 | 76.74 |
| Fertilizers | 3.762 | 0.533 | 9614 | 468034 |
| Iron and steel | 3.854 | 0.346 | 14859 | 2493056 |
| Cotton | 3.964 | 0.261 | 600.8 | 389959 |
| Upstream commodities | | | 6788.046 | 1843891 |
| Downstream commodities | | | 3953.329 | 1518660 |
| Concentrated commodities | | | 6538.436 | 1649678 |
| Non-concentrated commodities | | | 4202.939 | 1712873 |

*Note:* The names of the commodity are abbreviated and the order is sorted by the upstreamness index. The exposure is calculated by $\Sigma(PercentExports * NewCases)$ where $PercentExports$ denotes the percentage of exports of the commodity by each Chinese provincial/foreign country and $NewCases$ denotes the number of new cases of the Chinese province/foreign country. The benchmark to split upstream and downstream, concentrated and non-concentrated industries is the median of the two indices. High exposure means that the commodity is potentially more affected by the Covid-19 infection.

Table 3

*Trade exposure to Chinese and foreign Covid infection of the perfectly matched commodities*

Figure 2 presents the relationships between the midpoint growth rate[16] of trade value and the two indices. Both relationships are consistent with the theoretical model in Section 2. Note that I use the midpoint growth rate instead of the trade volume because the midpoint growth rate that uses the trade volumes last year as benchmarks provides a better visualization of Covid shock compared to the seasonally fluctuated absolute value of trade volume. In Figure 2a, commodities from upstream industries (labeled as high upstreamness) tend to be more volatile than those from downstream industries (labeled as low upstreamness) as the drop of midpoint growth rate is more drastic since April 2020.[17] In Figure 2b, the changes in midpoint growth rate are similar for commodities from concentrated and non-concentrated industries, meaning that the effect of industry concentration on trade is ambiguous.[18] These two visualizations support the conclusions drawn from the conceptual bullwhip effect.

Table 3 further reveals the Covid shock on the final 16 Chinese export commodities.[19] from the perspective of trade exposure to Chinese domestic and foreign Covid infection. The trade exposures are calculated as the weighted sum of new cases in Chinese provinces/foreign countries where the weights are given by the share of exports from each province/share of imports to each country in 2020. It measures the extent to which a particular commodity is exposed to Chinese domestic and foreign Covid-19 pandemic. Suppose, for instance, the United States imports all Chinese iron and steel but only 50% of

[16] The midpoint growth rate is calculated by $\frac{Trade_{pjkt}-Trade_{pjkt-12}}{0.5*(Trade_{pjkt}+Trade_{pjkt-12})}$ where $Trade_{pjkt}$ denotes the trade volume of commodity k from province p to foreign country j at time t. $t-12$ denotes the time one year before. The midpoint growth rate of trade value is developed by Bricongne, Fontagné, Gaulier, Taglioni, and Vicard (2010) and can correctly approximate the aggregate growth rate of exports and overcome the seasonality bias.

[17] I categorize commodities with upstreamness index smaller than the median to be low upstreamness and that greater than the median to be high upstreamness.

[18] I categorize commodities with concentration index smaller than 0.5 to be low concentration and that greater than 0.5 to be high concentration. 0.5 is calculated by the median of the two possible extremes, zero and one.

[19] These 16 commodities have perfectly matched upstreamness and concentration index and will be the main focus of my following empirical section.

fertilizers. If all the foreign new cases are in the United States, the iron and steel industry faces a stronger foreign demand shock than the fertilizers industry.

By splitting upstream and downstream, concentrated and non-concentrated industries based on the median of the two indices, I find that upstream industries tend to have more exposures to Covid infections both domestically and internationally while concentrated industries tend to expose more to domestic but less to foreign infections. In other words, the export provinces and import foreign countries of upstream commodities are hit harder by Covid-19, and the export provinces of concentrated commodities and the import foreign countries of non-concentrated commodities have relatively more severe pandemic. Although the results cannot apply universally to every commodity, the general trend they reflect is consistent with the results from Figure 2. Note that the higher trade exposure of upstream industries does not directly indicate the bullwhip effect but just shed light upon the potential Covid impact on different commodities. The bullwhip effect is demonstrated in the following Section 4 using a fixed effects model to control for province, foreign country, commodity, and time unobservables.

## 4 Empirical Result

In order to empirically test the bullwhip effect along the global supply chains from the Chinese perspective, I choose to use a fixed effect model to soak up the average difference across province-foreign country bilateral relations, commodity, and time. The sample of my baseline estimates is restricted in three ways: (1) the United States is excluded because the ongoing trade war might affect the empirical result;[20] (2) only the perfectly matched commodities in the data concordance are included; and (3) only the foreign countries that report complete Covid statistics from December 2019 to September

[20] For example, the Phase One trade deal in January $15^{th}$, 2020, right after the outbreak of Covid-19 in China and right before the global outbreak, reduces duties from 15% to 7.5% on $120 billion Chinese commodities. China also agrees to purchase at least an additional $200 billion worth of US commodities according to the trade deal. In this case, the deal will affect the import and export of Chinese products and therefore the trade volume within the supply chain.

2020 are included. My baseline results demonstrate the significance of the bullwhip effect, suggesting that upstream industries tend to suffer from a greater demand shock measured by the volume of exports compared to the downstream industries. I then test the sensitivity of my baseline results against alternative measures of the Covid shock, different fixed effect specifications, and various sample restrictions. Following the baseline analyses, I explore the dynamics of the hypothesized bullwhip effect on Chinese exports and estimate the time lagged effects of COVID-19 along the supply chain, which points to some discrepancies between the theory and the data.

### 4.1 Baseline Estimates

The baseline estimates are based on a fixed effects specification that models Chinese Exports ($X$) as a function of domestic Covid case counts ($DC$) and foreign case counts ($FC$) while controlling for bilateral province-foreign country pairs ($\alpha_{pj}$) as well as time-invariant differences across commodities ($\rho_k$) and common time trends and seasonal variation ($\mu_t$). To investigate the potential bullwhip effect along the supply chain and shed light on the influence of industry concentration, I interact foreign country cases with indicator variables that differentiate industries with below and above median upstreamness ($UP$) or concentration ($CON$). The standard errors are clustered at the province-foreign country bilateral level. The resulting specification can be described as follows:

$$X_{pjkt} = \beta_0 + \beta_1 DC_{pt} + \beta_2 FC_{jt} + \beta_3 FC_{jt} * UP_k + \beta_4 FC_{jt} * CON_k + \alpha_{pj} + \rho_k + \mu_t + \epsilon_{pjkt} \quad (8)$$

where $X_{pjkt}$ is the inverse hyperbolic sine (IHS) transformation of the volume of export of commodity k from province p to foreign country j at time t.[21] $DC_{pt}$ measured by

[21] While the frequently used logarithm transformation can cluster the extreme values to the middle and reduce their unnecessarily large effects on the empirical results, such transformation does not apply well on trade data because it cannot deal with zero value trade. In short, ln(0) is undefined. Therefore, I choose to use the IHS to transform my data as zero can be defined.

the IHS of Chinese domestic confirmed and death Covid cases at the province level indicates the severity of Covid-19 in China and serves as a proxy for Chinese domestic supply shock. $FC_{jt}$, on the other hand, measured by the IHS of foreign confirmed and death Covid cases at the foreign country level represent the international demand shock. Both $DC_{pt}$ and $FC_{jt}$ are good proxies because the number of Covid cases is closely related to the factory closures (R. Baldwin et al., 2020) and negatively correlated with consumers' income and expenditure (Coibion, Gorodnichenko, & Weber, 2020). $UP_k$ and $CON_k$ are binary variables that denote whether the commodity is upstream or concentrated respectively and the benchmark of separation is their median value. I use the binary instead of the continuous variables because one unit change in either index does not necessarily generate a linear effect on exports. For example, the difference in Covid shock between upstream and midstream industries is not necessarily the same as the difference in Covid shock between midstream and downstream industries.

While $\beta_1$ indicates the effect of Chinese domestic Covid-led supply shock, the primary coefficients of interest in equation 8 are $\beta_2$, $\beta_3$, and $\beta_4$, which reflect the direction and magnitude of foreign Covid-led demand shock on different industries. Specifically, $\beta_2$ measures the demand shock on non-concentrated, downstream industries; $\beta_3$ measures the additional demand shock for exports of upstream industries; and $\beta_4$ measures the additional demand shock for exports of concentrated industries. Based on the bullwhip effect N-stage model in Section 2, I expect $\beta_2$ and $\beta_3$ to be negative and significant while $\beta_4$ is ambiguous. In other words, upstream industries suffer from a greater demand shock than downstream industries do, and the role concentration plays varies by industries.

Table 4 shows the baseline coefficient estimates of equation 8. First, $\beta_1$ measuring the Chinese domestic supply shock is negative and significant at 0.01 level in all models, indicating that a 1% increase in Chinese new cases reduces Chinese exports by approximately 4.5%. This matches with my expectation and the estimates from Friedt and Zhang (2020) as the spread of Covid-19 would lead to factory closures and workers'

| Outcome Variable: IHS of trade | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Chinese new cases | -0.046 | -0.045 | -0.045 | -0.045 | -0.045 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Foreign new cases | -0.028 | -0.011 | -0.042 | -0.026 | -0.043 |
| | (0.000) | (0.026) | (0.000) | (0.000) | (0.000) |
| Up × Foreign new cases | | -0.031 | | -0.021 | 0.003 |
| | | (0.000) | | (0.000) | (0.661) |
| Con × Foreign new cases | | | 0.033 | 0.024 | 0.049 |
| | | | (0.000) | (0.000) | (0.000) |
| Up × Con × Foreign new cases | | | | | -0.055 |
| | | | | | (0.000) |
| Commodity | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Bilateral FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 42381 | 42381 | 42381 | 42381 | 42381 |
| R-Square | 0.521 | 0.522 | 0.522 | 0.523 | 0.523 |

*Note:* P-values are reported in the parentheses. All standard errors are clustered at the Chinese province-foreign country bilateral level. These regressions are based on the sample that is restricted in three aspects: (1) the United States is excluded; (2) only the most matched commodities are included; and (3) only the foreign countries that report complete Covid statistics from December 2019 to September 2020 are included.

Table 4
*Baseline Fixed Effect Estimates*

quarantines, and production process in China would therefore stagnate. Second, $\beta_2$ measuring the foreign demand shock is negative and significant at 0.01 level in all models, suggesting that a 1% increase in foreign new cases reduces Chinese exports from 1.1% to 4.3%. This is because foreign people's income and consumption decrease when they lose their jobs or are forced to furlough as Covid infections rise.

More importantly, the coefficient estimates for $\beta_3$ and $\beta_4$ are statistically significant and suggest that both an industry's position along the supply chain and its degree of concentration influence the pandemic-induced demand shock on Chinese exports. Models 2 and 4, reported in columns (2) and (4) of Table 4, imply that upstream producers and non-concentrated producers tend to be more vulnerable under the Covid demand shock.

Specifically, a 1% increase in foreign new cases reduces Chinese exports of downstream industries by 2.6% and those of upstream industries by 4.7%, suggesting that the bullwhip effect almost doubles the demand shock along the supply chain. The same unit of change in foreign new cases rises Chinese concentrated exports by 0.2% and drops non-concentrated ones by 2.6%, indicating that the Covid shock on non-concentrated industries is more severe. These can also be visualized via the Figure A.1a and Figure A.1b in the Appendix C that show the predicted value of trade of different types of industries over foreign new cases, the proxy for foreign demand shock. While the predicted value of trade decreases as the Covid shock becomes more severe, upstream industries in Figure A.1a and non-concentrated industries in Figure A.1b apparently experience a steeper drop in trade.

The story becomes more complicated when I add in the triple interaction term $FC_{jt} * UP_k * CON_k$ that indicates the joint effect of upstreamness and concentration. Model 5 in Table 4 shows that in the best case, a 1% increase in foreign new cases does not really affect Chinese exports of a downstream industry that is concentrated (like pharmaceutical and signalling equipment producers).[22] In the worst case, the same change in foreign new cases will drop Chinese exports by almost 10% for an upstream industry that is concentrated (like fertilizers and iron and steel producers).[23]

## 4.2 Robustness Checks and Heterogeneous Analysis

Table A.1 in Appendix B shows the empirical result with different fixed effect specifications. By controlling for province, foreign country, commodity, and time fixed effects individually or with some of them interacted with each other, the baseline results still hold. Model 2 through 4 show that upstream industries still suffer from an amplified negative shock compared to downstream industries (indicated by the negative sign of the interaction term between upstreamness and foreign new cases) and the size of amplification

[22] The effect is calculated by $-0.043 + 0.049 = 0.006$.

[23] The effect is calculated by $-0.043 - 0.055 = -0.098$.

depends on the fixed effect specifications. Concentrated industries also experience a weaker demand shock provided by the positive coefficient of the interaction between concentration binary and foreign new cases.

In order to visualize more nuances between industries, I split the upstreamness index into terciles.[24] Figure A.1c in Appendix C presents the predicted value of trade of downstream, midstream, and upstream industries over foreign new cases. The trend-line shows clearly that the Covid shock is greater on upstream and midstream industries compared to the downstream ones while the gap between upstream and midstream industries is not significant, which is consistent with my baseline results. Model 5 in Table A.1 further shows the coefficients when upstreamness and concentration index are continuous. While upstream industries still experience an amplified demand shock, the shock on concentrated and non-concentrated industries is numerically similar given that the coefficient of the interaction term between concentration index and foreign new cases approaches zero and the p-value exceeds 0.05. However, as I mention above that the continuous upstreamness and concentration index cannot generate a reliable result, model 9 only serves as a robustness check for my baseline estimates.

Table A.2 in Appendix B presents the estimates when I change the measurement of the Covid shock from new cases to death cases (see Panel A) and cumulative cases (see Panel B). While all three measurements represent slightly different aspects of the severity of Covid-19 (new and cumulative cases indicate the spread while death cases reveal the fatality of the pandemic), the signs of coefficients are consistent with my baseline estimates.

Additionally, I test the sensitivity of my estimates against alternative sample restrictions by, for example, including the United States or expanding the set of exported commodities to include less well matched commodities. Panel A in Table A.3, Table A.5, Table A.4 in Appendix B show the estimates under these relaxed sample restrictions. The magnitudes and signs of the three coefficients of interest ($\beta_2$, $\beta_3$, and $\beta_4$) are consistent

[24] The benchmark of the split is based on the 33 and 66 percentile of the upstreamness index.

with my baseline estimates.[25]

Finally, I explore the heterogeneity of my baseline findings by restricting the sample to include only Asian countries and only the top 30 Chinese major trading partners.[26] While the signs are consistent with my baseline estimates, the coefficients of the interaction between upstreamness binary and foreign new cases in Panel B and Panel C in Table A.3 in Appendix B are numerically 1% greater than that in my baseline result. Specifically, for a 1% increase in foreign new cases, the additional shock on upstream industries is 50% greater for trade among Asian countries and 100% greater for trade among the top trading partners, suggesting that the bullwhip effect tends to be stronger in regional supply chains and supply chains in which countries are closely connected.[27] Intuitively, this is because when upstream and downstream producers are closely connected geographically and/or economically, upstream industries tend to hold more inventory to prevent supply shortages. In this case, the same unit of change in downstream demand will lead to a greater fluctuation in inventory adjustment and therefore more volatility in demand for upstream industries.

### 4.3 Time Lagged Effect

While the baseline estimates are robust across a number of sensitivity analyses, they only reveal the the immediate impact of Covid-19 and fail to capture the nuance of the demand shock month by month after the outbreak of Covid-19. Table 5 shows the 1-month

[25] The coefficient of the interaction between concentration binary and foreign new cases in Table A.4 that includes the less well matched commodities is numerically smaller than my baseline estimates. But because the theory suggests that the effect of concentration on trade is ambiguous depending on the type of industries, mutually substitute or complement, the numerically smaller coefficients are acceptable.

[26] These 30 major trading partners occupy almost 70% of Chinese exports and each of them import a huge amount of industrial goods from China each year. Therefore, their industrial producers should be closely connected with Chinese industries.

[27] Note that numerically (in terms of percentage point) the coefficient of the interaction term between upstreamness and foreign new cases increases from 2.1% in the baseline estimates to 3.1% for trade among Asian countries and 4.4% for trade among Chinese major trading partners. But in terms of the trade volume, the increase becomes 50% and 100% respectively.

through 5-months lagged effects while controlling for the bilateral, commodity, and time fixed effects. The standard errors are clustered at the province, foreign country, and commodity level. First, the Chinese domestic shock measured by $\beta_1$ from $Lag_1$ to $Lag_5$ approaches zero overtime, meaning that the Chinese domestic supply shock is persistent over one quarter and that the domestic supply chains gradually reboot four months after the outbreak of Covid-19 in China. The foreign demand shock measured by $\beta_2$ is far less persistent and turns from negative to positive only two months after the outbreak of Covid-19.

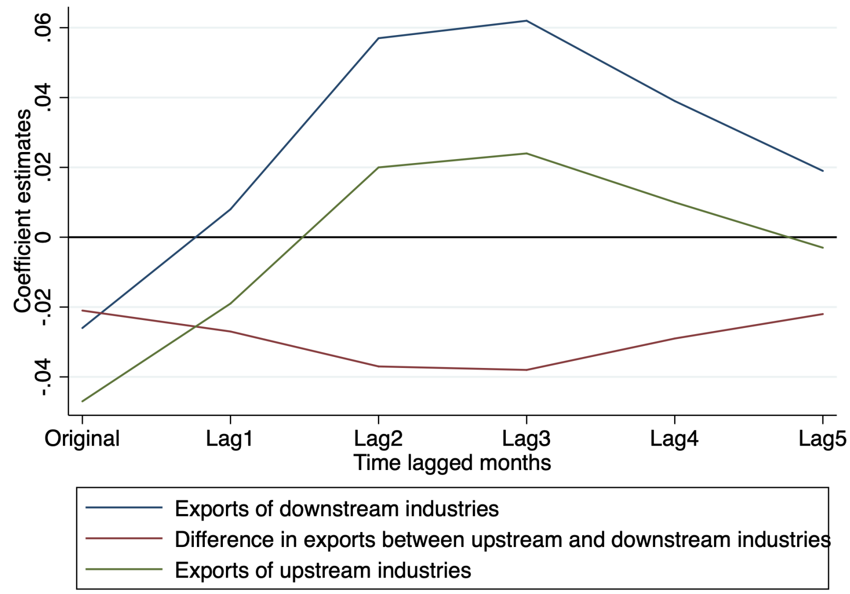
| Outcome Variable: IHS of trade | (Original) | ($Lag_1$) | ($Lag_2$) | ($Lag_3$) | ($Lag_4$) | ($Lag_5$) |
|---|---|---|---|---|---|---|
| Chinese new cases | -0.045 | -0.051 | -0.014 | -0.012 | 0.000 | -0.014 |
| | (0.000) | (0.000) | (0.012) | (0.050) | (0.966) | (0.072) |
| Foreign new cases | -0.026 | 0.008 | 0.057 | 0.062 | 0.039 | 0.019 |
| | (0.000) | (0.116) | (0.000) | (0.000) | (0.000) | (0.002) |
| Up × | | | | | | |
| Foreign new cases | -0.021 | -0.027 | -0.037 | -0.038 | -0.029 | -0.022 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Con × | | | | | | |
| Foreign new cases | 0.024 | 0.017 | 0.001 | -0.007 | -0.010 | -0.011 |
| | (0.000) | (0.001) | (0.843) | (0.143) | (0.046) | (0.029) |
| Commodity | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Bilateral FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 42381 | 37672 | 32963 | 28254 | 23545 | 18836 |
| R-Square | 0.523 | 0.526 | 0.533 | 0.537 | 0.544 | 0.559 |

*Note:* P-values are reported in the parentheses. All standard errors are clustered at the Chinese province, foreign country, and commodity level. These regressions are based on the sample that is restricted in three aspects: (1) the United States is excluded; (2) only the most matched commodities are included; and (3) only the foreign countries that report complete Covid statistics from December 2019 to September 2020 are included.

Table 5
*Baseline Fixed Effect Regressions with Time Lagged Effect*

In order to further visualize the dynamic bullwhip effect, I plot the coefficients of foreign new cases, that of the interaction between upstreamness binary and foreign new cases, and the sum of the two. These coefficients indicate the demand shock on

(a) Coefficient estimates of the foreign demand shock face by downstream and upstream industries




(b) Simple smoothed line graph of the theoretical model

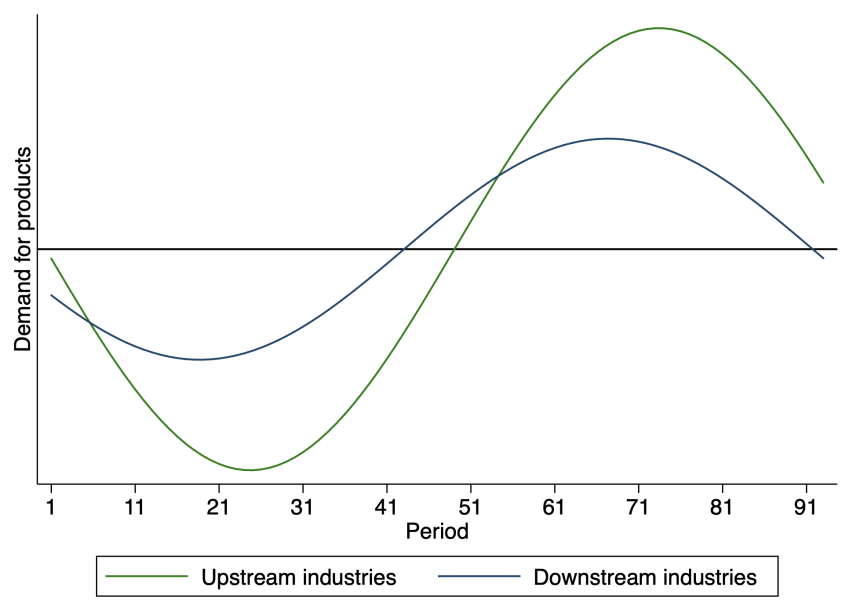



*Figure 3*. Comparison between theoretical model and empirical result

downstream industries, the additional shock on upstream industries, and the demand shock on upstream industries overtime respectively. In Figure 3a, it is clear that the foreign demand shock on downstream industries reduces their exports at first and then boost their exports one month after the pandemic outbreak. While the upstream exports share the same trend line, they experience a steeper and lengthier drop and a weaker and lagged recovery (two months after the Covid outbreak). Specifically, the rise and fall of downstream exports are generally one month earlier than the fluctuation of upstream exports. Furthermore, as the green line is always below the blue line, upstream exports undoubtedly are more negatively affected by the Covid shock compared to downstream ones, which is consistent with my baseline estimates.

To some extent, however, the results generated by the time lagged effect regressions do not completely match with the theory in Section 2. The N-stage bullwhip effect model suggests that the demand shock engendered by decreasing consumers' income will first hit the most downstream industries and then amplify along the supply chain until it hits the most upstream industries n periods later. This amplification process is explained by excessive inventory adjustment. Applying the bullwhip effect model to the Covid-19 scenario, the Covid-led demand shock in theory should decrease exports of both upstream and downstream industries among which the reduction in upstream industries should be relatively larger and lagged. When the pandemic is under control, downstream industries should recover earlier than upstream industries do. Theoretically, the fluctuation of the exports of upstream industries throughout this process should be greater than that of downstream industries as shown in Figure 3b which visualizes the theoretical bullwhip effect.

However, my empirical results reveal two main deviations from the theory. First, although the horizontal gap between the blue line and the green line in Figure 3a captures the lagged effect of the foreign demand shock on upstream industries, it fails to do so during the first months after the pandemic outbreak. In other words, the initial shock on upstream industries might be simultaneous with, instead of lagged behind, the shock on downstream industries. Second, the exports of Chinese upstream and downstream industries first decrease up to 2.6% (downstream industries) and 4.7% (upstream industries) and then start to increase to at most 6.2% (downstream industries) and 2.5% (upstream industries) for every 1% change in foreign new cases, meaning that the growing foreign new cases reverses the initial Covid-led export reduction. Also, when downstream industries recover and their exports increase one month after the outbreak of Covid-19, the fluctuation of the upstream exports is not as large as the model in Figure 3b predicts. That is, the green line doesn't surpass the blue line due to excessive inventory adjustment.

The first deviation can be explained by the rapid information flow along the supply chain given the advanced communication technology nowadays. Because bilateral trades are recorded at the monthly frequency, it is possible that upstream industries have already adjusted their inventory within the first month after the pandemic outbreak. In other words, although the shock in theory takes n period to transmit from the most downstream to the most upstream industry, in practice n periods might be shorter than a month.

The second deviation can be attributed to the import substitution. In detail, the theory, although it explains the bullwhip effect on supply chains, does not capture factors like foreign factory, especially upstream factory, closures that generate the import substitution, which boosts Chinese downstream exports and drags down upstream exports. Figure A.2 in Appendix C shows a simple example of the transformation of supply chain due to the Covid-led import substitution. Before the pandemic outbreak, the whole supply chain lies across China and Foreign Country A and B and eventually fulfill all foreign demand by Chinese downstream final goods producers. The global pandemic outbreak reduces foreign consumers' income and therefore Chinese downstream exports to all foreign consumers, which, according to the bullwhip effect theory, also reduces Chinese upstream exports due to inventory adjustments.

However, shortly after the outbreak, as industrial production in Foreign Country A is stagnating while the production in China is resuming, consumers in Foreign Country A have to purchase final goods from Chinese downstream industries for their basic needs. This import substitution then serves as a positive demand shock at the consumer end of the supply chain, which increases the exports of both downstream and upstream industries successively due to the upward inventory adjustment. But note that the stagnating foreign industrial production also cease the Chinese upstream exports to Foreign Country A as the pandemic shuts down factories there. The upstream production in Foreign Country A is temporarily replaced by producers from other countries. The integration of these two effects therefore explains why the Covid-led demand shock does not reduce Chinese exports persistently and why the recovery is more prominent in downstream than in upstream industries.

## 5 Conclusion

In this paper, I study the bullwhip effect of Covid-19 along the global supply chain from the Chinese perspective. My baseline estimates suggest that upstream industries tend to suffer from a stronger negative demand shock compared to downstream industries while concentrated industries in vast majority of the cases tend to have a weaker demand shock, which is consistent with the bullwhip effect theory. Specifically, a 1% increase in foreign new cases reduces Chinese exports by 2.6% for downstream industries, 4.7% for upstream industries, and 5.5% for both upstream and concentrated industries. These results are robust across different fixed effect specifications, measurements of Covid severity, and sample restrictions. A heterogeneity analysis indicates that the bullwhip effect tends to be stronger in the supply chains in which countries are geographically proximate and are more closely connected in terms of the trade volume.

A dynamic analysis of the bullwhip effect, however, indicates some deviations from the theory. On one hand, the bullwhip effect model mathematically suggests that upstream industries tend to face a stronger demand shock at a later time as the inventory adjustments can amplify the shock that takes n period to transmit through the supply chain. On the other hand, my estimates show that (1) the initial Covid-led demand shock hits downstream and upstream industries in the same month; (2) the change in exports of downstream and upstream industries turns from negative to positive, and the fluctuation of upstream exports is weaker than that of downstream exports, which is at odds with the bullwhip effect model. While the first deviations can be explained by the frequency of my trade data and the rapid information transmission given the high-tech communication technology nowadays, the second one cannot be fully explicated without the supplemental import substitutions theory. In short, it is the shut-down of foreign industrial production and the corresponding import substitution that leads to increasing demand for Chinese downstream final goods and decreasing demand for Chinese upstream raw or intermediate goods.

My study also sheds light upon the current Covid policies across different countries, suggesting that the global industrial recovery needs the combination of both demand and supply side supports from better control of the pandemic. Blindly reopening the economy is theoretically ineffective. In detail, countries like the United States, India, Brazil, France, and Italy need to strengthen their Covid-19 prevention measures to handle their over ten thousand daily new cases in February 2021. When the pandemic is to some extent under control, industrial production can be normalized (supply side) and consumers' income can be recuperated (demand side). In this case, a gradual Covid-prevention accompanying with economic reopening can not only effectively smooth out the fluctuation generated by the bullwhip effect but also reduce the inefficiency caused by the import substitution.[28]

From the global perspective, the regional and international corporation in Covid-19 prevention is also crucial in today's interconnected world. On one hand, regional trade is proved to be more volatile based on my heterogeneity analysis of the bullwhip effect, so

[28] The import substitution will expose producers to a less internationally competitive environment. As they are less likely to select trading partners, the production, communication and transportation might be inefficient.

cooperation among East Asian countries, for example, can theoretically promote their trade recoveries. On the other hand, as international trade accounts for 60.27% of the world GDP in 2019 according to the World Bank data, world economy and global supply chains are easily affected by the pandemic as long as it hits at least one country that engages in the trade. Therefore international cooperation is the only way to mitigate the potential damage of the pandemic.

While the bullwhip effect plus the import substitution theory provide some insights of the Covid-led demand shock across Chinese industries, future studies can conduct a more comprehensive analysis by including the complete 2020 and 2021 trade data, the inventory data, the import data, and more accurate upstream and concentration index. In addition, as my study mainly focuses on the global supply chains from the Chinese perspective, it is also worth examining the ones from the perspectives of the United States and the European Union and check if the bullwhip effect and the import substitution can be generalized to the foreign trade of these countries. Lastly, future analysis of the Covid impacts on Chinese exports can test whether the bullwhip effect and the import substitution is long-lasting. Politically, the pandemic-induced restructuring and reshaping of global trade and GVCs will promote the change of trade policies in many countries. Economically, although the bullwhip effect plus the import substitution that fluctuate Chinese exports may not be persistent, it is possible that certain micro adjustments in global and/or regional supply chains can be enduring as some producers have the chance to explore other possible trading partners and ways of trading. Covid-19 is drastically reshaping the world not only medically but also economically.

## References

Altomonte, C., Di Mauro, F., Ottaviano, G., Rungi, A., & Vicard, V. (2012). Global value chains during the great trade collapse: a bullwhip effect? *Firms in the international economy: Firm heterogeneity meets international business*, 277–308.

Antràs, P., Chor, D., Fally, T., & Hillberry, R. (2012). Measuring the upstreamness of production and trade flows. *American Economic Review*, *102*(3), 412–16.

Antras, P., Redding, S. J., & Rossi-Hansberg, E. (2020). *Globalization and pandemics* (Tech. Rep.). National Bureau of Economic Research.

Baker, S. R., Farrokhnia, R. A., Meyer, S., Pagel, M., & Yannelis, C. (2020). *How does household spending respond to an epidemic? consumption during the 2020 covid-19 pandemic* (Tech. Rep.). National Bureau of Economic Research.

Baldwin, R. (2020). To treat covid-19's economic impact, start by keeping the lights on. *Chicago Booth Review*.

Baldwin, R., di Mauro, B. W., & Tomiura, E. (2020). *Economics in the time of covid-19* (Vol. 59). Center for Economic and Policy Research Press.

Baldwin, R., & Taglioni, D. (2009). The great trade collapse and trade imbalances. *Centre for Economic Policy Research*, *6*, 47–58.

Baldwin, R. E. (2009). *The great trade collapse: Causes, consequences and prospects*. Center for Economic and Policy Research.

Balleer, A., Link, S., Menkhoff, M., & Zorn, P. (2020). Demand or supply? price adjustment during the covid-19 pandemic. *Center for Economic Studies and Ifo Institute for Economic Research Working Paper*.

Bekaert, G., Engstrom, E., & Ermolov, A. (2020). Aggregate demand and aggregate supply effects of covid-19: A real-time analysis. *Finance and Economics Discussion Series 2020-049*.

Bems, R., Johnson, R. C., & Yi, K.-M. (2012). *The great trade collapse* (Tech. Rep.). National Bureau of Economic Research.

Bonadio, B., Huo, Z., Levchenko, A. A., & Pandalai-Nayar, N. (2020). *Global supply chains in the pandemic* (Tech. Rep.). National Bureau of Economic Research.

Bricongne, J. C., Fontagné, L., Gaulier, G., Taglioni, D., & Vicard, V. (2010). Exports and sectoral financial dependence: evidence on french firms during the great global crisis. *European Central Bank Working Paper*.

Coibion, O., Gorodnichenko, Y., & Weber, M. (2020). *The cost of the covid-19 crisis: Lockdowns, macroeconomic expectations, and consumer spending* (Tech. Rep.). National Bureau of Economic Research.

Eppinger, P., Felbermayr, G., Krebs, O., & Kukharskyy, B. (2020). Covid-19 shocking global value chains. *Center for Economic Studies and Ifo Institute for Economic Research Working Paper*.

Fernandes, A., & Tang, H. (2020). How did the 2003 sars epidemic shape chinese trade? *Social Science Research Network*.

Friedt, F. L., & Zhang, K. (2020). The triple effect of covid-19 on chinese exports: First evidence of the export supply, import demand and gvc contagion effects. *Covid Economics, Vetted and Real-Time Papers*, 72–109.

Hassan, T. A., Hollander, S., van Lent, L., & Tahoun, A. (2020). *Firm-level exposure to epidemic diseases: Covid-19, SARS, and H1N1* (Tech. Rep.). National Bureau of Economic Research.

Hyun, J., Kim, D., & Shin, S.-R. (2020). The role of global connectedness and market power in crises: Firm-level evidence from the covid-19 pandemic. *Covid Economics: Vetted and Real-Time Papers*, *49*.

Leckcivilize, A. (2012). The impact of supply chain disruptions: Evidence from the japanese tsunami. *London School or Economics and Political Science, London*.

Lee, J.-W., & McKibbin, W. J. (2004). Globalization and disease: The case of sars. *Asian Economic Papers*, *3*(1), 113–131.

Meier, M., & Pinto, E. (2020). Covid-19 supply chain disruptions. *Covid Economics,* *Vetted and Real-Time Papers*, 139–170.

Patrinley, J. R., Berkowitz, S. T., Zakria, D., Totten, D. J., Kurtulus, M., & Drolet, B. C. (2020). Lessons from operations management to combat the covid-19 pandemic. *Journal of Medical Systems*, *44*(7), 1-2.

Wang, X., & Disney, S. M. (2016). The bullwhip effect: Progress, trends and directions. *European Journal of Operational Research*, *250*(3), 691–701.

World Trade Organization. (2020). Trade shows signs of rebound from covid-19, recovery still uncertain. *World Trade Organization 2020 Press Release*.

Zavacka, V. (2012). *The bullwhip effect and the great trade collapse*. European Bank for Reconstruction and Development.

## Appendix A: Theoretical Model Supplemental Explanation

Continuing the discussion of the Two-Stage Model, I will explain the rest of the five scenarios here. In the third scenario, suppose the negative demand shock hits producers at stage 0 at both time t-2 and t-1 and the shock is exacerbating ($A > B$),[29] the demand for products at stage 1 at time t will be

$$\begin{aligned} D_t^1 &= (1-A)(1+\alpha)D_{t-1}^0 - (1-B)\alpha D_{t-2}^0 \\ &= (1+\alpha)D_{t-1}^0 - (1+\alpha)AD_{t-1}^0 - \alpha D_{t-2}^0 + B\alpha D_{t-2}^0 \end{aligned}$$

In this case, as $A > B$ and $D_{t-1}^0 = D_{t-2}^0$, $(1+\alpha)AD_{t-1}^0$ is greater than $B\alpha D_{t-2}^0$, implying that the increasingly severe demand shock will drag down $D_t^1$. This is because producers at stage 0 suffer from a stronger demand shock at time t-1 and need to further reduce their inventory to meet the even lower demand.

In the fourth scenario, suppose the negative demand shock hits producers at stage 0 at both time t-2 and t-1 and the shock is mitigating ($A < B$), the demand for products at stage 1 at time t will be

$$\begin{aligned} D_t^1 &= (1-A)(1+\alpha)D_{t-1}^0 - (1-B)\alpha D_{t-2}^0 \\ &= (1+\alpha)D_{t-1}^0 - (1+\alpha)AD_{t-1}^0 - \alpha D_{t-2}^0 + B\alpha D_{t-2}^0 \end{aligned}$$

In this case, as $A < B$ and $D_{t-1}^0 = D_{t-2}^0$, the change in $D_t^1$ is ambiguous. If $(1+\alpha)AD_{t-1}^0$ is greater than $B\alpha D_{t-2}^0$, $D_t^1$ should decrease because the direct effect of the decrease in demand for product at stage 0 at time t-1 is dominant over the upward

[29] Note that the negative demand shock at time t-1 reduces $D_{t-1}$ by $A\%$ and that at time t-2 reduces $D_{t-2}$ by $B\%$.

inventory adjustment. Mathematically, when $(1+\alpha)AD^0_{t-1} > B\alpha D^0_{t-2}$,

$$
\begin{aligned}
(1+\alpha)AD^0_{t-1} &> B\alpha D^0_{t-2} \\
AD^0_{t-1} + A\alpha D^0_{t-1} &> B\alpha D^0_{t-2} \\
AD^0_{t-1} &> B\alpha D^0_{t-2} - A\alpha D^0_{t-1}
\end{aligned}
$$

where the left side denoting the demand reduction at time t-1 is greater than the right side denoting the increase in demand for inventory.

If $S(1+\alpha)AD^0_{t-1}$ is less than $B\alpha D^0_{t-2}$, $D^1_t$ should increase because the upward inventory adjustment is dominant over the direct effect of the decrease in demand for product at stage 0 at time t-1. Mathematically, when $A(1+\alpha)D^0_{t-1} < B\alpha D^0_{t-2}$,

$$
\begin{aligned}
A(1+\alpha)D^0_{t-1} &< B\alpha D^0_{t-2} \\
AD^0_{t-1} + A\alpha D^0_{t-1} &< B\alpha D^0_{t-2} \\
AD^0_{t-1} &< B\alpha D^0_{t-2} - A\alpha D^0_{t-1}
\end{aligned}
$$

where the left side denoting the demand reduction at time t-1 is weaker than the right side denoting the increase in demand for inventory.

In the fifth scenario, suppose the negative demand shock hits producers at stage 0 at both time t-2 and t-1 and the magnitude of the shock is the same in both periods ($A = B$), the demand for products at stage 1 at time t will be

$$
\begin{aligned}
D^1_t &= (1-A)(1+\alpha)D^0_{t-1} - (1-B)\alpha D^0_{t-2} \\
&= (1+\alpha)D^0_{t-1} - (1+\alpha)AD^0_{t-1} - \alpha D^0_{t-2} + B\alpha D^0_{t-2}
\end{aligned}
$$

In this case, as $A = B$ and $D^0_{t-1} = D^0_{t-2}$, $(1+\alpha)AD^0_{t-1}$ is greater than $B\alpha D^0_{t-2}$, implying that the continuous and invariant demand shock will drag down $D^1_t$. This is because producers at stage 0 suffer from the direct demand shock at time t-1. It is noteworthy that given $A = B$ and $D^0_{t-1} = D^0_{t-2}$, producers at stage 0 don't need to adjust their inventory ($I^0_{t-1} = AD^0_{t-1} = Q^0_{t-2} = BD^0_{t-2}$).

In conclusion, if the negative demand shock hits producers at stage 0 at both time t-2 and t-1 and the shock is exacerbating ($A > B$), the increasingly severe demand shock will drag down $D^1_t$. This is because producers at stage 0 suffer from the stronger demand shock at time t-1 and need to further reduce their inventory to meet the even lower demand. If the negative demand shock hits producers at stage 0 at both time t-2 and t-1 and the shock is mitigating ($A < B$), the change in $D^1_t$ is ambiguous. The result depends on whether the direct effect of the decrease in demand for product at stage 0 at time t-1 is dominant over the upward inventory adjustment at the same period. If the negative demand shock hits producers at stage 0 at both time t-2 and t-1 and the magnitude of the shock is the same in both periods ($A = B$), the continuous and invariant demand shock will drag down $D^1_t$ because producers at stage 0 suffer from the direct demand shock at time t-1.

## Appendix B: Tables

| Outcome Variable: IHS of trade | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Chinese new cases | -0.045 | -0.045 | -0.045 | -0.045 | -0.045 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Foreign new cases | -0.026 | -0.028 | -0.018 | -0.032 | 0.052 |
| | (0.000) | (0.000) | (0.115) | (0.000) | (0.000) |
| Up × Foreign new cases | -0.021 | -0.019 | -0.036 | -0.008 | |
| | (0.000) | (0.001) | (0.007) | (0.017) | |
| Con × Foreign new cases | 0.024 | 0.024 | 0.023 | 0.021 | |
| | (0.000) | (0.000) | (0.069) | (0.000) | |
| Up × Foreign new cases | | | | | -0.031 |
| (Continuous) | | | | | (0.000) |
| Con × Foreign new cases | | | | | -0.007 |
| (Continuous) | | | | | (0.688) |
| Province FE | No | Yes | No | No | No |
| Foreign Country FE | No | Yes | No | No | No |
| Commodity | Yes | Yes | No | No | Yes |
| Time FE | Yes | Yes | No | Yes | Yes |
| Bilateral FE | Yes | No | Yes | No | Yes |
| Commodity and Time FE | No | No | Yes | No | No |
| Bilateral and Commodity FE | No | No | No | Yes | No |
| Observations | 42381 | 42381 | 42381 | 42381 | 42381 |
| R-Square | 0.523 | 0.442 | 0.529 | 0.806 | 0.524 |

*Note:* P-values are reported in the parentheses. All standard errors are clustered at the Chinese province-foreign country bilateral level. These regressions are based on the sample that is restricted in three aspects: (1) the United States is excluded; (2) only the most matched commodities are included; and (3) only the foreign countries that report complete Covid statistics from December 2019 to September 2020 are included. Continuous in the parenthesis means that the measures of Upstreamness and Concentration become continuous instead of binary variable.

Table A.1
*Baseline Estimates with Varying Fixed Effect Specifications*

| **Panel A: Death Cases**<br>Outcome Variable:<br>IHS of trade | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Chinese new deaths | -0.065 | -0.066 | -0.066 | -0.067 | -0.067 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Foreign new deaths | -0.021 | -0.005 | -0.037 | -0.023 | -0.043 |
| | (0.000) | (0.440) | (0.000) | (0.003) | (0.000) |
| Up × Foreign death cases | | -0.032 | | -0.020 | 0.007 |
| | | (0.000) | | (0.011) | (0.370) |
| Con × Foreign death cases | | | 0.036 | 0.028 | 0.058 |
| | | | (0.000) | (0.000) | (0.000) |
| Up × Con × Foreign death cases | | | | | -0.066 |
| | | | | | (0.000) |
| Commodity | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Bilateral FE | Yes | Yes | Yes | No | Yes |
| Observations | 42381 | 42381 | 42381 | 42381 | 42381 |
| R-Square | 0.521 | 0.522 | 0.522 | 0.522 | 0.523 |
| **Panel B: Cumulative Cases**<br>Outcome Variable:<br>IHS of trade | (1) | (2) | (3) | (4) | (5) |
| Chinese cumulative cases | -0.024 | -0.025 | -0.025 | -0.026 | -0.026 |
| | (0.020) | (0.014) | (0.014) | (0.013) | (0.010) |
| Foreign cumulative cases | -0.029 | -0.024 | -0.032 | -0.027 | -0.039 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Up × Foreign cumulative cases | | -0.010 | | -0.008 | 0.009 |
| | | (0.000) | | (0.000) | (0.000) |
| Con × Foreign cumulative cases | | | 0.008 | 0.004 | 0.024 |
| | | | (0.000) | (0.055) | (0.000) |
| Up × Con × Foreign cumulative cases | | | | | -0.043 |
| | | | | | (0.000) |
| Commodity | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Bilateral FE | Yes | Yes | Yes | No | Yes |
| Observations | 84762 | 84762 | 84762 | 84762 | 84762 |
| R-Square | 0.514 | 0.514 | 0.514 | 0.514 | 0.515 |

*Note:* P-values are reported in the parentheses. All standard errors are clustered at the Chinese province-foreign country bilateral level. These regressions are based on the sample that is restricted in three aspects: (1) the United States is excluded; (2) only the most matched commodities are included; and (3) only the foreign countries that report complete Covid statistics from December 2019 to September 2020 are included.

Table A.2

*Baseline Estimates with Different Measurements of Covid Shock*

| **Panel A: Including the United States** | | | | | |
|---|---|---|---|---|---|
| Outcome Variable: IHS of trade | (1) | (2) | (3) | (4) | (5) |
| Chinese new cases | -0.045 | -0.045 | -0.045 | -0.044 | -0.044 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Foreign new cases | -0.026 | -0.006 | -0.038 | -0.016 | -0.038 |
| | (0.000) | (0.244) | (0.000) | (0.011) | (0.000) |
| Up × Foreign new cases | | -0.037 | | -0.030 | -0.000 |
| | | (0.000) | | (0.000) | (0.996) |
| Con × Foreign new cases | | | 0.030 | 0.016 | 0.049 |
| | | | (0.000) | (0.004) | (0.000) |
| Up × Con × Foreign new cases | | | | | -0.072 |
| | | | | | (0.000) |
| Commodity | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Bilateral FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 44145 | 44145 | 44145 | 44145 | 44145 |
| R-Square | 0.533 | 0.535 | 0.534 | 0.535 | 0.536 |
| **Panel B: Asian Countries** | | | | | |
| Outcome Variable: IHS of trade | (1) | (2) | (3) | (4) | (5) |
| Chinese new cases | -0.057 | -0.056 | -0.056 | -0.056 | -0.056 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Foreign new cases | -0.023 | 0.003 | -0.042 | -0.019 | -0.037 |
| | (0.000) | (0.682) | (0.000) | (0.043) | (0.000) |
| Up× Foreign new cases | | -0.045 | | -0.031 | -0.008 |
| | | (0.000) | | (0.001) | (0.432) |
| Con × Foreign new cases | | | 0.045 | 0.033 | 0.059 |
| | | | (0.000) | (0.000) | (0.000) |
| Up × Con × Foreign new cases | | | | | -0.048 |
| | | | | | (0.002) |
| Commodity | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Bilateral FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 19863 | 19863 | 19863 | 19863 | 19863 |
| R-Square | 0.524 | 0.526 | 0.526 | 0.527 | 0.527 |
| **Panel C: Major Trade Partners** | | | | | |
| Outcome Variable: IHS of trade | (1) | (2) | (3) | (4) | (5) |
| Chinese new cases | -0.045 | -0.043 | -0.044 | -0.043 | -0.042 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Foreign new cases | -0.032 | -0.006 | -0.045 | -0.013 | -0.043 |
| | (0.000) | (0.333) | (0.000) | (0.078) | (0.000) |
| Up × Foreign new cases | | -0.049 | | -0.044 | -0.003 |
| | | (0.000) | | (0.000) | (0.661) |
| Con × Foreign new cases | | | 0.030 | 0.011 | 0.056 |
| | | | (0.000) | (0.078) | (0.000) |
| Up × Con × Foreign new cases | | | | | -0.095 |
| | | | | | (0.000) |
| Commodity | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Bilateral FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 29664 | 29664 | 29664 | 29664 | 29664 |
| R-Square | 0.499 | 0.502 | 0.500 | 0.502 | 0.504 |

*Note:* P-values are reported in the parentheses. All standard errors are clustered at the Chinese province-foreign country bilateral level. These regressions are based on the sample that is restricted in two aspects: (1) only the most matched commodities are included; and (2) only the foreign countries that report complete Covid statistics from December 2019 to September 2020 are included.

Table A.3

*Baseline Fixed Effect Estimates with Geographic Heterogeneity*

| Outcome Variable: IHS of trade | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Chinese new cases | -0.036 | -0.036 | -0.036 | -0.036 | -0.035 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Foreign new cases | -0.022 | -0.008 | -0.021 | -0.004 | -0.010 |
| | (0.000) | (0.016) | (0.000) | (0.245) | (0.007) |
| Up $\times$ Foreign new cases | | -0.029 | | -0.030 | -0.020 |
| | | (0.000) | | (0.000) | (0.000) |
| Con $\times$ Foreign new cases | | | -0.001 | -0.006 | 0.003 |
| | | | (0.743) | (0.015) | (0.459) |
| Up $\times$ Con $\times$ Foreign new cases | | | | | -0.018 |
| | | | | | (0.000) |
| Commodity | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Bilateral FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 224271 | 224271 | 224271 | 224271 | 224271 |
| R-Square | 0.495 | 0.496 | 0.495 | 0.496 | 0.496 |

*Note:* P-values are reported in the parentheses. All standard errors are clustered at the Chinese province-foreign country bilateral level. These regressions are based on the sample that is restricted in two aspects: (1) the United States is excluded; (2) only the foreign countries that report complete Covid statistics from December 2019 to September 2020 are included.

Table A.4
*Baseline Fixed Effect Estimates with Lower Quality Matches*

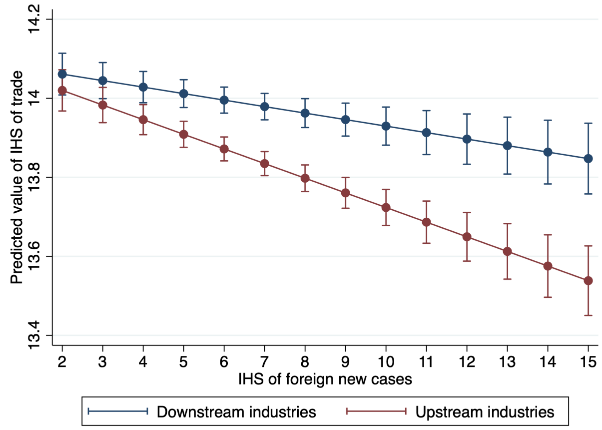
| Outcome Variable: IHS of trade | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Chinese new cases | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 |
| | (0.551) | (0.538) | (0.541) | (0.533) | (0.542) |
| Foreign new cases | -0.026 | -0.000 | -0.047 | -0.018 | -0.043 |
| | (0.001) | (0.955) | (0.000) | (0.083) | (0.000) |
| Up $\times$ Foreign new cases | | -0.053 | | -0.045 | -0.006 |
| | | (0.000) | | (0.000) | (0.540) |
| Con $\times$ Foreign new cases | | | 0.040 | 0.026 | 0.064 |
| | | | (0.000) | (0.002) | (0.000) |
| Up $\times$ Con $\times$ Foreign new cases | | | | | -0.077 |
| | | | | | (0.000) |
| Commodity | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Bilateral FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 152856.000 | 152856.000 | 152856.000 | 152856.000 | 152856.000 |
| R-Square | 0.486 | 0.486 | 0.486 | 0.487 | 0.487 |

*Note:* P-values are reported in the parentheses. All standard errors are clustered at the Chinese province-foreign country bilateral level. These regressions are based on the sample that is restricted in three aspects: (1) the United States is excluded; (2) only the most matched commodities are included; and (3) only the foreign countries that report complete Covid statistics from December 2019 to September 2020 are included.

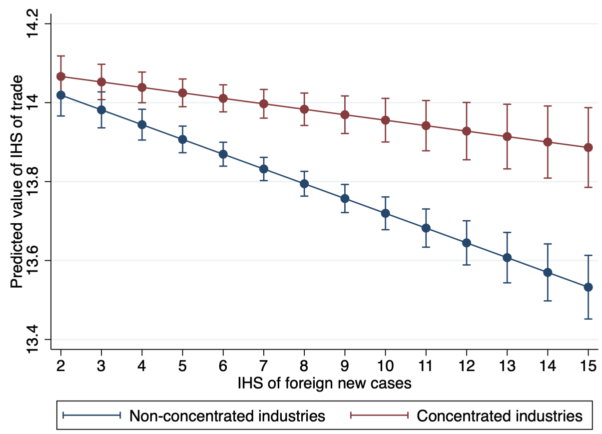
Table A.5
*Baseline Fixed Effect Estimates with Less Restricted Sample*

## Appendix C: Figures

(a) Margins plot of upstream and downstream industries




(b) Margins plot of concentrated and non-concentrated industries




(c) Margins plot of upstream, midstream, and downstream industries

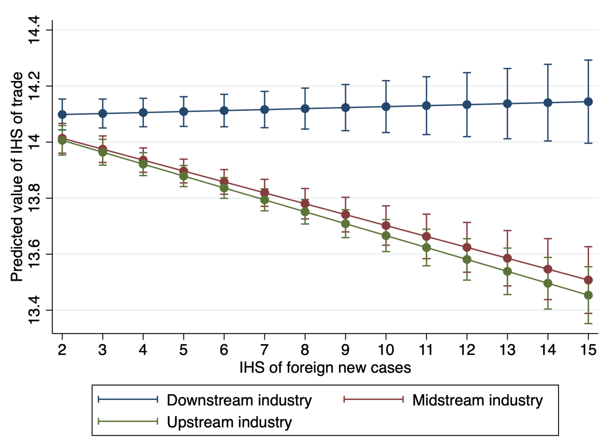
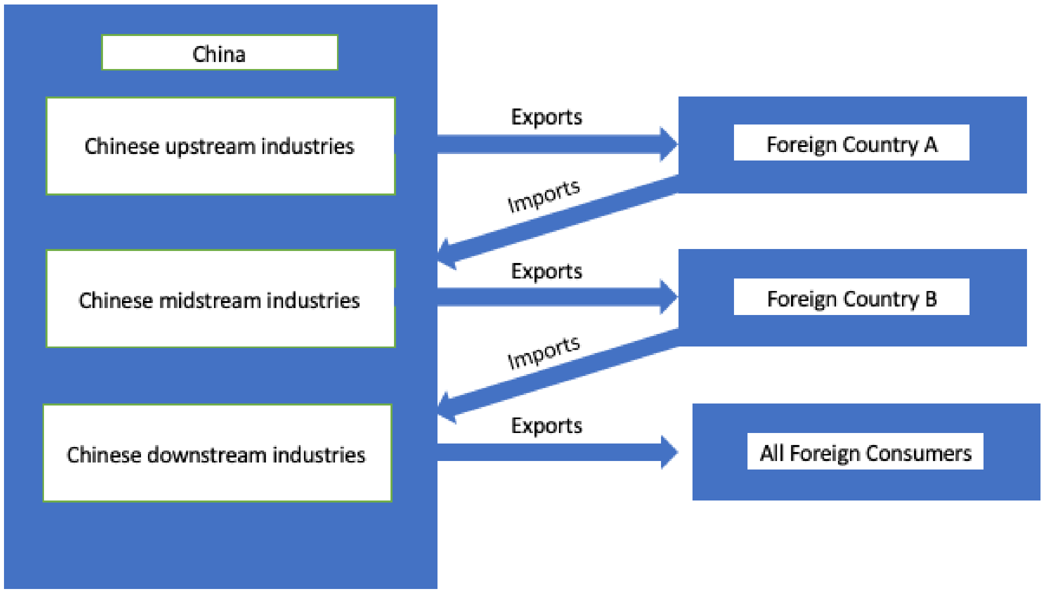



*Figure A.1*. Margins plot different types of industries

(a) Supply chain before the outbreak of Covid-19




(b) Supply chain after the outbreak of Covid-19

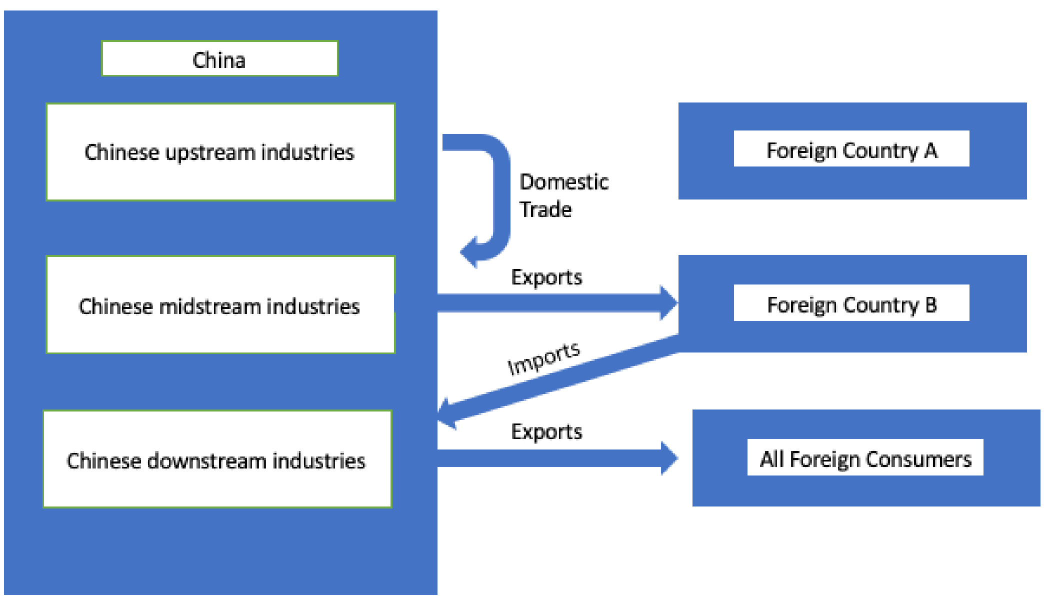



*Figure A.2.* The Covid-led transformation of supply chain