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Katharina Längle,
Research economist, WTO

Ankai Xu,
Research economist, WTO

Ruijie Tian,
PhD candidate, University of Gothenburg

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Katharina Längle,* Ankai Xu,† Ruijie Tian‡

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Abstract

This paper uses Chinese firm level data to detect the international propagation of adverse shocks triggered by the US hurricane season in 2005. We provide evidence that Chinese processing manufacturers with tight trade linkages to the United States reduced their intermediate imports from the United States between July and October 2005. We further show that the direct exposure to US supply shocks led to a temporary decline of firm exports between September and November 2005, although we do not find consistent evidence of international propagation of supply shocks along global value chains. Moreover, the paper finds that firms with more diversified suppliers tend to be less affected by the US hurricane disaster, pointing to firm sourcing diversification as a way to increase resilience to adverse shocks.

JEL classification: F12, F14, F15, F61, D56, L14, E23

Keywords: production networks; resilience; diversification; shock transmission; supply chains; natural disasters

*Research economist, WTO
†Research economist, WTO
‡PhD candidate, University of Gothenburg
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1 Introduction

In 2020, the outbreak of the COVID-19 pandemic drastically demonstrated how an adverse shock can abruptly halt social lives and economic activity around the globe. The pandemic has also heightened an emerging debate on the role of global value chains as amplifiers or absorbers of economic shocks provoked by pandemics and natural disasters. On the one hand, trade openness and integration in global production networks trigger a higher risk for disruptions of production processes as adverse shocks abroad can propagate along trading routes and value chains (Baldwin and Freeman, 2020; Carvalho et al., 2021; Acemoglu et al., 2012). On the other hand, there exists empirical evidence that diversified production networks support firms in coping with adverse shocks thereby enabling firms to quickly resume business operations (Caselli et al., 2020; Todo et al., 2015; Miroudot, 2020).

As the frequency and intensity of natural shocks such as epidemics, flood, and storms are projected to be on the rise, partly as a result of climate change, it is crucial to understand how shocks are transmitted through global value chains and under which circumstances global value chains contribute to economic resilience and recovery. The present paper fills this research gap by studying the effect of the US hurricane season in 2005 on the export performance of Chinese manufacturers. The 2005 hurricane season represented a substantial negative economic shock for an advanced country like the United States, so there is a high probability that its economic consequences spilled over to other industries across different countries. We focus on this hurricane season because two of the hurricanes that occurred during the season were among the three costliest and most devastating in US history (NHC, 2014, 2011). The United States was the fourth-largest intermediate input source for Chinese processing firms in terms of trade value in 2006, despite the geographical distance between the two countries, and the trade relationship between them has become increasingly important over the past decade.

In this context, it is particularly interesting to study economic consequences for firms in China, as the country has rapidly integrated into the world economy over the past few decades and continues to cover a growing number of production steps along global value chains (Kee and Tang, 2015; Wang et al., 2017; Criscuolo and Timmis, 2018). As a result of the strong integration in global value chains, Chinese manufacturers are especially exposed to adverse shocks provoked by natural disasters, so both the propagation of shocks and benefits from diversification are likely to be detected.

In this paper, we first investigate whether supply shocks tend to propagate directly and indirectly via import-export linkages. Second, we focus on identifying determinants that make firms more resilient to supply chain interruptions.

To investigate the propagation of the natural disaster shock, we measure the extent to which a US supply shock affects Chinese firms with direct imports from affected US states. The theoretical background of the paper builds on the multicountry sourcing model first developed by Antràs et al. (2017) and extended by Huang (2017) to show that firms more diversified in sourcing are more resilient to supply chain disruptions.

There are two major identification challenges in our empirical analysis. First, we study the 3 hurricanes that are the most devastating during the 2005 hurricane season. Given that these hurricanes affected only 7 out of 50 states, not all trade flows between the United States and China were affected by these natural disasters. Second, the Chinese firm-level data from custom authorities used in this paper contain no information about firm-level domestic production linkages. In view of the growing part of global value chains covered by Chinese manufacturers, this lack of information is problematic (Wang et al., 2017). To overcome the first identification issue, we leverage trade data of individual states and focus on sectors that are highly concentrated in affected US regions. To overcome the second issue, we focus our analysis on processing firms, as this allows us to minimise the 'black box' of domestic production linkages among firms.[1]

The key assumption in identifying the impact of US hurricane season on Chinese firms is that the unexplained factors that may affect Chinese firms' imports and exports with the United States are not correlated with the occurrence of the hurricanes. This is likely because even though natural disasters are likely to occur in certain locations, the exact location and magnitude of natural disasters are difficult to predict and therefore exogenous to any firm-specific trade pattern. In addition, to account for the fact that hurricanes are recurrent disasters in specific time periods, in most of the empirical specifications we consider firm performance indicators relative to the same months in the previous year.

Based on this data, we provide evidence that Chinese processing manufacturers with tight trade linkages to the United States saw a temporary decline in US intermediate imports between July and October 2005. More specifically, we find that such a decline occurred for Chinese processing manufacturers that, prior to the disaster, sourced more than 90% of their intermediate imports from US industries that are more concentrated in the hurricane-affected states. Moreover, we detect a statistically significant link between firms' *direct* exposure to supply shocks and their export performance. We also try to detect the *indirect* propagation of the shock through global value chains, although we did not find consistent evidence for a propagation of the supply shock via the international

[1] In China, processing firms are characterised by the ability to use imported raw materials and intermediates without tariff charges in local production or assembling of export products (Yu, 2015).

production network.[2]

The paper further investigates the heterogeneous effects of the 2005 US hurricane season on firms' resilience depending on their sourcing diversification. Defining resilience as the pass-through of a trade cost shock to a firm's marginal cost and imports as well as exports, we find that more diversified firms are more resilient to adverse shocks and are overall less volatile in exports. Furthermore, we find that Chinese processing firms heavily exposed to US supply shocks increased their diversification of suppliers in the aftermath of the US hurricanes.

The remainder of the paper is organised as follows. The subsequent section provides background information on the 2005 US hurricane season and reviews the related literature. Section 2 gives details on the data and descriptive statistics. Section 3 presents the empirical strategy and results for the *direct* effect of the US hurricane season on Chinese processing manufacturers. Section 4 provides evidence on the resilience and diversification of Chinese processing firms building on a theoretical framework. Section 5 concludes.

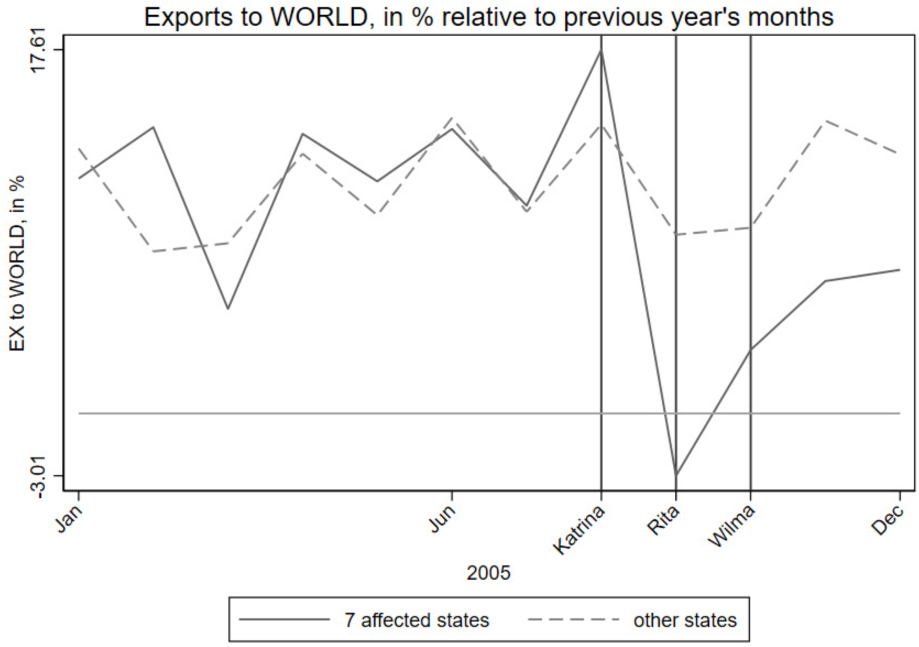
1.1 US Hurricanes

In 2005, the US southeast coast was hit by a devastating series of hurricanes. Between July and October, a total of 27 tropical storms formed, of which 3 storms developed into category 5 hurricanes, the maximum on the existing scale (National Aeronautics and Space Administration (NASA), 2006). According to the US National Hurricane Center (NHC), Hurricanes Katrina, Rita, and Wilma hit the United States in late August, September, and October, respectively.[3] With estimated damages of around \$108 billion and 1,300 deaths, Hurricane Katrina ranks among the "most devastating natural disasters in US history" (NHC, 2011; National Aeronautics and Space Administration (NASA), 2006). Katrina mainly hit Louisiana, Mississippi, Florida, Georgia, and Alabama, where it left wide swaths of the landscape, homes, and businesses devastated. It caused power outages affecting around three million people, which in some cases lasted for several weeks (NHC, 2011). Only about three weeks later, in late September, parts of Louisiana, Texas, Mississippi, Alabama, and Arkansas, as well as the Florida Keys, were hit by tornadoes and floodings caused by Hurricane Rita, with total damages of around \$12.037

[2] In previous versions of the paper, our identification strategy focused on the quantification of the propagation of the supply shock via the international production network. Estimation results are not consistently significant. Thus, so as not to blur the analysis of the present paper, results on the network propagation of the supply shock are provided in Appendix D.

[3] There were also other storms categorised as hurricanes in 2005, but we do not consider them in this paper. For a full list and more details of storms affecting the United States in 2005, see NHC (2005).

Figure 1: *US Exports Growth to the World by Hurricane-Affected and Unaffected States*



Note: The figure plots the year-on-year growth rate of the value of exports from US states, calculated as $(EX_t - EX_{t-12})/EX_{t-12} \times 100\%$, where EX_t indicates the export value of relevant states in a particular month. The solid line indicates the export growth of the seven states affected by the 2005 US hurricane season, while the dotted line indicates the export growth of other states.

billion (National Hurricane Center (NHC), 2011). Economic damage was not only caused by direct destruction from the storm but also resulted from a halt in business as a consequence of large-scale evacuations of up to two million people, such as in Texas (National Hurricane Center (NHC), 2011). Southern Florida was subsequently hit by Hurricane Wilma in October 2005, causing damages of roughly \$20.6 billion. Wilma ranks as the third-costliest hurricane in US history (behind Katrina, 2005, and Andrew, 1992) and accounted for the largest disruption of electrical service ever recorded in Florida (NHC, 2014).

Although the 2005 hurricane season resulted in significant damages, most of the effects were concentrated in seven states in the southeast region directly hit by the hurricanes: Alabama, Arkansas, Louisiana, Mississippi, Florida, Georgia and Texas. This is illustrated in Figure 1, where we plot the year-on-year export growth rate of the seven affected states compared with the other states. The seven states affected by the hurricane season experienced a significant drop in exports around the time the hurricanes hit, while the exports from other states remained relatively stable.

1.2 Literature Review

This paper can be placed in three threads of economic literature. First, it links to a well-established literature pointing to the fact that complementarities and multistage processing can lead to the amplification of shocks (Kremer, 1993). Problems at any point in a production chain can reduce output substantially if inputs enter production in a complementary fashion (Jones, 2011). A growing body of literature also focuses on the role of input-output networks as a mechanism to propagate and amplify shocks (Long and Plosser, 1983; Acemoglu et al., 2012). In particular, Acemoglu et al. (2012) posit that, if intersectoral input-output linkages exhibit asymmetries, a sectoral shock propagates strongly to the rest of the economy and affects aggregate outcomes.[4]

A related empirical literature documents the propagation of shocks over production networks. This includes a study by Acemoglu et al. (2016) that looks at the transmission of shocks at the industry level and a number of other studies that look at the propagation of shocks at the firm level (Barrot and Sauvagnat, 2016; Carvalho et al., 2021; Baldwin and Freeman, 2020; Dhyne et al., 2021; Huneeus, 2018; Demir et al., 2018). Among them, several studies exploit natural disasters as exogenous shocks to examine the propagation of such shocks in supply networks. For example, Barrot and Sauvagnat (2016) show that input specificity is a key determinant of the propagation of firm-level shocks. Firms' sales growth and stock prices drop significantly only when a major disaster hits one of their specific suppliers. Studying the 2011 Japanese earthquake, Carvalho et al. (2021) document that the disruption caused by the disaster propagated upstream and downstream along supply chains, affecting the direct and indirect suppliers and customers of disaster-stricken firms. The authors estimate that the earthquake and its aftermaths resulted in a 0.47 percentage point decline in Japan's real GDP growth in the year following the disaster.

While these studies look at the propagation of shocks within a country, there is limited evidence on the international transmission of shocks. Boehm et al. (2019) focus on the *direct* impact of the 2011 Japanese earthquake on imports of US-based Japanese multinationals in the months following the disaster. The authors find that the output of Japanese multinationals fell by a magnitude comparable to the drop in imports, indicating a very rigid supply chain relationship. Our paper fits into this literature by documenting

[4]More recent studies in this literature focus on the endogenous formation of production networks. Among them, Carvalho and Voigtländer (2014) and Acemoglu and Azar (2020) study the formation of production networks at the industry level, while Oberfield (2018), Baqaee (2018) and Lim (2018) look at the firm-level formation of production network. This literature can also be placed in a larger body of works studying the microeconomic origins of macroeconomic fluctuations, such as Gabaix (2011), di Giovanni et al. (2017) and Kramarz et al. (2020), who emphasise the role of firm-size distribution in translating micro shocks into macro fluctuations.

both the *direct* and *indirect* propagation of a major natural disaster shock in the United States on the performance of Chinese processing firms. Closest to our paper is the study by Kashiwagi et al. (2018), who investigate the indirect effects of shocks by Hurricane Sandy, which hit the United States in 2012, and show that the effect on their trade partners outside the United States is insignificant.

Second, this paper contributes to understanding the role of trade and diversification in mitigating the negative consequences of shocks. In this regard, it is related to the "technological diversification" mechanism used by Koren and Tenreyro (2013), who explain the country-level output volatility in a model with endogenous growth. Caselli et al. (2020) show that openness to international trade can lower income volatility by reducing exposure to domestic shocks and allowing countries to diversify the sources of demand and supply across countries, as long as country-wide shocks are important (as opposed to sector-specific shocks).

Our paper relates to empirical works on diversification, resilience, and volatility. Among them, Todo et al. (2015) examine how supply chain networks affected the resilience of firms (defined as the amount of time required to recover production) after the 2011 Great East Japan Earthquake and find that the positive effect of supply chain diversification exceeds the negative effect of higher exposure to disruptions. Hamano and Vermeulen (2019) study the effect of natural disasters on port-level exports after the 2011 Great East Japan Earthquake. They find that at least 40% of exports was substituted to other ports following the disaster, and the substitution effect is the strongest in technology-intensive industries. Huang (2017) looks at the diversification in global sourcing and the resilience of Chinese firms after the 2003 SARS epidemic and finds that firms with more diversified sourcing strategies are associated with higher resilience and lower volatility. Other papers link diversification with aggregate volatility. For instance, Burgess and Donaldson (2010) consider the specific case of railway expansion in India and demonstrate that the decline in transportation costs in India lowered the impact of productivity shocks on real income, implying a reduction in volatility. In comparison, our paper focuses on supplier diversification as a means to mitigate the impact of shocks from upstream suppliers on downstream firms. We also document that firms with more diversified sourcing strategies tend to have lower export volatility and that firms exposed to supply disruptions increased their level of diversification after a natural disaster.

Third, this paper also connects to a literature quantifying the economic consequences of natural disasters. Among them, some studies quantify the average effect of natural disasters on trade and economic output (Gassebner et al., 2010; Andrade da Silva et al., 2012; Cavallo et al., 2013; Felbermayr and Gröschl, 2014; Xu and Kouwoaye, 2019). Most find that exports seem to be affected negatively by the occurrence and severity of disasters, while the effects on imports are ambiguous (Osberghaus, 2019). A number of recent studies have investigated the effects of individual natural disaster events, such as the 2011 Great East Japan Earthquake (Boehm et al., 2019; Carvalho et al., 2021; Todo et al., 2015), the 2003 outbreak of SARS in China (Huang, 2017; Fernandes and Tang, 2020), and the Thai Flood in 2011 (Haraguchi and Lall, 2015). Pelli and Tschopp (2017) find that firms shift resources toward industries with a higher comparative advantage within the three years following a hurricane shock. Zhu et al. (2016) show that the 2011 Japanese earthquake had a positive effect on firms' offshoring in manufacturing activities, possibly because the damaged transport network in the Tohoku area forced some manufacturing firms to replace domestic contractors with foreign contractors. Todo and Inoue (2021) document that Japanese firms increased their level of supplier diversification between 2006 and 2016. Our paper adds to the literature by studying the impact of the 2005 US hurricane season, with a focus on the transmission of negative supply shock to the performance of downstream firms through global value chains.

2 Data Source and Descriptive Statistics

In this section, we describe the source of the data and provide several empirical facts that motivate our analysis.

2.1 Data Source

The data used in the paper are taken from three sources. The firm-level data are primarily from China Customs Statistics, which contain administrative customs data on product-level trade transactions by HS8 product and respective trade partners on a monthly frequency for individual Chinese firms between 2001 and 2006. Besides information on a unique time and firm identifier, a firm's name, the product code, trade partners, and values of transactions, this data set also contains information on quantities traded, a firm's address, its phone number, and its zip code, as well as identifiers for processing trade. A detailed explanation of the raw data set is provided in Appendix B.

To control for any reporting irregularities at the disaggregated HS-8 product level, we aggregate flows by firm at the HS-6 product level and convert all HS-6 product codes to HS Rev. 2007. Based on these unified product codes, we classify goods as intermediates using the Broad Economic Categories (BEC) classification (Rev. 4) and assign them to different two-digit ISIC (Rev. 3) manufacturing industries.[5] Moreover, transactions with

[5]Given that data are merged with information from the OECD ICIO database, which aggregates

a value of less than \$500 are dropped, as well as observations without information on the firm identifier, the date, the transaction value, or the import-export identifier.

We perform the following steps to process the data for our analysis. First, we identify and exclude all intermediaries that act as a link between manufacturers and customers, since these firms do not perform manufacturing activities themselves and thus respond differently to supply chain disruptions (Bernard et al., 2011). We rely on the data cleaning procedure proposed by Ahn et al. (2011) and drop all firms whose names contain the Chinese equivalents of 'exports', 'imports', 'imports and exports' or 'trade'. Second, we further remove observations that indicate trading partner as 'China', since according to China customs, destination or origin of 'China' is often assigned to goods consignments that have not been traded internationally, such as the movements of goods in and out of a special economic zone. Third, we focus our analysis on processing firms to capture the effect of import disruptions on exports and minimise the 'black box' of domestic production linkages. Processing firms are defined as those that have any processing transactions for a given year. Table 1 presents an overview of the number of firms as well as firm-product observations for the cleaned sample and the subsample of processing firms considered in this paper.

Table 1: *Number of Firms & Observations in Chinese Customs Statistics, 2001–2006*

Year	**Raw data**	**Cleaned sample**		**Processing firms**	
	# firms	# firms	# firm-prod.	# firms	# firm-prod.
2001	89,403	74,824	1,058,433	30,781	669,828
2002	103,017	86,680	1,174,884	31,800	661,589
2003	122,336	101,423	1,340,037	36,210	741,592
2004	151,327	123,558	1,598,692	38,089	797,150
2005	179,407	153,395	1,987,158	47,357	932,608
2006	207,872	162,811	2,078,356	48,912	995,388

As a second data source, the paper relies on trade data from the US Census Bureau accessed via *USA Trade Online* (US Census Bureau, 2020). This data set provides bilateral trade data at the HS-6 product level by US state at a monthly frequency. Thus, data are available defined by the state of origin.

As a third source, information on input-output linkages among industries is taken from the OECD ICIO database, 2016 edition (Organisation for Economic Co-operation and Development (OECD), 2016). This data set contains information on the intermediate use, final demand, value added, and output of industries in 63 different countries plus an aggregate rest-of-the-world region between 1995 and 2011. Importantly, the OECD ICIO database also provides specific information on processing industries in Mexico and China.

two-digit ISIC industries to different subcategories, our industry classification follows the OECD ICIO aggregation. A list of industries is provided in Table 6 in Appendix B.

Such information allows us to precisely determine international production linkages for processing firms, which is crucial because of the focus of this paper on this specific subgroup of firms.

2.2 Descriptive Evidence

Firms source multiple inputs from multiple countries. We provide evidence on the number of intermediate inputs imported and the number of products exported by Chinese processing firms in Table 2. On average, importers sourced 40 inputs from three foreign countries in 2006. However, this result was largely driven by a small number of firms that sourced a large variety of inputs. A median Chinese processing firm sourced 13 intermediate inputs from one country. Regarding exports, the Chinese processing firms exported to a higher number of destination markets with a lower number of varieties: the median firm exported 5 HS-6 products to four destinations on average in 2006.

Table 2: *Firm-Level Statistics on the Number of Sourcing and Exporting Countries and HS-6 Products*

	# source & destination countries per HS6 product				**# HS6 products per source & destination country**			
	Median	Mean	Std. dev.	Max	Median	Mean	Std. dev.	Max
Intermediate imports								
2004	1	2.76	3.26	43	13	46.82	133.49	1,402
2005	1	2.67	3.17	39	12	39.47	113.45	1,342
2006	2	2.86	3.21	43	13	41.54	124.65	1,477
Total exports								
2004	4	10.71	14.15	129	5	28.47	91.35	1,105
2005	3	10.41	14.12	138	6	23.37	70.80	1,002
2006	4	11.68	15.05	145	5	23.07	79.85	1,187

Source: Compiled from the Chinese customs data. **Note:** The first four columns report statistics on the number of countries from which a firm imported HS-6 intermediate inputs and to which a firm exported HS-6 products. The last four columns report statistics on the number of HS6 products that a firm imported from a source country or exported to a destination country.

Second, we provide information on the countries and economies Chinese processing firms sourced from. Table 3 reports the top 10 source economies for Chinese processing firms in 2006. Chinese Taipei was the largest source of intermediate inputs in terms of number of importers, followed by Japan, Hong Kong, China, and South Korea. As firms sourced from multiple locations, the percentages sum up to more than 100%. Japan was the largest source of inputs in terms of value of imports, followed by Chinese Taipei and South Korea. The United States was the fifth-largest source of intermediate inputs in terms of the number of importers, with about 27% of Chinese processing firms sourced from the United States in 2006; it was the fourth-largest source of inputs in terms of value, with about 10% of the value of intermediate inputs sourced from the United States. The sourcing pattern suggests that firms' sourcing decisions tended to be inversely correlated with distance: nearby sources were more likely to be the top providers of intermediate inputs to Chinese processing firms.

Table 3: *Top 10 Source Economies for Chinese Processing Firms, 2006*

	Rank by		Number of importers		Value of imports	
Source	Firms	Value	Firms	Percentage of total	Imports (million USD)	Percentage of total
Chinese Taipei	1	2	20,757	47%	49,658	28%
Japan	2	1	19,193	44%	53,960	31%
Hong Kong, China	3	5	19,189	44%	16,007	9%
South Korea	4	3	18,008	41%	46,718	27%
United States	5	4	11,845	27%	18,341	10%
Germany	6	8	8,064	18%	7,441	4%
Thailand	7	9	6,619	15%	7,039	4%
Singapore	8	7	5,983	14%	8,430	5%
Malaysia	9	6	5,621	13%	11,297	6%
Italy	10	11	5,305	12%	2,336	1%

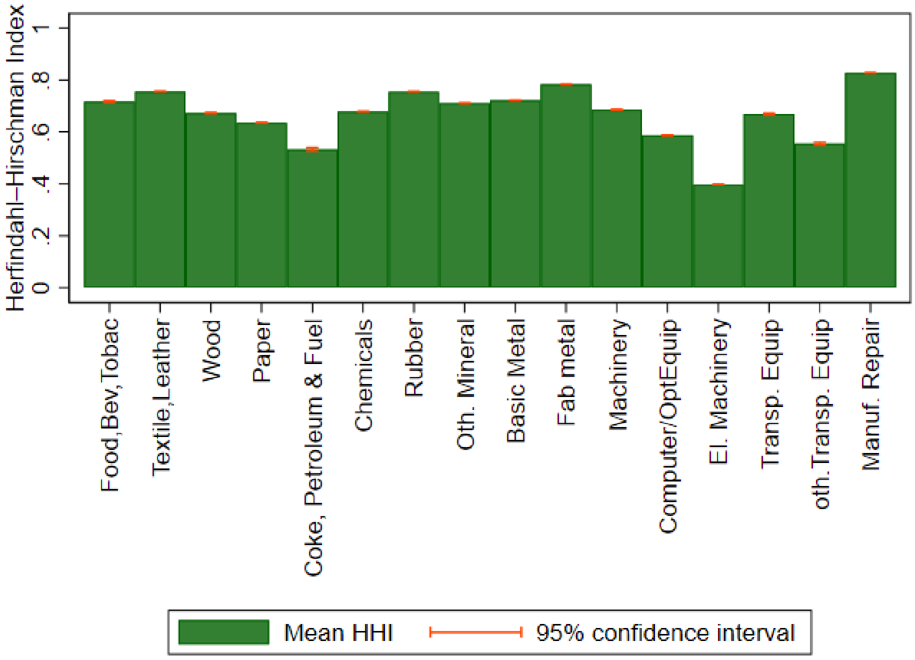
Note: The table reports the top 10 economies from which Chinese processing firms imported in 2006. The sample is the universe of Chinese processing firms after data-cleaning.

Third, we document the pattern of firm-level sourcing diversification using the Herfindahl-Hirschman Index (HHI). The HHI sums over the squares of input expenditure share from all sources, for each firm and each imported intermediate HS6 product, and the input expenditure share is measured by the share of source-specific inputs in total inputs. This can be expressed as $HHI_{fp} \equiv \sum_s \chi_{fps}^2$, where f stands for firm, p product, and s source, and χ_{fps} represents the input expenditure share from each source per firm per imported intermediate product. The HHI measures the sourcing concentration level: a value of 1 indicates full concentration (i.e., only one supplier), and a value close to zero indicates full diversification (i.e., intermediate imports spread over many suppliers). While the number of economies from which a firm sources represents the extensive margin of sourcing, the HHI captures both the intensive and extensive margins of sourcing.[6]

Figure 2 plots the HHI by industry, where we aggregate the HHI at HS6 level to industry level weighted by trade value. The average HHI ranges between 0.4 and 0.8, with the *manufacturing & repairing* industry having the highest concentration and *electrical machinery* the lowest concentration.

[6]To understand this, consider two firms, A and B. Firm A sources from two economies, with each contributing $\frac{1}{2}$ of total inputs; firm B sources from three economies, with one contributing $\frac{3}{4}$ and the other two contributing $\frac{1}{8}$. The concentration of firm A's sourcing strategy measured by HHI is $\frac{1}{2}^2 + \frac{1}{2}^2 = \frac{1}{2}$ and the HHI for firm B is $\frac{3}{4}^2 + \frac{1}{8}^2 + \frac{1}{8}^2 = \frac{19}{32} > \frac{1}{2}$. So B looks more diversified by the extensive margin, but less diversified after taking the intensive margin into account.

Figure 2: *Herfindahl-Hirschman Index (HHI) at Sector Level*



Note: The Herfindahl–Hirschman Index (HHI) is calculated as the sum over the squares of input expenditure share from all sources, while the input expenditure share is measured by the share of source-specific inputs in total inputs for each firm at an HS-6 product level at a quarterly interval for years 2004 to 2006. The HHI is then aggregated to sector level using the trade value as weights.

3 The *Direct* Effect of the US Trade Shock

In this section, we evaluate to what extent Chinese processing manufacturers were *directly* affected by the US hurricanes. In Section 3.1, we investigate whether exports and intermediate imports of Chinese processing firms are sensitive to negative shocks triggered by the US hurricane season. Second, based on these results, in Section 3.2, we assess whether firms' *direct* exposure to US hurricane supply shocks is associated with a decline in output. A complementary analysis of *indirect* effects of the US trade shock propagating via the international production network is provided in Appendix D.

3.1 Chinese Firm-Level Trade Flows during the US Hurricane Season

We begin by presenting the reduced-form evidence of the impact of the 2005 US hurricane season on firm-level US trade. We rely on a dynamic treatment effect specification. Accordingly, US-specific trade flows and respective extensive and intensive margins are regressed on time dummies for the calendar months around a disaster as well as interactions of these time dummies with an indicator for the treated group.

3.1.1 Empirical Strategy

We estimate the following model that captures the dynamic treatment effects of negative shocks on trade.

$$V_{fpt} = \alpha_f + \sum_{t=-3}^{2} \beta_t M_t + \sum_{t=-3}^{2} \gamma_t M_t \cdot TREATMENT_{fp}^{V} + \zeta_t XRATE_t + \epsilon_{fit}, \qquad (3.1)$$

where V_{fpt} refers to US exports (EX) and intermediate imports (IMI) measured in levels of firm f for product p in month t.[7] M_t indicates the six months from June to November 2005, with the hurricanes hitting the United States in August–November. To control for any time-specific shocks on firm f's exports or imports,[8] we include firm fixed effects, α_f, to control for time-invariant, unobserved firm characteristics. The dummy variable $TREATMENT_{fp}^{V}$ equals one if the trade flow of a Chinese processing firm f in product p is assigned to the treatment group. Moreover, China reformed its exchange rate regime in July 2005, which may have systematically affected Chinese firms' imports and exports. To control for the effect of such a reform on Chinese processing firms' imports and exports, we include a dummy variable $XRATE_t$ equal to 1 for months from July 2005 onward and 0 otherwise to take into account the revaluation of the Chinese yuan against the USD (Reuters, 2012).[9] The interaction term equals 1 if a firm had a trade flow with the states that were heavily hit by the hurricane season. The coefficients of interest are captured by γ_t, which estimate the differences of imports or exports of affected firms before and after the natural disasters took place.

One challenge in defining the treatment group is the fact that the hurricanes affected only 7 out of 50 states. Therefore, *not all* trade flows from and to the United States were affected by the hurricane. We use the following two criteria to define the treatment group. First, a firm's trade value with the United States must account for more than 90% of a firm's import and export of a given product prior to the disaster. We choose the threshold of 90% based on the density distribution of pre-disaster US trade shares. Density plots

[7]Following Boehm et al. (2019), we prefer to capture the trade flow V_{fpt} in levels for two reasons. First, measuring the dependent variable in levels allows us to include missing values as zeros. This is particularly important when firms' trade is interrupted for a certain time period by adverse shocks, such as natural disasters. Accordingly, we maintain zero trade flows in the sample by replacing missing values with 0 when a firm is 'active'. A firm is defined as 'active' if it first appeared in the full sample from 2001 to 2006 until its definite exit. Second, the specification of dependent variables in levels implicitly weights firms by their relative size.

[8]We remove firm-industry-specific trends from dependent variables, thus controlling for different development patterns of companies over the considered time span. Further controls for common seasonal patterns across firms are not necessary, as the treatment and control groups should follow the same seasonal fluctuations.

[9]The results of the dynamic treatment estimation are consistent including or excluding this dummy variable.

of US export and intermediate import shares are provided in Figure 7 in Appendix C. Second, we distinguish manufacturing industries that are relatively more concentrated in affected states based on state-specific trade flows.[10] Therefore, Chinese processing manufacturers are assigned to the treatment group if their US trade share for a given product exceeds 90% and if they are importing from or exporting to a manufacturing industry that is relatively more concentrated in affected states than other industries.[11] Firms that do not meet the above two criteria at the same time are in the control group. Accordingly, around 4.5% and 5% of firms are assigned to the treatment group when intermediate imports and exports are considered, respectively.

It is worth highlighting further technical details about the estimations of equation (3.1) as well as the considered product scope. One concern is that firms might self-select into the treatment group based on their size or their industries. To address this concern, we weight firms in the control group by the propensity scores of individual firms assigned to the treatment group. Thus, firms in the control group that share similar characteristics with firms in the treatment group are assigned a higher weight.[12] Accordingly, we estimate the likelihood of being assigned to the treatment group using a probit model, where we include dummies containing information on whether a firm exports or imports in a certain sector as well as the export and intermediate import values prior to the disaster.[13]

Moreover, it is important to highlight that we focus on processing firms' imports of *intermediate* goods rather than all kinds of goods. With respect to exports, however, we consider the whole range of products exported by processing manufacturers–namely, intermediate and final goods. We do this for the following two reasons. First, in the context of global value chains, it is of particular interest to investigate to what extent imported inputs are further processed to be eventually embodied in final or intermediate

[10] Details on export and import shares of affected US states by manufacturing industry are presented in Table 7 in Appendix C.

[11] According to this criterion, Chinese processing manufacturers that operate in the following industries are assigned to the treatment group if their export (intermediate import) share with the United States exceeded 90% prior to the disaster: For Chinese *importers*: textile; pulp, paper; coke; chemicals; machinery; electrical and optical equipment. For Chinese *exporters*: coke; machinery; electrical and optical equipment; wood; other non-metals; basic metals.

[12] We calculate firm-industry-specific weights as $weight_{fi} = \frac{p_{fi}}{1-p_{fi}}$, where p_{fi} stands for the propensity score of being assigned to the treatment group. Firms with propensity scores of more than 50% are weighted by a number greater than 1, while firms with propensity scores smaller than 50% are weighted by a number smaller than 1. Weights for firms in the treatment group are 1.

[13] More specifically, we estimate the following model where I_ω refers to a dummy equal one if a firm f exports in industry $i \in [1, N]$; $avgEX_f$ and $avgIMI_f$ measure a firm f's average exports and intermediate imports, respectively, prior to the disaster between August 2004 and July 2005:

$$TREATMENT^V_{fi} = \sum_{i=1}^{N} \alpha_i I_i + \beta avgEX_f + \gamma avgIMI_f + u_{fi} \tag{3.2}$$

goods' exports. Imports on final goods tend to reflect consumers' consumption habits in an economy rather than firms' involvement in global production sharing. Therefore, we exclude imports of final goods from our analysis and focus on intermediate imports instead. Second, we consider the whole range of exports with regard to the relative downstream position of Chinese firms in global value chains and their role as a global assembling hub especially during the early 2000s.[14]

3.1.2 Results

Figure 3 plots the estimation results for the reduced-form evidence of equation (3.1) on Chinese exports to the United States (the upper three graphs) and intermediate imports from the US (the lower three graphs). Individual graphs show the coefficient plots for estimations of parameter γ_τ along with their 90% and 95% confidence intervals, indicated by the capped spikes and spikes, respectively. Accordingly, estimates indicate how the imports and exports of the affected Chinese processing firms changed before and after the US hurricane season, with the hurricanes hitting during July and October 2005.[15] The dependent variable is measured as normal trade flows and trade margins for both exports and intermediate imports. Therefore, the extensive trade margin captures the number of goods exported to the United States, and the intensive margin captures the average value exported to (imported from) the United States.

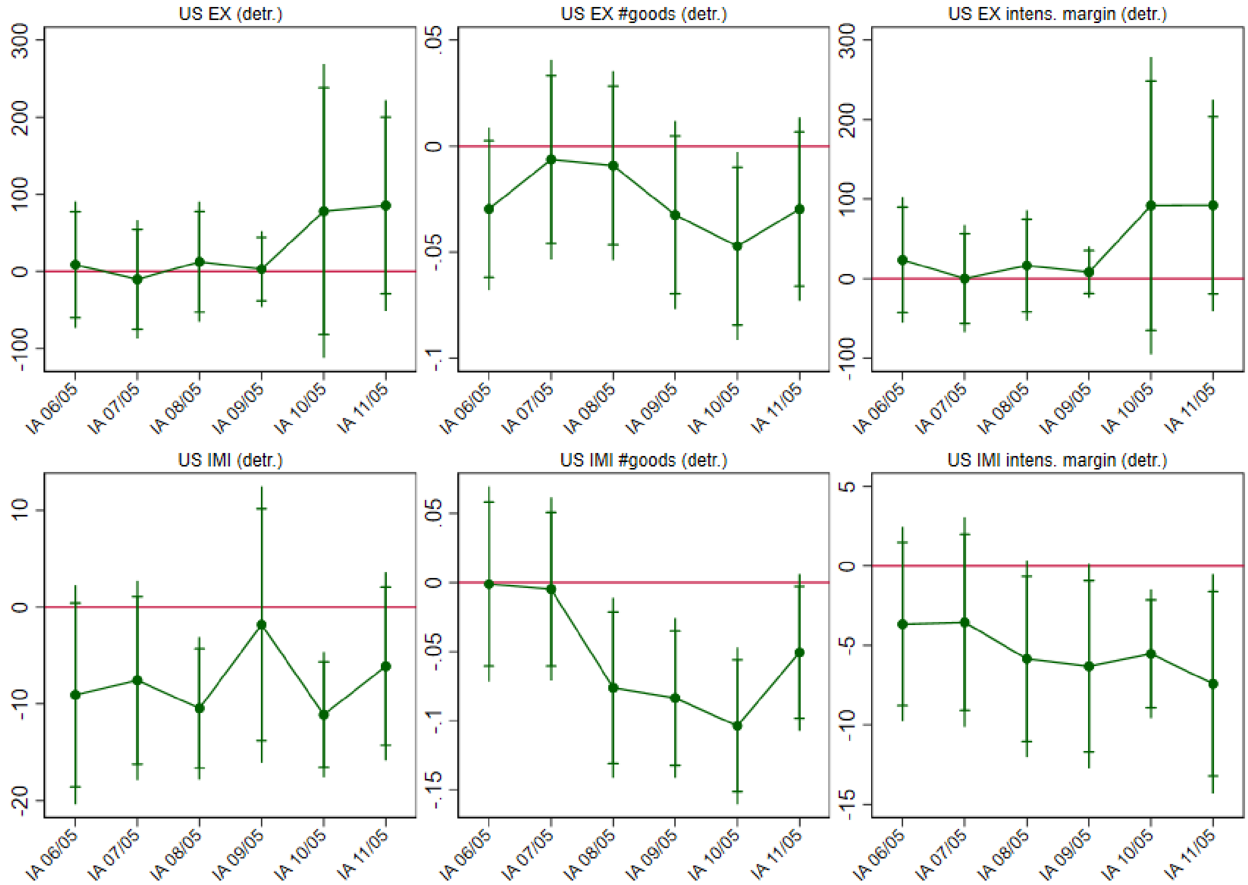
As shown in the upper three plots of Figure 3, exports of Chinese processing manufacturers with tight trade linkages to the United States did not significantly deviate from common exporting patterns of firms in the control group. However, with respect to the extensive margin, there was a decline in the number of goods exported to the United States starting in August 2005. We can therefore conclude that Chinese processing firms with a pre-disaster US trade share of more than 90% temporarily reduced the number of exported goods in industries that were highly concentrated in hurricane-affected states.

Considering estimation results for intermediate imports, the 2005 hurricane season appears to have played a more important role. As shown in the lower three plots of Figure 3, the overall intermediate imports of the treatment group significantly deviated from the sample's average estimate for October 2005. This is particularly driven by the extensive margin of intermediate imports: the number of products exported to the United States declined significantly between August and November 2005 and reached the lowest point

[14] Wang et al. (2013) consider China's trade position compared with that of the United States and show that Chinese exports of final goods include a relatively high share of foreign value added because of the use of foreign intermediates.

[15] Table 8 in Appendix C provides the coefficient estimates of equation (3.1).

Figure 3: *Coefficient Plots of Dynamic Treatment Effects*



Note: The figure plots the coefficient estimates of γ_τ in equation (3.1) capturing the interaction between dummies for months around the disaster and the $TREATMENT_{fi}^{EX,IMI}$ variable. The sample is the universe of Chinese processing firms. Firm-industry observations are assigned to the treatment group if their pre-disaster trade share was greater than 90% and if they traded with industries that were highly concentrated in affected states. Plots include 90% and 95% confidence intervals. The unit of the vertical axes of the plots for trade and intensive margins is thousand USD.

in October 2005. Because there is a time gap of around a month for container shipments from the US East Coast to China, it seems evident that the biggest drop in intermediate imports occurred in October 2005 after the United States had been hit by two severe hurricanes in late August and mid-September. Similarly, but to a lesser extent, there was a decline in the intensive margin of processing firms in the treated group in October and November 2005.

3.2 *Direct* Impact of Supply Shocks on Firm Output

This subsection investigates how negative US supply shocks are statistically linked to export fluctuations of Chinese firms. For this purpose, we focus on a subset of Chinese processing manufacturers that are *directly* exposed to US supply shocks because of *direct* import linkages to the United States. Unlike subsection 3.1, this analysis quantifies the actual *direct* exposure of Chinese firms to US supply fluctuations during the US hurricane season and examines to what extent temporary supply shortages triggered a temporary decline in firms' exports.

3.2.1 Empirical Strategy

We measure the firms' *direct* exposure to US supply shocks as fluctuations of direct imports from the United States during the 2005 hurricane season. To estimate how foreign supply shocks are associated with export fluctuations, we need to ensure that the explanatory *direct* supply shock variable effectively captures supply changes triggered by the US hurricane season and that it is not confounded by unobserved changes in import demand of Chinese firms. This assumption can be violated if, for instance, US import fluctuations of Chinese firms are caused by fluctuations of the firms' demand. We therefore construct the *direct* US import supply shock variable $direct\, SUPshock_{fjt}^{7USstates}$ using equation (3.3) to capture these import fluctuations as a supply-side shock:

$$direct\, SUPshock_{fjt}^{7USstates} = \sum_{p \in j} dirIMI_{fpjt}^{CHN \leftarrow US} \cdot EX_{pjt}^{7USstates \rightarrow RoW}. \tag{3.3}$$

Accordingly, the firm-specific dummy variables $dirIMI_{fpjt}^{CHN \leftarrow US}$ indicate whether a Chinese firm f imports a product p from the United States in month t. We match these dummies with export flows from the seven hurricane-affected states to the rest of the world, $EX_{pjt}^{7USstates \rightarrow RoW}$.[16] We then aggregate these matched US supply-side dummies at the industry level i and obtain the measure for the Chinese processing firms' *direct* exposure to the US supply shocks triggered by the 2005 hurricane season.

We estimate the relationship between negative foreign supply shocks and export fluctuations using the following model:

$$\begin{aligned} \Delta\, ln\, EX_{fpit} = {} & \alpha_f + \beta_j + \gamma_{it} \\ & + \zeta\, H^{Sep-Nov,2005} + \tau_1\, \Delta\, ln\, direct\, SUPshock_{fjt}^{7USstates} \\ & + \eta\, H^{Sep-Nov,2005} \cdot \Delta\, ln\, direct\, SUPshock_{fjt}^{7USstates} \\ & + \tau_2\, \Delta\, ln\, direct\, IMI_{fjt}^{ROW} + \epsilon_{fpit}. \end{aligned} \tag{3.4}$$

[16] While it seem counterintuitive that exports of affected states are used to calculate the supply shock for Chinese processing firms, it is important to stress that the US supply capacity is reflected by its exports.

Accordingly, firm f's exports of product p in industry i are explained by import supply fluctuations in the United States and the rest of the world, $direct\, SUPshock_{fjt}^{7USstates}$ and $direct\, IMI_{fjt}^{ROW}$, respectively, as well as by firm- and industry-specific characteristics. The effect of the supply shock triggered by the 2005 US hurricane season is captured by the interaction term between changes in the logarithm of $direct\, SUPshock_{fjt}^{7USstates}$ and the dummy variable $H^{Sep-Nov,2005}$, which equals one for the months between September and November 2005, indicating the months when hurricanes hit the states.

There are three features in the regression specification worth highlighting. First, we use year-on-year differences of logarithmic variables to control for outliers as well as to rule out firm-product specific seasonality in exports. Also, the year-on-year difference enables us to control for any year-invariant pattern of hurricanes and its relative impacts on firms to take into consideration that hurricanes hit the United States almost every year.

Second, we include firm, import industry, and export industry-time fixed effects α_f, β_j, and γ_{it}, respectively, with j indicating the import industry. It is important to stress that by including export industry-time fixed effects, we control for any industry-specific demand shocks. This is essential because it allows us to disentangle the demand shocks from the impacts of the US supply-side shocks.[17]

Third, by including $direct\, IMI_{fjt}^{ROW}$ in the regression, we control for both time-specific direct supply shocks in industry j from the rest of the world and import demand shocks at the firm level.

3.2.2 Results

In this subsection, we present estimation results on the impacts of the *direct* exposure to supply shocks on firms' exports, using the model presented in equation (3.4).

We expect a *positive* relationship between supply shocks and exports in case there is a drop of both the explained and explanatory variables. However, China has had a very strong export performance, especially from the early 2000s onward. Therefore, there might be a concern that a positive coefficient estimation only reflects a growing trade volume between the United States and China in general. To attenuate this concern, we show that there is evidence for a drop of direct supply from affected states between

[17] Previous versions of this paper aimed at studying the propagation of both demand- and supply-side shocks. However, there is a trade-off between the diligent identification of shocks and an adequate inclusion of controls. Consequently, a simultaneous identification of the effect of both shocks risks being blurred because identified effects can hardly be assigned to one or the other shock exclusively.

September and November 2005.[18]

Table 4: *Regression Results of Direct Supply Shocks*

	All	Textile	Paper	Coke	Chemicals	Machinery	El/OptEq.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ ln dir. SUPshock	0.003*	0.002	0.003**	0.003**	0.004***	0.004**	0.003**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
IA: Δ ln dir SUPshock$^{7\,USstates}$	0.014***	0.015***	0.014***	0.015***	0.014***	0.012***	0.012***
x Hurricane = 1	(0.006)	(0.006)	(0.006)	(0.007)	(0.005)	(0.006)	(0.005)
IA: Δ ln dir. SUPshock$^{7\,USstates}$		0.001	-0.001	-0.000	-0.004***	-0.003***	-0.001
x IMI-industry = column(2-7)		(0.004)	(0.003)	(0.016)	(0.004)	(0.003)	(0.008)
IA: Δ ln dir. SUPshock$^{7\,USstates}$		-0.003***	-0.001	-0.008***	-0.000	0.006***	0.010***
x Hurricane = 1		(0.012)	(0.014)	(0.008)	(0.011)	(0.012)	(0.034)
x IMI-industry = column(2-7)							
Firm-FE	✓	✓	✓	✓	✓	✓	✓
EXindustry-time-FE	✓	✓	✓	✓	✓	✓	✓
IMIindustry-FE	✓	✓	✓	✓	✓	✓	✓
ROW-control	✓	✓	✓	✓	✓	✓	✓
Observations	4,786,123	4,786,123	4,786,123	4,786,123	4,786,123	4,786,123	4,786,123

Note: The sample is processing firms that imported intermediate inputs from the United States during the pre-disaster period. The dependent variable is standardised $\Delta \ln EX$ for all regressions. $Hurricane$ refers to a dummy variable that equals 1 from September to November 2005. $IMI - industry$ dummy variables equal 1 if the importing industry corresponds to the industry indicated by the column. Individual $IMI - industry$ dummy variables are dropped due to common import industry fixed effects. Standard errors in parentheses, clustered at the firm level. *** p< 0.01, ** p< 0.05, and * p< 0.1.

Table 4 presents estimation results for the impact of the *direct* supply shock on firms' exports. Column 1 shows that Chinese firms' exports were positively associated with the exposure to the direct supply shocks induced by the 2005 US hurricane season. Accordingly, a drop in supply from the United States by one standard deviation triggered a drop in exports by 0.017 (0.003 + 0.014) standard deviations. Columns 2 to 7 add another interaction between the variable of supply shocks triggered by the US hurricane season and a dummy equal to one if firms are in the industry indicated in each column. These are the industries that are highly concentrated in the affected states, as discussed in Section 3.1.1. This exercise is in line with our empirical strategy, which pays particular attention to supply fluctuations of US industries. These triple interaction terms show that the effects of the direct supply shock are lower in textile and coke industries (columns 2 and 4), while they are higher in the machinery (column 6) and electrical/ optical equipment (column 7) industries. Interestingly, triple interaction terms for other industries are not positive and significant, with one exception being the electrical machinery industry, which also shows a positive and significant link of the direct supply shock to exports.[19] Estimation results for other sectors are presented in Tables 10 and 11 in Appendix C.

[18] Summary statistics of the supply shock variable $\Delta\, ln\, direct\, SUPshock^{7\,USstates}_{fjt}$ are presented in Table 9 in Appendix C.

[19] Triple interaction terms for other industries tend to show lower effects of adverse *direct* supply shocks. Still, the sum of relevant estimation coefficients remains positive, thus pointing to a propagation of supply shocks.

The results suggest that firms that are directly exposed to US supply shocks triggered by the 2005 hurricane season, slightly reduced their export production in the same period. In view of this finding, we can draw the conclusion that the *direct* exposure to supply shocks can affect manufacturing output.

4 Resilience to the US Trade Shock

So far, we have examined the direct impacts of the 2005 US hurricane season on the firms that imported from the United States. In this section, we explore firms' characteristics that affect their resilience, measured by the pass-through of adverse shocks to firm performance. The section contains three parts: subsection 4.1 outlines the theoretical background of our analysis, Subsection 4.2 analyzes the heterogeneous effects of the US hurricanes on firms directly affected, and Subsection 4.3 provides some evidence on the level of supplier diversification and export volatility and on the development of supplier diversification in the aftermath of the 2005 hurricane season.

4.1 Theoretical Background

To guide our empirical analysis, we use a model built on Antràs et al. (2017) and Huang (2017), which allows us to make theoretical predictions on firms' sourcing diversification and resilience to supply chain disruption. In this section we briefly describe the theoretical background. Appendix A provides a detailed derivation of the model.

We define a small, idiosyncratic trade cost shock that changes the iceberg trade cost τ_{cs} to τ'_{cs}. A firm's resilience is measured as the pass-through of adverse shocks to firm performance (e.g., import value, export value, marginal cost). A firm is defined to be more resilient if the pass-through is smaller.

Using an 'exact hat algebra' approach (Jones, 1965; Dekle et al., 2007), we denote $\widehat{X} \equiv \frac{X'}{X}$ and have the following:[20]

$$\frac{\partial \ln \widehat{(c_c(\varphi))}}{\partial \ln \widehat{\tau_{cs}}} \approx \chi_{cs}(\varphi) \tag{4.1}$$

This result suggests that the impact of the shock is determined by the intensive margin and increases with $\chi_{cs}(\varphi)$. As indicated in Section 2, χ_{cs} represents the input expenditure share of intermediate inputs from each source of supply. If the firm is not diversified at

[20]The result is based on the assumption that sourcing decisions are complementary, such that $\sigma-1 > \theta$, and the adverse shocks increase trade costs $\tau'_{cs} > \tau_{cs}$

all and relies solely on one supplier hit by a shock, the pass-through is 100%. On the other hand, high-productivity firms are more diversified and source from more places. Their share of inputs from any particular source is smaller, and so is the pass-through. This can be shown in the second derivative of equation (4.1):

$$\frac{\partial^2 \ln \widehat{(c_c(\varphi))}}{\partial \ln \widehat{\tau_{cs}} \partial \varphi} \leq 0 \tag{4.2}$$

Furthermore, if the adverse shocks on sources are not perfectly correlated and have the same variance ξ^2, we can show that opening to trade lowers the volatility of firms' source capabilities. Additionally, if we assume that sourcing decisions are complementary across sources and the adverse shocks are independent and identically distributed, the volatility of firm revenue is

$$var(\widehat{R(\varphi)}) \propto \xi^2 HHI(\varphi) \tag{4.3}$$

where HHI is the Herfindahl-Hirschman Index, which sums over the squares of input expenditure share from all sources.

Since marginal costs are not observable in our data, to generate empirically testable predictions, we study how firm-level import flows will respond to an adverse shock. The model delivers the following result: for a small trade cost shock thatincreases τ_{cs} to τ'_{cs},

$$-\frac{\partial \ln \widehat{M_{cs'}(\varphi)}}{\partial \ln \widehat{\tau_{cs}}} = \begin{cases} \theta + (\sigma - 1 - \theta)\chi_{cs'}(\varphi), & \text{if } s' = s \\ (\sigma - 1 - \theta)\chi_{cs'}(\varphi), & \text{otherwise} \end{cases} \tag{4.4}$$

where $M_{cs'}(\varphi)$ denotes a firm's intermediate input purchases from a country s'. The pass-through of the adverse shock endogenously depends on firm productivity φ and the usual Fréchet shape parameter θ, which captures the direct impact of the shock. An additional term $(\sigma - 1 - \theta)\chi_{cs'}(\varphi)$ is positive if sourcing decisions are complementary ($(\sigma - 1)/\theta > 1$) and negative if inputs are substitutable ($(\sigma - 1)/\theta < 1$).

According to equation (4.1), the trade cost shock reduces firms' sourcing capability and increases their marginal cost. This drives down marginal demand curve for all inputs if the sourcing decisions are complementary. Such a feedback effect through interdependencies amplifies the initial cost shock and reduces imports further. In contrast, if the inputs are substitutable, the cost shock reduces firm output and drives up the marginal demand curve. Such an increase in the marginal demand for the input dampens the initial negative shock. This difference allows us to identify whether sourcing decisions are complementary or substitutable. Furthermore, the pass-through also varies by the sourcing intensity

$\chi_{cs'}(\varphi)$. The feedback effect is stronger if a firm has a heavier load on inputs from a country affected by an adverse shock. Finally, the interdependency is also reflected by the result that imports also respond to shocks on other source countries in a firm's sourcing strategy.

4.2 Resilience of Firms to US Hurricanes

The theoretical model predicts that the effect of an adverse shock on imports depends on firms' pre-shock sourcing intensity. To verify such a prediction, we estimate the following equation, derived from equation (4.4):

$$\Delta \ln M_{fpst} = \alpha_f + \beta_{pt} + \nu_s + \iota_t + \gamma_1 \chi_{fp}^{US} + \gamma_2 H_t + \gamma_3 \chi_{fp}^{US} \cdot H_t + \epsilon_{fpst}, \tag{4.5}$$

in which we examine how the year-on-year change in firm f's imports of a particular intermediate product p sourced from country s at time t, $\Delta \ln M_{fps,t}$, would respond after a hurricane hit. The US sourcing intensity before the shock χ_{fp}^{US} is measured as the average expenditure share of firm f for inputs p from the United States before a hurricane (between August 2004 and July 2005). The time dummy H_t captures the duration of the US hurricane season, which equals one for months between September and November 2005. The interaction term between the hurricane shock dummy H_t and the pre-hurricane US sourcing intensity χ_{fp}^{US} captures the heterogeneous pass-through of the hurricane shock of Chinese processing firms. The main coefficient of interest, γ_3, is expected to be negative if sourcing decisions are complementary.

We control for a range of fixed effects: β_{pt} captures import-product-time fixed effects at quarterly intervals, which would absorb time varying trends specific to an imported product. Since the hurricane is defined at monthly intervals, an import-product-time fixed effects at quarterly intervals would not fully absorb the effect of the hurricane season. ν_s controls for time-invariant characteristics of the source country. Most important, we include firm fixed effects α_f to control for any time-invariant firm-level characteristics such as firm size and productivity, which may also affect firms' imports and performance.

The impact of the hurricane season may also differ by the intermediate products the firm imports. Specifically, as equation (A.28) in Appendix A indicates, products with higher elasticity of substitution may enable firms to substitute away from a source country hit by an adverse shock, and instead import from another source country unaffected by the natural disaster. To test the heterogeneous effects of the US hurricane shock on different imported products, we estimate the following triple difference-in-differences equation:

$$\Delta \ln M_{fpst} = \alpha_f + \beta_{pt} + \nu_s + \iota_t + \gamma_1 \chi_{fp}^{US} + \gamma_2 H_t + \gamma_3 \chi_{fp}^{US} \cdot H_t + \\ \gamma_4 H_t \cdot \theta_p + \gamma_5 \chi_{fp}^{US} \cdot \theta_p + \gamma_6 \chi_{fp}^{US} \cdot H_t \cdot \theta_p + \epsilon_{fpst}, \quad (4.6)$$

where θ_p is substitution elasticity for product p. The coefficient γ_4 captures the effect by which higher substitutability enables the firm to mitigate the impact of a disaster by substituting away from the source country hit by the shock; γ_5 captures the effect by which firms with a higher share of US imports prior to the disaster experienced a larger drop in imports as they substituted for imports from other sources; γ_6 captures the heterogeneous pass-through varying by products' substitution elasticity.

We use the monthly data on imports of Chinese processing firms between 2004 and 2006, aggregated by product to HS-3 digit level. The HS-3 import products are then matched with the product-level substitution elasticity estimated by Broda and Weinstein (2006) for China. To capture the fact that firms may drop out of importing because of an adverse shock, we use a value of zero for imports if a firm imported a product or exported in the beginning of the sample period and stopped trading in the middle of the sample period.

The estimation results are reported in Table 5. Along the columns, we add one more variable in each column. The effects of pre-hurricane US import intensity on imports are negative and significant in all columns, suggesting that imports were lower for firms with concentrated import sources for intermediate inputs prior to a hurricane. Column 2 suggests that, on average, the year-on-year import growth fell by roughly 19% during the hurricane season. In column 3, we add an interaction of the hurricane dummy variable and the pre-hurricane US import intensity. The result suggests that firms that imported relatively more intermediate inputs from the United States before the hurricane season could have experienced a greater decrease in their imports during the hurricane season. If a firm fully relied on imports from the United States before the hurricane season— that is, with a pre-hurricane US import intensity equal one—its year-on-year import growth could be reduced by about 33% between September and November 2005. Additionally, the effect of the hurricane shock is attenuated in column 3 compared with column 2, suggesting that the negative effect of the hurricanes was largely driven by firms that relied heavily on US intermediate imports. It is also worth noting that the negative coefficient of the interaction term between the hurricane dummy and the pre-hurricane US import intensity in column 3 corresponds to the parameter estimates of $\sigma - 1 - \theta$ in equation (4.4), implying that sourcing decisions are complementary: when imports from one source were hit by a natural disaster, year-on-year import growth from other sources also dropped in the short run.

Table 5: *Resilience of Firms to the US Hurricane*

Panel A: Dependent variable log imports	(1)	(2)	(3)	(4)
Pre-hurricane import intensity	-0.352***	-0.352***	-0.294***	-0.269***
	(0.026)	(0.026)	(0.029)	(0.033)
Hurricane = 1		-0.188***	-0.160***	-0.147***
		(0.014)	(0.015)	(0.016)
Hurricane = 1 × Pre-hurricane US import intensity			-0.253***	-0.256***
			(0.046)	(0.050)
Hurricane = 1 × θ_p				-0.003**
				(0.001)
US import intensity × θ_p				-0.005
				(0.004)
Hurricane = 1 × Pre-hurricane US import intensity × θ_p				-0.000
				(0.005)
Observations	4,440,066	4,440,066	4,440,066	4,432,747
R-squared	0.132	0.132	0.133	0.131
Firm FE	✓	✓	✓	✓
Import product-quarter FE	✓	✓	✓	✓
Source FE	✓	✓	✓	✓

Note: The dependent variable is the log of monthly imports at firm-product level of Chinese processing firms between September 2005 and December 2006. Pre-hurricane US import intensity is calculated as the share of imports from the United States over total imports for a firm-product. Indicator variable Hurricane equals 1 if the month is between September and November 2005. Trade elasticity at the HS-3 digit level is from Broda and Weinstein (2006). Robust standard errors clustered at firm level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Column 4 reports the coefficient estimates of equation (4.6), which provide evidence on heterogeneous effects of the US hurricanes varying by products' substitution elasticity. A negative coefficient on the interaction of US import intensity and the substitution elasticity θ_p in column (4) indicates that, firms with a higher US import share see a larger decrease in their imports of products with a higher substitution elasticity. For example, for firms that fully relied on US imports before the hurricane (i.e., a pre-hurricane US import intensity equal to one), the imports of stones (HS-710), with a substitution elasticity of more than 100, would fall 25% more than the imports of parts of electronic machinery (HS-854), with a substitution elasticity of close to 1.

4.3 Evidence of Sourcing Diversification

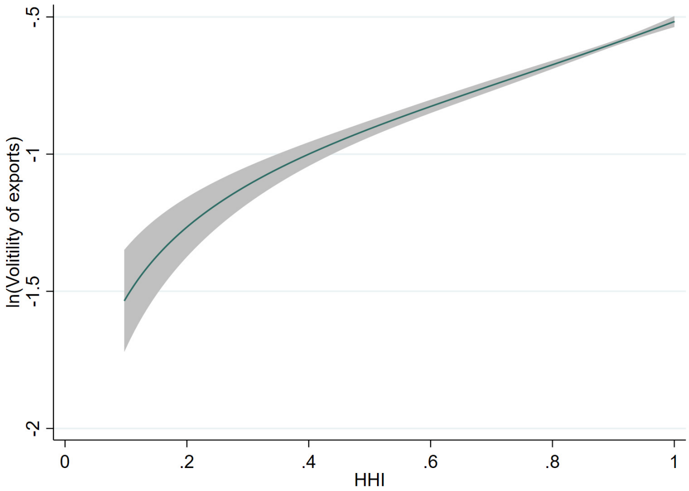
In this section, we provide evidence on the level of sourcing diversification. We demonstrate that firms with more diversified sourcing experience less volatility in exports and give some evidence on the evolution of firms' sourcing diversification around the 2005 US hurricane season.

As shown in equation (4.3), the volatility of firms' revenue is proportional to the level of supplier concentration measured by the HHI. This relationship is demonstrated in

Figure 4, which shows the relationship between firms' export volatility and their sourcing diversification. We define volatility as the variance of the year-on-year export growth rate of firms' quarterly exports from 2000 to 2006. To mitigate fluctuations of the index originating from different sourcing patterns across months, we aggregate all the variables to a quarterly level. Figure 4 plots a local polynomial regression of (logarithm) firm-level export volatility on sourcing concentration measured by the HHI at quarterly intervals, while controlling for firm fixed effects. The figure displays a general upward slope: firms with more concentrated sourcing have higher export volatility, whereas firms with more diversified sourcing strategies are associated with lower export volatility.

A linear regression of logarithm of export volatility over the firm sourcing HHI, while controlling for firm fixed effects, gives a coefficient of 0.8. This suggests that if a firm decreases its sourcing concentration such that its sourcing HHI falls by 0.1, the export volatility can decrease by 0.8%.

Figure 4: *Sourcing Concentration and Export Volatility*

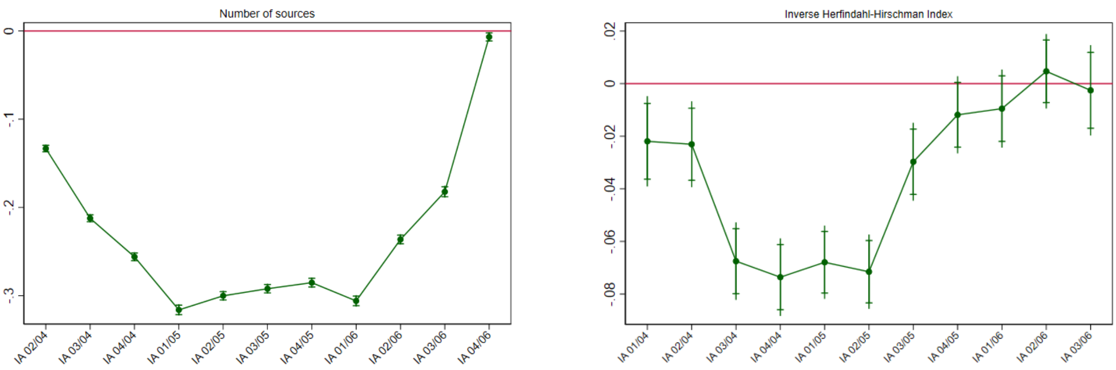


Note: The Herfindahl–Hirschman Index (HHI) is calculated as the sum over the squares of input expenditure share from all sources, while the input expenditure share is measured by the share of source-specific inputs in total inputs at an HS-6 product level at quarterly intervals. Volatility is measured as the export growth rate of firms' quarterly exports from 2000 to 2006.

Second, we provide some evidence on the evolution of firms' sourcing diversification. We have shown that diversification can be an important tool to mitigate the risk of supply shortages. However, it remains debatable whether firms will adjust their supply chains diversification following a temporary adverse shock. Antràs (2020), for instance, argues that the COVID-19 pandemic alone is unlikely to alter firms' supply chain organisation, as a temporary shock is unlikely to induce firms to sever international ties and incur fixed costs in identifying and establishing new suppliers.

Against this background, we test whether Chinese processing manufacturers changed their sourcing strategies after the 2005 US hurricane season. We identify both the extensive and intensive margins by considering two measures of diversification: (1) the number of suppliers per HS-6 product, capturing the extensive margin of sourcing, and (2) an inverse of the normalised HHI, capturing the degree of sourcing diversification. A higher inverse HHI indicates that firms not only source from a variety of suppliers but also spread the import share more evenly across different suppliers.

Figure 5: *Coefficient Plot for the Dynamic Treatment Effect of Supplier Diversification*



(a) *Number of partners* ***(b)*** *Inverse HHI*

Note: Regression equations are the same as the specification outlined in Section 3 with different outcome variables. Accordingly, firms are assigned to the treatment group when the US import share exceeds 90% in sectors that are highly concentrated in affected states. In the left panel, extensive margin is captured by the number of suppliers per firm per HS-6 product. In the right panel, import supply diversification is captured as the inverse of the normalised HHI. To account for different firm and product characteristics, we include firm and product fixed effects. Each respective quarter is indicated on the x-axis; for instance, 02/04 represents the second quarter in 2004, while 03/05 represents the third quarter in 2005.

Following an approach similar to the estimation of the dynamic treatment effects in equation (3.1), Figure 5 presents the coefficient estimates of firms' diversification for the treatment group (i.e., firms that import over 90% of their intermediate goods from the United States and in the industries heavily concentrated in affected states) in comparison with the control group. The left panel shows the evolution of the number of suppliers, and the right panel shows the evolution of diversification measured by the inverse HHI, before and after the US hurricane season. It is worth noting that by definition, firms in the treatment group are less diversified, since they are assigned to the treatment group if they rely heavily on intermediate imports from the United States. What we are interested in, however, is the evolution of supplier diversification of these firms before and after the hurricane season.

Figure 5 shows that the import diversification of Chinese processing firms with tight trade linkages to the United States was significantly lower than the average supplier diversification of firms in the control group in 2005. Nonetheless, there was a slight increase in diversification after the third quarter of 2005. The left panel indicates that the diversification is largely driven by the extensive margin, measured by the number of countries from which firms source intermediate inputs, and the right panel indicates that the level of diversification measured by inverse HHI has also increased. This growing diversification is likely to be associated with firms' choice to expand the import supplier base of intermediates in response to a supply shortage during the US hurricane season in the third and fourth quarters of 2005.

5 Conclusions

This paper has investigated the link between natural disaster shocks and global value chains. We have used the 2005 US hurricane season as a natural experiment to study how it affected the export performance of Chinese processing manufacturing firms. We constructed a firm-level data set that links three sources of data: trade data from Chinese custom authorities, input-output tables from the OECD ICIO database, and trade data from the US Census Bureau.

Following Acemoglu et al. (2016), we investigated how an adverse natural disaster shock in the United States directly affects firms in China. We showed that Chinese processing manufacturers with tight trade linkages to the United States reduced their intermediate imports from the United States between July and October 2005. We further estimated the heterogeneous effects of the US hurricane on firms' imports. We find that firms with more diversified suppliers tend to be less affected by the US hurricane in their imports of intermediate inputs and their exports. The evidence also points to a degree of complementarity in source decisions, such that an adverse shock affecting one supplier may induce a decline in sourcing from other suppliers.

At the same time, we do not find a significant impact of the cross-border propagation of supply shocks through input-output linkages, suggesting that a temporary supply reduction induced by an adverse shock in a foreign country does not impose a substantial risk for Chinese processing firms on their production of exports. This result stands in contrast to recent research that detects an indirect propagation of natural disaster shocks *within* countries (Barrot and Sauvagnat, 2016; Carvalho et al., 2021), which may be for several reasons. First, firms often form stronger input-output links within domestic supply chains; in contrast, firms participating in international production networks can more easily substitute alternative domestic or international suppliers for disaster-affected trading partners. This result is also in line with that of Kashiwagi et al. (2018), who mapped firm-to-firm transactions following 2012 Hurricane Sandy and find no propagation of the negative shock outside the United States. Second, the 2005 US hurricane season affected only a few states and thus did not constitute a major shock in comparison with the total amount of US exports.

Although this study focuses on a single type of natural disaster, the results can provide insights in a broader context for the analysis of supply chain effects of adverse shocks. First, the COVID-19 pandemic has raised concerns that global supply chains could potentially propagate a regional shock to a global scale. Our results indicate that although Chinese processing firms that directly import from the United States experienced a drop in their imports in the months following the 2005 US hurricane season, one standard deviation change in imports translates into about 0.017 standard deviation change in exports, suggesting a limited direct propagation of the shock. Furthermore, we do not detect an indirect propagation of the shock through global input-output linkages.

Second, we analyzed firms' levels of resilience according to their sourcing strategy and find that firms with more diversified supplier sources experienced a lower pass-through of the natural disaster shock in their imports. This finding is in line with the theoretical prediction that more productive firms have a more diversified sourcing strategy and are therefore more resilient to adverse trade shocks. Our results point to a potential way for firms to mitigate impacts of unexpected adverse shocks and enhance resilience to future risks from adverse shocks.

Third, we have also provided some preliminary evidence that supply chains can adjust after natural disasters. We find that firms heavily affected by the hurricanes increased their supplier diversification in the period after the hurricane. This could be due to firms' strategy adjustment to seek alternative suppliers and avert future shocks. The finding contributes to the debate on whether an adverse shock such as COVID-19 could lead to permanent adjustments in firms' sourcing decisions.

Appendices

A Theoretical Framework

In this section, we describe a multicountry model of international sourcing adapted from Antràs et al. (2017) and extended by Huang (2017). The model allows us to establish a relationship between firm's sourcing strategies, their sourcing diversification and resilience to adverse shocks. We also summarise a model in Acemoglu et al. (2016) that serves as basis for our empirical analysis of the propagation of shocks.

A.1 Demand Side

We consider a world consisting of W countries in which individuals value the consumption of differentiated varieties of manufacturing goods according to a standard symmetric CES aggregator.

$$U_{M_c} = \Big(\int_{\omega \in \Omega_c} q_c(\omega)^{(\sigma-1)/\sigma} \, d\omega \Big)^{\sigma/(\sigma-1)}, \sigma > 1 \tag{A.1}$$

where Ω_c is the set of manufacturing varieties available to consumers in country $c \in W$. The preferences are assumed to be common worldwide and give rise to the following demand for variety ω in country c:

$$q_c(\omega) = E_c P_c^{\sigma-1} p_c(\omega)^{-\sigma} \tag{A.2}$$

where $p_c(\omega)$ is the price of variety ω, P_c is the standard price index associated with equation (A.1), and E_c is aggregate spending on manufacturing goods in country c. For what follows it will be useful to define a market demand term for market c as

$$B_c = \frac{1}{\omega} \Big(\frac{\sigma}{\sigma - 1} \Big)^{1-\sigma} E_c P_c^{\sigma-1} \tag{A.3}$$

There is a unique factor of production, labour, which commands a wage w_c in country c.

A.2 Supply Side

There exists a measure N_c of final-goods producers in each country $c \in W$, and each of these producers owns a blueprint to produce a single differentiate variety. The market structure of final-goods production is characterised by monopolistic competition, and there is free entry into the industry. Production of final-goods varieties requires the assembly of a bundle of intermediates. We index final-goods firms by their productivity, which we denote by φ, and which governs the mapping between the bundle of inputs and final-goods production.

Following Melitz (2003), Antràs et al. (2017) assumes that firms learn their productivity φ only after incurring an entry cost equal to f_c units of labour in country c. This core productivity is drawn from a country-specific distribution $g_c(\varphi)$, with support in $\big[\underline{\varphi_c}, \infty)$, and with an associated continuous cumulative distribution $G_c(\varphi)$.

The bundle of intermediates contains a continuum of firm-specific inputs, assumed to be imperfectly substitutable for each other, with a constant and symmetric elasticity of substitution equal to ρ. Intermediates can be traded internationally, and a key feature of the equilibrium will be determining the location of production of different intermediates. All intermediates are produced with labour under constant return to scale technologies. $a_s(v, \varphi)$ denotes the unit labour requirement associated with the production of firm φ's intermediate $v \in [0, 1]$ in country $s \in W$.

A final-goods producer based in country c acquires the capability to offshore in s only after incurring a fixed cost equal to f_{cs} units of labour in country c. We denote by $\mathcal{W}_c(\varphi) \subseteq W$ the set of countries for which a firm based in c with productivity φ has paid the associated fixed cost of offshoring $w_c f_{cs}$. We will refer to $\mathcal{W}_c$ as the *global sourcing strategy* of that firm.

Intermediates are produced by a competitive fringe of suppliers who sell their products at marginal costs. Shipping intermediates from country s to country c entails iceberg trade cost τ_{cs}. As a result, the cost at which firms from c can procure input v from country s is given by $\tau_{cs}\, a_s(v, \varphi)\, w_s$, and the price that firm φ based in country c pays for input v can be denoted by

$$z_c\big(v, \varphi; \mathcal{W}_c(\varphi)\big) = \min_{s \in \mathcal{W}_c(\varphi)} \{\tau_{cs}\, a_s(v, \varphi)\, w_s\} \tag{A.4}$$

We can then express the marginal cost for firm φ based in country c of producing a unit of a final-goods variety as

$$c_c(\varphi) = \frac{1}{\varphi}\Big(\int_0^1 z_c\big(v, \varphi; \mathcal{W}_c(\varphi)\big)^{1-\rho}\, dv\Big)^{1/(1-\rho)} \tag{A.5}$$

Following Eaton and Kortum (2002), Antràs et al. (2017) assumes that the firm-specific intermediate input efficiencies for supplier in country s, $1/a_s(v, \varphi)$, are realised by drawing from the Fréchet distribution:

$$Pr(a_s(v, \varphi) \geq a) = e^{-T_s a^{\theta}}, \text{ with } T_s > 0 \tag{A.6}$$

where T_s governs the state of technology in country s, while θ determines the variability of productivity draws across inputs. A lower θ indicates more heterogeneity across inputs and thus fosters the emergence of comparative advantage *within* the range of intermediates across countries.

A.3 Firm-Level Sourcing Decision

Consider a firm based in country c with productivity φ that has incurred all fixed costs associated with a given sourcing strategy $\mathcal{W}_c$. In light of the cost function in (A.5), the firm will choose the location of production for each input v that solves $\min_{s \in \mathcal{W}_c(\varphi)}\{\tau_{cs} a_s(v, \varphi) w_s\}$.

Using the properties of the Fréchet distribution in (A.6), the share of intermediate input purchases sourced from any country s (including the home country c) is given by

$$\chi_{cs} = \begin{cases} \frac{T_s(\tau_{cs} w_s)^{-\theta}}{\Theta_c(\varphi)}, & \text{if } s \in \mathcal{W}_c(\varphi) \\ = 0, & \text{otherwise,} \end{cases} \tag{A.7}$$

where the term Θ_c summarises the *sourcing capability* of firm φ from c, such that

$$\Theta_c \equiv \sum_{k \in \mathcal{W}_c(\varphi)} T_k(\tau_{ik} w_k)^{-\theta}. \tag{A.8}$$

We further denote the term $\phi_s \equiv T_s(\tau_{cs} w_s)^{-\theta}$, which represents the *sourcing potential* of country s from the point of view of the firm in c.

After choosing the least-cost source of supply for each input v, WE CAN EXPRESS the overall marginal cost faced by firm φ from c as

$$c_c(\varphi) = \frac{1}{\varphi}\big(\gamma \Theta_c(\varphi)\big)^{1/(1-\theta)}, \tag{A.9}$$

where $\gamma = \left[\Gamma(\frac{\theta+1-\rho}{\theta})\right]^{\frac{\theta}{1-\rho}}$ and Γ is the gamma function. In light of equation (A.8), the addition of a new location to the set $\mathcal{W}_c$ increases the sourcing capability of the firm and necessarily lowers its effective marginal cost.

Using the demand function in (A.2) and the derived marginal cost function in (A.9), we can express the firm's profits conditional on a sourcing strategy $\mathcal{W}_c$ as

$$\pi_c(\varphi) = \varphi^{\sigma-1}\big(\gamma \Theta_c(\varphi)\big)^{(\sigma-1)/\theta} B_c - w_c \sum_{s \in \mathcal{W}_c(\varphi)} f_{cs}, \tag{A.10}$$

where B_c is the market demand term given in (A.3).

Equation (A.10) shows a firm's trade-off in sourcing decisions: when deciding whether to add a new country s to the set $\mathcal{W}_c(\varphi)$, the firm weights the reduction in costs associated with the inclusion of that country—which increases the sourcing capacity $\Theta_c(\varphi)$—against the payment of the additional fixed cost $w_c f_{cs}$.

For a firm with productivity φ, its intermediate input purchases from any country $s \in \mathcal{W}_c(\varphi)$ are a fraction $(\sigma - 1)\chi_{cs}(\varphi)$ of firm profits. Using (A.3) and (A.10), they can be expressed as

$$M_{cs}(\varphi) = \begin{cases} (\sigma-1)B_c\gamma^{(\sigma-1)/\theta}\varphi^{\sigma-1}\big(\Theta_c(\varphi)\big)^{(\sigma-1)/\theta}\chi_{cs}(\varphi), & \text{if } s \in \mathcal{J}_c(\varphi) \\ 0, & \text{otherwise.} \end{cases} \tag{A.11}$$

When $(\sigma - 1)/\theta > 1$, the sourcing decisions are complementary, and $M_{cs}(\varphi)$ is thus increasing in all the terms in $\Theta_c(\varphi)$. Intuitively, when demand is sufficiently elastic (i.e., σ is high enough) or the strength of comparative advantage in the intermediate-goods sector across countries is sufficiently high (i.e., θ is low enough), the scale effect through the demand response to lower costs dominates the direct substitution effect related to market shares, shifting toward the locations whose costs of sourcing have been reduced.

In this case, holding constant the market demand level B_c, whenever $(\sigma - 1)/\theta > 1$, an increase in the sourcing potential $\phi_c T_s(\tau_{cs} w_s)^{-\theta}$ or a reduction in the fixed cost of sourcing f_s for any country s (weakly) increases the input purchases by firms in c not only from s but also from all other countries. The intuition behind the result is as follows: since sourcing decisions are complementary, an increase in sourcing potential of any supplier is likely to raise the marginal benefit of including a supplier in the sourcing strategy, which makes it more attractive for a firm to add a new supplier.

A.4 Diversification and Resilience

Based on the framework of firms' sourcing decisions in Antràs et al. (2017), Huang (2017) extends the model to show results on firms' resilience to shocks on supply chains. We summarise these results in this section.

If sourcing decisions are complementary—that is $(\sigma - 1)/\theta > 1$—the concentration of firms' sourcing strategies as measured by the Herfindahl-Hirschman Index $HHI_c \equiv \sum_s \chi_{cs}(\varphi)^2$ is nonincreasing in φ. This is because high-productivity firms have greater sourcing capability and more alternatives. Therefore, high-productivity firms are more diversified even after considering the intensive margin.

We define a small, idiosyncratic trade cost shock that changes τ_{cs} to τ'_{cs}. A firm's resilience is measured as the pass-through of adverse shocks to firm performance. A firm is defined to be more resilient if the pass-through is smaller.

We can gauge the effect of adverse shocks using a "hat algebra" approach (Jones, 1965;

Dekle et al., 2007).

Proposition 1. *For a small, idiosyncratic shock that changes τ_{cs} to τ'_{cs} such that the firm does not abandon source s, (a) the pass through to the margin cost is given by*

$$\frac{\partial \ln \widehat{(c_c(\varphi))}}{\partial \ln \widehat{\tau_{cs}}} = \frac{\chi_{cs}(\varphi)}{1 - \sum_{s \in \mathcal{N}_s(\varphi)} \chi_{cs}(\varphi)} \tag{A.12}$$

where $\widehat{X} \equiv \frac{X'}{X}$ and $\mathcal{N}_s(\varphi)$ is the set of new suppliers chosen by the firm after the shock. (b) With complementarity of sourcing decisions across countries—$(\sigma-1)/\theta > 1$—and an adverse shock ($\tau'_{cs} \geq \tau_{cs}$), we have

$$\frac{\partial \ln \widehat{(c_c(\varphi))}}{\partial \ln \widehat{\tau_{cs}}} \approx \chi_{cs}(\varphi). \tag{A.13}$$

Proof. According to equation (A.9), in case of a shock to any supplier, the change in unit cost for the firm is given by:

$$\widehat{c_c} \equiv \frac{c'_c}{c_c} = \widehat{\Theta_c}(\varphi)^{1/\theta}, \tag{A.14}$$

which implies that $\frac{\partial \ln \widehat{c_c}}{\partial \ln \widehat{\Theta_c}} = -\frac{1}{\theta}$.

The change in sourcing capability of firm φ in country c, $\widehat{\Theta_c}(\varphi)$, can be expressed as

$$\begin{aligned} \widehat{\Theta_c}(\varphi) &= \frac{\sum_{s \in \mathcal{C}} \phi'_s + \sum_{s \in \mathcal{N}} \phi'_s}{\Theta_c(\varphi)} \\ &= \sum_{s \in \mathcal{C}} \frac{\phi'_s}{\phi_s} \frac{\phi_s}{\Theta_c(\varphi)} + \sum_{s \in \mathcal{N}} \frac{\phi'_s}{\Theta'_c(\varphi)} \frac{\Theta'_c(\varphi)}{\Theta_c(\varphi)} \\ &= \sum_{s \in \mathcal{C}} \widehat{\phi}_s \chi_{cs} + \widehat{\Theta_c}(\varphi) \sum_{s \in \mathcal{N}} \chi'_{cs} \\ &= \frac{\sum_{s \in \mathcal{C}} \chi_{cs} \widehat{\phi_{cs}}}{1 - \sum_{s \in \mathcal{N}} \chi'_{cs}} \end{aligned} \tag{A.15}$$

where $\mathcal{C}$ is the set of sources the firm continues to use, and $\mathcal{N}$ is the set of new sources used by the firm. Equation (A.15) indicates that one unit change in sourcing potential ϕ_s translates into $\frac{\sum_{s \in \mathcal{C}} \chi_{cs}}{1 - \sum_{s \in \mathcal{N}} \chi'_{cs}}$ unit change in sourcing capability $\widehat{\Theta_c}(\varphi)$.

For a small change in x, we know that $\ln(x) \approx x - 1$, thus $\widehat{\Theta_c}(\varphi) = 1 + \ln(\widehat{\Theta_c}(\varphi))$ and $\widehat{\phi}_s \chi_{cs} \approx 1 + \ln(\widehat{\phi}_s \chi_{cs})$. Then we have

$$\ln \widehat{\Theta_c}(\varphi) \approx \frac{\sum_{s \in \mathcal{C}} \chi_{cs} \ln(\widehat{\phi_{cs}})}{1 - \sum_{s \in \mathcal{N}} \chi'_{cs}} + \frac{\sum_{s \in \mathcal{C}} \chi_{cs} (\chi_{cs} - \chi'_{cs})}{1 - \sum_{s \in \mathcal{N}} \chi'_{cs}}, \tag{A.16}$$

which implies

$$\frac{\partial \ln \widehat{\Theta_c}(\varphi)}{\partial \ln \widehat{\phi_{cs}}} \approx \frac{\chi_{cs}}{1-\sum_{s\in\mathcal{N}} \chi'_{cs}}. \tag{A.17}$$

From the definition of sourcing potential $\phi_s = T_s(\tau_{cs} w_s)^{-\theta}$, we have $\frac{\partial \ln \widehat{\Theta_c}(\varphi)}{\widehat{\phi_{cs}}} = -\theta$. The pass-through of the trade cost shock $\widehat{\tau cs}$ to marginal cost of the firm is therefore given by

$$\begin{aligned}
\frac{\partial \ln \widehat{\Theta_c}(\varphi)}{\partial \ln \widehat{\tau_{cs}}} &= \frac{\partial \ln \widehat{c_c}}{\partial \ln \widehat{\Theta_c}} \cdot \frac{\partial \ln \widehat{\Theta_c}}{\partial \ln \widehat{\phi_{cs}}} \cdot \frac{\partial \ln \widehat{\phi_{cs}}}{\partial \ln \widehat{c_{cs}}} \\
&\approx \frac{\chi_{cs}}{1-\sum_{s\in\mathcal{N}} \chi'_{cs}}.
\end{aligned} \tag{A.18}$$

□

Equation (A.12) indicates that the pass-through of the adverse shock has two components: the intensive margin captured by $\chi_{cs}(\varphi)$ and the extensive margin captured by $1-\sum_{s\in\mathcal{N}_s(\varphi)} \chi_{cs}(\varphi)$. Both depend on firm productivity φ. However, assuming that sourcing decisions are complementary, no firm will add new suppliers facing adverse shock, and in this case, the pass-through depends only on the intensive margin.

Equation (A.13) suggests that the impact of the shock increases with $\chi_{cs}(\varphi)$. If the firm is not diversified at all and relies solely on one supplier hit by the shock, the pass-through is 100%. On the other hand, high-productivity firms are more diversified and source from more places. Their load of inputs on any particular route is smaller, and so is the pass-through. It also tells us that the pass-through is larger for sources with higher sourcing potential. These results can be shown in the second derivative of equation (A.13):

$$\frac{\partial^2 \ln \widehat{(c_c(\varphi))}}{\partial \ln \widehat{\tau_{cs}} \partial \varphi} \leq 0, \;\; \frac{\partial^2 \ln \widehat{(c_c(\varphi))}}{\partial \ln \widehat{\tau_{cs}} \partial \phi_s} > 0.$$

Furthermore, it can be shown that more diversified firms are also less volatile. This can be expressed in the following proposition:

Proposition 2. *(a) If the shocks on trade costs are not perfectly correlated and have the same variance ξ^2, opening to trade lowers the volatility of firms' source capabilities. (b) If sourcing decisions are complementary across sources and the adverse shocks are independent and identically distributed, the volatility of firm revenue is*

$$var(\widehat{R(\varphi)}) \propto \xi^2 HHI(\varphi) \tag{A.19}$$

which weakly decrease with productivity.

Proof. From the proof of Proposition 1, we know that the change in sourcing capability $\widehat{\Theta} = \sum \phi_s$ (For simplicity, we omit the subscript c.) for a particular firm is given by

$$\widehat{\Theta} = \frac{\sum_{s \in \mathcal{C}} \chi_s \widehat{\phi}_s}{1 - \sum_{s \in \mathcal{N}} \chi'_s}. \tag{A.20}$$

Denoting Ω and Ω' as the sets of sources before and after the shock, we further simplify the notation as

$$\widehat{\Theta} = \sum_{s \in \Omega} \chi_s \Delta_s, \tag{A.21}$$

where $\Delta_s = \widehat{\phi}_s \delta_s(\varphi, \widehat{\phi})$, with $\delta_s(\varphi, \widehat{\phi}) = \frac{1}{1 - \sum_{s \in \mathcal{N}} \chi'_s}$ if $s \in \mathcal{C}$, and 0 otherwise, which captures the extensive margin shock of sourcing capabilities. Under the assumption that δ_s has the same variance ξ^2 across source countries, we have

$$\begin{aligned}
var(\widehat{\Theta(\varphi)}) &= var(\sum_{s \in \Omega} \chi_s(\varphi) \Delta_s) \\
&= \sum_{s \in \Omega} \chi_s(\varphi)^2 var(\Delta_s) + \sum_{m \neq n, m, n \in \Omega} \chi_m \chi_n cov(\Delta_m, \Delta_n) \\
&= \xi^2 (\sum_{s \in \Omega} \chi_s(\varphi)^2 + \sum_{m \neq n, m, n \in \Omega} \chi_m \chi_n \rho(\Delta_m, \Delta_n) \\
&\leq \xi^2,
\end{aligned} \tag{A.22}$$

where $\rho \equiv \frac{cov(\Delta_m, \Delta_n)}{\xi^2}$ is the correlation of the shocks. The last inequality holds because $\left(\sum_{s \in \Omega} \chi_s(\varphi)\right)^2 = \sum_{s \in \Omega} \chi_s(\varphi)^2 + \sum_{m \neq n, m, n \in \Omega} \chi_m(\varphi) \chi_n(\varphi) = 1$. As long as the shocks are not perfectly correlated, we have $var(\widehat{R(\varphi)}) < \xi^2$.

If the shocks are i.i.d., such that $\rho_{mn} = 0$, we have

$$\begin{aligned}
var(\widehat{\Theta(\varphi)}) &= var(\sum_{s \in \Omega} \chi_s(\varphi) \Delta_s) \\
&= \xi^2 \sum_{s \in \Omega} \chi_s(\varphi)^2 \\
&= \xi^2 HHI(\varphi).
\end{aligned} \tag{A.23}$$

Since the firm's revenue is given by $R(\varphi) = \varphi^{\sigma-1} \left(\gamma \Theta(\varphi)\right)^{(\sigma-1)/\theta} B$ in equation (A.10), we have

$$\widehat{R(\varphi)} = \widehat{\Theta(\varphi)}. \tag{A.24}$$

Thherefore the variance of the firm revenue is proportional to the variation in sourcing capability, thus proportional to $\xi^2 HHI(\varphi)$. $\square$

To generate empirically testable predictions, we study how easily observed firm-level import flows will respond to an adverse shock. The model delivers the following result.

Proposition 3. *For a small trade cost shock that increases τ_{cs} to τ'_{sc} such that firms do not abandon source s, the import flows respond according to*

$$-\frac{\partial \ln \widehat{M_{cs'}(\varphi)}}{\partial \ln \widehat{\tau_{cs}}} = \begin{cases} \theta + (\sigma - 1 - \theta)\chi_{cs'}(\varphi), & \text{if } s' = s; \\ (\sigma - 1 - \theta)\chi_{cs'}(\varphi), & \text{otherwise.} \end{cases} \tag{A.25}$$

Proof. The trade flow at firm level is given by equation (A.11). Facing a supply shock, the change in trade flow is determined by

$$\begin{aligned} \widehat{M_{cs}}(\varphi) \equiv \frac{\widehat{M'_{cs}(\varphi)}}{\widehat{M_{cs}(\varphi)}} &= \widehat{\Theta(\varphi)}^{\frac{\sigma-1}{\theta}} \widehat{\chi_{cs}}(\varphi) \\ &= \widehat{\Theta(\varphi)}^{\frac{\sigma-1}{\theta}-1} \phi_{cs}, \end{aligned} \tag{A.26}$$

Taking the log on both sides of equation (4.4), we have $\ln \widehat{M_{cs}}(\varphi) = (\frac{\sigma-1}{\theta} - 1) \ln \widehat{\Theta}(\varphi) + \ln \phi_{cs}$. From the proof of Proposition 1, we know that for an adverse shock,

$$\frac{\partial \ln \widehat{\Theta_c}(\varphi)}{\partial \ln \widehat{\phi_{cs}}} \approx \chi_{cs} \text{ and } \frac{\partial \ln \widehat{\phi_{cs}}}{\partial \ln \widehat{\tau_{cs}}} = -\theta.$$

Thus Proposition 3 holds. □

Equation (A.25) indicates that the pass-through endogenously depends on firm productivity φ. Other than the usual Fréchet shape parameter θ, which captures the direct impact of the shock, there is an additional term $(\sigma - 1 - \theta)\chi_{cs'}(\varphi)$, which is positive if sourcing decisions are complementary ($(\sigma - 1)/\theta > 1$) and negative if inputs are substitutable ($(\sigma - 1)/\theta < 1$).

Accordingly, the trade cost shock reduces firms' sourcing capability and increases their marginal cost. This drives down the marginal demand curve for all inputs if the sourcing decisions are complementary. Such a feedback effect through interdependencies amplifies the initial cost shock and reduces imports further. In contrast, if the inputs are substitutable, the cost shock reduces firm output and drives up the marginal demand curve. Such an increase in the marginal demand for the input dampens the initial negative shock. This difference will allow us to identify whether sourcing decisions are complementary or substitutable.

The pass-through also varies by the sourcing intensity $\chi_{ck}(\varphi)$. The feedback effect is stronger if the firm has a heavier load on inputs from a source being shocked, which tends to be the case for a less diversified firm. Finally, the interdependency is also reflected by the result that imports also respond to shocks on other routes in the firm's sourcing strategy.

So far, we have assumed that the final-goods producers use inputs from the same industry. We can also generalise the model to allow firms to use inputs from different industries.

The firm's marginal cost is given by

$$c_c(\varphi) = \frac{1}{\varphi}\big(\sum_{i=1}^{I} c_c^i(\varphi)^{1-\eta}\big)^{\frac{1}{1-\eta}}, \eta > 1, \tag{A.27}$$

where η is the elasticity of substitution for inputs from different industries. The pass-through of an adverse shock is given by

$$-\frac{\partial \ln \widehat{M_{cs'}^i}(\varphi)}{\partial \ln \widehat{\tau_{cs}^i}} = \begin{cases} \theta_i + \big[(\sigma-\eta)\delta_c^i(\varphi) + (\eta - 1 - \theta_i)\big]\chi_{cs'}^i(\varphi), & \text{if } s' = s \\ \big[(\sigma-\eta)\delta_c^i(\varphi) + (\eta - 1 - \theta_i)\big]\chi_{cs'}^i(\varphi), & \text{otherwise} \end{cases} \tag{A.28}$$

where δ_c^i is the cost share of industry i's inputs, and $\chi_{cs'}^i(\varphi)$ is the share of industry i's inputs sourced from country s. The substitutability of varieties within each industry is captured by θ_i. On the one hand, a higher substitutability enables the firm to substitute away from source countries hit by a shock, which can lead to a higher pass-through. On the other hand, since the firm can find substitutable inputs from other sources, the marginal cost does not go up as much and thus this effect tends to decrease the size of the pass-through.

A.5 Input-Output Linkages

This paper also aims to assess the impact of natural disasters on Chinese manufacturing exporters via their production network. It is therefore important to highlight how the theoretical framework of Acemoglu et al. (2016) can be linked with insights from the input-output literature as described in, for example, Koopman et al. (2014) and Wang et al. (2013). While Acemoglu et al. (2016) show how an industry's output is affected by domestic shocks within the *national* input-output structure of an economy, this paper applies the theoretical concept to individual firms and generalises the model to include shocks affecting the *international* input-output structure underlying a firm's production.

Since we do not observe firm-to-firm sales in our data, we need to assess the supply chain propagation of a natural disaster shock in the context of industry-level input-output linkages. Assuming that firms follow the same profit maximisation across industries, the firm-level shock can be aggregated to the industry level, in which i and j represent the downstream and upstream industries, respectively. The corresponding input-output matrix $\mathbf{A}$ for N industries in the world can be represented as follows.

$$\mathbf{A} = \begin{pmatrix} a_{11} & a_{12} & \dots & \dots \\ a_{21} & a_{22} & \dots & \dots \\ \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & a_{NN} \end{pmatrix}$$

Accordingly, the individual output allocation coefficients a_{ji} provide information on how much of its output an industry j (indicated by the column) provides to another industry i (indicated by the row) for output production.[21] This plays an essential role in pinning down the input-output structure of the world economy.

To assess the change of output in response to exogenous changes of inputs, we consider the so-called *Ghosh inverse* matrix $\mathbf{G}$ based on the input-output matrix $\mathbf{A}$.[22]

Mathematically,

$$\mathbf{G} = (I - \mathbf{A})^{-1}.$$

The Ghosh inverse matrix is a compact representation of the ripple effects in an economy where industries are interconnected. Individual elements of the Ghosh inverse, such as g_{ji} contain information on the change in output of industry i in response to an exogenous change of inputs from sector j (Dietzenbacher, 1997).[23]

Against this background, one might also understand that a shock to upstream industry j in the form of a sudden drop in output influences the production of its downstream industry i. In this spirit, Acemoglu et al. (2016) use the input-output inverse matrices to show how different shocks of an industry can propagate up- and downstream through the production network. To evaluate the impact of the 2005 US hurricane season on the trade performance of Chinese processing manufacturers, we apply the idea of a shock propagation through the domestic production network to an international setting. In particular,

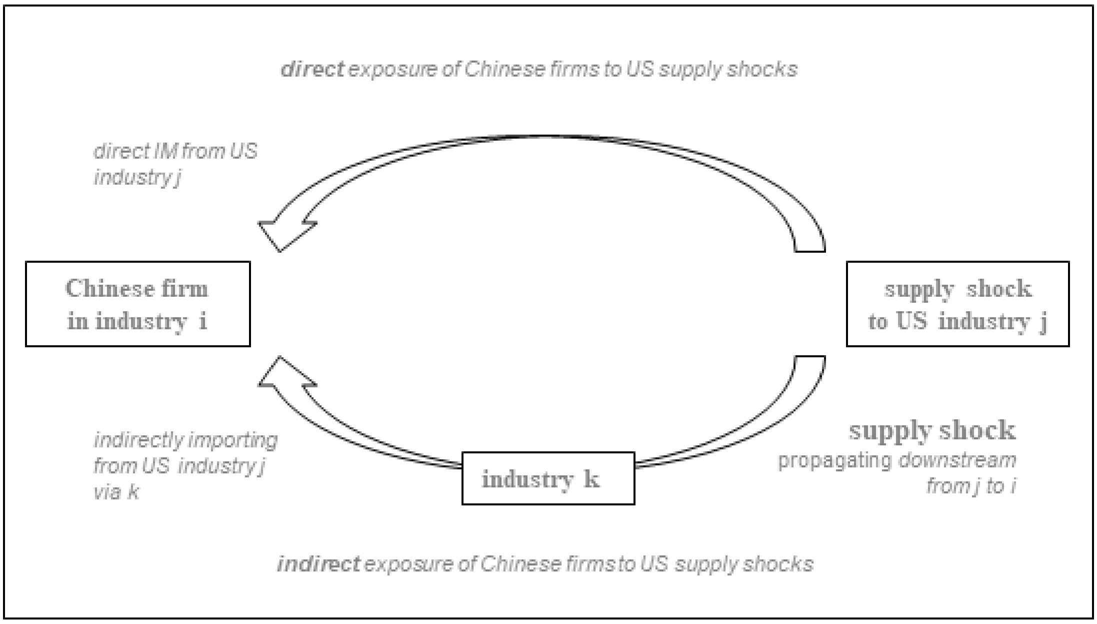
[21] With sales from i to j and industry output x_i, coefficients are calculated as $a_{ij} = z_{ij}/x_i$ (Galbusera and Giannopoulos, 2018).

[22] Alternatively, some studies use the common Leontief inverse indicating how much value added is needed to sustain the production of one more unit of output. Different from the Ghosh approach, the Leontief inverse considers the following technical coefficients to compute the inverse matrix: $e_{ij} = z_{ij}/x_j$. For a discussion on the approaches of both the Leontief and Ghosh models in studying the impacts of natural disasters, see Galbusera and Giannopoulos (2018).

[23] Similar to matrix $\mathbf{A}$, the Ghosh inverse matrix $\mathbf{G}$ is a matrix of N $\times$ N dimension.

we focus on two different channels through which a shock to industry j located in the United States might affect Chinese firms operating in industry i. Figure D summarises relevant mechanisms of a shock transmission from a US industry j to a Chinese firm operating in sector i.

Figure 6: *Propagation of Demand and Supply Shocks*



The downstream industry i might be affected either *directly* or *indirectly* by a shock in j. Regarding the former case, a firm in i is assumed to be *directly* affected by a supply shock in j if it directly imports from the affected industry j. With less supply from j, a firm in industry i has to reduce or even halt production of output, depending on the substitutability of intermediates sourced from industry j.

Regarding the latter case, a firm in i is assumed to be *indirectly* affected by a supply shock in j if i is not sourcing directly from j but *indirectly* via a third industry k (located anywhere in the world). With less supply from j, industry k has to reduce or halt its production of output so that, in turn, k supplies less to Chinese firms in industry i. Consequently, the US supply shock in industry j propagates *downstream* to Chinese firms in sector i via the production network involving industry k.

More concretely, we take the Ghosh inverse of the OECD Inter-Country Input-Output (ICIO) Tables to approximate the interlinkage of industries across countries. We then take the relevant portions of the Ghosh inverse matrix relating to the interlinkages between US and Chinese industries. The supply effect of upstream sector j in the United States on downstream sector i in China would be represented by the block in the lower left side of the matrix $\mathbf{G}^{USA \rightarrow CHN}$.

$$\mathbf{B} = \begin{array}{cc} & \begin{array}{ccccc} \cdots & CHN & \cdots & USA & \cdots \end{array} \\ \begin{array}{c} \cdots \\ CHN \\ \cdots \\ USA \\ \cdots \end{array} & \begin{bmatrix} & \cdots & & \cdots & \\ & \ddots & & \boxed{\begin{matrix} g_{11}^{CHN\to USA} & \cdots & \\ & \ddots & \\ & \cdots & g_{NN}^{CHN\to USA} \end{matrix}} & \\ & \cdots & & \cdots & \\ & \boxed{\begin{matrix} g_{11}^{USA\to CHN} & \cdots & \\ & \ddots & \\ & \cdots & g_{NN}^{USA\to CHN} \end{matrix}} & & \ddots & \\ & \cdots & & \cdots & \end{bmatrix} \end{array}$$

B Preparation of the China Customs Statistics

The China Customs Statistics is at the transaction-month level, and the raw data for 2001–2006 are in 2,051 subfiles, with each file containing 60,000 transactions. Therefore, as the first step, we converted all the files to UTF-8 encoded files and unified the variables' names in all the subfiles. Then we vertically merged all the files by year.

Next, we aggregated the transaction-level data to monthly firm-level import and export data by transition country and trading partner, including more than 200 countries and regions; customs port in China where the goods are loaded; customs regime, such as ordinary trade and processing trade; transporting method; and locations of importers and exporters. The aggregated data contain the monthly volume and value of imports and exports of firms.

Table 6: *OECD ICIO (2016 Edition) Industry Aggregation of ISIC Sectors*

2-digit ISIC industry	Industry description
C15T16	Food products, beverages & tobacco
C17T19	Textiles, textile products, leather & footwear
C20	Wood & products of wood & cork
C21T22P	Pulp, paper (products), printing & publishing
C23	Coke, refined petroleum products & nuclear fuel
C24	Chemicals & chemical products
C25	Rubber & plastics products
C26	Other non-metallic mineral products
C27	Basic metals
C28	Fabricated metal products
C29	Machinery & equipment, nec
C30T33	Computer, electronic & optical equipment
C31	Electrical machinery & apparatus, nec
C34	Motor vehicles, trailers & semi-trailers
C35	Other transport equipment
C36T37	Manufacturing nec; recycling

C The *Direct* Effect of the US Trade Shock

Figure 7: *Density Plots of Average US Trade Shares during the Pre-Disaster Period (08/2004-07/2005)*

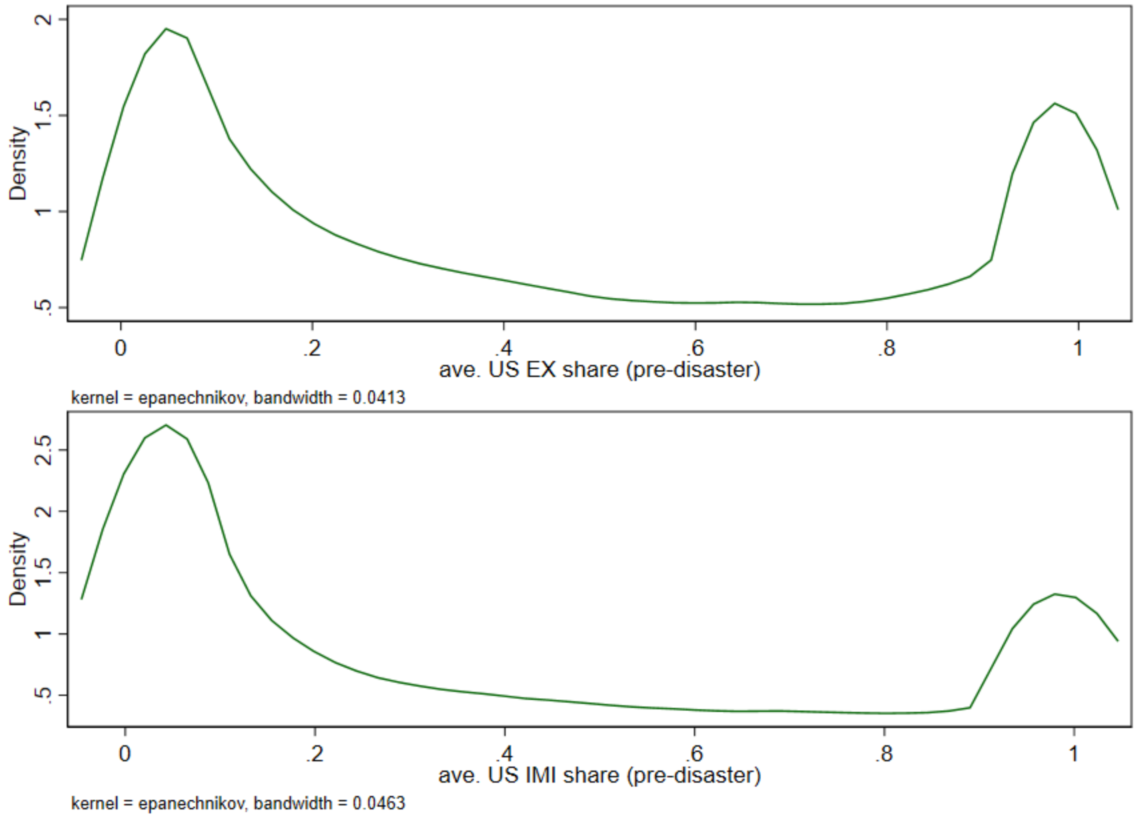


Table 7: *Shares of 7 States Affected by the US Hurricane Season 2005, by Sector*

Industry description	Share of 7 states in total exports of sectors (in %)	Share of 7 US states in total imports of sectors (in %)
Food products, beverages & tobacco	24	19
Textiles, textile products	34	14
Leather & footwear	24	11
Wood & products of wood & cork	16	20
Pulp, paper (products), printing & publishing	28	11
Coke, refined petroleum products & nuclear fuel	58	43
Chemicals & chemical products	32	18
Rubber & plastics products	22	17
Other non-metallic mineral products	16	23
Basic metals	21	23
Machinery & equipment, nec	26	24
Electrical & optical equipment	27	21
Transport equipment	19	13
Manufacturing nec; recycling	12	13

Table 8: Regression Results for Coefficient Plots of Figure 3

	US EX	US EX ext. margin	US EX int. margin	US IMI	US IMI ext. margin	US IMI int. margin
	(1)	(2)	(3)	(4)	(5)	(6)
XRATE	-6256.0**	-0.0440***	-2468.7	172.5	-0.00232	-114.0
	(3,149.826)	(0.005)	(1,763.232)	(646.463)	(0.002)	(346.505)
$\text{TREATMENT}_{fi}^{EX,IMI}$	-14156.4	0.0149	-7708.4	2613.0	0.0607***	1716.4
	(21,020.457)	(0.020)	(19,133.867)	(3,855.774)	(0.020)	(1,948.219)
07/05	3926.3	0.0244***	1114.9	-560.3	-0.00324	99.27
	(2,978.657)	(0.005)	(1,699.393)	(659.695)	(0.002)	(388.085)
08/05	4782.4	0.0210***	1496.2	-326.9	0.00269	56.38
	(3,026.481)	(0.005)	(1,599.216)	(636.876)	(0.002)	(345.433)
09/05	9688.5***	0.0179***	3869.3***	-535.9	0.00137	-104.1
	(3,398.534)	(0.005)	(1,404.904)	(614.059)	(0.002)	(330.226)
10/05	9210.3**	0.00264	4711.7***	-1327.8**	-0.0114***	-326.9
	(4,010.199)	(0.005)	(1,386.542)	(622.059)	(0.002)	(341.322)
11/05	8150.0**	0.00199	3699.4***	-818.2	-0.00108	-7.453
	(3,436.759)	(0.004)	(1,180.151)	(596.598)	(0.002)	(342.762)
IA 06/05	19903.1	-0.000951	21332.3	1340.9	0.00451	1415.8
	(20,612.198)	(0.016)	(19,418.855)	(2,976.408)	(0.027)	(1,849.500)
IA 07/05	5853.0	0.00700	3844.4	-1132.5	-0.0160	-1181.8
	(20,959.054)	(0.024)	(17,770.322)	(2,936.111)	(0.026)	(1,796.859)
IA 08/05	13763.8	-0.0108	8191.6	-2131.9	-0.0622**	-1026.0
	(21,224.309)	(0.023)	(18,152.225)	(2,461.755)	(0.025)	(1,725.233)
IA 09/05	5704.3	-0.0231	1967.8	4175.4	-0.0729***	-657.4
	(17,274.805)	(0.022)	(13,160.357)	(4,209.221)	(0.023)	(1,998.304)
IA 10/05	29805.7	-0.0419*	33404.6	-6045.9**	-0.103***	-3954.8**
	(39,802.648)	(0.022)	(38,158.509)	(2,531.462)	(0.022)	(1,579.730)
IA 11/05	26407.9	-0.0174	28574.5	-2886.0	-0.0588***	-3908.1**
	(29,801.822)	(0.020)	(28,048.612)	(2,725.469)	(0.022)	(1,830.252)
Firm-FE	✓	✓	✓	✓	✓	✓
Observations	587,240	587,240	587,240	911,188	911,188	911,188

Note: Standard errors in parentheses, clustered at the firm level. *** p < 0.01, ** p < 0.05, and * p < 0.1.

Table 9: *Summary Statistics for std.* $\Delta \ln dir.SUP\, shock$ *Variable*

# observations	Mean	Std. dev.	Min.	Max.
Sample period Sep. 2005–Dec. 2006				
4,786,158	-0.1073438	0.5059222	-4.358899	5.747049
Hurricane season 2005 Sep.-Nov. 2005				
1,081,193	-0.0870469	0.4744142	-3.872983	4.477215

Table 10: Regression Results in Addition to Table 4, Part I

	All	Food	Textile	Wood	Paper	Coke	Chem.	Rubber	o.nmMin
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ ln dir.SUPshock$^{7USst.}$	0.003*	0.002*	0.002	0.002	0.003**	0.003**	0.004***	0.003*	0.003**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
IA: Δ ln dir.SUPshock$^{7USst.}$	0.014***	0.014***	0.015***	0.015***	0.014***	0.015***	0.014***	0.014***	0.015***
x Hurricane = 1	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.005)	(0.006)	(0.006)
IA: Δ ln dir.SUPshock$^{7USst.}$		0.002***	0.001	0.006***	-0.001	-0.000	-0.004***	0.000	-0.002
x IMI-industry = col.2–9		(0.008)	(0.004)	(0.011)	(0.003)	(0.016)	(0.004)	(0.003)	(0.014)
IA: Δ ln dir.SUPshock$^{7USst.}$		0.000	-0.003***	-0.006***	-0.001	-0.008***	-0.000	0.001	-0.005***
x Hurricane = 1		(0.034)	(0.012)	(0.020)	(0.014)	(0.008)	(0.011)	(0.012)	(0.018)
x IMI-industry = col.2–9									
Firm-FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
EXindustry-Time-FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
IMIindustry-FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
ROW-Control	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	4,786,123	4,786,123	4,786,123	4,786,123	4,786,123	4,786,123	4,786,123	4,786,123	4,786,123

Note: (Standardised) Δ ln EX as dependent variables for all regressions. $Hurricane$ refers to a dummy variable that equals 1 from September to November 2005. $IMI - industry$ dummy variables equal 1 if the importing industry corresponds to the industry indicated by the column. Individual $IMI - industry$ dummy variables are dropped due to common import industry fixed effects. Standard errors in parentheses, clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 11: Regression Results in Addition to Table 4, Part II

	All	BasMet.	FabMet.	Mach.	El/OptEq.	ElMach.	TrEq.	o.TrEq.	M.Recyc
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ ln dir. SUPshock$^{7USst.}$	0.003*	0.002	0.003**	0.004**	0.003**	0.002	0.002*	0.003**	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
IA: Δ ln IMI$^{7USst.}$	0.014***	0.016***	0.014***	0.012***	0.012***	0.010***	0.014***	0.014***	0.014***
x Hurricane = 1	(0.006)	(0.007)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
IA: Δ ln dir. SUPshock$^{7USst.}$		0.001	-0.002	-0.003***	-0.001	0.002	0.001**	-0.005**	0.007***
x IMI-industry = col.2–9		(0.011)	(0.005)	(0.003)	(0.008)	(0.004)	(0.004)	(0.042)	(0.010)
IA: Δ ln dir. SUPshock$^{7USst.}$		-0.009***	-0.001	0.006***	0.010***	0.009***	0.001	-0.003**	-0.001
x Hurricane = 1		(0.024)	(0.013)	(0.012)	(0.034)	(0.018)	(0.033)	(0.031)	(0.023)
x IMI-industry = col.2–9									
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
EX-industry-time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
IMI-industry FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
ROW control	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	4,786,123	4,786,123	4,786,123	4,786,123	4,786,123	4,786,123	4,786,123	4,786,123	4,786,123

Note: (Standardised) Δ ln EX as dependent variables for all regressions. $Hurricane$ refers to a dummy variable that equals 1 from September to November 2005. $IMI - industry$ dummy variables equal 1 if the importing industry corresponds to the industry indicated by the column. Individual $IMI - industry$ dummy variables are dropped due to common import industry fixed effects. Standard errors in parentheses, clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

D The *Indirect* Effect of the US Trade Shock

This appendix evaluates the extent to which the US supply shock propagated through international production networks. Thus, the focus is on the *indirect* exposure of Chinese processing manufacturers to US supply shocks through international production network of Chinese firms. The following subsection explains the empirical strategy along with the precise calculation of the network supply shock.

D.1 Empirical Strategy

To calculate the US *network* supply shock, we combine exports of affected states to the rest of the world with information on international production linkages. Specifically, this approach uses input-output tables from the OECD to compute a Ghosh inverse matrix. Individual elements of the Ghosh inverse matrix allow us to "calculate changes in gross sectoral outputs for exogenously specified changes in the sectoral inputs" (Dietzenbacher, 1997). We therefore calculate a measure on the *indirect* exposure of Chinese processing firms to the US supply shock using equation (D.29).

$$netw.SUPshock_{fit}^{7USstates} = \sum_{j} \left[(g_{ji}^{2004} - dirIMI_{fjt}^{CHN \leftarrow US} \cdot g_{ji}^{2004})' \cdot EX_{jt}^{7USstates \rightarrow RoW} \right], \tag{D.29}$$

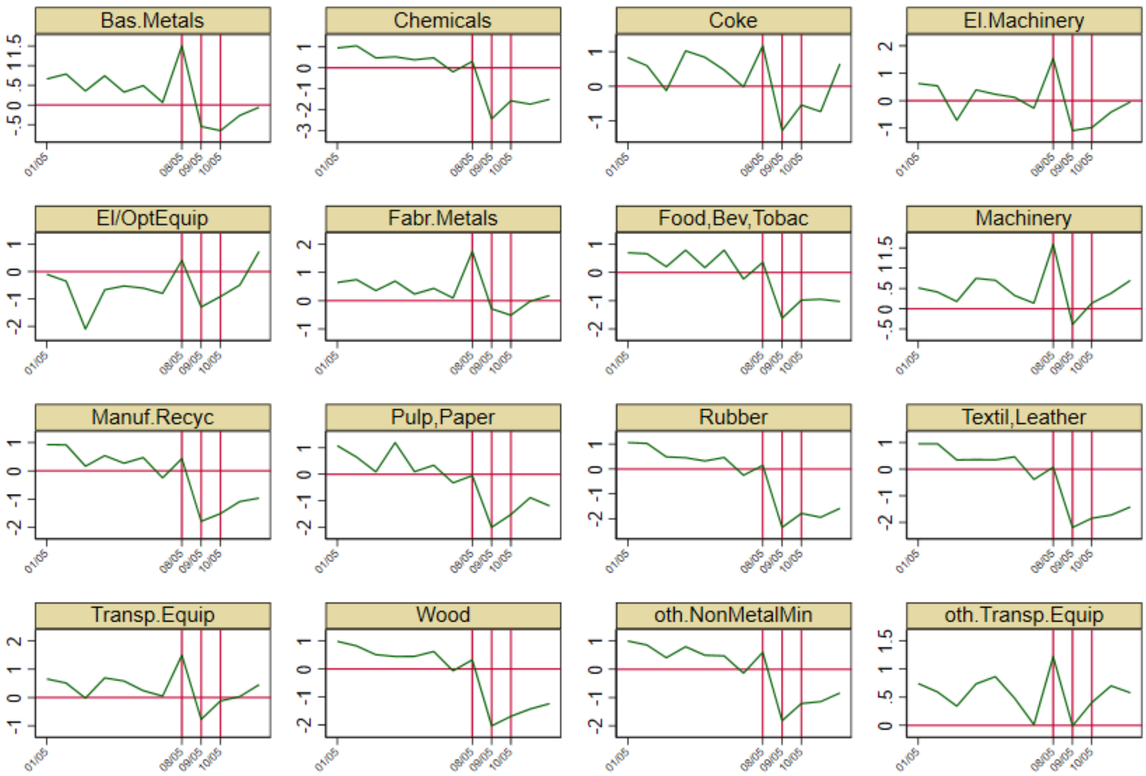
where g_{ji}^{2004} is the Ghosh inverse matrix element for industries j and i of 2004. In the spirit of equation 3.3, $EX_{jt}^{7USstates \rightarrow RoW}$ captures the supply capacity of hurricane-affected states, while $dirIMI_{fjt}^{CHN \leftarrow US}$ represents a dummy variable equalling 1 if a Chinese firm directly imports from the United States in industry j at time t.

The analysis of this paper distinguishes *direct* effects from *network* effects. Given that a calculation of *network* effects based on the Ghosh inverse, g_{ji}^{2004}, and $EX_{jt}^{7USstates \rightarrow RoW}$ would technically include *direct* imports from the United States, it is important to control for double counting of direct effects. We thus eliminate elements of the Ghosh inverse for industries from which Chinese processing firms are sourcing directly. Thus the network linkages, which are already captured by the direct shock variables, are canceled out. Technically, this approach is captured by the term $(g_{ji}^{2004} - dirIMI_{fjt}^{CHN \leftarrow US} \cdot g_{ji}^{2004})$, where $dirIMI_{fjt}^{CHN \leftarrow US}$ is a dummy variable equal to one if a firm is directly importing from US industry j at time t so that the corresponding Ghosh inverse element is zero. The network supply shock hence captures the extent to which a Chinese processing firm f operating in industry i is *indirectly* exposed to US supply fluctuations given the firm's international production networks.

D.2 Results

We begin the analysis of our results by presenting Figure 8, which illustrates the extent to which Chinese manufacturing industries were exposed to fluctuations of suppliers from the affected states. In line with equation (D.29), the *network* supply shock is calculated based on export fluctuations of the seven affected states in conjunction with information on input-output flows between the United States and Chinese manufacturing industries derived from the Ghosh inverse. For ease of interpretation, values in Figure 8 were standardised by Chinese importing industries. From the perspective of individual manufacturing industries in China, this supply shock variable captures the extent to which US supply fluctuation can propagate downstream to Chinese manufacturing industries along respective value chain linkages. The vertical lines in the charts denote the points in time when three of the most severe hurricanes made landfall in the United States, the end of August, September, and October in 2005.[24]

Figure 8: *Exposure of Chinese Manufacturing Industries to Supply Shocks Triggered by the 2005 US Hurricane Season*



Note: This figure presents network supply shocks by industry calculated using equation (D.29) and aggregated by Chinese manufacturing sectors over time. Each chart represents a different sector.

As shown in Figure 8, standardised network supply shock temporarily dropped in September and October 2005. This pattern suggests that Chinese processing firms were *indirectly*

[24]Because data from Chinese customs statistics represent values by the *end* of a given month, the area between the vertical lines *de facto* represents the months of September and October 2005.

exposed to a drop in supply from the affected states along their international production linkages. It should be noted that, the supply shock depicted in Figure 8 does not measure the actual drop in trade on the part of Chinese firms. It measures the *potential indirect exposure* of Chinese manufacturing industries to US supply shocks via the United States' and China's international production network throughout the rest of the world.[25]

We followed a similar empirical strategy in Section 3.2.1 to estimate the impact of firms' *indirect* exposure to negative US supply shocks on their exports.[26]

Hurricane season for the US East Coast occurs during a certain time of year, so it is important to verify that trade fluctuations triggered by the 2005 US hurricane season exceeded common seasonal fluctuations. To address this concern, we use the standardised year-on-year differences between export supply flows of 2004 and 2005. This causes the seasonal fluctuations to be differenced, out and a decline of respective shock variables implies that trade flow substantially deviated from the mean values in September and October 2005.

Table 12 presents the result estimations of the link between US supply shocks and exports of Chinese firms. Column 1 shows that the relationship of a positive link between the *direct* supply shock and exports is robust against the inclusion of the *network* supply shock variable. Still, regarding the latter, network supply is negatively associated with Chinese processing firms' exports during the 2005 US hurricane season. More precisely, a drop in the network supply shock by one standard deviation in $t-1$ triggers an increase in exports by 0.015 ($-0.014 - 0.001$) standard deviation at time t, thereby almost offsetting the impact of the *direct* supply shock on exports. This result is at odds with an expectation of a positive estimation coefficient, as should be the case when there is a propagation of adverse shocks to firm-level output.[27] It indicates that the US hurricane shock does not propagate along international supply chains.

[25] To demonstrate that the drop in supply from affected states is not due to a common decline in US output, we present supply shocks from the 43 unaffected US states that were not directly hit by the hurricanes during the 2005 season. These results are plotted in Figure 9.

[26] We estimate the effects of the indirect exposure to supply shocks on firms' exports using the following equation based on (3.4). The results are presented in Table (12).

$$\begin{aligned}\Delta\, ln\, EX_{fpit} = \alpha_f + \beta_j + \gamma_{it} + \zeta\, H^{Sep-Nov,2005} \\ &+ \tau_1\, \Delta\, ln\, direct\, SUPshock^{7\, USstates}_{fjt} + \tau_2\, \Delta\, ln\, netw.\, SUPshock^{7\, USstates}_{fit-1} + \\ &+ \eta_1\, H^{Sep-Nov,2005} \cdot \Delta\, ln\, direct\, SUPshock^{7\, USstates}_{fjt} \\ &+ \eta_2\, H^{Sep-Nov,2005} \cdot \Delta\, ln\, netw.\, SUPshock^{7\, USstates}_{fit-1} \\ &+ \tau_3\, \Delta\, ln\, direct\, IMI^{ROW}_{fjt} + \epsilon_{fpit}\end{aligned}$$

[27] Similar to our findings in Section 3, the theoretical reasoning suggests finding a positive relation between shock variables and exports in case there is a drop in both the explained and explanatory variables.

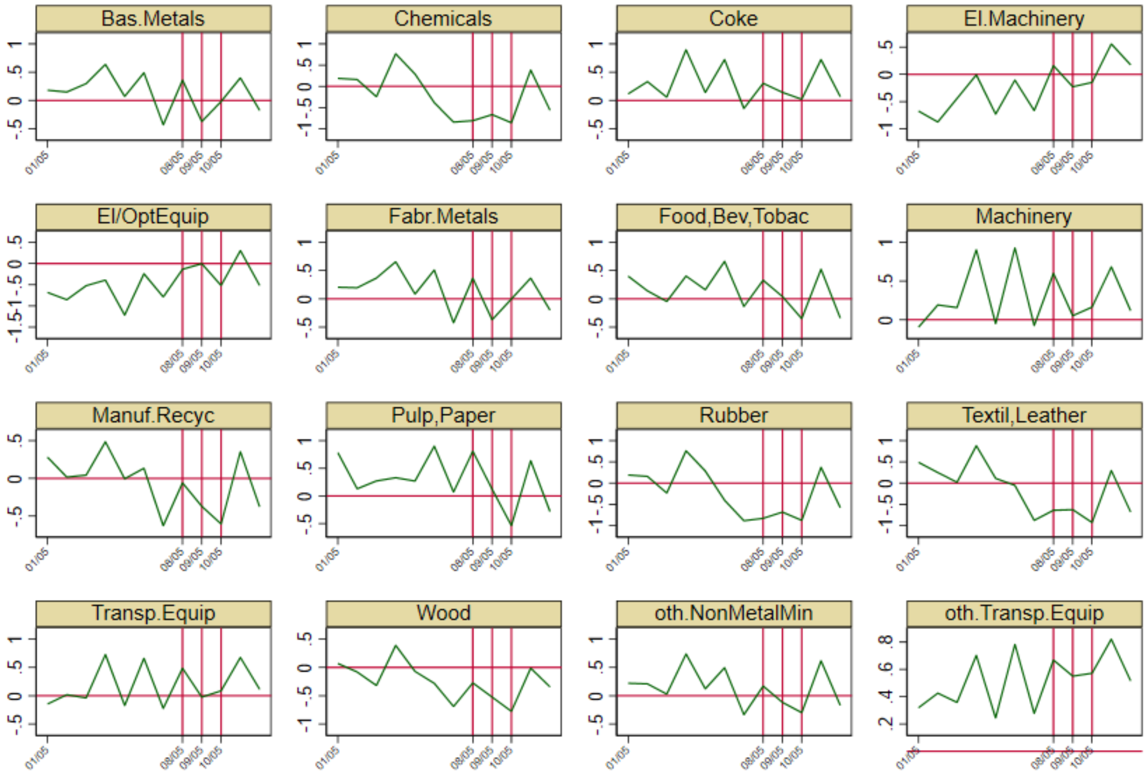
Table 12: *Regression Results of* Direct *and* Indirect *Supply Shocks*

	All	Textile	Paper	Coke	Chemicals	Machinery	El./Opt. Eq.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ ln dir. SUPshock$^{7\,USstates}$	0.003*	0.002	0.003**	0.003**	0.004***	0.003**	0.003**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
IA: Δ ln dir. SUPshock$^{7\,USstates}$	0.014***	0.015***	0.014***	0.016***	0.014***	0.012***	0.012***
x Hurricane = 1	(0.006)	(0.006)	(0.006)	(0.007)	(0.005)	(0.006)	(0.005)
IA: Δ ln dir. SUPshock$^{7\,USstates}$		0.001	-0.001	-0.001	-0.004**	-0.003***	-0.001
x IMI-industry = col. 2–7		(0.004)	(0.003)	(0.015)	(0.004)	(0.003)	(0.008)
IA: Δ ln dir. SUPshock$^{7\,USstates}$		-0.003**	-0.001	-0.008***	-0.000	0.006***	0.010***
x Hurricane = 1		(0.012)	(0.014)	(0.008)	(0.010)	(0.012)	(0.034)
x IMI-industry = col. 2–7							
netw. SUPshock$_{t-1}$	-0.001	-0.001	-0.002	-0.001	-0.000	-0.002	0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IA: netw. SUPshock$_{t-1}$	-0.014***	-0.014***	-0.014***	-0.014***	-0.016***	-0.014***	-0.014***
x Hurricane = 1	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IA: netw. SUPshock$_{t-1}$		0.003*	0.004***	0.001	-0.001	0.004***	-0.007***
x IMI-industry = col. 2–7		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IA: netw. SUPshock$_{t-1}$		0.001	-0.000	-0.000	0.004***	-0.001	-0.001
x Hurricane = 1		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
x IMI-industry = col. 2–7							
Firm FE	✓	✓	✓	✓	✓	✓	✓
EX-industry-time FE	✓	✓	✓	✓	✓	✓	✓
IMI-industry FE	✓	✓	✓	✓	✓	✓	✓
ROW control	✓	✓	✓	✓	✓	✓	✓
Observations	4,786,123	4,786,123	4,786,123	4,786,123	4,786,123	4,786,123	4,786,123

Note: (Standardised) Δ ln EX as dependent variables for all regressions. *Hurricane* refers to a dummy variable that equals 1 from September to November 2005. $IMI - industry$ dummy variables equal 1 if the importing industry corresponds to the industry indicated by the column. Individual $IMI - industry$ dummy variables are dropped due to common import industry fixed effects. Standard errors in parentheses, clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Columns 2–7 present estimations of the impacts of adverse supply shocks on firms' exports in China by industry of the US suppliers. These are the industries that are highly concentrated in the states that were heavily hit by the hurricane. The impacts are statistically significantly different from zero only in the chemical industry (column 5). Specifically, the negative effect of the indirect exposure of Chinese firms to US supply shocks is weaker (by 0.004 standard deviations) when intermediates are sourced from the chemical industry. However, the overall impact is still negative (-0.016 + 0.004), which is at odds with an expected positive sign of a shock propagation. Therefore, the result should be interpreted with caution. A potential explanation for this is that the US supply shock triggered by the 2005 hurricane season did not propagate to Chinese processing manufacturers through global value chains.

Figure 9: *Exposure of Chinese Manufacturing Industries to Supply Shocks of Remaining 43 States in 2005*



Note: Individual charts plot results of network supply shocks computed according to equation (D.29) and aggregated by Chinese manufacturing sectors over time.

Table 13: Regression Results in Addition to Table 12, Part I

	all	Food	Textile	Wood	Paper	Coke	Chemi.	Rubber	o.nmMin
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ ln dir. SUPshock(usa7)	0.003*	0.002*	0.002	0.001	0.003**	0.003**	0.004***	0.003*	0.003**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
IA: Δ ln dir. SUPshock	0.014***	0.014***	0.015***	0.015***	0.014***	0.016***	0.014***	0.014***	0.015***
x Hurricane = 1	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.005)	(0.006)	(0.006)
IA: Δ ln dir. SUPshock		0.002***	0.001	0.006***	-0.001	-0.001	-0.004**	0.000	-0.002
x IMI-industry = col.(2-9)		(0.008)	(0.004)	(0.011)	(0.003)	(0.015)	(0.004)	(0.003)	(0.014)
IA: Δ ln dir. SUPshock(usa7)		0.000	-0.003**	-0.006***	-0.001	-0.008***	-0.000	0.001	-0.005***
x Hurricane = 1		(0.035)	(0.012)	(0.020)	(0.014)	(0.008)	(0.010)	(0.012)	(0.017)
x IMI-industry = col.(2-9)									
netw. SUPshock_t-1	-0.001	-0.001	-0.001	-0.001	-0.002	-0.001	-0.000	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IA: netw. SUPshock_t-1	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.016***	-0.014***	-0.014***
x Hurricane = 1	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IA: netw. SUPshock_t-1		0.002**	0.003*	0.003***	0.004***	0.001	-0.001	0.001	0.003***
x IMI-industry = col.(2-9)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IA: netw. SUPshock_t-1		-0.002**	0.001	0.000	-0.000	-0.000	0.004***	-0.002**	-0.002***
x Hurricane = 1		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
x IMI-industry = col.(2-9)									
Firm-FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
EXindustry-Time-FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
IMIindustry-FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
ROW-Control	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	4,786,123	4,786,123	4,786,123	4,786,123	4,786,123	4,786,123	4,786,123	4,786,123	4,786,123

Note: (Standardised) Δ ln EX as dependent variables for all regressions. *Hurricane* refers to a dummy variable that equals 1 from September to November 2005. $IMI - industry$ dummy variables equal 1 if the importing industry corresponds to the industry indicated by the column. Individual $IMI - industry$ dummy variables are dropped due to common import industry fixed effects. Standard errors in parentheses, clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 14: Regression Results in Addition to Table 12, Part II

	all	BasMet.	FabMet.	Mach.	El/OptEq.	ElMach.	TrEq.	o.TrEq.	M.Recyc
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ ln dir. SUPshock$^{7USst.}$	0.003*	0.002	0.003**	0.003**	0.003**	0.002	0.002*	0.003*	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
IA: Δ ln dir. SUPshock$^{7USst.}$	0.014***	0.016***	0.015***	0.012***	0.012***	0.010***	0.014***	0.015***	0.015***
x Hurricane = 1	(0.006)	(0.007)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
IA: Δ ln dir. SUPshock$^{7USst.}$		0.001	-0.002	-0.003***	-0.001	0.002	0.001*	-0.005**	0.007***
x IMI-industry = col.(2-9)		(0.011)	(0.005)	(0.003)	(0.008)	(0.004)	(0.004)	(0.042)	(0.010)
IA: Δ ln dir. SUPshock$^{7USst.}$		-0.009***	-0.001	0.006***	0.010***	0.009***	0.001	-0.003**	-0.001
x Hurricane = 1		(0.023)	(0.013)	(0.012)	(0.034)	(0.017)	(0.033)	(0.031)	(0.023)
x IMI-industry = col.(2-9)									
netw. SUPshock_t-1	-0.001	-0.001	-0.002	-0.002	0.002	0.003	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IA: netw. SUPshock_t-1	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***
x Hurricane = 1	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IA: netw. SUPshock_t-1		0.002	0.004***	0.004***	-0.007***	-0.008***	0.001	0.002***	0.003**
x IMI-industry = col.(2-9)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IA: netw. SUPshock_t-1		-0.000	-0.001	-0.001	-0.001	0.001	-0.001	-0.001**	-0.002**
x Hurricane = 1		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
x IMI-industry = col.(2-9)									
Firm-FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
EXindustry-Time-FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
IMIindustry-FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
ROW-Control	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	4,786,123	4,786,123	4,786,123	4,786,123	4,786,123	4,786,123	4,786,123	4,786,123	4,786,123

Note: (Standardised) Δ ln EX as dependent variables for all regressions. *Hurricane* refers to a dummy variable that equals 1 from September to November 2005. $IMI - industry$ dummy variables equal 1 if the importing industry corresponds to the industry indicated by the column. Individual $IMI - industry$ dummy variables are dropped due to common import industry fixed effects. Standard errors in parentheses, clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

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