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Keywords: global value chains, inventories, Diversification

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Abstract

How do firms in global value chains react to input shortages? We examine micro-level adjustments to supply chain shocks, building on the COVID-19 pandemic as a case study. French firms sourcing inputs from China just before the early lockdown in the country experienced a drop in imports between February and April 2020 that is 7% larger than firms sourcing their inputs from elsewhere. This shock on input purchases transmits to the rest of the supply chain through exposed firms' domestic and export sales. Between February and April, firms exposed to the Chinese early lockdown experienced a 5.7% drop in domestic sales and a 5% drop in exports, in relative terms. The drop in foreign sales is entirely attributable to a lower volume of exports driven by a reduction in the number of markets served. We then evaluate whether mitigation strategies adopted by some exposed firms helped them weather the shock. Whereas the ex-ante geographic diversification of inputs does not seem to mitigate the impact of the shock, firms with relatively high inventories have been able to absorb the supply shock better.

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1 Introduction

International flows of intermediate inputs constitute as much as two-thirds of international trade and half of global trade is embodied in global value chains (GVCs) (Johnson, 2014, Antràs, 2020). In this context, international production processes appear as a key channel of transmission of shocks across countries (di Giovanni et al., 2018, Boehm et al., 2019). The Covid-19 pandemic offers plenty of anecdotal evidence of firms' vulnerability to shocks affecting their international supply chain. However, there is little quantitative evidence of the reaction of firms in GVCs to input shortages. This paper makes two contributions. First, it provides evidence of a firm-level transmission of shocks on imported inputs to the firm's domestic and export sales. Second, it evaluates how the diversification of the firm's supply chain and its inventory management can help mitigate the transmission of adverse shocks affecting its supply chain.

The empirical analysis exploits the January 2020 lockdown in China as a natural experiment of a shock to French firms' supply chain. We study the real transmission of the shock using detailed data on French firms' foreign and domestic activity. The Chinese lockdown offers a unique natural experiment to trace out the effect of a supply shock on firms engaged in GVCs. Firms relying on Chinese inputs before the beginning of the pandemic experienced a 5% decline in their exports and a 5.7% decline in domestic sales after the Chinese lockdown, in relative terms with respect to similar firms involved in GVCs that were not exposed to Chinese inputs. The drop in firm-level exports is almost entirely driven by the extensive margin: exposed exporters stopped serving some of their foreign partners. Whereas, the ex-ante geographic diversification of inputs does not seem to influence the transmission of the shock, we provide evidence that holding inventories offers a buffer for firms exposed to such temporary supply shocks.

We organize the paper into three parts. First, we describe the data and present evidence that the Chinese lockdown has caused a shortage of inputs for French firms importing from China. Our analysis builds on French customs data that cover the universe of French importers and exporters, merged with domestic sales recovered from VAT data. The final dataset contains transaction-level imports and exports as well as domestic sales, at the monthly frequency, before and during the pandemic. The monthly frequency of the data combined with information on the geography of firms' imports allows us to exploit the timing of the pandemic to identify the propagation of a supply shock downstream in the value chain. In early 2020, when the world was to a large extent ignorant of the pandemic risk, China adopted stringent measures to contain the spread of SARS-CoV-2, which led to shuttering factories in the aftermath of the Chinese new year. In February 2020, French imports from China had already dropped by more than 10% and they reached a minimum in March, one month before imports from the rest of the world. The drop in imports from China immediately after the lockdown is more severe than the usual seasonal slowdown. We thus interpret it as a supply shock for French importers of Chinese inputs.

A second advantage of the data is that we can match information on imports, exports and domestic sales at firm-level and study the micro-level propagation of a shock to foreign input purchases downwards in the value chain. Namely, we consider firms that both import intermediate inputs and export some of their output as being part of global value chains (GVCs) (WDR, 2020). We split this sample into two groups, a treatment group composed of firms exposed to China through imports of intermediate inputs, and a control group with firms also engaged into GVCs, that were not importing from China when the Covid crisis started. Having established that these groups display significantly divergent import patterns in the aftermath of the Chinese early lockdown, we examine the within-firm propagation of the supply shock. We estimate the strength of the propagation using firms' exports and domestic sales as outcome variables. Using an event-study design and differences-in-differences specifications, we find firms exposed to Chinese inputs incurred a 5.7% drop (respectively 4.8% drop) in their domestic sales (respectively exports) in comparison with the control group, in the five months following the Chinese lockdown. These numbers must be interpreted as lower bounds of the overall transmission of the shock as control firms were also exposed indirectly, through inputs that may themselves have been affected by the productivity slowdown in China. The relative drop peaks in April 2020 at -15% for exports and -12% for domestic sales. In June 2020, both groups have converged to the same contraction in sales, in comparison with their January level. Interestingly, the firm-level adjustment is mainly driven by the extensive margin. The average treated firm serves 4.5% less products and 4% less destinations in April, in comparison with the control group. Likewise, the (relative) recovery in May and June 2020 mostly involves (relative) extensive margin adjustments. We provide a series of robustness exercises supporting our interpretation of the relative drop in sales observed on firms exposed to the early lockdown in China as being a consequence of the transmission of the supply chain shock to downstream partners. We also examine the adjustment of export prices after the shock. We do not observe an increase in export prices, which suggests producers have not passed input shortages through their price during this episode.

In the third part of the paper, we ask whether risk management strategies can help mitigate the impact and the transmission of a supply shock to the rest of the supply chain. First, we explore the role played by the structure of the firm's supply chain. Given the vulnerability of input-output structures to localized shocks, diversifying the supply chain in the spatial dimension should be an efficient resilience strategy. One should thus expect the impact of being exposed to the Chinese early lockdown to be muted for firms with a diversified supply chain, that can increase their demand for non-Chinese inputs when the shock kicks in. To test this assumption, we quantify the extent to which geographic diversification of imported inputs prior to the shock helped firms withstand the Chinese supply shock. We do not find evidence that diversified firms performed better. Indeed, exposed firms that were not diversified ex-ante have managed to find new suppliers. Ex post diversification has helped to mitigate the shock, but not entirely. Therefore, the imports of exposed firms whether diversified or not have followed a similar trajectory, and their exports have not diverged after the shock either. We then evaluate whether stock-pilling can offer firms a buffer against short-lived supply chain disruptions. Formally, we investigate how the export performances of firms with more inventories differ from the performances of firms with just-in-time production strategies. The level of inventories is recovered from balance-sheet data covering firms' activity prior to the shock. We find that among firms exposed to the Chinese lockdown, those that held more inventories ex-ante performed better, with a non-significant drop in their relative exports following the shock. Inventory management has thus been a useful buffer in the early stages of the 2020 crisis.[1]

[1]Whereas holding inventories has proved useful in the early stages of the Covid crisis, the long-lasting nature of the crisis implies that such buffers are not sufficient, as proved by the historically low level of inventories in the manufacturing sector observed in 2021, after 18 months of the Covid crisis (INSEE, *Enquête mensuelle de conjoncture dans l'industrie*).

Related literature. Our work is related to recent papers examining international trade during the covid pandemics. Most of these papers use product-level data and show that containment policies had an adverse effect on trade in most product categories but products used to fight the pandemics (see, e.g. Liu et al., 2021, Bas et al., 2021, Berthou and Stumpner, 2021). Unlike these works, we examine trade at the firm-level through the perspective of GVCs. Bricongne et al. (2021) use similar firm-level data as ours to perform a margin decomposition of French exports during the Covid crisis. They show that the bulk of the drop in aggregate exports is driven by large firms, and that lockdown policies in destination markets explain part of the drop in exports, especially for the largest firms. In comparison with Bricongne et al. (2021), we pair domestic sales, exports and imports at the firm-level to trace the propagation of supply chain disruptions in GVCs. We focus on the propagation of the supply chain shock induced by the early lockdown in China, controlling for heterogeneity across French firms in their exposure to demand shocks, notably driven by heterogeneous lockdown policies.

In doing this, we participate to the growing literature on the transmission of shocks along GVCs during the Covid pandemic. For instance, Bonadio et al. (2020) and Gerschel et al. (2020) investigate the role of input-output linkages in the propagation of the (economic) covid-crisis. Eppinger et al. (2021) also exploit the early lockdown in China together with production and trade data at the sector level to quantify the gains and losses of decoupling GVCs. Closer to us, Meier and Pinto (2020) exploit the shortage of intermediate imports from China in early 2020 to assess the impact of a supply chain disruption on sectoral production, exports, and prices in the US. Heise (2020) further examines the impact of the Chinese lockdown on US imports from China, at the firm-level. In comparison with Heise (2020) and Meier and Pinto (2020), we go one step further into the analysis of the transmission of supply chain disruptions, by estimating the firm-level propagation of the shock to domestic and foreign sales and its heterogeneity across firms with different risk management strategies.

The paper also belongs to the broad literature on GVCs (see, e.g., Antràs and Chor, 2013, Baldwin and Lopez-Gonzalez, 2015, Johnson, 2018, Antràs, 2020). Our strategy to identify firms within GVCs exploits firm-level data on imports and exports. We connect exogenous changes in input purchases to firms' exports. In this respect, our work relates to the literature showing how imported inputs affect domestic (Goldberg et al., 2010, Huneeus, 2018) and export performances (Halpern et al., 2015, Feng et al., 2016, Bas and Strauss-Kahn, 2015, Amiti et al., 2014). In contrast to those studies, high-frequency data makes it possible to dig into the dynamics of the adjustment to a large but relatively short-lived supply-side shock.[2] Second, whereas this literature mostly focuses on the structure and geography of global value chains, we instead study the consequences of this structure for firms' exposure to localized shocks.[3]

In doing so, we contribute to the recent literature measuring the transmission of shocks along supply chains. Carvalho et al. (2020) and Boehm et al. (2019) study the transmission of supply chain disruptions induced by the 2011 Tohoku earthquake, respectively in Japan and in the US. Barrot and Sauvagnat (2016) focus more broadly on extreme weather events. Alessandria et al. (2010b) and Gopinath and Neiman (2014) examine the transmission of large currency crises through imports. As in Boehm et al. (2019), we exploit the monthly frequency of firm-level trade data to trace the dynamics of firms' adjustment to supply chain shocks. Our study complements this literature by digging further into heterogeneous adjustments to supply chain shocks. In particular, our data makes it possible to empirically assess the efficiency of two alternative strategies which have been argued to offer potential buffers against short-lived supply chain disruptions, namely the geographic diversification of input purchases, and inventories.[4] Unlike Kramarz et al. (2020) and Esposito (2020) who focus on the geographic diversification of sales, we here focus on the geographic diversification of inputs. Several papers have highlighted the role of inventories for firms engaged in international trade (Alessandria et al., 2010b, Khan and Khederlarian, 2021), notably during the 2008 Trade Collapse (Alessandria et al., 2010a). Here, we show inventories mitigate the international propagation of shocks along supply chains. This result is all the more relevant since buffer stocks are not widespread among importers as shown by Pisch (2020) who documents (and then models) the prevalence of just-in-time supply chains in France.

The paper is organized as follows. Section 2 describes the data and shows the Chinese lockdown has induced a shortage of inputs for French firms sourcing these inputs from China.

[2]Throughout the paper, we refer to the shock as being short-lived, even though the pandemic has had long-lasting consequences. The reason is that the identification exploits the one- to two-month delay between the productivity slowdown in China and in the rest of the world.

[3]Our analysis focuses on the short-run adjustment of firms to a shock. See Freund et al. (2021) for an analysis of the long-run adjustments of GVCs to a supply shock.

[4]See Grossman et al. (2021) for a discussion of the theoretical conditions under which promoting input diversification is desirable. Elliott et al. (2020) and Jiang et al. (2021) also investigate firms' incentive to build robust supply chains.

Section 3 provides evidence of the within-firm transmission of the Chinese shock to exports. Section 4 examines differences in adjustments to shocks across firms with heterogeneous risk management strategies. Section 5 concludes.

2 Data and evidence of a supply shock

This section presents the firm-level data used throughout the analysis and the definition of firms' involvement in GVCs. It then provides evidence that the Chinese lockdown has severely reduced the supply of inputs from China, and that firms exposed to the Chinese lockdown have experienced a drop in imports.

2.1 Data

The main source of data in our empirical analysis is provided to us by the French customs. The dataset covers every single transaction involving a French firm and a non-French partner. For each export and import transactions, we have information on the French firm at the root of the trade flow, the category of the product, the partner country, the value and quantity of the shipment, the mode of transportation and the date of the transaction, at the monthly level.[5] As discussed in Section 2.2, the monthly frequency is particularly useful as it captures the timing of the pandemic and its heterogeneous impact on bilateral trade.

We merge the estimation sample with an other two firm-level datasets. The INSEE-FARE dataset, available up to 2018, provides balance-sheet information on French firms, collected for tax purposes. Based on the balance-sheet data, we measure the ratio of imports over intermediate consumption and the share of exports in aggregate sales, which we use as proxies for the firm's degree of vertical specialization. The balance-sheet data are also used to recover information on firms' inventories. Second, we merge the data with monthly information on French firms domestic and overall sales, available in VAT statements. These data can be used to compare the dynamics of foreign and domestic sales in the aftermath of the early lockdown in China.

[5] Formally, the dataset is constructed from four sets of files, all collected by the French customs, namely export and import files, for intra-EU and extra-EU trade. We construct the final dataset following Bergounhon et al. (2018). Details are provided in Appendix A.1.

In the rest of the analysis, our objective is to identify the diffusion of supply chain disruptions induced by the Chinese lockdown on GVCs, using French firms involved in such GVCs as reference. To identify these firms, we follow the World Development Report on GVCs (WDR, 2020) and consider that a firm is engaged in GVCs if it both imports some of its inputs and exports part of its output. Based on this definition, it is straightforward to identify French firms involved in GVCs from the customs data, by merging import and export data using the French firm's identifier. In the rest of the analysis, we restrict our attention to firms that display strictly positive exports *and* strictly positive imports of intermediates, where the definition of intermediates follows the UN-BEC classification of products and firms' trade activities is measured between September 2019 and January 2020. Of course, there is ample heterogeneity in this sample regarding the intensity of these firms' international activity. 49.4% of the firms export more than 10% of their output and 60.5% purchase more than 10% of their inputs from abroad. Our baseline results pool all firms together but we later investigate the heterogeneity in the transmission of the shock across firms with varying degrees of import and export activities.

Table 1: Summary Statistics on the estimation sample

		Average...			Share in aggregate...		
	Nb. of firms	Imports	Dom. Sales	Exports	Imports	Dom. Sales	Exports
All GVC firms	33,483	6.8	64.1	13.3	89.5	29.8	91.6
Sourcing from China							
Yes	14,880	10.4	101.2	21.7	60.9	20.9	66.1
No	18,603	3.9	34.4	6.7	28.6	8.9	25.4
Sourcing monthly from							
China	4,495	20.3	139.0	41.85	36.06	8.7	38.6
Elsewhere	10,387	6.7	47.2	9.8	27.3	6.8	20.9

Note: Summary statistics computed in 2019 on firms that both import intermediates and export between September 2019 and January 2020. Statistics on imports are about intermediate goods. Average sales are in millions euros. Shares in %. Source: Customs and INSEE-VAT data.

Table 1 shows descriptive statistics on the sample under study. The estimation sample is composed of roughly 33,000 firms that both import intermediate products and export. Together, these firms account for about a third of French firms' domestic sales and roughly 90% of the total value of French exports and imports. These numbers are consistent with the view that, in tradable sectors, large firms tend to be involved into two-way trade (Bernard et al., 2018). Among these firms, 45% import some of their inputs from China and 14% have interacted with

Chinese producers on a monthly basis between September 2019 and January 2020.[6] Firms importing from China are roughly three times larger than other importers, in terms of the mean value of their overall imports and exports. This size discrepancy is not surprising as importing from China involves substantial fixed and variable costs which only the largest firms can afford to pay.[7] China is one of the largest suppliers to French firms, which explains that 61% of imports and 66% of exports originate from firms importing from China in the five months before the shock.

2.2 The early stages of the Covid-19 pandemic as a natural experiment

Supply chain disruptions have been at the heart of policy debates during the Covid-19 pandemic. However, their actual impact on the overall economic slowdown is difficult to establish. From the Spring of 2020, many countries have simultaneously adopted lockdown strategies that affected both supply and demand. To isolate the effect of a supply shock, we exploit the timing and geography of the pandemic. The pandemic started in China and the Chinese government has been the first to implement lockdown measures that induced a drop in output in China and delays in sea freight originating from China, at a time when the rest of the world was not contaminated yet.

Figure 1 illustrates the discrepancy in the rise of confirmed covid cases across countries. Whereas most countries have been hit by the pandemic in the first half of March, China has been hit earlier in January 2020. As a consequence, China has been the first country to impose a severe lockdown, in the Hubei region from January 23rd. In other countries, government responses came later, at the end of February or the beginning of March.[8] The rise in the

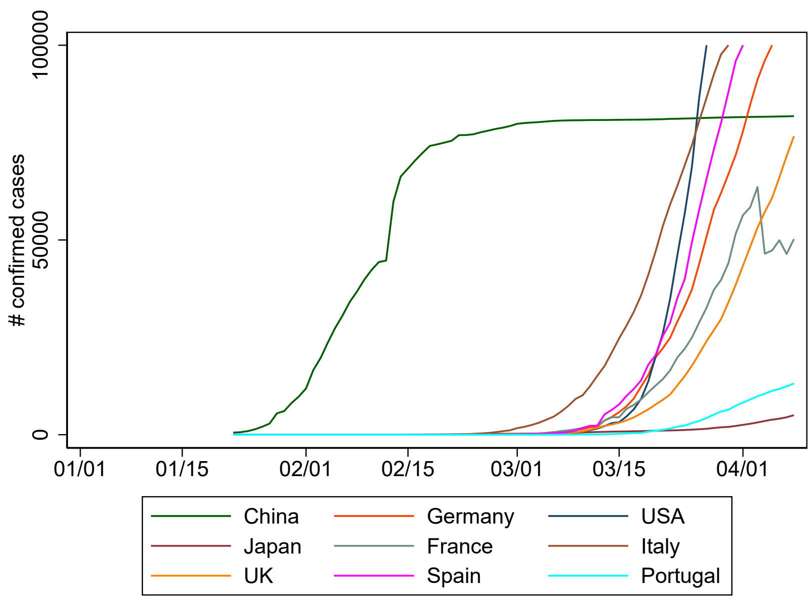
[6] A standard issue while working on Chinese trade data has to do with the status of trade with Hong Kong. Throughout the analysis, we decided to focus on direct trade with mainland China. We have also reproduced all results based on a dataset that considers imports from Hong Kong into the treatment group. The results obtained from this alternative definition (and available upon request) are unchanged because the volume of imports that is recorded in the customs flows as originating from Hong Kong is very limited. Adding firms importing from Hong Kong into the baseline treatment group thus moves 229 French firms from the control to the treatment groups.

[7] In the rest of the analysis, we control for systematic differences between firms exposed to China and those that are not using fixed effects. In a robustness exercise, we also rely on a matching algorithm to compare firms exposed to Chinese inputs with similar controls in terms of their trade activity.

[8] The Oxford Blavatnik School of Government systematically collects daily information on policy responses to the pandemic, which they aggregate into a "Government Response Index". For each country, it is possible to identify the first important adjustment in this index. China has been the first to adopt containment measures, whereas most countries have adopted similar measures four to five weeks later.

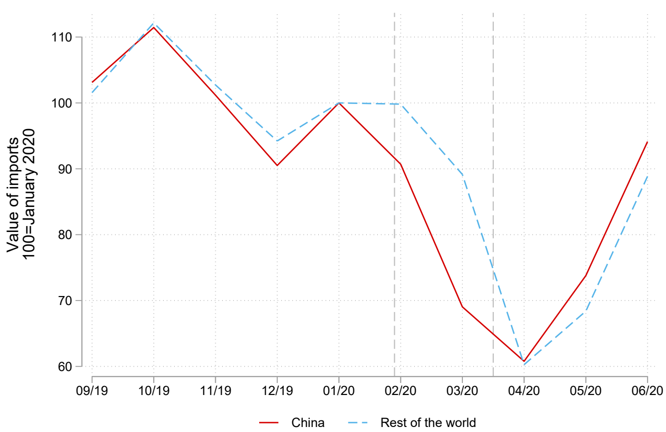
number of cases and the containment policies have led to early production disruptions in China. Like Eppinger et al. (2021), we exploit this one-month lag to separate in the data the impact of the productivity slowdown in China from the general drop in productivity induced by the pandemic.

Figure 1: Spread of the pandemic: number of confirmed cases for a selection of countries



Source: Oxford COVID-19 Government Response Tracker.

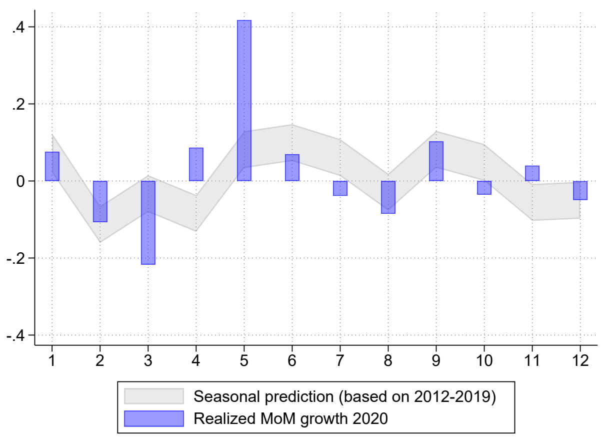
Figure 2: Value of French imports from China and the rest of the world



Source: French customs, import files. The figure shows the evolution in the value of French imports from China and from the rest of the world, between September 2019 and June 2020. Both time series are normalized to 100 in January 2020. COVID products are excluded using the list of HS6 products produced by the WTO.

A first hint that this one-month delay has had consequences on French firms is illustrated in Figure 2, which compares the monthly evolution of French imports from China and from the rest of the world.[9] Whereas the value of imports from the rest of the world was stable in February 2020, it decreased by almost 10% for imports originating from China. Imports from the rest of the world instead started to decrease in March, when imports from China were already close to their lowest level. During the Spring 2020, the evolution of imports from China and from the rest of the world is more synchronized. It is only in the Fall that the two series start diverging again, due to the second wave affecting most European and American countries when the situation was much more under control in China. Importantly, the early contraction of imports from China is not innocuous from the point of view of the French economy as China is the second most important source of imports.[10]

Figure 3: Actual versus predicted monthly growth of Chinese imports



Source: French customs, import files. The figure shows the monthly growth of imports from China in 2020 (blue bars) and the mean monthly growth estimated based on data over 2012-2019.

International trade displays important seasonal patterns, and the seasonality is in part

[9]Throughout the analysis, we exclude imports of Covid-related products, namely masks, anti-epidemic goods, medical equipments, medical supplies and medicines using the list of Covid-related products provided by the WTO. Covid-related products do not affect the dynamics of trade prior to March, when the number of cases was still very small in France. In particular, the one month delay between the drop in imports from China and from the rest of the world is the same whether Covid-related products are included or not. However, the dynamics of trade after April 2020 is strongly affected by imports of Covid-related products. Namely, the dynamics of imports sourced in China and in the rest of the world are very similar once Covid-related products are removed from the estimation sample. Instead, the value of imports from China is 20% higher in June than in January, when Covid-related products are included. See Bown (2021) for a more detailed discussion of trade in Covid-related products during the pandemic.

[10]In 2019, France imported 542.8 billion euros from abroad, 9.3% of which was imported from China. About 35.9% of French imports from China are final products, whereas intermediate goods and capital goods account for 26.7 and 37.1 percent of imports, respectively.

country-specific. One may thus wonder the extent to which the relative drop in imports from China observed in February and March 2020 is not a consequence of the specific seasonality of trade with China. Figure 3 compares the monthly growth of imports from China in 2020, against the seasonal component of monthly growth estimated using data from 2012 to 2019.[11] The relative drop in imports observed in February 2020 may be attributable to the normal seasonality of trade. The 20% drop observed between February and March is instead significantly larger than historical seasonal variations, as is the recovery in March and April.

2.3 Chinese lockdown and firm-level imports

Having documented the aggregate dynamics of imports from China and from the rest of the world in the early stages of the Covid crisis, we now provide indicative evidence that the aggregate drop in imports from China has induced a shortage of inputs for French firms. To this aim, we compare the evolution of overall firm-level imports before and after the Chinese lockdown for firms directly exposed to the Chinese lockdown and in a control group. Exposure (our treatment variable T1) takes the value of one for any French firm having imported an intermediate good from China in the second semester of 2019. The control group is composed of French firms that also import inputs but not from China. **We shall keep in mind that what we call control firms are not firms necessarily immune to the shock. Their suppliers may have been themselves exposed to supply chain disruptions from China. By the same token, firms we dubbed as treated may as well be indirectly exposed. Since the empirical strategy focuses on a relatively short window, the analysis is implicitly based on the premise that a direct exposure has earlier and stronger consequences on firms' input purchases than any indirect exposure. As such, our estimates recovered from the comparison of firms directly hit by the Chinese slowdown with firms that may be indirectly affected should be interpreted as a lower bound of the actual impact of the shock.**

To investigate the dynamics of the adjustment of exposed firms, we first use an event-study design:

[11] More specifically, we estimate a fixed effect model using monthly growth rates of imports from China between 2012 and 2019. Month-specific fixed effects capture the seasonal component of trade. Figure 3 compares the actual growth during the Covid episode (blue bars) with this seasonal component (grey area).

$$\ln Imports_{ft} = \sum_{l=-4}^{5} \beta^l \, Treated_f \times Time_{lt} + FE_f + FE_t + \varepsilon_{ft} \,, \tag{1}$$

with $Imports_{ft}$ the value of total import purchases of firm f at time t, $Treated_f$ a dummy equal to one if the firm is in the treatment group, $Time_{lt}$ a dummy equal to one l periods before/after the shock, and FE_f and FE_t that respectively denote firm- and time- fixed effects. Equation (1) thus compares the dynamics of imports before and after the Chinese lockdown, for firms directly exposed to the shock, in comparison with the control group. Any difference in firm-level characteristics that is constant over time is captured by the firm-level fixed effects. Coefficients are normalized to zero in January 2020.

Results of the event-study specification are presented in Figure 4. We see that before the lockdown in February, there is no significant difference in the evolution of imports for firms in the treatment and the control groups, except in November. Instead, we observe a relative drop in imports in the treatment group in the month that followed the Chinese lockdown. The effect seems transitory with a peak in April and then a rebound. In June, the level of imports is only marginally lower in the treatment than in the control group. The dynamics, recovered from a narrow comparison of firm-level imports in a treated and a control group, is in line with the overall behavior of imports displayed in Figure 2.

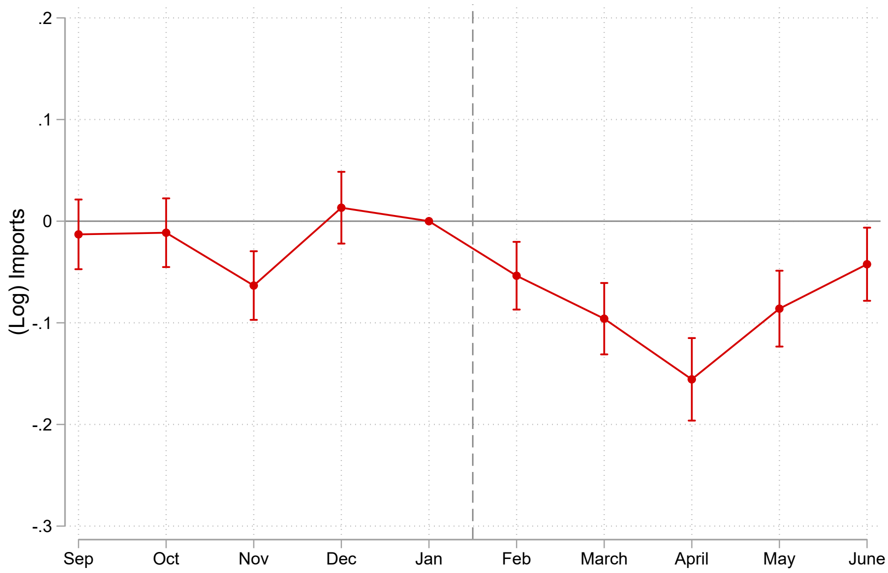
Having established a significantly different dynamics of imports for treated and control firms, we now investigate the robustness of the effect using a more compact difference-in-differences model:

$$\ln Imports_{ft} = \alpha Treated_f + \beta Post_t + \gamma Treated_f \times Post_t + FE + \varepsilon_{ft} \tag{2}$$

where $Post_t$ is equal to one from February 2020. FE denotes a set of fixed effects. In our preferred specifications, we use firm and period fixed effects.

Table 2 summarizes our results. In the simplest specification without firm fixed effects (column (1)), we estimate a positive and significant coefficient on the treated dummy, which is consistent with evidence in Table 1 showing that firms importing from China are systematically larger in terms of their imports. In this specification, the Chinese lockdown has no specific impact on importers exposed to China. In column (2), we add firm fixed effects to control for unobserved characteristics of firms importing from China. In this more demanding specification, we estimate that firms exposed to the Chinese lockdown experienced a 7% relative drop in

Figure 4: Chinese lockdown and firm-level imports



Notes: The figure shows the dynamics of imports before and after the Chinese lockdown, for treated firms in comparison with the control group. Standard errors are clustered at the firm-level. The confidence intervals are defined at 5%. Treated firms are those importing from China prior to the shock. Control firms are importers not exposed to China. The estimated equation includes firm and period fixed effects.

imports, our baseline estimate. In column (3), we define an alternative treatment variable that tracks, among the T1 treatment group, French firms with regular ties with China. More specifically, treated firms in group T2 are firms that have imported Chinese intermediates every month from September 2019 to January 2020. In that case, the control group is composed of firms that also display regular ties with a sourcing country, which is not China. The effect of the Chinese lockdown is stronger in this alternative treatment group whose imports drop by 12% after the shock, in relative terms. The stronger impact of the Chinese lockdown in this group is consistent with the interpretation in terms of a supply chain disruption, which is all the more costly since the firm relies heavily on Chinese inputs.[12]

In column (4), we further exploit the granularity of the data to work at the firm-product-month level, and control for unobserved heterogeneity with product-period fixed effects. In that case, the treatment is defined at the firm×product level and we thus estimate how product-level

[12]In Table 2, the estimation sample goes from September 2019 to June 2020. Figure 4 shows that most of the effect of the treatment occurs in February, March, and April. In unreported regressions, we have checked that results look similar if we restrict the sample to imports until the end of April 2020. As expected, point estimates are systematically larger in that case. For instance, the baseline specification in column (2) implies a relative drop in imports of -8.5%.

Table 2: Impact of the Chinese lockdown on treated firms' imports

	Dep. Var: log of imports			
	(1)	(2)	(3)	(4)
Treated firm	0.286^a			
	(0.028)			
Treatment × Post	0.001	-0.070^a	-0.120^a	-0.075^a
	(0.013)	(0.010)	(0.012)	(0.006)
Firm FE	N	Y	Y	× Product
Time FE	Y	Y	Y	× Product
# Treated	13,994	13,994	4,495	11,126
# Control	16,543	16,543	10,387	24,850
Sample	All	All	All	All
Treatment	T1	T1	T2	T1
R^2	0.004	0.861	0.861	0.869
# Obs.	244,896	244,896	144,701	2,217,183

Note: The table reports results of difference-in-difference estimations on firms' imports. "T1" means that the control group is made of firms that import inputs from abroad outside of China whereas treated firms are those exposed to Chinese inputs in the five months before the pandemic. "T2" means that the control group is made of firms that import inputs monthly from a specific country which is not China whereas treated firms import every month from China, in the five months before the pandemic. The date of treatment is February 2020 and the DiD compares the evolution of imports between September 2019 and January 2020 (pre-treatment period) and between February 2020 and June 2020 (post-treatment period). Columns (1)-(3) are estimates on firm-level imports and 'units' are firms, while Column (4) considers as treated units firm×product pairs. ^{a}, ^{b} and ^{c} denote significance at the 1, 5 and 10% level respectively.

imports reacted to a product-level exposure to the Chinese lockdown.[13] The estimated effect remains negative and significant at -7.5%.[14]

Results in Table 2 and Figure 4 thus show that total imports of firms exposed to the Chinese lockdown have dropped after January 2020. These results thus justify our interpretation of the

[13]The number of units in the control group increases as a consequence. A firm can indeed be exposed to China on one product, and thus belong to the treatment group, while sourcing all of its imports of other products from third countries, in which case it is considered as control.

[14]In Figure A.2 in the Appendix, we further show that the relative drop in imports materializes earlier in the data for firms that mostly import from China using air freight. The relative decline in imports is instead observed one month later in the rest of the sample. As it takes roughly a month for goods shipped by sea to arrive in Europe, the one-month delay is consistent with the consequences of the Chinese lockdown being felt with a delay for firms relying on sea freight, that have received shipments sent at the end of January at the beginning of March. Another source of heterogeneity in the size of the treatment across firms importing from China may arise from the early lockdown in China displaying heterogeneous stringency across Chinese provinces. In the absence of firm-level data on the within-country origin of the Chinese products, we have no choice but to assume that all importers importing from China are exposed to the productivity slowdown from the end of January. In section 3.3, we propose a robustness exercise that tackles this specific source of heterogeneity.

early lockdown in China as a (temporary) shock to French firms' input purchases. In the next section, we investigate the propagation of this supply shock along GVCs by studying how firms' exposure to the Chinese lockdown has impacted their exports.

3 Firm-level transmission along the supply chain

This section shows the shortage of Chinese inputs, which followed the Chinese early lockdown, had an adverse impact on the domestic and export sales of French firms relying on these inputs. We first discuss the economic magnitude of the effect, then its robustness to the identification strategy, before concluding on the heterogeneity of the transmission among treated firms.

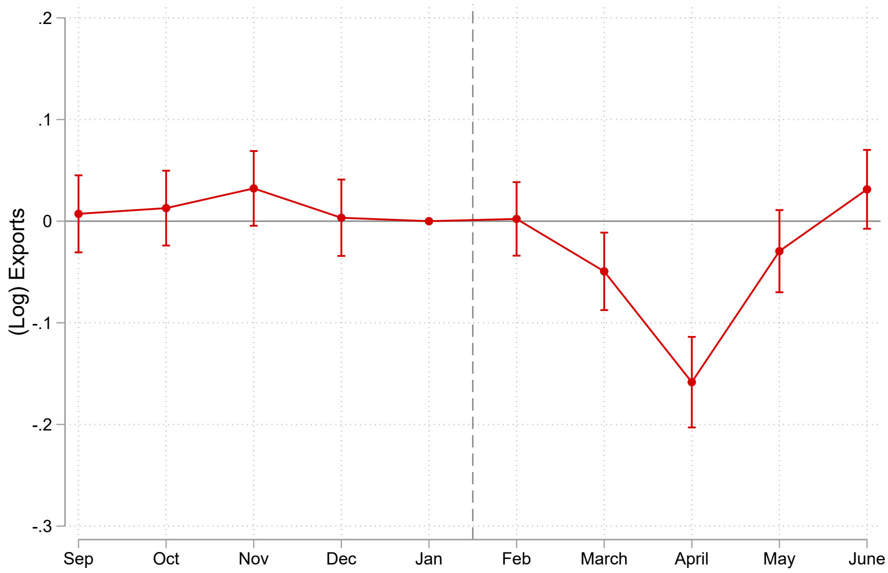
3.1 Baseline results

We compare the evolution of firm-level exports before and after the Chinese lockdown for firms directly exposed to the Chinese lockdown and firms in a control group. We use the same exposure variable as in the previous section (our treatment variable T1), which takes the value of one for any French firm having imported an intermediate good from China in the second semester of 2019. The control group is composed of French exporting firms that also import inputs but not from China. To investigate the dynamics of the adjustment of exposed firms, we first use an event-study design similar as in equation (1), but we consider the logarithm of firm-level exports rather than firm-level imports as the dependent variable.

Results are presented in Figure 5. We see that the treated and control groups exhibit similar trends in exports before the Chinese lockdown. Whereas exports do not exhibit a particular pattern the month following the Chinese lockdown, the exports of exposed firms then dropped abruptly relative to the control group in March and April 2020. The effect is transitory and the difference in exports of both groups is no longer significant from May 2020. In unreported results, we have extended the sample until December 2020 but did not find any sign of the two groups of firms diverging again later in the year.

We confirm the adverse impact of the Chinese lockdown on exports in various difference-in-differences estimations. The specification is the same as in equation (2) but the explained variable is the logarithm of exports at the firm-level. Table 3 summarizes our results. Column (1) reports our baseline specification comparing firm-level exports of firms exposed to the

Figure 5: Effect on exports of input shortages associated with the Chinese lockdown



Notes: The figure shows the dynamics of exports before and after the Chinese lockdown, for treated firms in comparison with the control group. Standard errors are clustered at the firm-level. The confidence intervals are defined at 5%. Treated firms are those importing intermediate inputs from China prior to the shock. Control firms are importers not exposed to China. The estimated equation has firm and period fixed effects.

Chinese lockdown (treatment group T1) with firms importing from outside of China. The specification includes time and firm-level fixed effects. The coefficient on the interaction term is negative and significant, and implies that firms relying on Chinese inputs have experienced a 4.9% drop in exports after the Chinese lockdown, relative to non-exposed firms. In column (2), we see the effect is slightly stronger – a 6.3% drop – if the treatment group is composed of firms importing every month from China before the lockdown (treament group T2).[15]

Column (3) further exploits the granularity of the data by estimating the effect of the treatment on exports at the firm-product-destination level. The upside of this specification is that it allows us to use product-destination-time fixed effects to control for monthly demand shocks in each destination. For instance, differences in the rise of cases or in the adoption of containment measures may induce heterogeneity in the dynamics of exports across destinations. For firms sourcing inputs from China, export sales of a given product and within a destination have dropped by 4.1% after the Chinese lockdown. The effect is thus a bit smaller than in the baseline specification (-4.8%). One possible interpretation of the dampening is that the

[15]The corresponding event study graph is reported in Figure A.3 in the Appendix.

Table 3: Impact of input shortages on exports: Difference-in-difference results

Dep. Var:	log of exports			log of X price	log of dom.sales
	(1)	(2)	(3)	(4)	(5)
Treatment × Post	-0.048[a]	-0.063[a]	-0.041[a]	-0.007[a]	-0.057[a]
	(0.011)	(0.015)	(0.004)	(0.002)	(0.007)
Firm FE	Y	Y	× Product	× Product	Y
Time FE	Y	Y	N	N	Y
Product×Destination×Period	N	N	Y	Y	N
# Treated	13,731	4,322	11,435	11,358	12,261
# Control	16,646	9,672	14,354	14,275	14,605
Sample	All	All	All	All	All
Treatment	T1	T2	T1	T1	T1
R^2	0.857	0.875	0.744	0.868	0.910
# Obs.	234,482	116,087	6,987,869	6,827,204	230,703

Note: The table reports estimation results of the difference-in-differences estimation using as left-hand side variable either the log of exports (columns (1)-(3)), the log of export unit values (column (4)) or the log of domestic sales (column (5)). "T1" denotes the control group of firms that import inputs from abroad outside of China whereas treated firms are those exposed to Chinese inputs in the five months before the pandemic. "T2" focuses on firms that import inputs monthly from a specific country, being China for treated firms and another country for control firms. The date of treatment is February 2020 and the DiD compares the evolution of imports between September 2019 and January 2020 (pre-treatment period) and between February 2020 and June 2020 (post-treatment period). In column (3), we ran the estimation at the Firm×Product×Destination×Period level. Standard errors are clustered at the firm-level (Firm×Product in column (3)). [a], [b] and [c] denote significance at the 1, 5 and 10% level respectively.

firm-level results capture extensive adjustments (the drop of destination-product pairs), which are neglected when we work at the firm-product-destination level. We come back to this issue when discussing the different adjustment margins of firm-level exports in Table 4.[16]

In column (4), we investigate how the supply chain disruption affects export prices. In contrast with what would be expected, export prices of exposed firms have *decreased* after January 2020, although the average effect is very small, at -0.7%.[17] In Section 3.3, we dig deeper into this result and show that the average effect hides important heterogeneities across sectors.

These results thus confirm a significant transmission of the shock to input purchases on firms' exports. A natural question is the extent to which the export adjustment comes from a

[16]Whereas the specification in column (3) of Table 3 fully controls for differences across firms in exposure to demand shocks, one may particularly worry about one source of heterogeneity being firms exposed to Chinese inputs are also more likely to *export* to China. In this case, the relative drop in exports for firms exposed to Chinese inputs may arise from a relative drop in the demand of the Chinese market. In order to control for this possibility, we have also reproduced the baseline regression in column (1) using exports to all countries but China as left-hand side variable. Results, available upon request, are very similar to those in column (1).

[17]This result is in contrast with the dynamics of *import* prices which have increased in relative terms for treated firms after the lockdown, by 1% on average. The corresponding regression is not reported here and is available upon request.

substitution away from foreign markets, to preserve the firm's *domestic* market. To tackle this question, we exploit an additional source of monthly information on French firms' real activity, recovered from their VAT records. This database allows us to measure each firm's domestic sales, before and during the pandemic, and implement the event-study design in equation (1) using the log of domestic sales as left-hand side variable. Results are summarized in column (5) of Table 3 as well as in figure A.4 in the Appendix. The general pattern is very similar for domestic sales as for foreign sales. Between February and June 2020, domestic sales have dropped by 5.7% in the treatment group in comparison with the control, with a negative peak in April. In unreported results, we found that the domestic to overall sales ratio did not adjust after the shock. Together, these results suggest that the drop in exports is not mostly attributable to a substitution away from foreign markets to maintain the firm's domestic market share.

Table 4 decomposes the adjustment of firms' exports after the Chinese lockdown into different margins. In columns (2) and (3), exports are broken down into the value of exports per destination and the number of destinations. In columns (4) and (5), the decomposition involves the value of exports per product and the number of products. Finally, columns (6) and (7) respectively display results based on the value of exports per product-destination and the number of product-destination pairs. The top panel reports these decompositions using the baseline specification.[18] The bottom panel considers the alternative treatment group (T2) that identifies firms with regular input-output ties with China. All specifications point towards the same direction. Export adjustments occur along the extensive margin, whereas the effect of the treatment is not significant at the intensive margin. Firms sourcing inputs from China have reduced the number of products and the number of destinations they serve after the Chinese lockdown. The result on extensive adjustments at the product margin level is consistent with the literature on multi-product firms showing that firms adjust to shocks by changing their product mix (see, e.g., Mayer et al., 2021). To our knowledge, this paper is however the first one to show evidence of adjustments to *temporary* supply shocks through the extensive margin.

The last column in Table 4 complements the analysis with a last model investigating extensive margin adjustments at the *firm* level. Up to now, the analysis has indeed been restricted to firm×periods with strictly positive exports and could thus be biased by extensive adjustments

[18]The corresponding event-study graphs are reproduced in Figure A.5.

Table 4: Margins decomposition of DiD results

	Baseline	Destination Int.	Destination Ext	Products Int.	Products Ext.	Markets Int.	Markets Ext.	Firm Firm
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A:								
Treatment × Post	-0.048^a	-0.008	-0.040^a	-0.003	-0.045^a	0.005	-0.053^a	0.008^a
	(0.011)	(0.009)	(0.004)	(0.010)	(0.004)	(0.009)	(0.005)	(0.002)
# Obs.	234,482	234,482	234,482	234,482	234,482	234,482	234,482	334,830
R^2	0.857	0.792	0.917	0.827	0.900	0.791	0.927	0.558
Panel B:								
Treatment × Post	-0.063^a	-0.018	-0.045^a	-0.004	-0.059^a	0.002	-0.065^a	0.009^a
	(0.015)	(0.013)	(0.005)	(0.013)	(0.007)	(0.012)	(0.007)	(0.003)
# Obs.	116,087	116,087	116,087	116,087	116,087	116,087	116,087	148,820
R^2	0.875	0.814	0.927	0.852	0.918	0.819	0.939	0.568

Note: Columns (1)-(7) use the log of the firm's exports (1), or one of its component (2-7), as left-hand side variable. Column (8) corresponds to a linear probability model of the likelihood that the firm exports. All variables are at the firm and period level. All specifications include firm fixed effects and time fixed effects. The treatment group in panel A is made of firms that import from China at least once before the treatment, "T1". The treatment group in panel B is made of firms importing from China every month, "T2". Standard errors in parenthesis are clustered at the firm-level.

at the firm level. We use a linear probability model to estimate the probability that the firm keeps on exporting before and after the shock.[19] In both panels, the estimated coefficient is positive and significant meaning that treated firms are relatively less likely to drop out of export than firms in the control group. As shown in Figure A.6 (bottom panel), the effect is however very small and coefficients estimated period by period are never significant. This result is in contrast to what we see from the probability of *importing*, which displays a significant drop in February 2020, before a rebound in March (top panel). From this, we conclude that firms suspending their activities is not an important driver of the downstream transmission of the shock.

3.2 Robustness analysis

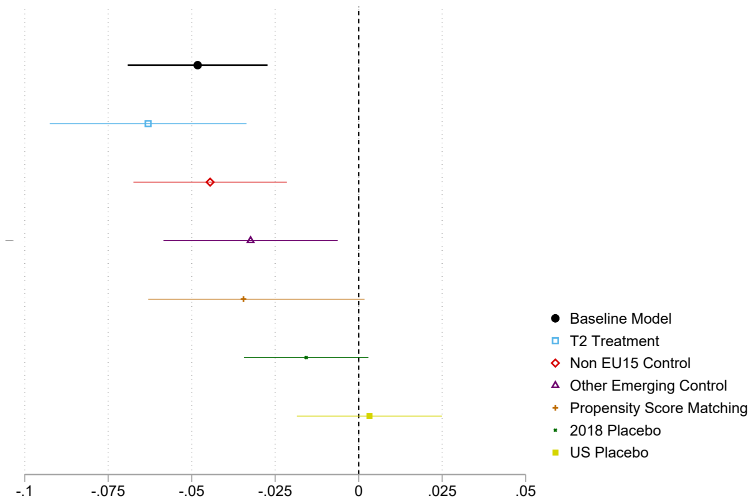
In this section, we test the robustness of our main findings. We first discuss how results vary with alternative definitions of the control group. We then test robustness to the estimation method, using a matching algorithm as an alternative. Finally, we conduct two placebo exer-

[19]The estimated equation reads:

$$\mathbb{1}_{ft} = \beta Treated_f \times Post_t + FE_f + FE_t + \varepsilon_{ft}$$

with $\mathbb{1}_{ft}$ that is equal to one when firm f displays strictly positive exports in period t.

Figure 6: Impact of the Chinese lockdown on firm-level exports: Robustness Analysis



Notes: The figure compares DiD coefficients recovered from the estimation of equation (2) using the log of firm-level exports as the LHS variable, in the various robustness exercises described in this section. The estimated equation includes firm and period fixed effects. Standard errors are clustered at the firm-level. The confidence intervals are defined at 5%.

cises. These are meant to provide support for our interpretation of the relative drop in exports as being the result of the transmission of the shock along the supply chain rather than the consequence of a global shock or country-specific seasonal patterns in trade data. Results of these robustness exercises are summarized in Figure 6, which displays the DiD coefficient recovered from each robustness. These coefficients are compared with the baseline, the black line for the T1 treatment and the blue line that corresponds to the T2 treatment, respectively columns (1) and (2) in Table 3. Detailed event-study results are provided in the Appendix.

First, one may worry that firms in the control group are exposed to systematically different supply shocks through their import portfolio. To deal with this issue, we exclude from the control group firms that solely import inputs from EU15 countries. The corresponding firms are small on average and given the degree of integration of the single market in these countries, the extent to which these firms participate to GVCs may be questionable. This restriction removes about six thousands firms from the control group. In an alternative exercise we restrict the control group to firms importing some of their inputs from less-developed and emerging countries.[20] The corresponding control group contains 7,255 firms which imports and exports

[20]The list of countries considered as "emerging" is the following: Algeria, Argentina, Bahrein, Bangladesh, Brazil, Brunei, Cambodia, Chile, Colombia, Egypt, Ecuador, India, Indonesia, Iran, Iraq, Israel, Jordan, Kuwait, Lao PDR, Lebanon, Libya, Malaysia, Mexico, Morocco, Oman, Paraguay, the Philippines, Qatar, Russia, Saudi

on average represent 70 and 47% of the average treated firm's pre-shock trade, respectively. Here as well, the objective is to move the average control firms closer to treated firms, in terms of their import activities.

Results of these two exercises are summarized in Figure A.7, with the corresponding DiD coefficients represented with the red and purple lines on Figure 6. Results obtained excluding firms solely importing from EU countries look very similar to those in Figure 5, which confirms that the identified transmission of the shock is not attributable to extra-EU imports being more strongly affected by the world trade shock than intra-EU imports. Focusing on firms importing from developing countries as in the bottom panel of Figure A.7 is costly in terms of the precision of the estimates. The relative drop in exports of treated firms in April 2020 is still significantly negative, although slightly lower.

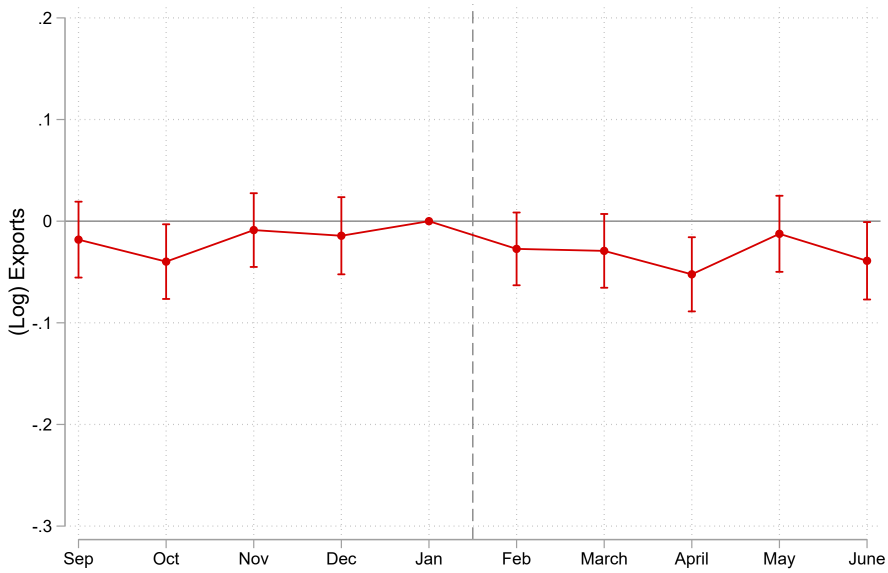
We then depart from the baseline specification and instead use a matching estimator. We back out propensity scores from a probit model in which we estimate the probability of being treated using the level of imports, the level of exports, the number of destination countries and the number of exported products in each month in the pre-period, as well as the 2-digit industry code of the firm. We keep units with a propensity score between .1 and .9 to ensure sufficient overlap in covariates distribution between treated and controls (see Crump et al., 2009). Armed with these scores, we can match each treated firm with a synthetic "control" based on its nearest neighbor in the population of control firms. We then use a simple inference method based on a generalized difference-in-differences to build the average treatment effect and use subsampling to construct confidence intervals.[21] The results presented in Figure A.8 and the orange line in Figure 6 confirm the negative impact of the Chinese lockdown on the exports of firms importing from China.[22] In unreported regressions, we show this result is robust if one compares treated firms to their 4-nearest neighbors, or if we use covariates matching from Mahalanobis' metric rather than propensity score matching.

Arabia, South Africa, Sri Lanka, Syria, Thailand, Tunisia, Turkey, United Arab Emirates, Uruguay, Venezuela, Vietnam, Yemen plus the Eastern European countries that joined the EU after 2000.

[21]More specifically, the average treatment effect $k \in [-5, 5]$ months after the shock is the sample average among treated of $Y_{i,k} - \hat{Y}_{i,k} - (Y_{i,-1} - \hat{Y}_{i,-1})$, where $\hat{Y}_{i,k}$ denotes the outcome for the firm chosen as control for treated firm i. As bootstrap cannot help for inference in this setting (Abadie and Imbens (2008)), we use subsampling instead. See Politis and Romano (1994) for the theory, and Alfaro-Urena et al. (2020), Deryugina et al. (2020) for recent applications.

[22]The DiD coefficient shown in Figure 6 is only significant at 10%. As Figure A.8 illustrates, this explains by standard errors being relatively large in this specification as well as December displaying a negative drop in treated firms' exports (although smaller in magnitude than the relative drop observed in March and April 2020.

Figure 7: Placebo test: Dynamics of firm-level exports between September 2018 and June 2019



Notes: The figure shows the dynamics of exports for treated firms in comparison with the control group. The treatment is based on imports from China between September 2018 and January 2019 and the placebo date of the treatment is considered to be February 2019. The estimated equation includes firm and period fixed effects. Standard errors are clustered at the firm-level. The confidence intervals are defined at 5%.

These results thus confirm that the estimated impact of the Chinese lockdown on exposed firms' exports is robust to changes in the definition of the control group. Although the stability is reassuring, identification in these exercises still relies on the comparison of firms that source inputs from China with firms that do not, which may be worrysome in light of the country-specific seasonal patterns characterizing trade data. Although we have already argued that this seasonality is unlikely to fully explain the large relative drop in imports observed on treated firms, one may still argue that it may have consequences for the relative drop in exports. Unfortunately, ruling out this possibility is not straightforward as matching exposed units with firms facing the same seasonality is statistically complex. Our strategy to deal with this issue thus relies on a placebo constructed from pre-Covid data. If seasonality was important in driving the relative drop in exports observed in the treatment group after January 2020, then the exact same pattern would be observed in a placebo treatment group after January 2019. Figure 7, summarized by the green line in Figure 6, shows that it is not the case. In 2018-2019 data, the dynamics of exports is the same before and after January, for firms importing from China in relative terms with respect to firms importing from elsewhere. This finding confirms that the dynamics identified in Figure 5 is specific to the Covid crisis period in early 2020.

Finally, one may also suspect that the identified effect is attributable to the Covid crisis quickly disturbing production processes in complex value chains, which may produce the dynamics in Figure 5 if firms importing from China are systematically more likely to have sophisticated supply chain structures. Whereas the use of various control groups, including those based on propensity score matching, is meant to control for this possibility, we ran another placebo exercise in which we defined the treatment as importing from the US. In early 2020, US production was still immune from Covid-related problems. If the results displayed in Figure 5 is indeed attributable to supply chain disruptions after the early Chinese lockdown, we should not see any difference between treated and control firms once treated firms are defined based on importing from the US. Instead, if the dynamics of exports is driven by the worldwide disruption of complex value chains in the early stages of the Covid crisis, we shall see a similar pattern in this placebo test as in the baseline case. Figure A.9 (yellow line in Figure 6) shows that it is not the case. Firms importing from the US do not display a different dynamics of exports than other firms in the first semester of 2020. If any, these firms' trade patterns start diverging in June 2020, when the Covid crisis was hitting the US much more severely.

3.3 Heterogeneity across treated firms

This section investigates the extent of the heterogeneity in the transmission, across treated firms from different sectors, size bins, or degrees of exposure to Chinese inputs. To this aim, we first run a number of difference-in-difference specifications in which the post-treatment-on-treated coefficient is interacted with a firm-specific variable that captures heterogeneity in the treatment among treated firms. Results are summarized in Table 5.

The baseline specifications implicitly assume that any pre-Covid import of intermediates from China signaled an exposure to supply chain disruptions once the Covid has hit the country. Moreover, we did not differentiate between firms that were exposed on a tiny fraction of their imported inputs and firms that mostly import inputs from China. The rational behind is that complementarities between inputs would imply that even a small exposure can disrupt the whole value chain. Column (1) in Table 5 provides support for this assumption. The treatment variable is interacted with a dummy that takes a value of one for the 25% of treated firms

Table 5: Impact of input shortages on exports: Heterogeneity across treated firms

	Dep. Var: log of exports							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment × Post	-0.081[a]	-0.024	-0.052[a]	-0.031[b]	-0.048[a]	-0.009	-0.059[a]	-0.033[a]
	(0.016)	(0.016)	(0.014)	(0.014)	(0.011)	(0.013)	(0.018)	(0.012)
... x 25% most exposed	-0.002							
	(0.023)							
... x Im. Intensity		0.085[c]						
		(0.031)						
... x Ex. Intensity			-0.108[a]					
			(0.029)					
... x Im. Intensity x Ex. Intensity				-0.014				
				(0.048)				
... x Largest 25%					-0.054[a]			
					(0.003)			
... x Hubei						-0.085[a]		
						(0.016)		
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
# Treated	13,731	10,973	11,516	10,973	11,709	13,731	6,994	11,259
# Control	16,646	11,918	12,510	11,918	12,792	16,646	7,383	13,108
Export Sample	All	All	All	All	All	All	Final	Interm.
Treatment	T1	T1	T1	T1	T1	T1	T1	T1
R^2	0.868	0.868	0.867	0.868	0.868	0.857	0.865	0.865
# Obs.	234,482	164,496	172,349	164,496	175,651	234,482	100,347	179,119

Note: The table reports results of difference-in-difference estimations on exporting firms. "T1" means that control group are firms that import inputs from abroad outside of China whereas treated firms are those exposed to Chinese inputs in the five months before the pandemic. The date of treatment is February 2020 and the DiD compares the evolution of imports between September 2019 and January 2020 (pre-treatment period) and between February 2020 and June 2020 (post-treatment period). Estimates are on firm-level exports and 'units' are firms. Column (1) augments the baseline specification with a categorical triple interaction between the "Treatment" dummy, the "Post" dummy and a dummy equal to 1 if the firm falls into the fourth quartile of the distribution of the share of Chinese inputs into the firm's imports of intermediates. Columns (2)-(4) add a continuous triple interaction to capture the treatment intensity based on three variables, all comprised between 0 and 1: import intensity ($\frac{\text{Total intermediate imports}}{\text{Total intermediate purchases}}$), export intensity ($\frac{\text{Total exports}}{\text{Total sales}}$) and vertical specialization ($\frac{\text{Total intermediate imports}\times\text{Total exports}}{\text{Total intermediate purchases}\times\text{Total sales}}$). Purchases, sales, total imports and exports are based on 2018 data. In column (5), the triple interaction involves a dummy which is equal to 1 if the firm's 2018 income is in the top quartile. In column (6), the interaction captures the likelihood that the firm imports intermediates from the Hubei region. As we do not observe the regional origin of imports in our data, we use 2014 product level export data from China, at the regional level to define as *Hubei product* a product whose Balassa ratio is above 1. A firm for wich the triple interaction term equals 1 would be a firm that imports a *Hubei product* at least once in the pre-treatment period. Finally, columns (7) and (8) reproduce the baseline regression on final goods exports (column (7)) and on intermediate goods (column (8)). Standard errors are clustered at the firm-level. [a], [b] and [c] denote significance at the 1, 5 and 10% level respectively.

with the highest share of Chinese products in their imported inputs. The coefficient on the triple interaction is not significant which is consistent with our prior that the intensity of the exposure does not matter much, conditional on being exposed.[23]

In columns (2)-(4), we then investigate heterogeneity across treated firms, depending on the intensity of their integration in Global Value Chains. More specifically, we measure the share of imported inputs in the firm's intermediate consumption ("Import Intensity") and the share of exports in its overall sales ("Export Intensity"), the product of the two being akin to a measure

[23] In unreported results, we have checked that this result is robust to our measure of the intensity of the treatment, that can be measured using the share of Chinese products in overall imports or using the number of products that the firm imports from China.

of vertical specialization at firm-level (Hummels et al., 2001). Each variable is then interacted with the $Treatment \times Post$ dummy. Results suggest the transmission to downstream partners is exacerbated for firms that export a larger share of their output (column (3)). The impact of the firm's import intensity is instead unclear. Firms that source a larger share of their inputs from abroad may be slightly less prone to transmitting the shock downstream but the effect is only marginally significant (column (2)). Given these ambiguous results, it is not surprising that the interaction between the firm's import and export intensities does not identify firms with a significantly different propensity to propagate the shock downstream (column (4)). Instead, the impact of the shock is shown larger among the largest firms in terms of their turnover (column (5)). This result is consistent with Bricongne et al. (2021) who show large firms have played a specific role during the Covid-induced trade collapse.

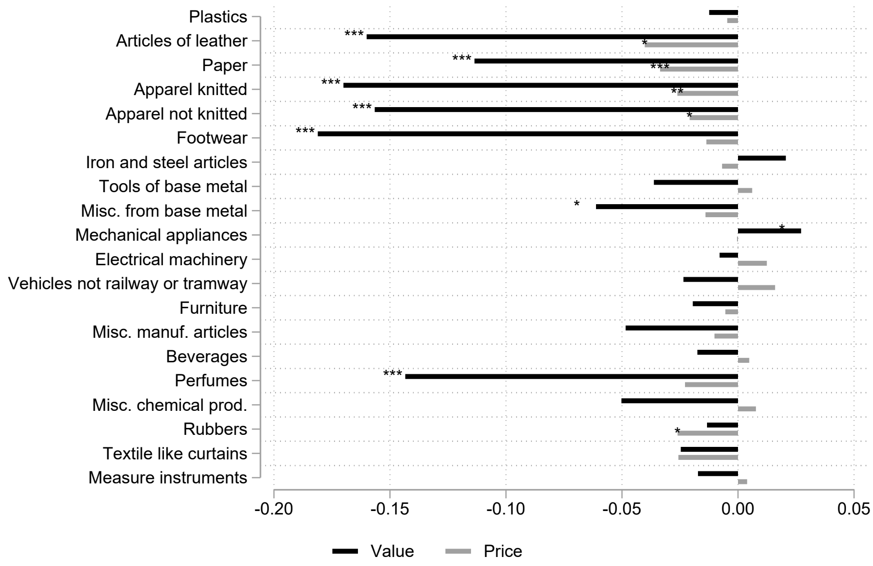
In column (6), we try to control for the heterogeneity in the *severity* of the treatment. Hubei is the first region hit by the pandemic, that has been under lockdown from January 23rd, 2020. Other Chinese regions have instead entered into lockdown later in February. By considering as treated in February all firms that were importing from China before the Covid crisis, we are de facto pooling firms that were treated at heterogeneous dates. To dig into the consequences of the pooling, we ran an additional specification where we distinguish between firms that are exposed to Chinese inputs and those importing products that Hubei is specialized into.[24] Results go in the expected direction. The relative drop in exports in the treatment group during the post-treatment period is almost entirely driven by firms that import products that Hubei is specialized into.[25]

Finally, we conclude the analysis of the heterogeneity of the treatment effect by digging into the heterogeneity across exported products. In columns (7) and (8) of Table 5, we show that the impact of the treatment is larger for final goods than for intermediates. In Figure 8, we further breakdown the effect across good categories (HS2 chapters). For each HS2 chapter, we run two DiD regressions, using either the value of exports (black bars) or the unit value of exports (grey bars) as left-hand-side variable. The figure confirms the stronger transmission of the shock in

[24] Our dataset does not allow to identify the regional origin of imports. To overcome this limitation, we used 2014 regional Chinese export data to identify the products most likely to originate from Hubei. We consider that Hubei has a comparative advantage in a product and is thus likely to supply it to French importers if the Balassa ratio for this product – computed as the ratio of a given product's share in Hubei's total exports to the same product's share of China's overall exports — is greater than one. Statistics on Chinese exports by regions have been kindly provided to us by Sandra Poncet, based on data used in Gourdon et al. (2021).

[25] The corresponding event-study graph is shown in Figure A.10.

Figure 8: Impact of input shortages on the value and unit value of exports, across sectors



Notes: The figure shows the DiD coefficient estimated using as left-hand side variable the log of exports (black bars) or the log of export unit values (grey bars), for the 20 biggest HS2 chapters in export flows over the sample period. Stars on top of bars indicates significance of the effect: ***, ** and * denote significance at the .1, 1 and 5% level respectively.

sectors that mostly produce final goods (apparel and footwear, perfumes and soaps). A possible reason is that trade in intermediates is more strongly gathered within long-term contractual relationships. Interestingly, while the majority of price effects is not statistically different from 0, goods that are more impacted tend to also experience a significant drop in their export price. We interpret this drop as a competition effect: as they lose market share, French exporters need to decrease their selling price. The corresponding figure recovered on imported values and unit prices, Figure A.11, shows that these relative price adjustments are in contrast with what is observed on foreign input prices, that either stay stable or increase after the shock. Together, these results suggest that some firms may have had to reduce their margin to compensate for increased production costs.

4 Weathering supply shocks: diversification and inventories

Section 3 has established a statistically significant impact of being exposed to the Chinese lockdown through upstream suppliers on the dynamics of firm-level exports between February and June 2020. Extensive adjustments identified on treated firms are consistent with disruptions in input purchases forcing firms to ration their exports and delay the delivery of some markets. The granularity of our data makes it possible to go beyond this result and examine whether the effect is similar for firms having different strategies in the management of their value chain. The vulnerability of modern value chains to localized supply shocks is often argued to be attributable to mostly two properties of these production organizations: i) the lack of diversification of production networks and ii) the absence of inventory buffers in organizations that to a large extent produce just-in-time (Pisch, 2020). We now consider these two arguments in turn, testing whether more diversified firms and firms with more inventories have been able to weather the supply chain disruption in the aftermath of the Chinese lockdown.

4.1 Diversification to hedge against localized supply chain disruptions

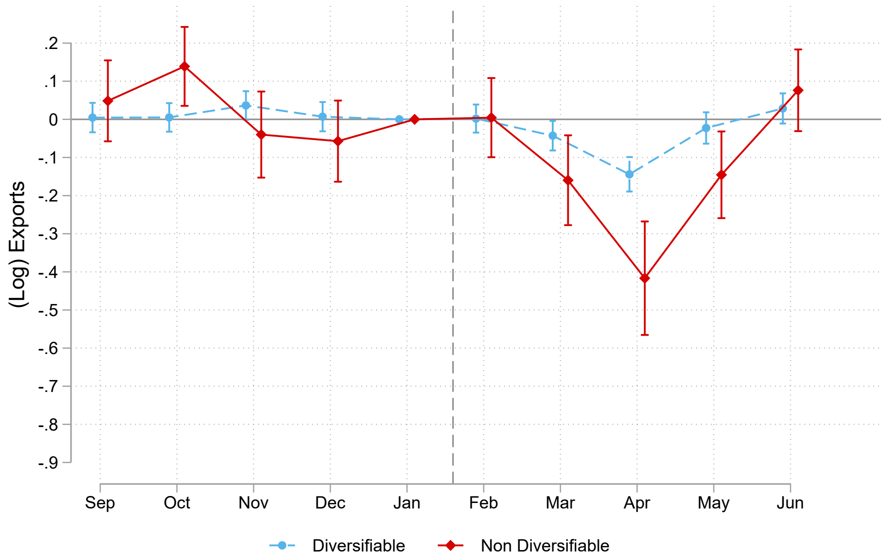
A popular argument in the literature discussing the vulnerability of global value chains is that the lack of diversification of production networks is at the root of the amplification of localized shocks. In this section, we investigate this claim, asking whether the geographic diversification of purchases helps firms perform better when hit by the Chinese lockdown shock.

We first examine whether firms that source Chinese inputs that can hardly be diversified have been hit more severely. We consider that a product can hardly be diversified away from China if at least 60% of world exports in this product category originate from China.[26] We then define a firm as locked with China if at least 10% of the value of its imports from China consist of hardly diversifiable products. About 5% of treated firms can hardly diversify away from China based on this definition. Figure 9 shows that firms importing non-diversifable inputs from China have experienced a more severe drop in their exports than firms importing more

[26] Among the 5,000 product categories of the HS classification, 205 products display a market share for China above 60%.

diversifiable inputs. This heterogeneity in the strength of the treatment is consistent with the stronger decline in imports of firms purchasing non-diversifiable inputs relative to others (see Figure A.12).

Figure 9: Dynamics of firm-level exports: Heterogeneity across products based on China's world market share



Notes: The figure shows the dynamics of exports for treated firms in comparison with the control group. The treatment group is separated into two sub-samples. The "Non Diversifiable" group is composed of firms which imports from China include at least 10% on products for which China represents more than 60% of world exports. The "Diversifiable" group is made of firms that import inputs from China that they could source from elsewhere. The estimated equation includes firm and period fixed effects. Standard errors are clustered at the firm-level. The confidence intervals are defined at 5%.

The analysis presented in Figure 9 shows that firms importing inputs that are not diversifiable away from China have been more strongly impacted by the shock. However, 95% of products can be sourced from other countries than China. A natural question is whether firms whose sourcing of inputs is geographically diversified have performed better than the others.

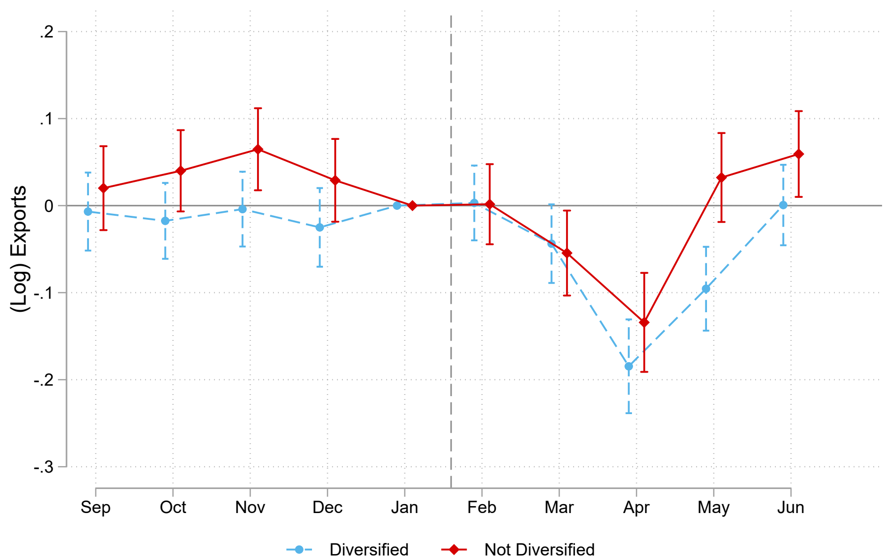
To test for this, we define a treated firm as being diversified if it imports its inputs from China and at least one other country prior to the shock. We first tag an input as diversified if it is imported by the firm from more than one country between September 2019 and January 2020. A firm is then diversified if its main inputs (accounting for more than 1% of firm-level imports) are diversified.[27] In the baseline sample, slightly more than 40% of treated firms are diversified

[27]We put the 1% threshold to abstract from secondary goods that are imported infrequently or in tiny quantities and are not likely to be key for the production process. Relaxing this threshold does not affect our

according to our definition. To test for a role of diversification strategies, we reproduce the baseline estimation, distinguishing between diversified and non-diversified treated firms.

Figure 10 shows that, among firms exposed to the Chinese shock, ex-ante diversified firms did not perform better than non-diversified. We verify in the first two columns of Table A1 that this result is robust to our definition of the treatment group. We have further tried a variety of alternative metrics of diversification that all lead to the same result.[28] To understand this absence of a divergence, we also studied the adjustment of imports among diversified and non-diversified firms. We found no effect of ex-ante diversification on the adjustment of firm-level imports to the Chinese lockdown (see Figure A.13 in appendix). This result is consistent with the main finding that ex-ante diversified firms have similar export performances as non-diversified firms.

Figure 10: Dynamics of firm-level exports: Heterogeneity across firms based on the ex-ante diversification of their supply chain



Notes: Baseline regression after splitting the treatment group into two sub-samples. Treated firms are labeled "diversified" if all their main inputs imported from China are also sourced from elsewhere in the pre-period. Main inputs are products accounting for at least 1% of the firm's imports in the pre-period. Standard errors are clustered at the firm-level. Confidence intervals are defined at 5%. The estimated equation includes firm and period fixed effects.

At first glance, this result thus contradicts the premise that diversifying supply chains can

results.

[28] We increased the threshold of 1% of firm-level imports to 5 and 10%. We have also computed the share of overall imports that are diversified, and tried various thresholds to split firms into a diversified and a non-diversified sub-samples, along this continuous measure.

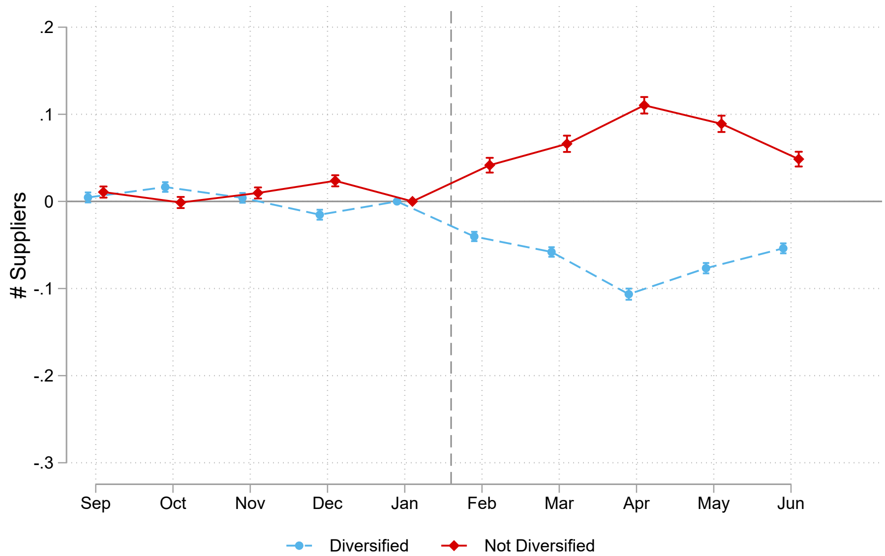
be a useful risk management strategy to insure against localized shocks hitting firms' supply chain. There are several potential reasons for this absence of result, which we now examine.

First, we may not be able to properly identify ex-ante diversified firms. Here, our implicit assumption is that a firm that has interacted in the past with two input suppliers of the same product will be able to increase its demand to non-Chinese suppliers in response to the Chinese input shortage. Implicitly, products sold by Chinese and non-Chinese suppliers are thus considered as substitutes, once we condition on a particular (8-digit) category. In table A1, columns (3)-(4) show results of the triple-difference estimation that defines diversified firms based on the diversification of inputs that are classified as non-differentiated by Rauch (1999). Among this subset of inputs, the assumption that inputs from different origins are substituable is more likely to be valid. When diversified products are restricted to homogenous products based on the Rauch classification, results go in the expected direction. The relative drop in exports is found larger for treated firms that are not diversified than for diversified firms. However, the focus on non-differentiated products strongly narrows the set of firms that we consider as being potentially diversified and the result is statistically weaker as a consequence.

Another possibility is that the pandemic has constrained firms in their ability to substitute away from China, even when knowing alternative sourcing partners from before. To test whether this could explain our results, we define a third dummy for "diversified" firms based on the sub-sample of diversified firms from Figure 10 with former partners in the EU15. The intuition behind is that it was probably easier to reshore input sourcing to partners in the EU at a time when the pandemic started disrupting value chains outside of China. Results are reported in table A1, columns (5)-(6). However, the triple interaction is still non-significant meaning that ex-ante diversified firms with partners in the EU15 have not performed better ex-post than other treated firms.

Finally, it is also possible that firms that do no diversify ex-ante can benefit from some form of ex-post diversification, by switching to new suppliers once the shock hits. Selection into diversification may actually explain the (lack of) result in Figure 10 if firms that do no diversify know that the type of inputs they are sourcing from China is easy to purchase in other countries in case of a shock. Again, it is difficult to formally test for this possibility although the results in Figure 11 provide some support for this interpretation. Namely, Figure 11 examines differences in extensive margin adjustments by diversified and non-diversified treated firms relative to the control group. We now work at the firm×product level and consider the *number of countries* from which firms import a given product before and after the shock. We see a surge in the number of sourcing countries for the ex-ante non-diversified firms when the number drops for diversified firms. Some of the firms that were not diversified ex-ante thus managed to diversify in the aftermath of the shock. For this reason, the ex-ante diversification is not associated with significantly better trade performances in the aftermath of the shock.

Figure 11: Diversification and the number of firms' suppliers



Notes: Baseline at the firm×product-level with treated firm×product pairs split into a "diversified" and "non-diversified" sub-samples. The diversified sample corresponds to firms importing the product from China and somewhere else whereas the non-diversified sub-sample includes firms that solely import from China. The outcome here is the (log-) number of countries the firm sources the product from. We perform a Poisson regression to account for the extensive margin at its full extent. Standard errors are clustered at the firm×product-level. Confidence intervals are defined at 5%. The estimated equation includes firm×product and product×period fixed effects.

4.2 Inventories as a buffer against input shortages

We now investigate the role of inventories in offering a buffer against input shortages. We merge the estimation sample with balance-sheet information provided by the French National Statistical Institute (FARE dataset). The dataset is exhaustive and contains information on the value of firms' inventories at the end of the accounting year. Using the variable, normalized by the value of the firm's activity, we obtain a proxy for the average level of inventories held by the firm. There are three caveats associated with the use of these data. First, the last year of data availability is 2018 and we will thus focus on firms in the estimation dataset that were already active in 2018 – more than 90% of the sample. Second, the inventory variable does not distinguish between inputs and output.[29] Third, inventories are measured at the end of the accounting year (December for 3/5 of the firms, March, June or September for the rest), and they may not be representative of inventories during the rest of the year. Using the variables in the balance-sheet data, we first define a dummy for firms displaying a relatively high level of inventories in 2018. Under the assumption that inventory strategies are relatively smooth and persistent over time, these firms should also be less exposed to disruptions induced by input shortages in early 2020 thanks to their inventory buffer.

The dummy variable is defined into two steps. First, we construct a measure of the level of inventories, defined by the value of end-of-the-year inventories, divided by the value of the firms' yearly turnover, times 365. The ratio can be interpreted as the average daily production held in inventories. Figure 12 shows the distribution of this variable in the estimation sample. Heterogeneity in the level of inventories is significant, in particular across firms in different sectors.[30] In the analysis, we focus on the heterogeneity within a sector and define as high-inventory a firm which ratio of inventories over sales falls in the fifth quintile of its sector-specific distribution.[31]

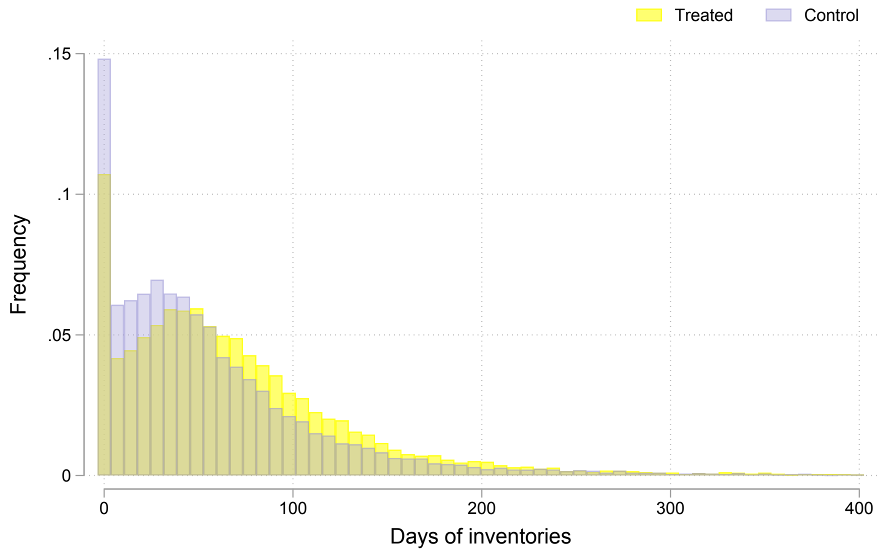
Results are displayed in Figure 13. They are based on a variant over equation (1), using either the log of imports (upper panel) or the log of exports (bottom panel) as left-hand side variable and distinguishing between the dynamics of trade of high-inventory and low-inventory firms. The dynamics of imports is not significantly different in both groups, and is very similar

[29] More precisely, we exploit two variables called "stocmpp" and "stocmar". "stocmpp" measures the stock of inventories for raw materials and output whereas "stocmar" measures the inventory stock of merchandises. Our baseline analysis uses the sum of both variables in the nominator of the ratio of inventories described in the text.

[30] Among the sectors with the largest level of inventories, one can cite the manufacture of sparkling wines (NAF: 1102A), the nuclear fuel enrichment industry (NAF: 2013A) or the manufacture of basic pharmaceutical products (NAF: 2110Z), with medians at 162, 144 and 92 days of inventories, respectively. At the other side of the distribution, the manufacture of bread; fresh pastry goods and cakes (NAF: 1071C) or the manufacture of industrial gases (NAF: 2011Z) for example display very low levels of inventories, with medians at 5 and 14 days respectively. These statistics are computed on all French firms. Firms in the estimation sample on average display higher levels of inventories than purely domestic firms.

[31] We have checked the robustness of results to this definition. In unreported results, we define as high-inventory any firm with more than 45 days of sales in inventories. Results obtained with this definition are qualitatively similar although the difference between low- and high-inventory firms is less significant.

Figure 12: Distribution of inventory ratios in the estimation sample



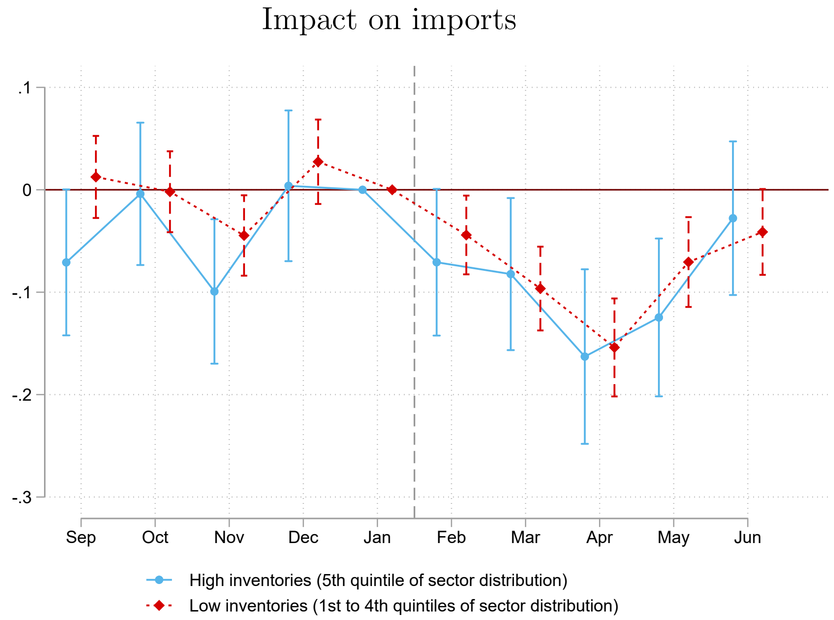
Notes: The figure shows the distribution of firms' inventories-to-sales ratios, in the estimation sample, for treated and control firms. Source: INSEE-FARE for 2018, merged with the customs data.

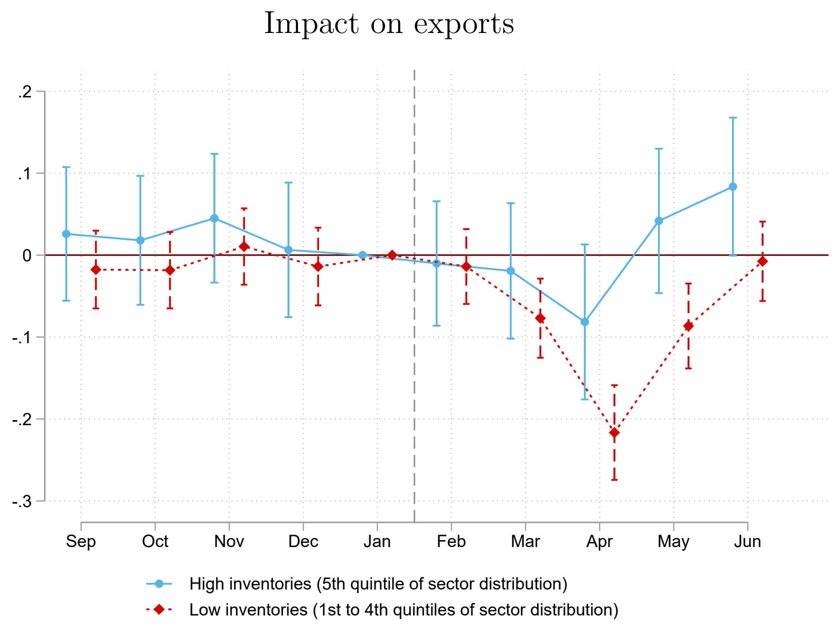
to Figure 4. Similar patterns are expected as inventories do not protect against input shortages. Instead, we expect the role of inventories to materialize into an heterogeneous transmission of the shock to the rest of the value chain as firms with more inventories can keep on serving their downstream partners, even when facing an input shortage. It is indeed the dynamics observed in the bottom panel of Figure 13. For firms with a high level of inventories, the dynamics of exports is not significantly different in the treatment and the control groups. Instead, firms exposed to the Chinese lockdown displaying low levels of inventories see their exports decline in relative to unexposed firms.

To our knowledge, such evidence of an heterogeneous transmission of the supply chain shock to the rest of the value chain among firms with different levels of inventories is new. These results offer empirical support to the statement that holding more inventories can be an efficient strategy to cover against (short-lived) supply chain disruptions.

What is the external validity of this result? The early Chinese lockdown starts at the end of January 2020 and we can not exclude that firms hit by the crisis were by chance particularly well-equiped to handle the supply chain disruption *because of* a relatively high level of inventories during this period. This concern is particularly legitimate given the seasonality of imports

Figure 13: Impact of the Chinese lockdown, on low- and high-inventory firms





Notes: The figure shows the results of the event-study estimation, distinguishing between firms with high inventories, as defined by a ratio of inventories over sales larger falling in the fifth quintile of the firm's sector-specific distribution, and the rest of the estimation sample. All coefficients interpret in relative terms with respect to firms in the control group that would display comparable inventory-to-sales ratios. The estimated equation has firm and period fixed effects and the standard errors are clustered in the firm dimension. The confidence intervals are defined at 5%.

from China discussed in Section 2.2. Since Chinese exports tend to slow down at the beginning of the year, firms importing from China may be used to accumulate inventories around these dates. Whereas this possibility cannot be ruled out in the absence of high-frequency data on inventories, it is unlikely that the seasonality of inventories entirely explains the above-mentioned results. First, firms had no incentives to accumulate inventories beyond what was expected to be optimal given the seasonality of Chinese shipments. Second, the result of inventories offering an efficient buffer against the shock is recovered from the comparison of treated firms with relatively high or low levels of average inventories, in 2018. The comparison conveys useful information beyond and above the overall impact of importing from China on firms' inventory management.

5 Conclusion

This paper uses detailed firm-level data to gauge the transmission of supply shocks along global value chains. We find French firms sourcing inputs from China just before the early lockdown in the country experienced a drop in imports between February and June 2020 that is 7% larger than firms sourcing their inputs from elsewhere. This shock on input purchases transmits to the rest of the supply chain through exposed firms' domestic and export sales. Between February and April, firms exposed to the Chinese early lockdown experienced a 4.8% drop in exports and a 5.7% drop in domestic sales, relative to French firms importing from other countries. The relative drop in export sales is entirely driven by the volume of exports, whereas export prices do not seem to adjust. Moreover, the adjustment is driven by the extensive margin with firms rationing their exports in some markets.

We then assess the role of risk management strategies in mitigating such supply shocks. We find firms diversifying the sources of their inputs before the shock have not performed better than others. Indeed, firms that were not diversified managed to find new suppliers in the aftermath of the shock. Unlike diversification, we find firms holding more inventories before the shock performed better than other firms exposed to the same supply chain disruption. This result confirms the popular idea than stockpiling may be an efficient buffer against supply chain disruptions.

Trade disruptions in GVCs such as the one induced by the early lockdown in China are not anecdotal. Semiconductors shortages have started to affect GVCs by the end of 2020, and supply chains disruptions are now reported for other critical materials.[32] Whereas less

[32]The shortage of semi conductors is expected to last through 2022 according to the chief fi-

easy to trace out, understanding how firms adjusted to this accumulation of input shortages during a long-lasting crisis that saw a surge in uncertainties is likely to be especially informative regarding the functioning of Global Value Chains, from both a positive and a normative points of view.

nancial officer of Fiat Chrysler and Peugeot PSA, quoted by CNBC: https://www.cnbc.com/2021/05/07/chip-shortage-is-starting-to-have-major-real-world-consequences.html. Plastic shortage is driven by constraints on raw chemicals, see details in https://hbr.org/2021/03/the-latest-supply-chain-disruption-plastics .

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Appendix

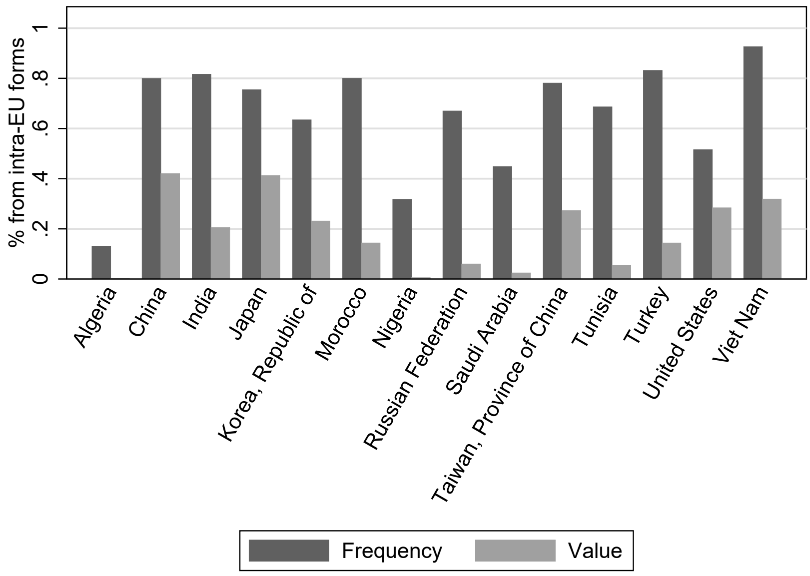
A.1 Data Appendix

The empirical analysis mostly uses French customs data between September 2019 and June 2020. The dataset is constructed from the raw customs forms filled by French firms and made available to us by the French customs. The final dataset is constructed from four types of customs forms depending on whether the firm declares an export or an import flow and whether the partner country belongs to the EU or not. The combination and treatment of these files is described in details in Bergounhon et al. (2018).

An important technical step in the process of constructing the final dataset concerns the treatment of imports originating from extra-EU countries that are intermediated by a third EU country before entry into France. This step is particularly important quantitatively as 80% of transactions accounting for almost half of the value of French imports from China are recovered from intra-EU customs forms. When the product enters Europe through another European country, say the Netherlands or Belgium, two countries that host major cargo ports, it is fairly common that two customs forms are filled. A first customs form, which is not part of our database, records the trade flow from China to the point of entry. A second customs form covers the intra-EU flow up to France and is thus included in our data. Thanksfully, the second form keeps information on the origin of the good, which makes it possible to count the second flow as imports from China. Throughout the analysis, we treat all import forms so that the country of origin is systematically the first country at the root of the trade flow, China in our example. Figure A.1 shows the importance of this treatment across bilateral trade flows for 2019.

Whereas the raw data offer a solution to treat the problem of intermediated trade flows, it is still tricky to measure the mode of transportation for the corresponding trade flows. The reason is that the only recorded transport mode corresponds to the last segment of the product journey. As is the case for the vast majority of intra-EU trade flows, the corresponding import flow is likely to be associated with a road transport mode. When the product enters France from Belgium or the Netherlands, it is quite likely that the good was shipped from China to Europe on a cargo. There is more uncertainty regarding the mode of transportation when

Figure A.1: Share of transactions and the value of imports from non-European countries recovered from intra-EU trade data



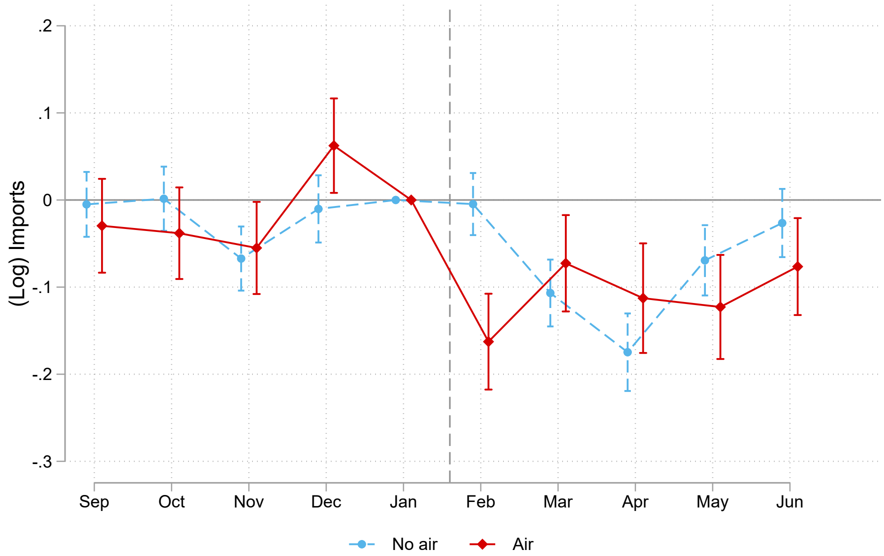
Notes: The figure shows the share of transactions and of the value of imports from one of the 15 largest non-European partners of France that is recovered from intra-EU trade data.

the product enters France through Germany, the third most likely point of entry. Germany hosts large logistic companies that may intermediate trade using both maritime and aeronautic modes of transportation. However, one would expect that a product that has been imported from China to Germany by air would also travel from Germany to France by air, in which case the recorded transportation mode is still correct. Given this uncertainty, the best we can do is to keep information on goods entering France by air, whether directly or indirectly. The vast majority of goods that do not fly from China to France are shipped on cargos, with a delay of roughly one month between the time when the products are put onto the cargo and the date of the customs clearance in Europe.[33]

A.2 Additional results

[33]Another possibility is that the good has travelled using the new transcontinental train line that links Chengdu to Rotterdam, which is faster than sea freight but still takes around two weeks.

Figure A.2: Chinese lockdown, firm-level imports, by transport mode

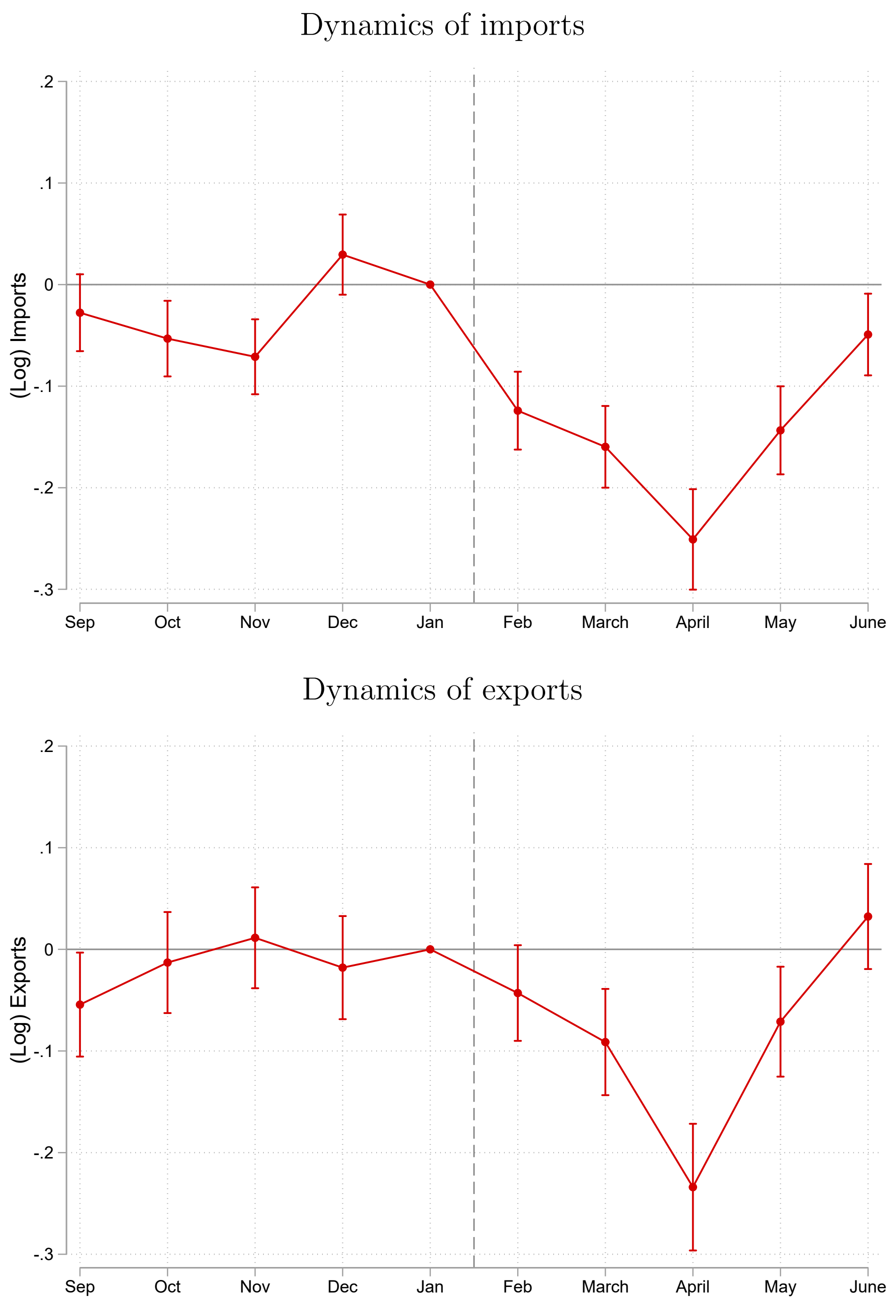


Notes: The figure shows the dynamics of imports before and after the Chinese lockdown, for treated firms in comparison with the control group. The estimated equation reads:

$$\begin{aligned} \ln Imports_{ft} &= \sum_{l=-4}^{5} \beta^l \; Treated_f \times Time_{lt} \times (1 - Air_f) \\ &+ \sum_{l=-4}^{5} \gamma^l \; Treated_f \times Time_{lt} \times Air_f + FE_f + FE_t + \varepsilon_{ft} \end{aligned}$$

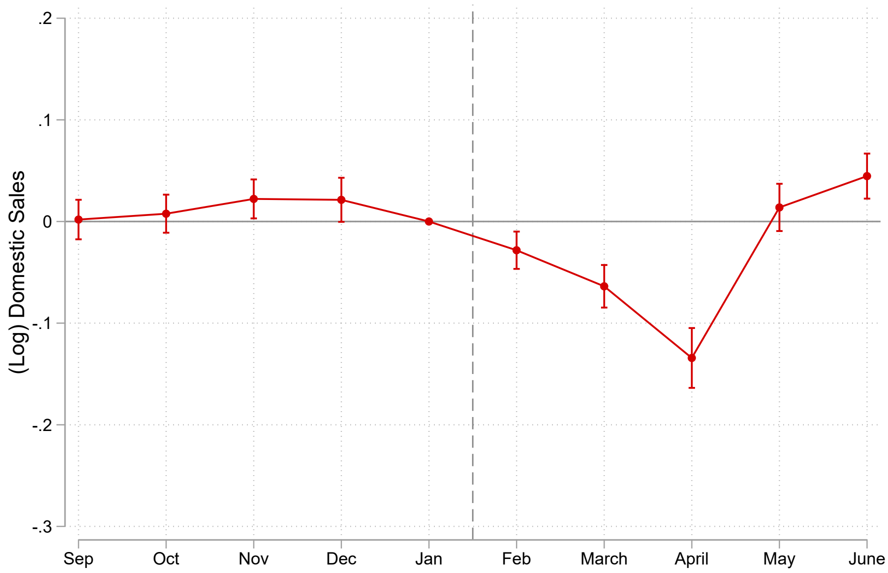
with $Time_{lt}$ a dummy equal to one l periods before/after the shock and Air_f equals to one if the firm uses air transport for at least 25% of its imports from China. Standard errors are clustered at the firm-level. The confidence intervals are defined at 5%. Treated firms are those importing from China prior to the shock. Control firms are importers not exposed to China.

Figure A.3: Chinese lockdown, firm-level imports and exports for monthly importers



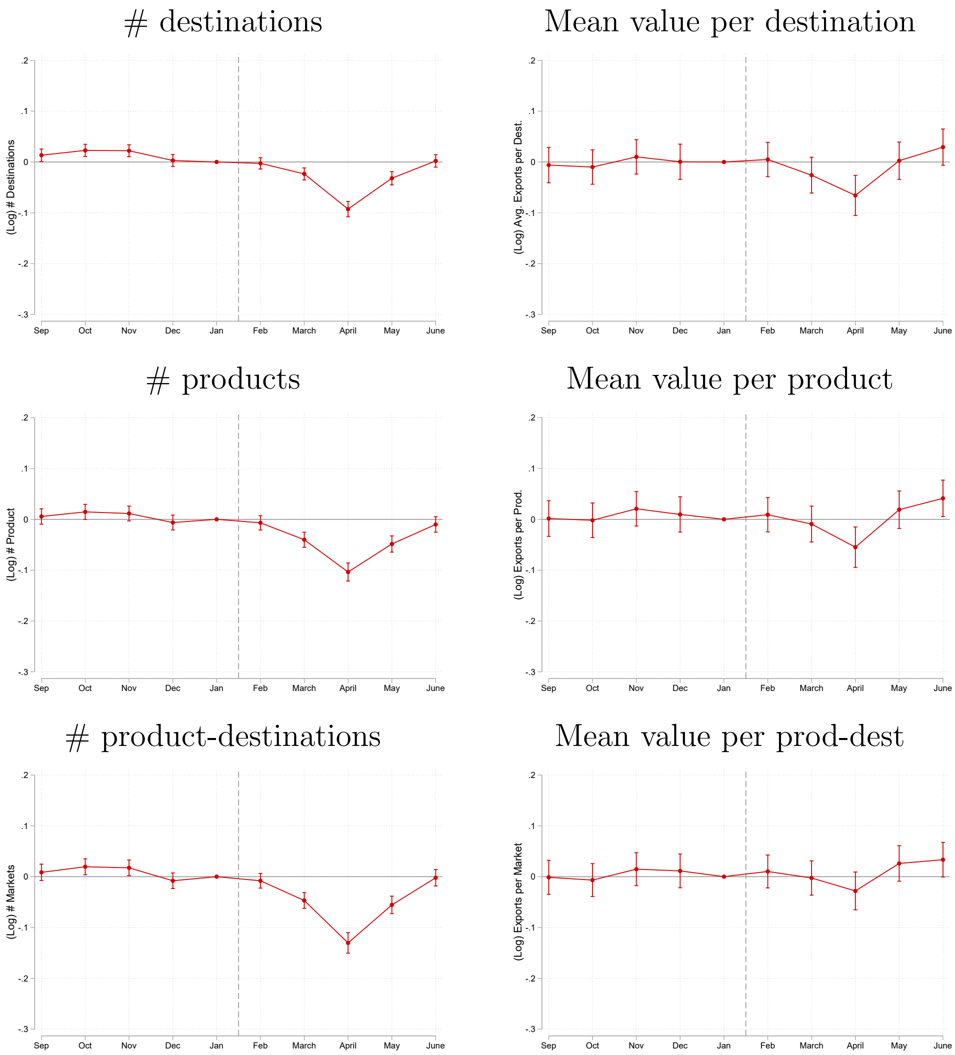
Notes: The figure shows the dynamics of imports (top panel) and exports (bottom panel) before and after the Chinese lockdown for treated firms in comparison with the control group. The treatment is based on monthly imports from China between September 2019 and January 2020 (T2) and the control corresponds to monthly importers from a third country and not importing from China. The estimated equation includes firm and period fixed effects. Standard errors are clustered at the firm-level. The confidence intervals are defined at 5%.

Figure A.4: Effect on domestic sales of input shortages associated with the Chinese lockdown



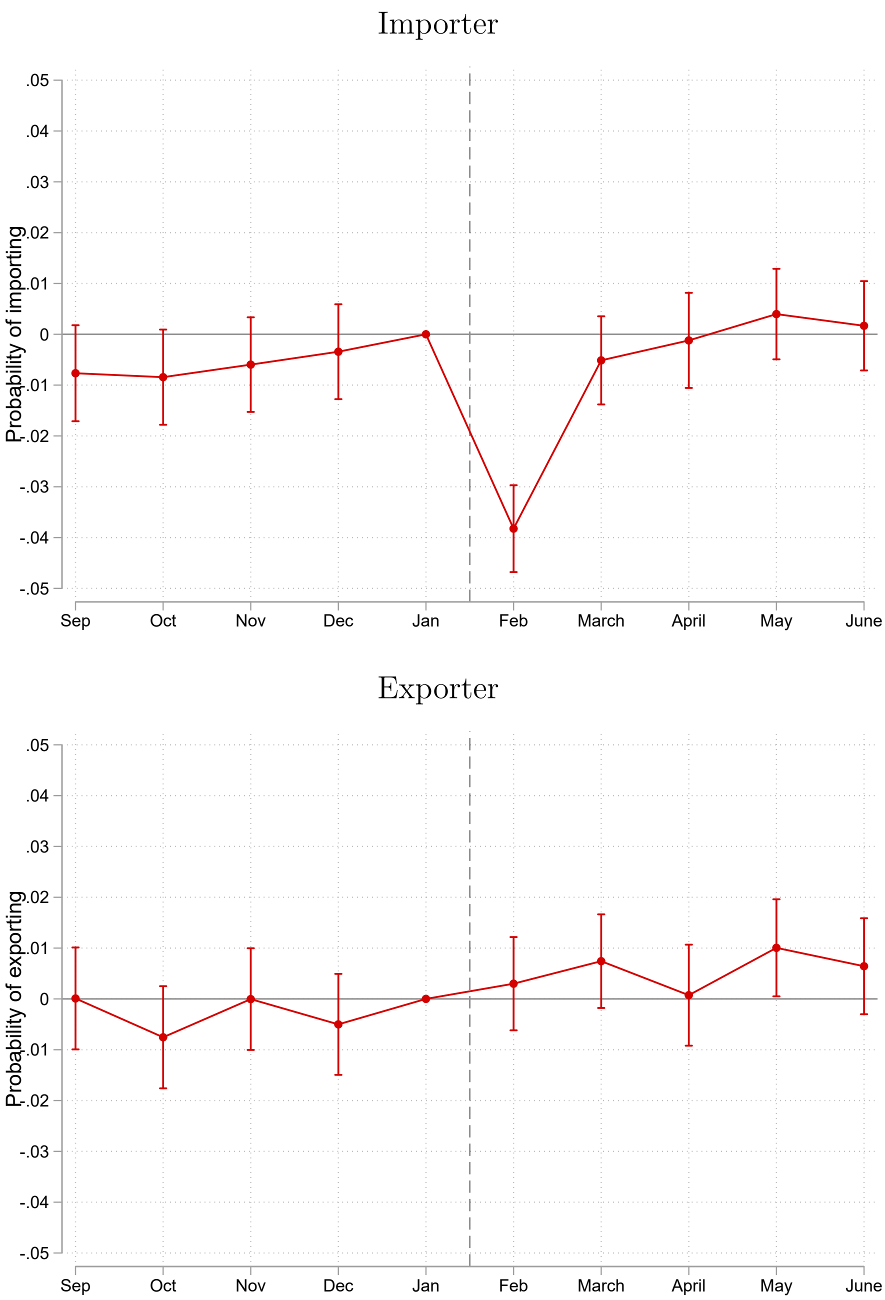
Notes: The figure shows the dynamics of domestic sales before and after the Chinese lockdown, for treated firms in comparison with the control group. Standard errors are clustered at the firm-level. The confidence intervals are defined at 5%. Treated firms are those importing intermediate inputs from China prior to the shock. Control firms are importers not exposed to China. The estimated equation has firm and period fixed effects.

Figure A.5: Effect of the Chinese lockdown on exports: Intensive versus extensive adjustments



Note: The figure shows the results of the event-study estimation, using the intensive and extensive components of firms' exports as left-hand side variable. The corresponding difference-in-differences estimates are summarized in Table 4, top panel. All specifications include firm and period fixed effects. Standard errors are clustered at the firm-level. The confidence intervals are defined at 5%.

Figure A.6: Effect of the Chinese lockdown on the probability of staying as an...

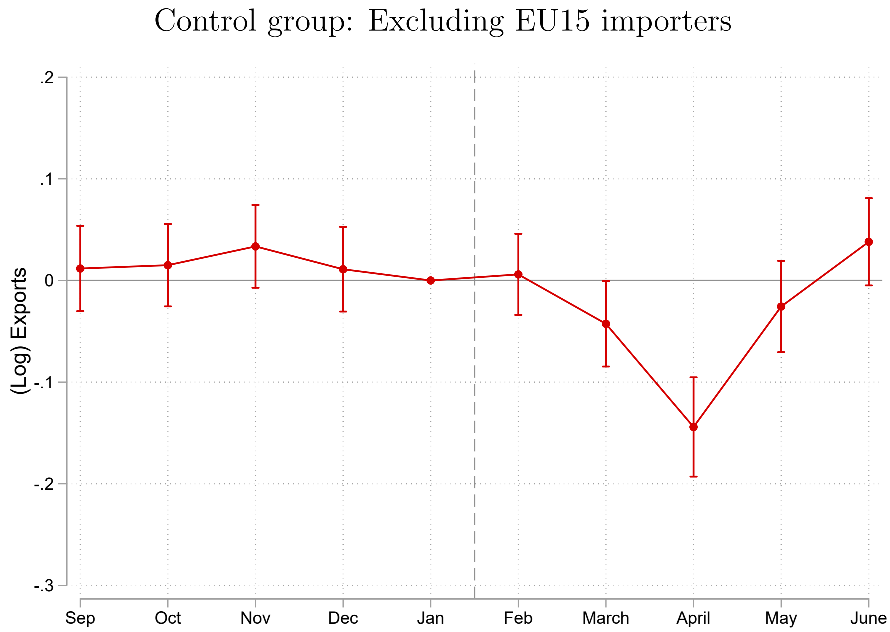


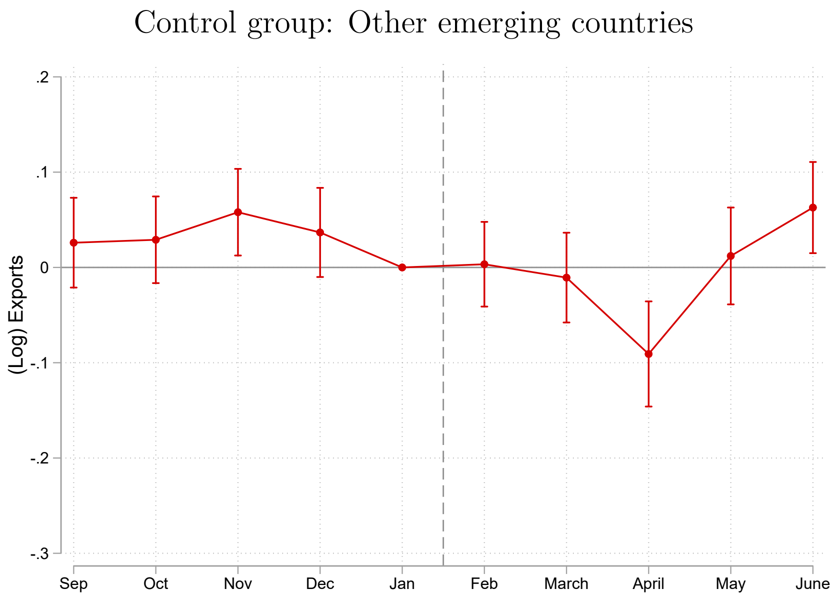
Note: Same specification as in Column (7) of Table 4 of the paper. The estimated equation reads:

$$\mathbb{1}_{ft} = \sum_{l=-4}^{5} \beta^l \; Treated_f \times Time_{lt} + FE_f + FE_t + \varepsilon_{ft} \; ,$$

with $\mathbb{1}_{ft}$ that is equal to one when firm f displays strictly positive imports (Top Panel) or exports (Bottom Panel) in period t.

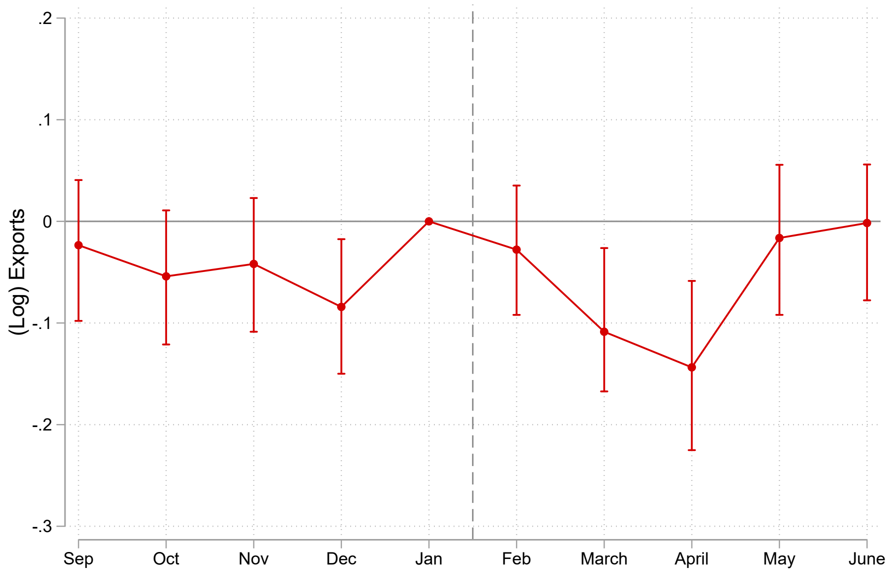
Figure A.7: Impact of the Chinese lockdown on firm-level exports: Alternative control groups





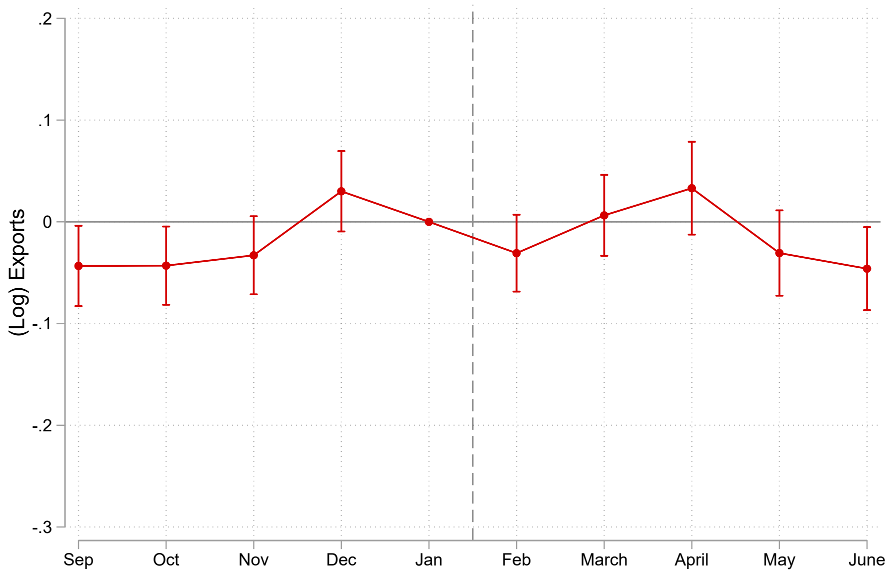
Notes: The figure shows the dynamics of exports before and after the Chinese lockdown for treated firms in comparison with the control group. The treatment is based on imports from China between September 2019 and January 2020. The control group is based on importers from other countries i) excluding firms that solely imports from the EU15 (Top Panel, 13,097 controls) and ii) restricting the analysis to firms that import from other emerging countries (Bottom Panel, 7,276 controls). The estimated equation includes firm and period fixed effects. Standard errors are clustered at the firm-level. The confidence intervals are defined at 5%.

Figure A.8: Impact of the Chinese lockdown on exports: Robustness based on propensity score matching and subsampling



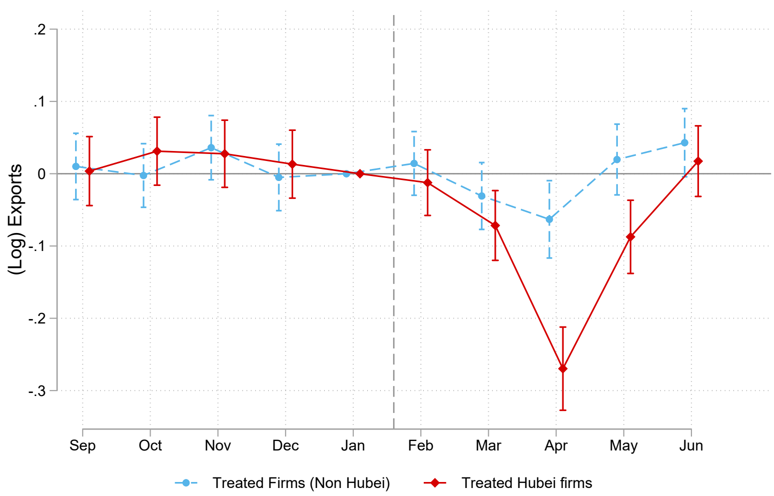
Note: Results based on propensity score matching and subsampling. The effect $k \in [-5, 5]$ months after the shock is the sample average over the 14,800 treated firms of $Y_{i,k} - \hat{Y}_{i,k} - (Y_{i,-1} - \hat{Y}_{i,-1})$, where $Y_{i,k}$ is the (observable) outcome for treated firm i and $\hat{Y}_{i,k}$ is the average outcome among firms chosen as control i. The nearest neighbor is selected by the propensity score matching. Inference is conducted using subsampling, using 500 repetitions with a tuning parameter $R = 3$ (Politis and Romano, 1994). The confidence intervals are defined at 5%.

Figure A.9: Placebo test: Dynamics of firm-level exports when the treatment is based on US importers



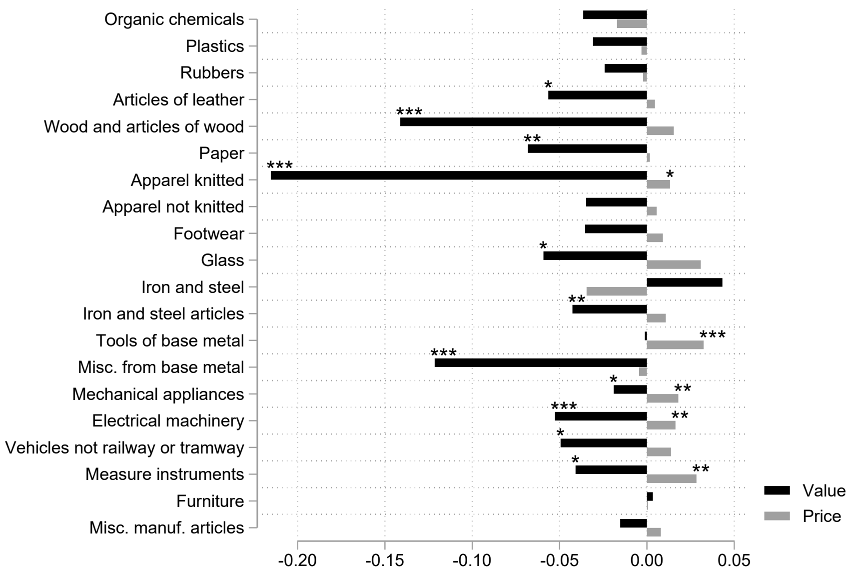
Notes: The figure shows the dynamics of exports for treated firms in comparison with the control group. The treatment is based on imports from the US between September 2019 and January 2020. There are 10,377 treated and 23,106 control firms. The estimated equation includes firm and period fixed effects. Standard errors are clustered at the firm-level. The confidence intervals are defined at 5%.

Figure A.10: Dynamics of firm-level exports: Heterogeneity between Hubei's and other provinces' comparative advantages



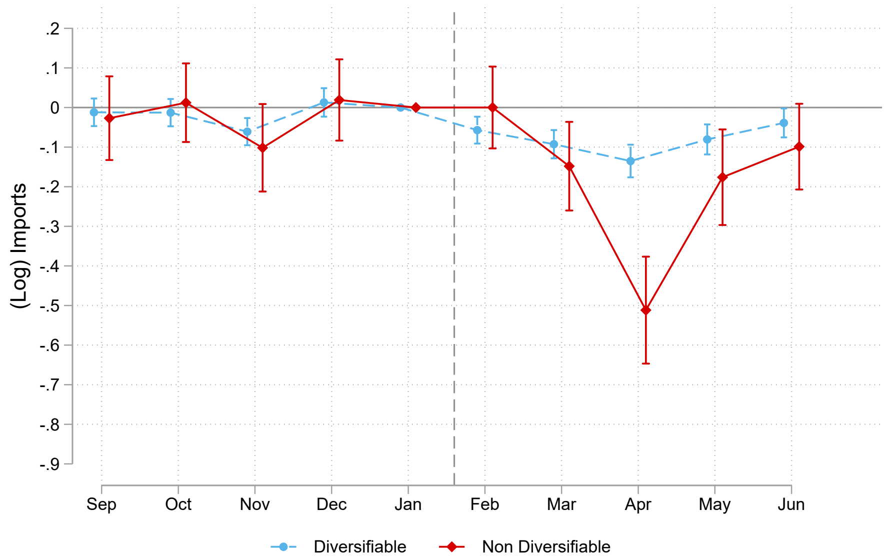
The figure shows the dynamics of exports for treated firms in comparison with the control group. The treatment group is separated into two sub-samples. The "Hubei" group is composed of firms that are exposed to Chinese inputs which the Hubei region is specialized into whereas the "Non-Hubei" group is composed of the rest of the treated sample. Hubei's specialization patterns are measured using data on Chinese exports to France, by region, in 2014. A product is considered a comparative advantage of Hubei if its share in Hubei's exports is larger than its share in Chinese's exports (Balassa ratio larger than 1). The estimated equation includes firm and period fixed effects. Standard errors are clustered at the firm-level. The confidence intervals are defined at 5%.

Figure A.11: Impact of input shortages on the value and unit value of imports, across sectors



Notes: The figure shows the DiD coefficient estimated using as left-hand side variable the log of imports (black bars) or the log of import unit values (grey bars), for the 20 biggest HS2 chapters in import flows over the sample period. Stars on top of bars indicates significance of the effect: ***, ** and * denote significance at the .1, 1 and 5% level respectively.

Figure A.12: Impact of the Chinese lockdown on firm-level imports: Impact of importing a non-diversifiable input



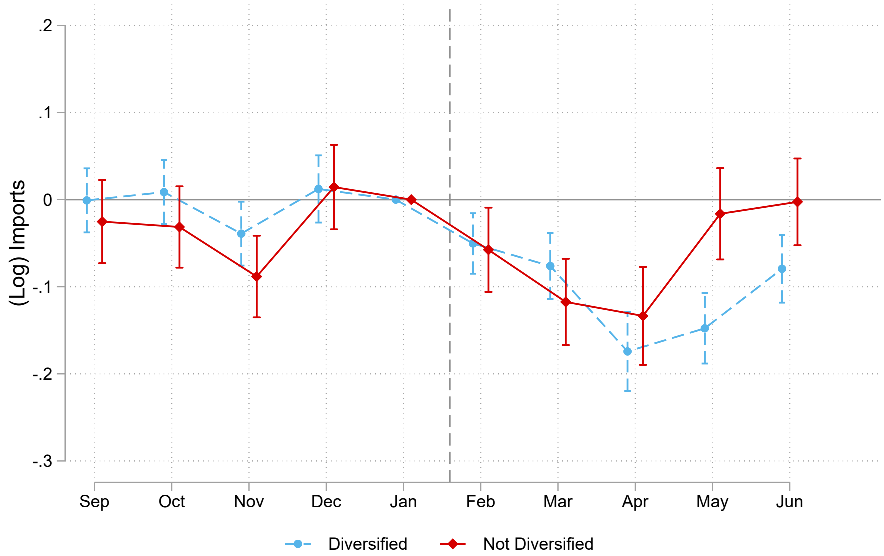
Notes: Baseline regression after splitting the treatment group into two subsamples. Treated firms are labeled “diversifiable” if more than 90% of the value of their imports from China cover products for which China displays a world market share below 60%. Confidence intervals are defined at 5%. The estimated equation includes firm and period fixed effects.

Table A1: Impact of input shortages on exports: Diversified and non-diversified exporters

	Dep. Var: log of exports					
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × Post	-0.047[a]	-0.057[a]	-0.053[a]	-0.068[a]	-0.042[a]	-0.055[a]
	(0.014)	(0.020)	(0.011)	(0.015)	(0.012)	(0.017)
−×−×Div	-0.003	-0.013	0.091[a]	0.133[b]	-0.018	-0.026
	(0.016)	(0.025)	(0.034)	(0.067)	(0.016)	(0.026)
Firm FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
# Treated	13,731	4,322	13,731	4,322	13,731	4,322
# Control	16,646	9,672	16,646	9,672	16,646	9,672
# Interacted	5,799	1,937	591	146	4,240	1,199
Treatment	T1	T2	T1	T2	T1	T2
R^2	0.857	0.875	0.857	0.875	0.857	0.875
# Obs.	234,482	116,087	234,482	116,087	234,482	116,087

Note: The table reports results of difference-in-differences estimations on exporting firms. "T1" means that the control group is composed of firms that import inputs from abroad outside of China whereas treated firms are those exposed to Chinese inputs in the five months before the pandemic. "T2" means that the control group is composed of firms that import inputs monthly from a specific country which is not China and treated firms are those that import every month from China, in the five months before the pandemic. The date of the treatment is February 2020 and the DiD thus compares the evolution of exports between September 2019 and January 2020 (pre-treatment period) and between February 2020 and June 2020 (post-treatment period). Here the treated firms are split into a group of "diversified" and a group of "non-diversified" firms. In columns (1) and (2), diversified firms are those that import all of their main inputs from at least two countries during the pre-treatment period. In columns (3) and (4), we focus on inputs classified as "non-differentiated" by Rauch (1999) and call a firm "diversified" if all of its main inputs sourced from China are non-differentiated and sourced from at least two countries in the pre-treatment period. In columns (5)-(6), "diversified" firms are those that source all of their main inputs from China and an other country of the European Union (EU15), in the pre-crisis period. Standard errors are clustered at the firm-level. [a], [b] and [c] denote significance at the 1, 5 and 10% level respectively.

Figure A.13: Dynamics of firm-level imports: Heterogeneity across firms based on the ex-ante diversification of their supply chain



Notes: Baseline equation in (1) with the treatment group split into two groups. Treated firms are labeled "diversified" if all their main inputs imported from China are also sourced from elsewhere in the pre-period. Main inputs are products amounting to at least 1% of the firm's imports in the pre-period. Standard errors are clustered at the firm-level. Confidence intervals are defined at 5%. The estimated equation includes firm and period fixed effects.