Supply shocks in supply chains:
Evidence from the early lockdown in China*

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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' exports. Between February and April, firms exposed to the Chinese early lockdown experienced a 5% drop in exports, in relative terms. The drop in firm-level exports is driven by a reduction in the number of markets served. Whereas the ex-ante geographic diversification of inputs does not seem to mitigate the impact of the shock, inventory management strategies help firms weather such adverse supply shock.

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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 exports. 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 the trade activities of French firms. 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 have experienced a 5% decline in their exports after the Chinese lockdown relative to 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 in 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. This dataset contains transaction-level imports and exports at the monthly frequency, before and during the pandemic. The level of details of the data has two main advantages. First, 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% on a monthly basis, when imports from the rest of the world were slightly above their January level. Tracking firm-level exports and imports at a monthly frequency allows us to isolate firms' exposure to the Chinese lockdown and estimate its impact on exports. A second advantage is that we are able to match information on exports and imports at the firm-level, which allows us to focus our analysis on firms that both import intermediate inputs and export some of their output. We consider firms in this restricted sample are engaged in 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. We estimate that the "treated" firms experienced a relative 7% drop in their overall imports following the Chinese lockdown, with a peak at -15% in April 2020. The relative import drop supports the use of this event as a natural experiment of a supply chain disruption. We also show that, although the lockdown started in late January, the input shortage mainly kicks in March and April. The reason is that transit time delayed somewhat the transmission of the shock to the French economy. For firms relying on air freight, the drop in imports is found as large as -11% in February. Instead, the rest of the treatment group, that mostly uses sea shipping, experienced a drop in imports one month later.

In the second part of the paper, we examine the within-firm propagation of this supply shock downstream in the value chain. We estimate the strength of this propagation using firms' exports as an outcome variable. Focusing on firm-level exports rather than production data has three advantages: (*i*) export data are made available to researchers with a short delay when production data are available with a delay of two to three years, (*ii*) export data are collected at the monthly frequency, (*iii*) measuring the propagation to exports allows us to capture the global nature of shock transmission within GVCs. Using an event-study design and differences-in-differences specifications, we find firms exposed to Chinese inputs reduced their exports by 4.9% in comparison with the control group, in the five months following the Chinese lockdown. Here as well, the export drop peaks in April 2020 at -15%. In June 2020, both groups have converged to the same export contraction, 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 exports for firms exposed to the early lockdown in China as being a consequence of the transmission of the supply chain shock to downstream partners.

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 the pre-shock geographic diversification of imported inputs has helped firms weathering 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 which has helped smooth out the shock, although 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 test whether the export performances of firms with more inventories have been better than 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 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 chains 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 exports 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.

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. 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

[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.

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.

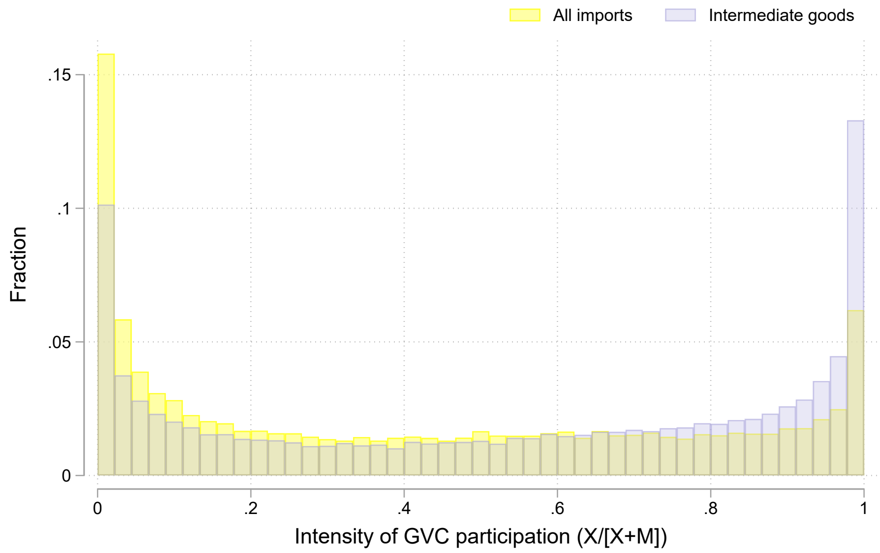
2.1 Data

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 helps capturing the timing of the pandemic and its heterogeneous impact on bilateral trade.

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 based on the French customs data, by merging import and export data using the French firm's identifier. A simple metric to evaluate firms' involvement in global value chains is the export to trade ratio, defined as the value of exports at the firm-level, divided by the sum of the firm's exports and imports. Figure 1 shows the distribution of this ratio for French firms engaged in two-way trade between September 2019 and January 2020. A value

[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). An important technical step consists in recovering import flows originating from non-EU countries that are recorded in the intra-EU trade data due to the flows being intermediated at entry into the EU through a third country. As explained in Bergounhon et al. (2018), about 50% of imports from China are intermediated and assigning these trade flows to bilateral imports from China is thus important quantitatively.

Figure 1: Firm-level participation to GVCs



Source: French customs, import and export files. GVC participation is measured by the ratio of exports over exports plus imports, at the firm-level. The yellow bars include all imported products whereas the lavender bars solely cover imports of intermediate inputs. Statistics are restricted to firms that both import and export between September 2019 and January 2020.

close to zero means that the firm exports very little relative to the value of its imports. A value close to one means that the firm is mostly engaged in export activities and relies little on direct imports. The yellow plot presents the distribution of this ratio considering all types of imports. There is a mass at low values, with 15% of importing firms in our sample displaying tiny exports. About 40% of firms have a ratio between .2 and .8 suggesting an important involvement on both types of activities.

The lavender plot presents a similar distribution recovered after excluding from the analysis imports of final consumption and capital goods using the UN-BEC classification of products. Focusing on imports of intermediaries brings us closer to the notion of GVCs whereby firms import intermediate inputs, and then export their production downstream in the chain. In this sample, there is a mass around one, which is driven by exporting firms that do not import much intermediate goods. About 38% of firms in this sample have a ratio between .2 and .8 suggesting an important involvement on both types of activities. In the rest of the analysis, we use this definition of imports.

Table 1 shows descriptive statistics on the sample under study. The estimation sample is

Table 1: Summary Statistics on the Estimation Sample

	Nb. of firms	Avg. imports (2019, mil. €)	Avg. exports (2019, mil. €)	% of aggregate Imports	% of aggregate Exports
All firms	33,483	6.8	13.3	89.5	91.6
Importers from					
China	14,880	10.4	21.7	60.9	66.1
Elsewhere	18,603	3.9	6.7	28.6	25.4
Monthly importers from					
China	4,495	20.3	41.8	36.0	38.6
Elsewhere	10,387	6.7	9.8	27.3	20.9

Note: The summary statistics are computed on firms that both import intermediaries and export between September 2019 and January 2020.

composed of roughly 33,000 firms that both import intermediate products and export. The estimation sample is constructed using import and export data covering the period prior to the shock, from September 2019 to January 2020. Together, these firms account for roughly 90% of the total value of French exports and imports, which is consistent with the view that 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. 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.

As detailed in the next section, our empirical analysis exploits the timing of the diffusion of the pandemic to isolate supply chain disruptions originating from China. In doing so, it will be important to take into account the fact the timing of the shock may have been felt

[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.

at heterogeneous dates depending on the mode of transportation, because shipping goods by airplanes is substantially faster than shipping goods on cargos. To this aim, we will leverage upon the information on the transportation mode available into the customs files and construct a dummy that takes the value of one if a good is transported by air from China. Note that, whereas the transport mode is well-measured for goods directly imported from China, we have to impute it for Chinese goods transiting through other EU countries. About 50% of the value of French imports from China is 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. However, the transport mode that appears in the data concerns the last segment of the product journey, most often a truck. 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 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.[7] Because of this difference in transit times, we expect the shock to be felt earlier in France for goods transported by air.

[7]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.

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 because 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 before the rest of the world and delays in sea freight originating from China.

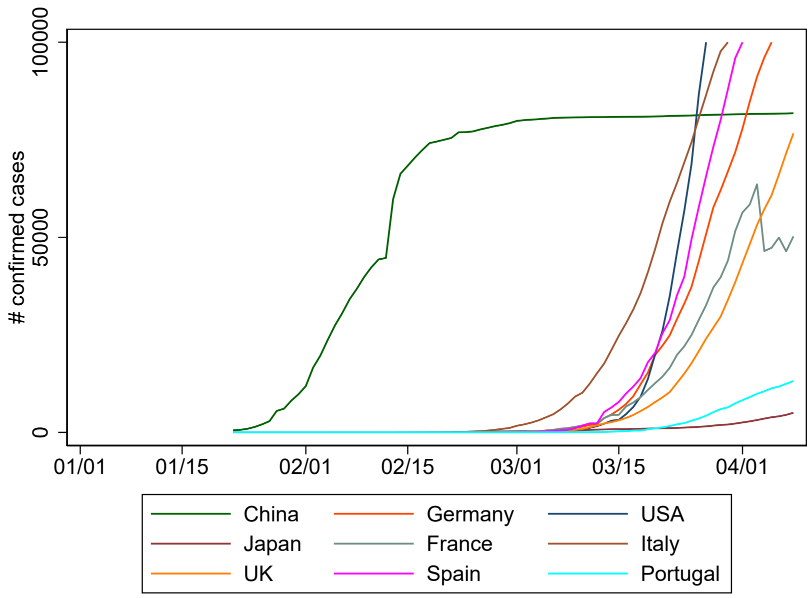
Figure 2 illustrates the discrepancy in the rise of confirmed covid cases across countries. Whereas most countries have been hit by the pandemic in the first half of March, China has been hit earlier in January 2020. As a consequence, China has imposed a lockdown in the Hubei region from January 23rd, whereas the government responses of others countries have been implemented by the end of February or the beginning of March.[8] The rise in the 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.

A first hint that this one-month delay has had consequences on French firms is illustrated in Figure 3, 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

[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.

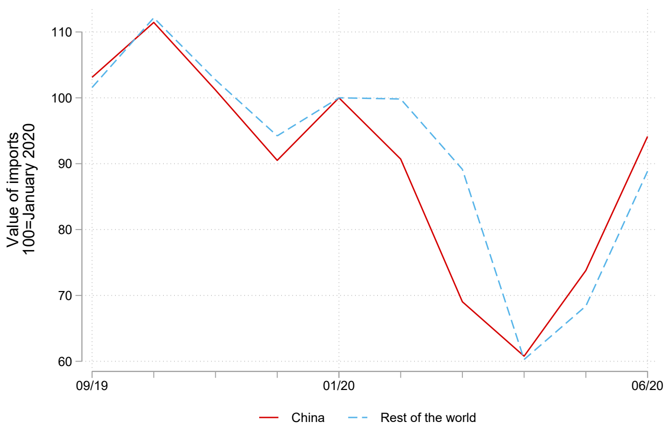
[9] Throughout the analysis, we exclude imports of Covid-related products, namely masks, anti-epidemic goods, medical equipments, medical supplies and medicines using the list of Covid-related products provided by the WTO. Covid-related products do not affect the dynamics of trade prior to March, when 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.

Figure 2: Spread of the pandemic: number of confirmed cases for a selection of countries



Source: Oxford COVID-19 Government Response Tracker.

Figure 3: 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.

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.[10] Importantly, the early contraction of imports from China is not innocuous from the point of view of the French economy as China

[10]The dynamics of final consumption and capital goods' imports looks very much the same.

is the second most important source of imports.[11]

Whereas the dynamics of imports suggests a one-month lag between the drop in imports from China and from the rest of the world, these dynamics are likely to differ across transport modes. The reason is that shipping goods from China to France takes time. The average transit time of containers between Chinese and French (or other European) ports is about 30 days. This observation implies that part of the value of imports originating from China and declared to the French customs in February 2020 was actually shipped before the Chinese lockdown. As explained in Section 2.1, our data provide us with valuable information on the mode of transportation at the transaction level. Using this variable, it is thus possible to control for the timing of the shock in a more precise way. Figure 4 illustrates the importance of such information through the comparison of the dynamics of imports from China for goods shipped by sea and by air. Sea imports started their decline in March 2020, one month after the lockdown, which is consistent with the idea that most of February imports were shipped before the lockdown. Air freight has instead been impacted instantaneously with a 60% drop between January and February 2020. The share of imports transported by airplane decreased from 12% before the lockdown to 6% in February 2020, as a consequence of this time discrepancy.[12]

The Chinese lockdown has thus severely reduced French firms' imports. Unlike imports from the rest of the world, the drop in imports from China has started as early as in February 2020. In the rest of the analysis, we use the one-month lag to investigate the response of firms to a productivity slowdown affecting foreign producers. We use the early lockdown in China as a natural experiment of such productivity slowdown and exploit the heterogeneity across French firms in their exposure to this shock to estimate the causal impact of the lockdown.

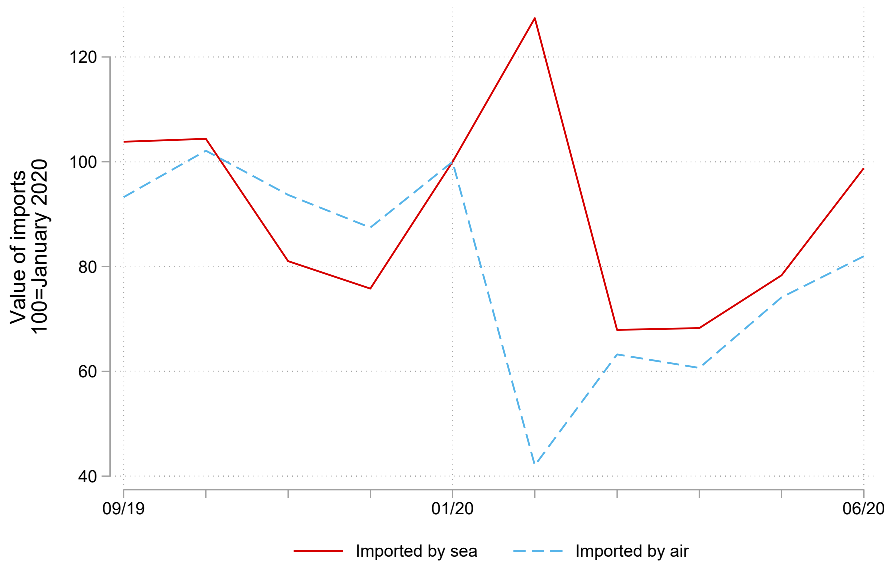
2.3 Chinese lockdown and firm-level imports

We now show that the aggregate drop in imports from China has induced a shortage of inputs for French firms. We compare the evolution of firm-level imports before and after the Chinese lockdown for firms directly exposed to the Chinese lockdown and in a control group. Exposure

[11] 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.

[12] Note that Figure 4 is restricted to non-covid products. We report in appendix (Figure A.1) the evolution for covid-products, which shows the tremendous increase in imports of covid-related products in the Spring of 2020 and the role of air transportation in bringing these products to France.

Figure 4: French imports from China by transport mode



Source: French customs, import files. The figure shows the evolution in the value of French imports from China by air and by sea, between September 2019 and June 2020. Both time series are normalized to 100 in January 2020. COVID products are excluded from the analysis.

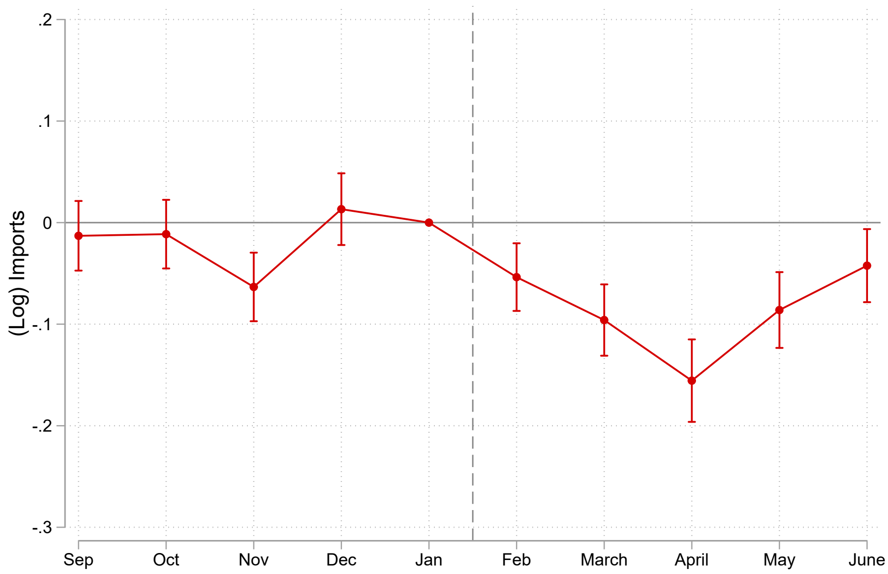
(our treatment variable T1) takes the value of one for any French firm having imported an intermediate good from China in the second semester of 2019. The control group is composed of French firms that also import inputs but not from China. To investigate the dynamics of the adjustment of exposed firms, we first use an event-study design:

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

with $Imports_{ft}$ the value of 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 5. 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 treated 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 3.

Figure 5: 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.

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 relative drop in imports of 7.0%, 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 made 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.[13]

In column (4), we reproduce column (2) on a narrower sample of firms with significant export activities (export to trade ratio greater than 10%), which are key in the second part of our analysis. Treated firms experienced a 7.3% drop of their imports in this subsample. In column (5), 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$\times$product level and we thus estimate how product-level imports reacted to a product-level exposure to the Chinese lockdown.[14] The estimated effect remains negative and significant at -7.5%.

Up to now, we have implicitly assumed that all treated firms were suffering from the Chinese lockdown from February 2020. However, we have also discussed in Section 2.2 the possibility that the shock is felt at heterogeneous dates depending on the transportation mode used by the firm on its imports from China. We test this possibility in columns (6) and (7) of Table 2 as well as in Figure 6. The estimated specification allows for a heterogeneous treatment effect across firms that import by airplanes and other importers from China. As shown by the negative coefficients recovered on the triple interaction term, firms importing from China

[13]In Table 2, the estimation sample goes from September 2019 to June 2020. Figure 5 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%.

[14]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.

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

	Dep. Var: log of imports						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treated firm	0.286^a						
	(0.028)						
Treatment × Post	0.001	-0.070^a	-0.120^a	-0.073^a	-0.075^a	-0.058^a	-0.101^a
	(0.013)	(0.010)	(0.012)	(0.010)	(0.006)	(0.011)	(0.014)
Treatment × Post × Air						-0.038^b	-0.067^a
						(0.016)	(0.022)
Firm FE	N	Y	Y	Y	× Product	Y	Y
Time FE	Y	Y	Y	Y	× Product	Y	Y
# Treated	13,994	13,994	4,495	13,054	11,126	13,994	4,495
# Control	16,543	16,543	10,387	15,202	24,850	16,543	10,387
# Interacted						4,719	1,249
Sample	All	All	All	$\frac{X}{X+M} \geq .1$	All	All	All
Treatment	T1	T1	T2	T1	T1	T1	T2
R^2	0.004	0.861	0.861	0.860	0.869	0.861	0.861
# Obs.	244,896	244,896	144,701	224,010	2,217,183	244,896	144,701

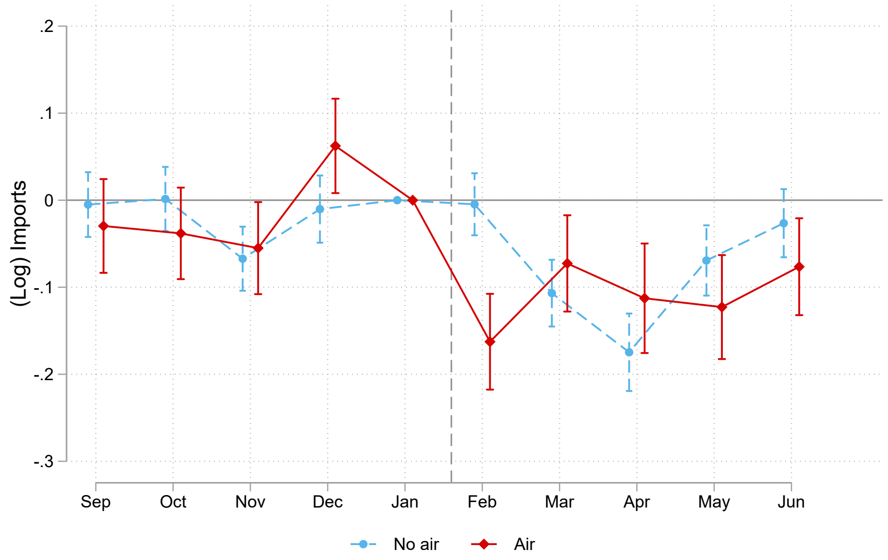
Note: The table reports results of difference-in-difference estimations on firms' imports. "T1" means that the control group is made of firms that import inputs from abroad outside of China whereas treated firms are those exposed to Chinese inputs in the five months before the pandemic. "T2" means that the control group is made of firms that import inputs monthly from a specific country which is not China wheereas treated firms 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 imports between September 2019 and January 2020 (pre-treatment period) and between February 2020 and June 2020 (post-treatment period). Columns (1)-(4) are estimates on firm-level imports and 'units' are firms, while Column (5) considers as treated units firm×product pairs. Columns (6)-(7) add to Columns (2) and (3) a triple interaction term with a variable equal to 1 if the firm imports from China by air. In Column (6), the dummy is equal to one if more than 25% of its inputs from China are sent by air. In Column (7), the dummy equals one if the firm receives products by air every month between September 2019 and January 2020. Standard errors are clustered at the firm-level (firm×product in Column (5)). ^{a}, ^{b} and ^{c} denote significance at the 1, 5 and 10% level respectively.

by air suffered from a stronger drop in imports, which we attribute to their early exposure to the Chinese lockdown. In column (6), we distinguish, within the baseline treatment group (T1), firms using air transport for at least 25% of their imports from China. Firms importing from China experienced a drop in their total imports, which has been 65% stronger for firms using air freight. As illustrated in Figure 6, the difference is entirely driven by the dynamics of imports in February, which was almost flat for firms shipping products by sea but dropped by a large 17% for firms that use air freight. In column (7), we consider as treatment group firms importing every month from China (T2), and distinguish within this group the subset of firms that import every month by air from China. Again, we find that the negative impact of the Chinese lockdown is stronger from firms importing part of their Chinese intermediate inputs by air.[15]

[15] Another source of heterogeneity in the size of the treatment across firms importing from China is attributable to the Chinese early lockdown displaying heterogeneous stringency across Chinese provinces. In the absence of firm-level data on imports by Chinese provinces, we implicitly assume all importers importing from China to be

Results in Table 2 and Figures 5 and 6 thus show that total imports of firms exposed to the Chinese lockdown have dropped after the shock. These results thus justify our interpretation of the 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.

Figure 6: 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.

exposed to the productivity slowdown in China from the end of January. In Section 3.2, we propose a robustness exercise that exploits product-level data on Chinese exports by province to identify a subset of inputs that are more likely to be produced in the Hubei province, which was the first region concerned by a lockdown, from January 23nd.

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 exports of French firms relying on these inputs. We first discuss the economic magnitude of the effect before assessing the robustness of results to the identification strategy.

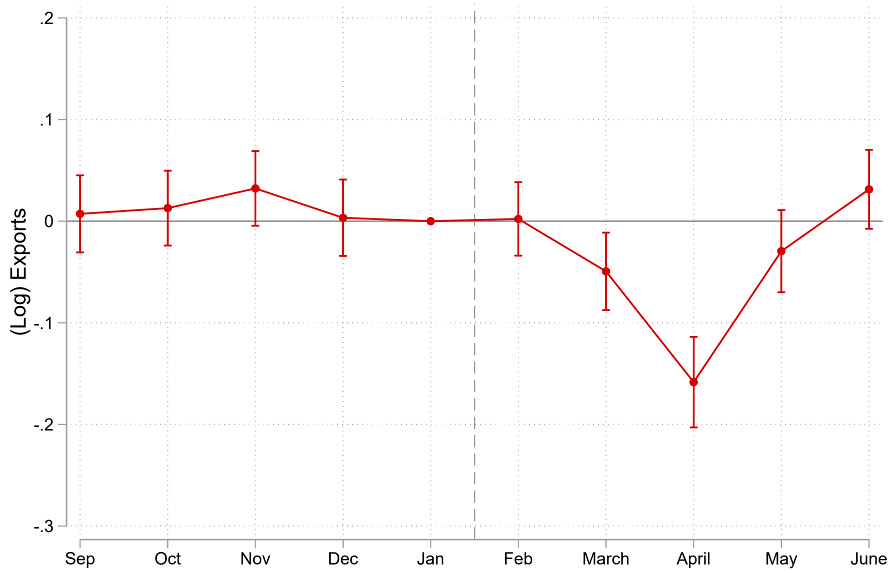
3.1 Baseline results

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 7. We see that the treated and control groups exhibit similar trends in exports before the Chinese lockdown in February 2020. 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 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.

Figure 7: 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.

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

	Dep. Var: log of exports						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment × Post	-0.048^a	-0.063^a	-0.049^a	-0.059^a	-0.034^a	-0.035^a	-0.058^a
	(0.011)	(0.015)	(0.011)	(0.018)	(0.005)	(0.012)	(0.017)
Treatment × Post × Air						-0.041^b	-0.016
						(0.017)	(0.027)
Firm FE	Y	Y	Y	Y	× Product	Y	Y
Time FE	Y	Y	Y	Y	N	Y	Y
Product×Destination×Period	N	N	N	N	Y	N	N
# Treated	13,731	4,322	13,074	7,383	12,025	13,731	4,322
# Control	16,646	9,672	15,820	6,994	14,320	16,646	9,672
# Interacted						4,693	1,215
Sample	All	All	$\frac{X}{X+M} \geq .1$	Final goods	All	All	All
Treatment	T1	T2	T1	T1	T1	T1	T2
R^2	0.857	0.875	0.853	0.865	0.736	0.857	0.875
# Obs.	234,482	116,087	227,901	100,347	6,794,403	234,482	116,087

Note: The table reports estimation results of the difference-in-differences estimation using the log of exports as left-hand side variable. "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" focuses on firms that import inputs monthly from a specific country, China for treated firms and another country for control firms. The date of the treatment is February 2020 and the DiD thus compares the evolution of imports between September 2019 and January 2020 (pre-treatment period) and between February 2020 and June 2020 (post-treatment period). Column (5) runs estimations at the Firm×Product×Destination×Period level and standard errors are clustered at the Firm×Product level. In Column (6), the "Air" dummy is equal to one if more than 25% of its inputs from China are sent by air. In Column (7), the dummy equals one if the firm receives products by air every month between September 2019 and January 2020. Standard errors are clustered at the firm-level (firm×product in Columns (5)). ^{a}, ^{b} and ^{c} denote significance at the 1, 5 and 10% level respectively.

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).[16] Column (3) is the same specification as in column (1) but estimated on the subsample of firms whose exports to trade ratio is greater than 10%. This restriction aims at excluding large importers of Chinese inputs with very little export activities. The restriction has little impact on the estimated effect. However, the effect is slightly larger if one restricts the analysis to exporters of final goods as in column (4). Firms importing inputs from China have experienced a 5.9% relative drop in their exports of final products. These results point to the key role of supply chains in transmitting shocks across borders.

Column (5) 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, the exports for a given product and within a destination have dropped by 3.5% after the Chinese lockdown. The effect is thus a bit smaller than in the baseline specification (-4.9%). One possible interpretation of the dampening is that the 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.[17]

Columns (6) and (7) evaluate whether the exports of firms importing from China by air have been more strongly affected than those relying on sea freight. The results point toward an additional reduction in exports for firms importing by air, though the effect is imprecisely measured in one of the two specifications. Indeed, the triple interaction term is negative and significant in column (6) but not significant in column (7) in which the treatment is defined as importing every month from China. In the event study specification, we do not find significant differences in the export drop for both groups of treated firms, neither in terms of the magnitude nor in terms of the timing of the adjustment (See Figure A.3 in the Appendix).[18]

[16]The corresponding event study graph is reported in Figure A.2 in the Appendix.

[17]Whereas the specification in Table 3, column (5), fully controls for differences across firms in exposure to demand shocks, there is one source of heterogeneity that one may particularly worry about, namely that firms exposed to Chinese inputs may also be 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).

[18]In unreported results, we have also tested whether the relative export drop was correlated with relative

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 number of destinations and the value of exports per destination. In columns (4) and (5), the decomposition involves the number of products and the value of exports per product. Finally, columns (6) and (7) respectively display results based on the number of product-destination pairs and the value of exports per product-destination. The top panel reports these decompositions using the baseline specification.[19] The bottom panel considers the alternative treatment group (T2) that identifies firms with regular input-output ties with China. All specifications point into 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.

Table 4: Margins decomposition of DiD results

	Baseline	Destination		Products		Markets		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: 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. The treatment group in panel B is made of firms importing from China every month. Standard errors in parenthesis are clustered at the firm-level. Columns (1)-(7) use the log of the firm's exports, or one of its component, as left-hand side variable. Column (8) corresponds to a linear probability model of the likelihood that the firm exports.

price adjustments, using unit values at the transaction-level as left-hand side variable. Results suggest a small decrease in the relative price of exports for treated firms in comparison with control firms, but the coefficients on both groups are never significantly different from each other when we ran the event study specification. From this, we conclude that price adjustments are not a quantitatively important channel of the transmission.

[19]The corresponding event-study graphs are reproduced in Figure A.4.

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 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.[20] In both samples, 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.5 (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 the previous analysis, we have compared the exports of firms exposed to the Chinese lockdown to the exports of a control group. We have restricted our sample to relatively large firms that are both importers of intermediate inputs and exporters. We have further included firm fixed effects in all specifications to control for firm-level characteristics that may explain (constant) differences in the level of exports across firms. In the previous section, we have also shown that the results are robust when controlling for differences in exports that may be driven by different portfolios of destinations and exported products.

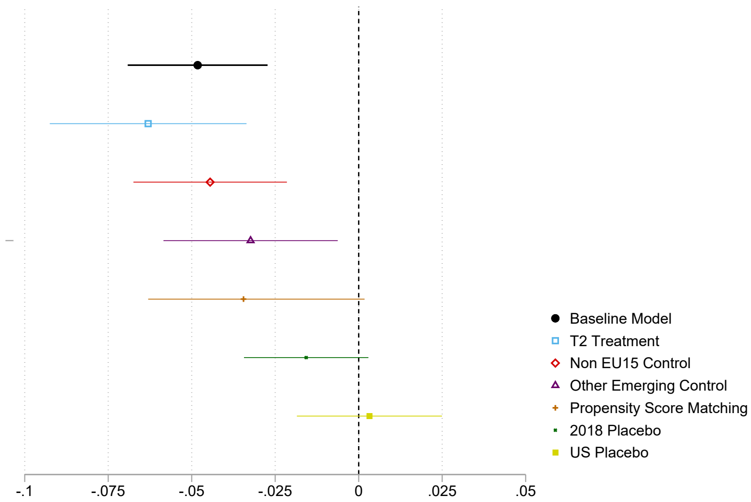
In this section, we further test the robustness of our main findings. We first discuss how results vary with alternative definitions of the control group. We then test robustness to the estimation method, using a matching algorithm as an alternative. Finally, we conduct two placebo exercises as well as various specifications using other definitions of the treatment, the role of which being 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. Results of these robustness exercises are summarized in Figure 8, which displays the DiD coefficient recovered

[20]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 8: 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%.

from each robustness, in comparison with the baseline (black line) and the alternative definition of the treatment (blue line which corresponds to column (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.[21] The corresponding control group contains 7,255 firms which imports and exports 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.

[21]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 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.

Results of these two exercises are summarized in Figure A.6, with the corresponding DiD coefficients displayed in the red and purple lines on Figure 8. Results obtained excluding firms solely importing from EU countries look very similar to those in Figure 7, 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.6 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.

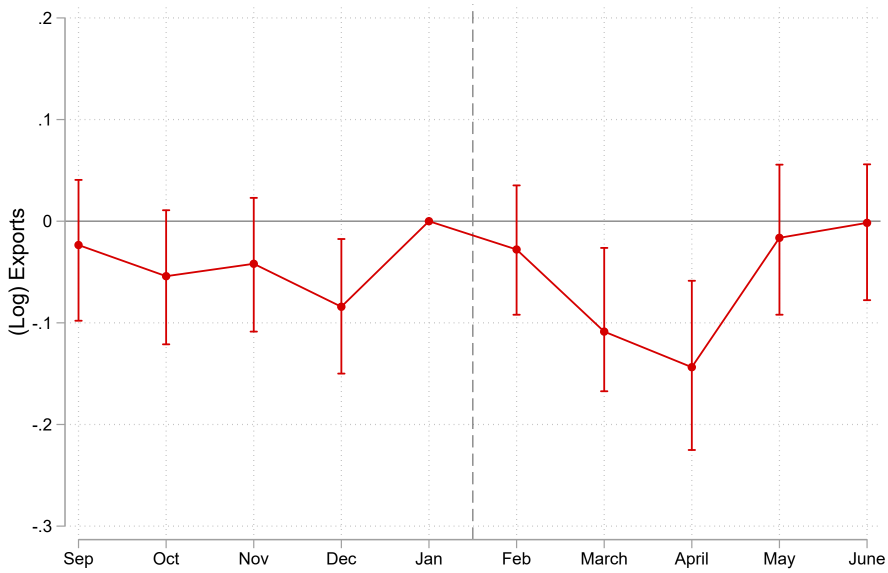
We then depart from the baseline specification by using a matching estimator. We back out propensity scores from a probit model in which we estimate the probability of being treated using the level of imports, the level of exports, the number of destination countries and the number of exported products 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.[22] The results presented in Figure 9 and the orange line in Figure 8 confirm the negative impact of the Chinese lockdown on the exports of firms importing from China.[23] 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.

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. We now use two placebo exercises and several additional specifications of the treatment to provide support to our interpretation of the results as being driven by the transmission of the supply chain shock

[22]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.

[23]The DiD coefficient shown in Figure 8 is only significant at 10%. As Figure 9 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 9: 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%.

to downstream firms.

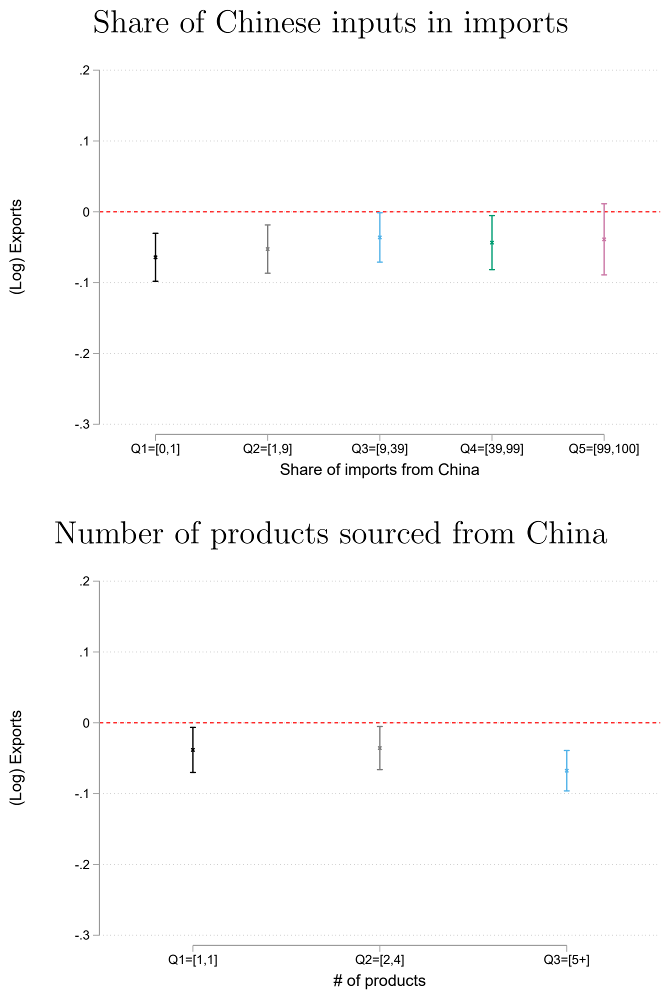
One may first wonder whether imports from China display some specific seasonality that could explain the dynamics of trade identified when comparing firms that import from China and firms that do not. To exclude this possibility, we perform a placebo exercise in which the exact same empirical strategy is reproduced using data one year backward. If such seasonality was the main driving force at the root of our results, we shall observe the same patterns in late 2018 /early 2019 than those reproduced in Figure 7. Figure A.7, summarized by the green line in Figure 8, 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 7 is specific to the Covid crisis period in early 2020.

Second, 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 7 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 7 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.8 (yellow line in Figure 8) 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.

Finally, results summarized in Figures 10 and 11 investigate the robustness of our results to the definition of the treatment. Until now, we have chosen to define the treatment using a binary variable, a firm being considered treated whenever it imports some of its inputs from China, whether in large or small volumes. The intuition is that a supply chain disruption, even on an input that accounts for a tiny share of the firm's overall costs, may lead to a production disruption if this input cannot be purchased elsewhere. Figure 10 provides support to this assumption. We compare the estimated impact of the treatment among groups of treated firms with heterogeneous *levels* of exposure to Chinese inputs, as measured by the share of Chinese inputs into overall imports (top panel), or the number of products sourced from China (bottom panel). In both cases, we find no significant differences in the size of the treatment, thus confirming the assumption that the size of the exposure does not matter much, in comparison with the very fact of being exposed.

Another source of heterogeneity across treated firms is due to lockdown policies being heterogeneous across Chinese provinces. The first region hit by the pandemic, that has been under lockdown from January 23rd, 2020, is the Hubei province. By considering as treated 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

Figure 10: Impact of input shortages on exports: Heterogeneity on the size of the exposure

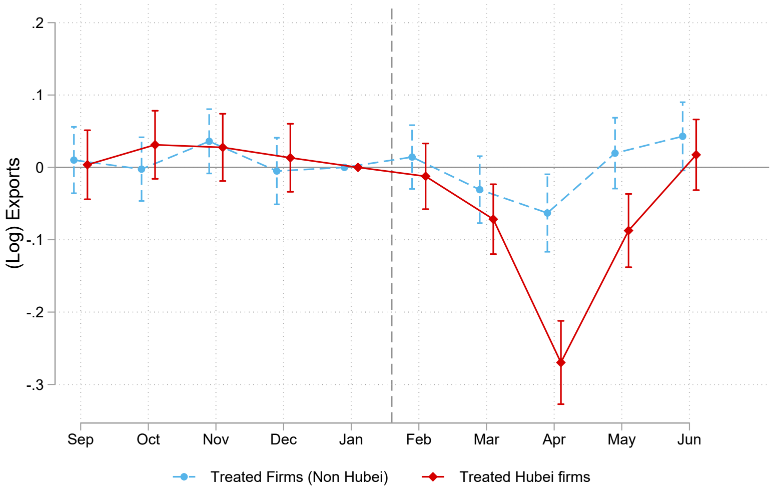


Notes: The figures show the estimated impact of being treated on post-January 2020 exports, across treated firms with heterogeneous exposures to Chinese inputs. In the top panel, exposure to Chinese inputs is measured by the mean share of imports from China in pre-shock imports, the population of treated firms being separated into five quintiles of equal size. In the bottom panel, exposure to Chinese inputs is measured by the number of products that are sourced from China in the pre-shock period. The estimated equation includes firm and period fixed effects. Standard errors are clustered at the firm-level. The confidence intervals are defined at 5%.

and those importing products that Hubei is specialized into.[24] Results, shown in Figure 11, 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. Whereas the lack of firm-level data on imports by province does not allow

[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 in 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).

Figure 11: 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%.

to dig deeper into each French firm's actual exposure, this result is reassuring regarding our interpretation of the consequences of the early lockdown on French firms' imports and exports.

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 leading firms to temporarily exit some of their export 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. 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 statement, asking whether the geographic diversification of purchases helps firms perform better once hit by the Chinese lockdown shock.

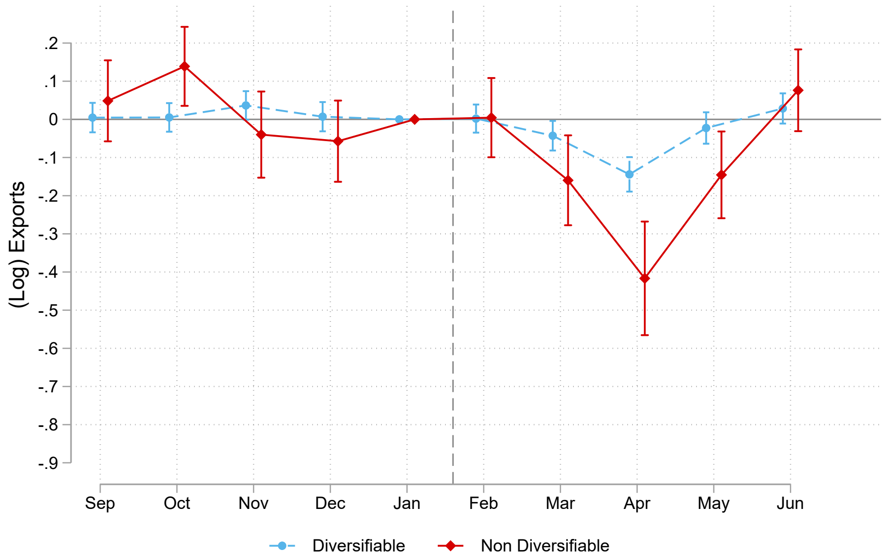
We first examine whether firms that source Chinese inputs that can hardly be diversified have been hit more severely by the shock. We consider that a product can hardly be diversified away from China if at least 60% of world exports in this product category originate from China.[25] We then define a 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 12 shows that firms importing non-diversifable inputs from China have experienced a more severe drop in their exports than firms importing more 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.9).

The analysis presented in Figure 12 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)

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

Figure 12: 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%.

are diversified.[26] In the baseline sample, slightly more than 40% of treated firms are diversified 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.

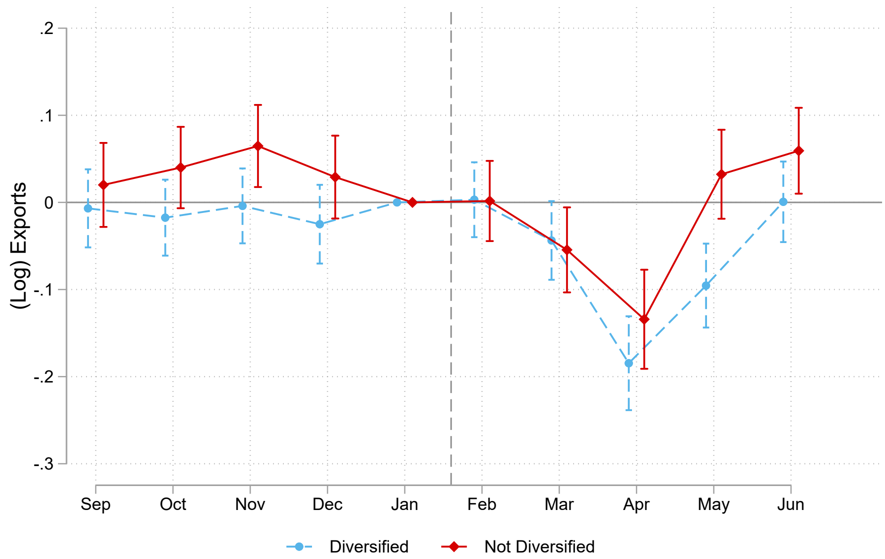
Figure 13 shows that, among firms exposed to the Chinese shock, ex-ante diversified firms did not performed better than non-diversified. We verify in the first two columns of Table A1 that this result is robust to our definition of the treatment group. We have further tried a variety of alternative metrics of diversification that all lead to the same result.[27] 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.10 in appendix), which is consistent with the

[26]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 results.

[27]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.

main finding that ex-ante diversified firms have similar export performances as non-diversified firms.

Figure 13: 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 subsamples. 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.

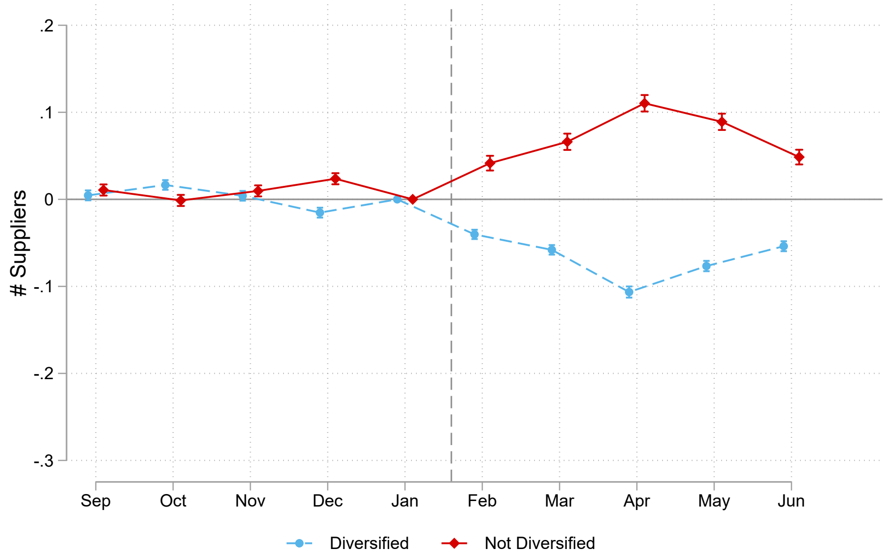
At first view, this result thus contradicts the premise that diversifying supply chains can be a useful risk management strategy to insure against localized shocks hitting firms' supply chain. There are several potential reasons for this absence of result, which we now examine.

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 thus a bit weak statistically 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 13 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 13 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 14 provide some support for this interpretation. Namely, Figure 14 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 14: 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

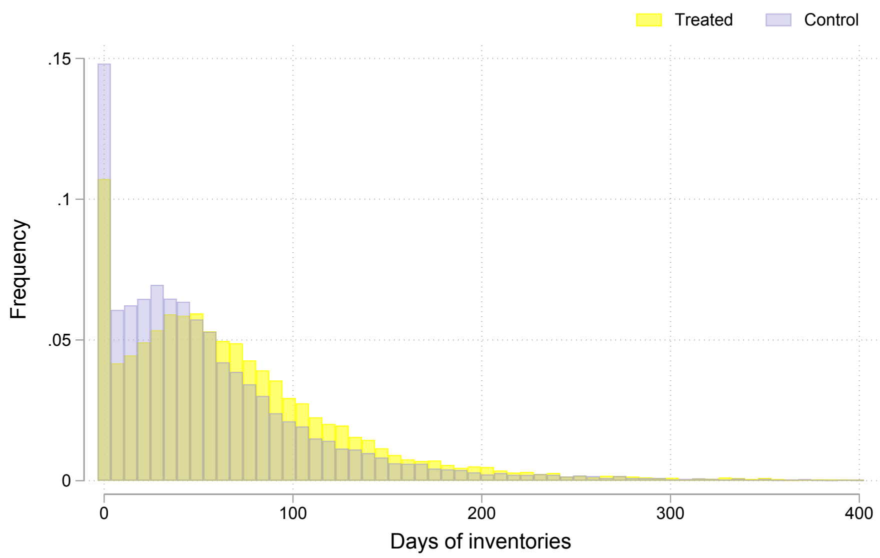
We now investigate the role of inventories in offering a buffer against input shortages. We merge the estimation sample with balance-sheet information provided by the French National Statistical Institute (FARE dataset). The dataset is exhaustive and contains information on the value of firms' inventories 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 two 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.[28] 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

[28]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.

the assumption that inventory strategies are relatively 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 15 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.[29] 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.[30]

Figure 15: Distribution of inventory ratios in the estimation sample

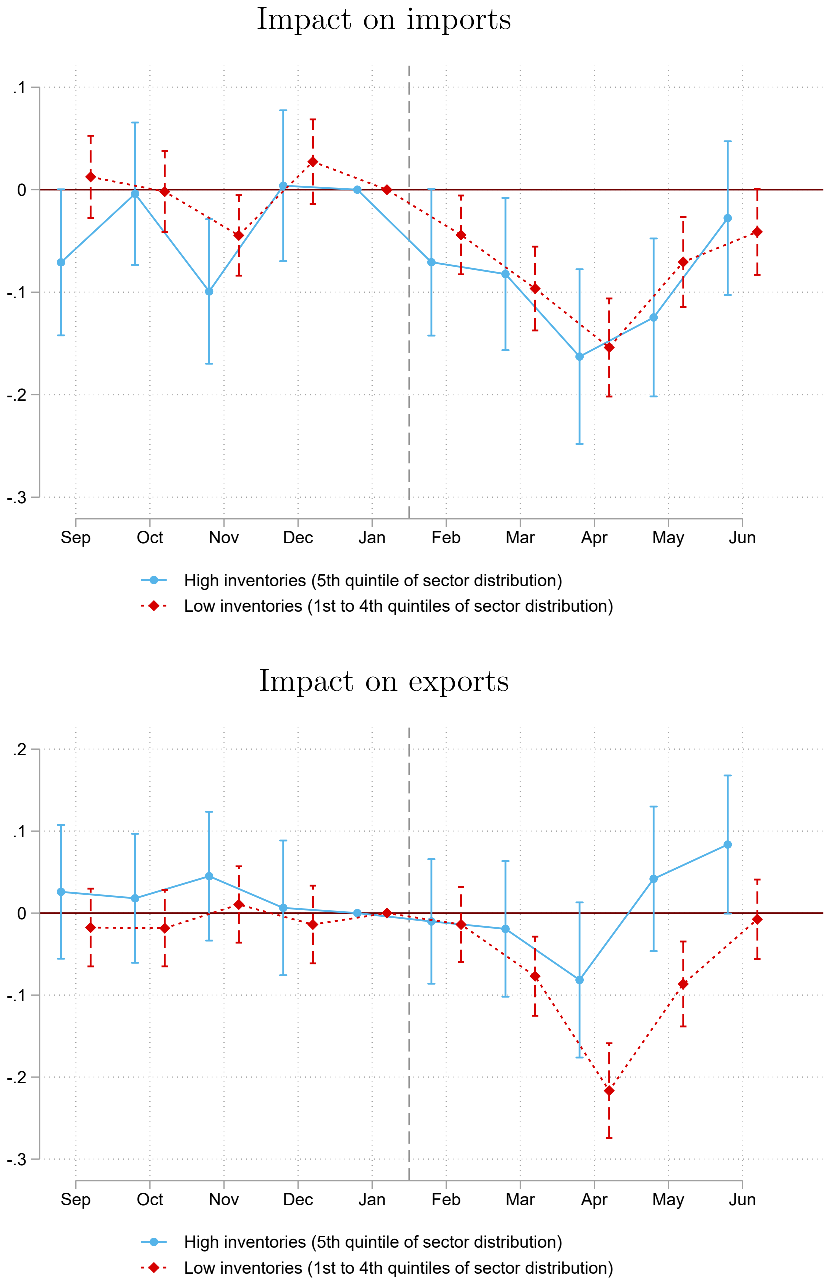


Notes: The figure shows the distribution of firms' inventories-to-sales ratios, in the estimation sample, for treated and control firms. Source: INSEE-FARE for 2018, merged with the customs data.

[29]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.

[30]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 16: 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%.

Results are displayed in Figure 16. 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 to Figure 5. 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 16. 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.

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 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' exports. Between February and April, firms exposed to the Chinese early lockdown experienced a 4.8% drop in exports relative to French firms importing from other countries. Firms' adjustment to the Chinese shock happens along the extensive margin. Firms temporarily stop exporting some products toward some destinations.

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 shocks performed better than other firms. 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 such as plastics.[31] Whereas less 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.

[31] The shortage of semi conductors is expected to last through 2022 according to the chief financial 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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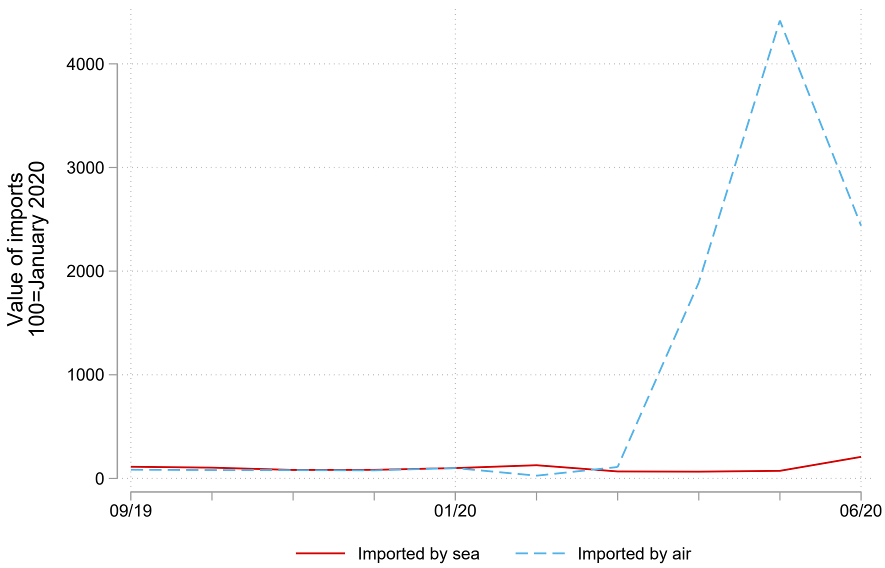
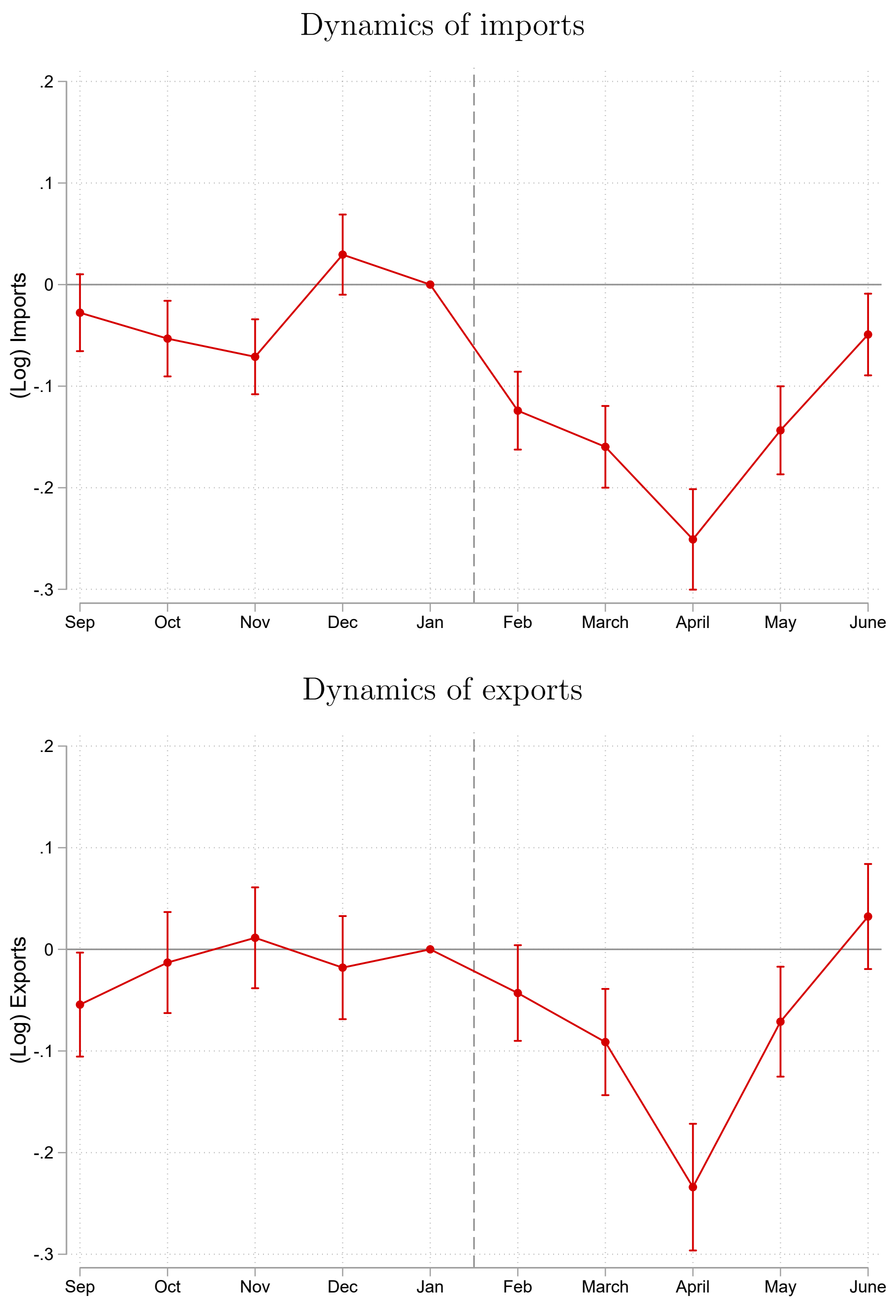
Appendix

Figure A.1: French imports of covid products from China by transport mode



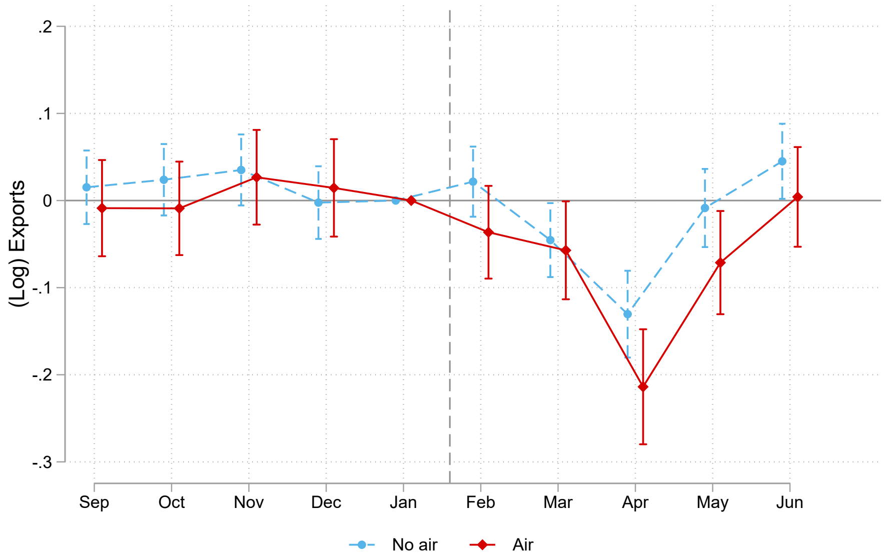
Source: French customs, import files. The figure shows the evolution in the value of French imports of Covid-products from China by air and by sea, between January 2019 and December 2021. Both time series are normalized to 100 in January 2020.

Figure A.2: Chinese lockdown, firm-level imports and exports for monthly importers



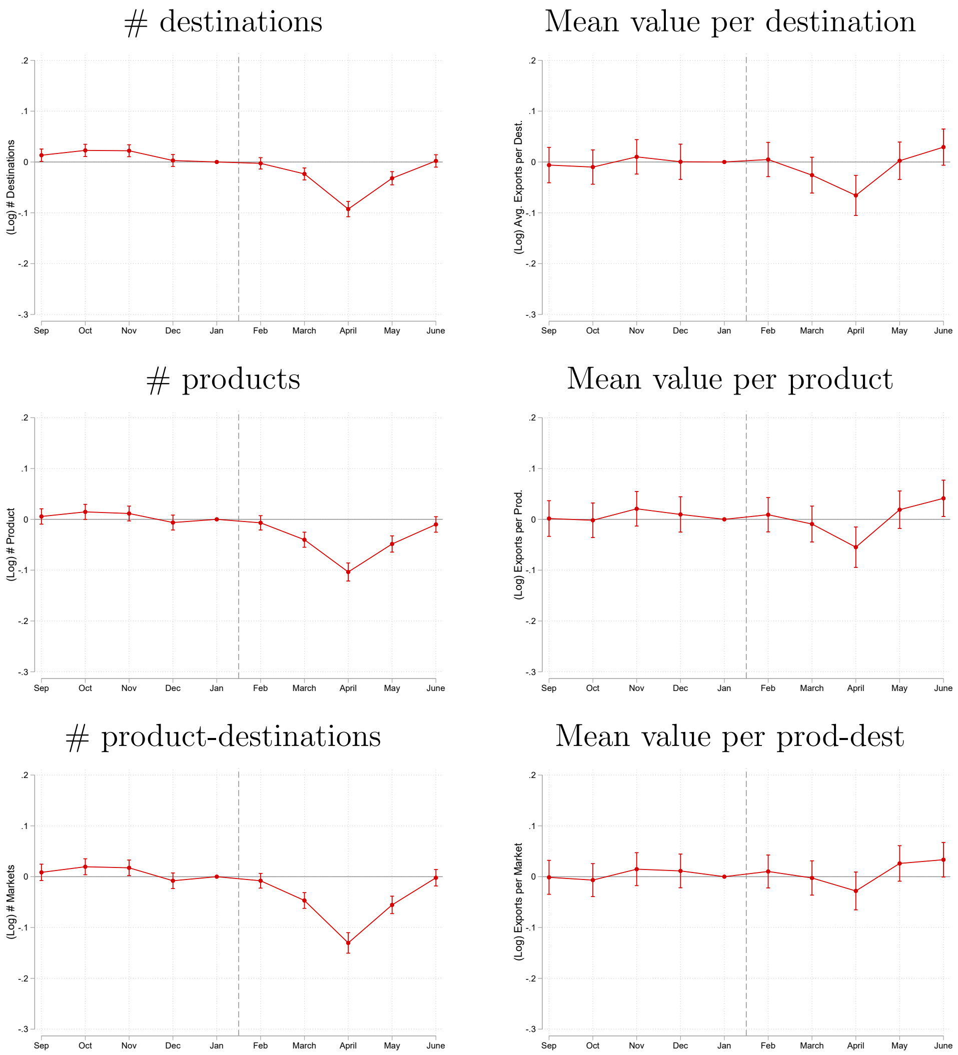
Notes: The figure shows the dynamics of imports (top panel) and exports (bottom panel) before and after the Chinese lockdown for treated firms in comparison with the control group. The treatment is based on monthly imports from China between September 2019 and January 2020 (T2) and the control corresponds 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.3: Chinese lockdown, firm-level exports, and air freight



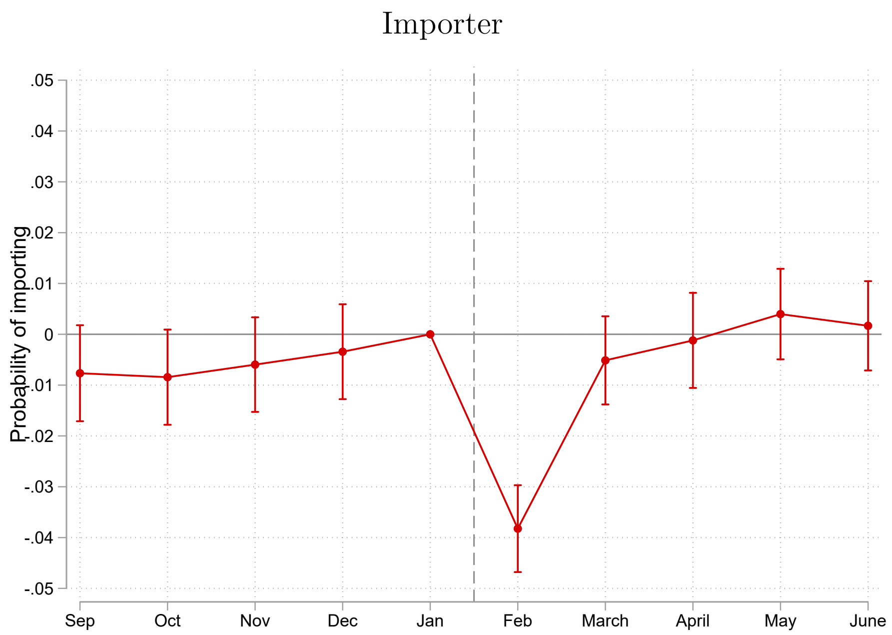
Notes: The figure shows the dynamics of exports before and after the Chinese lockdown for treated firms in comparison with the control group. The two lines respectively correspond to importers using air freight (red line) and other importers (blue line). The estimated equation includes firm and period fixed effects. 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.

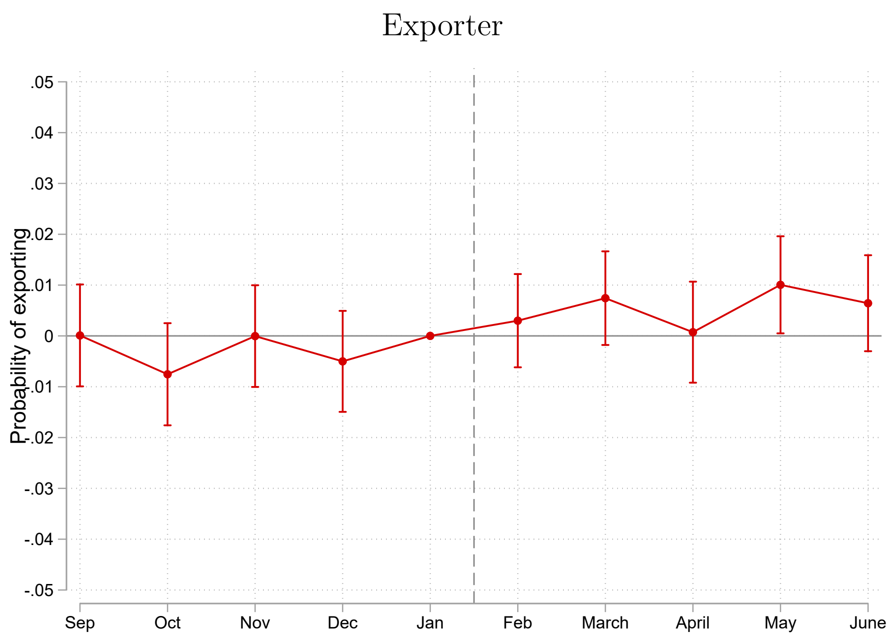
Figure A.4: Effect of the Chinese lockdown on exports: Intensive versus extensive adjustments



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.5: Effect of the Chinese lockdown on the probability of staying as an...



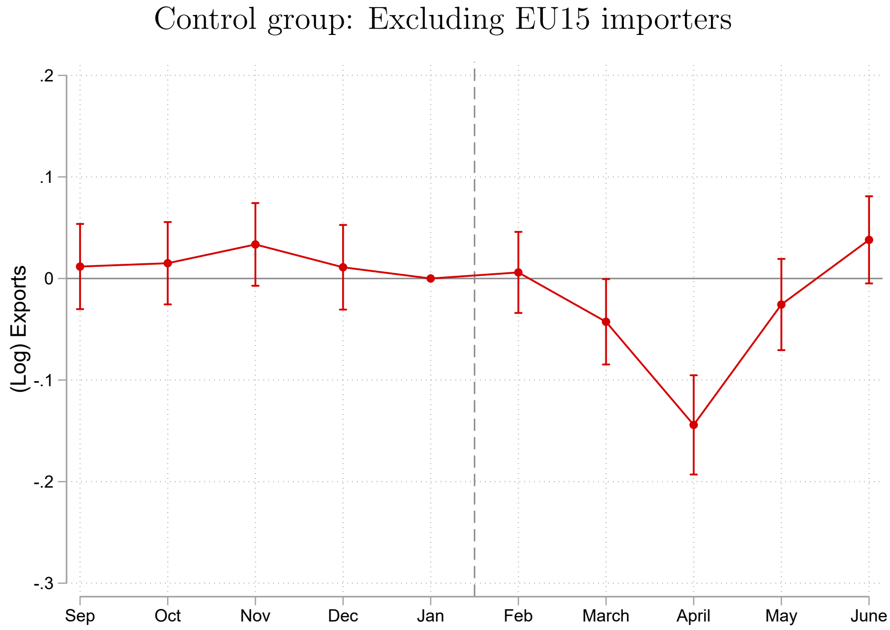


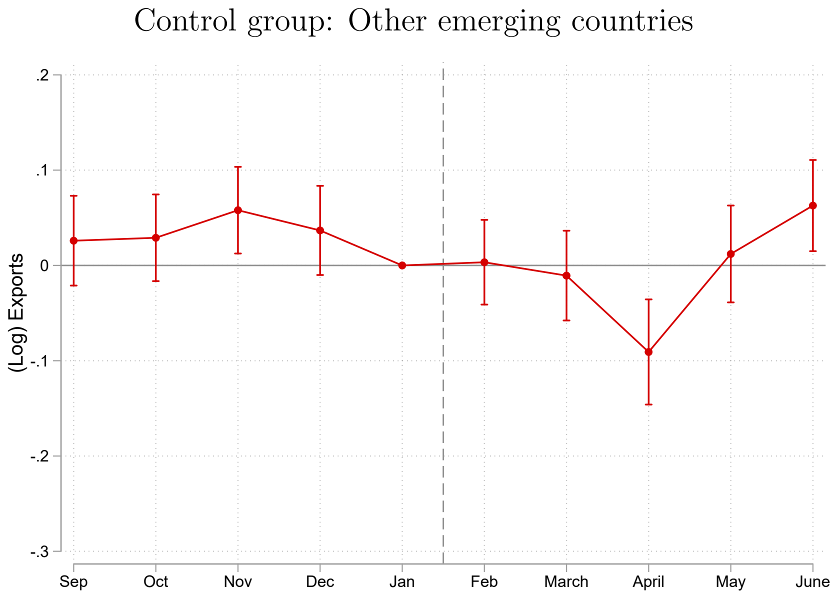
Note: Same specification as in Column (7) of Table 4 of the paper. The estimated equation reads:

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

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.

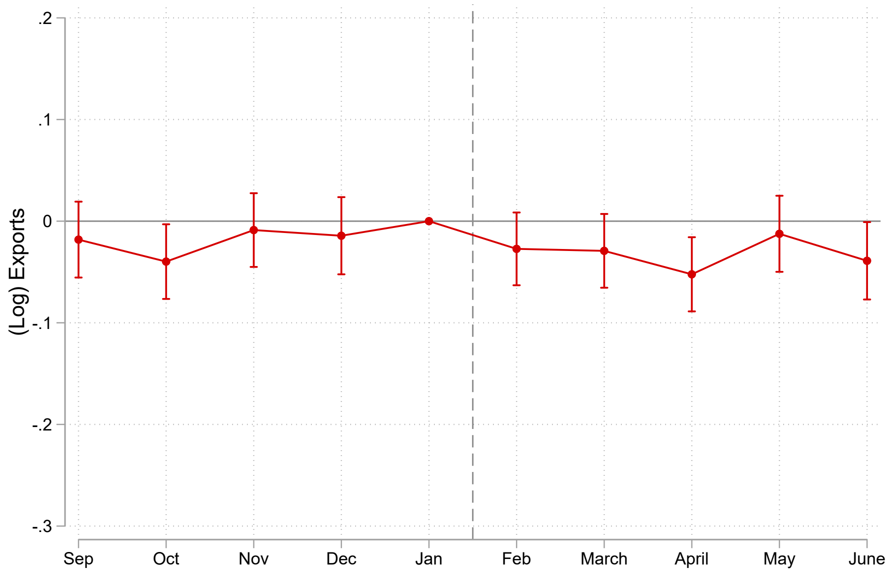
Figure A.6: Impact of the Chinese lockdown on firm-level exports: Alternative control groups





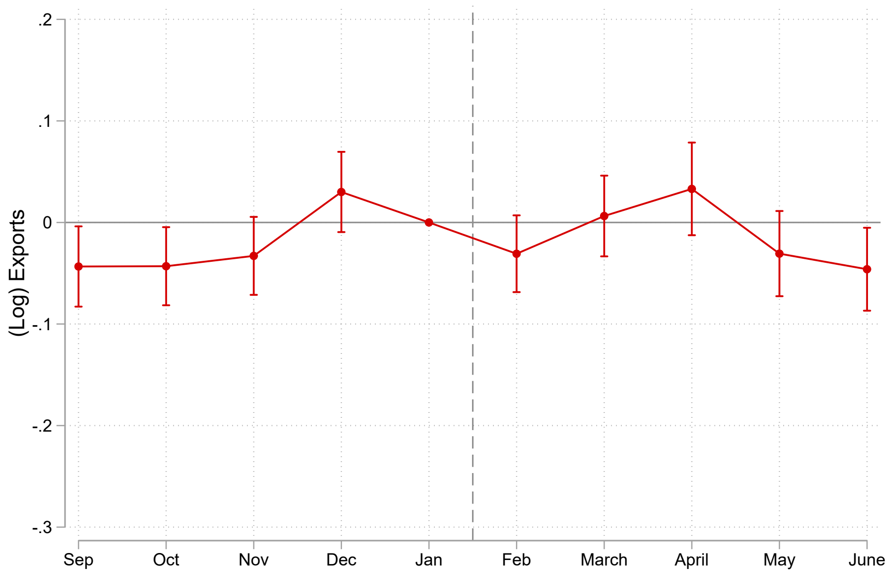
Notes: The figure shows the dynamics of exports before and after the Chinese lockdown for treated firms in comparison with the control group. The treatment is based on imports from China between September 2019 and January 2020. The control group is based on importers from other countries i) excluding 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.7: Placebo test: Dynamics of firm-level exports between September 2018 and June 2019



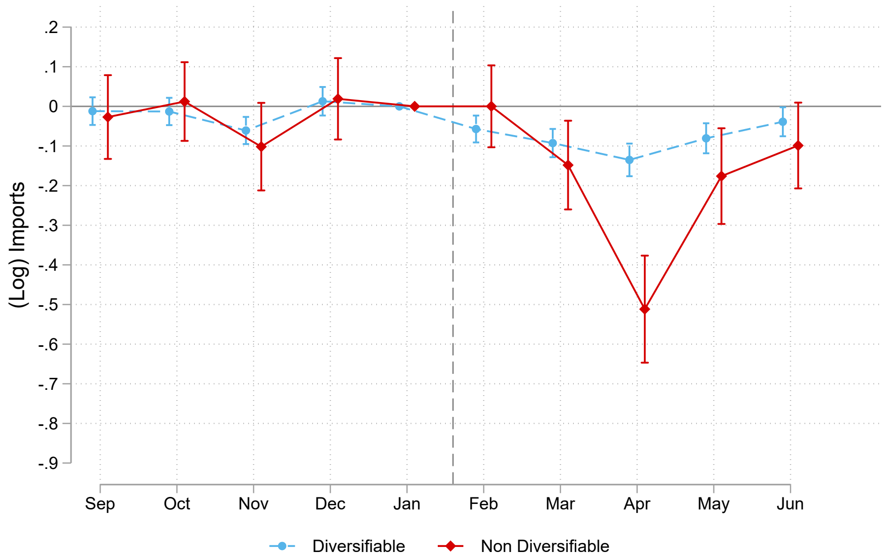
Notes: The figure shows the dynamics of exports for treated firms in comparison with the control group. The treatment is based on imports from China between September 2018 and January 2019 and the placebo date of the treatment is considered to be February 2019. The estimated equation includes firm and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

Figure A.8: Placebo test: Dynamics of firm-level exports when the treatment is based on US importers



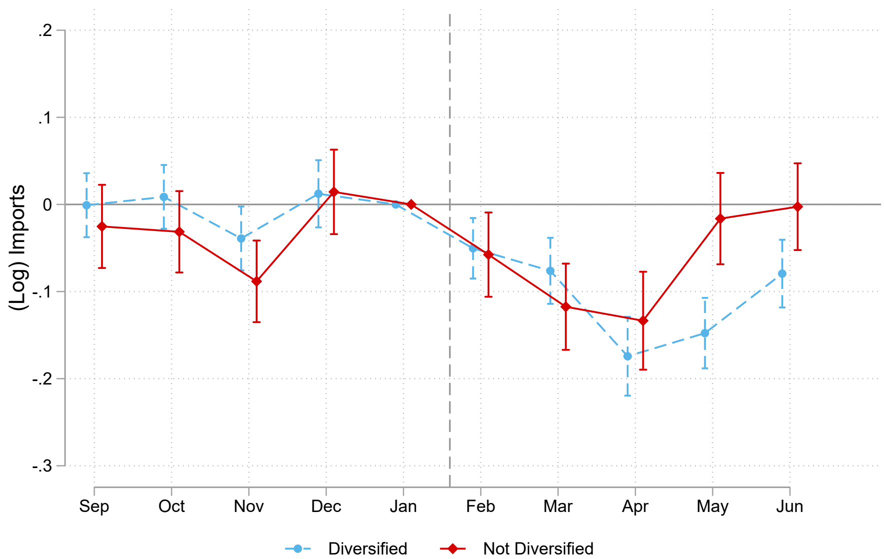
Notes: The figure shows the dynamics of exports for treated firms in comparison with the control group. The treatment is based on imports from the US between September 2019 and January 2020. There are 10,377 treated and 23,106 control firms. The estimated equation includes firm and period fixed effects.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

Figure A.9: 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.

Figure A.10: 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.

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.