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 4.8% 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 mitigate the impact of the shock, inventory management strategies help firms weathering such adverse supply shock.

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1 Introduction

Trade in intermediate inputs constitutes 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 for the firm-level transmission of a supply shock on imported inputs to individual exports. Second, it evaluates whether risk management strategies help mitigate the transmission of adverse shocks affecting the firm's 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 (temporarily) stopped serving some of their foreign partners. Whereas, the ex-ante geographic diversification of inputs does not influence the transmission of this negative supply shock, we find strong evidence that holding inventories offer a buffer for firms exposed to 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. A first advantage is that 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 very 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, 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. 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 -18% 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 main 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 reduce their exports by 5% 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 adjustment is mainly driven by the extensive margin. The average treated firm serves 10% less products and 10% less destinations in April, in comparison with the control group. Likewise, the (relative) recovery in May and June 2020 mostly involves extensive margin adjustments. The supply chain shock thus induces exits from export markets. We provide a series of robustness exercises confirming the negative impact of the Chinese lockdown on the exports of exposed firms.

In the third part of the paper, we ask whether risk management strategies can help mitigate the impact and the transmission of the supply shock to the rest of the supply chain. First, we explore the role played by the structure of firms' import basket. Given the vulnerability of input-output structures to local 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. 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 find it is not the case. The reason is that 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 strategies. The level of inventoriers 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 exports following the shock. Inventory management has thus been a useful buffer against the 2020 shock.

Related literature. We participate to the growing literature on the transmission of shocks through GVCs during the Covid pandemic. Bonadio et al. (2020) and Gerschel et al. (2020) investigate the role of input-output linkages in the propagation of the (economic) covid-crisis.

Berthou and Stumpner (2021) use product-level trade data to document the impact of lockdown policies on international trade. Closer to us, Heise (2020) examines the impact of the Chinese lockdown on US imports from China, at the firm-level. In comparison with Heise (2020), we can go one step further into the analysis of the transmission through GVCs, by estimating the propagation of the shock to firm-level exports. To our knowledge, this paper is the first to offer systematic evidence of supply chain disruptions in the aftermath of the Covid crisis.

The paper also belongs to the broad literature on GVCs (Antràs and Chor (2013), Baldwin and Lopez-Gonzalez (2015), Johnson (2018), Antrs (2020), among others). 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.[1] Second, while 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.

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. (2010) 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. Unlike Kramarz et al. (2020) and Esposito (2020) who focus on the geographic

[1]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.

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., 2010, Khan and Khederlarian, 2021). 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 from China. Section 3 provide evidence of the within firm transmission of the Chinese shock to exports. Section 4 examines differences in adjustment to shocks across firms with different risk management strategies. Section 5 concludes.

2 Data and evidence of a supply shock

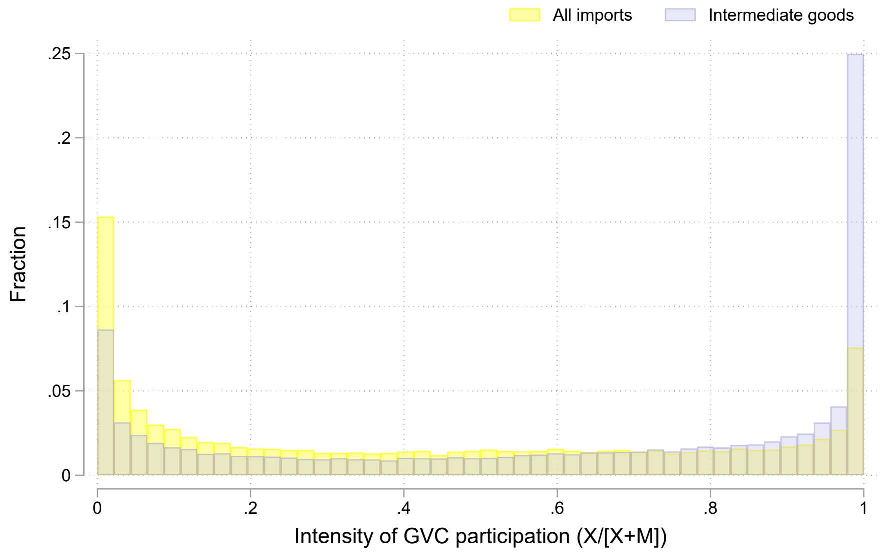
This section presents the firm-level data used throughout the analysis and the definition of firms' involvement in GVCs. It then provide evidence that the Chinese lockdown has severely reduced the supply of inputs from China, and that firms exposed to the Chinese lockdown have experienced a drop in imports.

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. 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 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

Figure 1: Participation to GVCs at the firm-level



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. Restricted to firms both importing and exporting between September 2019 and January 2020.

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 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 32% 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. Focusing on intermediary imports 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

Table 1: Summary Statistics on the Estimation Sample

	# firms	Mean value of imports (2019)	Contribution to aggregate Imports (%)	Contribution to aggregate Exports (%)
All firms	33,483	6.8M€	89.5	91.6
Importers from				
China	14,880	10.4M€	60.9	66.1
Elsewhere	18,603	3.9M€	28.6	25.4
Monthly importers from				
China	4,495	20.3M€	36.0	38.6
Elsewhere	9,406	7.1M€	26.4	19.1

Source: French customs. The summary statistics are computed on the estimated sample that covers firms importing and exporting at least once between September 2019 and January 2020.

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 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. Among these firms, 44% import some of their inputs from China and 13% have interacted with Chinese producers on a monthly basis between September 2019 and January 2020. Firms importing from China are roughly three times larger than other importers, in terms of the mean value of their overall imports. This size discrepancy is not surprising as importing from China involves substantial fixed and variable costs which only the largest importers 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.

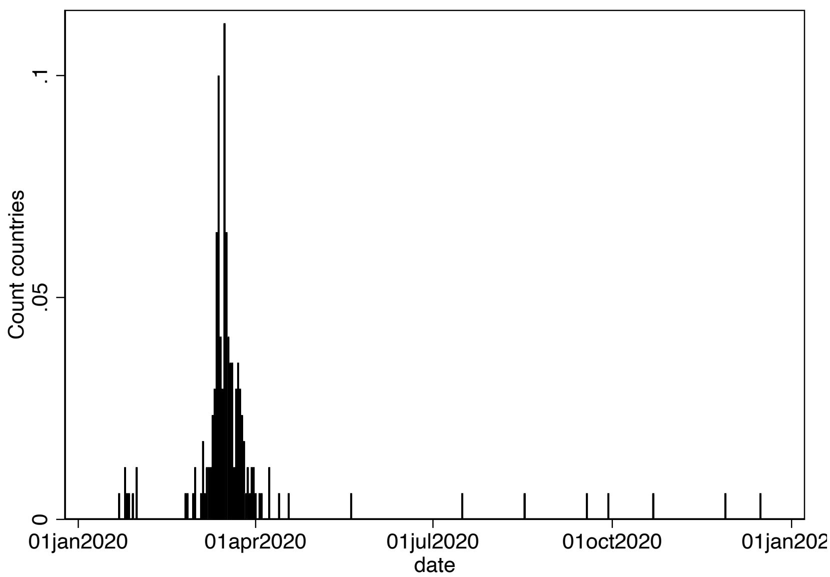
As detailed in the next section, our empirical analysis exploits the timing of the diffusion of the pandemic to isolate supply chain disruptions originating from China. In doing so, it will be important to take into account the fact the timing of the shock may have been felt at heterogeneous dates depending 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 observed for goods directly imported from China, we have to impute it for Chinese goods transiting through other EU countries. Indeed, 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 farily common that two customs forms are filled, one that records the trade flow from China to the point of entry and one that covers the intra-EU flow up to France. 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 at least three weeks of delay between the time when the products are put onto the cargo and the date of the customs clearance in Europe. We thus expect the shock to be felt earlier in France for goods transported by air.

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.

Figure 2 illustrates the discrepancy in the timing of policy responses across countries. We use the Oxford COVID-19 Government Response Tracker to date the first large policy response to the Covid Pandemic at the country level.[2] Whereas most countries have been hit by the pandemic at the end of February or the beginning of March 2020, a few countries have been hit earlier, which has induced policy responses as early as in late January. The first of these countries has been China, which has imposed a lockdown in the Hubei region from January 23rd. We exploit this one-month lag to separate in the data the impact of the productivity slowdown in China from the general drop in productivity induced by the pandemic.

Figure 2: Timing of the transmission of the pandemic to individual countries



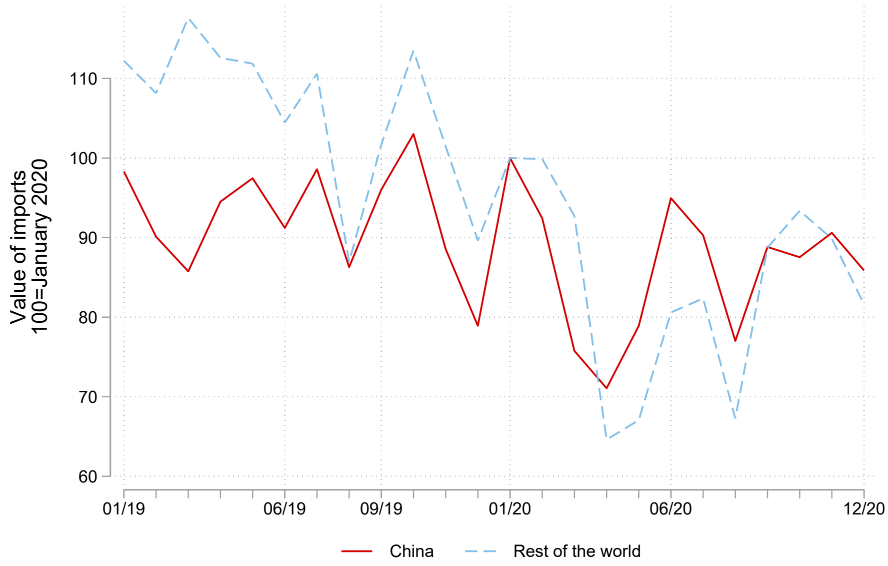
Source: Authors' calculations from the Oxford COVID-19 Government Response Tracker. For each country in the dataset, we identify the date of the first important change in the value of the Government Response Index, which we use as a proxy for the arrival of the pandemic in the country under study. The first countries hit by the pandemic according to this measure (in chronological order) are China (01/22), Australia and Malta (01/25), Portugal (01/26), Mongolia (01/27), Vietnam (01/29), Italy and Spain (01/31).

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.[3] Whereas the value of imports from the rest of the world was stable in

[2]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, we identify the first important adjustment in this index, defined by an increase larger than 10 in the value of the index.

[3]Throughout the analysis, we exclude imports of Covid-related products, namely masks, anti-epidemic goods,

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 January 2019 and December 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.

February 2020, it decreased by more than 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 and Summer of 2020, the evolution of imports from China and from the rest of the world is more synchronized. It is only in the Fall that the two series start diverging again, due to the second wave affecting most European and American countries when the situation was much more under control in China.[4] Importantly, the early contraction of imports from China is not innocuous from the point of view of the French economy as China is the second most important source of imports.[5]

Whereas the dynamics of imports suggests a one-month lag between the drop in imports

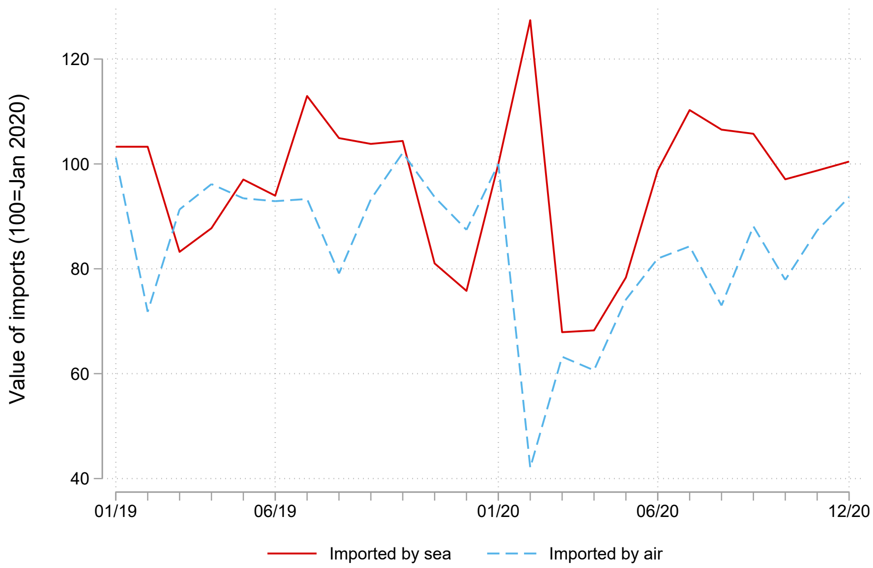
medical equipments, medical supplies and medicines using the list of Covid-related products provided by the WTO. Covid-related products do not affect the dynamics of trade prior to March, when the number of cases was still very small in France. In particular, the one month delay between the drop in imports 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.

[4]The dynamics of imports is very similar in both for final consumption and capital goods.

[5]In 2019, France imported 542.8 billion euros from abroad, 9.3% of which was imported from China. About 19.7% of French imports from China are final products, whereas intermediate goods and capital goods account for 34.6 and 45.7 percent of imports, respectively.

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.[6]

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 January 2019 and December 2020. Both time series are normalized to 100 in January 2020. COVID products are excluded from all series.

[6] 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 Spring 2020 and the role of air transportation in bringing these products to France.

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

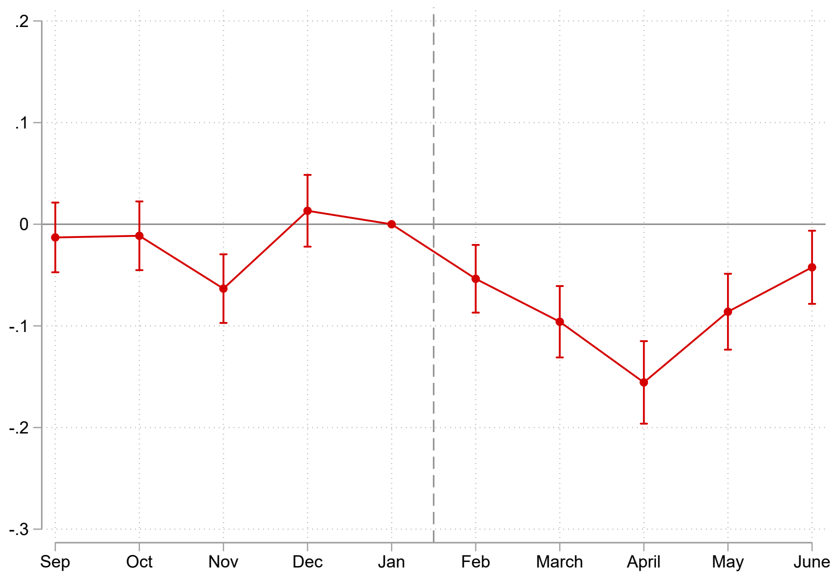
We now show that the aggregate drop in imports from China has induced a shortage of inputs for French firms. We compare the evolution of firm-level imports before and after the Chinese lockdown for firms directly exposed to the Chinese lockdown and in a control group. Exposition (our treatment variable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

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

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, except in November, there is no significant difference in the evolution of imports for firms in the treatment and the control groups. Instead, we observe a drop in imports of 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 dynamic, 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 for this alternative treatment group whose imports drop by 9.6% after the shock.[7]

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	-0.096^a	-0.076^a	-0.049^a	-0.058^a	-0.077^a
	(0.013)	(0.010)	(0.012)	(0.011)	(0.005)	(0.011)	(0.014)
Treatment×Post×Air						-0.038^b	-0.067^a
						(0.016)	(0.022)
Fixed Effects							
Firm	No	Yes	Yes	Yes	×Product	Yes	Yes
Period	Yes	Yes	Yes	Yes	×Product	Yes	Yes
Importing firms	All	All	All	X/(X+M)≥.1	All	All	All
# Treated firms	13,994	13,994	4,495	11,146	11,313	13,994	4,495
# Control firms	16,543	16,543	9,406	12,804	25,127	16,543	9,406
# Interacted firms						4,719	1249
Treatment	T1	T1	T2	T1	T1	T1	T2
M Coverage	All	All	All	All	All	All	All
# Obs	244,896	244,896	135,711	186,406	2,371,074	244,896	135,711
R^2	0.004	0.861	0.871	0.862	0.875	0.861	0.871

Note: The table reports results of difference-in-difference estimations on exporting firms. "T1" means that control group are firms that import inputs from abroad outside of China whereas treated firms are those exposed to Chinese inputs in the five months before the pandemic. "T2" means that control group is firms that import inputs monthly from a specific country which is not China and treated 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 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 ships 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.

In column (4), we reproduce column (2) but focusing on 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 7.6% 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

[7] 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%.

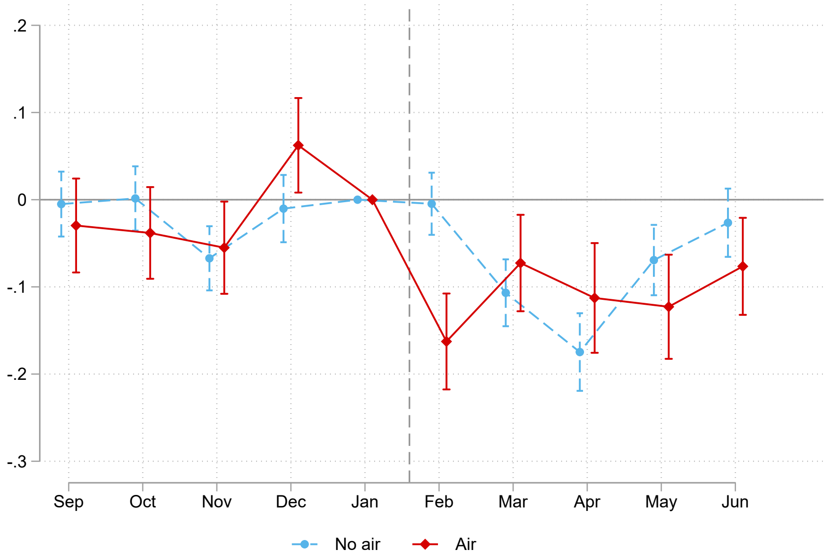
is defined at the firm×product level and we thus estimate how product-level imports reacted to a product-level exposure to the Chinese lockdown.[8] The estimated effect remains negative and significant but is smaller in absolute value (-4.9%). The difference in magnitude may be indicative of the supply chain shock having spillover effects on the rest of the firm's input purchases.

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 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 that ship at least 25% of their imports from China by air. 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 18% for firms that use air freight. In column (7), we consider as a 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.

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 looking at how the exposure to the Chinese lockdown has impacted firm-level exports.

[8]The number of firms 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 another product from third countries, in which case it is considered as control.

Figure 6: Chinese lockdown, firm-level imports, by mode of transportation



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 imports from China by air. 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.

3 Firm-level transmission along the supply chain

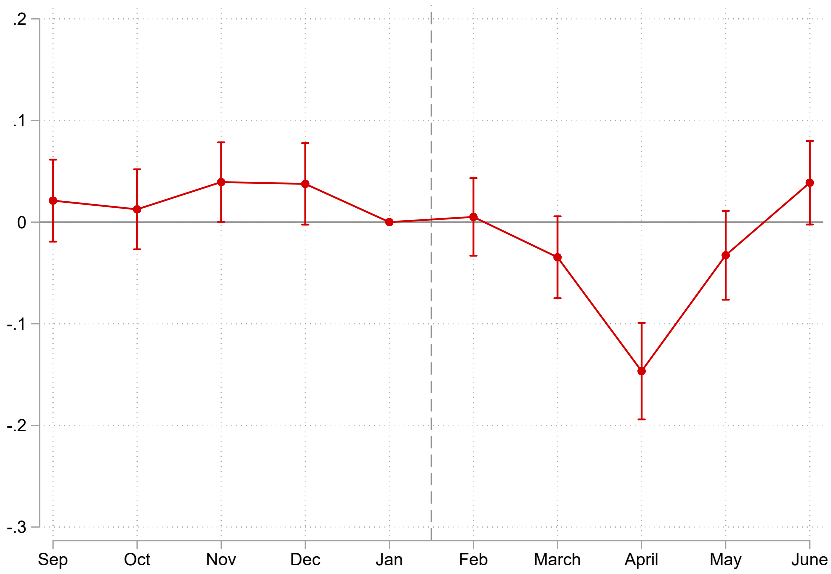
This section shows the shortage of Chinese inputs, which followed the Chinese early lockdown, had an adverse impact on the exports of French firms relying on these inputs. We first discuss the economic magnitude of the effect before assessing the robustness of results to the identification strategy.

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 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.

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.

We confirm the adverse impact of the Chinese lockdown on exports in various difference-in-differences estimations. The specification is similar to 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, showing that firms relying on Chinese inputs have experienced a 4.8% drop in exports after the Chinese lockdown, relative to non-exposed firms.

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

Dep.Var:				log of exports				log of price
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment×Post	-0.048^a	-0.059^a	-0.061^a	-0.028^a	-0.062^a	-0.034^a	-0.055^a	0.018^a
	(0.011)	(0.015)	(0.011)	(0.007)	(0.022)	(0.012)	(0.017)	(0.004)
Treatment×Post×Air						-0.041^b	-0.015	
						(0.017)	(0.027)	
Fixed Effects								
Firm	No	Yes	Yes	× product	Yes	Yes	Yes	× product
Period	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Product×Destination×Period	No	No	No	Yes	No	No	No	Yes
Sample	All	All	X/(X+M)≥.1	All	Exports of final goods	All	All	All
# Treated firms	13,437	4,266	11,216	4,977	13,561	13,437	4,266	11,758
# Control firms	16,116	8,542	13,475	5,092	16,265	16,116	8,542	13,802
# Interacted firms						4,590	1,209	
Treatment	T1	T2	T1	T1	T1	T1	T2	T1
# Obs	232,159	108,170	204,594	7,084,508	70,799	232,159	108,170	3,516,726
R^2	0.857	0.878	0.850	0.519	0.877	0.857	0.878	0.867

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 the estimation 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 ships products by air every month between September 2019 and January 2020. In column (8), the dependent variable is the log of prices (unit values) 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.

In column (2), we see the effect is stronger – a 5.9% drop – if the treatment group is made of firms importing every month from China before the lockdown (treament group T2).[9] Column (3) is the same specification as in column (1) but estimated on the subsample of firms whose export to trade ratio is greater than 10%. This restriction aims at excluding large importers of Chinese inputs with very little export activities. Again the effect of the Chinese lockdown is stronger on this subsample. Finally, Column (4) shows that the effect is even stronger if one restricts the analysis to exporters of final goods. Firms importing inputs from China have experienced a 6.2% 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 demand shocks in the destination countries. For firms sourcing inputs from China, the exports for a given product

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

and within a destination have dropped by 3.0% after the Chinese lockdown. The effect is thus a bit smaller than in the baseline specification (-4.8%). One possible interpretation of this result 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.

Columns (6) and (7) evaluate whether the exports of firms importing from China by air have been more strongly affected than those importing by sea. 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).

Last, column (8) examines the impact of the treatment on the price charged by French firms. The price are computed at the firm×product×country×month level as the ratio of exports to quantities. The interaction term is positive and significant, which suggests French exporters exposed to the Chinese shocks have charged higher prices to their clients abroad. The increase in price that followed the Chinese shocks implies that the quantity exported by exposed firms has decreased more strongly than the value of exports.[10]

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.[11] 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 temporarily

[10]We do not work with quantities directly because our main specifications are at the firm-level, and quantities cannot be summed across different product categories.

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

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., 2016). 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
		Density	Number	Density	Number	Density	Number	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: "T1"								
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: "T2"								
Treatment×Post	-0.059^{a}	-0.015	-0.044^{a}	-0.004	-0.056^{a}	0.004	-0.063^{a}	0.008^{b}
	(0.015)	(0.013)	(0.005)	(0.013)	(0.007)	(0.012)	(0.008)	(0.003)
# Obs	109,023	109,023	109,023	109,023	109,023	109,023	109,023	139,010
R^2	0.879	0.819	0.929	0.856	0.920	0.823	0.941	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.

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. We use a linear probability model to estimate the probability that the firm keeps on exporting before and after the shock.[12] Contrary to expectations, the estimated coefficient on the interaction term is found positive and significant meaning that treated firms are less likely to drop out of exports after the Chinese lockdown 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

[12] 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.

shock.

3.2 Robustness analysis

In our specifications, we compare the exports of firms exposed to the Chinese lockdown to the exports of a control group. We have restricted our sample to 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 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 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.

One may be worried that firms in the control group are exposed to systematically different supply shocks through their import portfolio. To deal with this issue, we first 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 five thousands firms from the control group. We then further restrict the control group to firms importing some of their inputs from less-developed and emerging countries.[13] The corresponding control group contains 7,276 firms which imports and exports on average represent 67 and 49% of the average treated firm's pre-shock trade, respectively. Here as well, the objective is to move the average control firms closer to treated firms, in terms of their import activities.

Results of the event study estimation are summarized in Figure 8. In the top panel, results obtained excluding firms solely importing from EU countries look very similar to those in Figure

[13] 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.

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. In the bottom panel of Figure 8 focusing on firms importing from developing countries, the reduction of the sample size is costly in terms of the precision of the estimates. However, the relative drop in exports of treated firms in April 2020 is still sizable and statistically significant.

We then depart from the baseline specification by using a matching estimator. We back out propensity scores from a logit 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. Armed with these scores, we can match each treated firm with a synthetic "control" based on its four nearest neighbors in the population of control firms. We then use a simple inference method based on a generalized difference-in-differences setting to build the average treatment effect and use subsampling to construct confidence intervals.[14] The results presented in Figure 9 confirm the negative impact of the Chinese lockdown on the exports of firms importing from China. In unreported regressions, we show this result is robust if one compares treated firms to their 1-nearest neighbor, or if we use covariates matching from Mahalanobis' metric rather than propensity score matching.

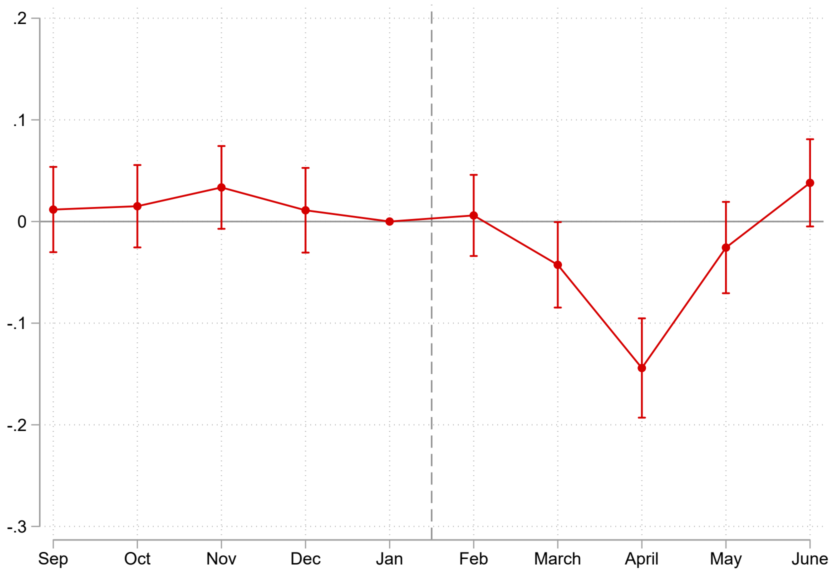
These results thus confirm that the estimated impact of the Chinese lockdown on exposed firms' exports is robust to changes in the definition of the control group and the estimation strategy. We now use two additional placebo exercises to check that the results are not driven by seasonality and do not reflect a specific adjustment of firms involved in GVCs (whether importing from China or not).

One may indeed wonder whether imports from China display some specific seasonality that could explain the dynamics of trade that is 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 10 shows that

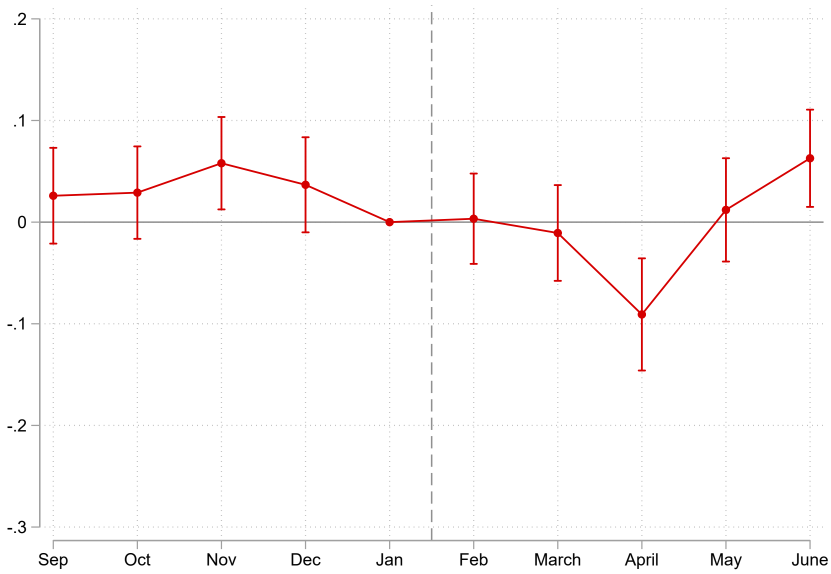
[14] More specifically, the average treatment effect $k \in [-5, 5]$ months after the shock is the sample average among treated of $Y_{i,k} - \hat{Y}_{i,k} - (Y_{i,-1} - \hat{Y}_{i,-1})$, where $\hat{Y}_{i,k}$ is the average outcome among firms chosen as control for treated firm i. As bootstrap cannot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

Figure 8: Impact of the Chinese lockdown on firm-level exports: Alternative control groups

Control group: Excluding EU15 importers

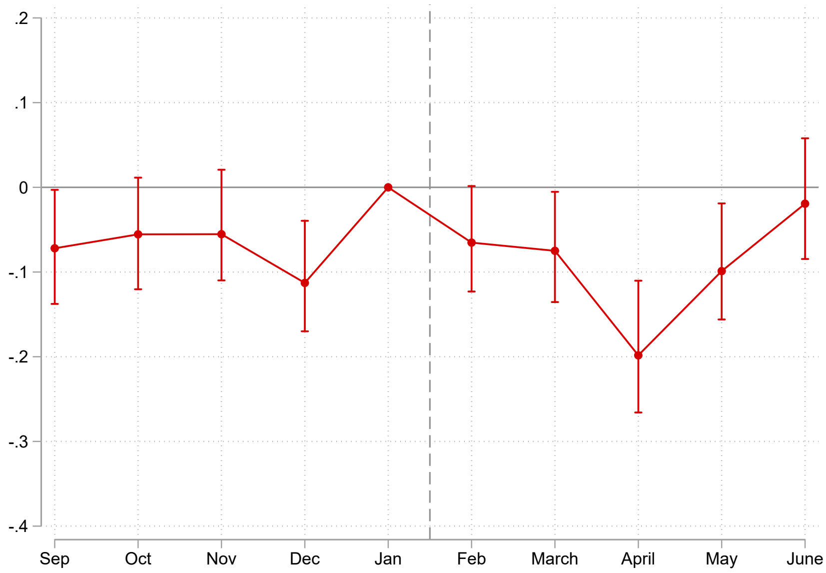


Control group: Other emerging countries



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 9: Impact of the Chinese lockdown on exports: Robustness based on propensity score matching and subsampling

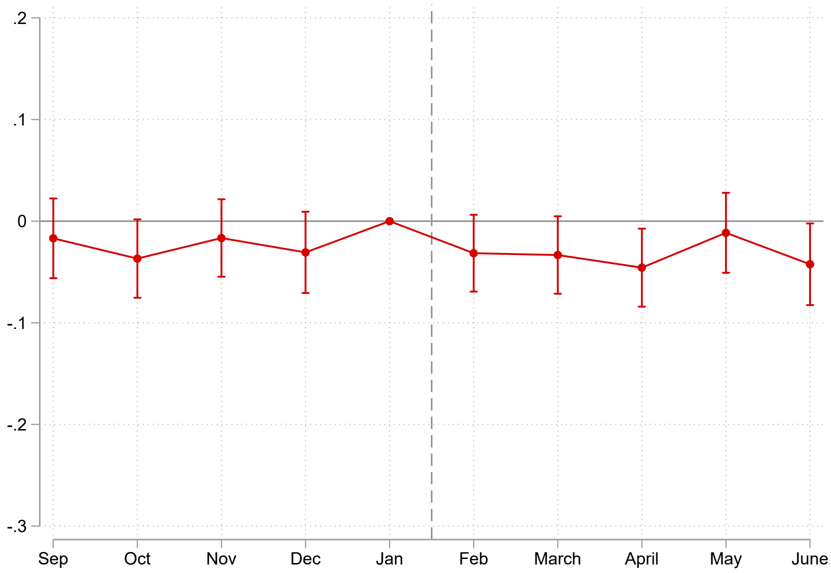


Note: Alternative to the baseline dynamic treatment effect analysis on firm-level exports where the effect $k \in [-5, 5]$ months after the shock is the sample average over the 14,800 treated firms of $Y_{i,k} - \hat{Y}_{i,k} - (Y_{i,-1} - \hat{Y}_{i,-1})$, where $Y_{i,k}$ is the (observable) outcome for treated firm i and $\hat{Y}_{i,k}$ is the average outcome among firms chosen as control i. Four controls are selected by propensity score matching. Inference is conducted using subsampling, using 500 repetitions with a tuning parameter $R = 3$ (Politis and Romano, 1994). The DiD specification pooling all periods before and all periods after the shock estimates an average effect of -.032 with a 95% confidence interval at $[-.063, .006]$. The same specification but on imports produces $-.082 \in [-.11, -.048]$.

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 that started in early 2020.

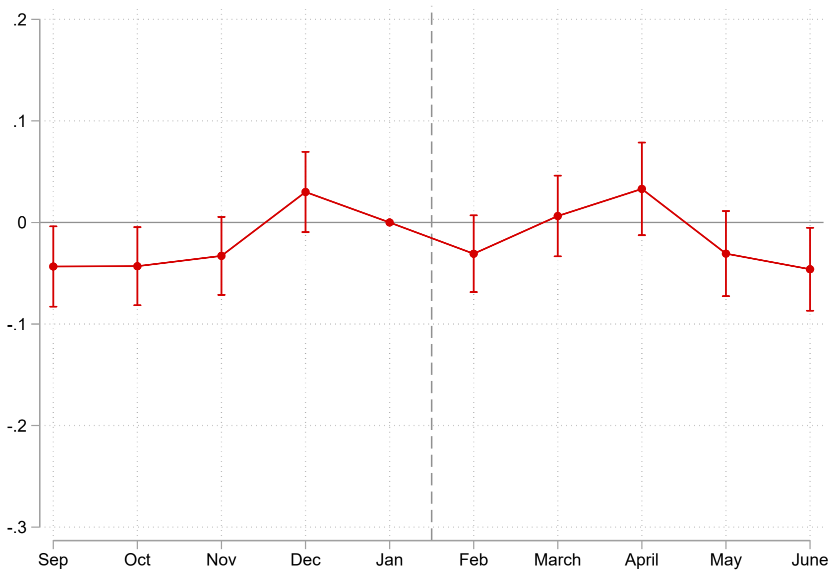
Finally, one may also suspect that the identified effect is attributable to the Covid crisis quickly disturbing production processes in complex value chains, which may produce the dynamics in Figure 7 if firms importing from China are systematically more likely to have sophisticated supply chain structures. Whereas the use of various control groups, including those based on propensity score matching, is meant to control for this possibility, we conclude the robustness analysis with a last test in which we define 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

Figure 10: 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 11: 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%.

lockdown, we shall see no 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 11 shows that it is not the case. Namely, 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.

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 from 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. Would firms systematically source their inputs from at least two suppliers localized in different countries, the transmission of shocks hitting one of these suppliers would be muted by substitution away from the impacted supplier. In this section, we investigate this statement, asking whether firms that were ex-ante diversified performed better once hit by the Chinese lockdown shock.

Measuring diversification is not straightforward though, in the absence of information regarding the substitutability between inputs. We define a firm as being *potentially* diversified if it imports the same product from two different countries prior to the shock. We first tag an input as diversified if it is imported by the firm from more than one country between September 2019 and January 2020. A firm is then diversified if its main inputs (accounting for more than 1% of firm-level imports) are diversified.[15] In the baseline sample, slightly more than 40% of 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.

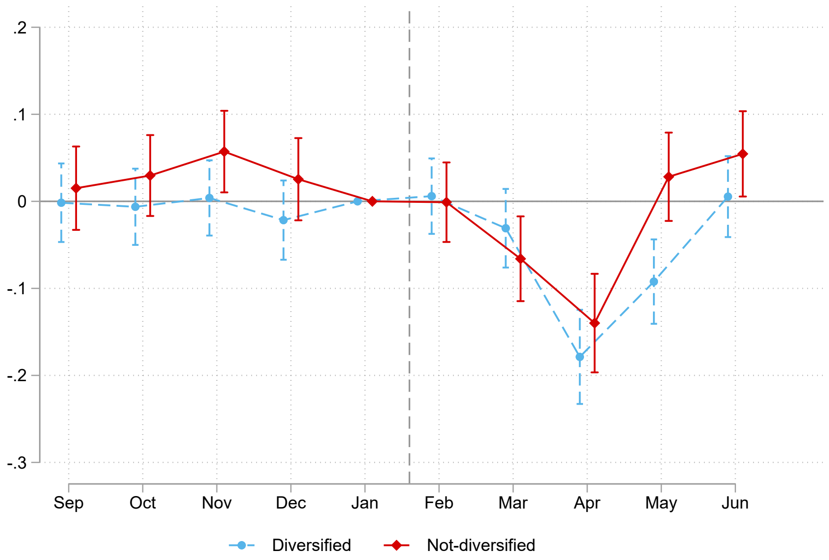
Figure 12 shows that, among firms exposed to the Chinese shock, diversified firms have not performed better than the others. We verify in the first two columns of Table A1 that this result is robust to our definition of the treatment group. We have further tried a variety of alternative metrics of diversification that all lead to the same result.[16] To understand this absence of effect, 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.6 in appendix), which is consistent with the main finding that ex-ante diversified firms have similar export performances as non-diversified firms.

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 at least two reasons for this negative result. First, we may not be able to properly identify 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 its 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

[15] 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.

[16] We increased the threshold of 1% of firm-level imports to 5 and 10%. We have also computed the share of imports diversified inputs amount to, and tried various thresholds to split firms along this continuous measure into diversified or not.

Figure 12: Diversification and firm-level exports: "T1"



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 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.

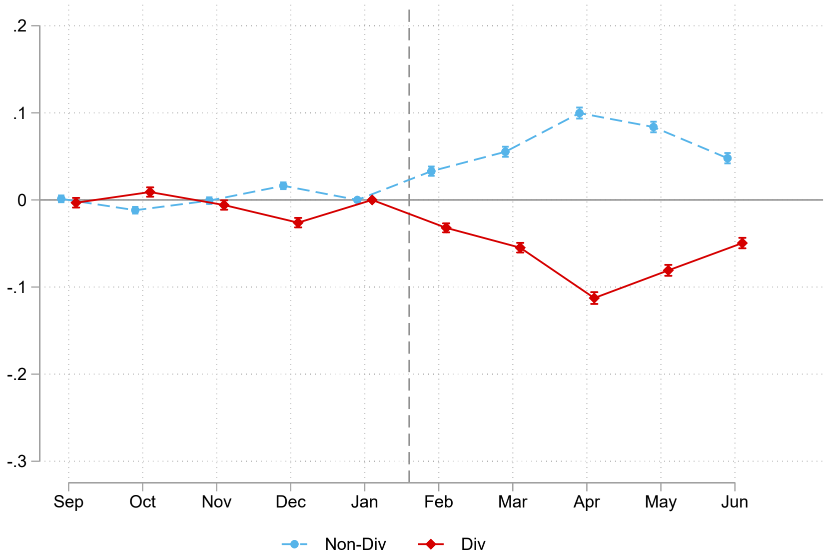
a particular (8-digit) category. But there is no way we can actually check that it is the case.[17] **we could add (eventually in the footnote) that we do not see a significant raise in imports from the rest of the world for diversified firms after the shock, which points towards inputs within a product category being poor substitutes.**

Another possibility is that firms that do no diversify 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 12 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 13 provide some support for this interpretation. Namely, Figure 13 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

[17]The best we can do is to restrict the analysis to diversified inputs that are classified as homogenous by Rauch (1999) or less sticky according to Martin et al. (2020), which arguably are more substitutable across input providers. None of these restrictions changes our qualitative result: even among more homogenous products, diversified firms do not show significantly different trade patterns as non-diversified firms.

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.

Figure 13: Diversification and firm×product-level suppliers: “T1”



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 using P. Guimaraes' *poi2hdfe* Stata command (2014). 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. To this aim, the estimation sample is merged 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, which represent more than 90% of the sample. Second, the inventory variable does not distinguish between inputs and output.[18] Using the variables in the balance-sheet data, we first define a dummy for firms displaying a relatively high level of inventories in 2018. Under the assumption that inventory strategies are relatively 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 14 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.[19] 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.[20]

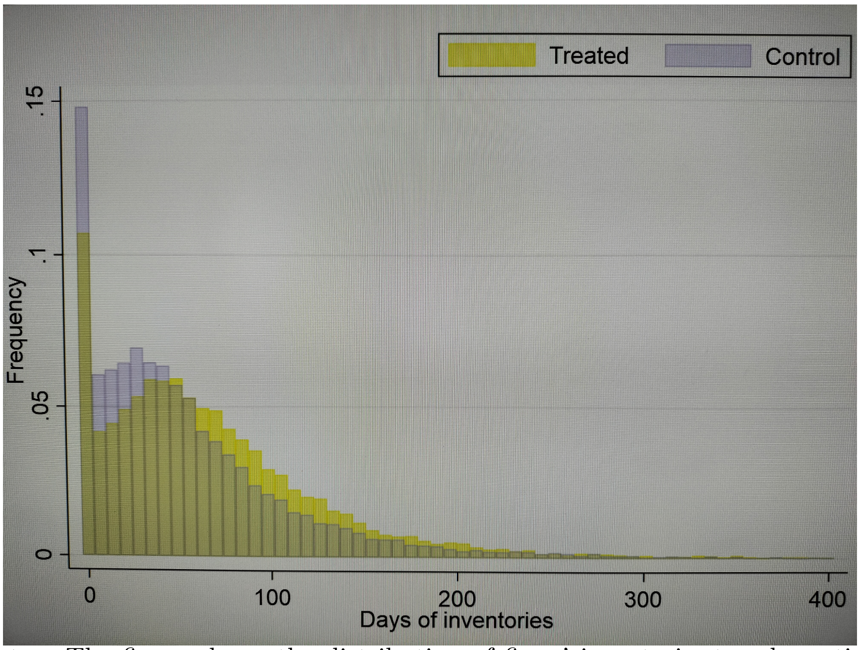
Results of the heterogeneity analysis are summarized in Figure 15. They are based on a variant over equation (1), using either the log of imports (upper panel) or the log of exports (bottom panel) as left-hand side variable and distinguishing between the dynamics of trade of high-inventory and low-inventory firms. The dynamics of imports is not significantly different in both groups, and very similar than in Figure 5. The similar patterns are to be expected as inventories do not protect against input shortages. Instead, their impact is expected 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 which is observed in the bottom panel of Figure 15. For firms with a high level of inventories, the dynamics of exports is not significantly different

[18] 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.

[19] 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.

[20] 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 14: 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.

in the treatment and the control groups. Instead, firms exposed to the Chinese lockdown that display low levels of inventories see their exports decline in relative terms with respect to unexposed firms.

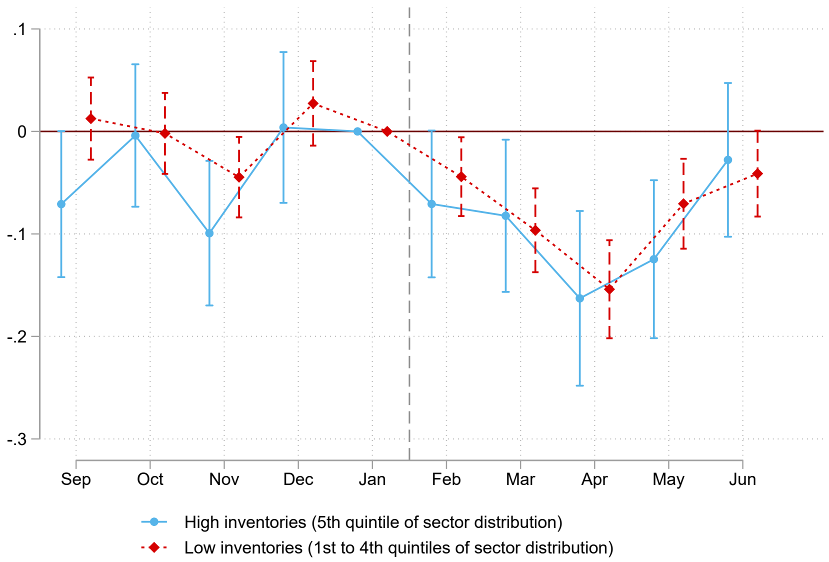
To our knowledge, such evidence of an heterogeneous transmission of the supply chain shock to the rest of the value chain, among firms with different levels of inventories is new to this paper. These results offer empirical support to the statement that holding more inventories can be an efficient strategy to cover against (short-lived) supply chain disruptions. Firms' adjustment to the Chinese shock happens along the extensive margin. Firms temporarily stop exporting some products toward some destinations.

5 Conclusion

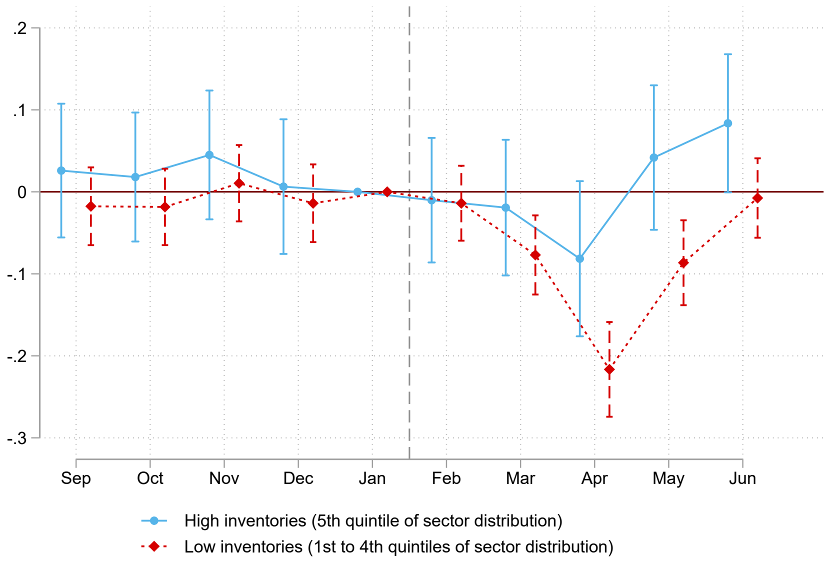
This paper uses detailed firm-level data to gauge the transmission of supply shocks along global value chains. We find French firms sourcing inputs from China just before the early lockdown in the country experienced a drop in imports between February and April 2020 that is 7% larger than firms sourcing their inputs from elsewhere. This shock on input purchases transmits to

Figure 15: Impact of the Chinese lockdown, on low- and high-inventory firms

Impact on imports



Impact on exports



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%.

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 confirm the popular ideas than efficient stock management may be an efficient buffer against supply chain disruptions.

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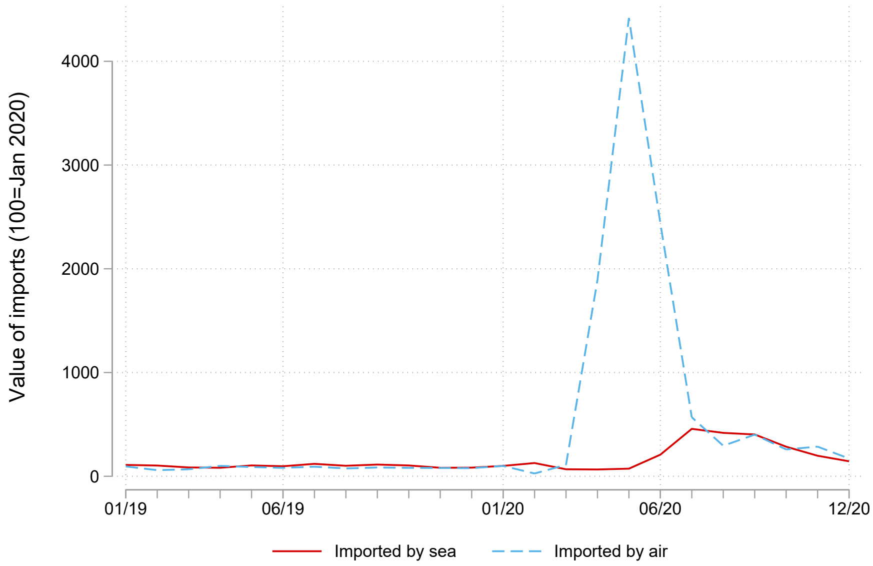
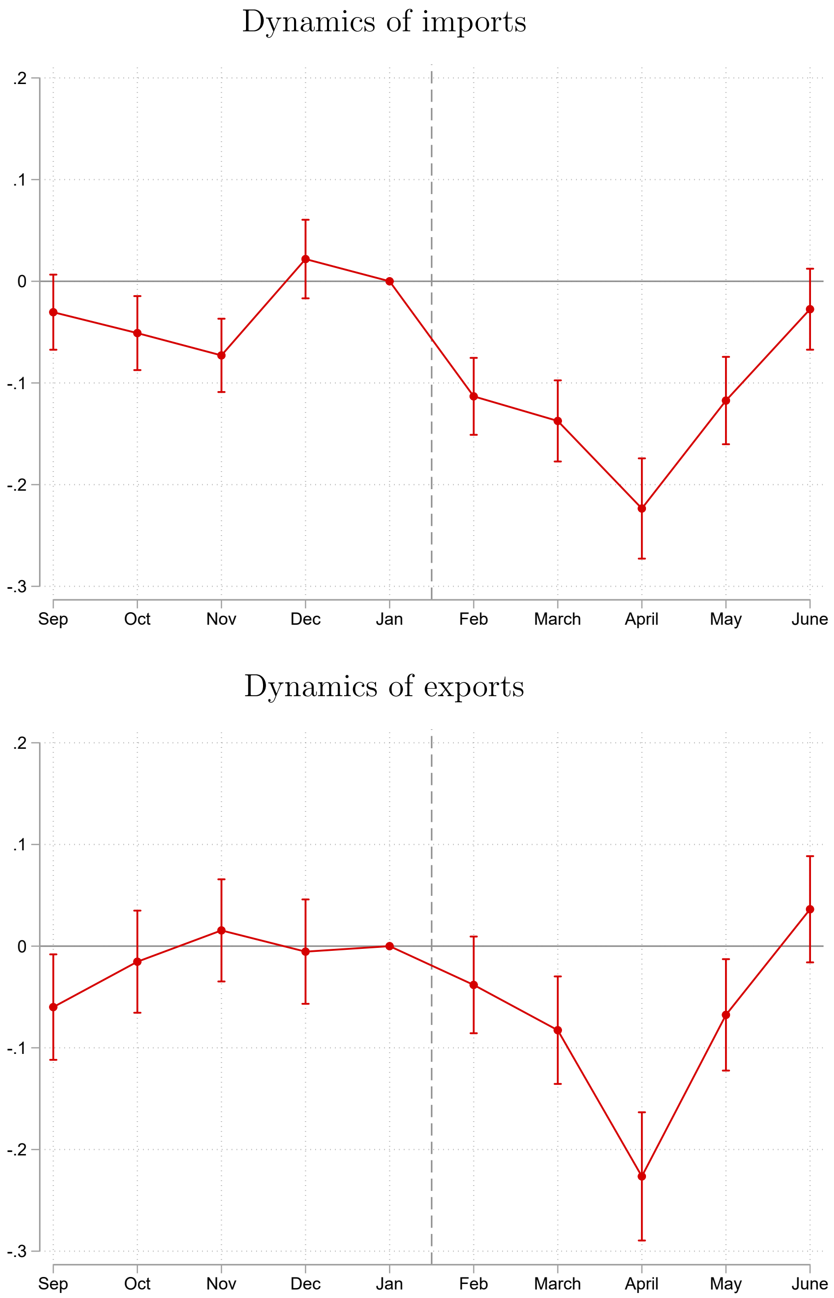
Figure A.1: French imports of covid products from China by transport mode



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.

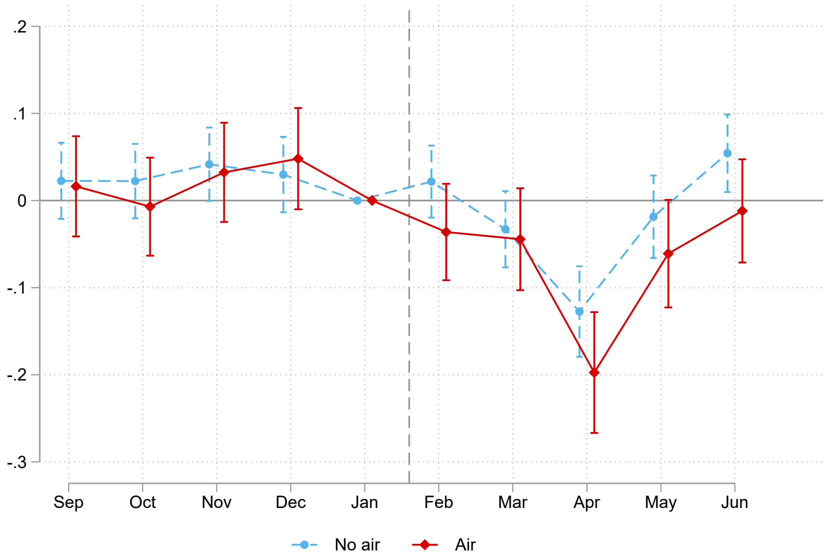
Appendix

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



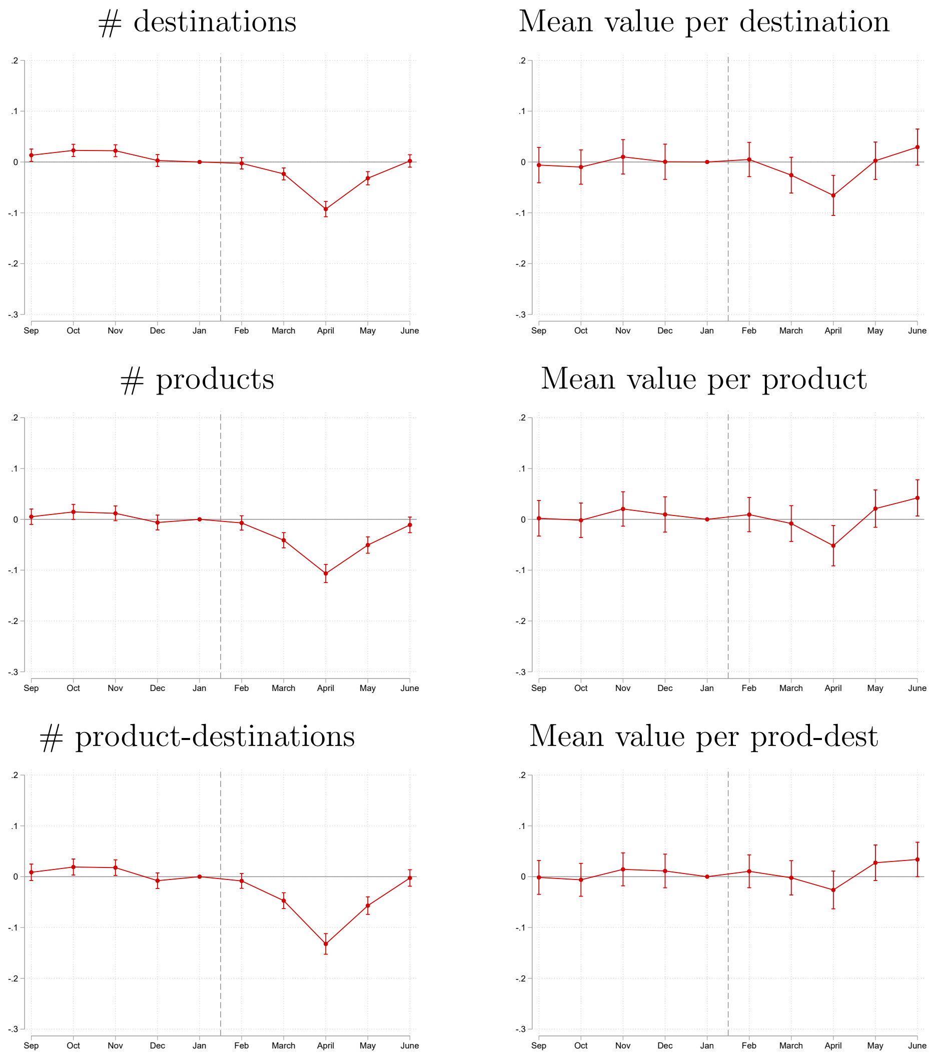
Notes: The figure shows the dynamics of imports (top panel) and exports (bottom panel) before and after the Chinese lockdown for treated firms in comparison with the control group. The treatment is based on monthly imports from China between September 2019 and January 2020 (T2) and the control corresponds to monthly importers from a third country. 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.

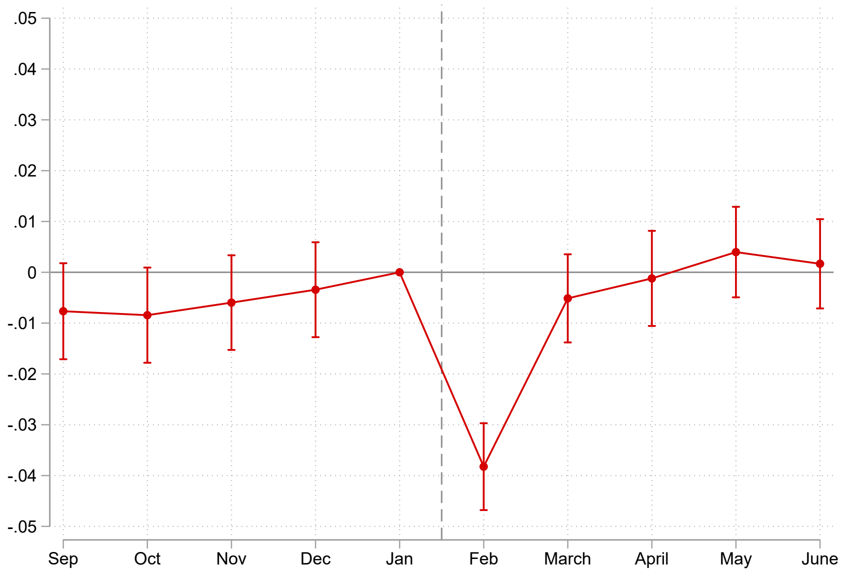
Figure A.4: Effect of the Chinese lockdown on exports: Intensive versus extensive adjustments



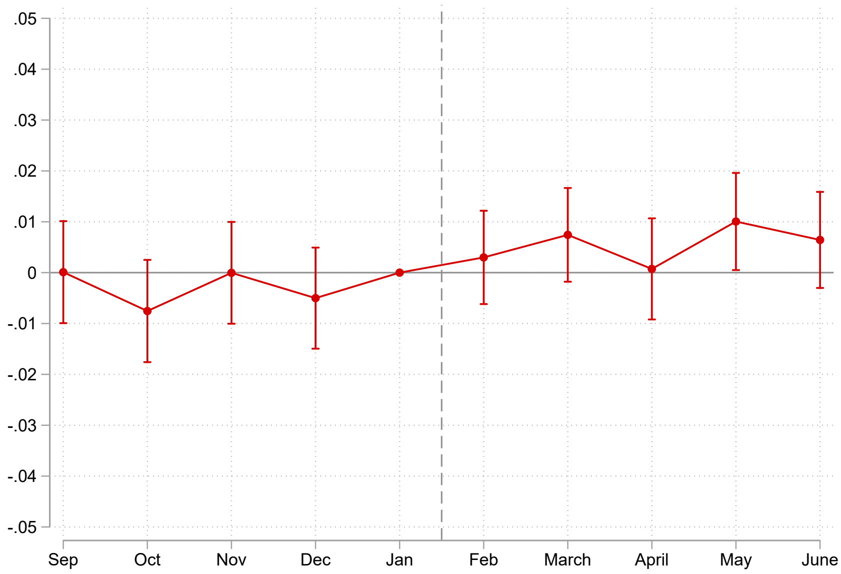
Note: The figure shows the results of the event-study estimation, using the intensive and extensive components of firms' exports as left-hand side variable. The corresponding difference-in-differences estimates are summarized in Table 4, top panel. All specifications include firm and period fixed effects.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

Importer



Exporter



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

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

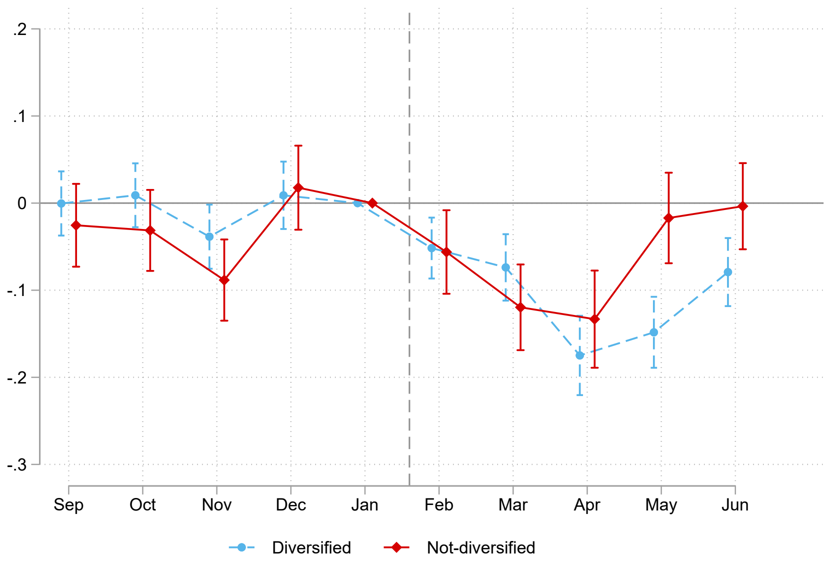
with $\mathbb{1}_{ft}$ that is equal to one when firm f displays strictly positive imports (Top Panel) or exports (Bottom Panel) in period t.

Table A1: Diversification, Stickiness and differential impact of the shock

	Dep.Var: log of exports			
	Diversification		*Stickiness*	
	T1	T2	T1	T2
Treatment×Post	-0.047^{a}	-0.050^{b}	-0.048^{a}	-0.053^{a}
	(0.013)	(0.020)	(0.013)	(0.020)
–×–×Div	-0.002	-0.020		
	(0.016)	(0.025)		
–×–×Sticky			-0.000	0.013
			(0.016)	(0.025)
Fixed Effects				
Firm	Yes	Yes	Yes	Yes
Period	Yes	Yes	Yes	Yes
# Obs	234,482	109,023	234,482	109,023
R^2	0.857	0.879	0.857	0.879

Note: The table reports results of difference-in-differences estimations on exporting firms. "T1" means that control group are firms that import inputs from abroad outside of China whereas treated firms are those exposed to Chinese inputs in the five months before the pandemic. "T2" means that control group is firms that import inputs monthly from a specific country which is not China and treated 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 in "diversified" and "non-diversified", and "sticky" and "not-sticky". Diversified is same as Fig. A.6-??. Treated firms are labeled "sticky" when the weighted average stickiness of their import basket in the pre-period ranks above the median among treated firms. The specification here in Columns 1-2 (resp. 3-4) tests whether "diversified" (resp. "sticky") firms do better in mitigating the shock. Standard errors are clustered at the firm-level. ^{a}, ^{b} and ^{c} denote significance at the 1, 5 and 10% level respectively.

Figure A.6: Diversification and firm-level imports: “T1”



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.