



**Centre for
Economic
Performance**

Discussion Paper

ISSN 2042-2695

No.1771

May 2021

The trade impact of the Covid-19 pandemic

Xuepeng Liu
Emanuel Ornelas
Huimin Shi

Abstract

Using a gravity-like approach, we study how Covid-19 deaths and lockdown policies affected countries' imports from China during 2020. We find that a country's own Covid-19 deaths and lockdowns significantly reduced its imports from China, suggesting that the negative demand effects prevailed over the negative supply effects of the pandemic. On the other hand, Covid-19 deaths in the main trading partners of a country (excluding China) induces more imports from China, partially offsetting countries' own effects. The net effect of moving from the pre-pandemic situation to another where the main variables are evaluated at their 2020 mean is, on average, a reduction of nearly 10% in imports from China. There is also significant heterogeneity. For example, the negative own effects of the pandemic vanish when we restrict the sample to medical goods and are significantly mitigated for products with a high "work-from-home" share or a high contract intensity for products exported under processing trade, and for capital goods. We also find that deaths and lockdowns in previous months tend to increase current imports from China, partially offsetting the contemporaneous trade loss, suggesting that trade is not simply "destroyed," but partially "postponed."

Key words: trade flows, covid-19, lockdown, stringency, China
JEL codes: F14

This paper was produced as part of the Centre's Trade Programme. The Centre for Economic Performance is financed by the Economic and Social Research Council.

We thank Joao Paulo Pessoa and participants at the Economics Seminar at Kennesaw State University for comments and suggestions.

Xuepeng Liu, Kennesaw University. Emanuel Ornelas, Sao Paulo School of Economics, CEPR, CESifo and Centre for Economic Performance, London School of Economics. Huimin Shi, Renmin University of China..

Published by
Centre for Economic Performance
London School of Economics and Political Science
Houghton Street
London WC2A 2AE

All rights reserved. No part of this publication may be reproduced, stored in a retrieval system or transmitted in any form or by any means without the prior permission in writing of the publisher nor be issued to the public or circulated in any form other than that in which it is published.

Requests for permission to reproduce any article or part of the Working Paper should be sent to the editor at the above address.

1 Introduction

The Covid-19 pandemic has drastically affected lives and livelihoods and, in the process, has also disrupted economic activities throughout the world. In this paper, we consider the effects of the pandemic on China's exports to worldwide, i.e., global imports from China in 2020. Worldwide trade flows decreased in 2020 relative to 2019, and this fall has, naturally, been associated with the pandemic.¹ However, the channel of causation is not unidimensional. Rather, there are several dimensions to the pandemic that are likely to affect international trade: its direct health impact and the associated behavioral changes on affected countries; the consequences of the actions that governments took to prevent the spread of the virus; and third-country effects due to the impact of the pandemic there. We provide what we believe are the first estimates of how each of these channels affected international trade flows in 2020, viewed through their impacts on imports from China.

Our empirical approach is conventional and straightforward. We carry out a gravity-like estimation with measures of a country's own covid incidence, own lockdown restrictions, and the same variables for the country's main trading partners. Our dependent variable is the monthly year-over-year growth of imports from China for all destinations to which China exported in 2019 and 2020, at the product (HS 6-digit) level. We find that the direct effects of covid incidence (as given by the number of deaths per capita) and of covid-induced government measures (as given by an index of the stringency of lockdowns) are clearly negative. This is probably unsurprising, but the magnitudes of the effects are worth highlighting. For example, according to the point estimates of our baseline specification, relative to the 2019 situation with no Covid-19 deaths, a country with 0.63 Covid-19 deaths per one thousand people in a month (the highest level achieved in our sample excluding micro-states, for Slovenia in December 2020) would experience a reduction of 13 percent of imports from China. Similarly, moving from no lockdowns to the maximum level of lockdown stringency in the sample (for Honduras in April and May, and Philippines in April) would generate a reduction of 17.6 percent of imports from China. This illustrates the finding that government measures to curb economic activities tend to have a large effect on a country's imports, even larger than the direct health and behavioral impacts of the pandemic.

¹According to the World Trade Organization (WTO), world merchandise trade declined by 7% in 2020 (https://www.wto.org/english/news_e/pres21_e/pr876_e.htm).

Perhaps even more surprising is our finding that, although on average lockdowns in third countries do not have a significant effect on a country's imports from China, the direct effect of Covid-19 in third countries does. Specifically, more deaths in the main trading partners of a country (excluding China) induces that country to import significantly *more* from China than otherwise it would. Interestingly, the positive effect coming from covid incidence in the main trading partners more than offsets the own negative covid incidence effect.

It is important to stress that, although it seems sensible to expect negative trade effects due to the pandemic, in principle the effect could go in either direction. The reason is that, as first pointed out at the onset of the pandemic by Baldwin and Tomiura (2020), the pandemic consists of a joint supply and demand shock. Since both are negative, the resulting impact on a country's import demand—defined as the difference between its domestic demand and domestic supply—is a priori ambiguous. On one hand, the health shock incapacitates some workers and causes preventive reactions by firms and workers, decreasing labor supply and the domestic supply of goods. Similarly, lockdown measures have a direct negative impact on domestic supply. By itself—that is, for a given level of domestic demand—this tends to increase the demand for imports. On the other hand, demand falls as workers are laid off, and as precautionary motives compel consumers to postpone consumption and firms to suspend investment plans. All of those decrease domestic demand, and therefore also the demand for imports. The net effect is therefore ambiguous. The repercussions of the pandemic in other trading partners of a country on its own demand for imports from one specific country (China, in our case) is similarly ambiguous. On one hand, if supply-side restrictions due to the pandemic (e.g., closure of port and airport facilities) make it harder for the country to import from them, its residual demand for imports from China increases. On the other hand, if demand falls more than supply in third countries, this “excess” of supply will be met by additional exports to the country, possibly outcompeting exports from China.

We seek to resolve these ambiguities, at least partially, by analyzing countries' imports from China, the world's largest exporter in goods. Our results indicate that the negative own demand effect on countries' imports from China prevails over the negative own supply effect, thus decreasing imports from China. This happens both because of the direct impact of the pandemic and because of lockdown-induced effects. In turn, the negative supply effect due to the direct impact of the pandemic on a country's trading partners prevails over possible negative demand effects. This

reduces a country’s imports from third countries and indirectly increases its imports from China.

Naturally, these are average effects, and there are important sources of heterogeneity, across products and countries. We explore several such possibilities. For example, the negative effects of the pandemic all but vanish when we restrict the sample to medical goods, highlighting that they follow a very idiosyncratic dynamic during the pandemic. The negative effects are also significantly mitigated for products that have a higher “work-from-home” share, for which a higher share of their value can be produced remotely. A similar weaker effect is present for goods with a high contract intensity, for which long-term relationships are more important (and hence disruption would be more costly), and for goods exported under processing trade. On the other hand, the negative results are more pronounced for durable consumption goods. The results for the average product apply in a similar fashion for intermediate goods, but less so for capital goods, for which long-term planning implies a different reaction to the temporary shock due to the pandemic.

Interestingly, the results for the average country are driven mainly by non-OECD countries. By contrast, in OECD members the impact of lockdown stringency reverses, indicating that domestic demand fell by less than domestic supply (or even increased), thus inducing an increase in imports from China. It is conceivable that this could reflect the fiscal policies that governments used to compensate workers and firms affected by the pandemic, which were generally much more generous in rich countries than in developing ones. However, when we introduce covid-related fiscal measures directly in our regression, the results hardly change. The results are also virtually unchanged when we exclude the U.S.—which has been engaged in a trade war with China since 2018—from the analysis, or when we exclude products affected by pandemic-related trade policies.

On the other hand, we do observe an important path-dependence: while the trade effect of the pandemic in a country in a month is negative, incidence of the shock in previous months has a positive effect on current trade volumes. This suggests that, over time, contemporaneous negative effects tend to be partially reversed, so that trade is not simply “destroyed,” but is partially “postponed.” Finally, we do not find evidence that trade at the extensive margin suffers; the effect appears to be concentrated on the intensive margin, on which our analysis focuses. This pattern is similar to what has been found for the “great trade collapse” that followed the financial crisis of 2008.²

²For example, using Belgium firm-level data, Behrens et al. (2013) find that nearly all of the fall in trade in that

The “hub” from which all imports in our sample come is China. The main reason why we use imports from China, and not from other countries, is that China’s monthly trade data up to December 2020 is already available. To the best of our knowledge, this makes our paper the first to evaluate the trade effects of the pandemic for 2020 as a whole. Now, if it is to take the perspective of one country’s trade with the rest of the world, China is presumably the best choice. First, because China has trade relationships with every other economy and is, by some margin, the largest exporter in the world, accounting in 2019 for 13.6% of world’s exports, according to the WTO’s World Trade Statistics 2020.³ Second, it has a particular advantage directly related to the pandemic. China suffered the most with Covid-19 in the first quarter of 2020, when the rest of the world was only starting to experience the consequences of the spread of the virus. From the second quarter onwards, which is when our variables of interest depart more significantly from zero, the situation reversed and China’s economy recovered swiftly. In fact, China’s GDP grew by 2.3% and its aggregated exports grew by 4% in the year, whereas no other major economy experienced positive growth. Thus, in the more relevant period for our estimation, between April and December, the main covid-related impediments of trade with China stemmed from (if not exclusively, at least largely) the situation of the pandemic in China’s trading partners. This avoids the difficulties of distinguishing between pandemic-related factors in exporting and importing countries, which is useful especially if there were interaction effects between them. Our analysis is therefore exclusively on the effects of the pandemic on countries’ imports.

Naturally, the Covid-19 pandemic has spurred a torrent of research on its various consequences, and trade is not an exception. Some of this research has developed structural models, sometimes merged with epidemiological models, to study the trade and welfare consequences of the pandemic and their interaction with global trade. A prominent example of this line of research is Antràs et al. (2020). Another strand of the literature, in which this paper fits, focuses instead on empirical studies following the approach of standard gravity analyses. While the details of the empirical approach—the level of aggregation, the types of goods studied, the data coverage—and the specific questions vary, the general goal of this line of research is to explore Covid-19’s impact on trade

episode happened at the intensive margin. Bricongne et al. (2012) obtain similar results for French exporters. Bems et al. (2013) provide a review of the literature on the great trade collapse. This is not to say that the two shocks had similar global effects, however. As Le Moigne and Ossa (2021) point out, in aggregate, world trade has displayed much greater resilience in 2020 than during the trade collapse of 2008-2009.

³https://www.wto.org/english/res_e/statis_e/wts2020_e/wts2020_e.pdf (see Table A4).

flows.

Some of these empirical studies focus on China (Che et al., 2020; Friedt and Zhang, 2020; Pei et al., 2021), but their data go only until mid-2020, thus stopping before the end of the first wave of the pandemic.⁴ Others use datasets from other specific countries, like Kenya (Socrates, 2020), from regional groups of countries, like the EU (Kejzar and Velic, 2020), or for multiple economies (Bas et al., 2021; Berthou and Stumpner, 2021; Espitia et al., 2021; Hayakwa and Mukunoki, 2021). A common finding is that the pandemic has negatively affected international trade flows, although the details of the results vary significantly across papers.

An important distinction between our paper and the existing empirical literature is that we use both Covid-19 death cases and lockdown policies while most existing papers focus on one or the other. While Covid-19 deaths are an intuitive proxy for the impact of the pandemic, it is well known that lockdowns (of various degrees of stringency) are implemented as a reaction to the pandemic, often exactly when the number of deaths is high or is expected to rise soon. As a result, studying either variable in isolation can lead to misleading results, for example with artificially large negative effects associated to Covid-19 deaths due to the omission of lockdown measures—and vice-versa. Like us, Bas et al. (2021) also use both Covid-19 deaths and lockdown stringency throughout their analysis. They use monthly import data for the U.S., Japan, Germany and France until July 2020, and conclude that the negative trade impact of the pandemic on these four countries stems mainly from inputs whose supply relies on China and that requires a high degree of customization.

Another key contribution of our paper is to take explicitly into account the influence of the pandemic in the rest of world on bilateral trade flows. The motivation for considering third countries in a gravity estimation context goes back the discussion of multilateral resistance by Anderson and Wincoop (2003), while the idea that shocks in a country will have repercussions in trade between other countries is the backbone of general equilibrium trade models. Yet most existing papers have not considered such effects.⁵ We find that they are quantitatively very important.

⁴Friedt and Zhang (2020) use China’s exports data until May 2020 at the province-country-product (HS2) level and find that China’s exports are very sensitive to foreign countries’ new cases and domestic new cases. Che et al. (2020) use China’s export data until May 2020 at the country-product (HS6) level and find that China’s exports decline when foreign cases increase, especially for processing trade and products that are more upstream. Pei et al. (2021) use data up to April 2020 for China’s exports at the city-country level to investigate how local lockdowns affect exports, finding that Chinese cities under lockdown experience a 34 percentage-point reduction in year-over-year export growth rate.

⁵We know of two exceptions. Berthou and Stumpner (2021) use trade data from 31 reporting countries with the rest of the world until November 2020. They concentrate on the influence of lockdown policies, and in a robustness

A limitation of our analysis is that we do not investigate the role of global value chains (GVCs) in shaping the impact of the epidemic on trade flows. The reason is two-fold. First, our empirical strategy is designed to explain variation within (6-digit) products, whereas to study GVCs properly one needs to consider variation across products in different stages of the production process, and most of the available GVC databases are at a highly aggregated manufacturing sector level, constrained by national and international input-output tables. Second, several other authors have focused precisely on that dimension, with rich frameworks and interesting insights.⁶ We see our within-product analysis as complementary to those studies. Another limitation is that we study only countries’ imports from China, our “hub” country, while the response of countries’ imports from other countries to Covid-19 can, of course, be different. Nevertheless, to draw a more complete picture of the pandemic’s trade effects, we also consider the repercussion effects arising from covid-related deaths and lockdown policies in third countries.

The remainder of the paper is as follows. In section 2, we discuss the data. In section 3, we explain our methodology. In section 4, we discuss the results. We conclude in section 5.

2 Data

We use China’s monthly export data at the HS 8-digit level over January 2019-December 2020, obtained from China Customs Statistics. Our dataset covers all of the 242 destination countries or regions that China exported to in 2019 and 2020. Starting in 2020, China’s Customs report the combined January and February data, rather than for each individually. Thus, we also combine January and February’s data of 2019 and consider it as one month. We aggregate our data to month-destination-product (HS6) level and control for China’s specific factors over the year with year-month fixed effects. We carry out the analysis at the HS 6-digit level, instead of doing it at

specification construct a similar measure for third-country stringency, although not for Covid-19 incidence variables. They find a significant positive effect of third countries’ lockdowns. Espitia et al. (2021) also consider a third-country effect, but in a very different way, based on changes in third countries’ industrial output, and without using Covid-19 variables.

⁶For example, Bonadio et al. (2020) model the pandemic-induced lockdown as a labor supply shock, studying quantitatively its trade and welfare impacts through input-output linkages that transmit the shock across countries through GVCs. Based on a quantitative Ricardian model including input-output features, Eppinger et al. (2021) analyze the influence of GVCs in mediating countries’ exposure to foreign shocks and how “decoupling” would affect those effects. Sforza and Steininger (2020) calibrate a Ricardian model with production networks with data from the first quarter of 2020, showing that the transmission of the Covid-19 shock through production networks magnifies the global impact of local supply disruptions. There are also authors who investigate the role of GVCs in the Covid-19 shock with reduced-form approaches (e.g., Hayakawa and Mukunoki, 2021, and Kejzar and Velic, 2020).

the 8-digit level, for two reasons. First, product classifications at higher than 6-digit levels are not internationally comparable. Second, some variables that we use in our analysis are also defined at the HS 6-digit level. At this level of aggregation, the number of observations in our analysis is already close to 2 million.

The Oxford Covid-19 Government Response Tracker (OxCGRT), compiled by Hale et al. (2021), systematically collects publicly available information on many covid incidences (cumulative cases, death cases, tests) and policy indicators.⁷ There are nine indicators, which record information on containment and closure policies, such as school and workplace closures and restrictions in internal and international movement.⁸ Based on these indicators, a stringency index is constructed to measure the strictness of “lockdown style” policies that primarily restrict individuals’ behavior. The original stringency index ranges from 0 to 100. We rescale it by dividing the original index by 100 to help the interpretation of estimated coefficients in the regressions. The higher the lockdown stringency index (*Stringency*) is, the more restrictions to individuals and to economic activities the country has.⁹

Among all Covid-19 incidence measures collected by OxCGRT, the death-related measures seem the most reliable and internationally comparable both across countries and within countries over time. Other measures, such as number of tests and number of positive cases, are highly dependent on a country’s testing capacity and reporting methods. More importantly, such capacity has changed significantly within countries during 2020. Accordingly, we use the measures of new deaths per thousand people as our proxy for Covid-19 incidence (*CovidD*). The original Covid-19 data from OxCGRT are available at daily frequency. The number of new deaths is smoothed over the last seven days to fill gaps when data is missing for a day. We aggregate the data to the monthly level.¹⁰

⁷Sources: <https://covid.ourworldindata.org/data/owid-covid-data.xlsx> and https://github.com/OxCGRT/covid-policy-tracker/raw/master/data/OxCGRT_latest.csv.

⁸Source: <https://github.com/OxCGRT/covid-policy-tracker/blob/master/documentation/codebook.md>.

⁹The lockdown policy indicators are updated on a bi-weekly basis. The original stringency index is constructed based on nine sub-indexes at daily frequency. The first eight relate to containment and closure: school closing, workplace closing, cancellation of public events, restrictions on gathering size, closure of public transport, stay-at-home requirements, restriction on internal movement, restrictions on international travel. The ninth relates to health systems, which is the public information campaign. For each subcategory, based on the judgement of the policy, a certain number of points is given, and then aggregated to generate the overall stringency index, which ranges from 0 to 100.

¹⁰Occasionally, a country may record a negative number for new Covid-19 deaths to adjust for previous over-reporting. Such negative values become very rare after we aggregate the data to a monthly frequency: they are present for only three country-month pairs among nearly two thousand pairs. We drop those three observations from our regressions.

We argue that a country’s imports from China may be affected not only by the country’s own Covid-19 situation, but also by how the rest of the world (ROW) handles the pandemic. Therefore, we also consider the Covid-19 variables of a country’s trading partners. We construct the ROW measures for both Stringency and CovidD. Specifically, country i ’s *Stringency_ROW* measure is the average stringency of the rest of the world in month t , weighted by country i ’s import share of product p in 2018 from all countries except China.¹¹ That is,

$$Stringency_ROW_{ipt} = \frac{\sum_{j=1}^N M_{ijp,2018} Srtingency_{jt}}{\sum_{j=1}^N M_{ijp,2018}},$$

where $M_{ijp,2018}$ denotes the value of imports of product p by country i from country j in 2018. We use an analogous procedure to construct *CovidD_ROW*. Both variables are defined to vary at the HS6-country-month level. The trade value data of 2018 used as weights are from BACI-CEPII. Because our regressions cover years 2019 and 2020, using the pre-determined trade data in 2018 as weights avoids potential endogeneity problems of bilateral trade.

In our heterogeneous analysis, we use several additional variables defined at the product or the country level. We explain below how each of them is defined and their data sources.

Since we study a health shock, we give special attention to medical goods (MG) in our analysis. The list of covid-related medical goods is provided by the World Customs Organization (WCO), together with the World Health Organization (WHO). We use its 3.01 Edition.¹²

As Bems et al. (2013) show in their review, during the “trade collapse” of 2008-2009, the largest group of goods affected were durable consumption goods. Accordingly, we investigate whether a similar conclusion applies to the current situation as well. We define consumer durable and non-durable goods based on the UN Broad Economic Category (BEC) classification (5th revision).

Also because of the nature of the shock, activities that can be performed from home are affected very differently than those that require physical presence. To make that distinction, we use the work-from-home shares from Dingel and Neiman (2020) and Bonadio et al. (2020). Dingel and Neiman (2020) calculate the work-from-home share at the occupational level. Based on it, Bonadio et al. (2020) compute the sectoral work-from-home intensity measure from the average of Dingel

¹¹We also exclude Hong Kong, SAR, and Macau, SAR, because they are entrepots handling mainly the exports of mainland China.

¹²Source: http://www.wcoomd.org/-/media/wco/public/es/pdf/topics/nomenclature/covid_19/hs-classification-reference.edition-3_es.pdf?la=en.

and Neiman (2020)’s, weighted using sectoral level expenditure shares on each occupation. We use the concordance between ISIC Rev.4 and ISIC Rev.3 and the concordance between HS 2017 and ISIC Rev. 3 to calculate the HS6 level work-from-home intensity following Bonadio et al. (2020).¹³

Another product-level feature that may lead to heterogeneous effects of Covid-19 on trade is the level of contract intensity, which determines how much relationship-specific capital is required to establish a trading relationship. We use the measure of contract intensity constructed by Nunn (2007), which corresponds to the share of intermediate inputs that require relationship-specific investment. We convert Nunn (2007)’s original data at the 3-digit level of ISIC Rev. 2 to the HS 2017 at the 6-digit level.

The trade modes in which products are exported could also yield different responses from the pandemic, because the level of relationships may vary depending on the trade regime. Our data from China Customs Statistics provide information on trade regimes, mainly processing trade and normal trade.¹⁴ Thus, we create the share of processing trade among processing and normal trade at the HS6 product level to investigate whether products exported in that way are affected differently. This share varies at the country-product-month level.

The effects of the pandemic may also vary depending on the position of products along global value chains, because the pandemic is likely to affect firms and families differently. To investigate that possibility, we use the UN BEC 5th Revision data to distinguish goods between capital goods, intermediate goods, and final goods for consumption, evaluating them separately.¹⁵

In addition to the covid-related deaths and the stringency index, we also take advantage of data collected by OxCGRT on worldwide government responses to the pandemic in the form of economic support policies. The economic support index records measures such as income support to those who lose jobs or cannot work, as well as debt relief.¹⁶ The original economic support index

¹³Concordance between ISIC Rev. 4 and ISIC Rev. 3 is from the WIOD SEA Source and Methods, <http://www.wiod.org/database/seas16>, pp. 26-27. Concordance between HS 2007 and ISIC Rev. 3 are obtained from the WITS, https://wits.worldbank.org/product_concordance.html.

¹⁴Processing trade refers to the business activity of importing all or part of the raw materials, parts and components, packaging materials from abroad in bond (i.e., duty-free), and re-exporting the finished products after processing or assembly by firms within China. Besides processing trade and normal trade, there are more than a dozen other minor trade regimes, but they only account for about 13% of total exports in China during 2019-2020, with normal and processing trade accounting for 59% and 28%, respectively. We exclude these minor categories when calculating the share of processing trade.

¹⁵Source: <https://unstats.un.org/unsd/trade/classifications/bec.asp>.

¹⁶Codebooks: <https://github.com/OxCGRT/covid-policy-tracker/blob/master/documentation/codebook.md#economic-policies> and https://github.com/OxCGRT/covid-policy-tracker/blob/master/documentation/index_methodology.md.

is at a daily frequency. We take a simple average to calculate the index at the monthly level, which ranges from zero to about 100 in our final dataset. We rescale it to between 0 and 1 by dividing the original index by 100, similar to the rescaling of the stringency index.

Finally, some countries have implemented trade policies in response to the pandemic. We use the measures compiled by the WTO on temporary Covid-19 related trade policies to investigate whether they affect our estimates.¹⁷ Since our analysis is on the pandemic effects on countries' imports, we only consider import measures, most of which aim to promote imports of selected medical products or materials. For a few cases when a policy applied to all medical goods, we use the WCO-WHO definition of medical goods discussed earlier. We consider the temporary nature of these policies based on their initiation and revocation dates. The trade policy indicators vary by country-product-month.

Table A.1 in the Appendix provides summary statistics for the variables used in our analysis. The data used in our baseline regressions cover a large number of countries/regions (174) and products at the HS6 level (4636) over 12 months of 2019 and 2020 (January and February combined).¹⁸ Naturally, the covid-related variables reflect only the information for 2020, since such data did not exist before 2020. The table shows that there is substantial variation in both our dependent and independent variables, including those that we use for the heterogeneity analysis.

Table A.2 in the Appendix shows the pairwise correlations among the four main independent variables. The correlation coefficients among them are all positive, as expected, but are below 0.5 for most of them, except for Stringency and Stringency_ROW, which have a correlation coefficient of 0.6. This indicates that multicollinearity should not be a major concern in our analysis.

3 Empirical Strategy

3.1 Pandemic, Lockdowns, and Trade

We study how worldwide imports from China were affected by the Covid-19 pandemic. Assessing those effects from the perspective of China is useful because, after the Covid-19 outbreak in January

¹⁷Source: https://www.wto.org/english/tratop_e/covid19_e/trade_related_goods_measure_e.htm (as of March 26, 2021).

¹⁸Some countries are covered by our trade data, but not by the covid-related data (mostly constrained by the availability of the stringency index). Nevertheless, our sample coverage of importing countries is among the largest among similar studies.

2020 and the implementation of strict measures to prevent its spread across the country, China was able to restore “almost normal” economic activities relatively early in the year. Since shocks in China affect their trade relationships with all countries and our analysis exploits within country and within country-product variation—as will become clear shortly—this may not appear to be a particularly important advantage. However, if there are interaction effects of the pandemic in importing and exporting countries, then having a “hub” country where the main effects of the pandemic have been circumscribed to the first quarter of 2020 is useful to isolate the effects in the importing countries.

We know that the aggregate level of international trade fell in 2020 because of the pandemic (even if not nearly as much as some analysts predicted initially). It is, however, far less clear how the local effects of the pandemic have affected bilateral trade flows. The reason is that there are potentially opposing forces at work.

Consider first the direct impact of the pandemic on importing countries, which we proxy with the number of covid-related deaths per thousand people. If it is higher, then more workers are getting sick (or dying) and isolating themselves socially, while at the same time more firms slow down (or halt) production and investment to prevent contagion among their workers. On the one hand, these effects reduce domestic income and, for that reason, lower the demand for foreign goods.¹⁹ On the other hand, they also reduce domestic production; for given total demand, this increases demand for foreign goods. Although it has been common to focus on the former (income) effect, in principle each force may dominate. Which one actually prevails is an empirical question, and the answer may depend on factors such as the type of product, the wealth of the country, the position in the global value chain, etc.

Now, as is widely known, governments around the world reacted in different ways to the health crisis, adopting a set of policies aimed at preventing the spread of the virus. In particular, various types of “lockdown” measures have been implemented worldwide. They vary significantly, across countries as well as over time within countries. The most extreme of those policies is a blanket closure of all non-essential economic activities in the country. But there are also partial lockdowns and other localized restrictions on economic activities. Hence, we measure the stringency of those

¹⁹An additional reason for the reduction of import demand is precaution. Given the uncertainty created by the pandemic, consumers may want to postpone consumption and firms may decide to postpone production and investment. This precautionary effect adds to the negative effect on imports.

policies as a continuous variable, as described in section 2. Although most previous related papers have focused on the direct impact of Covid-19, it is essential to account for this indirect, but central, impact of the pandemic on importing countries. First, because without controlling for that reaction the estimates of the effects of Covid-19 will be biased. Second, because it is useful to disentangle the trade effects of the pandemic between its direct and indirect, policy-related, effects. If the stringency measure is higher, it lowers domestic production by design. As a result, both domestic income and domestic supply fall. Hence, just as with covid-related deaths, Stringency has a positive effect (because domestic supply falls) and a negative effect (because domestic demand also falls) on the demand for imports. Again, whether the former or the latter dominates is an empirical question and may as well vary across types of products and countries.

Bilateral trade flows are also affected by factors that go beyond the pair of countries in analysis. In particular, as is well known from the gravity literature, bilateral trade flows are affected by policies in third countries. This is especially important in our context, since we study countries' imports from a single country (China). Surprisingly, this dimension has received very little attention in the literature on trade and Covid-19—the main exception are the studies of the role of GVCs in spreading the effects of the pandemic, as discussed in the introduction. Specifically, if the main sources of imports of a country are strongly affected by the pandemic and by policies to mitigate its impact, there will be repercussions on the country's demand for imports from other countries (and from China, in particular). To assess that, we define Covid-19 and stringency measures for the trading partners (except China) of a country, as detailed in section 2. The measures are defined at the country-product-month level, with weights given by the country's import shares of the corresponding product in 2018.

Once again, there are potentially opposing forces operating simultaneously. If the negative supply effects due to the direct and indirect incidence of Covid-19 are stronger than the corresponding negative demand effects, then export supply in third countries falls. As it becomes harder for a country to import from third countries, imports from China tend to increase to replace them. One may think of this as a “trade diversion” effect: pandemic-related difficulties to import from some countries inducing a diversion of imports to others (China, in our case). However, the effect may as well go in the other direction, if the negative demand effects dominate the negative supply effects in third countries, leading to an expansion of their export supply. In that case, imports from the third

countries will tend to displace imports from China. This third-country effect can also confound the supply-demand effects of countries' own covid-related deaths or lockdowns discussed earlier. For instance, even if a country's demand-side effect dominates the supply-side effect, this does not necessarily mean lower imports from China because imports from other trading partners may be replaced by corresponding imports from China when other partners are mired in Covid-19. Therefore, it is crucial to control for the third-country factors when estimating the effects of Covid-19 on bilateral trade.

Finally, as mentioned above, we expect to observe heterogeneous effects depending on the type of goods, on the level of development of the importing country, on whether value-added can be produced from home, etc. We discuss these heterogeneity results and other robustness analyses in detail in section 4.

3.2 Econometric Specification

We estimate how deaths from Covid-19 and the stringency of lockdowns affect countries' imports from China using monthly trade data at the HS 6-digit product level. We consider a country's own Covid-19 variables as well as those in its trading partners except China (ROW). A natural empirical specification for such an analysis is the standard log-linear gravity regression, as follows:

$$\begin{aligned} imports_{ipt} = & \beta_1 Stringency_{it} + \beta_2 CovidD_{it} + \beta_3 Stringency_ROW_{ipt} \\ & + \beta_4 CovidD_ROW_{ipt} + a_{ipy} + a_t + \epsilon_{ipt}. \end{aligned} \tag{1}$$

The dependent variable is the log of the volume of imports of product p by country i from China in period t , referring to a specific month between January 2019 and December 2020. The main explanatory variables are the number of covid-related deaths per thousand people (CovidD) and a stringency index capturing the overall strictness of a country's policies to control the spread of the virus (Stringency). The ROW measures of Stringency and CovidD are the average stringency and covid-related deaths in ROW, weighted by each country's imports of a product from all countries except China in 2018. In some regressions, we also include interaction terms between Covid-19 variables and other variables. Naturally, all covid-related variables are available only for the year 2020; for years before 2020, they are set to zero.

To control for other contemporaneous shocks and characteristics, we rely on a large set of fixed effects. We consider a particularly demanding set of fixed effects at the country-product-year level (a_{ipy}), which represent any factor that affects imports from China of a particular country-product pair in the same way over the months of a year. These effects capture differences in imports from China due to specific characteristics of the importing country, such as its size, and due to specific characteristics of the product, such as those that make it more or less appealing. They also capture similar effects at the country-product level—for example, factors that make a country have a particular large or small demand for imports from China of a specific product. Furthermore, they are allowed to vary by year.²⁰ In turn, a_t refers to time (year-month) fixed effects, which capture worldwide and Chinese-specific macro and health factors, as well as seasonal elements. With this wide set of fixed effects, the variation that our coefficients capture comes only from within-country or within country-product pairs over time.

Instead of estimating (1), we take the year-over-year (yoy) difference of trade and covid-related variables. This has the practical advantage of eliminating all time-invariant idiosyncratic country-product effects. Country-product effects that vary at the year level are still present, however, and in the yoy specification we denote them simply as α_{ip} . This gives our baseline specification:

$$\begin{aligned} \Delta imports_{ipt} = & \beta_1 Stringency_{it} + \beta_2 CovidD_{it} + \beta_3 Stringency_ROW_{ipt} \\ & + \beta_4 CovidD_ROW_{ipt} + \alpha_{ip} + m_t + \varepsilon_{ipt}. \end{aligned} \tag{2}$$

The dependent variable, $\Delta imports_{ipt}$, is the log difference between country i 's imports of product p from China in month t of 2020 and its imports in the same month of 2019, i.e., $\Delta imports_{ipt} = 100 \times [\log(imports_{2020})_{ipt} - \log(imports_{2019})_{ipt}]$. We multiply it by 100 to help with the visualization of the estimated coefficients, so it measures the yoy change in trade value in percentage terms. The explanatory variables are exactly the same as in equation (1), since they all take value zero during the whole 2019. Parameter m_t corresponds to a month fixed effect. Thus, this chained log difference yoy estimation at the monthly level also removes seasonality and avoids potential issues arising from combining the trade data for January and February. Considering that the trade of a product may be correlated across countries and over time (such as trade in medical goods) or

²⁰Observe that we allow the country-product effect to vary by year, but not by month of the year, which is the periodicity of our sample—otherwise it would absorb all of the variation in the dependent variable.

across country-product over time, we cluster the standard errors at the country-product level.²¹

Compared to the traditional log linear gravity regressions, our method has three advantages. First, we can avoid estimating equation (1) with a very large number of fixed effects corresponding to the two sets of country-product fixed effects (one for each year).²² Second, the yoy difference allows an apples-to-apples comparison of trade values, instead of comparing them month-over-month sequentially, where there may be large seasonal changes, especially since we have to combine January and February trade values. Even with the full sets of fixed effects, the traditional log linear gravity regression, based on demeaning the data along various dimensions, cannot fully address the country-product specific seasonality (e.g., the sudden drop in trade for most products during Chinese New Year except for holiday-related goods). Third, with the yoy measure, results are formatted as percentages, making it straightforward to interpret the economic significance of the results.

4 Results

4.1 Baseline Results

In Table 1, we consider our baseline specification, assessing the impact of our main variables on the monthly log difference of imports from China, defining goods at the 6-digit level. In columns 1 and 2, we have only the Stringency and CovidD variables. In the first column, to have an initial picture of how they are correlated with the dependent variable, we add only month dummies. In the second column, we then add country dummies and product fixed effects (absorbed). Naturally, this increases the fit of the regression significantly. In both cases, the two variables display negative and statistically significant effects, indicating that pandemic’s negative demand effect prevails over the negative supply effect. The absolute value of the coefficients drops considerably from column 1 to column 2, highlighting the importance of controlling for the additional fixed effects.

Now, just like in any other gravity estimation, it is important to control for changes in economic conditions in third countries. In our specific case, we are directly interested in understanding how

²¹In the few specifications where we have separate country and product fixed effects, we cluster the standard errors at the HS6 product level.

²²With 174 countries/regions and 4636 products at the HS6 level in our baseline analysis, this amounts to $2 \times 174 \times 4636 = 1,613,328$ fixed effects. Using yoy measures, we still have one set of fixed effects, but they do not cause similar computational difficulties.

the state of the pandemic in third countries affects trade flows between a country/region and China, as this can clarify the strength of diversion and complementary forces between China and other countries. To do so, we consider in our analysis Covid-19 incidence and lockdown policies in a country’s main trading partners (except China). The results from adding those variables to our regression are reported in columns 3 and 4. In column 3, we have the same set of fixed effects as in column 2, to make it clear the sole effect of adding the third-country variables. In terms of sign, the estimated coefficients on CovidD and on Stringency do not change with the introduction of third-country variables, remaining negative and estimated very precisely. In column 4, we have instead country-product fixed effects, which we keep in all subsequent specifications. As the results reveal, moving to that stricter specification increases the absolute magnitudes of all estimated coefficients, indicating that some trends at the country-product level mask the effects of the pandemic-related variables.

Table 1: Baseline regressions

	(1)	(2)	(3)	(4)
Stringency	-22.270*** (1.096)	-10.455*** (1.357)	-12.629*** (1.431)	-19.371*** (1.085)
CovidD	-6.362** (2.763)	-5.333** (2.680)	-7.154** (2.779)	-20.861*** (2.567)
Stringency_ROW			-0.663 (2.208)	-2.925 (2.242)
CovidD_ROW			20.302*** (4.365)	28.589*** (4.174)
Month dummies	Yes	Yes	Yes	Yes
Country FEs		Yes	Yes	
HS6 product FEs		Yes	Yes	
Country-HS6 FEs				Yes
Observations	2,032,389	2,032,389	1,923,335	1,923,335
R-squared	0.004	0.034	0.034	0.059

Notes: Dependent variable is year-over-year (yoy) log difference between a country i 's imports of product (p) from China in month t of 2020 and the corresponding import value in the same month of 2019, multiplied by 100, i.e., $\Delta \text{import}_{ipt} = 100 * \log(\text{import}_{2020})_{ipt} - \log(\text{import}_{2019})_{ipt}$. Stringency is a lockdown stringency index, rescaled to between 0 and 1. CovidD measures the number of new covid-related deaths per thousand people in the population in each month. The ROW variables are the corresponding Covid-19 measures for the rest of the world, excluding China, Hong Kong, Macau, and the importing country in question. Month dummies and various set of country, HS6 product, or country*HS6 fixed effects are included. Robust standard errors in parentheses, clustered at the HS6 product level in the first three regressions (at country-HS6 level in the last regression). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

We find that lockdown stringency in a country’s main trading partner does not have a significant effect on import growth, suggesting that either trade diversion and complementarity effects offset each other or neither is relevant. On the other hand, more Covid-19 deaths in a country’s main trading partners increases that country’s imports from China. That effect is statistically significant and large, indicating strong trade diversion when economic conditions in a country’s main trade partners are affected by the pandemic.

The three coefficients that are statistically significant are precisely estimated and are economically meaningful. For example, using the estimates from our baseline specification in column 4 of Table 1, we find that moving from a situation of no restriction to economic activities (as in 2019) to the highest level of stringency observed in 2020 (for Honduras in April and May, and for Philippines in April) would yield a reduction of imports of 17.6%.²³ For Covid-19 deaths, going from zero (as in 2019) to the highest level of Covid-19 deaths per capita excluding micro-states (0.63 per thousand people in Slovenia in December) would induce a reduction in imports from China of 12%.²⁴ The effect stemming from Covid-19 incidence in third countries goes in the opposite direction. It implies an increase of imports from China of 16.4% if the country’s main trading partners experience an increase in Covid-19 deaths from 0 to 0.628 per thousand people, the highest value in our sample (for Croatia in December).

In Table A.3, in the Appendix, we show the individual impact of each of the three statistically significant coefficients following a one standard deviation increase, a move from zero to the sample mean, and from zero to sample maximum. In the three thought experiments, the positive effect stemming from Covid-19 deaths in third countries prevails over the negative effect due to domestic Covid-19 deaths. However, for non-extreme values, the negative effect of a country’s own lockdown on imports from China is the dominating force. Combining all of them, the net effect when each variable goes from zero to the sample mean is a decrease in imports from China of nearly 10 percent.

4.2 Heterogeneity

Now, countries differ in how well they can absorb the consequences of the health crisis, and the effects likely differ by type of product as well. We explore various sources of heterogeneity, starting

²³ $1 - \exp(-19.371/100) = 17.6\%$, where -19.371 is the estimated coefficient of Stringency. We divide it by 100 because the dependent variable is in percentage terms.

²⁴ $1 - \exp(-20.861 \times 0.63/100) = 12\%$.

in Table 2, where we look more closely at two types of goods.

The most obvious distinction in our setting is whether the good is helpful in containing the virus during the pandemic. Thus, we split the sample between medical goods (MG) and non-MG. This group of products includes Personal Protective Equipment products, as well as many other goods, like ventilators, test kits, syringes, etc. As is well known, demand for some types of MG products skyrocketed at the onset of the pandemic and remains at historically high levels. However, while trade in MG goods is likely to display an idiosyncratic pattern, they correspond to only about 4% of the observations in our sample. Indeed, when we estimate our main specification without MG goods (column 1 of Table 2), we obtain results that are very similar to our baseline regression. Now, if we do the opposite and restrict the sample to MG goods (column 2), we observe that the pattern is indeed very different. Neither lockdowns nor the number of covid deaths has a significant effect on the imports of MG products from China, indicating that demand and supply effects offset each other. The impact of lockdown stringency in the main trading partners remains statistically not significant. Meanwhile, more covid-related deaths in the main trading partners increase imports from China, as it does with other goods, except that the magnitude of the effect is much larger for MG goods. Specifically, imports of MG from China would increase by 5.1% if the ROW experiences an increase in Covid-19 deaths from zero to 0.051 (the sample mean) per thousand people.

We carry out a similar analysis for durable consumption goods. We are motivated by the previous findings of, for example, Bems et al. (2010) and Eaton et al. (2016), who have showed that the decrease in the demand for durable goods was responsible for a large part of the sharp decline in international trade flows in 2008-2009. Thus, in column 3 of Table 2 we exclude durable goods from the analysis. The results are qualitatively similar to the baseline, but the magnitudes of the coefficients are between 12 and 33 percent lower in absolute value. Unsurprisingly, then, we observe the opposite pattern when we restrict the analysis to durable goods. All coefficients that are statistically significant in the baseline remain so, and maintain the same signs. However, they are between 35 and 92 percent higher than in the baseline. Furthermore, more stringent lockdowns in the main trading partners cause a statistically significant reduction in imports of durable goods from China. These results show that, despite many differences in the nature of the current crisis and the one after the 2008 financial crisis, both show a particularly strong negative impact on imports of durable consumption goods.

Table 2: Product level heterogeneity – medical goods and durable goods

	(1)	(2)	(3)	(4)
	w/o MGs	Only MGs	w/o durable	Only durables
Stringency	-20.520*** (1.105)	2.986 (5.367)	-17.048*** (1.241)	-26.192*** (2.221)
CovidD	-22.023*** (2.622)	13.275 (12.604)	-13.868*** (2.942)	-40.231*** (5.260)
Stringency_ROW	-2.587 (2.275)	-11.608 (12.729)	2.995 (2.474)	-15.814*** (5.251)
CovidD_ROW	25.709*** (4.230)	97.187*** (24.889)	22.293*** (4.676)	39.323*** (9.172)
Month dummies	Yes	Yes	Yes	Yes
Country-HS6 FEs	Yes	Yes	Yes	Yes
Observations	1,846,547	76,788	1,484,363	438,972
R-squared	0.054	0.150	0.057	0.068

Notes: Dependent variable is year-over-year (yoy) log difference between a country i 's imports of product (p) from China in month t of 2020 and the corresponding import value in the same month of 2019, multiplied by 100, i.e., $\Delta\text{import}_{ipt}=100*\log(\text{import}2020)_{ipt}-\log(\text{import}2019)_{ipt}$. See the footnote of Table 1 for definitions of covid-related variables (Stringency, CovidD and ROW variables). Month dummies and country-HS6 fixed effects are included in all regressions. Robust standard errors in parentheses, clustered at country-HS6 level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

In Table 3, we consider other aspects of product-level heterogeneity, related to how they are produced and traded. An important element mediating the impact of the pandemic in an economy is whether activities can be performed remotely. In particular, in countries where a large share of the population can work from home, both the direct effect and the indirect effect through government-mandated lockdowns of the pandemic can be absorbed more smoothly than in countries where most activities require workers to leave home to carry out their jobs. We assess whether that economic characteristic is quantitatively relevant for a country's imports by interacting a product's work-from-home share (wfh_sh) with our main variables of interest.²⁵ We confirm that presumption in Table 3, column 1. The negative coefficients of both lockdown stringency and covid-related deaths increase in absolute value but are partially offset by products' work-from-home share. Using the point estimates from column 1, they indicate that the effect of Stringency becomes positive for $\text{wfh_sh} > 0.74$, while the effect of CovidD becomes positive for $\text{wfh_sh} > 0.79$. In our data, only 0.5% of the HS6 products have a value of wfh_sh above 0.74 (same for the cutoff value 0.79), and the median of our sample has $\text{wfh_sh} = 0.33$. Still, the results reveal that having a substantial share

²⁵We do not add the work-from-home variable by itself in the regressions because it is fully absorbed by the country-product fixed effect.

of workers that can work from home can significantly dampen the negative income effect from the pandemic on imports. Note that the estimated coefficients on the ROW variables hardly change when the interactions with `wfh_sh` are introduced.

In column 2, we turn to the contractibility of products. Products with high levels of contract intensity tend to be more heterogeneous, depend on long-term arrangements and on relationship-specific investments, and be match-specific. This makes it more difficult to switch suppliers, at least in the short run. We assess whether that economic characteristic is quantitatively relevant by interacting contract intensity at the product level with our main variables of interest.²⁶ The estimates for Stringency and for CovidD remain negative but increase in absolute terms relative to the baseline, especially the CovidD estimate. On the other hand, their interactions with contract intensity are positive and significant. This reveals that, for products with high contract intensity, for which it is costly to sever relationships, imports are more resilient to the impact of Covid-19 deaths and to lockdowns, which have a temporary nature. This result resembles a key finding of Bas et al. (2021). Note that the estimated coefficients on the ROW variables remain virtually unchanged when the interactions with contract intensity are introduced.

Finally, in column 3 we consider potential differences in trade flows that are classified as “processing.” The estimates for the effects of our main variables remain very similar to the baseline results. The coefficient of the share of processing trade, which is defined at the country-product-month level, is positive, indicating that this type of trade has become more important compared to “normal” (non-processing) trade. Furthermore, its interaction with Stringency and CovidD are positive and statistically significant. This shows that, for products crossing borders with a greater share of processing trade, imports are more resistant to the negative impact of Covid-19 deaths and of lockdowns. This could reflect the fact that processing trade usually involves closer relationships between domestic processing firms in China and their foreign partners.

Product heterogeneity may also depend on the position of a good in the production process. In Table 4, we carry out that investigation by splitting products among consumption, intermediate and capital goods. Of the three categories, intermediate products behave more closely to the average product, which is partly explained by the fact that this group encompasses about half of the original

²⁶We do not add the contract intensity variable by itself in the regressions because it is fully absorbed by the country-product fixed effect.

Table 3: Product level heterogeneity – by product and trade characteristics

	(1)	(2)	(3)
	wfh_sh	Contract Intensity	Processing trade
Stringency	-39.826*** (3.231)	-34.125*** (7.280)	-19.232*** (1.135)
CovidD	-39.882*** (8.739)	-89.546*** (22.425)	-27.055*** (2.756)
Stringency_ROW	-2.357 (2.275)	-2.938 (2.268)	3.266 (2.295)
CovidD_ROW	27.232*** (4.272)	28.610*** (4.226)	25.125*** (4.289)
Stringency*wfh_sh	54.062*** (8.345)		
CovidD*wfh_sh	50.671** (22.420)		
Stringency*Contract Intensity		15.895** (7.861)	
CovidD*Contract Intensity		74.297*** (24.323)	
processing_sh			16.158*** (2.200)
Stringency*prc_sh			6.215* (3.437)
CovidD*prc_sh			31.114*** (9.622)
Month dummies	Yes	Yes	Yes
Country-HS6 FEs	Yes	Yes	Yes
Observations	1,854,101	1,885,797	1,792,892
R-squared	0.057	0.057	0.065

Notes: Dependent variable is year-over-year (yoy) log difference between a country i 's imports of product (p) from China in month t of 2020 and the corresponding import value in the same month of 2019, multiplied by 100, i.e., $\Delta \text{import}_{ipt} = 100 * \log(\text{import}_{2020}_{ipt}) - \log(\text{import}_{2019}_{ipt})$. See the footnote of Table 1 for definitions of covid-related variables (Stringency, CovidD and ROW variables). Wfh_sh measures work-from-home share at product level, based on sectoral level expenditure shares on each occupation. Contract intensity measures the degree to which a contract or relationship-specific investment is needed for a trading relationship in a sector. Prc_sh measures the share of processing trade among normal and processing trade in China's exports; it varies across destination countries, products, and over time. Month dummies and country-HS6 fixed effects are included in all regressions. Robust standard errors in parentheses, clustered at country-HS6 level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

sample. Stringency has a similar negative effect on the imports of each type of good, although higher for consumption and lower for capital goods. The sensitivity to own CovidD is substantially more diverse among the three groups: imports of consumption goods are heavily affected by CovidD, whereas capital goods are virtually unaffected. This difference may be explained by the temporary nature of the negative income shock, which has a larger effect on family consumption, but little impact on firms' long-run investment plans. The effect of lockdowns in the main trading partners on each group of products is even more diverse. It is mute for intermediate products (like for the average product), negative and significant for consumption goods and positive and significant for capital goods. This suggests that, if it is difficult to import capital goods from the main trading partners due to lockdown policies there, firms turn to China to keep their investment plans.

Table 4: Product level heterogeneity – by position in value chains

	(1)	(2)	(3)
	Consumption	Intermediate	Capital
Stringency	-25.480*** (2.467)	-17.296*** (1.581)	-15.731*** (2.479)
CovidD	-41.149*** (5.669)	-16.130*** (3.844)	1.858 (5.647)
Stringency_ROW	-16.336*** (5.521)	-0.760 (2.961)	20.107*** (5.467)
CovidD_ROW	31.678*** (9.635)	20.677*** (5.796)	22.257** (10.198)
Month dummies	Yes	Yes	Yes
Country-HS6 FEs	Yes	Yes	Yes
Observations	394,896	936,281	352,491
R-squared	0.077	0.056	0.045

Notes: Dependent variable is year-over-year (yoy) log difference between a country i 's imports of product (p) from China in month t of 2020 and the corresponding import value in the same month of 2019, multiplied by 100, i.e., $\Delta \text{import}_{ipt} = 100 * \log(\text{import}_{2020}_{ipt}) - \log(\text{import}_{2019}_{ipt})$. See the footnote of Table 1 for definitions of covid-related variables (Stringency, CovidD and ROW variables). The three regressions use the subsamples of final goods for consumption, intermediate goods, and capital goods based the UN BEC classification. Month dummies and country-HS6 fixed effects are included in all regressions. Robust standard errors in parentheses, clustered at country-HS6 level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Now, the level of development, and of the wealth, of a country is also likely to be an important mediator of how a country reacts to the pandemic. For example, we have seen that, on average, both CovidD and Stringency have a strong negative effect on countries' imports from China. This is likely caused by the negative income effect of the pandemic, which tends to lower consumption

especially in nations where individuals are more credit constrained and have lower savings/wealth that could be used to smooth consumption. In contrast, in rich countries the temporary loss of income, which is likely to have a small effect on lifetime income, may have a smaller impact due to better access to credit and to personal savings. To verify that possibility, in Table 5 we split the sample between OECD countries (column 1) and non-OECD countries (column 2). The sample without OECD countries yields results that are qualitatively similar to the baseline results in Table 1. This is to be expected, since they comprise 69 percent of the sample. In contrast, column 1 reveals that rich countries have reacted very differently to lockdowns with respect to their imports from China. Specifically, the effect of stricter lockdowns is positive for them, indicating that the negative demand effect is dwarfed by the negative supply effect, which induces local consumers and firms to turn to China to replace domestic goods when these cannot be produced locally due to restrictions on economic activities. The other coefficients are, however, relatively similar to those in the group of non-OECD countries.

One possible reason for the differential effects of a country's own lockdown on its imports for developed and developing economies may be their fiscal redistributive policies during the pandemic. Generally, they have been significantly more generous in rich countries than in poor ones, not only in absolute terms but also as a percentage of GDP.²⁷ We consider that explicitly in column 3, where we introduce a measure of the value of a country's economic support to the population due to the pandemic. The coefficient on that variable is positive, as expected, and is statistically significant at the 10% level. Nevertheless, the estimates of the four main variables are hardly affected by the inclusion of that variable in the regression, indicating that the pandemic-motivated fiscal policies increased demand for imports, but did so in a way that was largely unrelated to the specific effects of the pandemic on imports from China.

In column 4 of Table 5, we do something different: eliminate the U.S. from the regression. A concern is that, because of the ongoing trade war between the U.S. and China, and because the U.S. is the largest importer of China, there could be confounding effects due to the extra tariffs on Chinese exports. We do not expect the trade war to play a central role in our estimations, since it took off in 2018 and between 2019 and 2020 there were relatively few policy changes (despite an ambitious but unenforced bilateral agreement to manage bilateral trade flows). The results in

²⁷See United Nations (2021).

Table 5: Country level heterogeneity – level of development

	(1)	(2)	(3)	(4)
	OECD	w/o OECD	Econ support	w/o USA
Stringency	6.401*** (2.258)	-22.721*** (1.266)	-23.563*** (1.153)	-19.587*** (1.088)
CovidD	-40.218*** (3.724)	-38.937*** (4.053)	-18.821*** (2.586)	-20.073*** (2.606)
Stringency_ROW	-5.148 (5.123)	1.270 (2.537)	-2.112 (2.241)	-3.341 (2.263)
CovidD_ROW	14.841* (7.756)	18.168*** (5.007)	27.717*** (4.182)	28.042*** (4.227)
Economic Support			1.261* (0.695)	
Month dummies	Yes	Yes	Yes	Yes
Country-HS6 FEs	Yes	Yes	Yes	Yes
Observations	613,318	1,310,017	1,904,897	1,886,201
R-squared	0.111	0.058	0.060	0.058

Notes: Dependent variable is year-over-year (yoy) log difference between a country i 's imports of product (p) from China in month t of 2020 and the corresponding import value in the same month of 2019, multiplied by 100, i.e., $\Delta \text{import}_{ipt} = 100 * \log(\text{import}_{2020}_{ipt}) - \log(\text{import}_{2019}_{ipt})$. See the footnote of Table 1 for definitions of covid-related variables (Stringency, CovidD and ROW variables). The first regressions use the subsample of OECD countries that became members before 2010. The second regression covers all other countries except the OECD members. In the third regression, we add an additional variable – economic support, which is an index for income supports and debt relief. The last regression drops the observations related to the imports from China by the USA. Month dummies and country-HS6 fixed effects are included in all regressions. Robust standard errors in parentheses, clustered at country-HS6 level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

column 4 confirm our prior: the estimates are remarkably similar to those in the baseline estimation, indicating that including or not the U.S. in the estimations makes little difference, and therefore the U.S.-China trade war is not a driver of our results.

4.3 Path-dependence, Extensive Margin and Robustness

In Table 6, we consider four additional issues: path-dependence, pandemic-related trade policies, time-varying sector level heterogeneity, and the extensive margin of trade. Both the Stringency and the CovidD variables are serially autocorrelated. Thus, it is plausible that the trade effects of the pandemic in a month may be affected by the level of those variables in previous periods. In column 1 of Table 6 we evaluate that possibility, adding the two variables measuring the cumulative sum of Stringency and covid-related deaths in the previous months of 2020. The results show that the estimates for the own variables remain similar to the baseline after the introduction of their previous values, as do the estimates for the ROW variables, with relatively small changes in the magnitudes of the estimated coefficients. In contrast, both previous Stringency and previous CovidD have a positive and statistically significant sign. This indicates that the pandemic introduces a component of intertemporal substitution in countries' imports. A nation that restricts its imports in a month when it is badly hit will at least partially compensate for that reduction in the future. We note further that, relative to their contemporaneous effects, the magnitude of this intertemporal compensatory effect is greater for CovidD than for Stringency effects.²⁸

A few countries have implemented temporary trade policies in 2020 to cope with Covid-19. Most of these measures sought to promote imports or restrict exports of medical goods or materials to meet the increasing domestic demand, with a few cases of import restriction measures. Omitting these policies may lead to biased estimates. Since we study countries' imports, we consider only the import measures, as reported by the WTO. Specifically, in column 2 of Table 6 we drop the observations affected by these policies (about 1% of the sample). The estimated coefficients are very similar to what we obtain from the baseline regression.²⁹

²⁸Here we compare the coefficient of the CovidD previous cumulative value relative to the absolute value of the coefficient of its contemporaneous effect (i.e., $4.02/20.26 = 0.2$) with the analogous ratio for Stringency ($2.44/26.54 = 0.09$).

²⁹Alternatively, we add to our baseline regression two indicator variables for observations covered by a temporary import liberalization or import restriction policy. The result, available upon request, shows that the coefficient of the import liberalization dummy variable is positive, as expected, but is not statistically significant. The coefficient of the import restriction measure is negative and statistically significant, indicating that these measures, although

Table 6: Path-dependence, trade policies, HS2*Month fixed effects, and the extensive margin

	(1)	(2)	(3)	(4)
	Path-dependence	Trade policies	HS2*Month FEs	Extensive Margin
Stringency	-26.541*** (1.224)	-19.153*** (1.088)	-18.685*** (1.086)	-0.034 (0.043)
CovidD	-20.262*** (2.638)	-20.292*** (2.573)	-20.865*** (2.556)	-0.196* (0.108)
Stringency_ROW	-3.306 (2.242)	-2.930 (2.249)	1.209 (2.258)	0.049 (0.161)
CovidD_ROW	31.224*** (4.176)	28.047*** (4.193)	20.193*** (4.217)	-0.052 (0.287)
Stringency_prev	2.444*** (0.003)			
CovidD_prev	4.019*** (1.060)			
Month dummies	Yes	Yes	Yes	Yes
Country FEs				Yes
Country-HS6 FEs	Yes	Yes	Yes	
HS2-Month FEs			Yes	
Observations	1,923,335	1,903,711	1,923,335	1,772
R-squared	0.059	0.058	0.062	0.385

Notes: See the footnote of Table 1 for definitions of covid-related variables (Stringency, CovidD and ROW variables). The first three regressions are similar to the last regression in Table 1 except that (1) in the first regression, we add two additional variables: Stringency_prev and CovidD_prev, which are the cumulative sums of their values in the previous months of 2020; (2) in the second regression, we drop observations when the covid-related temporary import liberalization or restriction measures apply; (3) in the third regression, we add HS2-Month dummies as additional covariates. In the last regression, the dependent variable is the log difference between the total number of HS6 level product lines with positive import values in 2020 and that in 2019. Robust standard errors in parentheses, clustered at country-HS6 level in the first three regressions while at country level in the last regression, respectively. *** p<0.01, ** p<0.05, * p<0.1.

Recall that our empirical strategy, based on yoy changes and country-product fixed effects, eliminates country-product-specific heterogeneity that is either fixed over time or varies annually. Now, there may also exist product-specific short-term shocks at the monthly level. To control for that, in column 3 of Table 6 we add HS2-month fixed effects along with the HS6-country fixed effects. The signs and significance of the coefficients are the same as in our baseline regression. Except for the estimate for the effect of CovidD_ROW, which falls by about 30%, the magnitudes of the estimated coefficients hardly change either, indicating that those shocks are not central for our estimation.

Now, since our dependent variable is the log difference of imports from China at the country-product level, we are effectively carrying out the analysis at the intensive margin; any country-product pair not observed in a month does not contribute to the estimations. We can also look at the extensive margin. A simple way to do that is to consider how the number of products imported from China by a country has changed from a given month in 2019 to the same month in 2020. More precisely, we compare the change in the number of HS6 product lines at the country-month level between the two years, so the dependent variable is also a yoy measure at the country-month level. The results are in column 4 of Table 6. Interestingly, the effects are almost all mute.³⁰ Although the sample is substantially smaller in this case, it still has almost 1800 observations. The absence of effects suggests that the impacts are mostly at the intensive rather than at the extensive margin. This is consistent with the findings about the nature of the great trade collapse following the financial crisis of 2008, which was also largely driven by the intensive margin of trade (Bems et al., 2013).

Finally, in Table 7 we evaluate whether our results may be driven by outliers. The histogram of our dependent variable (Figure 1) shows that its distribution is fairly “well-behaved,” indicating the presence of few outliers. However, Table A.1 shows that the maximum and minimum of the distribution are indeed very large in absolute values. To check whether they are key to our findings, we run three different specifications. In column 1, we drop all observations where the absolute value of the dependent variable is above 500 percent. This amounts to dropping approximately 2.6% of

relatively rare, did reduce countries’ imports. The other coefficients of the regression change very little.

³⁰In contrast to us, Berthou and Stumpner (2021) find a negative and significant effect of Stringency on the extensive margin of trade, defined just as we define here. An important difference between the two analyses is that Berthou and Stumpner include only Stringency as the explanatory variable. If we drop from our regression CovidD, Stringency_ROW and CovidD_ROW, the coefficient on Stringency turns negative and significant also in our dataset.

the observations. In column 2, we drop all the observations for micro-states, defined as countries with population smaller than a half million in 2018. They correspond to 18 of the 174 countries in the baseline regression. Since those tiny countries may behave differently and be responsible for outliers both in the dependent variable and in some of the key independent variables—as in the case of San Marino, which has the highest value for CovidD in the sample—we want to investigate whether they are disproportionately affecting the results. Finally, in column 3 we run a median regression instead of an OLS. The results in column 1 are very similar to our baseline. The results in column 2 are almost identical to the baseline, showing that micro-states are largely irrelevant for the estimates. Similarly, the median regression also shows results that are strikingly similar to our baseline, indicating that the latter is not highly affected by outliers.

Table 7: Outliers

	(1)	(2)	(3)
	Abs(depvar)<5	Drop Micro-States	Median Regression
Stringency	-15.794*** (0.912)	-19.420*** (1.093)	-19.557*** (1.571)
CovidD	-21.165*** (2.079)	-20.608*** (2.568)	-21.302*** (3.820)
Stringency_ROW	-2.715 (1.850)	-2.912 (2.250)	-2.410 (3.090)
CovidD_ROW	21.304*** (3.451)	28.696*** (4.190)	28.583*** (6.541)
Month dummies	Yes	Yes	Yes
Country-HS6 FEs	Yes	Yes	Yes
Observations	1,873,358	1,900,726	1,923,335
R-squared	0.058	0.060	

Notes: Dependent variable is year-over-year (yoy) log difference between a country i 's imports of product (p) from China in month t of 2020 and the import value in the same month of 2019, multiplied by 100, i.e., $\Delta\text{import}_{ipt}=100*\log(\text{import}_{2020})_{ipt}-\log(\text{import}_{2019})_{ipt}$. See the footnote of Table 1 for definitions of covid-related variables (Stringency, CovidD and ROW variables). The first regression drops the outliers defined as $\text{abs}(\Delta\text{import})>500$. The second one drops micro-states, defined as countries with population in 2018 less than a half million. The last regression is a median regression. Month dummies and country-HS6 fixed effects are included in all regressions. Robust standard errors in parentheses, clustered at country-HS6 level in the first two regressions. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

5 Conclusion

We provide estimates for the 2020 trade effects of the Covid-19 pandemic. To our knowledge, this is the first paper on the topic covering the whole year of 2020. We use data on exports from China

to every country and region in the world. This allows us to isolate the effects of the pandemic on importing countries. We carry out the analysis at country-product level, which allows us to investigate a variety of heterogeneous effects at the country and product levels.

Because Covid-19 represents both a demand and a supply shock, its effect on a country's demand for imports is a priori ambiguous. Here we show the net effects, as can be inferred from country's imports from China. Moreover, we distinguish between the direct effects of the pandemic captured by Covid-19 deaths on the economy and the indirect effects due to governments shutting down economic activities by decree. We find that the negative demand effects prevail in both dimensions, and are far from trivial. For example, according to the point estimates of our baseline specification, a monthly increase equivalent to one standard deviation in covid-related deaths per capita and in the level of lockdown stringency would generate a reduction of nearly 6 percent of imports from China (1.5 percent stemming from the former, 4.2 percent due to the latter). If we consider a change from zero to the sample mean for each of those variables, the joint effect would be an 11.3 percent decrease in imports from China, while moving from zero to the highest levels in the sample would imply a joint effect of just over 30 percent.

This is an incomplete picture, however, because one also needs to consider how a country's imports from China are affected by the consequences of the pandemic in the country's other trade partners. For example, for given domestic pandemic conditions, a country may decide to import more of a product from China if its main trading partners cannot supply it because of covid-related restrictions there. But just like in the domestic economy, the impact due to the pandemic's direct and indirect effects in the trading partners are a priori ambiguous. Empirically, we find that such a substitution does take place and the effect is sizeable. In fact, the same level of covid-related deaths at home and in the partner countries would induce an *increase* in imports from China, because the positive third-country effect more than offsets the negative domestic effect. Accounting for the third-country effects, the net impact on imports from China due to a one standard deviation increase, a change from zero to the sample mean, and a change from zero to the sample maximum in the main variables would be a decrease of, respectively, 3.9, 9.8, and 10.9 percent.

Unsurprisingly, we find that these average effects hide significant heterogeneity. Medical goods display a very different pattern. The effects are potentialized for durable consumption goods, but are moderated for those with a high "work-from-home" share or a high contract intensity,

for those exported under processing trade, and for capital goods. The average effects for OECD countries are quite distinct from those for the average non-OECD country, but our findings in the baseline regression are not affected much by fiscal policies related to the pandemic. There is also an important path-dependence, in that Covid-19 incidence of deaths and lockdowns in previous months tend to mitigate the negative effects of contemporaneous Covid-19 incidence and lockdowns, suggesting that part of the reduction of trade may simply reflect a postponement of economic activities. This could help to explain why the aggregate drop in international trade in 2020 has been smaller than what many economists predicted at the onset of the pandemic.

The Covid-19 pandemic remains in progress and its trade impacts during 2021 and beyond may differ from its more immediate impacts, as workers, firms and governments learn how to deal with and adapt to it, and as vaccinations start to allow societies to return to their pre-pandemic modes. How these effects vary over time is an interesting question that we do not address here. Given that our data are from China, we do not investigate either the possible interaction between covid-related effects in importing and exporting countries. These are promising avenues for future research on this topic.

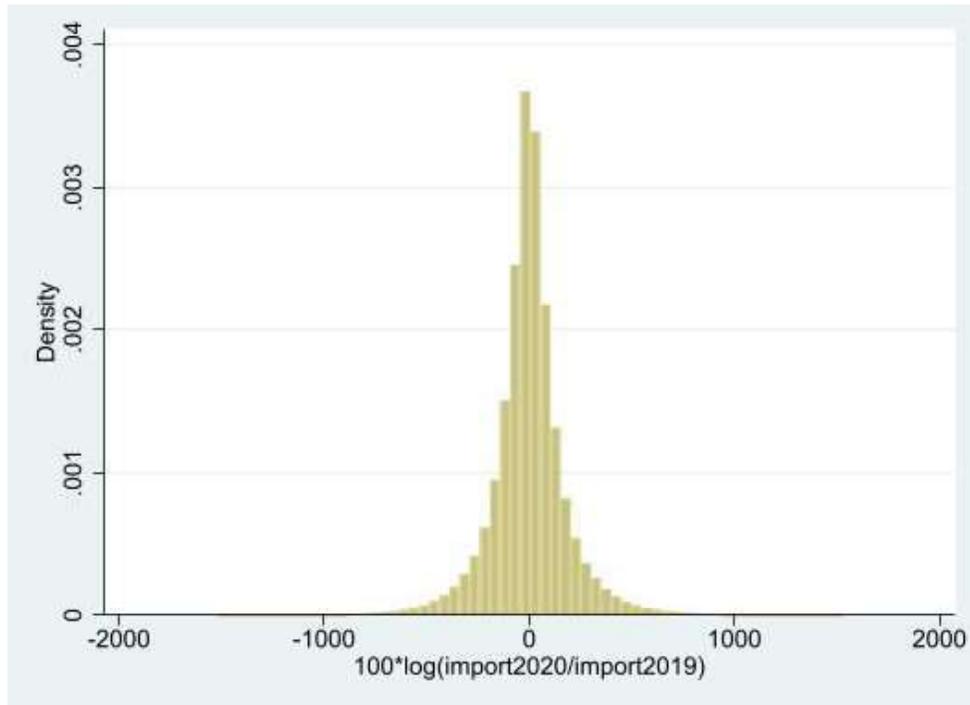
References

- Anderson, James, and Eric Wincoop (2003). Gravity with Gravitas: A Solution to the Border Puzzle. *American Economic Review*, 93(1), 170-192.
- Antràs, Pol, Stephen J. Redding, and Esteban Rossi Hansberg (2020). Globalization and pandemics. *Covid Economics* 49, 1-84.
- Baldwin, Richard, and Eiichi Tomiura (2020). Thinking ahead about the trade impact of covid-19. In R. Baldwin, & B.Weder di Mauro (Eds.), *Economics in the Time of COVID-19*, 59-71, CEPR Press.
- Bas, Maria, Ana Fernandes, and Caroline Paunov (2021). The resilience of trade to COVID-19. *Mimeo*.
- Behrens, Kristian, Gregory Corcos, and Giordano Mion (2013). Trade Crisis? What Trade Crisis? *The Review of Economics and Statistics*, 95(2), 702–709.

- Bems, Rufolfs, Robert C. Johnson, and Kei-Mu Yi (2010). Demand spillovers and the collapse of trade in the global recession. *IMF Economic Review*, 58(2), 295–326.
- Bems, Rufolfs, Robert C. Johnson, and Kei-Mu Yi (2013). The Great Trade Collapse. *Annual Review of Economics*, 5(1), 375-400.
- Berthou, Antoine, and Sebastian Stumpner (2021). Trade Under Lockdown. Mimeo.
- Bonadio, Barthelemy, Zhen Huo, Andrei A. Levchenko, and Nitya Pandalai-Nayar (2020). Global Supply Chains in the Pandemic, CEPR Discussion Paper, 14766.
- Bricongne, Jean-Charles, Lionel Fontagné, Guillaume Gaulier, Daria Taglioni, and Vincent Vicard (2012). Firms and the global crisis: French exports in the turmoil. *Journal of international Economics*, 87(1), 134-146.
- Che, Yi, Weiqiang Liu, Yan Zhang, and Lin Zhao (2020). China’s Exports during the Global COVID-19 Pandemic. *Frontiers of Economics in China*, 15(4), 541–574.
- Dingel, Jonathan I. and Brent Neiman (2020). How Many Jobs Can be Done at Home? *Journal of Public Economics*. 189, 104235.
- Eaton, Jonanthan, Samuel Kortum, Brent Neiman, and John Romalis (2016). Trade and the Global Recession. *American Economic Review*, 106(11), 3401-3438.
- Eppinger, Peter, Gabriel Felbermayr, Oliver Krebs, and Bohdan Kukharsky (2021). Decoupling Global Value Chains. Mimeo.
- Espitia, Alvaro Aaditya Mattoo, Nadia Rocba, Michele Ruta, and Deborah Winkler (2021). Pandemic Trade: Covid-19, Remote Work and Global Value Chains. *The World Economy*, forthcoming.
- Friedt, Felix L., and Kaichong Zhong (2020). The triple effect of Covid-19 on Chinese exports: First evidence of the export supply, import demand and GVC contagion effects. *Covid Economics* 53: 72-109.
- Hale, Thomas, Noam Angrist, Rafael Goldszmidt, Beatriz Kira, Anna Petherick, Toby Phillips, Samuel Webster, Emily Cameron-Blake, Laura Hallas, Saptarshi Majumdar, and Helen Tattlow. (2021). A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). *Nature Human Behaviour* 5, 529–538.

- Hayakawa, Kazunobu, and Hiroshi Mukunoki (2021). Impacts of COVID-19 on global value chains. *The Developing Economies*, forthcoming.
- Kejzar, Katja Z., and Alan Velić (2020). Covid-19, trade collapse and GVC linkages: European experience. *Covid Economics* 61, 219-240.
- Le Moigne, Mathilde, and Ralph Ossa (2021). Crumbling Economy, Booming Trade: The Surprising Resilience of World Trade in 2020. Working Paper 01-21 Kühne Center Impact Series.
- Nunn, Nathan (2007). Relationship-specificity, incomplete contracts, and the pattern of trade. *Quarterly Journal of Economics*, 122(2), 569–600.
- Pei, Jiansuo, Gaaitzen de Vries, and Meng Zhang (2021). International Trade and Covid-19: City-level Evidence from China’s Lockdown Policy. Working Paper, University of Groningen.
- Sforza, Alessandro, and Marina Steininger (2020). Globalization in the Time of Covid-19. CESifo working paper 8184.
- Socrates, Majune K. (2020). The Effect of Lockdown Policies on International Trade Flows from Developing Countries: Event Study Evidence from Kenya. Working Paper, University of Nairobi.
- United Nations (2021). World Economic Situation and Prospects: February 2021 Briefing, No. 146.

Figure A.1: Histogram of the dependent variable.



Notes: This diagram shows a histogram of the dependent variable, defined as 100 times the log difference between countries' imports from China in 2020 and that in 2019 at HS6 product level, monthly, i.e., $\Delta \text{import}_{i,pt} = 100 \cdot \log(\text{import}_{2020})_{i,pt} - \log(\text{import}_{2019})_{i,pt}$.

Table A.1: Summary statistics

Variables	Obs	Mean	Std. Dev.	Min	Max
100*log(exp2020/exp2019)	1,923,335	0.600	183.5	-1522.8	1533.7
Stringency	1,923,335	0.577	0.222	0	1
CovidD	1,923,335	0.034	0.071	0	0.665
Stringency_ROW	1,923,335	0.565	0.173	0	1
CovidD_ROW	1,923,335	0.051	0.063	0	0.628
Wfh_sh	1,854,101	0.375	0.11	0.134	0.808
Contract Intensity	1,885,797	0.914	0.095	0.46	0.995
processing_sh	1,792,892	0.065	0.201	0	1
Economic Support	1,904,897	0.489	0.307	0	1
Stringency_prev	1,923,335	2.797	2.014	0	7.993
CovidD_prev	1,923,335	0.110	0.207	0	1.408

Notes: The summary statistics of the first five variables are based on the sample used in the last regression of Table 1. The summary statistics for wfh_sh, contract intensity, and prc_sh are based on the samples used in Table 3, respectively. The summary statistics for economic support variable is based on the sample used in regression (3) of Table 5. The summary statistics for Stringency_prev and CovidD_prev are based on the sample used in the first regression of Table 6 (same as the sample used in the last regression of Table 1).

Table A.2: Pairwise correlation among key Covid-related variables

	Stringency	CovidD	Stringency_ROW
CovidD	0.2477	1.0000	
Stringency_ROW	0.5976	0.2188	1.0000
CovidD_ROW	0.2602	0.4259	0.4922

Notes: This matrix is based on the sample used in the last regression of Table 1.

Table A.3: Economic significance of the estimates

Variable	Impact of each variable on imports from China, in percentage			
	coefficients	1 std. dev. increase	0 to sample mean	0 to sample max.
Stringency	-19.37	-4.21	-10.58	-17.61
CovidD	-20.86	-1.47	-0.71	-12.95
CovidD_ROW	28.59	1.82	1.47	19.67
Total effect (in percentage)		-3.86	-9.81	-10.9

Notes: This matrix is based on the sample used in the last regression of Table 1.

CENTRE FOR ECONOMIC PERFORMANCE
Recent Discussion Papers

1770	Tito Boeri Edoardo di Porto Paolo Naticchioni Vincenzo Scrutinio	Friday morning fever. Evidence from a randomized experiment on sick leave monitoring in the public sector
1769	Andrés Barrios-Fernández Jorge García-Hombrados	Recidivism and neighborhood institutions: evidence from the rise of the evangelical church in Chile
1768	Stephen J. Redding	Suburbanization in the United States 1970-2010
1767	Anna Valero	Education and management practices
1766	Piero Montebruno Olmo Silva Nikodem Szumilo	Court severity, repossession risk and demand in mortgage and housing markets
1765	Ghazala Azmat Katja Kaufmann	Formation of college plans: expected returns, preferences and adjustment process
1764	Anna Valero	Education and economic growth
1763	John Van Reenen	Innovation and human capital policy
1762	Sarah Flèche Anthony Lepinteur Nattavudh Powdthavee	The importance of capital in closing the entrepreneurial gender gap: a longitudinal study of lottery wins
1761	Elodie Djemai Andrew E. Clark Conchita D'Ambrosio	Take the highway? Paved roads and well-being in Africa
1760	Sabrina T. Howell Jason Rathje John Van Reenen Jun Wong	Opening up military innovation: causal effects of 'bottom-up' reforms to U.S. defense research

1759	Marcus Biermann	Remote talks: changes to economics seminars during Covid-19
1758	Yatang Lin Thomas K.J. McDermott Guy Michaels	Cities and the sea level
1757	Maria Cotofan Robert Dur Stephen Meier	Does growing up in a recession increase compassion? The case of attitudes towards immigration
1756	Jo Blanden Andrew Eyles Stephen Machin	Trends in intergenerational home ownership and wealth transmission
1755	Martin Beraja David Y. Yang Noam Yuchtman	Data-intensive innovation and the State: evidence from AI firms in China
1754	Rafael Dix-Carneiro João Paulo Pessoa Ricardo Reyes-Heroles Sharon Traiberman	Globalization, trade imbalances and labor market adjustment
1753	Niklas Gohl Peter Haan Elisabeth Kurz Felix Weinhardt	Working life and human capital investment
1752	Holger Breinlich Harald Fadinger Volker Nocke Nicolas Schutz	Gravity with granularity
1751	Bernardo Guimaraes João Paulo Pessoa Vladimir Ponczek	Non-compete agreements, wages and efficiency: theory and evidence from Brazilian football

The Centre for Economic Performance Publications Unit

Tel: +44 (0)20 7955 7673 Email info@cep.lse.ac.uk

Website: <http://cep.lse.ac.uk> Twitter: @CEP_LSE