# International trade spillovers from domestic COVID-19 lockdowns*

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January 2023

**Abstract**

While standard demand factors perform well in predicting historical trade patterns, they fail conspicuously in 2020, when pandemic-specific factors played a key role above and beyond demand. Prediction errors from a multilateral import demand model in 2020 vary systematically with the health preparedness of *trade partners*, suggesting that pandemic-response policies have *international spillovers*. Bilateral product-level data covering about 95 percent of global goods trade reveals sizable negative international spillovers to trade from supply disruptions due to domestic lockdowns. These international spillovers accounted for up to 60 percent of the observed decline in trade in the early phase of the pandemic, but their effect was short-lived, concentrated among goods produced in key global value chains, and mitigated by the availability of remote working and the size of the fiscal response to the pandemic.

**JEL Classification:** F14, F60, I18
**Keywords:** Trade, Spillover effects, Lockdown, COVID-19

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# 1 Introduction

The COVID-19 pandemic constituted both a demand and a supply shock and the twin nature of the shock was expected to lead to a sharp decline in trade (Baldwin and Tomiura, 2020; Buchel *et al.*, 2020; Liu *et al.*, 2022). For an economy experiencing COVID-19, the economic contraction resulting from domestic pandemic containment policies, such as restrictions on mobility (and social distancing), was expected to lead to a large contraction in demand, and thus a decline in imports. From the supply side, the sudden halt in production following strict lockdowns and outright closings of establishments would also imply a contraction in the exports of a COVID-19 hit country to its trading partners—or equivalently—the bilateral imports of trading partners (Baldwin and Freeman, 2022; Cerdeiro and Komaromi, 2020; Espitia *et al.*, 2022; Lafrogne-Joussier *et al.*, 2022). The former channel may be thought of as the direct impact of the pandemic on trade. The latter channel constitutes a spillover effect on global trade, resulting from domestic measures to contain the pandemic.

Trade indeed fell sharply with the onset of the pandemic, declining by more than 15 percent in the aggregate and by even more in services. However, despite the expectations of a prolonged collapse in global trade, there was a rapid and vigorous rebound, in striking contrast to previous global recessions (Figure 1, panel A). Another distinguishing feature of the pandemic trade shock is that the V-shaped recovery was driven by the strong performance of goods imports, which in 2021 overshot pre-pandemic levels, while services trade continued to languish well below pre-pandemic levels even two years after the start of the pandemic (Figure 1, panel B).

These patterns in global trade are usually explained by a constellation of factors, including the collapse and subsequent strong rebound in aggregate demand and the impact of travel restrictions and social distancing on key in-person traded services. In this paper, however, we focus primarily on the supply side spillover effects of containment policies. In particular, we use detailed product-level bilateral goods trade data to estimate the international spillover effect of lockdowns in a gravity setting, from the onset of the pandemic until mid-2021.

While the bulk of the analysis presented in this paper relies on granular bilateral trade data, a natural starting point to guage the role of factors other than domestic demand is to estimate a standard import demand model using multilateral data, and evaluate how well it can explain the observed trade patterns. Deviations of observed import growth from model predictions would suggest that drivers other than those related to demand also mattered. In particular, we focus on pandemic intensity indicators (number of COVID-19 cases and deaths, and measures of lockdown intensity and mobility). We find that while a standard demand model fits rather well observed historical goods and services import growth, it performs poorly in predicting what happened in 2020. Imports of goods fell by much less than predicted (and those of services much more than predicted) by the demand model. Moreover, countries whose trade partners had better health preparedness experienced larger prediction errors (goods imports fell by less than predicted), suggesting that policies implemented in partner countries in response to COVID-19 mattered.

Figure 2 shows that the fall in goods imports during the first half of 2020 was larger for countries whose *trading partners* implemented more severe containment policies.[1] To explore this relationship further, we quantify the supply shock spillover channel of the crisis-induced lockdowns using bilateral product-level trade data in a gravity model. This setting makes it possible to absorb demand factors through a set of time-varying fixed effects defined at the country-industry level. In practice, we look at a country (e.g., the U.S.) and we compare the imports of a product—for instance, vehicles—in each month from countries with different containment policies. In this way, assuming that changes in the U.S. demand for vehicles follow the same pattern across partners, demand is controlled for, and the variation in the severity of containment policies across trade partners captures spillovers operating throgh supply. We find that international spillovers from lockdowns were economically large, but they were short-lived and concentrated in the early phase of the pandemic. Compared to a counterfactual with no lockdown restrictions, trade partners' lockdowns explain up to 60 percent of the observed decline in imports in the first five months of 2020. But moving past the initial phase of the pandemic, the elasticity of trade to partners' lockdown intensity becomes insignificant, as trade begins to recover despite the stringency of lockdowns being relaxed only marginally.

The average spillover effect masks several sources of heterogeneity. First, we consider the size of the fiscal response to the COVID-19 pandemic in trade partners and find that spillovers are stronger from countries that were less able to deploy large discretionary fiscal measures to mitigate

[1] Unless specified otherwise, throughout the paper we measure the severity of containment policies using the Oxford COVID-19 Government Response Stringency Index, as computed by Hale *et al.* (2021). For simplicity, we refer to it as the *stringency index*.

the effects of the pandemic. Second, we exploit cross country heterogeneity in teleworkability—as measured by Dingel and Neiman (2020)—to show that the spillover effect of lockdowns is more than twice as strong from partner countries which are less able to rely on remote working compared to those that have a higher share of jobs that can be done from home. Third, we decompose the effect of the containment policies across GVC-intensive industries, pooling all the others into a residual category, and find that the effect of lockdowns is stronger in GVC-intensive industries, and especially in electronics, than in non GVC-intensive ones.[2] Fourth, we exploit the fact that the effect of containment policies is likely to differ across products depending on their position along the value chain, with more downstream industries, for which output is closer to the end user, relatively more exposed to GVCs and, therefore, to the restrictions imposed by lockdowns. In addition, by interacting the stringency index with a measure of upstreamness proposed by Antràs *et al.* (2012), we can fully control for multilateral resistance as in standard gravity models including exporter-time fixed effects. While in this setting we cannot estimate the average effect of the lockdown, we can better identify its differential effect across industries at different points along the value chain. The results show that the negative effect of stringency measures is dampened for industries which are further upstream (like metals and minerals products), while it is stronger for those downstream (like transportation and textiles).

Finally, our findings support the notion that the pandemic was accompanied by a rotation in demand from services and towards goods. Indeed, the greater the intensity of the pandemic in a given country, the smaller the decline in goods imports relative to the predictions of the standard import demand model. In other words, it appears that domestic containment policies *boosted* demand for imported goods—as distinct from the negative spillover effect on imports due to partner country lockdowns. In addition, services imports *fell by much more* than would be predicted by demand alone in countries for which tourism services comprised a large share of total imports.

[2] GVC-intensive industries include automobiles, electronics, textiles and garments, and medical goods. The mapping of goods from the "six-digit" level under the Harmonized System to the inputs and final goods in these GVCs are compiled from Frederick and Lee (2017) (electronics), Sturgeon *et al.* (2016) (automobiles), and Frederick (2019) (textiles and garments, medical devices).

**Related literature.** Our paper contributes to a burgeoning literature on the propagation of the COVID-19 pandemic shock through global trade (e.g., Bonadio *et al.*, 2021; Espitia *et al.*, 2022; Lafrogne-Joussier *et al.*, 2022; Liu *et al.*, 2022).

First, we build on contemporaneous analyses looking at the effect of domestic lockdowns on trade partners. A set of papers zooms in on the experience of individual countries. Heise (2020) shows that imports of U.S. firms that sourced from China before the pandemic fell by 15% more than those of comparable firms that were importing from other countries. Similarly, Lafrogne-Joussier *et al.* (2022) consider French firms engaged in GVCs and show that those relying on Chinese inputs experienced a 7% greater decline in their overall imports following the Chinese lockdown relative to firms that were not exposed to Chinese inputs.[3] Also using data on French firms, Brussevich *et al.* (2022) explore trade patterns vis-a-vis several countries finding evidence that the pandemic shock propagated through supply chains and that more restrictive lockdown policies in trading partners resulted in larger drops in exports and imports by French firms, with the adjustment borne mostly at the intensive margin and by smaller and less automated firms. Evidence from Portuguese firms shows that the severity of the health crisis and mobility restrictions are associated with a large contraction in trade flows, although there is evidence of a progressive adaptation of trading firms to new circumstances, as the effect of lockdowns turns insignificant in the second half of 2020 (Pimenta *et al.*, 2021).[4]

Closer to our approach, Cerdeiro and Komaromi (2020) disentangle the supply and demand channels in global trade and quantify the effect of supply spillovers from lockdowns using daily data on bilateral seaborne trade and tracking the transmission of supply disruptions across space. Their analysis suggests a downstream propagation of countries' lockdowns through global supply chains and points to short-lived supply spillovers of lockdowns through international trade. Espitia *et al.* (2022) are among the first to use product-level bilateral trade data to look at the heterogeneous trade effects of the pandemic across sectors. Their analysis, based on data covering the trade of 28 countries in the first six months of the pandemic, shows that a decline in mobility

[3]The result that the COVID-19 shock had a larger effect on trade for products that reply on intermediate inputs from China is also shown in a cross-country setting by Bas *et al.* (2022).

[4]Similar evidence is shown also using trade data. Majune and Addisu (2021) find that the introduction of lockdown measures by Kenya's trading partners had a negative effect on imports, which fell by 23% on average after the measures were put in place. Looking the the Philippines, Arenas *et al.* (2022) find that the drop in imports has been even larger (-57% compared to pre-pandemic levels).

in trade partners is associated with a reduction of imports of durable goods. Also, the negative effect of lower mobility is stronger for sectors which rely more on imported inputs. Contemporaneous work by Berthou and Stumpner (2022) is based on 31 reporting countries and documents a significant effect of lockdowns put in place by exporting and importing countries on bilateral trade.[5]

With respect to this literature, we show evidence of the international spillover effects of lockdowns based on a large product-level dataset covering 98 reporting countries and 95% of global trade in goods over 18 months. With these data we can fully control for time-varying factors which could affect product-specific demand in different importing countries. We also investigate in detail the (lack of) persistence in lockdown spillovers and identify industries more exposed to containment policies. Exploting differences across industries in their position along the value chain, we are also able to quantify the differential effect of lockdowns on trade partners controlling for all unobserved time-varying factors that differ across exporters and that could confound the spillover effect of lockdowns.

Second, by examining the trade dynamics of goods and services, we document the large shift of imports from services to goods and the sharp increase in goods imports, which cannot be fully explained by demand factors. In this respect, our evidence is in line with previous research looking at domestic consumption patterns in several economies—see Bounie *et al.* (2020) for France, Andersen *et al.* (2022) for Denmark, Carvalho *et al.* (2021a) for Spain, Baker *et al.* (2020) for the United States, and Chronopoulos *et al.* (2020) for the United Kingdom. Our analysis suggests that these trends are common across countries, driven by pandemic-specific factors, such a shift in preferences across sectors (e.g., Guerrieri *et al.*, 2022) and pent-up demand, and partly reflected in trade flows.

Our paper also contributes to a large literature which analyzes the (potential) health-economy trade-offs associated with lockdowns and pandemic-related containment policies (Baqaee *et al.*, 2020; International Monetary Fund, 2020; Aum *et al.*, 2021). The decision to impose a lockdown,

[5] A related literature investigates the disruptions in agricultural trade during the pandemic, showing that containment policies and reduced mobility are associated with the decline in bilateral trade, although the size of decline has been smaller than for non-agricultural trade and the effect of containment polices has weakened over time (Arita *et al.*, 2022). More generally, our analysis builds on an extensive literature that measures the effects on trade flows of a variety of domestic shocks, natural disasters (Barrot and Sauvagnat, 2016; Boehm *et al.*, 2019; Carvalho *et al.*, 2021b) and financial sector shocks (Amiti and Weinstein, 2011).

and to mandate how severe the lockdown should be, is challenging given the need to strike a balance between protecting lives and minimizing the harm to economic activity. While most of the economic literature focuses on the potential *domestic* costs of lockdowns in terms of reduced mobility and lower economic activity (Chen *et al.*, 2020; Deb *et al.*, 2021), our analysis tries to quantify the *international* costs borne by other countries via the trade channel. In this respect, by showing a large but relatively short-lived fall in trade due to lockdowns, our results provide additional evidence to inform policy makers about the potential costs of containment policies.

## 2 Were the effects of the pandemic on imports "unprecedented"?

Many consequences of the pandemic have been assessed as *unprecendented*. To assess whether the same can be said of its impact on trade – and especially imports – we perform the following exercise. First, we estimate a simple demand model based on the work of Bussière, Callegari, Ghironi, Sestieri and Yamano (2013), who used it in the context of the Great Trade Collapse in 2008-2009, on a sample of 127 countries over the period 1985-2019.[6] Second, we use the estimated model to predict import growth in 2020 and obtain country-level prediction errors.[7] Third, we aggregate the errors across countries and compare the aggregate prediction error in 2020 with similarly aggregated errors in the previous years, to establish whether the change in imports observed during the pandemic year can be explained by standard economic forces. Fourth, we correlate the errors in the 2020 cross-section with country level factors to understand their drivers.

### 2.1 A simple empirical import demand model

As in Bussière *et al.* (2013), we begin by estimating country-level regressions of importer country $m$'s log change in real imports in year $t$ ($M_{mt}$) on a country specific constant ($\pi_m$), the log change in a measure of import-intensity adjusted demand ($D_{mt}$) and import prices relative to the domestic GDP deflator ($P_{mt}$):

$$\Delta \ln M^{\tau}_{mt} = \pi_m + \beta^{\tau}_{Dm} \Delta \ln D^{\tau}_{mt} + \beta^{\tau}_{Pm} \Delta \ln P_{mt} + \varepsilon^{\tau}_{mt}, \quad \forall \tau \in \{g, s\} \tag{1}$$

[6] The sample is selected based on data availability: a country is in the sample if we can observe at least 16 complete observations between 1985 and 2019.

[7] In what follows we use the term *prediction* errors to refer both to in-sample and out-of-sample prediction errors. The former type of error is computed for years 1985 to 2019, the years included in our estimation sample. The latter type of error is computed for 2020, as data for that year are not included in the estimateion sample.

The regressions are estimated separately for imports of goods ($\tau = g$) and services ($\tau = s$).

Following Bussière *et al.* (2013), import-intensity adjusted demand is a harmonic weighted average of different domestic demand components (private consumption $C$, government consumption $G$, investment $I$ and exports $X$ to take into account the import content of export demand). It is defined as:

$$D^{\tau}_{mt} = C_{mt}^{\omega_{\tau Cm}} G_{mt}^{\omega_{\tau Gm}} I_{mt}^{\omega_{\tau Im}} X_{mt}^{\omega_{\tau Xm}}, \quad \forall \tau \in \{g, s\}, \tag{2}$$

where the weights ($\omega$'s) represent the total import content of each component and are computed from the Eora Global Supply Chain Database following the method in Bussière *et al.* (2013). The import relative prices are computed using data from the World Economic Outlook database of the International Monetary Fund.

In Table 1, we report various statistics from the distribution of estimated coefficients from the country-by-country specifications in equation 1. The average estimated coefficient on demand is about 1.3 and the median estimate is quite close to that for goods while it is slightly lower (1.1) for services. Most estimated coefficients on demand are positive. The coefficients on relative prices are mostly negative, with the mean (median) estimates at -0.2 (-0.14) for goods and -0.30 (-0.23) for services. While in most cases import demand covaries negatively with prices, in some countries the estimated coefficient on prices is positive. This is possibly due to standard endogeneity (prices increasing with demand) which would bias the coefficient upwards. Since the main goal of our exercise is to *predict* import growth, we do not address this issue; the model turns out to perform well in sample as we highlight in the next subsection.[8]

## 2.2 Model performance

As shown in Figure 3 (top panels), combining the estimates from the country-by-country regressions (weighted by shares in world imports) yields accurate predictions–i.e. fitted values–of im-

[8]Table A1 also reports the results from a panel version of the equation in 1, including importer and time fixed effects ($\alpha_m$ and $\gamma_t$):

$$\Delta \ln M^{\tau}_{mt} = \alpha^{\tau}_{m} + \gamma^{\tau}_{t} + \beta^{\tau}_{D} \Delta \ln D^{\tau}_{mt} + \beta^{\tau}_{P} \Delta \ln P_{mt} + \epsilon^{\tau}_{mt}, \quad \forall \tau \in \{g, s\} \tag{3}$$

Consistent with economic intuition, the estimated coefficients on relative prices are negative and significant across all specifications and close to 0.3. The coefficient on import-intensity adjusted demand is positive and close to 1 for goods, and around 1.1 for services. The adjusted $R^2$ suggests that the model for imports of goods explains about 40% of the variation in the data, while it is just shy of explaining 10% of the variation in the growth of service imports.

port growth up to 2019. But for 2020 the model fails at predicting the large observed fall in services trade (the model predicts a growth rate of about -8%, while in 2020 trade fell by 25%) and slightly overpredicts the fall in goods trade (10% predicted vs 6% observed fall). The bottom panels of Figure 3 report the prediction errors series: the error for services in 2020 is 0.2 log-points, quite literally "off-the-charts" with respect to previous years.[9]

To understand what drove the poor performance of the model in 2020, we proceed by linking the prediction errors for 2020 to various pandemic related variables and other country features.

### 2.3 The drivers of pandemic prediction errors: going beyond demand

To fix ideas concerning this analysis, notice that equation 3 can be derived from the following expression for import demand (the index $\tau$ for the type of import has been omitted for simplicity):

$$M_{mt} = D_{mt}^{\beta_D} \left( \frac{\tilde{P}_{Mmt}}{\tilde{P}_{mt}} \right)^{\beta_P} \exp\{\alpha_m t + c_t + \eta_{mt}\} \equiv D_{mt}^{\beta_D} P_{mt}^{\beta_P} \exp\{\alpha_m \times t + c_t + \eta_{mt}\} \tag{4}$$

In words, import demand by country $m$ at time $t$ can be though of as a function of a measure of domestic demand ($D_{mt}$, in our case the import-intensity adjusted measure), prices of imports relative to domestic prices $\frac{\tilde{P}_{Mmt}}{\tilde{P}_{mt}}$, a country- specific linear time trend $\alpha_m t$, aggregate shocks captured by $c_t$ and other time varying specific factors captured by $\eta_{mt}$ (e.g., preferences, trade costs not subsumed in the price indexes, the impact of demand on imports not captured by the measure of demand or supply factors faced by country i and different from aggregate supply shocks that are not immediately priced in). The estimated equation 3 can be obtained by taking logs, differencing over time, adopting the definitions $\gamma_t \equiv \Delta c_t$ and $\epsilon_{mt} \equiv \Delta \eta_{mt}$, and—concerning the trend—noticing that $\alpha_m \times t - \alpha_m \times (t-1) = \alpha_m$.

Hence the residual in the equation captures elements such as changes in preferences, or supply shocks having an impact on imports not immediately captured by standard price indexes. The pandemic likely produced various shocks of this sort and the following results confirm this intuition.

[9] Figure A1 summarizes the distribution of prediction errors in 2019 and 2020. Concerning services, the distribution in 2020 is more disperse than the distribution in 2019, has a lower mean and a prominent negative skew. While the distributions of the errors coming from the model for the import growth of goods are closer to each other, the variance of errors in 2020 is still larger and the distribution features a prominent long right tail, consistent with the positive average prediction error observed in aggreagate. The mean square errors reported in Figure A2 in the appendix deliver a similar message, although the mean square errors for goods was higher in 2000 than 2020.

Results are reported in Table 2. The pandemic induced higher than expected goods imports. Countries that experienced a more severe pandemic (more cases, more stringent measures or less mobility) show better than expected good import growth. Consistent with the previous discussion, it is possible that the pandemic induced a shift in preferences away from services (domestic like restaurants, and imported like travel) towards goods. The insignificant coefficients on imported services, however, suggest that possibly the shift away from services mostly affected domestic rather than imported services.[10]

Importantly for what follows, trade partners' health preparedness was associated with more goods imports. The ability of countries to increase their goods import above the expected amount was associated with their partners' health preparedness as captured by the *Global Health Security Index*.[11] These results are shown in Table 3, where the relevant variable is an import-weighted average of the index. These results suggest that containment policies in partner countries likely played a role beyond those countries' borders, spilling over internationally through trade connections. To investigate this possibility more formally, we turn next to an analysis of country-to-country trade linkages.

# 3 International spillover effects of lockdowns

## 3.1 Modeling international spillovers

Having assessed the role of pandemic-related factors and policies on the exceptional fall in imports, we turn now to the spillover effects that lockdowns could have on trade partners. To quantify the international spillover effects of containment policies, we estimate the following standard gravity equation at the country pair-industry-month level (see Yotov, 2022, for a recent review of gravity models), in which goods imports are a function of trade partners' containment policies:

$$M_{meit} = exp[\beta Stringency\ Index_{et} + \delta Controls_{met} + \alpha_{mei} + \gamma_{mit}] + \epsilon_{meit} \quad (5)$$

[10]While imported services such as travel indeed declined, this was not the case for other categories such as communication. Relatedly, as countries closed their borders to contain the spread of the virus, tourism collapsed, explaining much of the fall in service imports. Large importers of tourism (as captured by the average value of travel imports as a share of GDP between 2016 Q1 and 2019 Q4) saw a much larger than expected drop in service import growth, as shown in Table A2 in the appendix.

[11]For details on the index, see Cameron *et al.* (2019), as well as other material that can be found on the Global Health and Security Index website at https://www.ghsindex.org/about/.

The bilateral imports of products in industry $i$ ($M_{meit}$) by importer country $m$ from exporter country $e$ in month $t$ is regressed on: i) the time-varying index of lockdown intensity in the exporter country $e$ ($Stringency\ Index_{e,t}$), measured using the monthly average values of the Oxford COVID-19 Government Response Stringency Index (Hale *et al.*, 2021); ii) a set of variables that vary across country pairs and time ($Controls$); and iii) a set of fixed effects ($\alpha_{mei}$,$\gamma_{mit}$).

The main dataset covers bilateral goods imports disaggregated at the 6-digit product level in the Harmonized System (HS6). These data are available at a monthly frequency from Trade Data Monitor (TDM) from January 2020 to June 2021.[12] The original sample includes 99 importing countries which trade with 196 exporting countries. These data have been used recently to look at the recent effects of trade tensions and of the COVID-19 pandemic on trade flows (Berthou and Stumpner, 2022; Grant *et al.*, 2021; Arita *et al.*, 2022). Figure A3 shows that TDM covers almost the universe of goods trade, as the aggregation of all import flows account for about 95 percent of goods trade, as reported by the IMF Direction of Trade Statistics. When looking at a common sample made by 99 reporting countries, the coverage is very close to 100 percent.

We aggregate bilateral monthly data on goods imports at the HS6 codes over about 300 industries, to be able to match import flows with a measure of insustry upstreamness, as computed by Antràs *et al.* (2012). The aggregation is done using the concordance between the 6-digit HS codes and I-O commodity codes, as published by the Bureau of Economic Analysis.[13]

The trade data are also matched with a set of other variables at the exporting country level. First, we merge the TDM data with a monthly measure of the stringency of pandemic containment policies in exporting countries (the Oxford COVID-19 Government Response Stringency Index), as computed by Hale *et al.* (2021), and with the number of new COVID-19 cases and death per capita, as reported by Our World in Data (Ritchie *et al.*, 2020). Second, we use the Global Trade Alert (GTA) data (Evenett, 2019) to construct a measure of export restriction at the country-pair level, by counting, at the quarter level, the number of new export interventions (e.g., bans, quotas, non-tariff measures, tariffs, etc.) implemented by the exporter country $e$ versus the importing country $m$. For completeness, the model also includes the number of export barriers which have been removed.[14]

[12] Trade Data Monitor data are available by subscription at https://tradedatamonitor.com/ and cover also exports.

[13] See: https://www.bea.gov/industry/historical-benchmark-input-output-tables.

[14] See: https://www.globaltradealert.org/data_extraction for details on the coverage and the methodology of the

This dataset, which is the basis for our main analysis, includes 98 importing countries and 163 exporting ones, for a total of 15,880 country pairs and 4,652,840 unique industry-exporter-importer trade corridors.

The key parameter of interest $\beta$ measures the effect of trade partners containment policies on imports. Figure 1 (panel B) illustrates that the increase in mobility restrictions at the outbreak of the pandemic coincided with the sharp collapse in goods imports in the first two quarters of 2020. However, the stringency index could be correlated with other simultaneous changes in the exporter country. In particular, an important element to consider is the response of trade policy to the pandemic, as several governments imposed new export restrictions on specific goods (see, for instance Evenett, 2020; Evenett *et al.*, 2021, on export restrictions on medical supplies and food products). To account for the role of trade restrictions, we include the number of new export restrictions and the number of removed export barriers at the country-pair level, constructed from the GTA data. To further mitigate the omitted variable bias, the set of controls includes the number of new COVID-19 cases and deaths per month (per million inhabitants) measured in the exporter country.[15]

Country-pair-industry fixed effects ($\alpha_{mei}$) control for differences in industry-specific trade flows between each pair of importer and exporter countries, such as time-invariant natural, cultural and geographical factors, as well as the presense of trade agreements (as long as they are present throughout the sample period). The importer-industry-time fixed effects ($\gamma_{mit}$) absorb unobserved time-varying heterogeneity across both importers and industries. In other words, all unobserved changes in demand for goods in a given industry, including those coming from domestic lockdowns, should be absorbed by the fixed effects.

Conditional on this rich set of controls and fixed effects, the coefficient $\beta$ captures the impact of lockdowns on imports via the supply channel. A negative coefficient on the stringency index indicates that the size of the decline in imports for a given country is related to the severity of the

GTA data.

[15] Another potential variable to control for would be mobility, measured by the average of all the components of the Google mobility score excluding parks and residential. However, a decline in mobility is an inevitable consequence of a lockdown, making it strongly correlated with the stringency index. In the sample 2020:m1-2021:m6, the elasticity of mobility to the stringency index (computed by a simple regression controlling for time and country fixed effects) is -0.5. As the analysis focuses on the effects of the containment policy measures (e.g., lockdowns) rather than on actual behavior (which could also reflect individual choices), the empirical model incorporates the stringency index rather than mobility.

pandemic restrictions imposed by its trade partners, due to the corresponding reduction in the supply of goods by those trade partners.

Before turning to the results it is worth considering a final caveat when interpreting the coefficient $\beta$ as a measure of a supply channel. Import demand is controlled for under the assumption that the proportional change in country-specific demand for products in a given industry (in a given month) is the same across countries. For instance, we assume that the proportional change in demand for vehicles by U.S. consumers in April 2020 was the same for both Japanese and German cars. As the analysis looks at monthly changes and focuses on a period of high uncertainty, it is plausible to assume that consumers did not adjust their demand differentially across producers in different countries.

Since the truncation of import flows at zero biases the standard log-linear OLS approach and leads to inconsistent coefficient estimates, we follow an extensive trade literature on gravity models (Silva and Tenreyro, 2006, 2022; Anderson and Yotov, 2016; Espitia *et al.*, 2022; Arita *et al.*, 2022; Yotov, 2022) and estimate equation 5 by Poisson pseudo-maximum likelihood (PPML), as implemented by Correia *et al.* (2020). Standard errors are clustered at the exporter level, which is the source of variation in the stringency index.

### 3.2 Baseline Results

The main results are shown in Table 4 and reported in Figure 4. The first five columns show the negative and significant association between the stringency of partners' containment policies and domestic imports. Moving from a model with time varying importer fixed effects (column 1) to one with time varying importer-industry fixed effects (column 2) shows that the point estimate of coefficient of the stringency index is stable and suggests that the model captures most of the variation from the demand side. The spillover effect is robust to controlling for the extent of the health crisis (measured by the number of COVID-19 cases and deaths per capita) and changes in export restrictions put in place by trade partners, including when controlled for jointly (columns 3-5). The effect is also economically meaningful. The semielasticity is about -0.15 and implies that that a one percentage point increase in the stringency index is associated with a 0.15 percent reduction in imports.[16]

[16]Interestingly, this finding is very close to the results of Pimenta *et al.* (2021) using firm-level Portuguese data.

The pandemic was a novel shock, so it is plausible that over time there was adaptive behaviour, with the implication that the size of spillover effects could be changing from month to month. To examine this possibility we split the coefficient $\beta$ over time and estimate the spillover effects of trade partner containment policies in each month. Figure 4 shows the dynamics of the spillover effect of lockdowns. The effects were strongest in the first 5 months of 2020, gaining in strength in February and March when COVID-19 evolved from a regional crisis to a pandemic, but then declining and becoming insignificant in June, when goods imports started to rebound. Interestingly, there is a smaller but significant effect in the Spring of 2021, coincident with the spread of the Delta variant. As containment policies persisted throughout the period—the stringency index does not show any visible decline (Figure 4)—this would suggest that countries started adjusting to the presence of lockdowns and pandemic-related restrictions, consistent with evidence found by Heise (2020), Cerdeiro and Komaromi (2020), Lafrogne-Joussier *et al.* (2022), Berthou and Stumpner (2022), Pimenta *et al.* (2021), and Arita *et al.* (2022) in different settings.[17]

Since the impact of lockdowns on imports is found to be large but short-lived, we estimate the baseline model over the first half of 2020 to better gauge the economic effect during the first phase of the crisis. The results, reported in column 6, indicate that the semielasticity is more than twice that estimated for the whole sample. This point estimate is used to generate the evolution of goods imports under a counterfactual with no containment policies in trade partners. Comparing this series with the actual evolution of imports indicates that containment policies accounted for about 60 percent of the observed fall in imports (Figure 5), the headline quantification of the spillover effect discussed in the chapter.[18]

### 3.3 Heterogeneous Effects of Lockdowns

The spillover effects of containment policies could depend on the capacity of countries to mitigate them and adapt to the new prevailing circumstances. A first aspect is the size of the fiscal policy response to the COVID-19 pandemic. We use data collected by the IMF on COVID-19 related fiscal

[17] An alternative interpretation is that, after the initial shock, the stringency index does not capture adequately the intensity of the lockdown measures relevant for production and trade. However, measuring containment policies exclusively by an index of workplace closings delivers similar results, mitigating concerns about measurement issues—see Section 3.5.

[18] The effective fall in imports is equal to the value of the series in January (96.5) minus the value in May (72.5). In the same way, the fall in the counterfactual without containment policies is 100-90.3. Thus, lockdowns account for (24-9.6)/24 = 59.7 percent of the actual import decline.

measures taken or announced between January and June 2020. These data cover government discretionary measures that supplement existing automatic stabilizers and include both above-the-line (additional spending and forgone revenue) and below-the-line (equity, loans, and guarantees) fiscal operations. All numbers are scaled by GDP.[19] We estimate the semi-elasticity of imports to the stringency index in countries which implemented a relatively small fiscal response to the crisis (the bottom quartile of the distribution) and in those which implemented a relatively large fiscal reponse. The results, reported in Table 4 (column 7) and at the top of Figure 6, indicate that the international spillovers from lockdowns are significantly larger for countries whose trade partners have been less able to combat the effects of the pandemic with discretionary fiscal measures.

A second key aspect is the capacity to rely on remote working. The results shown in columns 8 and 9 in Table 4 exploit cross country heterogeneity in the proportion of jobs which can be done at home to test whether the supply effect due to the lockdown is stronger for countries which import more from countries where jobs are less likely to be done remotely. Teleworkability is measured using the cross-country data computed by Dingel and Neiman (2020) and the sample of trade partners is split between those with a low share of jobs that can be done remotely (the bottom quartile of the distribution) and those with a high share of teleworking. As the use of the teleworkability measure reduces the sample size, the baseline model is estimated on the restricted sample (column 8). Even in this case there is a negative (albeit smaller) and significant spillover effect. What is more interesting is that the spillover effect of lockdowns is more than twice stronger for countries which are less able to rely on remote working compared to those that have a higher share of jobs that can be done from home (column 9). This finding, shown also in Figure 6, is consistent with existing evidence showing that the feasibility of remote work mitigated the negative effects of reduced worker mobility (Pei *et al.*, 2021), while suggesting that the benefits extended beyond national boudaries to trade partners.

A third dimension of heterogeneity is across industries. Column 10 in Table 4 and Figure 6 report the results obtained from decomposing the effect of containment policies across four GVC-intensive goods, defined to include inputs and finished goods in automotive industries, electronics, textiles and garments, and medical goods. Together these goods account for about 24 percent

[19]See: https://www.imf.org/en/Topics/imf-and-covid19/Fiscal-Policies-Database-in-Response-to-COVID-19; we use the June 2020 vintage of the database to focus on the initial fiscal reponse as the international spillovers are concentrated in the first 6 months of 2020 (Figure 4).

of global goods trade, and are typically considered to be at the forefront of GVCs (Sturgeon and Memedovic, 2010). All other products are pooled into a residual category (non-GVC-intensive industries). The results indicate that the effect of lockdowns is stronger in GVC-intensive industries, and especially in electronics, than in non GVC-intensive ones. This finding is consistent with some recent evidence based on firm-level data (Pimenta *et al.*, 2021) as well as product-level flows (Berthou and Stumpner, 2022). It supports the intuition that imports in GVC-intensive industries are relatively more exposed to disruptions in the supply chain (in this case due to lockdowns).

### 3.4 A Full-Fledged Gravity Model

The baseline analysis does not fully control for multilateral resistance as in standard gravity models since it does not include time-varying exporter fixed effects. Adding this term makes it impossible to identify the semielasticity of the stringency index, given that its source of variation is also at the exporter-time level. However, the richness of the product-level data allows to go one step further and better identify the supply channel of lockdowns exploiting the fact that the effect of the lockdown is likely to differ across industries.

The sensitivity of imports could depend on the industry's reliance on the sourcing of inputs, as measured by the industry's upstreamness (i.e., the average distance from final use). Using a Bartik (1991)-style approach, the stringency index is interacted with a measure of GVC upstreamness computed by Antràs *et al.* (2012) from U.S. input-output tables.[20] This leads to an augmented version of equation 5:

$$M_{meit} = g(\beta Stringency\ Index_{et} \times Upstream_i + \delta Controls_{eit} + \alpha_{mei} + \gamma_{mit} + \mu_{et} + \epsilon_{meit}), \qquad (6)$$

which includes both multilateral resistance terms ($\gamma_{mit}$ and $\mu_{et}$) and identifies the differential effect of the stringency index across industries. In other words, the (time-invariant) upstreamness of the industry is a measure of its exposure to the (time-varying) lockdown supply shock. The intuition is that more downstream industries, for which output will go to the end user (e.g., automobile, electronics), would be relatively more exposed to GVCs and sourcing inputs and, therefore, to the restrictions imposed by lockdowns.

[20] Antràs *et al.* (2012) also compute the industry measure of upstreamness for other economies with I-O tables and show that this is generally stable across countries. Given the primary goal of keeping bilateral trade flows in the gravity model as large as possible, the US measure of upstreamness is applied to all exporter countries.

Table 5 shows the results. When the exporter-time fixed effects are not included, the results show that the negative effect of stringency measures is dampened in industries which are very upstream (like metals and minerals products), while it is stronger for those downstream (like transportation and textiles). A one standard deviation of the upstream index (SD = 0.82) reduces the supply effect of the lockdown by about 20 percent (column 1).[21] More importantly, once fully controlling for unobserved (time-varying) heterogeneity across exporters including the multilateral resistance term (column 2), the differential effect of the lockdown across industries with different degree of upstreamness remains statistically significant and similar in size. This evidence is in line with the results of Brussevich *et al.* (2022) using data from French firms.

### 3.5 Robustness

Our results are robust to additional exercises aimed at testing the sensitivity of the findings to the choice of variables, sample and methodology.

**Measuring containment policies.** The main results are robust to measuring containment policies with an index measuring only the severity of workplace closures. This index, which assumes discrete values from 0 (no restrictions) to 3 (closing down or working from home for all-but-essential workplaces), is one of the 8 containment and closure policy indicators used to calculate the Oxford COVID-19 Government Response Stringency Index (Hale *et al.*, 2021).[22] While its categorical nature compresses its variability over time, the index is the closest to the idea of measuring how lockdowns could affect production and spillover to international trade. The index of workplace closings and the stringency index are highly correlated, and they show a very similar evolution over time (Figure A4). In particular, the correlation in the pooled sample is equal to 0.82 and a regression of the stringency index against the workplace closings index with month and country fixed effects gives a coefficient equal to 13.3 (s.e. $= 0.56$). We replicate the baseline results using the measure of workplace closings and show that our findings are still valid. Table 6 shows that more stringent containment policies in workplaces put in place by trade partners are

[21] Given that average value of the upstreamness indicator is equal to 2.07, the coefficient on stringency (measured at the average level of upstreamness) is equal to $-0.00234 + 0.00039 * 2.07 = -0.0015$. A one standard deviation increase in upstreamness increases the coefficient by $0.00039 * .81 = 0.0003$, which correspond to about one fifth of teh average effect ($.0003/.0015 = 0.20$).

[22] See https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker for further details on the Oxford stringency index and its individual components.

associated with a significant decline in imports (columns 1-3). This effect is significantly stronger for trade partners which implemented a smaller discretionary fiscal response to the COVID-19 pandemic (column 5) and for trade partners with a low capacity to work remotely (column 6), while it is larger for goods upstream in the value chain (column 8).

**Robustness across different country groups.** Because of the asynchronous dynamics of the COVID-19 pandemic and its differential intensity across countries, one could imagine that results are sensitive to specific countries or regions. To address this concern, we estimate the baseline model by dropping, one at a time, specific country groups classified by income and region from the set of exporting countries. Figure 7 shows that the significance of the spillover effect is robust to alternative samples. However, it also suggests that the semielasticity of the stringency index becomes smaller when emerging markets and Asian countries are excluded. This evidence is consistent with the impact of containment policies being larger in the first phase of the crisis, when the COVID-19 shock disproportionately affected Asian countries, shutting down production and disrupting global trade. By contrast, the semielasticity is higher when advanced economies and European countries are excluded, suggesting that containment policies in Europe (which occured later in the year) had weaker spillover effects. In a second exercise we zoom in on the role of China, given its importance for global trade and its prominent role in the early phase of the pandemic. We re-estimate the baseline model dropping China from the set of exporters and focusing on the heterogeneous effects of lockdowns over time. Figure A5 in the appendix, which replicates Figure 4, illustrates that our results on the international spillover of lockdown are not China-specific and remain economically meaningful in the sample excluding China. The smaller spillover effects in February and March and the larger ones in April and May could indicate that the initial spillover effect on global trade was driven by the lockdowns in China. By constrast, lockdowns in other countries matter more in the Spring of 2020, when China started easing restrictions, while other regions (e.g., Europe and the United States) were still under severe lockdowns.

**Clustering.** Table A3 in the appendix reports the main results discussed in the chapter estimated by clustering the standard error at the exporter-month level. The significance of the findings is not affected, and the estimated standard errors are—if anything—smaller.

## 4 Conclusions

Goods trade fell sharply in the early stages of the pandemic, but rebounded quickly. Trade in services, on the other side, has not yet recovered at the time of writing in mid-2022. We show that standard factors of import demand observed in 2020—components of domestic demand and relative import prices—are consistent with weaker than observed demand in goods imports and stronger than observed demand in services imports. Indeed, feeding these standard factors into a simple model of import demand estimated on historical data suggets that non-standard drivers of imports came to the fore during the pandemic. We show countries whose trade partners had better health preparedness experienced smaller declines in goods imports relative to model predictions in 2020, hinting at the possibility of spillovers from partner country pandemic responses on trade.

We then show that pandemic containment policies in partner countries played an important role beyond those countries' borders. Using product-level bilateral trade data, we document that international spillovers from supply disruptions due to lockdowns were sizable and negative. Specifically, we estimate the extent to which more stringent pandemic containment policies in a given country affected imports from that country, after controlling for import demand. We find that a percentage point increase in the stringency index is associated with a 0.15 percent reduction in imports. This is a economically sizeable impact, implying that up to 60 percent of the observed fall in imports between January and May 2020 can be explained by lockdowns. We also document that such spillover effects were (i) short-lived, fading out starting in the second half of 2020, (ii) stronger for goods belonging to GVC-intensive industries, and (iii) mitigated if exporting countries were more conducive to teleworking and implemented large discretionary fiscal measures in response to the pandemic.

Finally, we show that where the pandemic was more intense, goods imports rebounded faster than predicted by the import demand model. This is consistent with the oft-made argument, (e.g., in Guerrieri *et al.*, 2022), that the pandemic induced a shift in preferences away from services (domestic services, like restaurant meals, and imported services, like travel) towards goods. These findings are relevant to a better understanding of how the economic effects of the pandemic propagated across countries via trade linkages.

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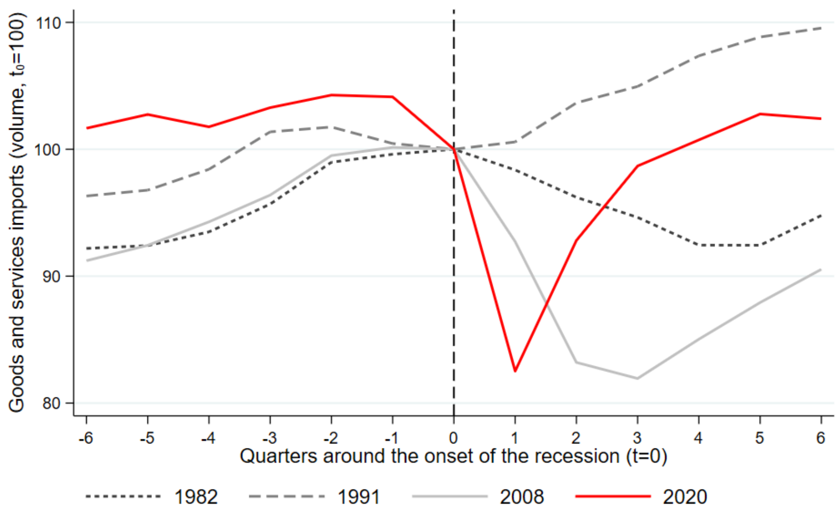
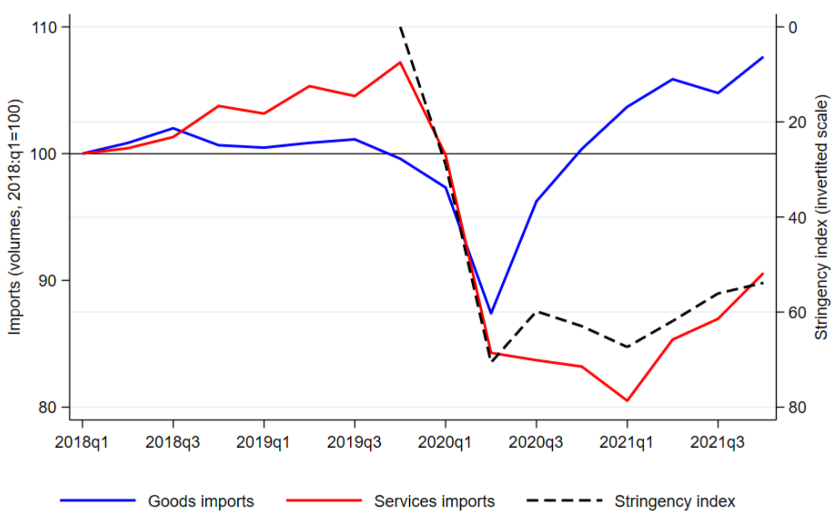
## Figures

Figure 1: Trade in the pandemic



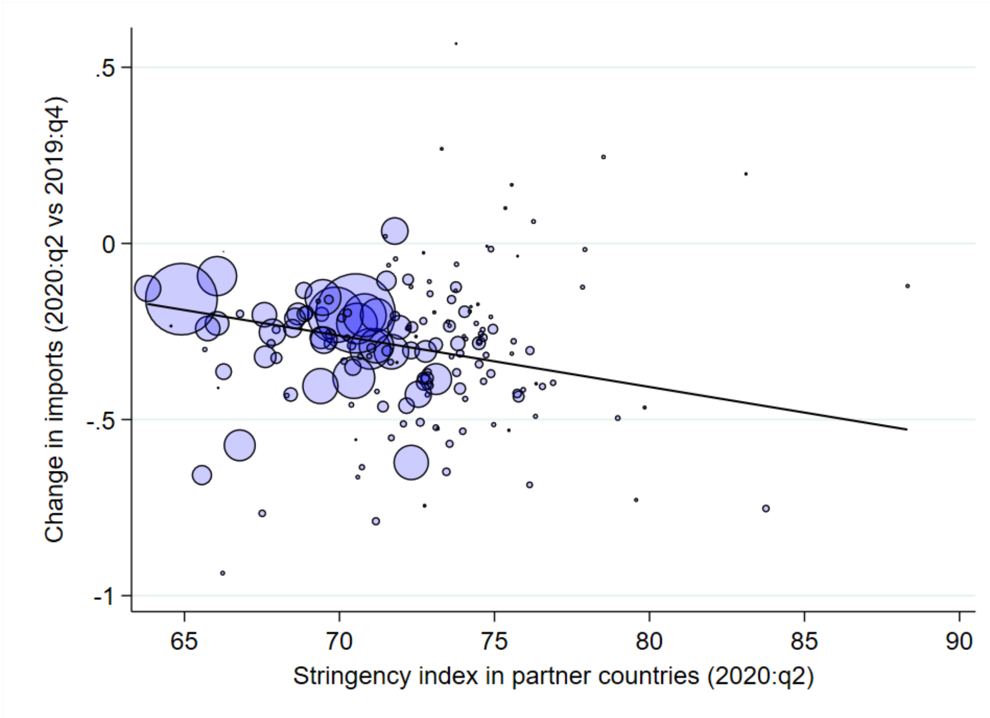

(a) Trade around global recessions




(b) Trade in goods and services during the pandemic

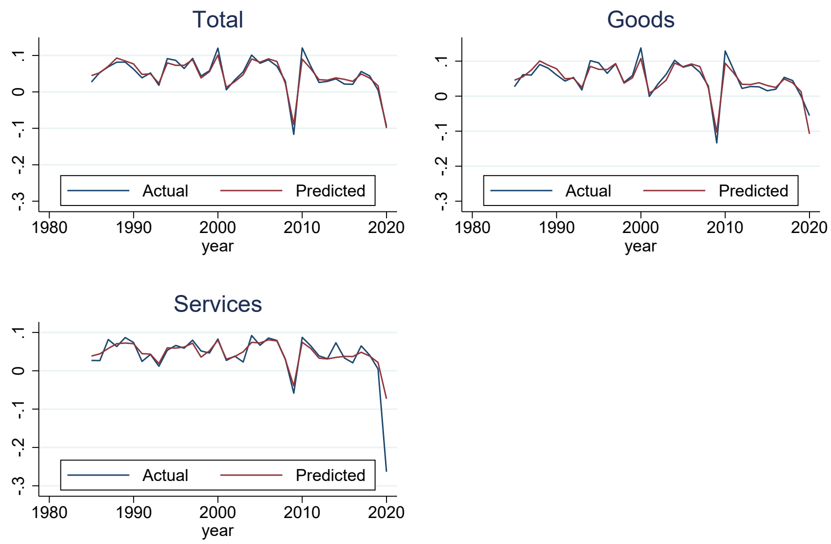
Notes: Panel A plots the evolution of real imports of goods and services for 12 quarters around global recessions, as dated by Kose *et al.* (2020). Real imports are set to 100 in the initial quarter of the recession. Quarterly imports data are from the IMF World Economic Outlook. Panel B plots global trade in goods and services between 2018:q1 and 2021:q4. Quarterly volumes of goods and services imports, taken from CPB World Trade Monitor, are normalized at 100 in 2018:q1. The dashed line plots the world import-weighted average of the Oxford COVID-19 Government Response Stringency Index (Hale *et al.*, 2021).

Figure 2: Change in imports and partner countries' lockdown stringency

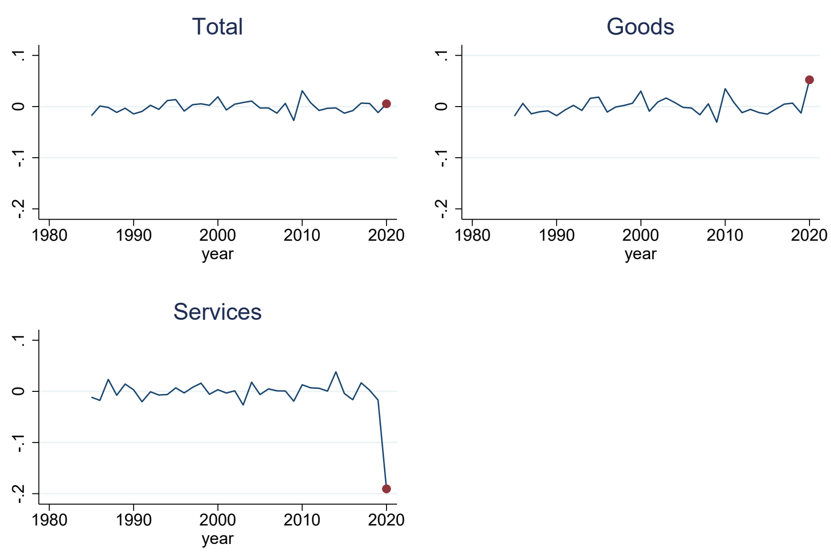



Notes: The chart plots the change in the values of imports (in USD) between 2020:q2 and 2019:q4 against the Oxford stringency index (Hale *et al.*, 2021) in partner countries, constructed taking import flows over 2018:q3-2019:q4 as weights. The change in imports is computed as: $\frac{M_{2020:q2} - M_{2019:q4}}{0.5 \times M_{2020:q2} + 0.5 \times M_{2019:q4}}$ The size of the bubble is proportional to the value of imports (in USD) in 2019:Q4. The solid line is the linear fit of a weighted regression of the change in imports between 2020:Q2 and 2019:Q4 against the Oxford stringency index in partner countries. The estimated coefficient is equal to -0.015 (t-stat = -2.44). Data on bilateral imports are teh the IMF Direction of Trade Statistics.

Figure 3: Trade in the pandemic: Results from an import demand model



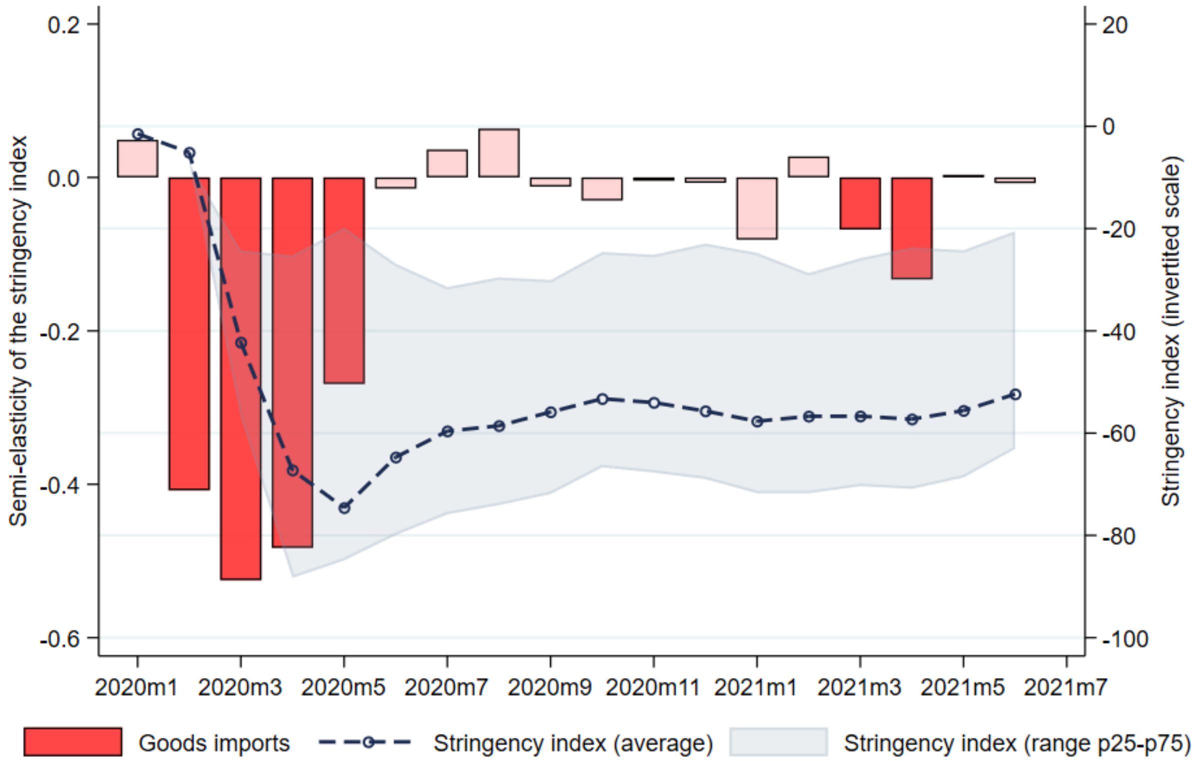

(a) Actual and predicted values of import growth




(b) Differences between actual and predicted values of import growth

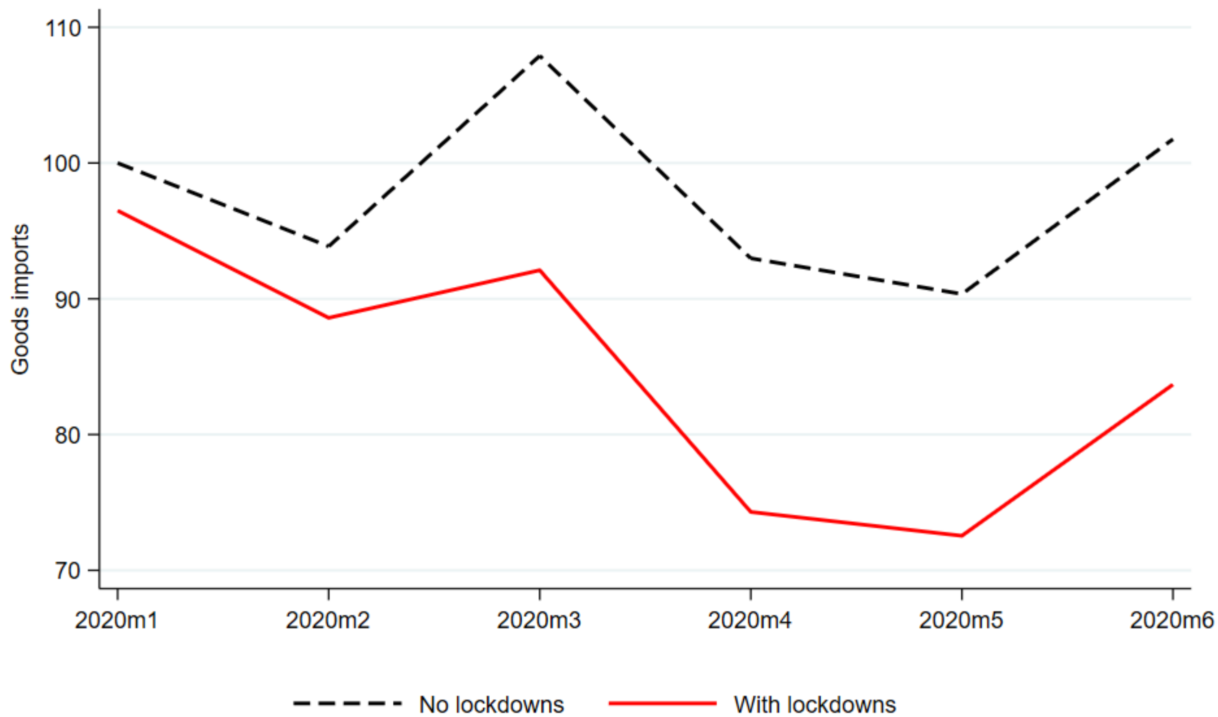
Notes: The charts in panel A plots the observed global growth in real imports (Total, Goods and Services) and the predicted growth from the model estimated in equation 1 on 1985-2019 data on a sample of 127 countries. Predictions are obtained country by country and then aggregated using each country's share in global imports. The charts in panel B simply reports the differences between the actual and the predicted growth in imports.

Figure 4: The international spillover effect of lockdowns over time



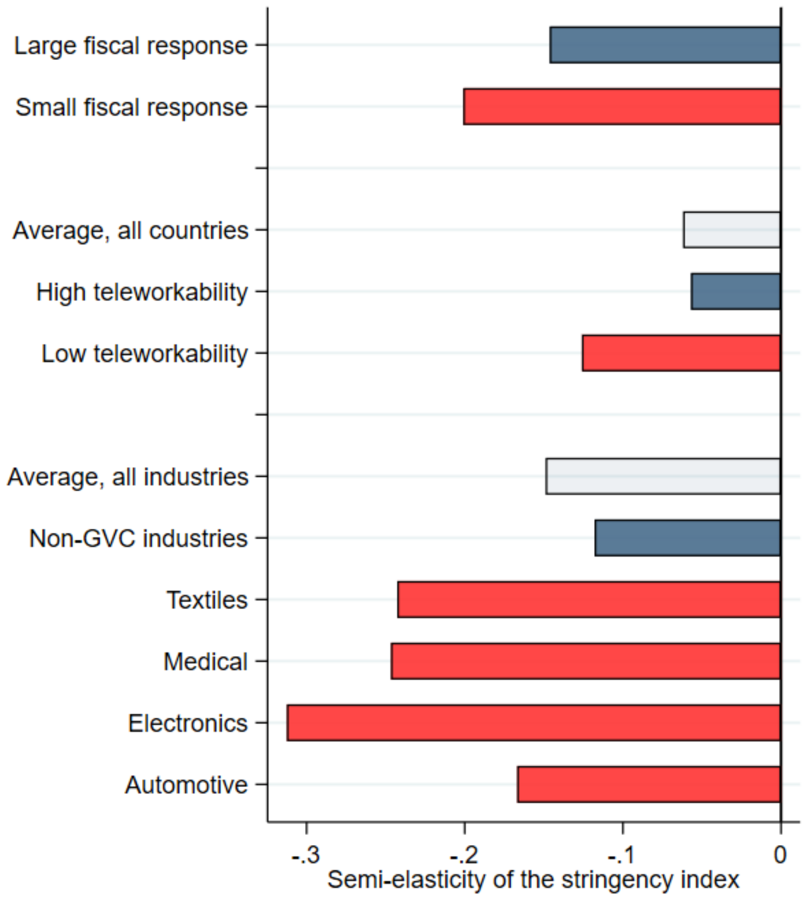

Notes: The chart plots the semi-elasticity of the stringency index for each month obtained estimating the baseline specification of equation 5 (Table 4, column 2) and interacting the stringency index with the time dummies. Darker bars show semi-elasticities which are statistically significants, lighter bars show those that are not. The dashed line measures the average stringency index of partner countries and the shaded are measures its interquantile range.

Figure 5: Quantifying the international spillover effect of lockdowns



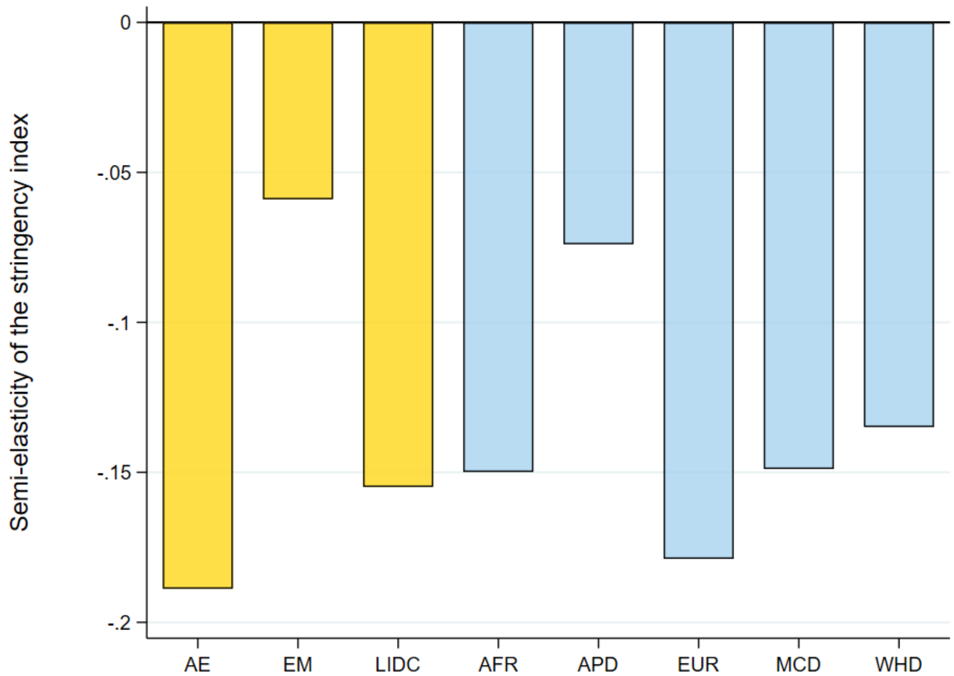

Notes: The chart plots the evolution of good imports under a counterfactual without any containment policy in place in trade partner countries. The counterfactual of no lockdown (dashed line) is obtained using the results reported in Table 4 (column 6) and imposing a value of zero for the Stringency index over the entire period. The solid line plots the actual evolution of imports (in the same sample) in percent of the value with no lockdown in January 2020. Goods imports are measured in percent of predicted value with no lockdown in January 2020.

Figure 6: The heterogeneous international spillover effect of lockdowns




Notes: The chart plots the semi-elasticity of the stringency index separately for: 1) trade partners which have annnounced and implemented high and low discretionary fiscal measures in response to the pandemic between January and June 2020 (fiscal spending is scaled by GDP and the sample is split along the first quartile of the distribution of fiscal spending over GDP); 2) trade partners with high and low values of the teleworkability index, as computed by Dingel and Neiman (2020) (the sample is split along the first quartile of the distribution of the index; the average value is smaller than in the overall sample as the sample is different from the baseline); and 3) for goods in GVC-intensive industries (Automotive, electronics, medical, textiles) and in non-GVC-intensive ones. The semi-elasticities are computed based on the results reported in Table 4 (columns 7-10, respectively).

Figure 7: Robustness: the international spillover effect of lockdowns dropping country groups




Notes: The chart plots the semi-elasticity of the stringency index obtained estimating the baseline specification of equation 5 (Table 4, column 2) for different sub-samples. For each column, the sample is obtained excluding all exporting countries in the country group listed at the top of the chart. AE: advanced economies; EM: emerging markets; LIDC: low income developing countries; AFR: Africa; APD: Asia and Pacific; EUR: Europe; MCD: Middle East and Cetral Asia; WHD: Western Hemisphere.

# Tables

Table 1: Import demand model: Summary statistics from the country-by-country estimates

| | | Total | Services | Goods |
|---|---|---|---|---|
| **Demand coefficients** | Mean | 1.2955 | 1.3472 | 1.3305 |
| | Median | 1.3468 | 1.0932 | 1.3574 |
| | Interquantile range | [0.95,1.54] | [0.68,1.76] | [0.99,1.69] |
| **Price coefficients** | Mean | -0.2230 | -0.2931 | -0.2030 |
| | Median | -0.1913 | -0.2266 | -0.1390 |
| | Interquantile range | [-0.39,0.00] | [-0.57,0.09] | [-0.43,0.10] |
| Number of countries | | 127 | 127 | 127 |

*Notes:* Results from regressions estimated country by country on a sample of 127 countries with at least 16 observations between 1985 and 2019.

Table 2: Residual analysis: Pandemic-relevant variables

| | (1) Total | (2) Services | (3) Goods | (4) Total | (5) Services | (6) Goods | (7) Total | (8) Services | (9) Goods |
|---|---|---|---|---|---|---|---|---|---|
| Total COVID-19 cases | 0.00321 | -0.00639 | 0.00812** | | | | | | |
| | (0.00360) | (0.0123) | (0.00408) | | | | | | |
| *Standardized coefficient* | 0.0574 | -0.0416 | 0.121** | | | | | | |
| Stringency index | | | | 0.00172* | 0.00177 | 0.00229** | | | |
| | | | | (0.000895) | (0.00231) | (0.00103) | | | |
| *Standardized coefficient* | | | | 0.197* | 0.0738 | 0.217** | | | |
| Mobility | | | | | | | -0.00236** | -0.00183 | -0.00363*** |
| | | | | | | | (0.000918) | (0.00330) | (0.00117) |
| *Standardized coefficient* | | | | | | | -0.239** | -0.0674 | -0.305*** |
| Observations | 125 | 125 | 125 | 121 | 121 | 121 | 99 | 99 | 99 |
| Adjusted R-squared | -0.004 | -0.006 | 0.009 | 0.038 | -0.003 | 0.049 | 0.074 | -0.005 | 0.104 |

*Notes:* Results from a regression of the import demand model prediction errors in 2020 on COVID-19 related variables. The total number of COVID-19 cases in 2020 (in logarithm), mobility and the stringency index are extracted from the Our World in Data database. The stringency index and mobility are computed as averages over 2020. Changes in the number of observations originate from the variable of interest being missing. Standardized coefficients represent the number of standard deviation changes in the dependent variables associated to one standard deviation change in the variable of interest. Standard errors, in parenthesis, are robust to heteroscedasticity. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Residual analysis: Trade partners' health preparedness

| | (1) Total | (2) Services | (3) Goods |
|---|---|---|---|
| Trade partners' health preparedness | 0.00213 | -0.00520 | 0.00518*** |
| | (0.00212) | (0.00546) | (0.00183) |
| *Standardized coefficient* | 0.0964 | -0.0854 | 0.195*** |
| Observations | 122 | 122 | 122 |
| Adjusted R-squared | 0.002 | -0.001 | 0.036 |

*Notes:* Results from a regression of the import demand model prediction errors in 2020 on trade partners health preparedness, computed as the import-weighted average of the Global Health Security Index across all countries from which country *i* imports goods. Standardized coefficients represent the number of standard deviation changes in the dependent variables associated to one standard deviation change in the variable of interest. Standard errors, in parenthesis, are robust to heteroscedasticity. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4: The international spillover effect of lockdowns

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Stringency index | -0.00141*** | -0.00149*** | -0.00183*** | -0.00160*** | -0.00182*** | -0.00307*** | | -0.00062*** | | |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | | (0.000) | | |
| Covid cases per million, lagged | | | 0.00002 | | 0.00002 | | | | | |
| | | | (0.000) | | (0.000) | | | | | |
| Covid deaths per million, lagged | | | -0.00056 | | -0.00051 | | | | | |
| | | | (0.001) | | (0.001) | | | | | |
| Number of new export restrictions | | | | 0.01631 | 0.00917 | | | | | |
| | | | | (0.011) | (0.010) | | | | | |
| Number of removed export restrictions | | | | -0.00299 | -0.00199 | | | | | |
| | | | | (0.002) | (0.002) | | | | | |
| Stringency index x Small fiscal response | | | | | | | -0.00211*** | | | |
| | | | | | | | (0.000) | | | |
| Stringency index x Large fiscal response | | | | | | | -0.00146*** | | | |
| | | | | | | | (0.000) | | | |
| Stringency index x Low telework | | | | | | | | | -0.00126*** | |
| | | | | | | | | | (0.000) | |
| Stringency index x High telework | | | | | | | | | -0.00058*** | |
| | | | | | | | | | (0.000) | |
| Stringency index x Automotive | | | | | | | | | | -0.00169** |
| | | | | | | | | | | (0.001) |
| Stringency index x Electronics | | | | | | | | | | -0.00312*** |
| | | | | | | | | | | (0.001) |
| Stringency index x Medical | | | | | | | | | | -0.00246*** |
| | | | | | | | | | | (0.001) |
| Stringency index x Textiles | | | | | | | | | | -0.00243*** |
| | | | | | | | | | | (0.000) |
| Stringency index x non-GVC industries | | | | | | | | | | -0.00118*** |
| | | | | | | | | | | (0.000) |
| Observations | 23,594,169 | 23,531,808 | 21,787,468 | 23,531,808 | 21,787,468 | 6,118,735 | 23,256,563 | 14,764,840 | 14,764,840 | 23,531,808 |
| Exporter-importer-industry FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Importer-month FE | Y | - | - | - | - | - | - | - | - | - |
| Importer-industry-month FE | N | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Industry-month FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Sample | All | All | All | All | All | 2020H1 | All | TW | TW | All |
| Semielasticity | -0.1413 | -0.1494 | -0.1828 | -0.1594 | -0.1818 | -0.3068 | | -0.0616 | | |

*Notes:* The table reports the results of the estimation of equation 5 by Poisson pseudo-maximum likelihood. The stringency index is the Oxford COVID-19 Government Response Stringency Index, computed by Hale *et al.* (2021). The sample spans the period 2020:m1-2021:m6; in column 6 the sample is restricted to the first six months of 2020, while in columns 8-9 it is limited to exporting countries for which the measure of teleworkability computed by Dingel and Neiman (2020) is available. The coefficient of the stringency index is estimated separately for: i) trade partners which have announced and implemented high and low discrectionary fiscal measures in response to the pandemic between January and June 2020 (fiscal spending is scaled by GDP and the sample is split along the first quartile of the distribution of fiscal spending over GDP); ii) trade partners with high and low values of the teleworkability index (the sample is split along the first quartile of the distribution of the index); and iii) for goods in GVC-intensive industries (Automotive, electronics, medical, textiles) and in non-GVC-intensive ones. Standard errors in parenthesis are clustered at the exporter level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. TW = teleworkability.

Table 5: The international spillover effect of lockdowns across industry upstreamness

| | (1) | (2) |
|---|---|---|
| Stringency index | -0.00234*** | |
| | (0.001) | |
| Stringency index x Upstreamness | 0.00039* | 0.00057*** |
| | (0.000) | (0.000) |
| Observations | 23,531,808 | 23,531,808 |
| Exporter-importer-industry FE | Y | Y |
| Importer-industry-month FE | Y | Y |
| Exporter-month FE | N | Y |

*Notes:* The table reports the results of the estimation of equation 6 by Poisson pseudo-maximum likelihood. The stringency index is the Oxford COVID-19 Government Response Stringency Index, computed by Hale *et al.* (2021). The sample spans the period 2020:m1-2021:m6. Standard errors in parenthesis are clustered at the exporter level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6: The international spillover effect of lockdowns: Workplace closings

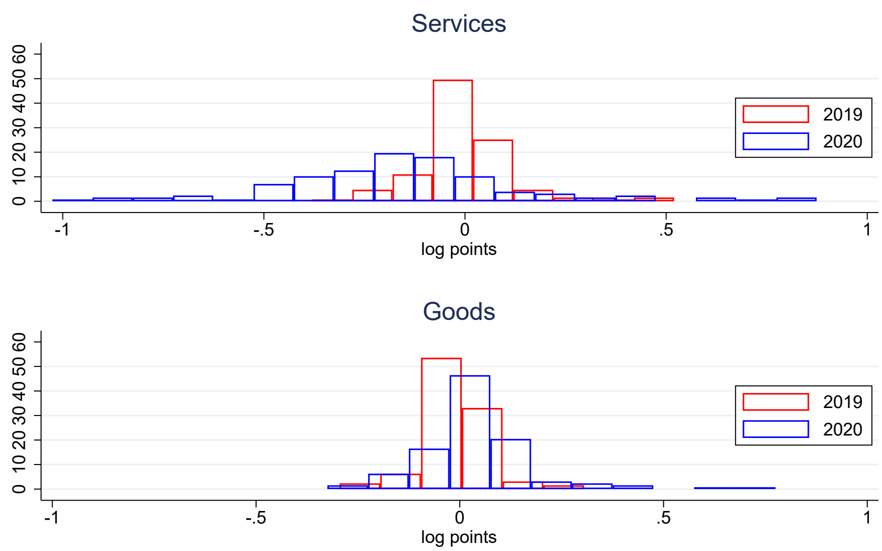
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Workplace closings | -0.02831*** | -0.02840*** | -0.07762*** | -0.00885 | | | -0.04202*** | |
| | (0.010) | (0.010) | (0.021) | (0.006) | | | (0.016) | |
| Covid cases per million, lagged | | 0.00001 | | | | | | |
| | | (0.000) | | | | | | |
| Covid deaths per million, lagged | | -0.00089 | | | | | | |
| | | (0.001) | | | | | | |
| Number of new export restrictions | | 0.00797 | | | | | | |
| | | (0.010) | | | | | | |
| Number of removed export restrictions | | -0.00309* | | | | | | |
| | | (0.002) | | | | | | |
| Stringency index x Small fiscal response | | | | | -0.04878*** | | | |
| | | | | | (0.013) | | | |
| Stringency index x Large fiscal response | | | | | -0.02696*** | | | |
| | | | | | (0.010) | | | |
| Workplace closings x Low telework | | | | | | -0.02177* | | |
| | | | | | | (0.012) | | |
| Workplace closings x High telework | | | | | | -0.00814 | | |
| | | | | | | (0.006) | | |
| Workplace closings x Upstreamness | | | | | | | 0.00622 | 0.00801*** |
| | | | | | | | (0.004) | (0.003) |
| Observations | 23,531,808 | 21,787,468 | 6,118,735 | 14,764,840 | 23,256,563 | 14,764,840 | 23,531,808 | 23,531,808 |
| Exporter-importer-industry FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Importer-industry-month FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Exporter-month FE | N | N | N | N | N | N | N | Y |
| Industry-month FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Sample | All | All | 2020H1 | TW | All | TW | All | All |

*Notes:* The table reports the results of the estimation of equation 5 (columns 1-6) and equation 6 (columns 7-8) by Poisson pseudo-maximum likelihood. Rather the using the Oxford stringency index, the table uses the index of workplace closings, also computed by Hale *et al.* (2021). The sample spans the period 2020:m1-2021:m6; in column 3 the sample is restricted to the first six months of 2020, while in columns 5-6 it is limited to exporting countries for which the measure of teleworkability computed by Dingel and Neiman (2020) is available. The coefficient of the stringency index is estimated separately for: i) trade partners which have announced and implemented high and low discretionary fiscal measures in response to the pandemic between January and June 2020 (fiscal spending is scaled by GDP and the sample is split along the first quartile of the distribution of fiscal spending over GDP); and ii) trade partners with high and low values of the teleworkability index (the sample is split along the first quartile of the distribution of the index). Standard errors in parenthesis are clustered at the exporter level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. TW = teleworkability.

# Online Appendix—Not for Publication

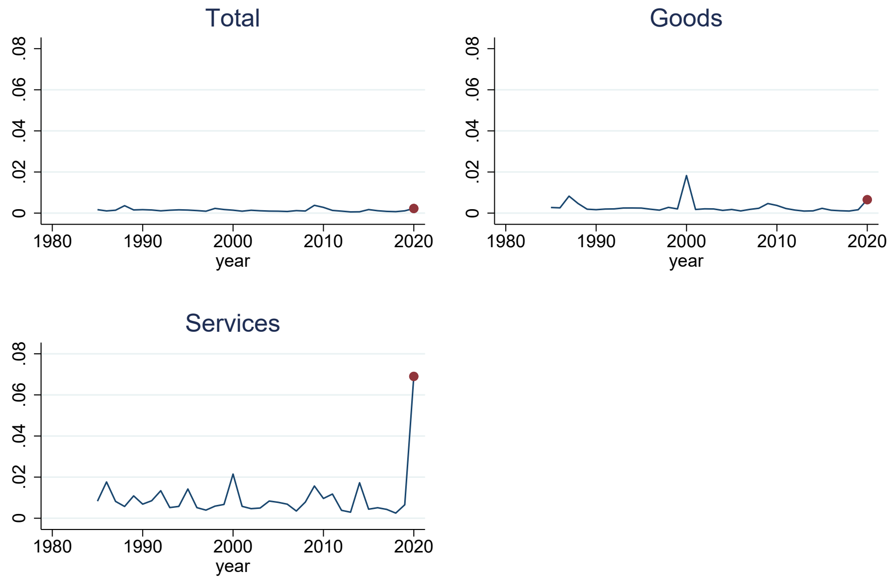
## Additional Figures

Figure A1: Performance of the import demand model: 2019 vs 2020



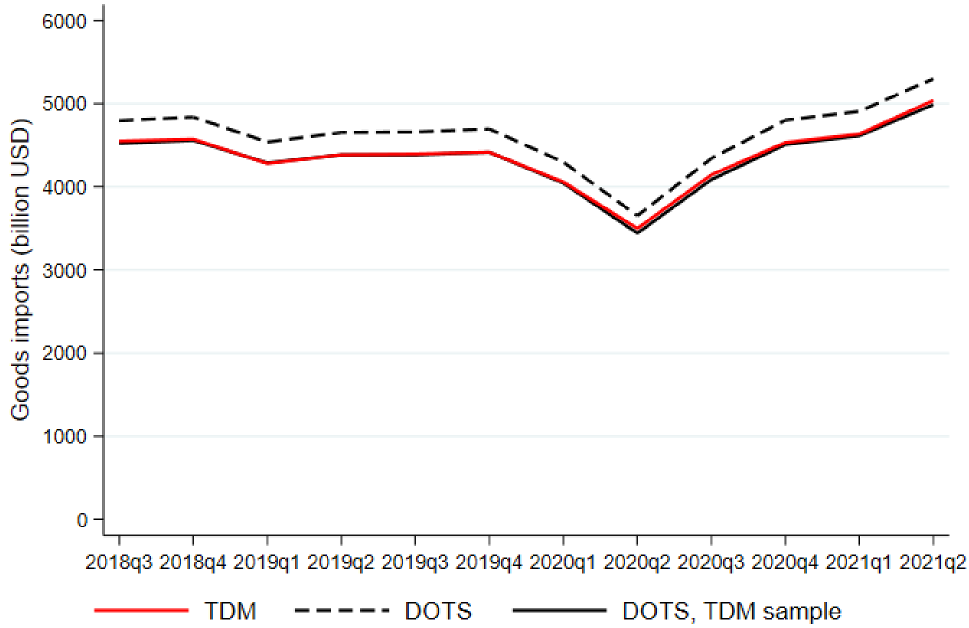

Notes: The charts reports the historgrams of the prediction errors from the model in equation 1 estimated on 1985-2019 data on a sample of 127 countries, country-by-country.

Figure A2: Performance of the import demand model: Mean square errors



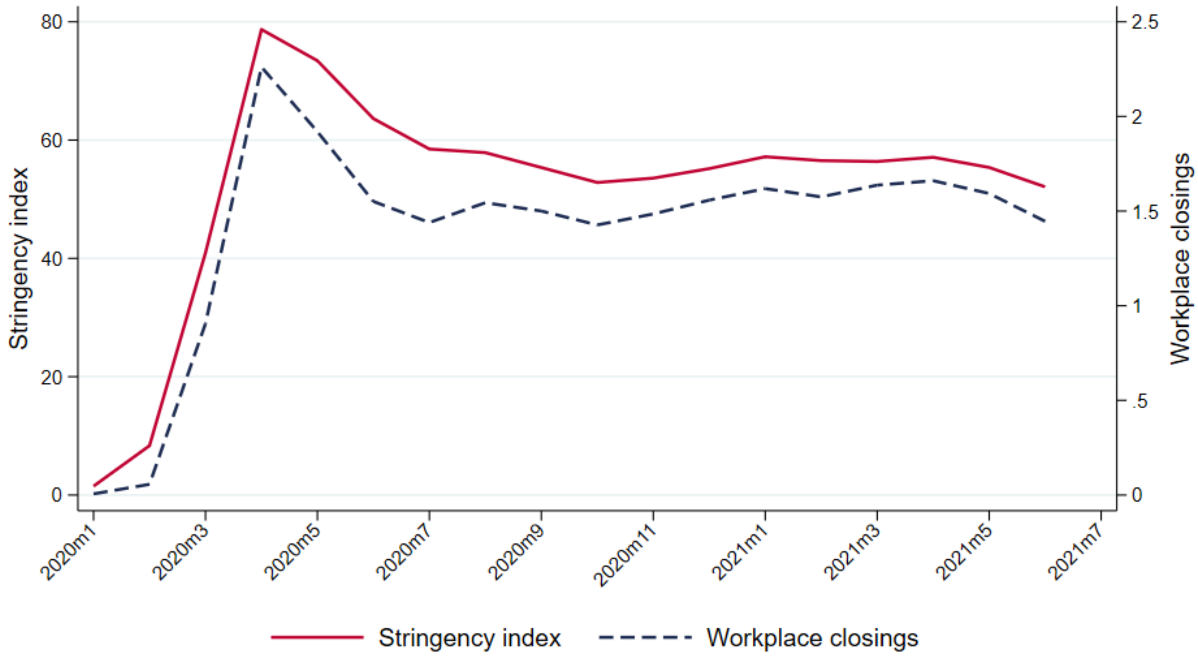

Notes: The charts plots the observed mean square prediction error in real imports (Total, Goods and Services) obtained from the model estimated in equation 1 on 1985-2019 data on a sample of 127 countries. The mean square errors are obtained are obtained by estimating the model country by country, computing the square of the prediction error and taking a weighted avrage using each country's share in global imports as weights.

Figure A3: Representativeness of the TDM data



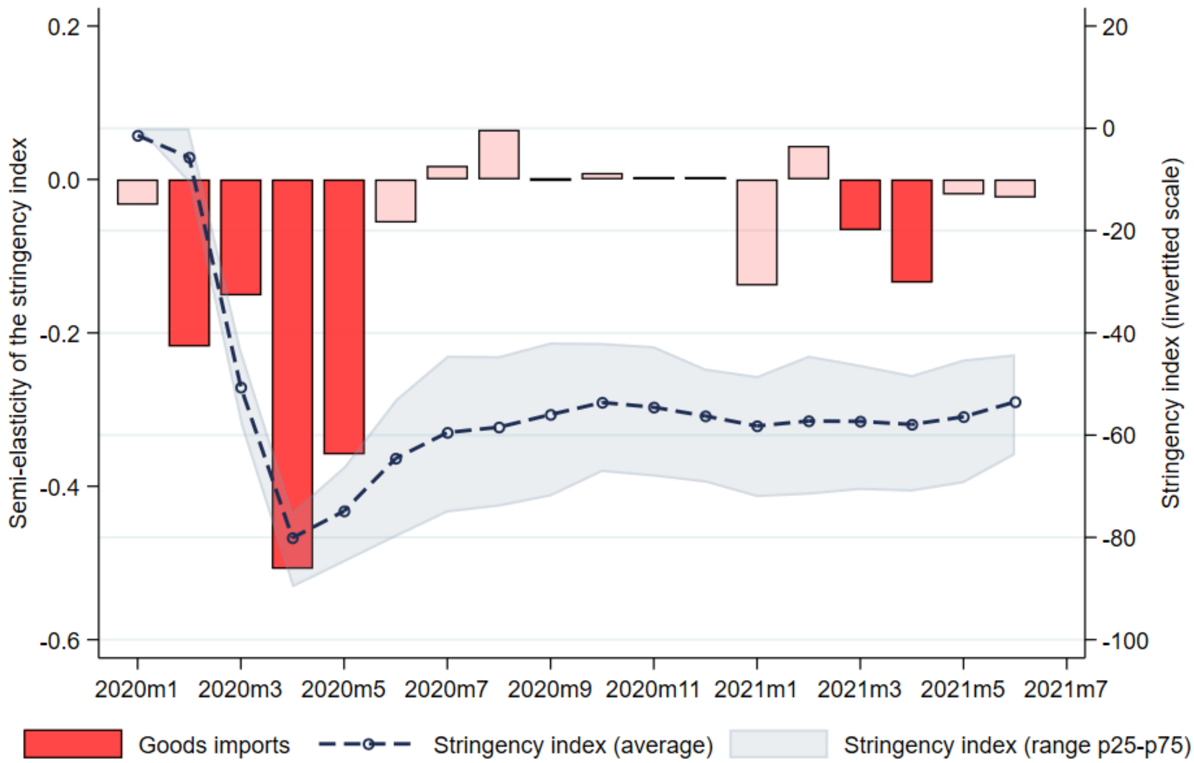

Notes: The chart plots quarterly goods imports in billions of current USD from: 1) the Direction of Trade Statistics (DOTS) for the entire sample of countries (dashed blacked line); the DOTS, restricted to the 99 importer countries included in the Trade Data Monitor (TDM) (solid black line); and the TDM data used in the analysis.

Figure A4: The stringency index and workplace closings




Notes: The chart plots the average values of the stringency index and of the measure of workplace closings across exporting coountries for each month. The country-level monthly values of the indexes are calculated as averages of daily values of the month.

Figure A5: The international spillover effect of lockdowns over time, excluding China as an exporter




Notes: The chart plots the semi-elasticity of the stringency index for each month obtained estimating the baseline specification of equation 5 (Table 4, column 2) and interacting the stringency index with the time dummies. China as exporting country is excluded from the sample. Darker bars show semi-elasticities which are statistically significants, lighter bars show those that are not. The dashed line measures the average stringency index of partner countries and the shaded are measures its interquantile range.

## Additional Tables

Table A1: Import demand model: Panel estimates

| | (1) Total | (2) Total | (3) Services | (4) Services | (5) Goods | (6) Goods |
|---|---|---|---|---|---|---|
| Relative Price | -0.29*** | -0.30*** | -0.24** | -0.25** | -0.31** | -0.32** |
| | (0.099) | (0.10) | (0.11) | (0.11) | (0.13) | (0.13) |
| IAD - Total | 0.99*** | 0.94*** | | | | |
| | (0.088) | (0.090) | | | | |
| IAD - Services | | | 1.11*** | 1.09*** | | |
| | | | (0.15) | (0.16) | | |
| IAD - Goods | | | | | 0.96*** | 0.91*** |
| | | | | | (0.096) | (0.096) |
| Adj. $R^2$ | 0.51 | 0.53 | 0.086 | 0.088 | 0.39 | 0.41 |
| Country FE | Y | Y | Y | Y | Y | Y |
| Year FE | N | Y | N | Y | N | Y |
| Number of countries | 127 | 127 | 127 | 127 | 127 | 127 |

*Notes:* Results from a panel regression estimated on a sample of 127 countries with at least 16 observations between 1985 and 2019. IAD = imported adjusted demand. Standard errors in parenthesis are clustered at the country level. Standard errors in parenthesis are clustered at the country level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A2: Residual analysis: Travel imports as a share of total service imports

| | (1) Total | (2) Services | (3) Goods |
|---|---|---|---|
| Travel imports over total service imports | -0.00158 | -0.00760*** | -0.000426 |
| | (0.00101) | (0.00235) | (0.000966) |
| *Standardized coefficient* | -0.189 | -0.331*** | -0.0423 |
| Observations | 105 | 105 | 105 |
| Adjusted R-squared | 0.024 | 0.105 | -0.008 |

*Notes:* Results from a regression of the import demand model prediction errors in 2020 on the share of travel import over total service import, computed from the WTO service import database and averaged over the period 2016-2019. Standardized coefficients represent the number of standard deviation changes in the dependent variables associated to one standard deviation change in the variable of interest. Standard errors, in parenthesis, are robust to heteroscedasticity. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A3: The international spillover effect of lockdowns: Alternative clustering

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Stringency index | -0.00149*** | -0.00182*** | -0.00307*** | -0.00062*** | | | -0.00234*** | |
| | (0.000) | (0.000) | (0.001) | (0.000) | | | (0.001) | |
| Covid cases per million, lagged | | 0.00002 | | | | | | |
| | | (0.000) | | | | | | |
| Covid deaths per million, lagged | | -0.00051 | | | | | | |
| | | (0.001) | | | | | | |
| Number of new export restrictions | | 0.00917 | | | | | | |
| | | (0.008) | | | | | | |
| Number of removed export restrictions | | -0.00199 | | | | | | |
| | | (0.002) | | | | | | |
| Stringency index x Small fiscal response | | | | | -0.00201*** | | | |
| | | | | | (0.000) | | | |
| Stringency index x Large fiscal response | | | | | -0.00146*** | | | |
| | | | | | (0.000) | | | |
| Stringency index x Low telework | | | | | | -0.00126*** | | |
| | | | | | | (0.000) | | |
| Stringency index x High telework | | | | | | -0.00058*** | | |
| | | | | | | (0.000) | | |
| Stringency index x Upstreamness | | | | | | | 0.00039** | 0.00057*** |
| | | | | | | | (0.000) | (0.000) |
| Observations | 23,531,808 | 21,787,468 | 6,118,735 | 14,764,840 | 23,256,563 | 14,764,840 | 23,531,808 | 23,531,808 |
| Exporter-importer-industry FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Importer-industry-month FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Exporter-month FE | N | N | N | N | N | N | N | Y |
| Industry-month FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Sample | All | All | 2020H1 | TW | All | TW | All | All |

*Notes:* The table reports the results of the estimation of equation 5 (columns 1-6) and equation 6 (columns 7-8) by Poisson pseudo-maximum likelihood. The stringency index is the Oxford COVID-19 Government Response Stringency Index, computed by Hale *et al.* (2021). The sample spans the period 2020:m1-2021:m6; in column 3 the sample is restricted to the first six months of 2020, while in columns 5-6 it is limited to exporting countries for which the measure of teleworkability computed by Dingel and Neiman (2020) is available. The coefficient of the stringency index is estimated separately for: i) trade partners which have announced and implemented high and low discretionary fiscal measures in response to the pandemic between January and June 2020 (fiscal spending is scaled by GDP and the sample is split along the first quartile of the distribution of fiscal spending over GDP); and ii) trade partners with high and low values of the teleworkability index (the sample is split along the first quartile of the distribution of the index). Standard errors in parenthesis are clustered at the exporter-month level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. TW = teleworkability.