CHAPTER 4

ONLINE ANNEX

This Annex provides further detail on the methods, data sources, robustness exercises and extensions applicable to Chapter 4 of the April 2022 World Econoimc Outlook, which is entitled "Global Trade and Value Chains in the Pandemic." It is designed to be read jointly with the main text, so it does not repeat information from there. The Annex is divided into four parts. The first part describes the analysis of multilateral trade data through an import demand model; the second part describes the spillover effect of trading partner containment policies on import flows using granular bilateral trade data; the third part provides further evidence of the recent trends in trade in GVC-related goods; and the fourth part describes the model-based analysis of policies to increase GVC resilience.

Annex 4.1. Results from an Import Demand Model

Model Estimates and Data

The following import demand growth model is estimated using a standard panel regression with country and year fixed effects:

$$\Delta\ln M_{i,t} = \alpha_i + \pi_t + \beta_D \Delta lnD_{i,t} + \beta_P \Delta lnP_{i,t} + \varepsilon_{i,t} \quad (1)$$

Where $M_{i,t}$ is (real) imports of goods or services in country i, $D_{i,t}$ is a measure of demand ("Import-Intensity Adjusted Demand" IAD[1]) as in Bussiere and others 2013, $P_{i,t}$ is relative prices of imports (good import deflator over GDP deflator). The sample includes 127 countries with at least 16 observations between 1985 and 2019.[2] The data combine information from the World Economic Outlook (GDP components and relative prices), Balance of Payments data (real imports) and EORA (as the input output matrices are used to compute the import intensity of each GDP components).

The results reported in Table 4.1.1, show that (i) services have a higher elasticity to demand (IAD from Bussiere and others 2013) than goods (ii) services have a lower elasticity to price (import price deflator over domestic GDP deflator) (iii) all coefficients are significant (iii) adding year fixed effects to the specification makes little difference.[3]

[1] The Import intensity weights defined in Bussiere and other 2020 are computed for each GDP components as their long-term average import content between 1991 and 2015.

[2] The included countries are: Afghanistan, Albania, Algeria, Angola, Argentina, Armenia, Australia, Austria, Bahamas, The, Bahrain, Belarus, Belgium, Benin, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Brunei Darussalam, Burkina Faso, Burundi, Cabo Verde, Cambodia, Cameroon, Canada, Central African Republic, Chad, Chile, China, Colombia, Congo, Republic of, Costa Rica, Côte d'Ivoire, Croatia, Czech Republic, Democratic Republic of the Congo, Denmark, Djibouti, Dominican Republic, Ecuador, Egypt, El Salvador, Eritrea, Estonia, Eswatini, Ethiopia, Finland, France, Gabon, The Gambia, Germany, Ghana, Greece, Haiti, Honduras, Hong Kong SAR, Iceland, India, Indonesia, Iran, Ireland, Israel, Italy, Japan, Jordan, Kenya, Korea, Kuwait, Lebanon, Lesotho, Luxembourg, Macao SAR, Madagascar, Malawi, Malaysia, Maldives, Mali, Mauritius, Mexico, Moldova, Mongolia, Montenegro, Rep. of, Morocco, Mozambique, Myanmar, Namibia, Netherlands, New Zealand, Niger, Norway, Oman, Pakistan, Peru, Philippines, Poland, Portugal, Romania, Russia, Rwanda, São Tomé and Príncipe, Saudi Arabia, Senegal, Serbia, Seychelles, Sierra Leone, Singapore, Slovak Republic, Slovenia, South Africa, Spain, Sri Lanka, Sweden, Switzerland, Syria, Taiwan Province of China, Tanzania, Thailand, Togo, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Venezuela, West Bank and Gaza, Yemen and Zambia.

[3] The results are similar if the coefficients are allowed to vary across country groups across 15 groups obtained by intersecting 5 geographic areas (AFR APD, EUR, MCD, and WHD) and three income groups (low income, emerging economies, advanced economies).

A similar specification is also estimated at the country level (without year fixed effects) on the 127 countries for which we observe at least 16 years of data between 1985 and 2019. Table 4.1.2 reports the summary statistics from the different regressions on total import, goods import and services imports. The average of the estimated elasticities is broadly consistent with the panel results: the coefficients on the measure of demand are mostly positive and above 1, while the coefficients on prices are mostly negative and average between -0.2 and -0.3.

Model Performance

As shown in Figure 4.1.1, combining the estimates from the country-by-country regressions (weighted by shares in world imports) yield good predictions of import growth up to 2019. Yet, 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). Figure 4.5 in the main text reports the prediction errors series: the error for services in 2020 is 0.2 log-points, quite literally "off-the-chart" with respect to any other previous forecast error.

Looking at the cross-sectional distribution of errors in 2020 depicted in Figure 4.1.2 it is clear that (i) errors are more widely dispersed in 2020 than in 2019 (ii) errors in services in 2020 stand out for magnitude and negative skew. The panels in Figure 4.1.3 plot the mean square prediction error (MSE) in each cross section of countries between 1985 and 2020, in order to take a longer run view on the model performance, confirming the findings from the comparison between 2019 and 2020. Indeed, the MSE in services import growth in 2020 was much larger than in any previous years.

Analysis of the Residuals

To understand what drove the poor performance of the model in 2020, the forecast errors for 2020 are linked to various variables pandemic related variables and other country features. Data sources for this exercise include: the World in Data database for data on COVID cases; Oxford Stringency Index; Google Mobility Index; IMF COVID Policy database for data on unanticipated health expenditure in 2020; Global Health Security Index; The Eora Global Supply Chain Database, and the WTO database for the data on different types of service imports. All the countries with both the relevant variables and the residuals are included in the regressions, which therefore comprise a subset of the 127 countries considered in the analysis. Since not all the variables of interest are available for all countries, the number of observations vary between a maximum of 125 and a minimum of 99.[4]

To fix ideas concerning this analysis, notice that the previously estimated import demand model can be derived from the following expression for import demand:

$$M_{it} = D_{it}^{\beta_D} \left(\frac{\tilde{P}_{Mt}}{\tilde{P}_{it}}\right)^{\beta_p} e^{\alpha_i t + c_t + \eta_{it}} \stackrel{\text{def}}{=} D_{it}^{\beta_D} P_{it}^{\beta_p} e^{\alpha_i t + c_t + \eta_{it}} \qquad (2)$$

[4] While in the tables we report Huber-White heteroskedasticity-robust standard errors, the significance of all reported coefficients is unaffected if standard errors are computed bootstrapping the observations.

where imports M_{it} in country i at time t are simply a function of domestic demand D_{it} (whose impact on import is arguably mediated by the import intensity of each demand component), price of imports relative to domestic prices $\tilde{P}_{Mt}/\tilde{P}_{it}$, a country-specific linear time trend is captured by $\alpha_i t$, an aggregate shock at time t is captured by c_t and other time varying and country specific factors are captured by η_{it}. (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). Taking logs and first differences, yields the estimated equation

$$\Delta \ln M_{i,t} = \alpha_i + \pi_t + \beta_D \Delta lnD_{i,t} + \beta_P \Delta lnP_{i,t} + \varepsilon_{it}$$

(where the following definitions are adopted: $\pi_t \stackrel{\text{def}}{=} \Delta \mathrm{c_t}$ and $\varepsilon_{it} \stackrel{\text{def}}{=} \Delta \eta_{i,t}$). 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. The following results confirm such intuition.

The pandemic induced higher than expected good imports. As shown in Table 4.1.3 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) into goods. The insignificant coefficients on imported services, however, suggest that possibly the shift away from services mostly affected domestic rather than imported services. While imported services such as travel indeed declined, this was not the case for other categories such as communication.

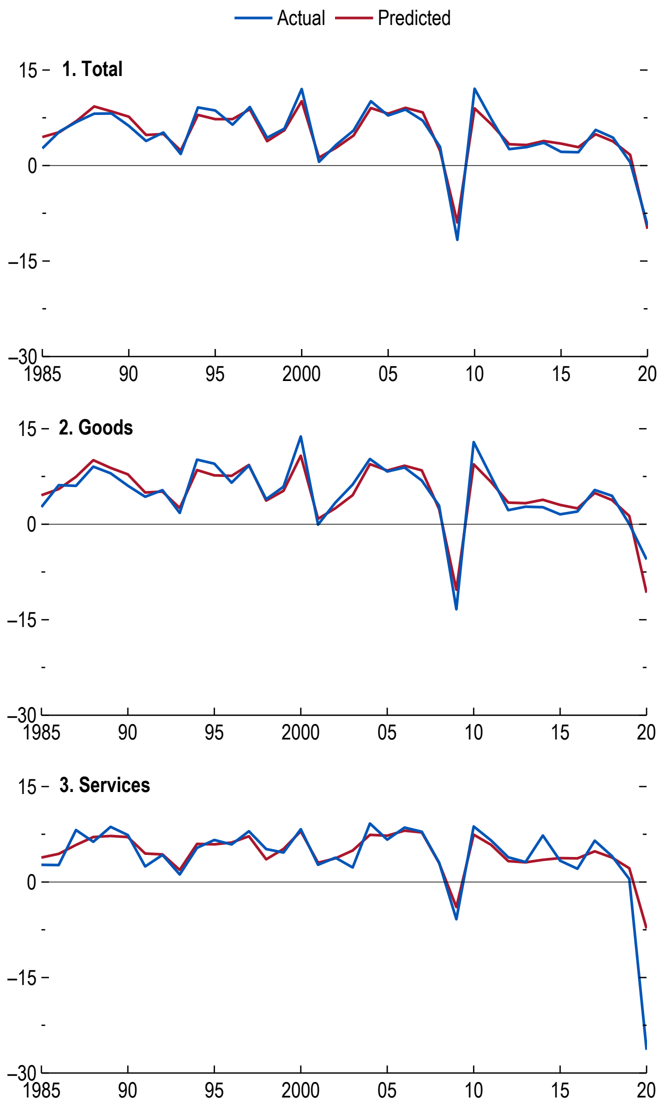
Looking at *supply* of imports, trade partners' health preparedness was associated with more goods imports. The ability of countries to increase their goods import above the expected amount was associated with their partners' health preparedness as captured by the "global health security" index. These results are shown in Table 4.1.4, where the relevant variable is an import-weighted average of the index.

Moreover, as countries shut down 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 4.1.5.

Robustness

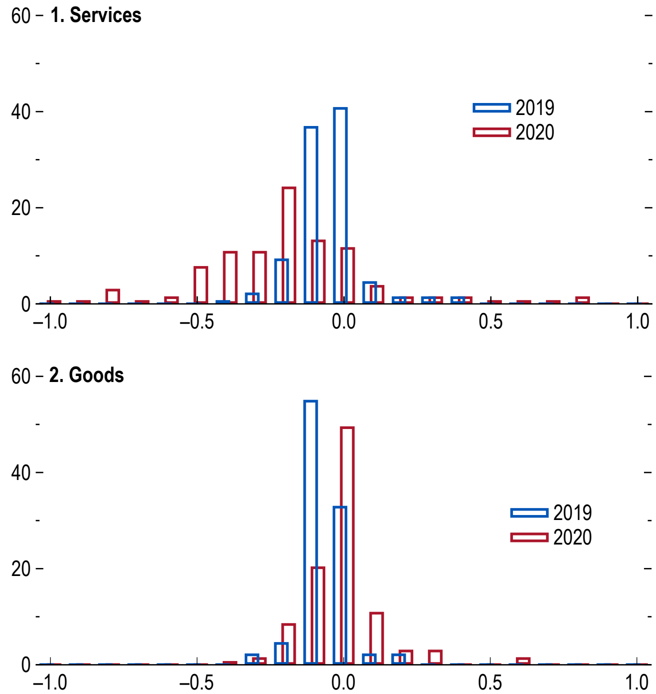
The analysis of the residuals is based on estimates including 1985-2019 data, *excluding* 2020. Hence, the 2020 forecast errors may conflate the deviation from a historical relationship (as interpreted in the chapter) with the fact that data for 2020 are not included in the sample. To address this concern, the model is re-estimated excluding one year at the time. Then, the errors are recomputed in each year from the model estimated excluding such year. The results, reported in Figure 4.1.4, show that the errors are very similar to those in Figure 4.1.3 mitigating the initial concern.

Annex Figure 4.1.1. Observed and Predicted Import Growth between 1985 and 2020
(Percent)



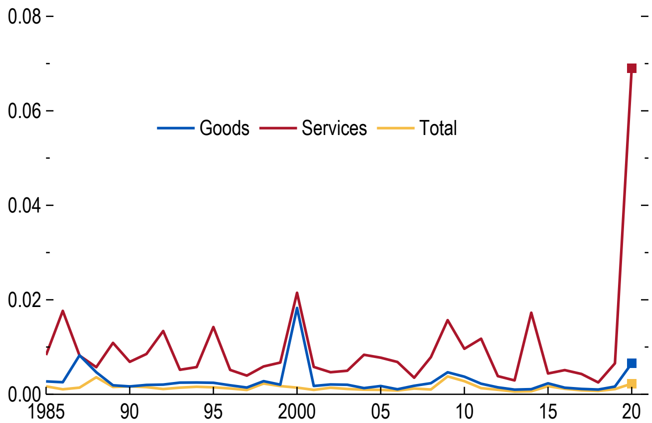
Sources: Eora Global Supply Chain Database; IMF, *Balance of Payment Statistics*; and IMF staff estimates.
Note: Models estimate country by country on a sample of 127 countries with at least 16 observations between 1985 and 2019.

Annex Figure 4.1.2. Forecast Errors across Countries
(Percent)



Sources: Eora Global Supply Chain Database; IMF, *Balance of Payment Statistics*; and IMF staff estimates.
Note: Forecast errors are the difference between the observed import growth and the predicted import growth from models estimated country by country for 127 countries with at least 16 observations between 1985 and 2019.

Annex Figure 4.1.3. Import Growth—Model Mean Square Error between 1985 and 2020
(Log points)



Sources: Eora Global Supply Chain Database; IMF, *Balance of Payment Statistics*; and IMF staff estimates.
Note: Models estimate country by country on a sample of 127 countries with at least 16 observations between 1985 and 2020.

Annex Figure 4.1.4. Import Growth—Model Average Forecast Errors Leaving Out One Year at the Time
(Log points)

Sources: Eora Global Supply Chain Database; IMF, *Balance of Payment Statistics*; and IMF staff estimates.
Note: Models estimate country by country on a sample of 127 countries with at least 16 observations between 1985 and 2020. Errors in each year *t*, are obtained from a model estimated on data excluding year *t*.

Annex Table 4.1.1. Import Demand Model Estimated from a Panel Regression

	Total		Services		Goods	
	(1)	(2)	(3)	(4)	(5)	(6)
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)
Adjusted R^2	0.51	0.53	0.086	0.088	0.39	0.41
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	Yes	No	Yes	No	Yes
Number of Countries	127	127	127	127	127	127

Source: IMF staff calculations.

Note: Results from panel regressions on a sample of 127 countries with at least 16 observations between 1985 and 2019. Standard errors in parenthesis are clustered at the country level. IAD = Import Intensity-Adjusted Demand.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Annex Table 4.1.2. Import Demand Model Estimates Country-by-Country, Summary Statistics

		Total	Services	Goods
Demand Coefficients	Mean	1.30	1.35	1.33
	Median	1.35	1.09	1.36
	[25p - 75p]	[0.95,1.54]	[0.68,1.76]	[0.99,1.69]
Price Coefficients	Mean	-0.23	-0.29	-0.20
	Median	-0.19	-0.23	-0.14
	[25p - 75p]	[-0.39,0.00]	[-0.57,0.09]	[-0.43,0.10]
Number of Countries		127	127	127

Source: IMF staff calculations.

Note: Results from regressions estimated country by country on a sample of 127 countries with at least 16 observations between 1985 and 2019. Standard errors in parenthesis are clustered at the country level.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Annex Table 4.1.3. Residual Analysis. Pandemic-Relevant Variables

	Total	Services	Goods	Total	Services	Goods	Total	Services	Goods
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log Total Covid Cases in 2020	0.00321	-0.00639	0.00812**						
	(0.00360)	(0.0123)	(0.00408)						
Standardized Coefficient	0.0574	-0.0416	0.121**						
Stringency 2020 Average				0.00172*	0.00177	0.00229**			
				(0.000895)	(0.00231)	(0.00103)			
Standardized Coefficient				0.197*	0.0738	0.217**			
Mobility 2020 Average							-0.00236**	-0.00183	-0.00363***
							(0.000918)	(0.00330)	(0.00117)
Standardized Coefficient							-0.239**	-0.0674	-0.305***
Number of Observations	125	125	125	121	121	121	99	99	99
Adjusted R^2	-0.004	-0.006	0.009	0.038	-0.003	0.049	0.074	-0.005	0.104

Source: IMF staff calculations.

Note: The tables report the results from a regression of the forecast errors in 2020 (see previous explanation) on the relevant variable. All the variables of interest are extracted from the Our World in Data Covid database. Changes in the number of observations originate from the variable of interest being missing. Standardized coeffcients 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.

*** p<0.01, ** p<0.05, * p<0.1.

Annex Table 4.1.4. Residual Analysis. Trade Partners' Health Preparedness

	Total	Services	Goods
	(1)	(2)	(3)
Trade Partners Health Preparedness	0.00213	-0.00520	0.00518***
	(0.00212)	(0.00546)	(0.00183)
Standardized Coefficient	0.0964	-0.0854	0.195***
Number of Observations	122	122	122
Adjusted R^2	0.002	-0.001	0.036

Source: IMF staff calculations.

Note: The tables report the results from a regression of the forecast errors in 2020 (see previous explanation) on the relevant variable. The variable of interest for country i is computed as the import-weighted average of the Global Health Security Index across all countries from which country i imports goods. Changes in the number of observations originate from the variable of interest being missing. Standardized coeffcients 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.

*** p<0.01, ** p<0.05, * p<0.1.

Annex Table 4.1.5. Residual Analysis. Travel Imports as a Share of Total Service Imports

	Total	Services	Goods
	(1)	(2)	(3)
Travel Imports over Total Service Imports (Average 2016–2019)	-0.00158	-0.00760***	-0.000426
	(0.00101)	(0.00235)	(0.000966)
Standardized Coefficient	-0.189	-0.331***	-0.0423
Number of Observations	105	105	105
Adjusted R^2	0.024	0.105	-0.008

Source: IMF staff calculations.
Note: The tables report the results from a regression of the forecast errors in 2020 (see previous explanation) on the relevant variable. The share of travel import over total service import is computed from the WTO service import database. 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.
*** p<0.01, ** p<0.05, * p<0.1.

Annex 4.2. Gravity Model for Bilateral Trade Flows

Methods and Data

The chapter estimates the effect of trade partners' pandemic containment policies on goods import flows using a standard gravity model, that allows isolating the supply channel due to lockdowns from changes in demand for imported goods.

The sample used in the main analysis covers the period from January 2020 to June 2021 and includes 98 importing countries which trade with 163 exporting countries. Bilateral imports are available at the 6-digit product level in the Harmonized System (HS6), at monthly frequency, provided by Trade Data Monitor (TDM). Bilateral monthly data on goods imports over more than 5000 HS6 codes are aggregated over about 300 industries. The aggregation is done using the concordance between the 6-digit HS codes (used in the TDM data) and I-O commodity codes, as published by the Bureau of Economic Analysis. Overall, the sample includes 15,880 country pairs and 4,652,840 unique industry-exporter-importer trade corridors.

The identification of the spillover effect of trade partners' pandemic containment policies is based on the supply shock due to the COVID-19 pandemic, which translated into a wide array of containment policies whose severity—measured by the Oxford Stringency Index—varied over time and across countries.

The main gravity equation estimated to model goods imports as a function of trade partners' containment policies is:

$$M_{m,e,i,t} = g(\beta Stringency\ Index_{e,t} + \delta Controls_{m,e,t} + \alpha_{m,e,i} + \gamma_{m,i,t} + \varepsilon_{m,e,s,t}) \qquad (1)$$

where bilateral imports of products in industry *i* ($M_{m,e,i,t}$) 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 Stringency Index; ii) a set of variables that vary across country pairs and time ($Controls$); and iii) a set of fixed effects ($\alpha_{m,e,i}, \gamma_{m,i,t}$) described further below.

The key parameter of interest is β, which measures the effect of trade partners containment policies on imports. Figure 4.1 in the main text illustrates in the time series that the increase of restrictions at the outbreak of the pandemic has been associated with the sharp collapse in goods imports in the first two quarters of 2020. However, the Stringency Index could capture not only the severity of the lockdown and of the containment policies, but also the effect of other simultaneous changes in the exporter country. In particular, an important element to consider are trade barriers. To account for the role of trade restrictions, the Global Trade Alert (GTA) data allow 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. To minimize 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 and lagged by one period.[5]

Country-pair-industry fixed effects ($\alpha_{m,e,i}$) control for differences in industry-specific trade flows between each pair of importer and exporter countries. The importer-industry-time fixed effects ($\gamma_{m,i,t}$) 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, are absorbed by the fixed effects.

Conditional on this rich set of controls and fixed effects, the coefficient β captures the impact of lockdowns on imports via the supply channel. For instance, consider two countries: the model allows for different changes in the demand for imported goods between them, due to the severity of the economic slowdown during the pandemic. Controlling for this difference, a negative coefficient on the Stringency Index would indicate that the country which was importing from partners which imposed more severe restrictions during the pandemic experienced a larger decline in imports, because of a stronger reduction in the *supply* of goods by trade partners.

A first caveat when interpreting the coefficient β as a measure of a supply channel is that there could be other factors and policies that vary across exporters and over time and that confound the identification of containment policies. This concern is addressed by controlling for the intensity of the COVID-19 crisis and by trade barriers. The second caveat is that import demand is controlled for under the assumption that the country-specific demand for products in a given industry (in a given month) is the same across countries. In other words, is assumed that the 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 and realistic to assume that consumers did not adjust their demand differentially across producers in different countries.

In line with an extensive trade literature on gravity models, equation (1) is estimated by Poisson pseudo-maximum likelihood (PPML, Santos Silva and Tenreyro 2006)—as implemented by Correia et al. (2020). Standard errors are clustered at exporter level.

Results

Baseline Results

The main results are shown in Table 4.2.1 and reported in Figure 4.8 in the main text. 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)

[5] Results are robust to controlling also for the contemporaneous number of COVID-19 cases and deaths per capita. Another potential variable to control for is mobility, measured by the average all the components of the Google mobility score excluding parks and residential. However, mobility is the first effect of the lockdown and the two variables are strongly correlated. 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 equal to -0.5. As the analysis focuses on the effect of the containment policy measures (e.g., lockdown) rather than on the actual behavior (which could also reflect individual choices), the empirical model considers the Stringency Index rather than mobility. Finally, looking at the size of the fiscal response in exporting countries does not show significant results.

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). Results do not show any significant negative effect of export restrictions on trade flows, even when allowing the coefficient to vary over time.

The effect is also economically meaningful. The semielasticity is about -0.15 and implies that one additional point in the stringency index is associated with a 0.15% reduction in imports. To get a more realistic quantification of the spillover effect of lockdowns, it is possible to split the coefficient β over time and estimate the spillover effects of trade partner containment policies over each month. Figure 4.2.1 shows that the dynamics of the spillover effect of lockdowns is concentrated in the first five months of 2020. It increases in February and March, when the COVID-19 crisis evolved from a regional crisis to a pandemic, but then it starts declining and becomes not significant in June, when goods imports started the rebound. Interestingly, there is a smaller but significant effect in the Spring of 2021, in coincidence with the spread of the Delta variant. As the containment policies persisted throughout the period—the stringency index does not show any visible decline (Figure 4.2.1)—this evidence would suggest that countries started adjusting to the presence of lockdown and pandemic-related restrictions, consistent with what shown in Box 3 in the main text, and found by Heise (2020), Lafrogne-Joussier et al. (2021), and Berthou and Stumpner (2021) in different settings.[6]

As the impact of lockdowns on imports is large but short-lived, the baseline model is also estimated 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 the one estimated on the whole sample. This point estimate is used to generate the evolution of good imports under a counterfactual without any containment policies in place in trade partners. Comparing this series, normalized to 100 in January 2020, with the actual evolution of imports indicates that containment policies can account for up to 60 percent of the observed fall in imports (Figure 4.2.2), the headline quantification of the spillover effect discussed in the chapter. This estimate can be interpreted as an upper bound, as the empirical exercise does not allow for substitution effects across exporting countries.[7]

Extensions

The effect of containment policies on trade flows could depend on the capacity of countries to mitigate them and adapt. A key dimension in this respect is the capacity to rely on remote working. Results shown in columns 7 and 8 exploit cross country heterogeneity in the proportion of jobs which could 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

[6] 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 the robustness section below.

[7] 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.

Dingel and Neiman (2020) and the sample of trade partners is split between those with a low share of jobs which can be done remotely (the bottom quartile of the distribution) and the 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 7). 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 8).

A second dimension of heterogeneity is across industries. Column 9 and Figure 4.8 in the chapter reports the results obtained decomposing the effect of the containment policies across four GVC-intensive industries (automotive, electronics, medical equipment, and textiles) and pooling all the others in a residual category. The results indicate that the effect of lockdowns is stronger in GVC-intensive industries, and especially in electronics, than in non GVC-intensive ones.

A Fully-Fledged Gravity Model

The baseline analysis does not fully control for multilateral resistance as in standard gravity models since it does not include the 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 "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 Antras et al. (2012) from U.S. input-output table.[8] This leads to an augmented version of equation (3):

$$M_{m,e,i,t} =$$
$$= g(Stringency\,Index_{e,t} * Upstream_i + \delta Controls_{m,e,t} + \alpha_{m,e,i} + \gamma_{m,i,t} + \mu_{e,t} + \varepsilon_{m,e,s,t}) \qquad (4)$$

which includes both multilateral resistance terms ($\gamma_{m,i,t}$ and $\mu_{e,t}$) and identify the differential effect of the stringency index in exporting countries 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.

[8] Antras 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 the bilateral trade flows in the gravity model as large as possible, the US measure of upstreamness is applied to all exporter countries.

Table 4.2.2 show 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 = 0.85) reduces the supply effect of the lockdown by almost one third (column 1). 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 remain statistically significant and similar in size.[9]

Robustness

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

- **Measuring containment policies**. The main results are robust to measuring the containment policies with an index measuring only the severity of workplace closures. This index, which assume discrete values from 0 (no restrictions) to 3 (closing or work from home for all-but-essential workplaces), is one of the 8 containment and closure policy indicators and restrictions in movement used to calculate the Oxford stringency index (Hale et al. 2021).[10] While its categorical nature compresses the variability over time, the index is the closest to the idea of measuring how lockdown 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 4.2.3).[11] Table 4.2.3 replicates the main results using the measure of workplace closings and shows that more stringent containment policies in workplaces put in place by trade partners are associated with a decline in imports.

- **Robustness across different country groups**. Because of the asynchronous dynamics of the COVID-19 pandemic and of its different intensity across countries, one could imagine that results are sensitive to specific countries or regions. To address this concern, the baseline model is estimated by dropping, one at the time, specific country groups, considering income and regional classifications. Figure 4.2.4 shows that the significance of the spillover effect is robust to alternative samples. However, it also points out that the semielasticity of the stringency index becomes smaller when emerging markets and Asian countries are excluded. This evidence is consistent with the effect of containment policies being concentrated in the first phase of the crisis, when the COVID-19 shock affected Asian countries first, shutting down production and halting global trade. On the contrary, the semielasticity is higher when

[9] In a set of additional tests, equation (2) has been estimated taking a measure of product teleworkability as the exposure to the lockdown. Two proxies have been used: the Dingel and Neiman (2020) measure of suitability for remote work, computed at the 2-digit NAICS level, and an alternative measure of remote labor at the 2-digit ISIC 3.1 level, proposed by Espitia et al. (2021), which is constructed from trade data multiplying the share of labor which could be done remotely with the internet density in the exporting country. However, in both case there are no significant effect of the lockdown across the different degree of product teleworkability.

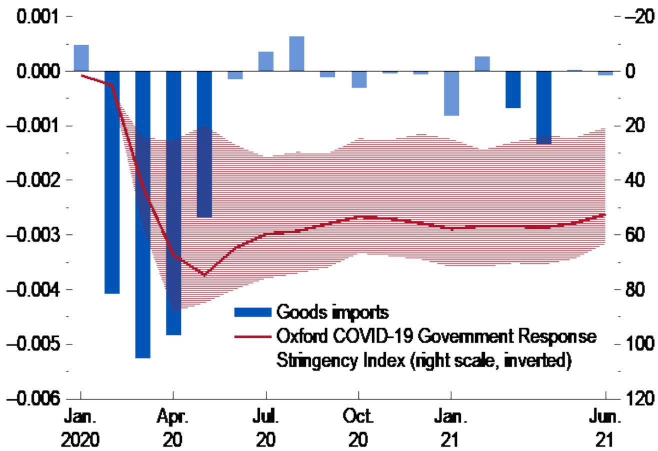
[10] See https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker for further details on the Oxford Stringency Index and its single components.

[11] 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).

advanced economies and European countries are excludes, suggesting that containment policies in Europe had weaker spillover effects.

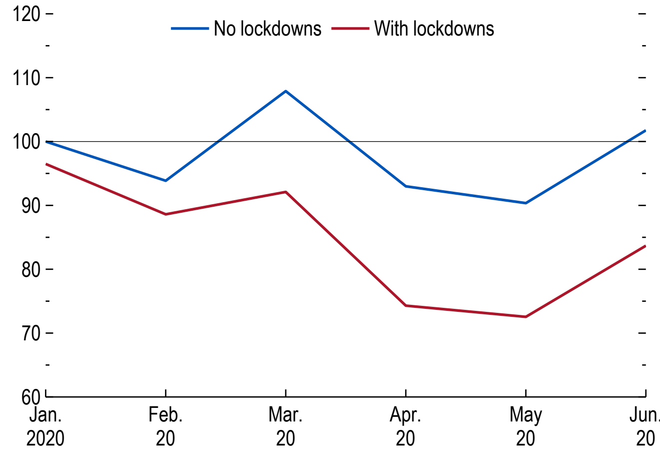
- **Clustering**. Table 4.2.4 reports the main results discussed in the chapter estimated by clustering the standard error at the exporter-month level. The significance of the findings is not affected, and the estimated standard errors are—if anything—smaller, suggesting that the results reported in the chapter are conservative.

Annex Figure 4.2.1. Spillover Effect of Trade Partner Containment Policies over Time
(Index)



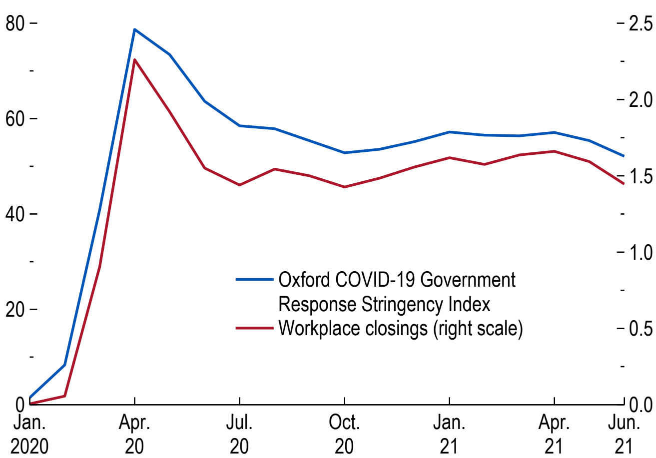
Sources: Hale and others (2021); Trade Data Monitor; and IMF staff calculations.
Note: Darker bars show coefficients that are statistically significant; lighter bars show those that are not. The line represents the coefficients of the stringency index for each month obtained estimating the baseline specification of equation (3) (Annex Table 4.2.1, column 2) and interacting the stringency index with the time dummies. The shaded area represents the interquartile range of the stringency index across countries.

Annex Figure 4.2.2. Spillover Effect of Lockdowns
(Percent of predicted value with no lockdown in January 2020)



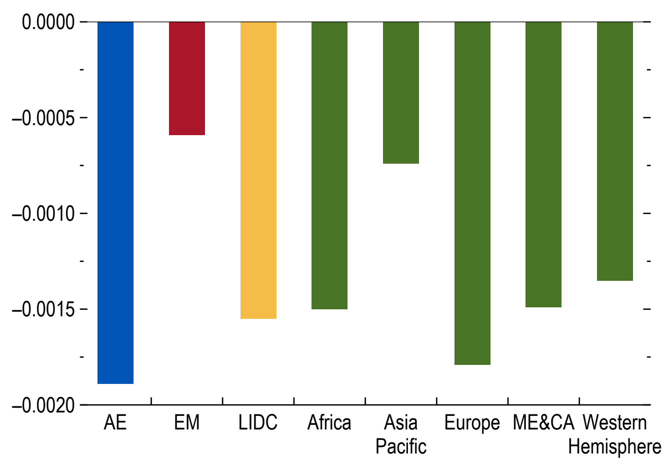
Sources: Hale and others (2021); Trade Data Monitor; and IMF staff calculations.
Note: The blue line denotes the evolution of good imports under a counterfactual without any containment policy in place in trade partner countries, obtained using the results reported in Annex Table 4.2.1. (column 6) and imposing a value of zero for the stringency index over the entire period. The red line denotes the actual evolution of imports in the same sample, in percent of the value with no lockdown in January 2020.

Annex Figure 4.2.3. Lockdown Stringency and Workplace Closings
(Index)



Sources: Hale and others (2021); and IMF staff calculations.

Annex Figure 4.2.4. Robustness Dropping Specific Country Groups
(Index)



Sources: Hale and others (2021); Trade Data Monitor; and IMF staff calculations.
Note: The bars represent the coefficient of the stringency index for each month obtained estimating the baseline specification of equation (3) (Annex Table 4.2.1, column 2) and interacting the stringency index with the time dummies. AE = advanced economy; EM = emerging market; LIDC = low-income developing country; ME&CA = Middle East and Central Asia.

Annex Table 4.2.1. The Spillover Effect of Containment Policies, Baseline Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
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 × Low Telework								-0.00126***	
								(0.000)	
Stringency Index × High Telework								-0.00058***	
								(0.000)	
Stringency Index × Automotive									-0.00169**
									(0.001)
Stringency Index × Electronics									-0.00312***
									(0.001)
Stringency Index × Medical									-0.00246***
									(0.001)
Stringency Index × Textiles									-0.00243***
									(0.000)
Stringency Index × Non-Gvc Industries									-0.00118***
									(0.000)
Number of Observations	23,594,169	23,531,808	21,787,468	23,531,808	21,787,468	6,118,735	14,764,840	14,764,840	23,531,808
Exporter-Importer-Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Importer-Month Fixed Effects	Yes	-	-	-	-	-	-	-	-
Importer-Industry-Month Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-Month Fixed Effects	No	No	No	No	No	No	No	No	No
Industry-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	All	All	All	All	2020:H1	TW	TW	All
Semielasticity	-0.1413	-0.1494	-0.1828	-0.1594	-0.1818	-0.3068	-0.0616		

Source: IMF staff calculations.
Note: The tables report the results of the estimation of equation (3) by Poisson pseudo-maximum likelihood. The sample spans the period 2020:m1-2021:m6; in columns 6 it is restricted to the first six months of 2020, while in columns 7-8 it is limited to exporting countries for which the measure of teleworkability computed by Dingel and Neiman is available. Standard errors in parenthesis are clustered at the exporter level. TW = teleworkability.
*** p<0.01, ** p<0.05, * p<0.1.

Annex Table 4.2.2. The Spillover Effect of Containment Policies: Heterogeneity across Industry Upstreamness

	(1)	(2)
Stringency Index	-0.00234***	
	(0.001)	
Stringency Index × Upstreamness	0.00039*	0.00057***
	(0.000)	(0.000)
Number of Observations	23,531,808	23,531,808
Exporter-Importer-Industry Fixed Effects	Yes	Yes
Importer-Industry-Month Fixed Effects	Yes	Yes
Exporter-Month Fixed Effects	No	Yes

Source: IMF staff calculations.

Note: The tables report the results of the estimation of equation (4) by Poisson pseudo-maximum likelihood. Standard errors in parenthesis are clustered at the exporter level.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Annex Table 4.2.3. The Spillover Effect of Workplace Closings Restrictions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
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)					
Workplace Closings × Low Telework					-0.02177*		
					(0.012)		
Workplace Closings × High Telework					-0.00814		
					(0.006)		
Workplace Closings × Upstreamness						0.00622	0.00801***
						(0.004)	(0.003)
Number of Observations	23,531,808	21,787,468	6,118,735	14,764,840	14,764,840	23,531,808	23,531,808
Exporter-Importer-Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Importer-Industry-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-Month Fixed Effects	No	No	No	No	No	No	Yes
Industry-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	All	2020:H1	TW	TW	All	All

Source: IMF staff calculations.

Note: The tables report the results of the estimation of equations (3) (columns 1–5) and (4) (columns 6–7) by Poisson pseudo-maximum likelihood. The Oxford stringency index is replaced by the categorical measure of workplace closings. The sample spans the period January 2020 to June 2021; in column 3 it is restricted to the first six months of 2020; in columns 4–5 the sample is limited to exporting countries for which the measure of teleworkability computed by Dingel and Neiman is available. Standard errors in parenthesis are clustered at the exporter*month level. TW = teleworkability.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Annex Table 4.2.4. The Spillover Effect of Containment Policies: Clustering at the Exporter-Month Level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
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 × Low Telework					-0.00126***		
					(0.000)		
Stringency Index × High Telework					-0.00058***		
					(0.000)		
Stringency Index × Upstreamness						0.00039**	0.00057***
						(0.000)	(0.000)
Number of Observations	23,531,808	21,787,468	6,118,735	14,764,840	14,764,840	23,531,808	23,531,808
Exporter-Importer-Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Importer-Industry-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-Month Fixed Effects	No	No	No	No	No	No	Yes
Industry-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	All	2020:H1	TW	TW	All	All

Source: IMF staff calculations.

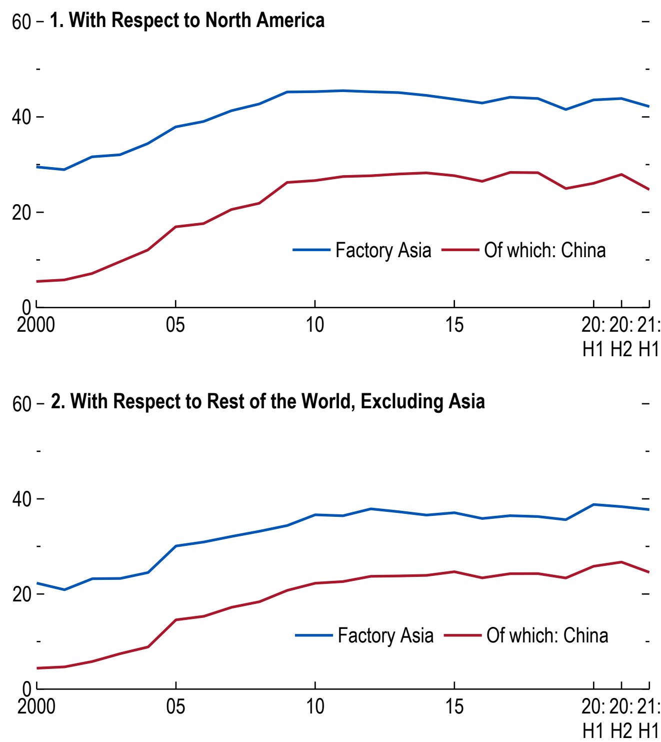
Note: The tables report the results of the estimation of equations (3) (columns 1–5) and (4) (columns 6–7) by Poisson pseudo-maximum likelihood. The sample spans the period January 2020 to June 2021; in column 3 it is restricted to the first six months of 2020; in columns 4–5 the sample is limited to exporting countries for which the measure of teleworkability computed by Dingel and Neiman is available. Standard errors in parenthesis are clustered at the exporter*month level. TW = teleworkablity.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Annex 4.3 Evidence on recent trends in GVCs from trade data

The chapter shows recent changes in the exports market shares for goods in GVC-intensive industries across three main regions (Figure 4.9 in the main text): Factory Asia (Australia, China, India, Indonesia, Japan, South Korea, and Taiwan), Factory Europe (Germany, France, Italy, Netherlands, Spain, Switzerland, Turkey, and United Kingdom), and Factory North America (Canada, Mexico and the United States).[12] This section provides a set of additional findings to complement the stylized facts discussed in the main text.

Annex Figure 4.3.1. Market Shares
(Percent)



Sources: Trade Data Monitor; and IMF staff calculations.
Note: Market shares are computed using only product in GVC-intensive industries, and with respect to North America and rest of the world (excluding Asia), as defined in the text. GVC = global value chain.

First, the increase in the market share of GVC-related goods experienced by the Asian region during the first phase of the pandemic is mostly evident with respect to Europe, especially in an historical context. The gain in market share vis-à-vis North America is limited and has been fully reversed by mid-2021, while that with respect to the rest of the world is sizable, but lower than in the case of Europe and it also partially reversed in the first half of 2021 (Figure 4.3.1).

Second, these changes are a specific feature of trade in GVC-related goods, which has revealed a specific dynamism and capacity to adapt through the pandemic. Figure 4.3.2 reports the change in market shares computed considering exclusively non-GVC-related goods. The top panel shows that the initial gains of Asian countries are more limited (for instance, 0.4 percentage points vis-à-vis Europe, against 4.6 percentage points in GVC-related goods), and Asia lost market shares vis-à-vis North America. By the second half of 2021, most of the changes are broadly modest, with North American and European countries still lagging the pre-pandemic levels, while market shares of Asian countries are about 1 percentage points higher than in 2019 (Figure 4.3.2, bottom panel).

Third, the differences in the change of market shares in GVC-related goods across countries during the collapse in trade (2020:H1) and the recovery phase (2021:H1), measured with respect to the pre-pandemic levels in 2019, reflect in part the severity of the health crisis and of the

[12] GVC-intensive industries are defined to include traded goods in electronics, automobiles, textiles, and medical goods. The HS-6 codes for the inputs and final goods traded in these industries are taken from studies of the respective global value chains of these industries: Frederick and Lee 2017 (electronics), Sturgeon and others 2016 (automobiles), and Frederick 2019 (textiles, medical devices).

containment policies. Figure 4.3.3 points to a positive correlation between the changes in exports market shares relative to 2019 and the index of mobility (computed from Googles' Community Mobility Reports). This positive association is statistically significant in both periods and indicates that a decline in mobility by 30 points is associated with a 0.25 percentage point decline in the market share. This finding indicates that differences in the spread of the COVID-19 crisis and in the severity of the containment policies across countries translated into shift in trade in GVCs-related products across countries. These adjustments have mostly benefited Asian countries, which took advantage of earlier re-openings compared to European and North American countries. At the same time, this finding would suggest that some of these changes are likely to be temporary: as mobility returns towards the pre-pandemic levels, market shares are also likely to move closer to the pre-pandemic levels.

Annex Figure 4.3.2. Changes in Regions' Market Shares of Non-GVC-Intensive Products

(Percentage points)

1. 2020:H1 versus 2019

Importer regions \ Exporter regions	North America	Europe	Asia	Rest of the world
Rest of the world	–0.4	–0.1	0.4	0.1
Asia	–0.2	–0.9	1.5	–0.5
Europe	0.3	–1.6	0.4	0.9
North America	–2.4	1.9	–1.9	2.4

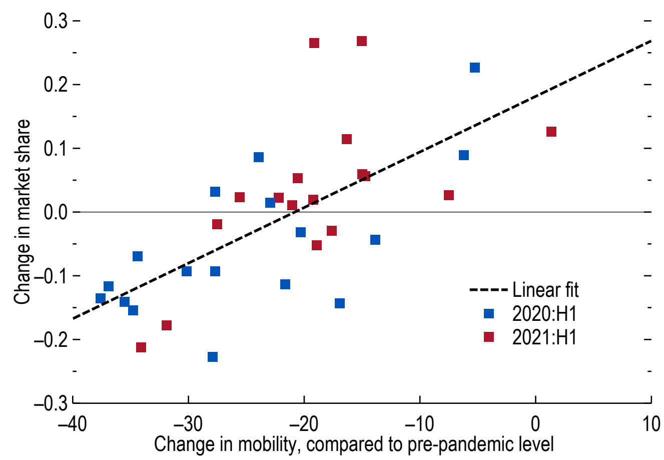
2. 2021:H1 versus 2019

Importer regions \ Exporter regions	North America	Europe	Asia	Rest of the world
Rest of the world	–1.6	0.0	1.2	0.4
Asia	–1.5	–0.1	1.1	0.5
Europe	–1.0	–1.6	1.4	1.2
North America	–0.6	–0.9	–0.4	1.9

Sources: Trade Data Monitor; and IMF staff calculations.
Note: GVC = global value chain.

Annex Figure 4.3.3. Change in Mobility and Market Shares in GVC-Related Exports

(Percent)



Sources: Google, Community Mobility Reports; Trade Data Monitor; and IMF staff calculations.
Note: The chart plots the percent change in market shares computed on exports in GVC-intensive industries against the change in mobility. The sample includes 18 countries (see footnote 25 for the list, which exclude China because mobility data are not available) observed over two periods (2020:H1 and 2021:H1). The percent changes in market shares are computed compared to the previous six-month period, while changes in mobility are measured compared to the pre-pandemic level.
GVC = global value chain.

Annex 4.4 Strengthening Resilience in GVCs

Data Sources

The key data for the analysis of GVC resilience are bilateral trade in intermediate and final goods between country—sector pairs, which are obtained from the 2018 edition of the OECD Inter-Country Input—Output Tables. The analysis uses data for 2015, which is the latest year available in this dataset. Trade values are expressed in nominal US dollars. Data for taxes and subsidies are excluded. The data include 64 economies, after consolidating the split tables for China and Mexico by summation.[13] The data contain 36 sectors at the two-digit level of aggregation, which are collapsed to 33 sectors by adding together the values for the three categories of mining activity (energy products, non-energy products, and support services) and by adding together the values for the arts and recreation sector with those of private household activities. In the data, every country—sector sources intermediates from every country—sector.[14]

Other datasets are used for calibrating the general equilibrium model, as described in Bonadio and others (2021). In particular, labor income shares are derived from OECD STAN (2010 reference year). The Penn World Tables version 10.0 is used obtain historical logarithmic growth rates in total factor productivity under national accounts definitions. Since Bahrain, Cambodia and Vietnam are missing from the Penn World Tables, their total factor productivity growth is taken to be the average across countries in Asia.

Measuring Room for Diversification

The left panel of Figure 4.10 in the main text shows room for countries and sectors to source more of their intermediate inputs from abroad. This room for diversification is calculated at the level of individual country—sector pairs (n, j), following the three steps described below, and then averaged across countries and sectors (n, j) within each geographic region in the chart (e.g. the Western Hemisphere).

- The first step is to calculate the actual domestic shares, which are the solid blue bars. Let $x_{mi,nj}$ be the nominal value of intermediate inputs from (source) country m and sector i used in (destination) country n and sector j.[15] Then the share of expenditure of country n and sector j on intermediate inputs from country m and sector i is

$$\pi^x_{mi,nj} = \frac{x_{mi,nj}}{\sum_l \sum_k x_{lk,nj}}.$$

  The solid blue bars show the share of expenditure of country n and sector j that goes towards domestic intermediates, which is

[13] The economies are Argentina, Australia, Austria, Belgium, Brazil, Brunei, Bulgaria, Cambodia, Canada, Chile, China, Colombia, Costa Rica, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Kazakhstan, Korea, Latvia, Lithuania, Luxembourg, Malaysia, Malta, Mexico, Morocco, Netherlands, New Zealand, Norway, Peru, Philippines, Poland, Portugal, Romania, Russian Federation, Saudi Arabia, Singapore, Slovak Republic, Slovenia, South Africa, Spain, Sweden, Switzerland, Taiwan POC, Thailand, Tunisia, Turkey, United Kingdom, United States and Vietnam.

[14] The exception is Singaporean mining, which has zero input and output in the data. To avoid computational errors, the analysis sets Singaporean mining to produce a negligibly small (but positive) value of intermediate output, which it uses entirely for its own production.

[15] To ease notation, this annex follows Bonadio and others (2021) in using notation of the form $x_{mi,nj}$ to mean $x_{m,i,n,j}$.

$$\sum_i \pi^x_{ni,nj} = \frac{\sum_i x_{ni,nj}}{\sum_l \sum_k x_{lk,nj}}.$$

- The second step is to calculate world production shares, which are used in the next step. These give an idea of the degree of diversification or concentration in world production of each type of intermediate. World production of sector i is $\sum_{l,n,j} x_{li,nj}$, so the share of world production of sector i contributed by source country m is

  $$\omega_{mi} = \frac{\sum_{n,j} x_{mi,nj}}{\sum_{l,n,j} x_{li,nj}}.$$

  A measure of concentration that is analogous to the domestic share is the concentration ratio of world production (the market share of world production) accounted for by the largest producer. Denote the largest $\omega_{m,i}$ across all countries m as $\omega_i^{(1)}$.

- Given a particular (destination) country n and sector j, we would like a benchmark for the degree of diversification or concentration across countries in the inputs to that country—sector. For this purpose, one needs a measure of the diversification or concentration across countries in the world production of all intermediate inputs used in the production by country n and sector j. One way to achieve this is to average the concentration measures for world production of each sector i in proportion to the amount of sector i intermediates used in the production of country n and sector j. To get the sector weights for this aggregate, one must aggregate out the source country dimension of the intermediate input shares, π^x, which applies to a given country n and sector j. Formally, one obtains the sector weights

  $$\lambda_{i,n,j} = \sum_m \pi^x_{mi,nj} = \frac{\sum_m x_{mi,nj}}{\sum_{l,k} x_{lk,nj}}.$$

  These weights can be used to aggregate the concentration measure for world production, $\omega_i^{(1)}$, to obtain

  $$\sum_i \left(\lambda_{i,n,j}\omega_i^{(1)}\right),$$

  which is the benchmark concentration of world production of sector i intermediates used in the production of country n and sector j, and is shown as the diamonds in Figure 4.10 of the main text.

The right panel of Figure 4.10 in the main text is similar to the left panel. However, rather than examining the shares of intermediates that are sourced from all countries in the world (domestic and foreign), it only examines the shares of intermediates that are *imported* from abroad. Therefore, it asks, within the intermediates that are sourced from abroad, what is the diversification or concentration in the distribution of sourcing across foreign countries? As in the previous paragraph, the concentration measures are computed at the level of individual country—sector pairs (n,j) and then averaged across countries and sectors (n,j) within each geographic region in the chart. The share of all intermediate inputs used by country n and sector j that are imported is $\sum_{m \neq n} \sum_i \pi^x_{mi,nj}$, and the share of foreign country l in the intermediate imports of (destination) country n and sector j is

$$\varpi_{l,n,j} = \frac{\sum_i \pi^x_{li,nj}}{\sum_{m \neq n} \sum_i \pi^x_{mi,nj}} = \frac{\sum_i x_{li,nj}}{\sum_{m \neq n} \sum_i x_{mi,nj}},$$

which is a univariate distribution that sums to 1 over all foreign countries $l \neq n$. The solid red bars to the right of Figure 4.10 in the main text show the Herfindahl concentration index of this distribution of import shares across countries, which is $\sum_l \varpi^2_{l,n,j}$. World export shares are the appropriate benchmark for import shares, as opposed to the world production shares used in the previous paragraph.[16] Since world exports of sector i are $\sum_{l,n \neq l,j} x_{li,nj}$, the share of world exports of sector i contributed by source country m is

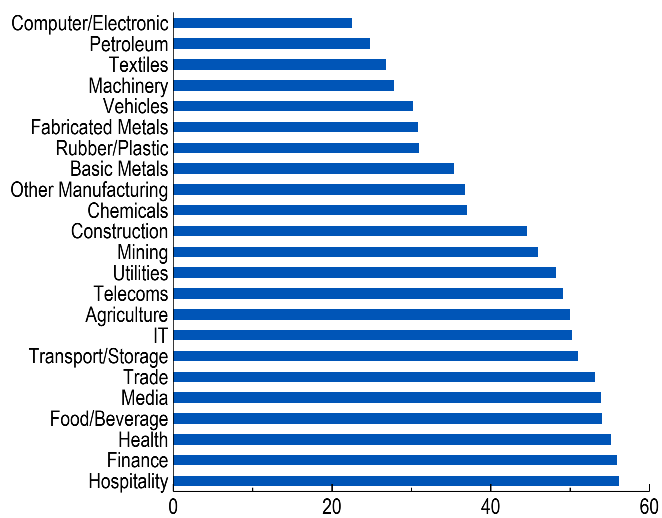
$$\iota_{m,i} = \frac{\sum_{n \neq m,j} x_{mi,nj}}{\sum_{l,n \neq l,j} x_{li,nj}},$$

which is also a univariate distribution that sums to 1 over all source countries m, for each given sector i. Therefore, the Herfindahl concentration index of world export shares for sector i intermediates is $\sum_m \iota^2_{m,i}$. The diamonds in the red bars to the right of Figure 4.10 in the main text show the benchmark concentration of world exports of sector i intermediates used by country n and sector j, which follows the same sector weighting scheme as in the previous paragraph, yielding

$$\sum_i \left(\lambda_{i,n,j} \sum_m \iota^2_{m,i} \right).$$

Annex Figure 4.4.1 shows the analog of Figure 4.10 in the main text, for sectors rather than countries. Specifically, it averages across all countries n for each given sector j, and it shows the difference between the domestic share (solid bars in Figure 4.10 in the main text) and its benchmark (the diamonds in Figure 4.10 in the main text). Figure 4.4.1 shows that the sectors with most room to diversify away from domestically sourced intermediates are services industries like hospitality, finance and healthcare. The higher room for

Annex Figure 4.4.1. Room to Diversify Away from Domestic Sources
(Percentage points)



Source: IMF staff calculations.
Note: The figure shows the excess share of intermediates that are sourced domestically rather than abroad. The excess is measured relative to the shares that would arise if each country and sector sourced only as much of its intermediate inputs domestically as are produced by the largest world producer.

[16] The reason is that the existing concentration of world exports constrains the ability of countries and sectors to diversify their imports in the short term (i.e. without changing the structure of world exports).

international diversification in services than in goods is not surprising, because industries source most of their intermediate inputs from within their own industry, and services are less traded than goods.

General Equilibrium Model and Extensions

The analysis adopts a multi-sector quantitative framework to study the role of a more resilient global supply chain on GDP when facing different shock scenarios. More details about the model setup and calibration are available in Bonadio, Huo, Levchenko, and Pandalai-Nayar (2021). The baseline model considers an economy of N countries and J sectors that produces using labor inputs provided by households. A representative firm in sector j country n produces with a constant returns to scale (CRS) technology

$$Y_{nj} = \left(Z_{nj}^{\alpha_j} H_{nj}^{1-\alpha_j}\right)^{\eta_j} X_{nj}^{1-\eta_j},$$

where Z_{nj} denotes total factor productivity and H_{nj} is an aggregate of labor inputs from all occupations. $1 - \alpha_j$ is labor share in value added and η_j is the share of value added in gross output. Households provide labor and consume final goods and services. In the original model of Bonadio and others (2021), firms source from all countries and sectors. X_{nj} aggregates inputs from all countries and sectors

$$X_{nj} = \left(\sum_i \sum_m \mu_{mi,nj}^{\frac{1}{\sigma}} X_{mi,nj}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}},$$

where σ denotes the elasticity of substitution across intermediate inputs, which is common across countries and sectors. $X_{mi,nj}$ are inputs from (source) country m sector i used in the production of (destination) country n sector j and $\mu_{mi,nj}$ is the corresponding taste shifter. The aggregate price index for sector i in (source) country n is denoted as P_{mi} and the iceberg trade cost from country m sector i to country n is τ_{mni}. The firm then chooses the share of intermediates from (source) country m sector i in the total intermediate expenditure of (destination) country n sector j to be

$$\pi_{mi,nj}^{x} = \frac{\mu_{mi,nj}\left(\tau_{mni} P_{mi}\right)^{1-\sigma}}{\sum_{li} \mu_{li,nj}\left(\tau_{lni} P_{li}\right)^{1-\sigma}}.$$

The substitutability analysis considers extending the above model to distinguish intermediate goods substitutability across sectors (ϵ) and across countries (v). This helps to avoid conflating the effects of two fundamentally different notions of substitutability. In the extended model, the intermediate input X_{nj} aggregates the sectoral inputs in country n,

$$X_{nj} = \left(\sum_i \vartheta_{i,nj}^{\frac{1}{\epsilon}} X_{i,nj}^{\frac{\epsilon-1}{\epsilon}} \right)^{\frac{\epsilon}{\epsilon-1}}.$$

where $X_{i,nj}$ is the use of sector i inputs in sector j and (destination) country n and $\vartheta_{i,nj}$ is the associated taste shifter. $X_{i,nj}$ is an Armington aggregate across different source countries,

$$X_{i,nj} = \left(\sum_m \mu_{mi,nj}^{\frac{1}{v}} X_{mi,nj}^{\frac{v-1}{v}} \right)^{\frac{v}{v-1}},$$

where $X_{mi,nj}$ is the input from sector i and country m used in the production of sector j and country n. Denote as $P_{i,nj}^X$ the corresponding price index of sector i inputs used in the production of country n sector j.

The extended model generates two different expenditure shares reflecting the source of intermediate goods. $\pi_{i,nj}^s$ denotes the share of sector i in total intermediates spending by sector j country n, and $\pi_{mi,nj}^x$ denotes the share of intermediates from sector i country m in total intermediate expenditure by sector j country n on sector i.

$$\pi_{i,nj}^s = \frac{\vartheta_{i,nj}\left(P_{i,nj}^X\right)^{1-\epsilon}}{\sum_k \vartheta_{k,nj}\left(P_{k,nj}^X\right)^{1-\epsilon}} \quad \text{and} \quad \pi_{mi,nj}^x = \frac{\mu_{mi,nj}\left(\tau_{mni}P_{mi}\right)^{1-v}}{\sum_l \mu_{li,nj}\left(\tau_{lni}P_{li}\right)^{1-v}}.$$

With the extended production function and updated sourcing shares, the demand for intermediate goods changes to $\sum_m \sum_i (1-\eta_i) P_{mi} Y_{mi} \pi_{j,mi}^s \, \pi_{nj,mi}^x$, and the market-clearing condition for each sector j country n becomes

$$P_{nj}Y_{nj} = \sum_m P_m F_m \pi_{nmj}^f + \sum_m \sum_i (1-\eta_i) P_{mi} Y_{mi} \pi_{j,mi}^s \, \pi_{nj,mi}^x.$$

This market clearing condition says, for each (source) country n sector j, the gross output equals the demand of intermediate from all destination countries and sectors, plus final demand from all destination countries. The market-clearing condition and first-order conditions with respect to the composite labor and intermediate goods define the generation equilibrium conditions.

The log-linearized market clearing condition, together with the log-linearized first-order conditions with respect to the composite labor and intermediate goods give the same influenced matrix as defined in Bonadio and others (2021) with redefined matrices[17]. Log-linearization of the market-clearing condition allows one to express the prices as a function of the quantities in matrix form,

$$\ln P + \ln Y = (\Psi^{\mathrm{x}} + \Psi^f \gamma)(\ln P + \ln Y) + \Phi^{\mathrm{x}} \ln P + \Phi^{\mathrm{f}} \ln P,$$

[17] This analysis redefines the Φ^{x} and Φ^{f} matrices in the log-linearized market clearing condition to make the influence matrix in the extended model exhibit the same functional form as in Bonadio and others (2021) equation (8).

where matrices Φ^{x} and Φ^{f} in the extended model are redefined as

$$\Phi^{x} = (1-\gamma)(diag(\Psi^{f}) - \Psi^{f}\Pi^{f}),$$
$$\Phi^{f} = \Psi^{x}(1-\epsilon)(\Pi^{2x} - \Pi^{1x}) + (1-\nu)(\Psi^{x} - \Psi^{x}\Pi^{2x}),$$

and share matrices are redefined as follows:

- $\Psi^{x}(nj,mi) = \frac{(1-\eta_i)P_{mi}Y_{mi}\pi^{s}_{j,mi}\pi^{x}_{nj,mi}}{P_{nj}Y_{nj}}$ is the (nj,mi)th element of matrix Ψ^{x}. This matrix stores the share of total revenue in the row country-sector that comes from the intermediate expenditures in the column country-sector.
- $\Pi^{1x}(nj,mi) = \pi^{s}_{i,nj}\pi^{x}_{mi,nj}$ is the (nj,mi)th element of matrix Π^{1x}. This matrix stores the intermediate expenditure on goods coming from the column in the country-sector of the row.

Shock Scenarios

The analysis considers three types of scenarios, to illustrate different aspects of resilience. They are calibrated as follows.

- *Uncorrelated shock to a large supplier.* The analysis considers a shock that is uncorrelated across countries in that it originates only in one country, for both the higher diversification and higher substitutability experiments. To have appreciable effects on world output, the country is chosen to be a large supplier of intermediates. The scenario is calibrated by assuming that the shock originates in China, which has a standard deviation of 2.6 percent in total factor productivity growth rates. Under the Cobb—Douglas production function assumed in the general equilibrium model, a labor supply shock (i.e. a change in the log of the labor supply contraction parameter denoted by ξ) equals a total factor productivity shock divided by $-(1-\alpha)\eta$, which is -0.23 for the average sector in the data. Therefore, a two-standard deviation contraction in labor supply for this country is $2 \times 2.6\% \div -0.23 \approx 22\%$, which is rounded up here to 25 percent.

- *Correlated shocks.* All countries of the world are hit simultaneously with shocks that are drawn from historical productivity data. Specifically, 100 years of total factor productivity changes are sampled with replacement (bootstrapped) from yearly Penn World Tables data between 1995 and 2019. These shocks should be seen as having a medium-to-high correlation with one another, because OECD countries make up a large portion of the sample. The average pairwise correlation between the shocks is 25 percent.

- *Foreign shocks.* As a robustness exercise, the effects of higher substitutability in protecting against foreign shocks when each country faces a shock to labor supply in all foreign countries, is examined. With one shock for each country, there are 64 shock scenarios. The results for the change in log GDP under the foreign shock are averaged across countries in each region. The magnitude of the foreign shocks is set to a 20 percent labor supply contraction in every case, which is consistent with a two-standard deviation change in the average country's yearly total factor productivity growth; this uses the same parameters and calculation as in the above scenario of an uncorrelated shock to a large supplier.

Counterfactuals for Diversification and Substitutability

The analysis above, and in Figure 4.10 of the main text, reveals that countries have room to reduce their domestically sourced share of intermediate inputs by about one-half. Therefore, the counterfactual, high-diversity world approximates this, for each country n and sector j, by taking the simple average of two sourcing distributions. The first is the actual sourcing distribution across source countries m, $\sum_i \pi^x_{mi,nj}$. The second is a distribution that sources equal shares, $1/64$, from each of the 64 countries in the analysis.[18] Therefore, in the high-diversification world, country n and sector j sources the share

$$\frac{1}{2}\left(\sum_i \pi^x_{mi,nj} + \frac{1}{64}\right)$$

from each source country m. To translate these shares into shares sourced from each country m and sector i, the analysis makes use of a very convenient property of the OECD input—output tables: $\pi^x_{mi,nj} = \sum_i \pi^x_{mi,nj} \times \sum_m \pi^x_{mi,nj}$. In other words, the share sourced from a given country—sector pair is the product of the share sourced from the country and the share sourced from the sector.[19] This property allows us to preserve the sourcing behavior across sectors, and therefore the production technology, even while diversifying the sourcing behavior across countries. Using this property, the share of all intermediates that country n and sector j sources from country m and sector i is therefore

$$\frac{1}{2}\left(\sum_i \pi^x_{mi,nj} + \frac{1}{64}\right) \times \sum_m \pi^x_{mi,nj}.$$

To examine symmetry of the effects of diversification, a low-diversification world is also considered, where sourcing is more geographically concentrated on domestic sources. In the low-diversification world, country n and sector j sources the share

$$\frac{1}{2}\left(\sum_i \pi^x_{mi,nj} + I(m = n)\right)$$

from each source country m, where $I(\cdot)$ denotes the indicator function.

Note two important features of the diversification counterfactual:

- First, the counterfactual, high-diversity world is constructed, for each country n and sector j, by making the sourcing behavior of intermediate inputs more diversified across countries, while holding it constant across sectors. It is important to hold the distribution constant across sectors, to avoid implicitly changing the production technology.

[18] The exposition here simplifies by ignoring the "rest of the world" category, which in some ways acts as a 65th country in the sample. In designing the high-diversification counterfactual, the analysis holds constant the share of intermediates that country n and sector j sources from the rest of the world, and only diversifies within the other 64 countries in the sample.

[19] In the language of statistics, this property says that the bivariate distribution of sourcing of intermediates across countries m and sectors i is *independent* across the country and sector dimensions.

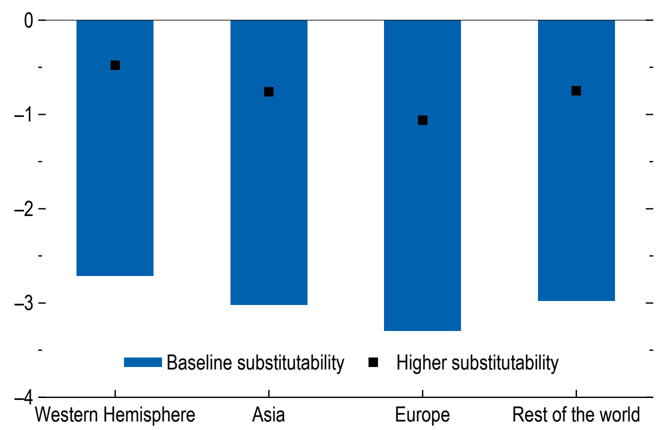
- Second, the diversification is achieved at the level of a given country (n) and sector (j), without making assumptions about firm-level behavior. This means that not every firm need diversify its sourcing.

The key parameter of interest in the substitutability exercise is v, reflecting the elasticity of substitution between intermediate inputs of different countries[20]. It is a crucial parameter in international trade and a fundamental primitive that shapes the international transmission of shocks through price and quantities. However, there is no consensus on its value. Feenstra and others (2018) find the median estimates of the elasticity governing the substitution between home and foreign goods is about 2.[21] Gallaway and others (2003) estimate that the average short-run elasticity is 0.95 and the average long-run elasticity is 1.55.[22] To be comparable with the original model, the analysis in this chapter considers the baseline a parameter value of 0.5, which is also used as a short-run elasticity in Bonadio and others (2021). The counterfactual analysis chooses a parameter value of 2.

Model Results and Robustness Exercises

Figure 4.4.2 shows the impact on each region if labor supply contracts by 20 percent in all foreign countries. In the foreign shock scenarios, higher substitutability between intermediate goods produced by different countries reduces the impact of foreign supply shocks by about three-quarters, from 3 percent to 0.76 percent. With a higher substitutability, a country can protect itself from foreign shocks, because it can more flexibly substitute away from its trading partners that are experiencing a negative shock. This rigorously demonstrates and quantifies the intuition about using higher substitutability as protection against supply disruptions. However, as discussed in the main text and shown there in Figure 4.12, this protection comes at the cost of the source country, with no net benefit to the world.

Annex Figure 4.4.2. GDP Losses from Supply Disruptions in Foreign Countries
(Percent)



Source: IMF staff calculations.
Note: Simple averages across countries within each region. Baseline elasticity of substitution = 0.5. Higher elasticity of substitution = 2.0.

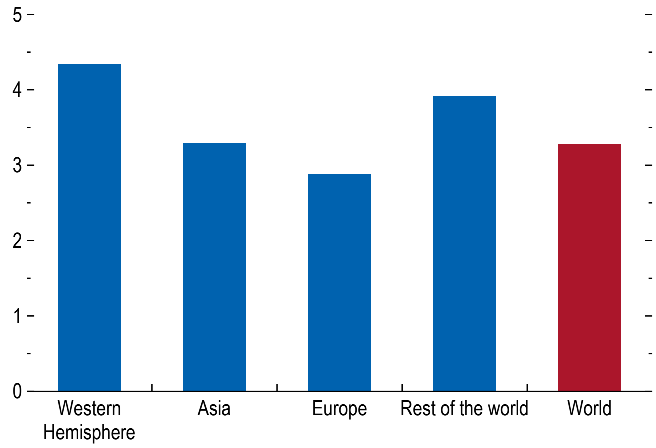
[20] The elasticity of substitution between inputs of different countries is also called the Armington elasticity. It is a parameter commonly used in models of international trade and is based on the assumption that products traded internationally are differentiated by country of origin (Armington, 1969).

[21] Feenstra and others (2018) distinguish between the elasticity governing the substitution between home and foreign goods (which they called macroelasticity) and the elasticity governing the substitution between varieties of foreign goods (microelasticity). They find that the microelasticity is twice as large as the macroelasticity and median estimates of the microelasticity are 3.22 and 4.05 under two-stage least squares and two-step generalized method of moments methodologies, respectively. Thus, the median macroelasticity is about 2.

[22] Another approach to calibrate the elasticity of substitution between goods of different countries is to leverage the relationship between the trade elasticity and the elasticity of substitution. Boehm and others (2020) estimate a long-run elasticity of tariff-exclusive trade flows with respect to tariffs of between -2.25 and -1.75. The (absolute value of) the tariff-exclusive trade elasticity equals the elasticity of substitution in an Armington/Krugman setting. This relationship gives an elasticity of substitution of between 1.75 and 2.25.

The effects of diversification on GDP volatility are symmetric, in that more diversification reduces the volatility that arises from multi-country correlated supply shocks, and less diversification amplifies their effects. Specifically, a reduction in diversification consistent with a 10-percentage point increase in the share of domestically sourced intermediates increases GDP volatility in the correlated shock scenarios by 3 percent (Figure 4.4.3).[23]

Annex Figure 4.4.3. Increase in GDP Volatility from Less Diversification
(Percent)



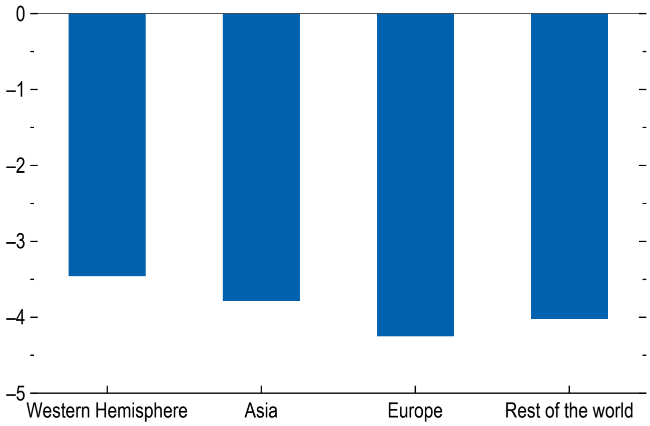
Source: IMF staff calculations.
Note: The bars show simple averages within each region of the percentage increase in volatility from a drop in diversification. For a given country, volatility is measured across the model-implied GDP gains or losses under 100 multi-country shock scenarios, bootstrapped from the last 25 years of total factor productivity growth rates in the Penn World Tables.

Further modeling exercises show that diversification can be achieved by reducing the costs of trading in intermediate goods and services. The model implicitly uses trade costs and preferences to account for the observed patterns of trade in intermediates across countries. The analysis simulates new equilibrium trade shares by reducing the bilateral trade cost by a factor τ_{mni}, which is an exogeneous parameter in the original model. Specifically, the results indicate that a one-quarter reduction in trade costs would lower the Herfindahl index of geographic concentration in the sourcing of intermediates by about 4 percentage points (Figure 4.4.4). This diversification is achieved by reducing the share of inputs sourced domestically, by about 3 percentage points, (as opposed to diversifying imported intermediates). The Herfindahl index of geographic concentration in imported intermediates remains virtually unchanged. The increase in diversification is similar across regions. Interestingly, the most diversification occurs in Europe, where diversification is highest to begin with (Figure 4.4.5). Separately, the model results indicate that reducing the costs of trading in *final* goods and services would not have a material effect on diversification.

[23] This result does not follow simply from the fact that the solution to the model is (log-)linearized. Log-linearization makes the effects of positive and negative shocks symmetric; by contrast, the effects of diversification depend on the interaction between the structure of shocks and form of diversification.

Annex Figure 4.4.4. Lower Concentration from Lower Trade Costs

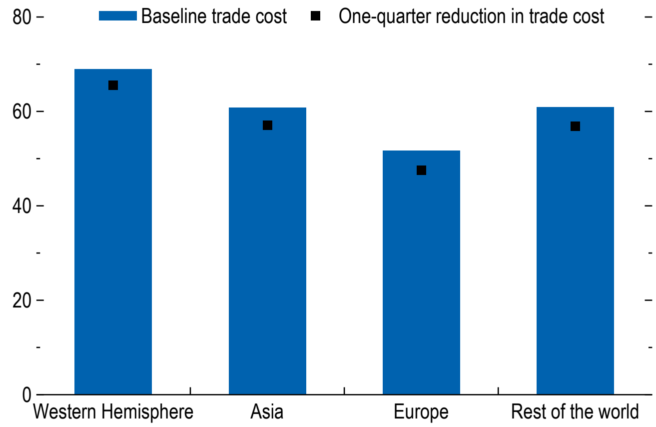
(Percentage point change in Herfindahl index)



Source: IMF staff calculations.
Note: The figure shows the change in the Herfindahl index of geographical concentration in the sourcing of intermediate inputs when trade costs fall by one quarter. The bars show the simple average of the change across all sectors and countries within each region.

Annex Figure 4.4.5. Geographic Concentration of Sourcing

(Percent Herfindahl concentration)



Source: IMF staff calculations.
Note: The figure shows the Herfindahl index of geographical concentration in the sourcing of intermediate inputs in the data (bars) and when trade costs fall by one quarter (squares). The bars and squares show simple average across all sectors and countries within each region.

References

Antràs, Pol, Davin Chor, Thibault Fally, and Russell Hillberry. 2012. "A measure of upstreamness of production and trade flows." *American Economic Review: Papers & Proceedings*, 102(3): 412–416.

Armington, Paul. 1969. "A Theory of Demand for Products Distinguished by Place of Production." *IMF Staff Papers* 16 (1): 159–78.

Bartik, Timothy. 1991. "Boon or Boondoggle? the Debate over State and Local Economic Development Policies." W.E. Upjohn Institute for Employment Research (1), pp. 1-16.

Berthou, Antoine and Sebastian Stumpner. 2022. "Trade Under lockdown," Banque De France Working Paper 867. Paris. https://www.banque-france.fr/sites/default/files/medias/documents/wp867.pdf.

Boehm, Christoph E., Andrei A. Levchenko, and Nitya Pandalai-Nayar. 2020. "The Long and Short (Run) of Trade Elasticities." NBER Working Paper 27064, National Bureau of Economic Research, Cambridge, MA.

Bonadio, Barthélémy, Zhen Huo, Andrei A. Levchenko, and Nitya Pandalai-Nayar. 2021. "Global Supply Chains in the Pandemic." *Journal of International Economics* 133: 103534.

Bussière, Matthieu, Giovanni Callegari, Fabio Ghironi, Giulia Sestieri, and Norihiko Yamano. 2013. "Estimating Trade Elasticities: Demand Composition and the Trade Collapse of 2008–2009." *American Economic Journal: Macroeconomics* 5 (3): 118–51.

Correia, Sergio, Pablo Guimaraes and Tom Zylkin. 2020. "ppmlhdfe: Fast Poisson Estimation with High-Dimensional Fixed Effects." *Stata Journal* 20(1): 95-115.

Dingel, Jonathan L., and Brent Neiman. 2020. "How Many Jobs Can Be Done at Home?" *Journal of Public Economics* 189: 104235.

Feenstra, Robert C., Philip Luck, Maurice Obstfeld, and Katheryn N. Russ. 2018. "In Search of the Armington Elasticity." *Review of Economics and Statistics* 100 (1): 135–50.

Frederick, Stacey, and Jonkoo Lee. 2017. "Korea and the Electronics Global Value Chain." Global Value Chains Center, Duke University, Durham, NC. https://gvcc.duke.edu/cggclisting/chapter-3-korea-and-the-electronics-global-value-chain/.

Frederick, Stacey. 2019. "Global Value Chain Mapping." Chapter 1 in *Handbook of Global Value Chains*, edited by Stefano Ponte, Gary Gereffi, and Gale Raj-Reichert. Northampton, MA: Elgar.

Gallaway, Michael P., Christine A. McDaniel, and Sandra A. Rivera. "Short-run and long-run industry-level estimates of US Armington elasticities." *The North American Journal of Economics and Finance* 14, no. 1 (2003): 49-68.

Hale, Thomas, Noam Angrist, Beatriz Kira, Anna Petherik, Toby Phillips, and Samuel Webster. 2020. "Variation in Government Responses to COVID-19." Blavatnik School of Government Working Paper 2020/032, University of Oxford, Oxford, UK.

Heise, Sebastian. 2020. "How Did China's COVID-19 Shutdown Affect U.S. Supply Chains?" *Liberty Street Economics,* Federal Reserve Bank of New York, May 12.

https://libertystreeteconomics.newyorkfed.org/2020/05/how-did-chinas-covid-19-shutdown-affect-us-supply-chains/

Lafrogne-Joussier, Raphael, Julien Martin, and Isabelle Mejean. 2021. "Supply Shocks in Supply Chains: Evidence from the Early Lockdown in China." CEPR Discussion Paper 16813, Center for Economic and Policy Research, Washington, DC.

Santos Silva, J. M. C., and Silvana Tenreyro. 2006. "The Log of Gravity." *Review of Economics and Statistics* 88 (4): 641–58.

Sturgeon, Timothy, Jack Daly, Stacey Frederick, Penny Bamber, and Gary Gereffi. 2016. *The Philippines in the Automotive Global Value Chain.* Durham, NC: Center on Globalization, Governance and Competitiveness, Duke University. https://hdl.handle.net/10161/12484.