EXECUTIVE BOARD MEETING

EBS/22/18

March 18, 2022

To: Members of the Executive Board

From: The Secretary

Subject: **April 2022 World Economic Outlook—Analytical Chapter 4 and Online Annex**

Board Action:	Executive Directors' **consideration** (Formal)
Tentative Board Date:	**Monday, April 11, 2022**
Publication:	Yes, it is intended that the full set of the World Economic Outlook documents will be released to the public at the time of the World Economic Outlook press conference, tentatively scheduled for **Tuesday, April 19, 2022**. The analytical chapters will be made available to the public on the IMF website in advance of the publication of the full document.
Questions:	Mr. Mohommad, RES (ext. 36332) Mr. Presbitero, RES (ext. 38961) Mr. Sher, EUR (ext. 37070)
Additional Information:	The paper will be revised for publication in light of the Executive Board discussion. If Executive Directors have comments, they should notify Ms. Mohommad, Mr. Presbitero, and Mr. Sher by **5:30 p.m. on Friday, April 1, 2022**.

CHAPTER 4

GLOBAL TRADE AND VALUE CHAINS IN THE PANDEMIC

BOXES

FIGURES

CHAPTER 4

GLOBAL TRADE AND VALUE CHAINS IN THE PANDEMIC

When COVID-19 hit, the combined supply and demand shock was expected to lead to a dramatic collapse in trade. However, although trade in services remains sluggish, trade in goods bounced back surprisingly quickly. This chapter finds that factors specific to the pandemic played a key role in the rotation of trade from services to goods, above and beyond the impact on demand. Imports of goods fell by less and imports of services by more than can be explained by demand and relative prices. The pattern was more pronounced in countries where the pandemic—and associated containment policies—was more severe. Further, an examination of granular bilateral trade data reveals that international spillovers from lockdown-induced supply disruptions were a key driver of the decline in trade early in the pandemic. These negative spillover effects tended to be short-lived, and were mitigated to the extent that telework was possible. Moreover, the spillover effects diminished over subsequent waves of the pandemic, suggesting adaptability and resilience in global value chains (GVCs). Indeed, with differences in the timing of pandemic outbreaks and containment policies across different regions, some regions with significant participation in GVCs were able to increase their share in the imports of other regions, but these changes also appear to be unwinding over time. In view of the overall resilience of global trade and value chains during the pandemic, this chapter argues that policies such as reshoring are likely misguided. Instead, supply chain resilience to shocks is better built by increasing diversification away from domestic sourcing of inputs; and greater substitutability in input sourcing (easier switching of input supplies between countries). Increasing supply chain resilience is important to deal with not only health emergencies like the pandemic, but also other types of shocks such as the war in Ukraine, cyberattacks, and extreme weather events related to climate change. While much of the work of building resilience must be done by firms (as private sector actors), governments can still play a useful role by filling information gaps in supply chains, investing in trade and digital infrastructure, reducing trade costs, and minimizing policy uncertainty. Widespread vaccination will be crucial to mitigating spillovers from future shocks related to the spread of COVID-19.

Introduction

With the onset of the COVID-19 pandemic, trade collapsed in a dramatic fashion. At its trough in the second quarter of 2020, the volume of global trade in goods fell 12.2 percent and trade in services fell even more sharply by 21.4 percent compared with the last quarter of 2019 (Figure 4.1). However, the recovery in trade was also surprisingly quick, compared to the much more protracted recoveries after other global recessions (Figure 4.2) (Baldwin 2020). Trade in goods had recovered to pre-pandemic levels by October 2021—a very rapid rebound compared, for example, with the global financial crisis. However, the aggregate trends mask considerable heterogeneity, and further disruptions are likely due to the conflict between Russia and Ukraine.[1]

- Trade in services remains sluggish, driven mainly by the collapse of travel. Transport services appear to be recovering, although disruptions in seaborne trade remain elevated (see Komaromi and others, forthcoming, on the evolution of delays in shipping). Trade in other services has been more robust (Figure 4.3), notably telecommunication services.

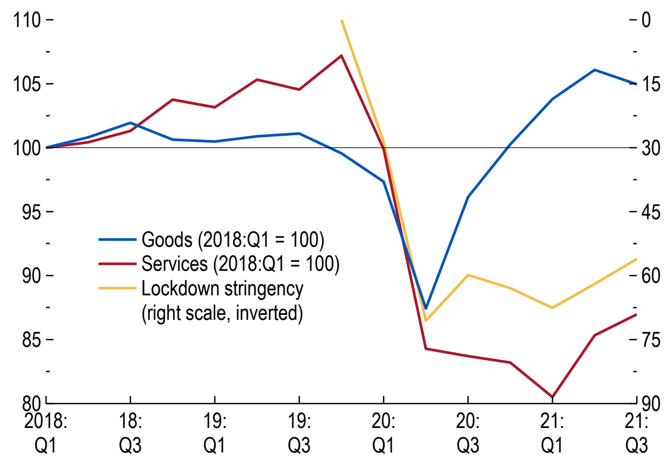
This chapter was prepared by Ting Lan, Davide Malacrino, Adil Mohommad (lead), Andrea Presbitero, and Galen Sher, under the guidance of Shekhar Aiyar, and with support from Shan Chen, Bryan Zou, Youyou Huang, and Ilse Peirtsegaele. It includes contributions from Mariya Brussevich, Diego Cerdeiro, Andras Komaromi, Yang Liu, Chris Papageorgiou, and Pauline Wibaux. Andrei Levchenko was a consultant for the project.

[1] The analysis presented in this chapter was concluded in early 2022, prior to the outbreak of the Russia-Ukraine conflict, and does not focus on the implications of the conflict on global trade and value chains.

- Trade in goods that rely heavily on global value chains (GVC-intensive goods) was more volatile than that of other goods (Figure 4.3). Between January and April 2020, exports of GVC-intensive goods fell 30 percent, while exports of other goods fell by about 18 percent.[2] The recovery in GVC-intensive goods was also more rapid. The initial drop, however, was relatively more severe in some industries like automobiles, amid disruptions to key inputs such as semiconductors (see Box 4.1 for further details on the evolution of supply disruptions, including in automobile and semiconductor trade). Amid the volatility in trade among GVC-intensive goods, calls to explore policy options to increase GVC resilience to shocks have gained prominence.

Figure 4.1. Global Import Volume and Lockdown Stringency
(Index)

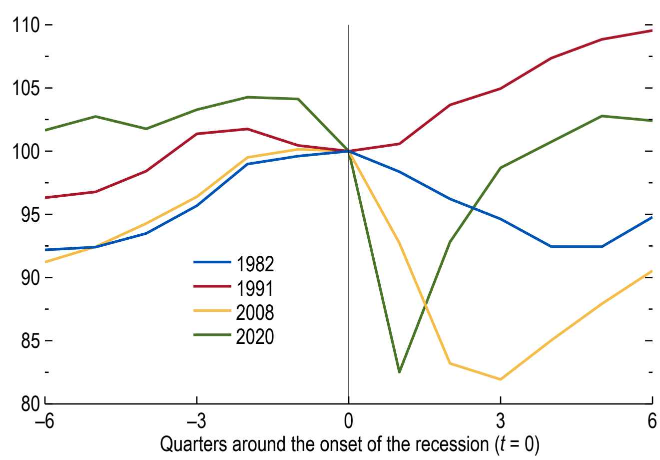
Goods trade has recovered rapidly, although services trade remains sluggish.



Sources: CPB World Trade Monitor; Hale and others (2021); and IMF staff calculations.
Note: The lockdown stringency Index is the world import-weighted average of the Oxford Stringency Index.

Figure 4.2. Trade Patterns around Global Recessions: Goods and Services Import Volume
(Index)

The recovery in goods trade was more rapid than in previous recessions.



Sources: Kose and others (2020); and IMF staff calculations.
Note: The goods and services import volume index is normalized to 100 at the onset of the recession (t = 0).

Against this backdrop, the chapter first formally examines potential explanations for observed patterns in trade during the pandemic. In particular it asks three questions: (1) How well can trade patterns be accounted for by a standard model of demand and prices, compared to previous large recessions?; (2) What factors specific to the pandemic were important in determining the trade patterns?; and (3) What international spillover effects were generated by the mobility restrictions in response to the pandemic? These questions are investigated using an empirical framework based on standard models from the trade literature, and relying on granular bilateral trade data at monthly frequency to examine spillovers.

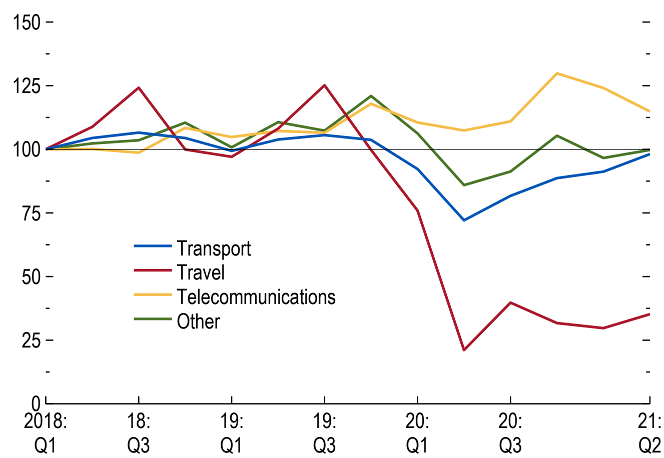
The second set of questions in this chapter probes developments in GVCs, and examines how to build up their resilience. It is difficult to paint a precise picture of changes in the structure of GVCs though the pandemic, given lags in high-frequency input-output data

[2] GVCs are internationally distributed activities, such as design, production and distribution, involved in bringing a product or service from conception to end use (Ponte, Gereffi, and Raj-Reichert 2019). Operationally, GVC-trade has been defined to include trade in goods that cross at least two international borders (Hummels, Ishii, and Yi, 2001). In this chapter, GVC-intensive goods are defined to include inputs and finished goods in the following industries: automobiles, electronics, textiles and garments, and medical goods. Together these goods account for about 24 percent of global goods trade, and are typically considered to be at the fore-front of GVCs (Sturgeon and Memedovic, 2010).

on them. Hence, the chapter tracks GVC developments as inferred from trade data. And, in response to concerns about how well GVCs can weather global shocks, it examines options to increase the resilience of the world economy in a modeling framework. Using a model that spans multiple sectors and countries, it examines the gains in resilience from (1) increasing the geographic diversification of input sourcing across countries; and (2) increasing the substitutability of inputs across sources in different countries.

Figure 4.3. Imports of Commercial Services by Main Sectors
(Index, 2018:Q1 = 100)

The decline in services trade is mainly due to travel services.



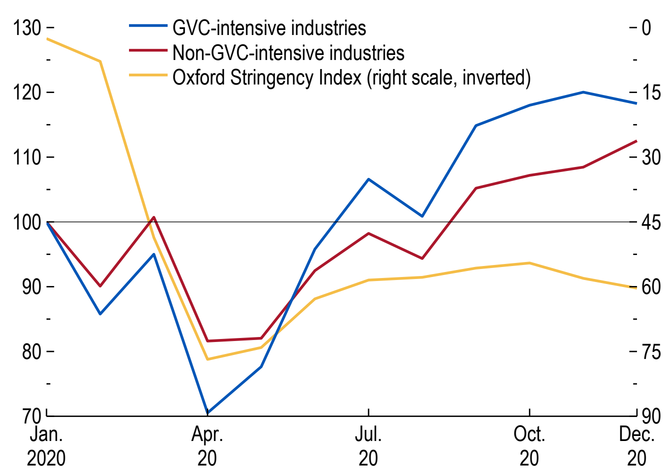
Sources: World Trade Organization; and IMF staff calculations.
Note: Telecommunications comprises telecommunications, computer, and information services. "Other" comprises commercial, goods-related, construction, financial, insurance and pension, intellectual property, other business, personal, cultural, and recreational services.

The main conclusions of the chapter are as follows:

- Factors specific to the pandemic had an important role in determining trade patterns. Goods imports were larger, and services imports were smaller in 2020 than would be predicted by a model of import demand. Moreover, the deviations in actual trade from model predictions were much larger than in previous recessions. The "excess" goods imports were larger in countries with more severe pandemic outbreaks, more stringent containment policies, and larger declines in mobility. On the other hand, "deficit" services imports were larger where the pandemic was more severe.

Figure 4.4. Volatility of Trade in GVC-Intensive Industries versus Non-GVC-Intensive Industries Early in the Pandemic
(Index)

Trade in GVC-intensive industries was relatively more volatile than trade in non-GVC intensive industries.



Sources: Hale and others (2021); Trade Data Monitor; and IMF staff calculations.
Note: GVC = global value chain.

- Lockdown policies to contain the pandemic had significant—if unintended—international spillovers. Lockdowns in a country's trading partners on average accounted for up to 60 percent of the observed decline in imports in the first half of 2020. International spillovers were significantly larger in GVC-intensive industries than in non-GVC-intensive industries; and they were larger in downstream (close to final user) industries than in upstream (input) industries. However, the ability to work from home (teleworkability) in partner countries mitigated the spillovers from lockdowns, and the effects also diminished over time. These findings on spillovers suggest two things. First, containing the pandemic domestically is important not just for domestic activity, but also because future outbreaks leading to lockdowns could have negative spillovers on trading partners. Second, the reduction of spillovers over time, including for

GVC-intensive goods suggests that global supply chains were able to adjust. This should sound a cautionary note regarding policies seeking to effect permanent changes in the structure of global production and trade.

- GVCs were able to adjust to the asynchronous development of the pandemic, as reflected in changes in market shares among GVC regions during the pandemic. To further build resilience in GVCs, there is potentially substantial room to diversify away from domestic inputs. The chapter shows that resilience to shocks may be gained by further diversification of inputs across countries, and by making inputs from different countries more substitutable. Diversification significantly reduces global GDP losses in response to shocks in key upstream suppliers. It also reduces GDP volatility following productivity shocks to multiple countries that are correlated in line with what is observed in historical productivity data over the past 25 years. Reducing diversification on the other hand increases volatility. Greater input substitutability across source countries reduces GDP losses from shocks in individual countries. Thus, it is important to find avenues to expand trade opportunities, which can boost resilience in the world economy in the face of a variety of shocks.

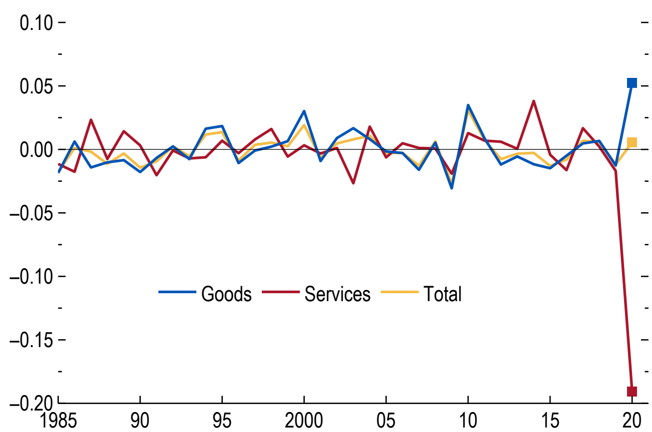
Drivers of Trade during the Pandemic

Demand and Relative Prices Alone do not Explain Pandemic Trade Patterns

Unlike previous global recessions such as the global financial crisis, changes in services and goods trade growth early in the pandemic are poorly explained by a model including conventional factors alone (domestic demand and relative prices). Such a model performs well in explaining total trade, but produces large forecast errors for goods and services import growth in 2020 when they are considered separately. Moreover, these forecast errors are significantly correlated with pandemic-specific factors, pointing to the unique nature of this trade shock.

Figure 4.5. Average Forecast Errors of the Growth in Imports from the Import Demand Model
(Log points)

The large errors in 2020 show that conventional factors alone cannot explain the changes in goods and services imports.



Sources: Eora Global Supply Chain Database; IMF, *Balance of Trade Statistics*; and IMF staff estimates.

A standard import demand model is used to estimate the historical relationship between demand and import growth. The model links real import growth of goods and services to growth in demand and the relative price of imports for a sample of 127 countries over 1985–2019.[3] Consistent with economic intuition and previous studies (see, for example, Chapter 2 of the October 2016 *World Economic Outlook* [WEO]), the estimated coefficients on the measure of import adjusted demand (a combination of demand components weighted by their import content, as in Bussière and others, 2013) are positive for most countries and greater than

[3] As explained in Bussière and others (2013), an import demand equation, which relates growth in real imports to changes in absorption and relative price levels, can be derived from virtually any international real business cycle model. In this chapter, the following empirical specification $\Delta \ln M_{i,t} = \pi_i + \beta_{D,i} \Delta lnD_{i,t} + \beta_{P,i} \Delta lnP_{i,t} + \varepsilon_{i,t}$, in which $M_{i,t}$, $D_{i,t}$, and $P_{i,t}$ refer to imports, demand, and relative prices in country i and time t, is estimated together with other more parsimonious versions as described in Online Annex 4.1.

1. The coefficients on relative price are mostly negative and average between negative 0.2 and negative 0.3 (Online Annex 4.1).

Combining the estimates from the regressions—using world import shares as weights—yields good predictions of import growth up to 2019. Yet, for 2020 the model underpredicts the large observed decline in services trade. (The model predicts a growth rate of about negative 8 percent while trade in 2020 fell by 25 percent). It overpredicts the fall in goods trade (predicting a 10 percent decline, against the 6 percent observed fall) (Figure 4.5).[4] The forecast errors are unprecedented in size, by contrast, the global financial crisis and the global recession of the early 1990s are much better explained by standard factors.

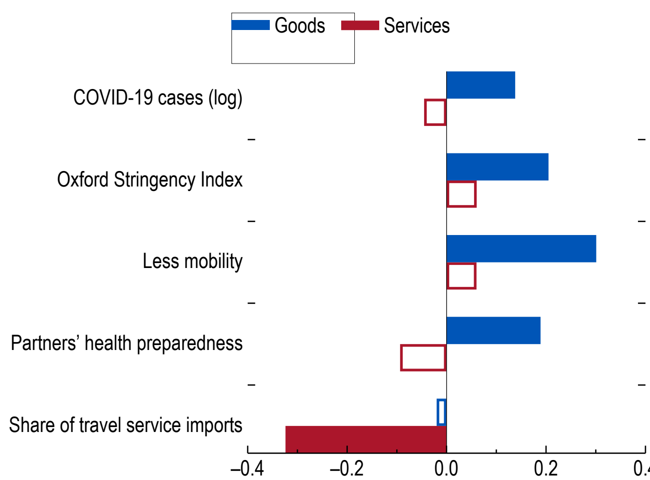
Pandemic Intensity and Containment Policies were Key Drivers of Trade Patterns in this Crisis

Several features of—and policy responses to—the pandemic are key to explaining the discrepancies between predicted and actual import growth. Relating the forecast errors to country-specific factors suggests that countries whose experience of the pandemic was more severe (more COVID-19 cases, more stringent containment measures or less mobility) show "excess import demand" for goods—that is, the fall in goods imports was smaller than predicted by the model (Figure 4.6). The forecast error for goods imports was 3 percentage points more positive for countries in the third quartile of the distribution in the number of COVID-19 cases than for those in the first quartile.[5]

Figure 4.6. Factors Associated with the Demand Model's Forecast Errors in 2020

(Standard deviation, unless noted otherwise)

Domestic factors specific to the pandemic played an important role in determining trade patterns in 2020.



Sources: Google, *Community Mobility Database*; Hale and others (2021); Our World in Data; World Trade Organization; IMF, COVID-19 Policy Tracker; and IMF staff calculations.
Note: The figure reports standardized coefficients of a regression of residuals from the demand model onto the listed variables. Solid bars show coefficients that are statistically significant at the 5 percent level; hollow bars show those that are not. Trading partners' health preparedness for the pandemic is measured by the Global Health Security Index. Share of travel service imports captures the share of travel services in a country's total service imports.

For imports of services, the most important factor accounting for the model's overprediction is the extent to which a country imported travel services. That is, the unexplained portion of the fall in service imports was most pronounced in countries where travel services accounted for a large share of total service imports.

[4] The performance of the model in 2020 is the worse since the beginning of the sample (1985) looking at additional metrics other than the average forecast error such as the mean squared forecast error. Online Annex 4.1 discusses the distribution of errors in 2020, comparing it with that of previous years.

[5] If such disruptions are not fully incorporated by changes in the relative prices, in countries hit hardest by the pandemic the model will predict a decline in the imports of goods larger than actually occurred.

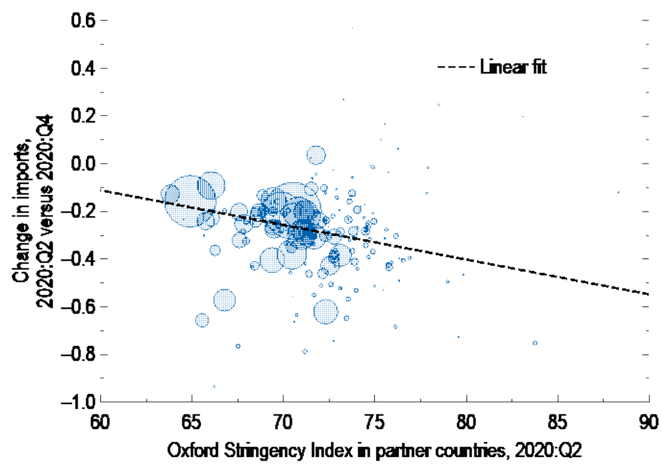
These findings are consistent with various conjectures regarding the impact of pandemic-specific factors on trade. First, the rapid recovery in goods trade may reflect a general switching in consumer spending away from services to goods—such as remote-working equipment and medical goods—created by pandemic-specific conditions.[6] Second, part of the shift could be driven by a simple reallocation of income towards goods because some service were unavailable. Third, it is possible that as countries with more severe lockdowns experienced a sharp contraction in the production of some goods domestically, they were pushed to import them instead (for the impact of lockdowns on domestic production, see Chapter 1 of the October 2020 WEO).

Interestingly, the better the health-preparedness of an importing country's *trading partners,* the less imports of goods fell relative to predictions. Trading partners' preparedness for the pandemic is measured here by the Global Health Security Index, and is associated with more positive forecast errors for goods imports.[7] This suggests some degree of international spillovers; specifically, countries whose trading partners experienced smaller disruptions in domestic supply were less negatively affected by shock transmission in trade networks. Accordingly, the next seection focuses on spillovers from lockdown policies in trading partners, which constitute supply shocks from a domestic perspective.

Figure 4.7. Change in Imports and Partner Countries' Lockdown Stringency

(Percent, unless noted otherwise)

Spillovers from the lockdown policies of trading partners are associated with lower imports.



Sources: Hale and others (2021); IMF, *Direction of Trade Statistics*; and IMF staff calculations.
Note: The Oxford Stringency Index in partner countries is constructed taking 2018:Q3–2019:Q4 import flows as weights. The size of the bubble is proportional to the value of imports (in US dollars) in 2019:Q4. The solid line is a 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, in which the weights are the values of imports (in US dollars) in 2019:Q4. The estimated coefficient is equal to –0.015 (*t*-stat = –2.44).

International Spillovers from Pandemic Containment Policies

Supply Shock Spillovers from Lockdowns Accounted for a Large Part of the Decline in Trade

The decline in imports at its trough in mid-2020 appears to be correlated with the stringency of lockdowns in exporting trading partners (Figure 4.7). Intuitively, tighter lockdowns in exporters would constitute a supply shock from the point of view of the importing country. Indeed, controling for demand factors, more stringent lockdowns in trading partners had a large and significant negative impact on goods imports. A comparison of the actual evolution of imports between January and May 2020 against a counterfactual without any containment policies in place in trade partners indicates that containment policies accounted for up to 60 percent of the observed decline in imports. That said, the spillover effect from lockdown stringency appears to

[6] Among many studies confirming this trend, see Bounie and others (2020) for France; Andersen and others (2020) for Denmark; Baker and others (2020) for the United States; and Chronopoulos, Lukas, and Wilson (2020) for the United Kingdom.

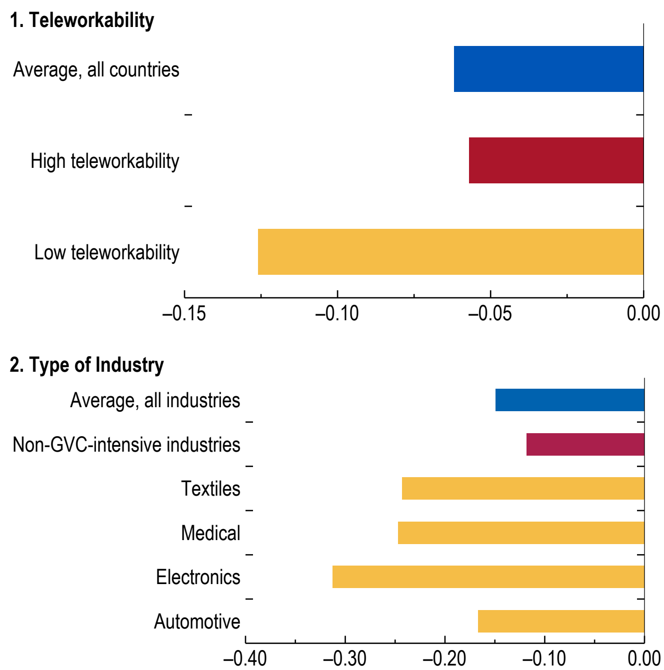
[7] For details on the index, see Cameron, Nuzzo, and Bell (2019), and other material that can be found at Global Health and Security Index https://www.ghsindex.org/about/

have been short lived. The impact first materialized in February 2020, with the first round of restrictions in Asia, grew in strength in March and April, when lockdowns became more geographically widespread, including in Europe, and started declining in May. In June, when goods imports rebounded strongly, even as the stringency of lockdowns eased only moderately, the spillover effects became indistinguishable from zero (see Box 4.2 for further evidence on the declining rate of spillovers, using data at daily frequency for seaborne trade).[8]

These findings are based on estimates of a gravity model, widely used in the trade literature (Santos Silva and Tenreyro 2006), using bilateral data on monthly imports at the 6-digit product level from Trade Data Monitor.[9] The model includes a set of time-varying fixed effects that absorb the effects of all observed and unobserved factors specific to importing countries and industries, including demand shifts, and of factors such as trade agreements that could affect (product-specific) trade flows across each pair of importer and exporter countries. The methodology and results are described in more detail in Online Annex 4.2.

Figure 4.8. Semi-Elasticity of the Oxford Stringency Index

Spillovers were larger in GVC-intensive industries and among partner countries less able to rely on teleworking.



Sources: Dingel and Neiman (2020); Hale and others (2021); Trade Data Monitor; and IMF staff calculations.
Note: GVC = global value chain.

The spillover effect of lockdown stringency is also robust to controlling for the extent of the health crisis in the exporter country, measured by the number of new COVID-19 cases and deaths per capita (both contemporaneous and lagged), changes in export restrictions put in place by trade partners, and the fiscal policy response in trade partners.

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[8] Similar results are obtained by Berthou and Stumpner (2022). Heise (2020) also documents the close to 50 percent decline in U.S. imports from China in March 2020 relative to January 2020, when factories were temporarily closed, before bouncing back in April 2020. Lafrogne-Joussier Martin, and Mejean (2021) show that French firms sourcing inputs from China just before the lockdown experienced a drop in imports between February and April 2020 that was 7 percent larger than that of firms sourcing their inputs from elsewhere.

[9] The chapter estimates the following specification: $M_{m,e,i,t} = g(\beta Stringency\ Index_{e,t} + \delta Controls_{m,e,t} + \alpha_{m,e,i} + \gamma_{m,i,t} + \varepsilon_{m,e,s,t})$. Bilateral imports of products in industry i ($M_{m,e,i,t}$) by importer country m from exporter country e in month t are regressed on: (1) 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; (2) a set of variables that vary across country pairs and time ($Controls$); and (3) a set of fixed effects ($\alpha_{m,e,s}, \gamma_{m,i,t}$). The Oxford Stringency Index records the strictness of 'lockdown style' policies that restrict people's behavior. It ranges from 0 to 100 and is calculated using eight ordinal containment and closure policy indicators (such as school and workplace closures) and restrictions on movement, plus an indicator recording public information campaigns. The Stringency Index used in this chapter is highly correlated with the component related to workplace closings, but has less variability, being a categorical variable (assuming four values). The model considers an importing country (such as the United States) and compares its imports of a product (such as vehicles) in each month from trade partners with different containment policies. Under the plausible assumption that U.S. demand for vehicles is the same across partner countries, the analysis controls for demand factors, including the role of domestic containment policies, and exploits only the variation in the intensity of lockdowns across trade partners.

Spillovers were More Pronounced within GVCs; and were Mitigated by the Extent of Teleworking

The average spillover effects mask several sources of heterogeneity.

- First, the spillover effect of lockdowns is more than twice as strong for countries whose exporting partners are less able to rely on remote working (Figure 4.8, panel 1). The finding is consistent with existing evidence showing that the feasibility of remote work mitigated the negative effects of reduced worker mobility (Pei, de Vries, and Zhang 2021).[10]
- Second, spillover effects are stronger in GVC-intensive industries (yellow bars, Figure 4.8, panel 2), and especially in electronics, than in non GVC-intensive ones (red bar). Intuitively, imports in GVC-intensive industries would be relatively more exposed to disruptions in the supply chain (in this case due to lockdowns).[11]
- Third, the negative effect of stringency measures is dampened in industries that are more upstream in the production process (such as metals and minerals products), while it is stronger for those downstream (such as transportation and textiles).[12] A one standard deviation increase in the upstreamness index reduces the spillover supply effect of the lockdown by almost one third. This is consistent with the intuition that downstream industries are more likely to be affected by disruptions to the supply chain, such as lockdowns in countries supplying intermediate goods used as inputs (see Box 4.3 for a detailed analysis using customs data from France).

To summarize, evidence from granular bilateral trade data shows that after controlling for demand in importing countries, there were significant negative spillovers from lockdowns in partner countries, consistent with findings in the literature (Espitia and others 2021; Berthou and Stumpner 2022). These spillovers were larger in GVC-intensive industries, and in downstream industries. However, the spillovers tended to be short-lived, and were mitigated to the extent that partner countries were able to use telework. Moreover, the spillover effects waned in magnitude over time, as countries gained experience with functioning under mobility restrictions; thus imports fell by much less in response to lockdowns in partner countries in 2021 than in 2020 (Box 4.2).

Resilience in GVCs

Trade Data Suggest that GVCs Adapted to Pandemic Conditions During the Crisis

The preceding analysis suggests that with the rotation in demand toward goods, and the short-lived negative impact of spillovers from lockdowns, goods trade was resilient overall, including in GVC-intensive goods. The resilience of trade in goods can also be traced to the adaptability of

[10] Teleworkability is measured using the cross-country data computed by Dingel and Neiman (2020). 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 the those with a high share of teleworking.

[11] The 6-digit product codes for goods in GVC-intensive industries are compiled from Frederick and Lee 2017 (electronics), Sturgeon and others 2016 (automobiles), and Frederick 2019 (textiles, medical devices).

[12] To test the upstreamness hypothesis, the model includes the interaction between the Stringency Index and a measure of industry "upstreamness" (the average distance from final use) computed by Antràs and others (2012) from U.S. input-output table. The (time-invariant) upstreamness of the industry is a measure of its exposure to the (time-varying) lockdown supply shock. This specification makes it possible to control for exporter-time effects, making the model fully consistent with gravity models that control for time-varying "multilateral resistance" factors.

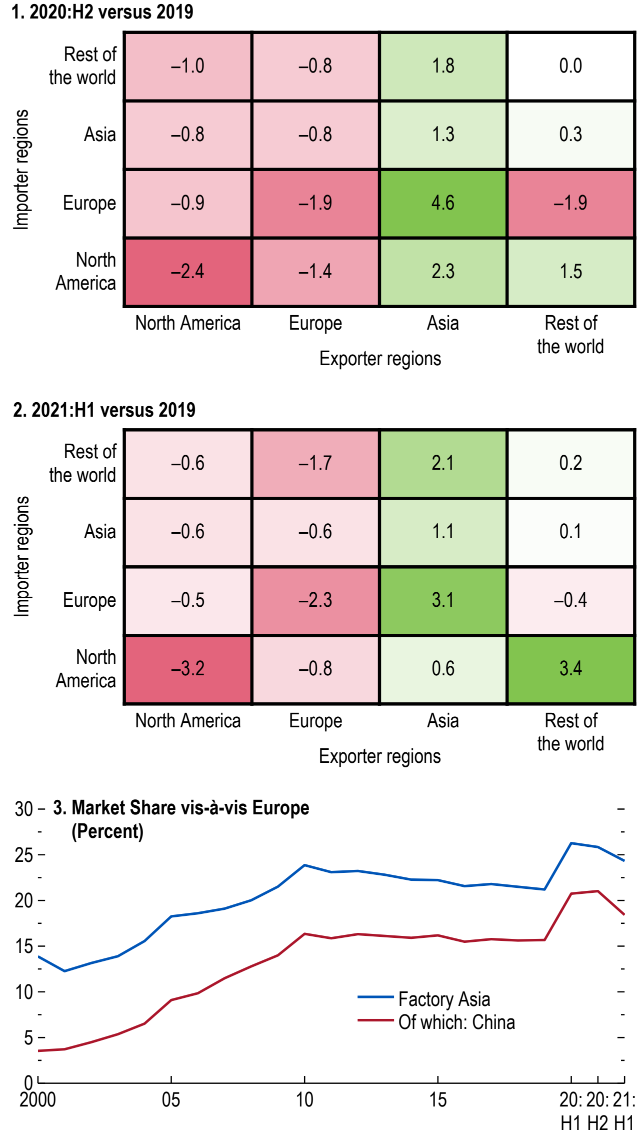
GVC networks. Trade data show that there were sizable changes in trade market shares between regions with significant participation in GVCs (GVC-regions) early in the pandemic.[13] With the asynchronous development of the pandemic, regions that exited lockdowns earlier experienced sizable increases in market share vis-à-vis other regions, especially in GVC-intensive industries. However, these changes in market shares appear to be reversing course over time, suggesting that they are unlikely to persist as countries learn to adjust to pandemic-related restrictions.

Asian countries, which were hit early by the COVID-19 shock but then managed to contain the virus—while other regions were experiencing surges in COVID-19 infections and lockdowns—gained market share compared with 2019; European and North American countries lost market share. By June 2020, "Factory Asia" countries increased their market share in GVC-intensive industries by 4.6 percentage points in "Factory Europe" and by 2.3 percentage points in "Factory North America".[14] Factory Europe is the regional block that lost the most during the first phase of the crisis (Figure 4.9 panel 1).

Figure 4.9. Changes in Regions' Market Shares of GVC-related Products

(Percentage points, unless noted otherwise)

Changes in trade market shares in the pandemic indicate that GVCs adjusted to asynchronous lockdowns in different countries/regions.



Sources: Trade Data Monitor; and IMF staff calculations.
Note: Market shares are computed using only products and with respect to Factory Europe, as defined in the chapter. GVC = global value chain.

However, the most recent data, up to June 2021, show that the initial gains in market share for Factory Asia and the initial losses in market share for Factory Europe were both pared back during the recovery phase, suggesting that the change in market shares may be temporary. Factory North America continued to lose market share, predominantly within its own domestic markets (Figure 4.9, panel 2). To put these changes in a longer historical context, panel 3 of Figure 4.9 shows the

[13] Due to lags in input-output data availability, granular analysis of changes in GVC participation is difficult. Bilateral trade data can thus shed some light on recent trends. For 2020, GVC participation metrics show that at the macroeconomic level, disruptions in supply chains led to a sharp reduction in GVC participation compared with 2019 (WTO 2021), especially in some sectors (such as transportation and electrical equipment).

[14] The classification of countries included in each of the three regional blocks follows Baldwin and Freeman (2020). Factory Asia comprises Australia, China, India, Indonesia, Japan, the Republic of Korea, and Taiwan Province of China, Factory Europe comprises France, Germany, Italy, The Netherlands, Spain, Switzerland, Turkey, and the United Kingdom; Factory North America comprises Canada, Mexico, and the United States

evolution of Asia's market share in Europe since 2000, before China's accession to the World Trade Organization (WTO).[15] The recent gains in Asia's market by mid-2020 were large and quick relative to historical changes, but also appear to be reversing rapidly.

Notwithstanding the overall resilience of GVCs, some industries such as automobiles have faced large supply disruptions. Moreover, shipping costs remain elevated along some routes despite coming down from their peaks, and some ports remain congested, contributing to continuing supply chain disruptions (Box 4.1; Komaromi and others, forthcoming). Other types of shocks—not just health emergencies but also international or civil conflicts, cyberattacks or extreme weather events associated with climate change—could also pose challenges (Baumgartner and others 2020; McKinsey Global Institute 2020). In this light, assessing options to strengthen resilience in GVCs is important, especially in view of growing calls to reshore production. The next section uses a model based framework to analyze two options for building supply chain resilience that have been proposed in the literature: greater geographical diversification of input sources, and greater substitutability of inputs from one source with inputs from another source (OECD 2021).

Policies to Boost Resilience: Insights from a Model-Based Approach

To analyze these options, this chapter extends the general equilibrium model of global production networks and trade proposed by Bonadio and others (2021). The model includes trade in intermediate goods (such as raw materials, parts and energy, which are produced by one firm and used in production by another firm) and services, and thus captures global value chains.[16] Each sector in each country has a representative firm that produces using a technology characterized by constant return to scale. The model is calibrated to 64 countries and 33 sectors, as described in Online Annex 4.4. Note that the model does not feature endogenous input-output linkages, and cannot speak to possible trade-offs between diversification and efficiency.

In the model, supply disruptions in source countries spill over to other countries through trade in intermediates. The analysis considers two scenarios: supply disruption in a single, large, input supplier country; and supply shocks to multiple countries. It compares outcomes under high levels of diversification or substitutability with those under the levels actually observed. The precise sense in which these options are considered is as follows:

- *Diversification:* Countries could diversify their suppliers of intermediate inputs internationally, sourcing them in more equal amounts across countries. Diversification is a widely used term in economics (see, for example, Cadot, Carrère, and Strauss-Kahn 2013), but the meaning here is very specific. This chapter refers to diversification: (1) across countries, not across products; (2) of intermediate goods and services, not final goods and services; and (3) of the use of intermediate inputs, not the production or export thereof. Diversification might enhance resilience by reducing reliance on a single country or by establishing relationships in good times that can be tapped during a crisis. In principle there could also be downsides to

[15] While China predominated in the increase in Asia's market share in Europe, changes in global market shares have seen winners and losers. Online Annex 4.3 shows that across countries, the increase in market share was positively correlated with an increase in mobility during the pandemic period.

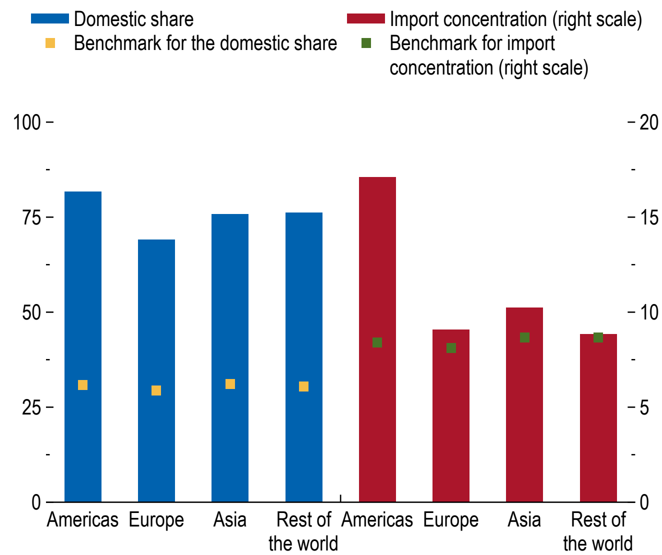
[16] In the model intermediate goods and services from one country are used as inputs into production in a second country, and then the resulting intermediate or final goods are exported to a third country.. The model does not include inventory management, and therefore cannot address risk mitigation options such as inventory management practices and their impact on trade (Alessandria and others 2011).

diversification. For example, diversification could expose a country to more volatile supplier countries. Empirical evidence to date on the benefits of diversification is mixed.[17]

- *Substitutability*: This refers to how easy it is in the production process for a producer to switch inputs from a supplier in one country with those from another country. While geographic diversification is about establishing relationships with suppliers in different countries, substitutability can be interpreted either as making firms' production technologies more flexible, in the sense that they can accommodate slightly different inputs of the same type from different suppliers, or as standardizing intermediate inputs internationally. An example of greater flexibility in production is Tesla's response to the semiconductor shortage. The company rewrote software to enable it to use alternative semiconductors that were more available at the time. As an example of standardization, General Motors recently announced that it is working with chipmakers to reduce the number of unique semiconductor chips that it uses by 95 percent, down to just three families of microcontrollers. In principle, each family of microcontrollers would replace a host of chips, eliminating any costs of substituting between them.[18]

Figure 4.10. Room to Diversify the Sourcing of Intermediates
(Percent)

Substantial home bias in sourcing inputs suggests room for international diversification.



Sources: Organisation for Economic Co-operation and Development, Inter-Country Input-Output Tables; and IMF staff calculations.
Note: Blue bars show the share of intermediates sourced domestically. Yellow squares show the benchmark concentration in world production. Red bars show the extent of import concentration (Herfindahl concentration index) across foreign countries within the share of intermediates that is imported. Green squares show the world exports concentration benchmark. See Online Annex 4.2 for details.

The evidence suggests that countries and sectors have substantial room to diversify away from domestic sourcing of intermediate inputs internationally. For example, the blue bars in Figure 4.10 show that, on average, firms in the Americas source 82 percent of their intermediates domestically, which is far above a benchmark of 31 percent that reflects the concentration of world production of these intermediates.[19] This points to a significant "home bias" in the

[17] An emerging body of literature shows mixed benefits of diversification. Caselli and others (2020) find benefits at the national level of greater openness to overall trade (that is, exports and imports, and to trade in intermediate and final goods and services). At the firm level, Jain, Girotra, and Netessine (2015) find that diversification exposes firms to smaller suppliers that take longer to recover from a disruption, and Lafrogne-Joussier, Martin, and Mejean (2021) find negligible gains from diversification.

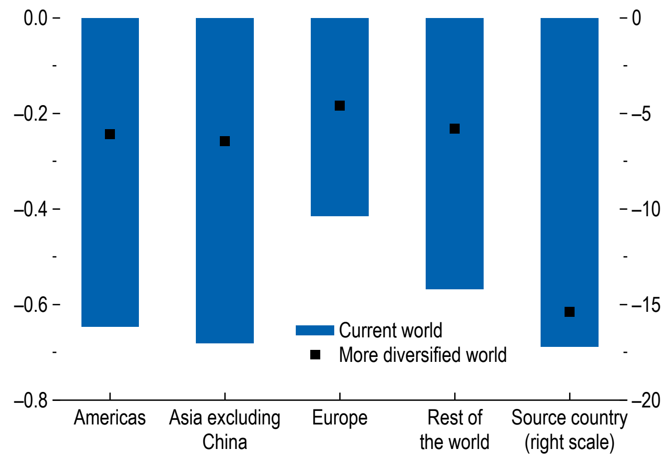
[18] See, for example, https://www.nytimes.com/2021/11/18/business/ford-globalfoundries-chip-shortage.html.. Note that if substitutability is achieved by standardization, then it might also carry the cost to producers that suppliers are less "locked in" and could more easily switch between producers.

[19] This benchmark illustrates the limits on how much a firm can diversify its sourcing of intermediates in the short term. For each country-sector pair, the share of *domestically sourced* intermediates is compared with a benchmark of the concentration of world production of those intermediates. The concentration of *imported* intermediates is compared with a benchmark of the concentration of exports of those intermediates. For example, suppose the US motor vehicles industry uses two inputs, A and B, in equal parts. Suppose that the country producing the largest share of input A has a 20 percent share in world production, and the country producing the largest share of input B has a 40 percent share. Then the (cont'd) benchmark concentration for domestic sourcing of these inputs A and B for the US motor vehicles industry is 30 percent $(= (20 + 40)/2)$. The benchmark of 31 percent in the text then averages across all country–sector pairs in the Americas. The room for diversification shown here may look different within more narrowly defined product categories.

sourcing of intermediates.[20] One important implication of this home bias is that any re-shoring of production would *lower* diversification even further, thereby increasing concentration risk. This is a simple argument against reshoring. Fuller analyses of reshoring find that this increased concentration would indeed result in more volatile economic activity, even after the structure of the economy adjusts by expanding some sectors and shrinking others (OECD 2021; Bonadio and others, 2021).

Figure 4.11. Gains from Diversification Following a Supply Disruption in a Large Supplier Country
(Percent)

Greater diversification reduces GDP losses by about four-fifths on average following a shock to a large input supplier.



Source: IMF staff calculations.
Note: The figure shows GDP declines in response to a 25 percent labor supply contraction in a country that is a large global supplier of intermediates. The bars and squares show simple averages of GDP declines across countries within each region. Elasticity of substitution = 0.5.

In contrast, there is not much room to diversify further among inputs sourced from abroad, except in the Americas (Figure 4.10). Therefore, the main scope for diversification is in diversifying away from domestic sources, by sourcing more intermediates from abroad. Online Annex 4.4 shows that the sectors with the greatest room to diversify are services industries such as hospitality, finance and healthcare.

Greater diversification is modeled by constructing a simple average of (1) a distribution that sources from each country with equal weight, and (2) the actual data. Effectively, the domestically sourced share is set to roughly half of what it is in the observed data.

To increase substitutability across suppliers in different countries, an increase in the elasticity of substitution between intermediate inputs from different countries from 0.5 to 2.0 is modeled; similar to the range found in Feenstra and others (2018).[21] The increase is equivalent to going from the short-term elasticity used in Bonadio and others (2021) to an estimate closer to the long-term substitutability implied by Boehm and others (2020).[22]

Diversification and Substitutability can Boost Resilience to Cross-Border Supply Shocks

Diversification substantially reduces the GDP losses in all regions of the world following a sizable (25 percent) labor supply contraction in a single, large global supplier of intermediate

[20] This is similar to the home bias identified in overall trade by McCallum (1995).

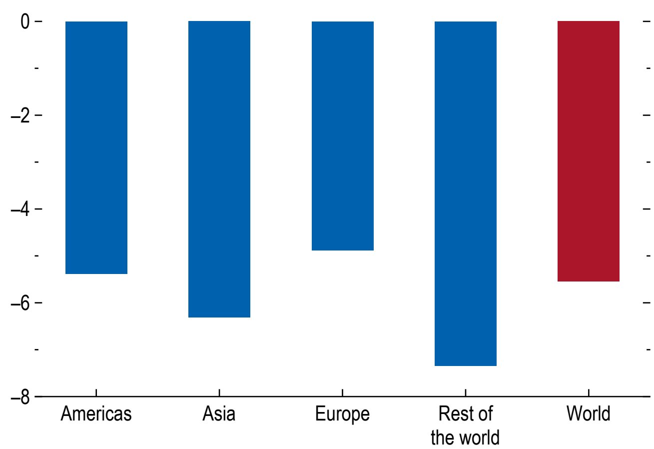
[21] This is an extension of the baseline model of Bonadio, Huo, Levchenko, and Pandalai-Nayar and (2021) as explained in Online Annex 4.4.

[22] The elasticity of tariff-exclusive trade flows to tariffs changes estimated in Boehm, Levchenko, and Pandalai-Nayar (2020) equals the elasticity of substitution in the Armington (1969)/Krugman (1980) setting. They estimate that the long-term elasticity ranges from 1.75 to 2.25. The counterfactual analysis chooses a parameter value of 2.0 to discipline the upper bound of short-term elasticity. Online Annex 4.4 discusses the selection of the parameter value in detail.

inputs.[23] In this scenario, the average economy's GDP falls by 0.8 percent under the baseline level of diversification. In the high-diversification scenario, Figure 4.11 shows that the decline in GDP is reduced by almost half.[24] Most of this benefit accrues to countries other than the source country, as higher diversification makes them less dependent on intermediates produced by the source country. The source country also benefits, as diversification makes it less dependent on domestic sources.

Figure 4.12. Gains from Diversification under Shocks to Total Factor Productivity
(Percent)

Greater diversification reduces the volatility of GDP by 5 percent under correlated TFP shocks.



Source: IMF staff calculations.
Note: The bars show simple averages within each region of the percentage reduction in volatility. The shock is calibrated by drawing 100 years of changes in total factor productivity across multiple countries with replacement from yearly Penn World Tables data between 1995 and 2019. The average pairwise correlation between the shocks is 25 percent. TFP = total factor productivity.

Higher diversification also reduces the volatility of GDP growth when a shock affects more than one country, with some correlation across countries. Figure 4.12 shows the results from simulations that draw multi-country shock scenarios from historical productivity data.[25] Diversification offers some protection against shocks with this level of correlation, reducing the volatility of GDP growth in the average country by 5 percent.[26]

By contrast, diversification offers little protection against exceptionally highly correlated shocks. For example, under the scenario calibrated to the first four months of the COVID-19 pandemic that Bonadio and others (2021) analyze, world GDP falls by the same amount under high diversification as it does under levels of diversification observed in the data.

Turning to substitutability, countries benefit from being able to more easily substitute away from one country's inputs to those produced in another country. Considering again the scenario of the 25 percent labor supply contraction in a large global supplier of intermediate inputs, the results show that with greater substitutability—even though it amplifies the shock in the source country—all countries other than the source country benefit as their GDP losses are reduced by about four-fifths (Figure 4.13).[27]

[23] The global supplier is calibrated to closely match China. The scenario assumes a drop of two-standard deviations in China's total factor productivity using Penn World Tables data, which is equivalent to a labor supply contraction of about 22 percent (rounded up to 25 percent in the scenario), assuming Cobb–Douglas production with Organisation for Economic Co-operation and Development (OECD) averages of labor supply elasticity and labor share of income (as explained in Online Annex 4.4).

[24] These are simple averages across countries. The GDP -weighted average across countries is a loss of 3.2 percent under baseline levels of diversification (with China contributing 2.7 percentage points of that loss) and 2.6 percent in the high-diversification world (with China contributing 2.4 percentage points).

[25] Specifically, 100 years of multi-country 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.

[26] Online Annex 4.4 shows that the results on diversification and volatility are symmetric, in that lower diversification would increase volatility.

[27] For modelling purposes, the characteristics of the large global supplier are calibrated to China. However, the conclusions are robust to using other countries for calibration.

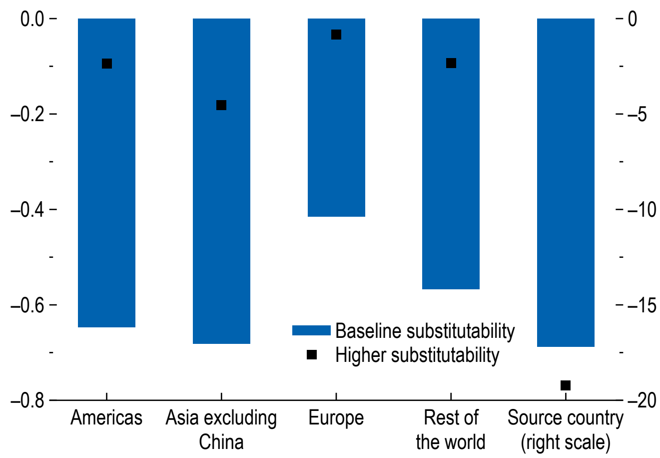
In terms of achieving greater diversification, the model also shows that reducing trade costs can help. A one-quarter reduction in the costs of trading in intermediates lowers the Herfindahl index of geographic concentration in the sourcing of intermediates by 4 percentage points, from 60 percent as observed in actual data.[28]

Conventional policy tools for reducing trade costs include tariffs and nontariff barriers. With tariff barriers having declined globally to low levels, there is still ample scope to reduce nontariff barriers, particularly in emerging markets and low-income developing countries (Figure 4.14). Consistent with the model, other evidence from the literature suggests that such trade cost reductions could lead to sizable GDP gains (October 2021 *Regional Economic Outlook: Asia and Pacific*; Estefania-Flores and others 2022).

The model's results on the benefits of diversification and substitutability naturally raise the question of why profit-maximizing firms do not already take advantage of these opportunities. To some extent this could reflect government policies that favor domestic sourcing and thus tilt the scales against greater diversification (for example, "Made in China 2025", "Make in India Initiative", United States Innovation and Competition Act of 2021).[29] But it is also important to emphasize that the model does not capture all the factors feeding into firm-level decisions. There are likely to be costly trade-offs for firms in building resilience, including the costs of holding larger inventories, fixed costs of establishing new supply relationships, or efficiency gains from dealing with a smaller number of suppliers—which if large, could reduce gains from diversification. That

Figure 4.13. Gains from Substitutability Following a Supply Disruption in a Large Supplier Country
(Percent)

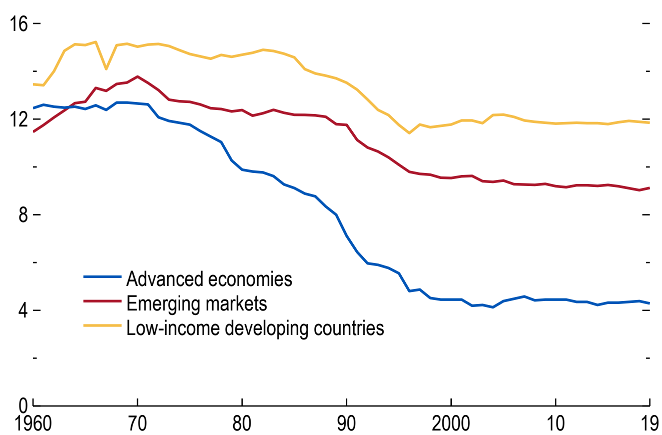
Greater substitutability reduces GDP losses by about four-fifths relative to the baseline in non-source countries.



Source: IMF staff calculations.
Note: The figure shows GDP declines in response to a 25 percent labor supply contraction in a country that is a large global supplier of intermediates. The bars and squares show simple averages of GDP declines across countries within each region. Baseline elasticity of substitution = 0.5. Higher elasticity of substitution = 2.0.

Figure 4.14. Nontariff Barriers Index
(Simple average)

There is room to lower nontariff barriers among emerging markets and low-income developing countries.



Source: Estefania-Flores and others (2022).

[28] The increase in diversification is similar across regions.

[29] See McBride and Chatzky (2019) for China, Press Information Bureau (2017) for India; and Hufbauer and Jung (2021) for the United States.

said, the trade-off between efficiency and lower risk may not be acute, given that firms that are best at mitigating risks also tend to be the most efficient.[30]

To summarize, the evidence from a modeling approach suggests that resilience to cross-border supply shocks can be increased with greater input source diversification (using more foreign inputs) and greater input substitutability (across suppliers), although the benefits are smaller if shocks are more widespread and correlated across countries. From a policy perspective, these findings on gains from diversification and substitutability suggest the need to provide a supportive environment for firm-level measures to enhance GVC resilience.

Policy Implications

The role of factors specific to the pandemic in shaping trade patterns suggests that the rotation in demand from services to goods may not be lasting. In particular, services trade should recover as travel restrictions are lifted. The pace of the recovery is therefore likely to be closely related to the success of global public health efforts, and a quicker-than-expected easing of mobility restrictions could pose an upside risk to global trade projections.[31] Facilitating the full return of mobility should therefore be an important element in boosting services demand back to pre-pandemic trends. That said, it is possible that some changes in services trade may be more persistent. For instance, increasing familiarity with virtual interactions may reduce certain kinds of travel more permanently (Antràs 2021).

The evidence on international spillovers presented in this chapter further underscores the urgency of dealing with the pandemic everywhere. Vaccinating widely across countries is important not just from the perspective of domestic economic activity, but also to minimize supply disruption spillovers on partner countries. Moreover, strengthening health systems, and investing in digital infrastructure would help mitigate the transmission of shocks in future shock scenarios, including further COVID-19 variants or other possible pandemics.

The chapter emphasizes that overall, trade was fairly resilient in the pandemic—falling sharply initially but then recovering rapidly in line with economic activity and demand, despite significant bottlenecks in trade logistics. Trade was also resilient in key GVC-intensive industries—with the notable exception of the automotive sector. Policy proposals to reduce dependence on foreign suppliers, especially in strategic sectors, have gained prominence (Javorcik 2020), including in major markets such as the United States and Europe (White House 2021; Le Maire 2020). The resilience of trade through the pandemic suggests that such proposals may be premature, if not misguided (Baldwin and Freeman 2021; Antràs 2021; OECD 2021; Miroudot 2020; Eppinger and others 2021).

This chapter argues instead that greater diversification in international sourcing of inputs, and greater substitutability in input sourcing, could enhance GVC resilience. The lessons from Toyota's adaptations following the Tohoku earthquake are instructive (APEC 2021). Toyota took measures to increase diversification and substitutability, much in line with the model-based evidence presented by this chapter. In particular the company: (1) standardized some components across vehicle models to enable global sharing of inventory and flexibility in production across various sites; (2) built a comprehensive database of its suppliers and parts held

[30] For example firms with just-in-time inventory management also enjoy lower inventory costs, and would be best placed to increase inventories if needed, while remaining competitive (Miroudot 2020; van Stekelenborg 2020).

[31] Separately, advances in digital technology could provide a further boost to trade in services going forward, for example in areas such as health and education (Baldwin and Freeman, 2021).

in inventory; (3) regionalized its supply chains to avoid depending on a single location; and (4) asked its single-source suppliers to disperse production of parts to multiple locations or hold extra inventory. Firms may also choose to adopt greater mechanization as a way to gain resilience against shocks to labor supply (Box 4.3).

- While firm-level decisions will predominantly shape the future resilience of GVCs, government policies can help by providing a supportive environment and lowering the costs of greater diversification and substitutability. One obvious area is infrastructure. The pandemic has shown that infrastructure investments in certain areas are critical to mitigate supply disruptions related to trade logistics. For example, upgrading and modernizing port infrastructure on key global shipping routes would help reduce global chokepoints.

- Governments could also step in to resolve informational externalities, which could help firms to make more strategic decisions. For example, evidence suggests that automobile manufacturers on average have about 250 Tier1 suppliers (with which the manufacturers conduct business directly), but this number rises to 18,000 suppliers in the full value chain (Baumgartner, Malik, and Padhi 2020).[32] It is easy to see how visibility over the supply chain would be challenging for firms that lack the resources of large corporate entities. Filling informational gaps could thus be a key role that governments can play. Advancing digitalization of firms' document filings, such as tax returns, can help generate more information on inter-firm transactions and supply chain networks.[33] This information could be useful in stress-testing exercises to identify supply chain weaknesses and risks.

- Finally, reducing trade costs can help boost diversification in inputs. There is considerable scope exists to reduce non-tariff barriers in particular, which would carry significant medium-term growth benefits especially in emerging markets and low-income developing countries (October 2021 *Regional Economic Outlook: Asia Pacific*). In addition reducing trade policy uncertainty, and providing an open and stable, rules-based trade policy regime, can also support greater diversification (Handley and others 2020; OECD 2021).

[32] Tier 1 suppliers provide parts or systems directly to "original equipment manufacturer" or OEM enterprise (such as Chevrolet). Tier 2 suppliers in turn supply inputs to Tier 1 suppliers.

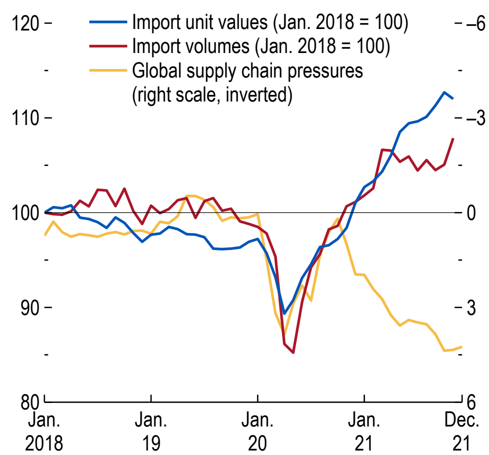
[33] For example, Gadenne, Nandi, and Rathelot (2019) use value added tax (VAT) data from the state of West Bengal (India) to map supply chains. VAT-paying firms are required to report transactions with other tax-registered firms, providing matches between client and supplier tax identifiers. Similarly, Alfaro-Ureña, Manelici, and Vasquez (2020) use tax identification data in firms' tax declarations in Costa Rica to match the buyer firms with supplier firms.

Box 4.1.: Effects of Global Supply Disruptions During the Pandemic

Supply chain pressures increased to unprecedented levels at the onset of the pandemic, and after a significant easing in the second half of 2020 accelerated again to reach a new peak by the end of 2021. Shipping costs steadily increased until September 2021, when they started a moderate decline. Delivery times lengthened in 2021, and indices of future delivery times indicate that supply chain disruptions persist. Trade flows closely mimicked the evolution of supply chain disruptions in the first phase of the crisis. Although the recovery in trade continued even when supply chain pressures resumed in late 2020 (Figure 4.1.1), flat import volumes and rising unit values in 2021 suggest that supply disruptions have contributed to inflationary pressures (Helper and Soltas 2021; Leibovici and Dunn 2021).

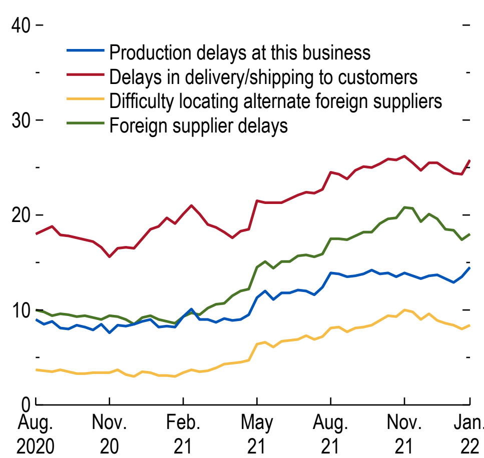
Supply chain disruptions have large real effects on firm inventories, production, and sales (Bonadio and others 2021; Carvalho and others 2021). These effects were still in evidence in the first weeks of 2022. High-frequency data from the United States show that the share of firms that reported foreign supplier delays increased from 9 percent in October 2020 to 20 percent in December 2021. A growing share of small businesses have also reported difficulties in locating alternative foreign suppliers. These developments are particularly severe in the manufacturing, construction, and trade sectors and have translated into an increase in the share of firms reporting delays in production and delivery to their customers, which reached 14 percent and 26 percent respectively, in December 2021 (Figure 4.1.2). These persistent pressures, which increased in January 2022 as the Omicron wave spread in the United States, indicate a need to discuss policy options to improve global value chains' risk management through more flexibility, better knowledge and information, and better adaptability to shocks.

Figure 4.1.1. Global Goods Trade and Supply Chain Pressures
(Index)



Sources: Benigno and others (2022); CPB World Trade Monitor; and IMF staff calculations.
Note: The index of global supply chain pressures is a composite measure of several variables combining cross-border transportation costs with country-level supply chain measures on delays, backlogs, and inventories from manufacturing surveys.

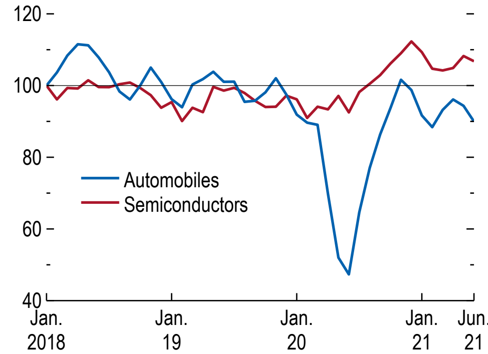
Figure 4.1.2. Foreign Suppliers, Production, and Delivery Delays in the United States
(Percent)



Sources: US Census Bureau, Small Business Pulse Survey; and IMF staff calculations.
Note: Data are as of January 20, 2022.

Disruptions in some industries have been particularly conspicuous. The automotive industry is a case in point. Trade in (and sales of) automobiles collapsed during spring 2020 and then started rebounding in the second half of the year, although without reaching prepandemic levels. The shortage of automotive chips has been a key factor behind this drop. At the beginning of the pandemic, the shift to remote working led to a sharp increase in demand for semiconductors. By contrast, the demand for cars fell and pessimism about the economy led car producers to limit their orders for semiconductors. When pent-up demand for cars accelerated more than expected in the second half of 2020, the semiconductor industry had limited production capacity to meet the demand for automotive chips because it had already shifted production to meet demand from other sectors (such as consumer electronics) (Deloitte 2021). Trade tensions and domestic shocks (such as a drought in Taiwan Province of China) aggravated this shortage, which has constrained recovery in the automotive sector, despite strong demand (Figure 4.1.3), and has resulted in higher prices. More generally, the shortage of semiconductors, a key component for many products, has highlighted the vulnerabilities of global value chains and driven calls for reshoring and for increasing supply chain resilience.

Figure 4.1.3. Trade in Automobiles and Semiconductors
(Index, January 2018 = 100)



Sources: Trade Data Monitor; and IMF staff calculations.
Note: "Automobiles" comprises HS 6-digit codes for manufactured intermediate inputs and final goods (vehicles). "Semiconductors" comprises HS 6-digit codes 854150 and 854190.

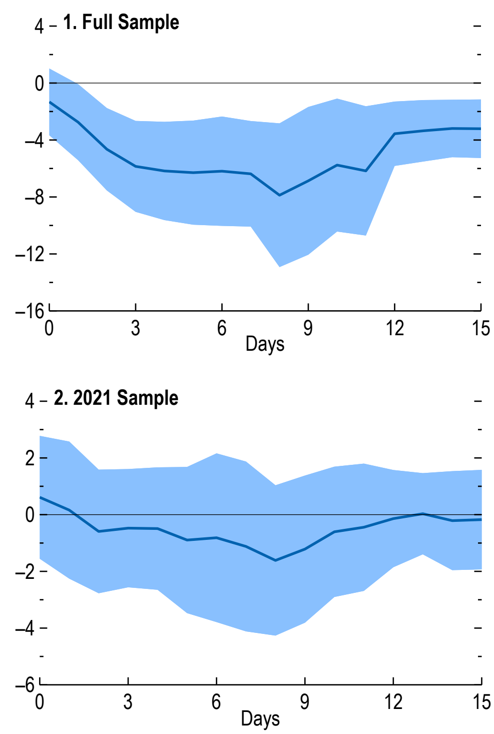
Box 4.2.: The Impact of Lockdowns on Trade: Evidence from Shipping Data

This box examines the effect on trade of pandemic containment measures, using a unique dataset of daily bilateral seaborne trade volumes (see Cerdeiro and others, 2020). A country's imports during the pandemic are affected by lockdowns imposed by trading partners (suppliers). Domestic factors (health situation, macroeconomic policies, consumer sentiment) are also likely to influence bilateral trade. The following import equation is estimated at the *daily* frequency to measure the effect of a lockdown imposed by country j on the growth of country i's imports from country j (bilateral import growth) at horizon h, $\widehat{M}_{ij,t+h}$:

$$\widehat{M}_{ij,t+h} = \gamma_{it} + \alpha_{ij} + \beta LS_{jt} + \mathbf{X}'_{jt}\delta + \sum_{k=1}^{7}\widehat{M}_{ij,t-k} + \varepsilon_{ij,t+h},$$

in which bilateral import growth from j to i ($\widehat{M}_{ijt}$) is the seven-day moving average of year-over-year growth rates with respect to pre-pandemic (2017–19) averages, and LS_{jt} denotes the lockdown stringency (0–100) of the exporter country (Hale and others, 2020).[1] The specification includes importer-time fixed effects, γ_{it}, to control for any unobserved time-varying factors affecting country i's imports; a bilateral pair fixed effect α_{ij}; and a vector of control variables $\mathbf{X}'_{jt}$ (ratio of new COVID-19 cases to the population, and an aggregate measure of exporter's exposure to foreign lockdowns).[2]

Figure 4.2.1. Response of Bilateral Import Growth to Exporter Lockdowns
(Percent)



Sources: IMF staff estimates based on Cerdeiro and others (2020). Automatic Identification System data were collected by Marine Traffic.
Note: The shaded area indicates 95 percent confidence bands; robust standard errors.

Over the full 2020–21 sample, exporter lockdowns have a large and significant impact on bilateral trade volumes (Figure 4.2.1, panel 1). As the stringency variable has a range of 0–100, the point estimates of around 5 imply that less than a full lockdown (a change in stringency of just 20 points) can temporarily halt bilateral trade. Notably, lockdowns have no significant effect on trade volumes in 2021 (Figure 4.2.1, panel 2). This finding is consistent with activity becoming less susceptible to lockdowns as economies adapt to the pandemic, and underscores the resilience of global value chains.

The authors of this box are Andras Komaromi, Diego Cerdeiro and Yang Liu.

[1] Lockdown measures are lagged to account for delivery lags in shipping. For example, if all voyages from country j to country i take three days, then lockdown stringency measures in j are lagged by three days in the equation for imports into i.

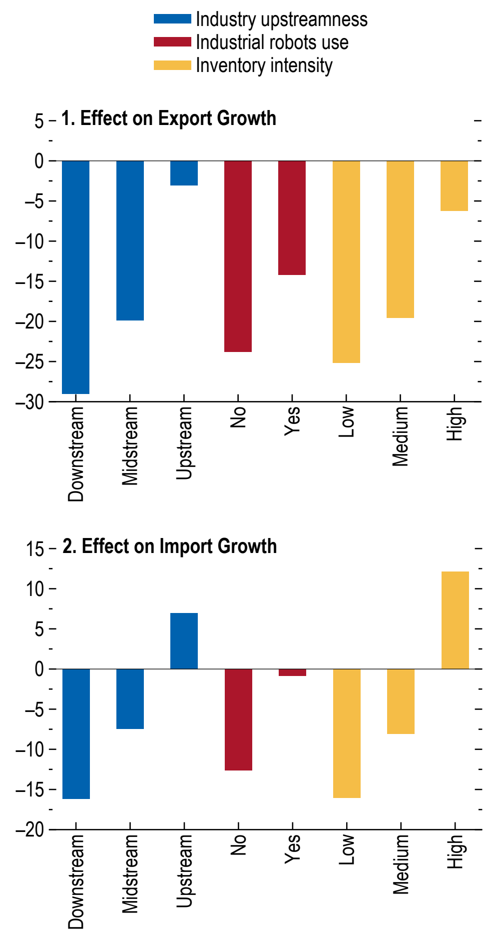
[2] This empirical specification captures lockdown-induced trade disruptions at the bilateral level, but it does not rule out cases in which a drop in bilateral imports is made up for by sourcing the goods from a different country. For an alternative approach that takes into account potential substitution effects and measures lockdown disruptions in terms of aggregate imports, see Cerdeiro and Komaromi (2020). The bilateral specification presented here has the important advantage that one can control for any time-varying confounding factors specific to the importer.

Box 4.3.: Firm-Level Trade Adjustment to the COVID-19 Pandemic in France

This box uses monthly French Customs data on firms' imports and exports for 2019 and 2020 to examine the duration and margins of adjustment to the shock. Adjustment occurred mainly along the intensive margin (volumes). The extensive margin, with varieties dropping out of France's trade basket, contributed marginally to the total trade adjustment, indicating the temporary nature of the shock (Antràs, 2021).[3] The trade recovery was supported by the rebound in consumer demand and extensive economic relief policies implemented by the French government.

- *The trade of downstream firms was more affected.* The average impact of importing-country lockdowns on exports of firms selling final consumer goods (downstream firms) was nearly nine times larger than for firms selling intermediate inputs (upstream firms).[4]
- *Greater automation was associated with more resilience.* The impact of lockdowns and the spread of the virus (measured by COVID-19 deaths) on exports was almost 67 percent larger for firms that are less automated (Figure 4.3.1, panel 1).
- *Firms in low-inventory industries experienced larger contractions in trade.* Imports of firms in industries holding the lowest stocks of inventories fell more than twice as much as among firms in industries with average inventory intensity (Figure 4.3.1, panel 2).[5] Firms in industries with the highest inventory intensity increased imports. Exporters in more inventory-intensive industries also experienced a smaller drop in sales (Figure 4.3.1, panel 1), suggesting that inventories play a shock-absorbing role.

Figure 4.3.1. Impact of Supply Chain Upstreamness, Automation, and Inventories on Trade Adjustment
(Percent)



Sources: Antràs and others (2012); French Customs data; Hale and others (2021); and IMF staff calculations.
Note: Each bar corresponds to the average effect for a given group of firms derived from the regression of firms' exports and imports on COVID-19 lockdown intensity and COVID-19 deaths in trade partner countries interacted with the industry's upstreamness index, median ratio of inventories to sales, and firms' use of industrial robots. Downstream industries are closest to the final consumer, whereas upstream and midstream industries specialize predominantly in production of intermediate inputs.

The authors of this box are Mariya Brussevich, Chris Papageorgiou, and Pauline Wibaux. For details on data and estimation methodology, see Brussevich, Papageorgiou and Wibaux, forthcoming.

[3] A variety is defined as a trade partner-specific product following the 8-digit Combined Nomenclature classification.

[4] To evaluate the heterogeneous effects of lockdown stringency and deaths by industry or firm characteristics, stringency and deaths variables are interacted with one of the variables of interest: an industry-level measure of upstreamness (Antràs and others, 2012), firm-level imports of industrial robots as a proxy for automation, and an industry-level measure of inventory intensity (ratio of inventory to sales).

[5] The results on inventory intensity are sensitive to the measure of industry-average inventory-to-sales ratios.

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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

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

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

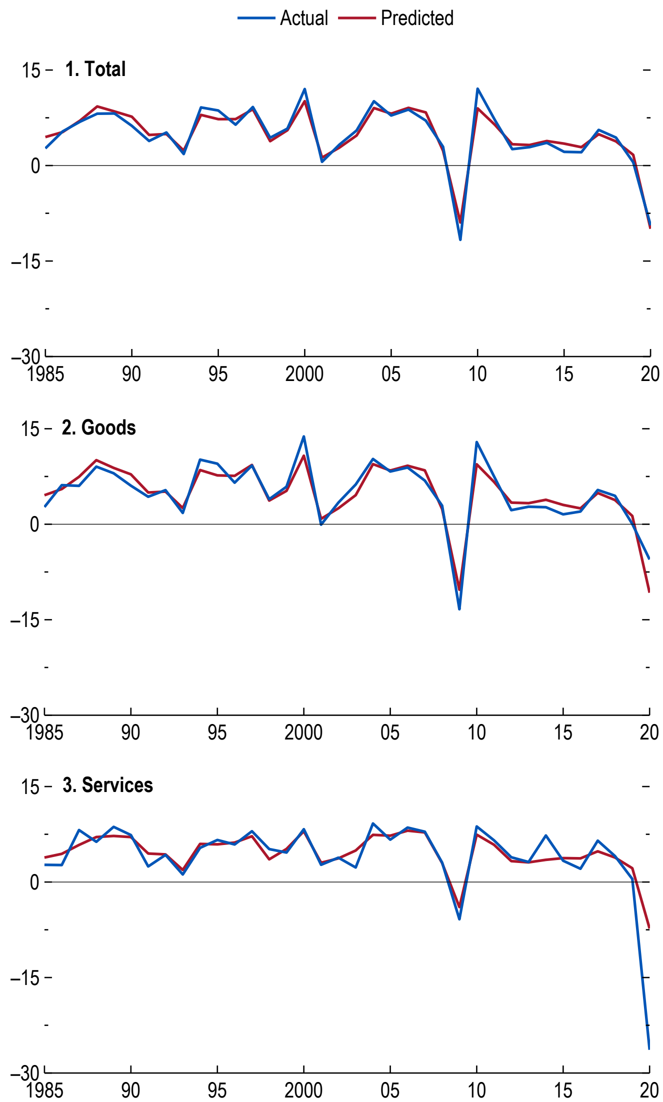
Looking at *supply* of imports, trade partners' health preparedness was associated with more goods imports. The ability of countries to increase their goods import above the expected amount was associated with their partners' health preparedness as captured by the "global health security" index. These 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

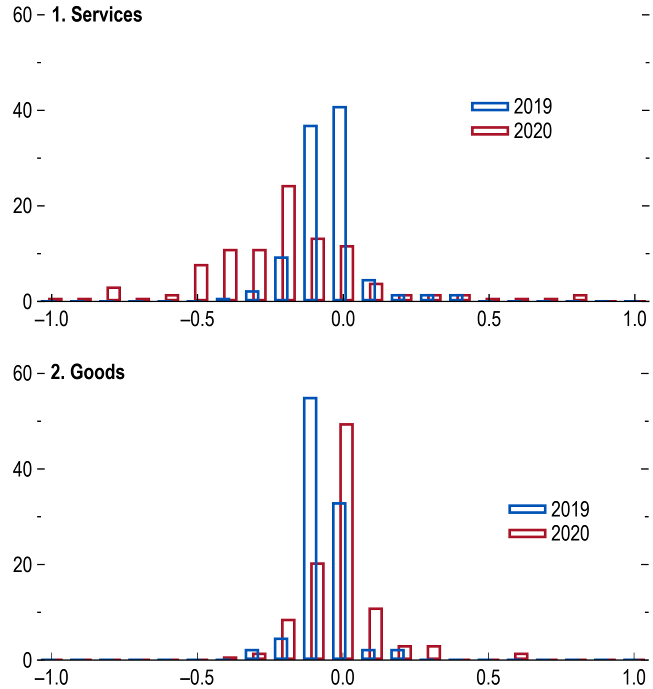
The analysis of the residuals is based on estimates including 1985-2019 data, *excluding* 2020. Hence, the 2020 forecast errors may conflate the deviation from a historical relationship (as interpreted in the chapter) with the fact that data for 2020 are not included in the sample. To address this concern, 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 2021
(Percent)



Sources: Eora Global Supply Chain Database; IMF, *Balance of Trade 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.

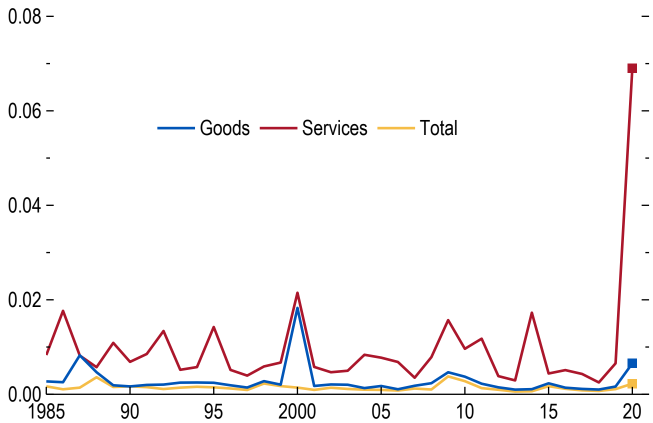
Annex Figure 4.1.2. Forecast Errors across Countries
(Percent)



Sources: Eora Global Supply Chain Database; IMF, *Balance of Trade 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 Trade 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 Trade 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.
*** 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.

	(1) Total	(2) Services	(3) Goods	(4) Total	(5) Services	(6) Goods	(7) Total	(8) Services	(9) Goods
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.

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

	(1)	(2)	(3)
	Total	Services	Goods
Travel Imports over Total Service Imports (Avg 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 ($\alpha_{m,e,s}, \gamma_{m,i,t}$) 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

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[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

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[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.

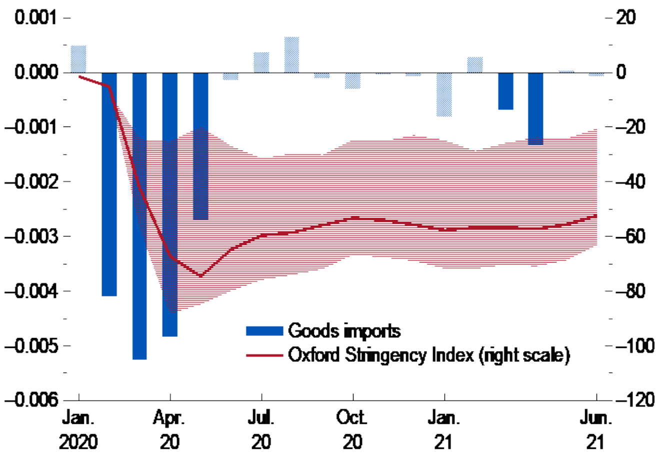
[10] See https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker for further details on the Oxford Stringency Index and its single components.

[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.

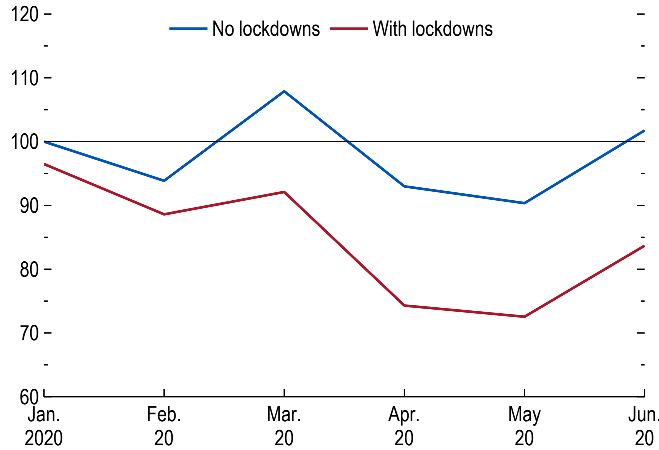
- **Clustering**. Table 4.2.4 reports the main results discussed in the chapter estimated by clustering the standard error at the exporter-month level. The significance of the findings is not affected, and the estimated standard errors are—if anything—smaller, suggesting that the results reported in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

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



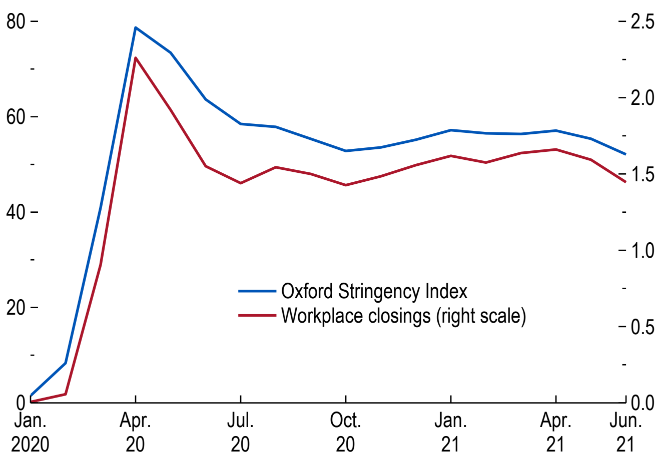
Sources: Hale and others (2021); Trade Data Monitor; and IMF staff calculations.
Note: Darker bars show coefficients that are statistically significant; lighter bars show those that are not. The line represents the coefficients of the stringency index for each month obtained estimating the baseline specification 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)



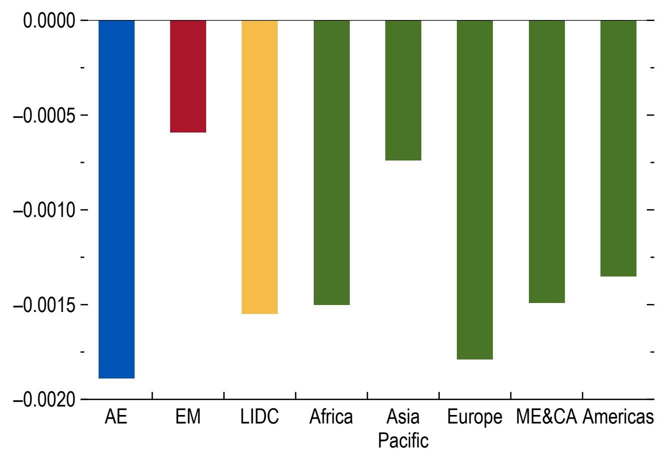
Sources: Hale and others (2021); Trade Data Monitor; and IMF staff calculations.
Note: The blue line denotes the evolution of good imports under a counterfactual without any containment policy in place in trade partner countries, obtained using the results reported in Annex Table 4.2.1. (column 6) and 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 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Importer-Month FE	Yes	-	-	-	-	-	-	-	-
Importer-Industry-Month FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-Month FE	No	No	No	No	No	No	No	No	No
Industry-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	All	All	All	All	2020H1	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. TW stands for teleworkablity. Standard errors in parenthesis are clustered at the exporter level.
*** 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 FE	Yes	Yes
Importer-Industry-Month FE	Yes	Yes
Exporter-Month FE	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 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Importer-Industry-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-Month FE	No	No	No	No	No	No	Yes
Industry-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	All	2020H1	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 2020:m1-2021:m6; 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. TW stands for teleworkablity. Standard errors in parenthesis are clustered at the exporter*month level.

*** 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 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Importer-Month FE	-	-	-	-	-	-	-
Importer-Industry-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-Month FE	No	No	No	No	No	No	Yes
Industry-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	All	2020H1	TW	TW	All	All

Source: IMF staff calculations.

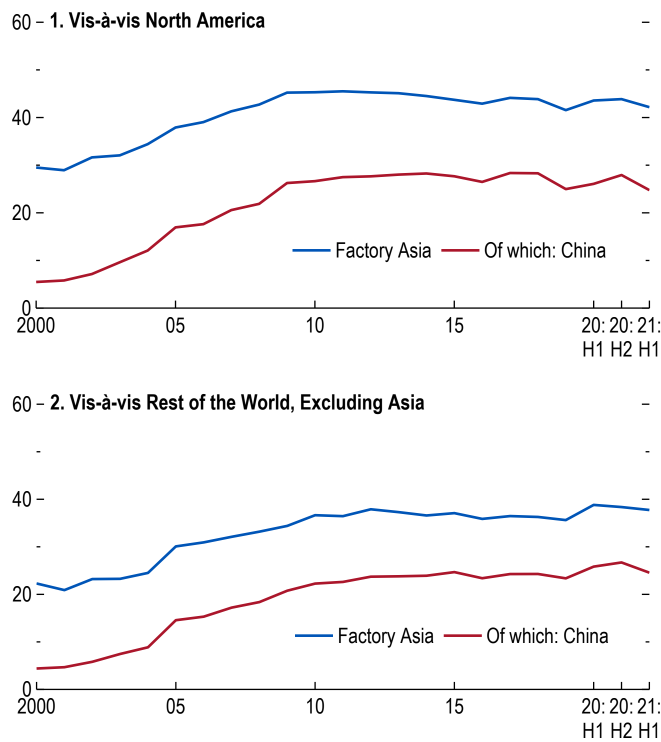
Note: The tables report the results of the estimation of equations (3) (columns 1-5) and (4) (columns 6-7) by Poisson pseudo-maximum likelihood. The sample spans the period 2020:m1-2021:m6; in column 3 it is restricted to the first six months of 2020; in columns 4-5 the sample is limited to exporting countries for which the measure of teleworkability computed by Dingel and Neiman is available. TW stands for teleworkablity. Standard errors in parenthesis are clustered at the exporter*month level.

*** 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

[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).

Annex Figure 4.3.2. Changes in Regions' Market Shares of Non-GVC-Related Products
(Percentage points)

1. 2020:H1 versus 2019

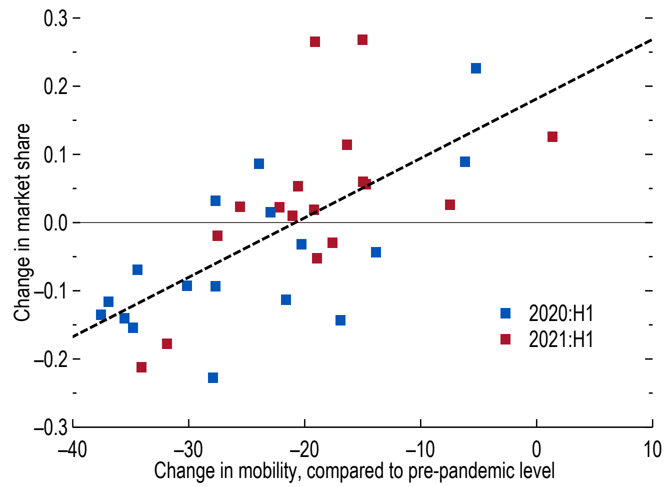
Importer regions \ Exporter regions	North America	Europe	Asia	Rest of the world
Rest of the world	–0.4	–0.1	0.4	0.1
Asia	–0.2	–0.9	1.5	–0.5
Europe	0.3	–1.6	0.4	0.9
North America	–2.4	1.9	–1.9	2.4

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.

to the pre-pandemic levels in 2019, reflect in part the severity of the health crisis and of the 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 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 Americas).

- 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

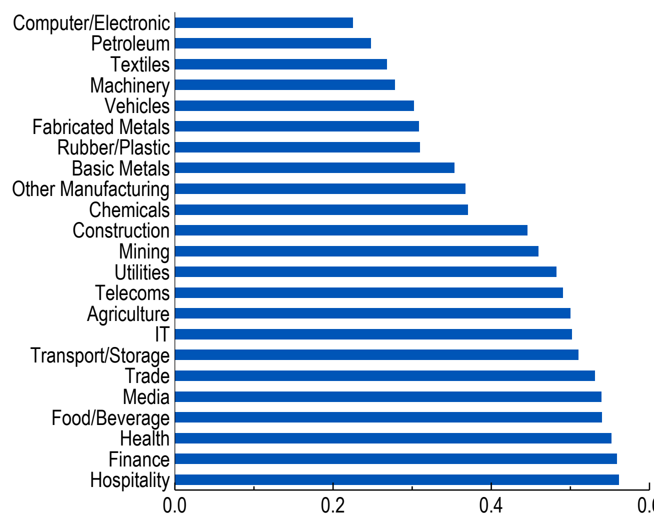
$$\iota_{m,i} = \frac{\sum_{n\neq m,j} x_{mi,nj}}{\sum_{l,n\neq l,j} x_{li,nj}},$$

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

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).

hospitality, finance and healthcare. The higher room for 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,

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

[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

$$\Phi^{\mathrm{x}} = (1-\gamma)(diag(\Psi^{f}) - \Psi^{f}\Pi^{f}),$$

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

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 19 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.

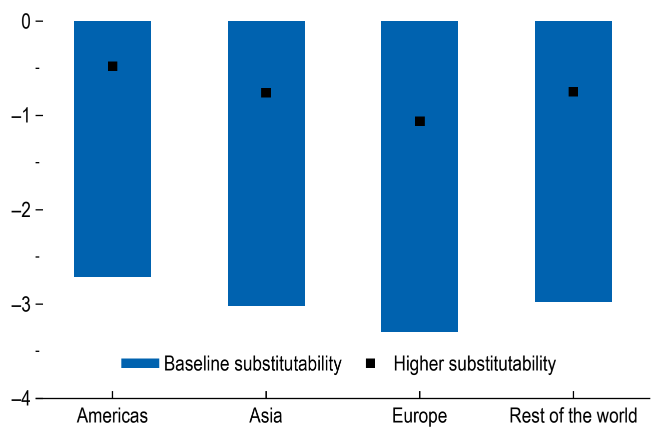
- Second, the diversification is achieved at the level of a given country (n) and sector (j), without making assumptions about firm-level behavior. This means that not every firm need diversify its sourcing.

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 a Supply Disruption in a Large Supplier Country
(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.

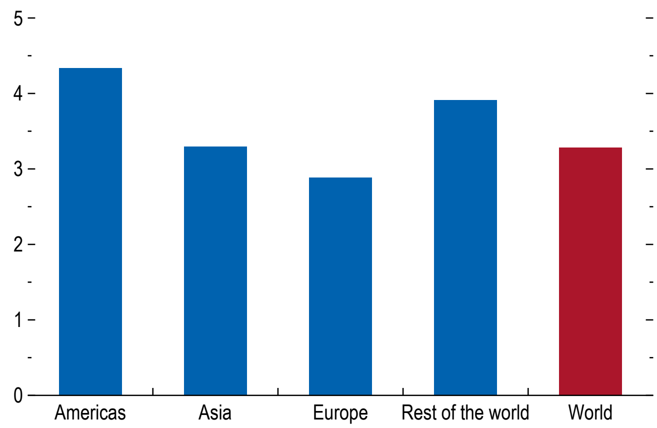
[20] The elasticity of substitution between inputs of different countries is also called the Armington elasticity. It is a parameter commonly used in models of international trade and is based on the assumption that products traded internationally are differentiated by country of origin (Armington, 1969).

[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) tariff-exclusive trade elasticity equals the elasticity of substitution in Armington/Krugman setting. These estimates give the elasticity of substitution 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)

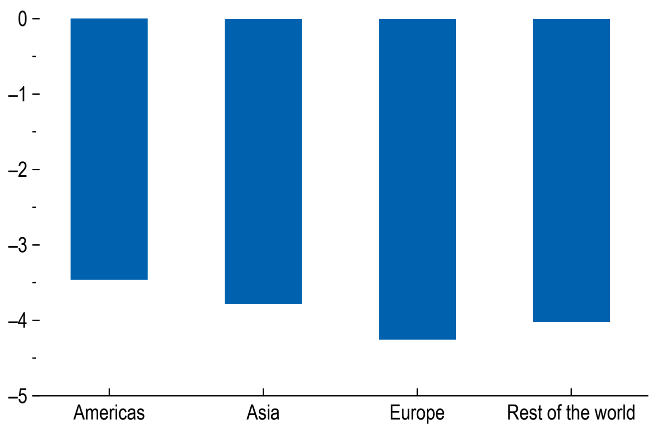


Source: IMF staff calculations.
Note: The bars show simple averages within each region of the percentage increase in volatility from a drop in diversification. For a given country, volatility is measured across the model-implied GDP gains or losses under 100 multi-country shock scenarios, bootstrapped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

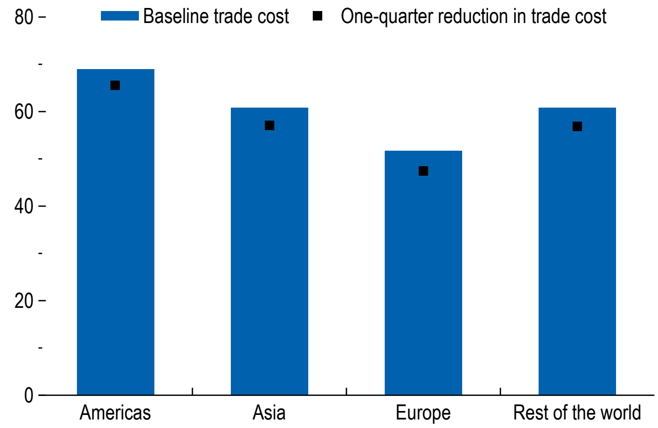
[23] This result does not follow simply from the fact that the solution to the model is (log-)linearized. Log-linearization makes the effects of positive and negative shocks symmetric; by contrast, the effects of diversification depend on the interaction between the structure of shocks and form of diversification.

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)



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.

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