How did GVC-trade respond to previous health shocks? Evidence from SARS and MERS*

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Abstract

Using difference-in-difference analysis in a gravity model, we examine the response of GVC-trade to two previous health shocks, SARS and MERS. Our estimates show a decline in GVC-trade, both gross and value-added, from SARS-induced supply and demand shocks, though a similar finding is not observed for MERS. There is suggestive evidence for "reshoring" and "near-shoring" in the stylized facts on SARS while empirical analysis points to MERS being associated with geographical diversification and widening of value chains. The adverse effects of SARS are found to get accentuated over time suggesting that the associated value-chains were non-resilient to that shock. The findings are observed at both the intensive (value) and extensive (number of products) margins and for both GVC-based intermediate and final goods. The SARS results are driven by non-OECD countries that were also more downstream in GVCs, while more competitive exporters, differentiated intermediates and technology-intensive products were relatively insulated.

JEL classification: F1, F14

Key words: GVC-trade; SARS; MERS; COVID-19; reshoring; diversification

*The data that support the findings of this study are available from the corresponding author upon reasonable request.

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1 Introduction

COVID-19 is proving to be an unprecedented health and economic crisis with long-term implications for countries across the world. It has already affected over 470 million lives since its outbreak in Wuhan, China in December 2019. A burgeoning literature has developed around analysing the epidemiological and macroeconomic impact of this pandemic (Baldwin and di Mauro, 2020; Baqaee and Farhi, 2020a,b; Djankov and Panizza, 2020; Eichenbaum et al. 2020; Fornaro and Wolf, 2020; Guerrieri et al. 2020; McKibbin and Fernando 2020). The crisis also has significant implications for trade and investment due to disruption of global value chains (GVCs). These disruptions emanate from the demand shock that lockdowns and stalled economic activity have caused as well as the supply shock resulting from temporary or permanent breaks in supply networks. Additionally, there is the GVC contagion effect (Baldwin and Freeman, 2020; Friedt and Zhang, 2020) - the pandemic has affected many locations simultaneously and the high level of interconnectedness of the global economy has amplified the impact, especially on the global hubs.

While these disruptions have reignited the discussion on geographical/supplier diversification, nearshoring and repatriation of value-chains, it may be both too soon and premature to examine the extent, nature and impact of these disruptions using data currently available. We thus aim to inform the discussion by studying GVC responses to two past health epidemics, SARS and MERS, both to understand how value-chains may have responded to those crises and to draw implications, if at all, for the COVID-19 outbreak. We focus on SARS and MERS for reasons that are common to the current pandemic - both outbreaks originated at an epicentre but spread around quickly; the diseases are characterized by flu-like symptoms; and manufacturing value-chains were likely disrupted by both episodes.[1] Besides, these outbreaks are separated by a decade, and the share of GVC-trade in total trade was rising and falling, respectively, at these points in time (World Bank, 2020), which also makes it interesting to examine the impact of both epidemics from a GVC perspective.

Infectious disease outbreaks have a profound impact on GVCs, simultaneously affecting multiple countries and industries, with the fear of contagion resulting in unanticipated changes in demand and supply of products (Sheffi, 2015). This fear can lead to under-reporting of an outbreak, especially if the country fears an ex-post application of trade sanctions against it by non-outbreak countries (Brahmbhatt and Dutta, 2008). It is believed that epidemic outbreaks are a unique type of supply-chain risk characterized by long-term disruption in

[1] We do not look at Zika (sporadic occurrence through 2000-18), Ebola (localized in West Africa, with the region significantly less integrated in GVCs) and H1N1 (concurrence with the global financial crisis renders identification challenging).

demand, supply and logistics as well as unpredictable ripple effects. The location of supply bases in severely affected regions creates disruptions in supply networks; suppliers may close their plants or may be unable to deliver their products (Ivanov, 2020; Miroudot, 2020). For example, a supply-side contagion in East Asia's (China, Japan, Korea and Taiwan) manufacturing sectors may hurt manufacturing sectors of other countries as well due to supply linkages, especially in automobile, textiles and ICT goods sectors (Baldwin and Tomiura, 2020). Similarly, the decrease in domestic output in Thailand due to COVID-19 is attributed to increasing trade costs and under-utilization of capital, especially in the ICT goods industry that has the highest level of fragmentation of production in that country (Maliszewska et al. 2020). Moreover, the scope and timing of disruptions play a vital role in determining the impact of an epidemic outbreak on supply chains; the asynchronous opening and closing of facilities creates uncertainty at the firm-level, necessitating a guided framework for better decision-making (Ivanov, 2020).

Building resilience during a pandemic is thus the topmost priority for firms integrated in supply chains. Brandon Jones et al. (2014) and Miroudot (2020) distinguish between building robustness and resilience in supply chains - the ability to recover in the post-crisis period is resilience, while the ability to continue firm operations during a crisis is robustness. Extant literature proposes two opposing solutions to build resilience. One, insurance against a disruption by diversifying the supplier base, albeit at an additional cost, to reduce excess dependence on one country and compensate loss from a few supplier breakdowns (Henriet et al. 2012; Baldwin and Tomiura, 2020); and two, isolation from any disruption through reshoring manufacturing firms back home (Henriet et al. 2012; di Mauro, 2020).

Exclusive reliance on suppliers from one or a few countries can be detrimental by exposing importers to localized risks from health crises or natural disasters. Hence diversifying to alternative suppliers or locations of production during a crisis is more of a robustness strategy compared to reshoring manufacturing back home to a localized setting (Miroudot, 2020). However, long-term firm-to-firm relationship with a single supplier can assist in an easy bounce-back in the post-crisis period (Antràs, 2020), besides avoiding sunk costs from diversification at the eleventh-hour. Hence, there is an apparent downside to diversification vis-à-vis recovery, as supplier diversification is associated with slower recovery from interruptions (Jain et al. 2016). Strange (2020) recommends diversification over reshoring citing increased firm costs, reduced competitiveness and foreign sale of goods due to reshoring of firms closer home. The quantitative analyses in Bonadio et al. (2020) and Eppinger et al. (2020) also find reshoring to be sub-optimal from an economic welfare perspective. The negative sentiment around reshoring is also corroborated by firms: 32% of executives interviewed in an UNCTAD survey associated reshoring of manufacturing functions with a significant decline in global FDI (UNCTAD, 2015). Similarly, Hassan et al. (2020) show that discussions about diversifying supply chains in firm-level conference calls on corporate sector resilience during epidemics peaked during Q1 of 2003, clashing with the SARS outbreak.

Existing literature has studied the macroeconomic consequences of natural disasters, including health crises (Toya and Skidmore, 2007; Noy, 2009; Raddatz, 2009). Previous research suggests that economic development and institutional quality may provide implicit insurance against natural disasters (Kahn, 2005). Recent work provides both historical evidence (Ceylan et al. 2020) and empirical analysis (Fernandes and Tang, 2020; Friedt and Zhang, 2020; Hayakwa and Mukunoki, 2021; Liu et al. 2021), including on the the role of GVCs in the propagation of the COVID-19-induced shock (Bonadio et al. 2020; Eppinger et al. 2020; Kejzar and Velic, 2020; Sforza and Steininger, 2020; Espitia et al. 2021).

We aim to contribute to this literature by studying GVC responses to SARS and MERS as observed in actual trade data. In doing so, we also explore the following hypotheses: one, the disease outbreaks were associated with a rise in domestic production at the expense of total imports of GVC-based products ("reshoring"); two, there was a tendency to reduce reliance on disease epicentres during the epidemics towards alternative suppliers ("geographical diversification of value-chains"); three, the disease outbreaks were associated with a decline in the concentration of the partner distribution ("GVC-widening"); four, there was a tendency to import more from suppliers in the geographical neighbourhood at the expense of the disease epicentres ("near-shoring"); and five, disruptions to GVC-trade coincided with the time period of the virus outbreaks but dissipated over time ("GVC-resilience").[2]

Our empirical strategy involves using difference-in-difference analysis to examine the effect of supply and demand shocks induced by SARS and MERS on the value of bilateral trade in GVC-based products, the number of such products traded and value-added trade in a gravity setting. We measure the shocks using binary dummy variables that take the value one for the SARS-worst-affected countries (China, Hong Kong, Canada, Singapore and Vietnam) in 2003, and for the MERS-worst-affected countries (Saudi Arabia, South Korea and the

[2]We take these terms from the international business literature, where 'reshoring' and 'near-shoring' are defined more on the basis of the location of production of multinational enterprises (MNEs) and whether they create foreign or domestic affiliates (or affiliates in neighbouring countries for near-shoring). In that sense, we use these terms differently; for instance, we use reshoring to mean 'renationalization' (Bonadio et al. 2020) or 'repatriation' (Eppinger et al. 2020) of value-chains.

UAE)[3] over 2013-17, 2015 and 2014, respectively.[4] Our identification strategy thus exploits differences in the time period of severe incidence of each disease ("diff 1") and in the samples covering exporting (supply-shock) and importing (demand-shock) countries that were more adversely affected than others ("diff 2").

We use bilateral trade data from BACI (Gaulier and Zignago, 2010), disaggregated at the HS 6-digit level over the 2000-2018 period, for over 200 countries (see Annex Table 1). The HS 6-digit products are classified as intermediate and final products in GVCs in the apparel, automobiles, electronics, footwear, pharmaceuticals and textiles sectors, following Sturgeon and Memedovic (2010) and the World Bank WITS classification[5]. In complementary analysis, we also use data from the UNCTAD-EORA GVC database (Casella et al. 2019) to examine how value-added trade was affected during these outbreaks.

Our baseline estimates suggest a 16.1% reduction in exports of GVC-based final goods over 2001-06 from the SARS-induced shock, which is consistent with firm-level findings on the impact of SARS on Chinese trade in Fernandes and Tang (2020). There is stronger evidence for the adverse effect of SARS at the extensive margin and for value-added trade. For MERS, a statistically significant effect of that outbreak is not observed at the intensive/extensive margins or for value-added trade. The results are found to be robust to using alternative estimation strategies and to matrix completion analysis (Athey et al. 2017; Xu, 2017).

We also find suggestive evidence for reshoring and near-shoring in the stylized facts - the SARS epidemic, for instance, may have been associated with an increase in US imports from Mexico and EU15 imports from Turkey at the expense of Chinese exports in some sectors. Our empirical analysis also provides evidence for geographical diversification of value-chains - the MERS-induced supply-shock was accompanied by a rise in the number of trading partners for GVC-based intermediate products and by a decline in partner concentration for GVC-based final goods. The value-chains also seem to have been non-resilient to the SARS

[3] These countries reported the largest number of cases and amongst the highest case fatality rates according to data from the WHO (https://www.who.int/csr/sars/country/table2004_04_21/en/; https://www.who.int/emergencies/mers-cov/en/). For instance, the number of SARS cases in China (the disease epicentre) and Hong Kong during January-June 2003 were 5327 and 1755, respectively, while the case fatality rate was 17% in Hong Kong and Canada (251 cases), 14% in Singapore (238 cases) and 7% in China. Vietnam reported 63 SARS cases and a case fatality rate of 8%. Similarly, Saudi Arabia, where MERS originated, had 158, 662, 454, 249 and 233 cases during each year of 2013-2017, followed by 185 cases in South Korea in 2015 and 86 cases in the UAE in 2014. While Saudi Arabia again witnessed a spike in MERS cases in 2019, there was a distinct break in trend in 2018, which we exploit in our identification strategy. Significantly, this break is also consistent with the stylized facts observed in Section 3 (see Figure 3 for details), where the decline in imports of GVC-based intermediates from Saudi Arabia in some sectors seems to have been arrested in 2018.

[4] The time periods span severe incidence of the virus outbreaks in the worst-affected countries.

[5] The classification is available at https://wits.worldbank.org/referencedata.html.

outbreak - the adverse effects at both margins and for value-added trade were accentuated significantly over time. These results are consistent with SARS's medium term impact observed on Chinese firm-level trade in Fernandes and Tang (2020); they also underline the need for countries to adopt strategies to minimize any longer-term disruptions to GVCs from the COVID-19 pandemic.

We also exploit the heterogeneity of our dataset along different dimensions to explore the likely drivers of GVC-disruptions associated with SARS. Consistent with conceptual aspects of GVCs and their participation (Antràs, 2020), the SARS results are found to be driven by non-OECD countries that were also more downstream in GVCs; in contrast, more competitive exporters, differentiated intermediates and technology-intensive products were relatively insulated from the SARS shock.

Firms participating in GVCs exchange highly customized inputs on a repeated basis (Antràs, 2020); our results can thus be explained using the theoretical framework in Acemoglu and Tahbaz-Salehi (2020). The virus outbreaks result in negative shocks to the economy (observed as lower productivity or higher fixed costs of operation for some firms, sectors, or in aggregate) that alter the distribution of surplus throughout the production network, causing customized firms to fail either due to the direct negative shock to their production technology or indirectly from a break in their supplier network; reduced demand from their customers; or other losses along their network. This firm failure also leads to a decline in trade, which is more likely to be pronounced for firms and clients located in countries more severly affected by the disease outbreaks, a fact that we exploit in our empirical strategy that focuses on both the supply and demand shocks emanating from these health crises.

Our paper adds to the existing literature on the impact of health epidemics; it also provides stylized facts on and an empirical analysis of hypotheses underlying GVC-responses to external shocks. The paper is also related to different strands of the empirical literature examining the determinants and effects of (i) the 2008/09 global financial crisis (Baldwin, 2009; Bems et al. 2010; Levchenko et al. 2010; Ahn et al. 2011; Crowley and Luo, 2011; Chor and Manova, 2012) and (ii) natural disasters, especially the 2011 earthquake in Japan (Todo et al. 2015; Barrot and Sauvagnat, 2016; Carvalho et al. 2016; Zhu et al. 2016; Boehm et al. 2019; Freund et al. 2020). Finally, our diversification analysis adds value by departing from existing studies that focus on ex-ante diversification before the realization of shocks (Huang, 2017; Caselli et al. 2020; Esposito, 2020).

The rest of the paper is organized as follows. Section 2 provides a brief background on the two virus outbreaks and studies examining their impact. Section 3 provides stylized facts on the evolution of GVC-trade patterns in the aftermath of the two epidemics. Section 4 discusses the empirical methodology used to examine the impact of SARS and MERS on GVC-trade. Section 5 discusses results from estimation while Section 6 provides additional exploratory and sensitivity analysis. Section 7 concludes with a discussion of the possible relevance of our findings for the COVID-19 pandemic.

2 Background: SARS, MERS and their impact

Severe Acute Respiratory Syndrome or SARS is a viral infectious disease caused by SARS-related coronavirus. It was first detected in China in November 2002, but spread rapidly to over thirty countries (including in neighbouring Asia) by the first quarter of 2003. SARS was declared a global threat with 8,437 cumulative cases, of which, 7,452 reported recoveries (WHO, 2003), putting the mortality rate at 9.6%. Majority of the cases were concentrated in China (63.1%) and Hong Kong (20.8%) and these also accounted for 79.5% of the total SARS-reported deaths (WHO, 2003). As the virus spread through contact with the infected individual, controlling measures consisted of an early warning system, isolation of suspected cases, and contact tracing. SARS had costs beyond immediate health concerns; it created widespread panic, halted tourist activity in the region as well as greatly impacted trade and the overall far-eastern economy with losses worth US$ 30 billion by May 2003 (Demmler and Ligon, 2003). The disruption to international travel also impacted business meetings, leading to cancellation of factory orders and adding to the medium-term impact of the disease (Fernandes and Tang, 2020).

Several studies have examined the economic cost of SARS (Hai et al. 2004; Hanna and Huang, 2004; Lee and McKibbin, 2004; Smith, et al. 2019). The overall impact was felt across sectors, as diverse as seafood to microchips (ADB, 2003; NIC, 2003; IMF, 2004). SARS deterred global FDI in industrial production in China (Fan, 2003; Hanna and Huang, 2004) and in Hong Kong and Japan (Keogh-Brown and Smith, 2008). The threat to manufacturing sectors in China was to the extent that new orders were placed on hold and investors halted expansion plans for the year. Lee and McKibbin (2004) show that Hong Kong and China experienced the largest shocks to their GDPs from the SARS outbreak compared to Taiwan and Singapore, primarily due to their greater reliance on trade. In fact, Taiwan may have faced a wave of delayed shocks to its trade and investment due to linkages with mainland China (Chou et al. 2004). More recently, Fernandez and Tang (2020) show that firms in the affected regions of China experienced a YoY decline in export and imports for three consecutive quarters during the outbreak. Moreover, they continued to experience unfavorable growth even during the last quarter of 2005, supporting the claim that the SARS outbreak had a medium-term impact on Chinese trade.[6]

A similar contagion fear was felt soon after the outbreak of the Middle East Respiratory Syndrome, identified as a high-risk pathogen by the WHO (Memish et al. 2020). MERS is a viral respiratory disease caused by the novel coronavirus that was first detected in Jeddah, Saudi Arabia on 13 June 2012 (WHO, 2019). Outbreaks were reported in 27 countries including Saudi Arabia, UAE, Jordan, Oman, Qatar, Germany and South Korea, though the incidence of cases was concentrated in Saudi Arabia over 2013-2017; the UAE in 2014 and in South Korea in 2015. Notably, 84.2% of the reported cases of infection in Saudi Arabia were acquired mostly from hospitals and health workers treating infected patients; 65.7% of these cases were identified in the period 2014-2016 alone. The next highest number of cases was reported outside of the Middle-east in South Korea with 158 cases and 38 fatalities that resulted in an economic loss of US$ 8.5 billion in that country (Myoung-don et al. 2018) and contracted overall export activity (Smith et al. 2019). Of the 2,499 global cumulative cases reported, 858 died due to compromised immunity and severe co-morbidities, taking the case-fatality rate to 34.3% (Memish et al. 2020; WHO, 2019).

3 Stylized facts

In this section, we use disaggregated HS6-digit-level data to look at the pattern of import shares of GVC-based products from the SARS- and MERS-worst-affected countries, before, during and after the incidence of these outbreaks to explore the hypotheses outlined in the introduction. We also see if these episodes were associated with a fall in the number of intermediate products exported by the worst-affected countries or with a fall in the number of their export destinations. Our analysis covers GVC-based intermediates in the apparel, automobiles, electronics, footwear and pharmaceuticals sectors; note that a few HS6-digit products are classified as intermediates common to the automobiles and electronics sectors.

We begin by exploring the "reshoring" hypothesis by looking at the trend of mean total imports and domestic production of GVC-based intermediate and final products over 2000-2017, with the period covering the two virus outbreaks.[7] Figure 1 shows that mean imports of GVC-based intermediate and final products may not have declined during the SARS

[6] In contrast, Hong Kong returned to pre-SARS GDP levels by the end of 2003, while 2004 showed slight growth over the previous year (Keogh-Brown and Smith, 2008).

[7] Disaggregated data on domestic output for GVC-based products included in our analysis are only available from UNIDO's INDSTAT database according to the ISIC Rev.3 and Rev.4 classification. Since the four-digit ISIC classification is more aggregate than the HS6 classification, the HS6 products in the data were aggregated to the four-digit ISIC Rev.3 level using concordance tables in United Nations (2002) for the purpose of this analysis.

outbreak suggesting an absence of reshoring in the wake of that epidemic. In contrast, these imports seem to have witnessed a clear decline during the MERS outbreak in automotives and electronics (intermediates) and in the electronics and textiles sectors (final goods). This decline in imports seemed to have been accompanied by a rise in domestic output in the auto and electronics sector for intermediates and in electronics for final products, which is suggestive of reshoring in these sectors during the MERS outbreak.

<Insert Figure 1 here>

Figures 2 and 3 show the intensive (mean share in total imports by value in the top panel) and extensive margin (mean number of importers and mean number of products imported in the middle and bottom panels, respectively) trends of GVC-based intermediate imports from SARS-worst-affected suppliers (China, Hong Kong and Singapore); and from MERS-worst-affected suppliers (Saudi Arabia, the UAE and South Korea), respectively.

<Insert Figures 2-3 here>

Figure 2 (top panel) suggests a consistent decline in the share of intermediate imports by value across sectors from Hong Kong and Singapore (barring auto and pharma) in the wake of the SARS outbreak. This decline seems to have been arrested for most sectors by 2005-2006 with the exception of apparel in Hong Kong and auto & electronics in Singapore, which suggests that SARS may have had a medium-term impact on exporters of these intermediate products in the two countries. Hong Kong also seems to have exported intermediate products to fewer destinations in the apparel and pharma sectors (middle panel) in the wake of the SARS outbreak, while Singapore seems to have exported fewer number of intermediate products across sectors (bottom panel) during the outbreak and even in the period that followed. In contrast, intermediate imports from China seem to have been unaffected by SARS at both the intensive and extensive margins.

A decline in the share of intermediate imports by value across sectors (barring footwear and pharma) was also observed for South Korea and the UAE during the MERS epidemic (see Figure 3 top panel); for Saudi Arabia, a consistent decline was observed in auto and electronics over 2014-17. These countries also seem to have witnessed a decline in the number of their trading partners (middle panel) and in the number of GVC-based intermediates (bottom panel) exported across sectors in the wake of this outbreak.

Thus, there is suggestive evidence for GVC-disruptions in the data along both extensive and intensive margins and it may well have been the case that importing countries were bringing the value-chains closer home. To explore this "near-shoring" hypothesis, Figure 4 plots the ratio of US (EU15) imports of GVC-based intermediate products from Mexico (Turkey) to those from China over time in the top (bottom) panel to examine if these countries may have imported more GVC-based intermediates from Mexico and Turkey, respectively, at the expense of China in the wake of the SARS epidemic. To explore if the value-chains were indeed brought closer home and not simply moved to other low-cost suppliers, the figure also traces the evolution of the ratio of US and EU15 imports from two geographically-distant but competitive comparator countries relative to China - Thailand and Vietnam.

Figure 4 suggests that the US may have switched imports of auto, electronics and pharmaceutical intermediates to Mexico[8]; and the EU15 may have preferred Turkey for intermediate imports of apparel and auto & electronics; all at the expense of Chinese exports. This can be seen from the spikes in the respective sectoral ratios for the US and EU15 in 2004 and 2005, one and two years after the SARS outbreak. The US spikes in these sectors are much bigger in the case of Mexico compared to Thailand and Vietnam, suggesting that the associated value-chains may have been brought closer home following SARS, though the US may have also increased its reliance on Thailand for intermediate imports of apparel products in 2004. Meanwhile, the EU15 also seems to have enhanced its preference for Thailand in particular, for sourcing intermediates across all six sectors in 2004-2005 and to some extent, for Vietnam in 2005, for importing apparel intermediates, thereby providing strong preliminary evidence for the geographical diversification of all associated value-chains.

<Insert Figure 4 here>

While these stylized facts are suggestive of a reconfiguration of GVCs in response to these disease outbreaks, they do not provide conclusive evidence of the "impact" of these health crises on GVC-trade. The identification of these effects requires more rigorous causal inference, which is the subject of the following section.

4 Empirical strategy

Our empirical strategy is embedded in a structural gravity framework. Following Anderson and van Wincoop (2004), the value of exports from country i to country j at time t can be written as follows:

[8]Note that the figure also highlights that two decades ago, the US was hugely reliant on Mexico (and not China) for importing its GVC-based intermediate-goods across sectors except footwear.

$$X_{ijt} = \frac{E_{jt}Y_{it}}{Y_t}\left(\frac{\phi_{ijt}}{P_{it}\Pi_{jt}}\right)^{(1-\sigma)} \tag{1}$$

where X_{ijt} denotes the value of exports from country i to j at time t, E_j is the expenditure in the destination country j, Y_i denotes the total sales of exporter i towards all destinations, Y is the total world output, ϕ_{ij} are the bilateral trade costs and σ is the elasticity of substitution. P_{it} and Π_{jt} are the outward and inward Multilateral Resistance Terms (MRTs).

Trade costs in ϕ_{ijt} can arise from different sources such as import tariffs (τ_{ijt}); geographical distance between trading partners [$ln(DIST_{ij})$]; cultural distance proxied by dummy variables identifying whether the trading partners share a common border ($CNTG_{ij}$), had a colonial relationship ($CLNY_{ij}$) and share a common language ($LANG_{ij}$); and membership of preferential trade agreements (PTA_{ijt}). Recent advancements in the estimation of structural gravity advocate the use of three-way fixed effects to mitigate endogeneity-induced biases in estimation (for instance see Baier and Bergstrand, 2007; Piermartini and Yotov, 2016). The dyadic trade cost variables ($lnDIST_{ij}$, $CNTG_{ij}$, $CLNY_{ij}$ and $LANG_{ij}$) are thus subsumed in bilateral pair-wise fixed effects.

4.1 Intensive margin analysis

The baseline equations take the following forms:

$$ln(X^{I/F}_{ijt}) = \beta_1 SARS_{ijt} + \beta_2 PTA_{ijt} + \alpha_{ij} + \mu_{it} + \gamma_{jt} + \epsilon_{ijt} \tag{2}$$

$$ln(X^{I/F}_{ijt}) = \psi_1 MERS_{ijt} + \psi_2 PTA_{ijt} + \alpha_{ij} + \mu_{it} + \gamma_{jt} + \epsilon_{ijt} \tag{3}$$

where $X^{I/F}_{ijt}$ is the value of country i's exports of GVC-based intermediate/final (I/F) products in destination country j at time t; PTA_{ijt} denotes membership of preferential trade agreements; μ_{it}, γ_{jt} and δ_{ij} are time-varying exporter and importer and dyadic fixed effects; and ϵ_{ijt} is the error term. The shocks are measured on the supply- and demand-side by binary dummy variables that take the value one for the SARS-and the MERS-worst-affected countries amongst the sample of exporting and importing countries, respectively.[9] However,

[9]Stylized facts in Figures 2 and 3 show that imports from the affected countries fell in the GVC-sectors during or immediately after the outbreaks, which is suggestive of supply-side disruptions. Moreover, using exporter- and importer-specific variables as measures of the supply- and demand-side-shocks is now becoming standard practice in this literature (for instance see Freidt and Zhang, 2020; Liu et al. 2021).

in a global general equilibrium setting with integrated value-chains, the distinction between supply and demand shocks becomes nebulous. Thus, we combine the shocks into single binary dummy variables - in equation (2), $SARS_{ijt}$ that takes the value one when exporting and importing countries include {China, Hong Kong, Canada, Singapore and Vietnam} and the year is 2003; in equation (3), $MERS_{ijt}$ that takes the value one for the following exporting and importing countries: Saudi Arabia over 2013-2017, UAE in 2014, and South Korea in the year 2015.[10] The equations are estimated separately over the time periods 2001-2006 and 2011-2018, respectively, to examine the effects of SARS and MERS in the aftermath of each outbreak. A priori, we expect the estimates of β_1 and ψ_1 to be negative.[11]

4.2 Extensive margin analysis

Variants of equations (2) and (3) were also used to examine empirically if the epidemics were associated with a change in the number of HS6-digit products exported ($Prod_{ijt}^{HS6}$). Negative values of the estimated coefficients would provide evidence for the adverse effects of SARS and MERS at the extensive margin in each case.

4.3 Geographical diversification of value-chains

To examine if the supply-shocks emanating from the disease outbreaks were associated with a widening of value-chains, we depart from the gravity framework and estimate baseline and augmented[12] versions of the following equations at the disaggregated HS6-digit level for GVC-based products for SARS and MERS separately:

$$HHI_{ipt} = \varphi_1 SARS_{it} + \mu_{pt} + \gamma_{ip} + \epsilon_{ipt} \tag{4}$$

$$HHI_{ipt} = \varphi_2 MERS_{it} + \mu_{pt} + \gamma_{ip} + \epsilon_{ipt} \tag{5}$$

[10] Combining the supply- and demand-side shocks into a single variable also enables cleaner identification as the time-varying exporter and importer fixed effects would otherwise be completely collinear with $SARS_{it}/MERS_{it}$ and $SARS_{jt}/MERS_{jt}$, respectively.

[11] In sensitivity analysis, we also used matrix completion analysis (Athey et al. 2017; Xu, 2017) that nests synthetic control and unconfoundedness in a generalized approach and was implemented in R using the Gsynth package; these estimates were found to be qualitatively similar and are available upon request.

[12] Consistent with literature on the determinants of GVC participation (for instance see World Bank, 2020), augmented versions of equations (4)-(7) include the log of nominal GDP ($lnGDP_{it}$) and government effectiveness (GE_{it}) as measures of supply-side capacity and institutional quality in the exporting country. In specifications using disaggregated data, the log of tariffs [$ln(1 + Tar_{ijpt})$] was also included.

where HHI_{ipt} is the Hirschmann-Herfindahl index of partner concentration[13] for country i at the HS6-digit level (p) at time t; μ_{pt} and γ_{ip} are the HS6-year and exporter-HS6 fixed effects; and ϵ_{ipt} is the error term. Estimated $\varphi_1, \varphi_2 < 0$ would provide evidence for widening of value-chains from the outbreaks-induced supply-shocks.

Finally, to examine if the supply-shocks were associated with a change in the number of destination markets for the exported GVC-products, we estimate the baseline and augmented versions of the following equations for SARS and MERS separately:

$$PAR_{it} = \alpha_1 SARS_{it} + \mu_t + \gamma_i + \epsilon_{it} \tag{6}$$

$$PAR_{it} = \alpha_2 MERS_{it} + \mu_t + \gamma_i + \epsilon_{it} \tag{7}$$

where PAR_{it} is the number of destination markets for the exported GVC-products for country i at time t; μ_t and γ_i are the year and exporter fixed effects; and ϵ_{it} is the error term. Estimated $\alpha_1, \alpha_2 < 0$ would provide evidence for a decline in the number of destination markets for the exported GVC-products from the outbreaks-induced supply-shocks. Note that our diversification analysis also adds value by departing from existing studies that focus on ex-ante diversification before the realization of shocks (Huang, 2017; Caselli et al. 2020; Esposito, 2020).

Equations (2)-(3) and their variants in the extensive margin analysis as well as equations (4)-(7) are estimated using OLS. Summary statistics are reported in Annex Table 2. Trade data, gross and value-added, are taken from BACI (Gaulier and Zignago, 2010) and the UNCTAD-EORA GVC database (Casella et al. 2019), respectively. Data on GDP are sourced from World Bank's World Development Indicators and those on tariffs from UNCTAD Trains. Data on government effectiveness come from World Bank's World Governance Indicators (Kaufmann et al. 2010).

5 Results and analysis

5.1 Intensive margin

The results from estimating equations (2) and (3) at the intensive margin are reported in Table 1 columns (1)-(2) for GVC-based intermediate and final goods, in the top and bottom

[13] The value of the HHI lies between 0 (fully diversified) to 1 (unitary partner).

panel for SARS and MERS, respectively. All estimations include three-way fixed effects and the standard errors are clustered by dyad-year in each case.

The SARS-induced shock is associated with a 16.1% reduction in exports of GVC-based final goods over 2001-06, though a similar effect is not observed for GVC-based intermediates exports. The inability of firms producing GVC-based final products to substitute customized inputs used in production with generic inputs (Acemoglu and Tahbaz-Salehi, 2020) likely explains the adverse magnitudes observed for GVC-based final products in these results. The SARS finding is also consistent with that in Fernandes and Tang (2020) wherein Chinese firms located in SARS-affected regions observed 11 and 6 percentage-point lower export and import growth relative to unaffected firms and the pre-SARS period. In contrast, the estimated coefficient on $MERS_{ijt}$ is statistically indifferent from zero, suggesting that the MERS outbreak may not have been associated with a decline in GVC-trade at the intensive margin. This may be the result of the more localized spread of that infection; the relatively low GVC-integration of countries in the Middle-east; and the absence of China amongst the MERS-worst-affected countries.

PTA membership is found to enhance the value of exports of both GVC-based intermediate and final products in these results during 2011-18 (bottom panel) but not during 2001-06 (top panel). The latter may be an outcome of the relatively short time period analyzed which may prevent any adjustment effects of PTA-membership from fructifying; indeed, PTA membership is found to have a statistically significant positive effect on GVC-trade when the time period for analysis increases to 2001-08 (see Table 3, columns 3 and 6).

<Insert Table 1 here>

5.2 Extensive margin

There is more conclusive evidence for the adverse effect of SARS at the extensive margin for both GVC-based intermediates and final goods in the results reported in Table 1, columns (3)-(4). SARS-induced disruptions are associated with a 7.2% and 9.4% decline in the number of HS6-digit intermediate and final goods exported, respectively.

In contrast, supply and demand shocks emanating from MERS may not have been associated with a decline in the number of HS6 products exported; the coefficient estimates in the bottom panel in columns (3)-(4) are statistically insignificant. These findings are consistent with the results observed for MERS at the intensive margin in Table 1. PTA membership is also found to have a positive impact at the extensive margin for both intermediate and final products during 2011-18 (bottom panel), though this is not observed during 2001-06 (top panel).

5.3 Widening of value-chains

There is some evidence for geographical diversification in the form of widening of value-chains for final products in response to the supply-shock emanating from the MERS outbreak; the coefficient estimates reported in Table 2, columns (7)-(8) in the bottom panel suggest that the shock may have been associated with a 1.0% to 1.2% decline in the Hirschmann-Herfindahl index of partner concentration. While a similar diversification in distribution is not observed for GVC-based intermediate products (the coefficient estimates in Table 2, columns (3)-(4) in the bottom panel lack statistical significance), MERS may have also been associated with a rise in the number of trading partners (coefficient estimates reported in columns (1)-(2) in the bottom panel are positive).

<Insert Table 2 here>

While the corresponding HHI results for SARS are also statistically indifferent from zero for GVC-based final products, the coefficient estimates in Table 2, columns (3)-(4) in the top panel are positive, suggesting that the distribution of partners for GVC-based intermediate products may have become more concentrated in the wake of the SARS-induced supply-shock. However, SARS may not have been associated with a change in the number of trading partners (coefficient estimates in columns (1)-(2), top panel are statistically insignificant).

5.4 GVC-resilience

We would need data for 2019 and beyond to examine GVC-resilience to the MERS outbreak; the confounding influence of the COVID-19 pandemic would also render such an assessment challenging. We thus focus on examining resilience of value-chains to the SARS epidemic. The results reported in Table 3 suggest that the magnitude of the export declines associated with SARS-induced supply- and demand shocks increased significantly over time, which is consistent with the epidemic's medium term impact observed on Chinese firm-level exports and imports in Fernandes and Tang (2020). Illustratively, the average treatment effect at the extensive margin increases (in absolute value terms) from -7.3% (-9.5%) over 2001-06 to -13.7% (-14.4%) over 2001-08 for intermediate (final) goods exports; at the intensive margin, final goods exports are reduced by 20% over 2001-08 up from 16% during 2001-06, underlining the medium to long-term impact of the outbreak. Thus, the associated value-chains may not have been resilient to the SARS epidemic.

<Insert Table 3 here>

5.5 Value-added trade

So far we have examined the effects of SARS and MERS on gross trade in GVC-based intermediate and final products. In this sub-section, we use data from the UNCTAD-EORA GVC database (Casella et al. 2019) and estimate equations (2) and (3) to examine the impact on value-added trade. The results, reported in Table 1 columns (9)-(10), provide qualitatively similar findings for SARS-induced decline in value-added trade, together with the absence of a statistically significant effect of the MERS outbreak. Moreover, the adverse effects of SARS on value-added trade were also found to be get accentuated over time (Table 3, bottom panel), confirming the non-resilience of value-chains to that outbreak.

On the whole, the results in this section suggest that there may have been a disruption to GVCs from the SARS outbreak at both intensive and extensive margins and for value-added trade and that the decline in trade also seems to have persisted and intensified over time. We discuss the potential relevance of these findings for the current pandemic in Section 7, but before that we dig deeper into the results for SARS to examine their likely drivers.

6 Additional analysis

6.1 What drives the SARS results?

In this sub-section, we exploit the heterogeneity of our dataset along different dimensions to examine the likely drivers of GVC-disruptions associated with the SARS epidemic using both aggregate and disaggregated data on gross trade in GVC-based products. This additional analysis is only undertaken for SARS, as more conclusive adverse trade effects are only observed for SARS, which makes it interesting to examine any underlying heterogeneities.

6.1.1 Aggregate analysis

To explore the likely drivers of the SARS results from aggregate analysis, we estimate equation (2) with additional interaction terms - $SARS_{ijt} * Var_i$ and $SARS_{ijt} * Var_j$ - where

$Var_{i/j} = \{NonOECD_{i/j}, U_{i/j}\}$ over 2001-08. These time-invariant variables denote, respectively, the exporting/importing country not belonging to the group of OECD countries; and being upstream[14] from final demand.

<Insert Table 4 here>

The incidence of weak contract enforcement on GVC-trade is disproportinately large (Antràs, 2020). Since institutional quality is correlated with economic development, high income countries are more likely to manage crises better by, inter alia, providing contractual security to minimize shock-induced GVC-disruptions effectively. This inference seems to be corroborated by the results reported in columns (1) and (2) of Table 4 - the estimates of $SARS_{ijt}$, that reference OECD countries, are statistically insignificant; in contrast, the sums of the estimates of $SARS_{ijt}$ and the respective interaction terms for exporting and importing countries are negative for GVC-based intermediate and final goods, respectively. The coefficient estimates translate into a 13.7% intermediate goods and a 21.7% final goods reduction for non-OECD exporting and importing countries, respectively.

Results reported in columns (3) and (4) of Table 4 suggest that countries more upstream from final demand may have been less adversely affected by SARS, which is consistent with the findings in Fernandes and Tang (2020). The sums of the estimate of $SARS_{ijt}$ and the interaction terms are less negative than $SARS_{ijt}$ for both intermediate and final goods for both exporting and importing countries. In contrast, the $SARS_{ijt}$ estimates, which reference countries whose position is more downstream in GVCs, are strongly negative. The coefficient estimates translate into export reductions for countries downstream from final demand ranging from 30.9% for intermediate goods to and 28.7% for final goods. Trade costs have a higher incidence on downstream stages (Antràs, 2020) and these trade costs get compounded by shocks, which likely explains these results.

6.1.2 Disaggregated analysis

To examine the likely drivers of the SARS results using disaggregated product-level data, we estimate a modified version of equation (2) at the product-level (*a la* Dai et al. 2014) thus:

$$X_{ijpt}^{I/F} = exp[\beta_1 SARS_{it}.Var_{ip} + \beta_2 SARS_{jt}.Var_{jp} + \beta_3 ln(1+TAR_{ijt}) + \alpha_{ij} + \mu_{ip4t} + \gamma_{jp4t}] + \epsilon_{ijpt} \quad (8)$$

[14]Following Antràs and Chor (2018), upstreamness was measured by the share of a country's output sold directly to final consumers in the year 2000; the smaller the share, the more upstream is the country's position in GVCs.

where $Var_{ip/jp} = \{HRCA_{ip/jp}, HGLI_{ip/jp},\ MED\_TECH_p,\ HIGH\_TECH_p\}$. These time-invariant variables denote, respectively, dummy variables that are unity when value of the normalized revealed comparative advantage (RCA) and Grubel-Lloyd Index (GLI)[15] are greater than the respective median values for the sample of exporters/importers in the year 2000; and belonging to the technology class classified as medium- and high-tech. Note that Var_{ip} and Var_{jp} are constructed at the HS6-digit level, so to prevent complete collinearity of $SARS_{it}.Var_{ip}$ and $SARS_{jt}.Var_{jp}$ with the fixed effects, the product dimension of the time-varying exporter and importer fixed effects in equation (8) is defined at the HS4-digit level. This is a crucial element of our identification strategy in disaggregated analysis examining the likely drivers of the SARS effects[16].

<Insert Table 5 here>

Exporting countries more competitive in producing certain goods are also likely to be less adversely affected by supply-side macroeconomic shocks affecting such products. This is observed in the results reported in Table 5 columns (1) and (2) for GVC-based intermediate and final goods. The analysis makes use of the normalized revealed comparative advantage (RCA) indicator as a product-level proxy for competitiveness[17]. The estimated interaction term $SARS_{it}.HRCA_{ip}$ is strongly positive for both intermediate and final goods.

More differentiated and technology-intensive[18] products are also likely to be more sophisticated and less easily substitutable, and hence, prone to fewer disruptions (Fernandes and Tang, 2020). Results reported in column (3)–(6) of Table 5 confirm these hypotheses in the context of SARS-induced disruptions to GVC-trade. The $HGLI_{ip/jp}$ interaction terms with the $SARS_{it}$, $SARS_{jt}$ estimates are strongly positive in column (3) for GVC-based intermediate products, suggesting a non-adverse effect of that outbreak on more differentiated inputs in both exporting and importing countries; however, a similar result is not observed for final products. Likewise, in the estimates reported in columns (5)-(6), exporters and importers of medium- and high-tech products seem to have been insulated from the SARS shock.

In sum, the analysis in this subsection suggests that shock-induced GVC-disruptions may be more pronounced for non-OECD countries that are also more downstream in GVCs; while more competitive exporters, differentiated intermediates and technology-intensive final goods

[15] $GLI_{ip/jp} = 1 - \left[(X_{ip/jp} - M_{ip/jp})/(X_{ip/jp} + M_{ip/jp})\right]$ where X = exports; M = imports. The value of the GLI lies between 0 (completely homogeneous) and 1 (completely differentiated).

[16] Note that we cannot follow this approach in our baseline specifications as the supply- and demand-shock variables are not product-specific.

[17] Negative values of the normalized RCA indicate a comparative disadvantage in exporting while positive values indicate the converse.

[18] The technology classification of products is taken from UNCTAD.

products may be relatively insulated. The results from this subsection also show that our overall findings on the trade decline associated with SARS are robust to using different sub-samples.

6.2 Sensitivity analysis: alternative data and estimation strategy

To disentangle the effects associated with the supply- and demand-side shocks, we use an alternative dataset that also includes data on intra-national trade flows to examine the robustness of our findings on SARS, using the following specification:

$$X_{ijt}^{I/F} = exp[\beta_1 SARS_{it}.INTL_{ij} + \beta_2 SARS_{jt}.INTL_{ij} + \beta_3 PTA_{ijt} + \alpha_{ij} + \mu_{it} + \gamma_{jt}] + \epsilon_{ijt} \quad (9)$$

The inclusion of data on intra-national trade flows in the dependent variable in equation (9) not only makes the model theory-consistent (Fally, 2015) but also enables us to directly estimate the effect of SARS-induced supply- and demand-shocks (which are otherwise collinear with the time-varying exporter and importer fixed effects) using interaction terms between $SARS_{it}$, $SARS_{jt}$ and a binary dummy ($INTL_{ij}$) that takes the value one for international trade flows (see Piermartini and Yotov, 2016 for similar applications). As an additional robustness check, equation (9) is estimated using the Poisson Pseudo-Maximum Likelihood (PPML; Silva and Tenreyro, 2006), which also accounts for heteroskedasticity-related concerns in estimation. Data on cross-border and intra-national trade flows in GVC-intensive sectors[19] come from the EORA26 MRIO database (Lenzen et al. 2012, 2013).

The results from this estimation are reported in Table 6 and confirm both the adverse effects of SARS-induced supply- and demand-shocks[20] on trade as well as their intensification over time. The coefficient estimates translate into average treatment effects of -8.3% for intermediate goods exports over 2001-06, increasing to -11.8% over 2001-08. Meanwhile, PTA membership is found to have a positive impact on both intermediate and final goods exports in all these results; the effects are both statistically significant and larger in magnitude relative to the results reported in Table 3, which likely emanates from using a different dataset and estimation strategy.

[19] These include electrical and machinery; textiles and wearing apparel; and transport equipment.

[20] Given the way in which MRIO databases are constructed, the coefficients of $SARS_{it}$ and $SARS_{jt}$ could not be estimated together in combined regressions as one of these variables was dropped due to collinearity. However, when the supply- and demand-shock covariates were estimated in distinct regressions, the estimated effects were found to be identical.

<Insert Table 6 here>

7 Conclusion

Using difference-in-difference analysis in a gravity framework, we examine the response of GVC-trade to two previous health shocks to draw implications, if at all, for the COVID-19 pandemic. Our baseline estimates suggest a decline in gross trade in GVC-based products at both margins and for value-added trade from SARS-induced supply and demand shocks, though a similar finding is not observed for MERS. Empirical analysis also reveals geographical diversification of value chains as well as their non-resilience to SARS in particular; even a relatively localized epidemic like MERS was associated with widening of value-chains from the outbreak-induced supply-shock.There is also suggestive evidence in the stylized facts for reshoring after MERS and nearshoring after SARS.

It is tempting to compare SARS and COVID-19 given that both originated in China, but one must be mindful of the evolution of China's share in global GDP and trade over time, the inter-connectedness of the world economy and the severity of the current pandemic. During SARS, China accounted for 4% of global output; today, that number has quadrupled. Thus, any slowdown in China today will likely impact the world much more severely than in 2003. Moreover, GVC participation continues to be an important mechanism for international transmission of shocks (Berthou et al. 2020; Cigna and Quaglietti, 2020; Friedt and Zhang, 2020) though some early analysis suggests that it may have also been a source of resilience during the current pandemic (de Lucio et al. 2021; Giglioli et al. 2021; Simola, 2021).

Meanwhile, the unique spatial dimension of the COVID-19 pandemic will not only yield a large global impact emanating from China, but also smaller localized disruptions creating regional contagion effects. These effects will exhibit heterogeneity depending on a region's level of integration in global trade and the response of governments to the resultant economic crisis (OECD, 2020). For example, the EU is highly integrated in GVCs and is also a large producer and consumer of manufacturing goods; national governments in the region have responded with complete lockdowns, intermittently, during the pandemic. These shutdowns are likely to create strong ripple-effects in the exports of other countries located in Asia, Africa and the Americas that are dependent on European supply chains through backward and forward linkages (Solleder and Velasques, 2020).

The overall impact of COVID-19 is also likely to be worse than SARS because of three additional reasons. One, the current scale of the pandemic is much larger than that of SARS both in terms of incidence of cases and geographical spread (less than 10,000 lives were affected by the relatively more localized-SARS versus 470 million confirmed cases of COVID-19 worldwide as of mid-March 2022). Two, the state-mandated lockdowns in March 2020 resulted in immediate supply and demand shocks with lingering adverse effects on economies. Three, services trade is being more severely impacted this time as upto 75% of international services transactions by value require physical proximity betweeen buyers and sellers and the latter is the first casualty of travel bans and social-distancing practices in the wake of this pandemic (Shingal, 2020; WTO, 2020).

At the same time, the impact of COVID-19 will also depend on the type of products being traded through supply networks. Fernandes and Tang (2020) found capital and skill-intensive products to have been more resilient to the export disruption caused by SARS. These results are also consistent with our findings and with Taiji et al. (2018) who found that sourcing of differentiated inputs is less vulnerable to trade-shocks. The Chinese economy now specializes in a variety of products that are tech- and skill-intensive, which likely explains its faster recovery given the inability of countries to find alternative sources for intermediates that are harder to substitute. This said, we find SARS' adverse effects on GVC-trade to have intensified significantly over time, which suggests that countries may need to continue deploying unilateral strategies like economic stimulus packages and also co-ordinate collective action to mitigate likely medium to longer-term GVC-disruptions from the current pandemic.

While any prior epidemic experience may be significantly associated with a less negative sentiment towards COVID-19 (Hassan et al. 2020), one possible lesson from the findings of our study for managing the current and future crises more effectively would be to diversify the portfolio of suppliers geographically. Anecdotal evidence suggests that this may already be happening[21], as part of a larger China+1 strategy that began in 2019 following the US-China trade war with the aim of diversifying away from China towards other low-cost Asian countries. However, a second-order effect of the pandemic will still impact companies willing to relocate to ASEAN countries as the latter continue to be dependent on China for imports of intermediate inputs.

While Southeast Asian countries seem to be the most preferred destinations after China, Mexico is also emerging as a close favourite especially for American and Japanese firms. Trade data are beginning to show that US companies are opting for suppliers closer home, chiefly local suppliers and those based in Mexico, a trend that resonates with the stylized

[21]For example, Apple will manufacture some mobile phones in Vietnam, India, Taiwan and Mexico and has already planned for an expansion into these new markets. Google smartphone unit is set to move to Northern Vietnam, while it has already chosen Thailand for its smart-home product unit. Microsoft is also expected to start manufacturing in Vietnam soon. Meanwhile, the Indonesian textiles industry has witnessed a 10% rise in the number of orders, primarily from global brands looking to substitute trade with China. The Japanese megabrand UNIQLO has also moved sourcing from China to Vietnam.

facts on SARS presented in this paper. It seems that the US has also used the pandemic as an excuse to move pharmaceutical production back home from China. Moreover, US companies have already begun relying on locally-sourced electronic parts rather than sourcing them from China. This has led to an increase in orders from both local and Mexican firms.

Many non-US firms are also seeking new markets to shock-proof their supply chains. There is talk of nearshoring by companies in the Eurozone, for instance, to Hungary, Czech Republic, Slovakia, Romania and Poland (Javorcik, 2020). EU members have also urged automobile and pharmaceutical companies to strengthen local value chains as a way to reduce dependence on China. Japan is another country that has expressed concerns over reliance on China for imported inputs. As part of its COVID-19 stimulus package, the government set aside US$ two billion to incentivize shifting production back home for high-tech manufacturing and in other sectors to South-east Asian economies or to India.

In sum, while value-chains may have exhibited selective resilience to previous health shocks despite disruptions, there may be more permanent changes this time around, including a conscious move towards geographical and supplier diversification. At the same time, the pandemic has spurred e-commerce and is also likely to accelerate the fourth industrial revolution through adoption of automation, 3D printing and extreme customization. It would be interesting to study these changes and their ramifications on GVCs in future research.

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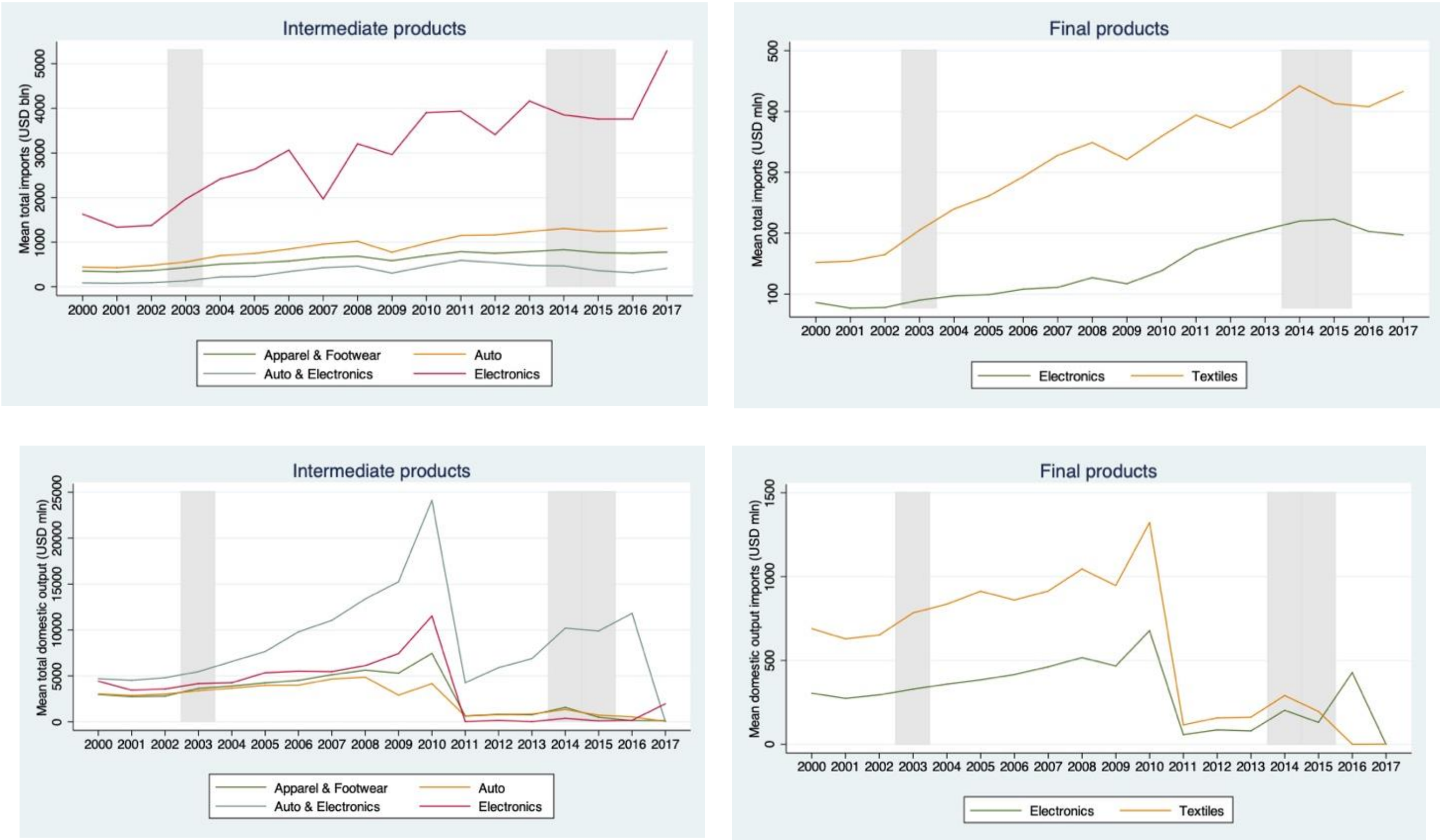
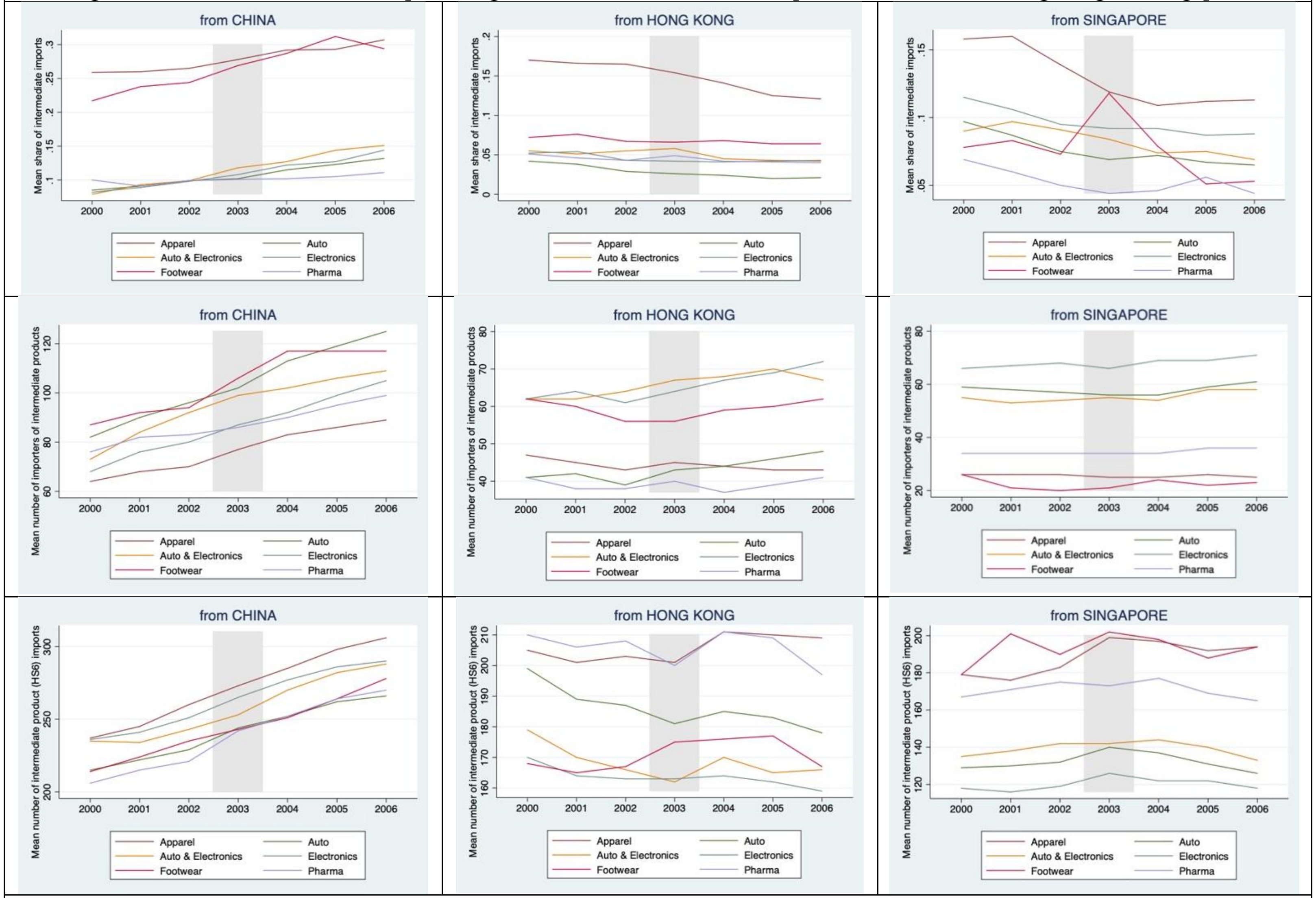
Figure 1: Imports (top panel) and domestic output (bottom panel) of GVC-based intermediate and final products overtime



Source: UNIDO IndStat dataset; own calculations

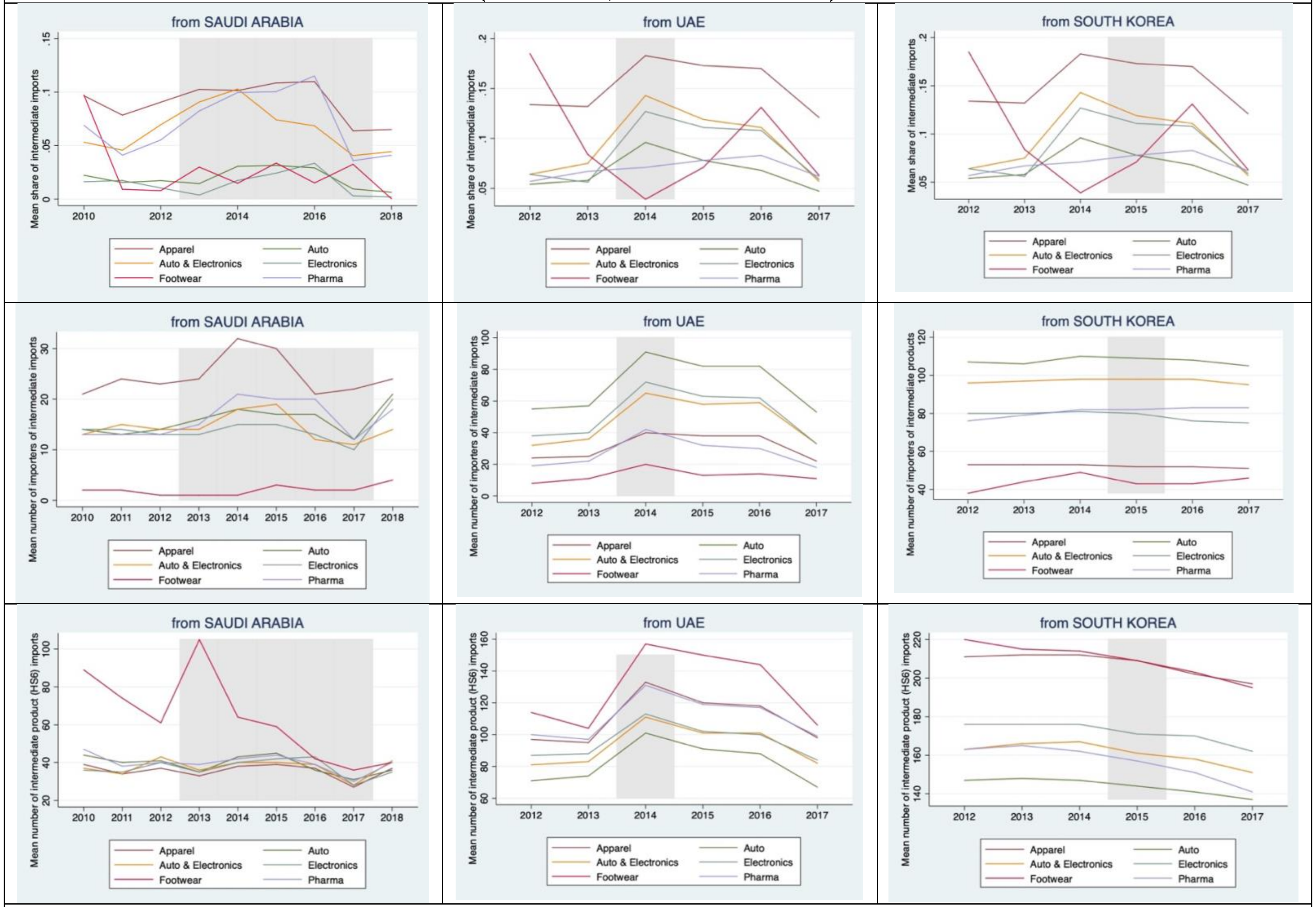
Note: The two-coloured slabs denote the time periods corresponding to the incidence of SARS and peak cases in the three worst-affected countries during the MERS outbreak, respectively.

Figure 2: Intensive and extensive import margins of GVC-based intermediate products from China, Hong Kong and Singapore



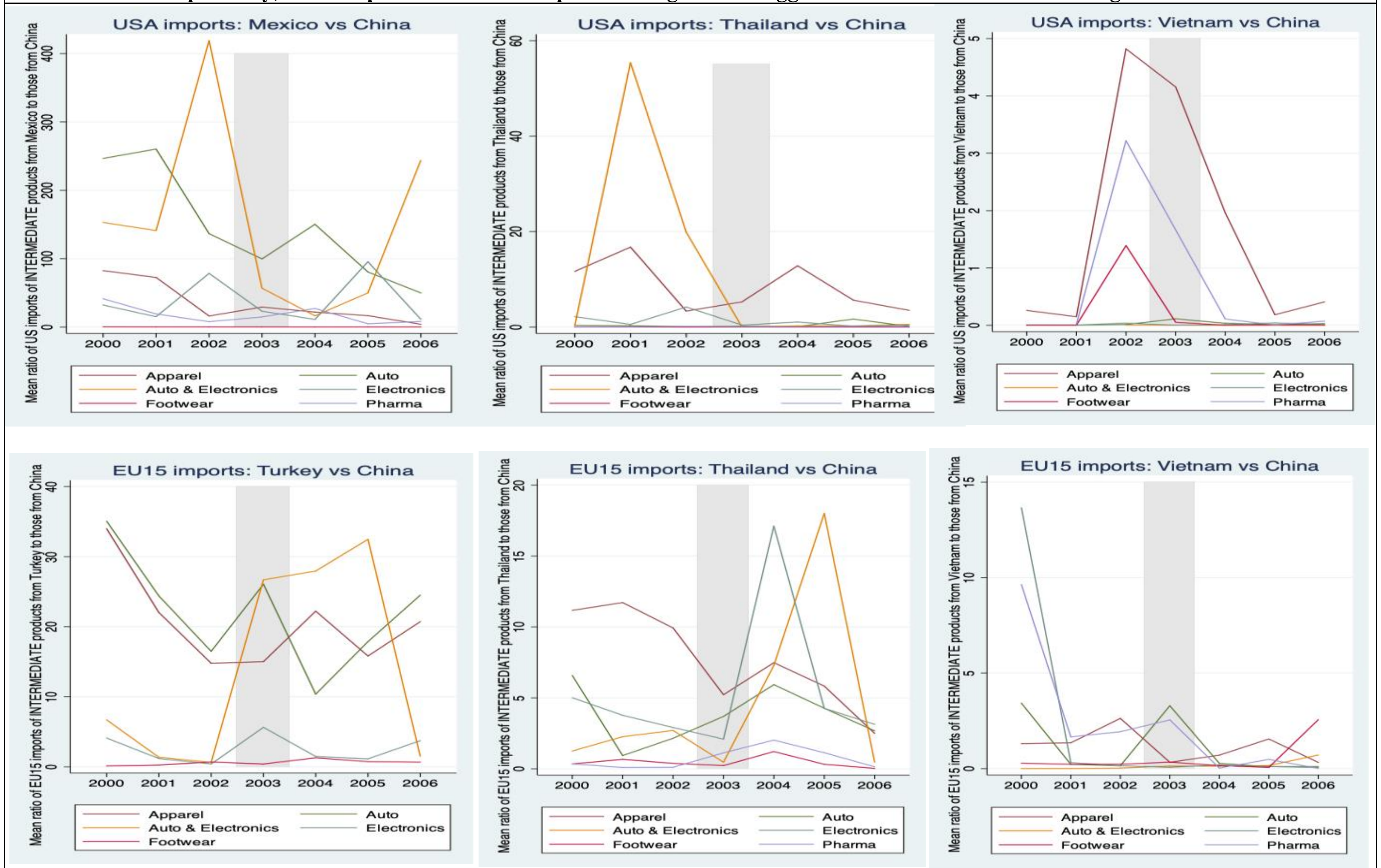
Source: BACI dataset; own calculations

Figure 3: Intensive and extensive import margins of GVC-based intermediate products from MERS-affected countries (Saudi Arabia, UAE and South Korea)



Source: BACI dataset; own calculations

Figure 4: USA (top) and the EU15 (bottom panel) may have imported more GVC-based intermediates from Mexico and Turkey, respectively, at the expense of Chinese exports during SARS: suggestive evidence for "near-shoring" of GVCs



Source: BACI dataset; own calculations

Table 1: Baseline estimates, OLS (SARS, 2001-06; MERS, 2011-18)

Variables	$\ln(X_{ijt})$ INT (1)	FNL (2)	$\ln(Prod^{HS6}{}_{ijt})$ INT (3)	FNL (4)	$\ln(VA_{ijt})$ TOT (5)
$SARS_{ijt}$	-0.097	-0.175*	-0.075**	-0.099***	-0.011*
	(0.082)	(0.093)	(0.031)	(0.032)	(0.009)
PTA_{ijt}	-0.003	0.058*	-0.064***	-0.061***	0.006**
	(0.031)	(0.031)	(0.012)	(0.014)	(0.002)
Observations	86,799	97,183	88,170	98,529	98,472
R-squared	0.931	0.930	0.961	0.956	0.999
$MERS_{ijt}$	0.108	-0.321	-0.241	-0.175	-0.036
	(0.296)	(0.196)	(0.139)	(0.129)	(0.054)
PTA_{ijt}	0.056*	0.062**	0.048***	0.047***	0.005
	(0.034)	(0.030)	(0.013)	(0.013)	(0.006)
Observations	128,386	145,175	130,332	147,056	144,412
R-squared	0.926	0.928	0.957	0.952	0.997

Note: All estimations include exporter-year, importer-year and dyadic fixed effects. Robust standard errors, clustered by dyad-year, are reported in parentheses. Levels of significance: *10%, **5%, ***1%. Legend: INT = Intermediate; FNL = Final; TOT = Total.

Table 2: Geographical diversification analysis (OLS estimates)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$ln(PAR_{it})$		HHI_{ipt}		$ln(PAR_{it})$		HHI_{ipt}	
	Intermediate products				Final products			
$SARS_{it}$	0.016	0.033	0.006***	0.010***	0.023	0.022	0.002	0.001
	(0.025)	(0.022)	(0.001)	(0.001)	(0.021)	(0.018)	(0.001)	(0.001)
$ln(1+Tar_{ijpt})$			-0.006***	-0.009***			0.000	0.001***
			(0.001)	(0.001)			(0.000)	(0.001)
$ln(GDP_{it})$		0.288***		-0.022***		0.318***		-0.018***
		(0.085)		(0.004)		(0.106)		(0.003)
GE_{it}		0.121		0.008***		-0.007		0.012***
		(0.103)		(0.003)		(0.118)		(0.002)
Observations	1,080	728	340,094	290,811	1,080	728	730,769	616,947
R-squared	0.990	0.993	0.884	0.891	0.991	0.993	0.863	0.873
Period				2001-06				
Fixed effects:								
Exporter	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES
Exporter-Product	NO	NO	YES	YES	NO	NO	YES	YES
Product-Year	NO	NO	YES	YES	NO	NO	YES	YES
$MERS_{it}$	0.232**	0.156*	0.002	0.005	0.206*	0.137	-0.012***	-0.010***
	(0.094)	(0.091)	(0.002)	(0.002)	(0.119)	(0.128)	(0.001)	(0.001)
$ln(1+Tar_{ijpt})$			-0.003***	-0.003***			-0.004***	-0.003***
			(0.000)	(0.000)			(0.000)	(0.000)
$ln(GDP_{it})$		-0.014		0.008***		0.030		-0.008***
		(0.059)		(0.002)		(0.067)		(0.001)
GE_{it}		0.107*		0.021***		0.075		0.006***
		(0.064)		(0.002)		(0.077)		(0.001)
Observations	1,763	1,439	685,067	673,205	1,761	1,438	1,714,659	1,655,840
R-squared	0.986	0.991	0.863	0.862	0.984	0.988	0.841	0.844
Period				2011-2018				
Fixed effects:								
Exporter	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES
Exporter-Product	NO	NO	YES	YES	NO	NO	YES	YES
Product-Year	NO	NO	YES	YES	NO	NO	YES	YES

Note: Robust standard errors, clustered by exporter-year, reported in parentheses. Levels of significance: *10%, **5%, ***1%.

Table 3: SARS effects at the intensive and extensive margins and for value-added trade get accentuated over time (OLS estimates)

	(1)	(2)	(3)	(4)	(5)	(6)
	Intermediate products			Final products		
Variables	**2001-06**	**2001-07**	**2001-08**	**2001-06**	**2001-07**	**2001-08**
	Dependent variable = $\ln(X_{ijt})$					
$SARS_{ijt}$	-0.097	-0.206**	-0.246***	-0.175*	-0.195**	-0.219**
	(0.082)	(0.090)	(0.094)	(0.093)	(0.095)	(0.096)
PTA_{ijt}	-0.003	0.033	0.061**	0.058*	0.044	0.055**
	(0.031)	(0.029)	(0.027)	(0.031)	(0.028)	(0.025)
Observations	86,799	103,534	120,569	97,183	116,090	135,166
R-squared	0.931	0.926	0.921	0.930	0.926	0.922
	Dependent variable = $\ln(Prod^{HS6}_{ijt})$					
$SARS_{ijt}$	-0.076**	-0.117***	-0.147***	-0.100***	-0.126***	-0.155***
	(0.031)	(0.033)	(0.034)	(0.032)	(0.032)	(0.033)
PTA_{ijt}	-0.063***	-0.057***	-0.061***	-0.060***	-0.077***	-0.084***
	(0.012)	(0.011)	(0.010)	(0.014)	(0.013)	(0.012)
Observations	86,799	103,534	120,569	97,183	116,090	135,166
R-squared	0.961	0.958	0.956	0.956	0.953	0.950
	Dependent variable = $\ln(VA_{ijt})$					
$SARS_{ijt}$	-0.011*	-0.023**	-0.033**			
	(0.009)	(0.011)	(0.013)			
PTA_{ijt}	0.006**	0.005**	0.005**			
	(0.002)	(0.002)	(0.002)			
Observations	98,472	117,396	136,289			
R-squared	0.999	0.999	0.999			

Note: All estimations include exporter-year, importer-year and dyadic fixed effects. Robust standard errors, clustered by dyad-year, are reported in parentheses. Levels of significance: *10%, **5%, ***1%.

Table 4: Drivers of SARS effects (OLS; aggregate data, 2001-2008)

	Income status		GVC position	
	Dependent variable = $\ln(X_{ijt})$			
	INT	FNL	INT	FNL
Variables	**(1)**	**(2)**	**(3)**	**(4)**
PTA_{ijt}	0.060**	0.052**	0.054**	0.057**
	(0.027)	(0.025)	(0.027)	(0.025)
$SARS_{ijt}$	-0.182	0.026	-0.369***	-0.338***
	(0.098)	(0.100)	(0.109)	(0.112)
$SARS_{ijt}$*$NonOECD_i$	-0.147*	-0.071		
	(0.076)	(0.090)		
$SARS_{ijt}$*$NonOECD_j$	0.050	-0.244***		
	(0.058)	(0.048)		
$SARS_{ijt}$*U_i			0.178**	0.140
			(0.090)	(0.099)
$SARS_{ijt}$*U_j			0.143**	0.141**
			(0.064)	(0.059)
Observations	120,569	135,166	109,019	121,090
R-squared	0.921	0.922	0.923	0.925
Fixed effects				
Exporter-Year	YES	YES	YES	YES
Importer-Year	YES	YES	YES	YES
Exporter-Importer	YES	YES	YES	YES

Note: Robust standard errors, clustered by dyad-year, reported in parentheses. Legend: INT = Intermediate products; FNL = Final products. Levels of significance: *10%, **5%, ***1%.

Table 5: Drivers of SARS effects (OLS; disaggregated data, 2001-2008)

	RCA		GLI		TECH	
			Dependent variable = $\ln(X_{ijt})$			
	INT	**FNL**	**INT**	**FNL**	**INT**	**FNL**
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$SARS_{it}$*$HRCA_{ip}$	0.159***	0.271***				
	(0.051)	(0.038)				
$SARS_{jt}$*$HRCA_{jp}$	0.015	-0.150				
	(0.084)	(0.062)				
$SARS_{it}$*$HGLI_{ip}$			0.178***	-0.035		
			(0.050)	(0.042)		
$SARS_{jt}$*$HGLI_{jp}$			0.152**	0.067		
			(0.077)	(0.061)		
$SARS_{it}$*MED_TECH_p					0.423***	1.487***
					(0.123)	(0.428)
$SARS_{it}$*$HIGH\_TECH_p$					0.748***	3.301***
					(0.199)	(0.549)
$SARS_{jt}$*MED_TECH_p					0.414***	1.862***
					(0.160)	(0.682)
$SARS_{jt}$*$HIGH\_TECH_p$					0.334	2.779***
					(0.274)	(0.761)
Observations	564,537	1,258,517	476,727	1,022,343	603,280	967,679
R-squared	0.513	0.521	0.532	0.550	0.405	0.519
Fixed effects:						
Exporter-Product-Year	YES	YES	YES	YES	YES	YES
Importer-Product-Year	YES	YES	YES	YES	YES	YES
Exporter-Importer	YES	YES	YES	YES	YES	YES

Note: The product is defined at the HS4-digit level in constructing the fixed effects. Coefficients of $\ln(1+TAR_{ijpt})$, $HRCA_{ip/jp}$, $HGLI_{ip/jp}$, MED_TECH_p, $HIGH\_TECH_p$ are not reported. Robust standard errors, clustered by dyad-product-year, reported in parentheses. Levels of significance: *10%, **5%, ***1%. Legend: INT = Intermediate products; FNL = Final products

Table 6: Adverse effects of SARS over time are robust to using alternative data and estimation strategy (PPML estimates)

	Dependent variable = X_{ijt}							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	Intermediate products				**Final products**			
Variables	**2001-05**	**2001-06**	**2001-07**	**2001-08**	**2001-05**	**2001-06**	**2001-07**	**2001-08**
$SARS_{it}.INTL_{ij}$	-0.028	-0.087***	-0.113***	-0.126***	-0.067***	-0.151***	-0.217***	-0.263***
	(0.024)	(0.021)	(0.019)	(0.019)	(0.025)	(0.026)	(0.032)	(0.038)
PTA_{ijt}	0.169***	0.129***	0.100***	0.069**	0.159***	0.153***	0.138***	0.128***
	(0.042)	(0.036)	(0.032)	(0.028)	(0.027)	(0.025)	(0.024)	(0.021)
Observations	167,445	200,934	234,423	267,912	167,445	200,934	234,423	267,912
Pseudo R-squared	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999
Fixed effects:								
Exporter-Year	YES	YES	YES	YES	YES	YES	YES	YES
Importer-Year	YES	YES	YES	YES	YES	YES	YES	YES
Exporter-Importer	YES	YES	YES	YES	YES	YES	YES	YES

Note: Data on X_{ijt} also include intra-national trade flows. $INTL_{ij}$ is a binary dummy that takes the value one for international flows and zero otherwise. $SARS_{it}$, $SARS_{jt}$ and $SARS_{jt}.INTL_{ij}$ omitted due to collinearity in combined regressions; identical effects obtained in separate regressions. Robust standard errors, clustered by dyad-year, reported in parentheses. Levels of significance: *10%, **5%, ***1%.

Annex table 1: Country coverage

Afghanistan, Albania, Algeria, American Samoa, Andorra, Angola, Anguilla, Antarctica, Antigua and Barbuda, Argentina, Armenia, Aruba, Australia, Austria, Azerbaijan, Bahamas, Bahrain, Bangladesh, Barbados, Belarus, Belgium, Belize, Benin, Bermuda, Bhutan, Bolivia, Bonaire, Bosnia and Herzegovina, Botswana, British Indian Ocean Territory, British Virgin Islands, Brazil, Brunei Darussalam, Bulgaria, Burkina Faso, Burundi, Cabo Verde, Cambodia, Cameroon, Canada, Cayman Islands, Central African Republic, Chad, Chile, China, Hong Kong, Macao, Christmas Islands, Cocos Islands, Colombia, Comoros, Congo, Cook Islands, Costa Rica, Croatia, Cuba, Curácao, Cyprus, Czech Republic, Cote d'Ivoire, Democratic People's Republic of Korea, Democratic Republic of the Congo, Denmark, Djibouti, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Eritrea, Estonia, Ethiopia, FS Micronesia, Falkland Islands, Fiji, Finland, Fr. South Antarctic Terr., France, French Polynesia, Gabon, Gambia, Georgia, Germany, Ghana, Gibraltar, Greece, Greenland, Grenada, Guam, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hungary, Iceland, India, Indonesia, Iran, Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Kiribati, Kuwait, Kyrgyzstan, Lao People's Dem. Rep., Latvia, Lebanon, Liberia, Libya, Lithuania, Luxembourg, Madagascar, Malawi, Malaysia, Maldives, Mali, Malta, Marshall Islands, Mauritania, Mauritius, Mexico, Mongolia, Montenegro, Montserrat, Morocco, Mozambique, Myanmar, N. Mariana Islands, Namibia, Nauru, Nepal, Neth. Antilles, Netherlands, New Caledonia, New Zealand, Nicaragua, Niger, Nigeria, Niue, Norfolk Islands, Norway, Oman, Pakistan, Palau, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Pitcairn, Poland, Portugal, Qatar, South Korea, Republic of Moldova, Romania, Russia, Rwanda, Saint BarthÇlemy, Saint Helena, Saint Kitts and Nevis, Saint Lucia, Saint Maarten, Saint Pierre and Miquelon, Saint Vincent and the Grenadines. Samoa, San Marino, Sao Tome and Principe, Saudi Arabia, Senegal, Serbia, Seychelles, Sierra Leone, Singapore, Slovakia, Slovenia, South Africa, Solomon Islands, Somalia, South Sudan, Spain, Sri Lanka, State of Palestine, Sudan, Suriname, Sweden, Switzerland, Syria, TFYR of Macedonia, Tajikistan, Thailand, Timor-Leste, Togo, Tokelau, Tonga, Trinidad and Tobago, Tunisia, Turkey, Turkmenistan, Turks and Caicos Islands, Tuvalu, USA, Uganda, Ukraine, United Arab Emirates, United Kingdom, United Rep. of Tanzania, Uruguay, Uzbekistan, Vanuatu, Venezuela, Viet Nam, Wallis and Futuna Islands, Yemen, Zambia, and Zimbabwe.

Annex table 2: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
$\ln(X_{ijt})$	817,293	5.92	3.57	-6.91	19.22
$\ln(Prod^{HS6}_{ijt})$	817,378	2.10	1.85	0.00	6.48
$\ln(PAR_{it})$	12,268	5.24	2.65	0.00	11.18
HHI_{ipt}	36,031,536	0.48	0.20	0.00	1.00
$\ln(VA_{ijt})$	714,880	6.17	3.20	-15.68	21.42
$SARS_{it}$	817,378	0.003	0.05	0.00	1.00
$SARS_{jt}$	817,378	0.002	0.05	0.00	1.00
$SARS_{ijt}$	817,378	0.005	0.07	0.00	1.00
$MERS_{it}$	817,378	0.003	0.05	0.00	1.00
$MERS_{jt}$	817,378	0.003	0.05	0.00	1.00
$MERS_{ijt}$	817,378	0.006	0.08	0.00	1.00
PTA_{ijt}	804,877	0.21	0.41	0.00	1.00
$\ln(GDP_{it})$	773,781	18.57	2.17	9.49	23.75
GE_{it}	743,778	0.47	1.00	-2.48	2.44
$\ln(1+Tar_{ijpt})$	7,491,238	0.53	0.94	0.00	4.81