Working Paper DTC-2021-1

Modeling Global Value Chains: From Trade Costs to Policy Impacts

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July 6th, 2021.

Abstract: I use an approach from the family of "new quantitative trade models" to explore the links between trade costs and integration in Global Value Chains (GVCs). The model conceptualizes GVC trade through a multi-country, multi-sector Ricardian model that nests the standard structural gravity model. It provides a general framework in which to assess the impacts of changes in iceberg trade costs on GVC trade, understood as the sum of backward linkages and pure double counting, in line with recent work on trade in value added. As an example, I use the model to show that observed changes in trade facilitation performance between 2015 and 2019 have strong explanatory power for observed changes in GVC trade during the same period: the model accounts for over one-third of the observed change, albeit with substantial variation across countries and sectors.

JEL Codes: F13; F14; F15/

Keywords: Trade policy; Gravity model; Global value chains; Trade facilitation.

[1] I am very grateful to Andrew Silva, who expertly programmed the model in Python, based on code made available by Lorenzo Caliendo and Inga Heiland, who also provided helpful advice. I would also like to thank Silvia Sorescu for sharing data.

1 INTRODUCTION

The growth of world trade in the 1990s and 2000s has been notable for the important role played by intermediate goods. Data from the Asian Development Bank's Multi-Region Input-Output Table (MRIO) show that the proportion of intermediates in total goods exports for the 63 countries (including an aggregate rest of the world) in the database rose from 62.1% in 2000 to 69.2% in 2019. Intensive trade in intermediates is consistent with an increase in global and regional production sharing, often used in the policy literature as an observable proxy for integration into Global Value Chains (GVCs), in which a lead firm coordinates a geographically dispersed production process. The business literature abounds with examples, such as Apple's consumer electronics products (Xing, 2019). In the economics literature, attention has focused on two areas. On the one hand, Yi (2003) shows how the rise of production sharing modifies standard trade theories. Then on the empirical side, a number of contributions have focused on reconciling the rise of this production model with the interpretation of standard trade data, which are measured in gross shipments terms, and which therefore potentially both mischaracterize value added flows and double count movements of intermediates (Johnson and Noguera, 2012; Koopman et al., 2014; Wang et al., 2013).

At the same time, the policy literature (e.g., World Bank, 2020) has emphasized the need to go beyond tariffs in examining the full range of policies that determine the ability of firms to access world markets . With tariff rates at historically low levels in most countries, attention has increasingly shifted to non-tariff measures, i.e. other types of regulations that can influence prices or quantities of trade goods (De Melo and Nicita, 2018). Trade facilitation—interpreted as streamlining Customs and border procedures—fits within this framework (De Melo and Shepherd, 2018), although not within the narrower range of NTMs considered by the international MAST classification. Nonetheless, there is clear potential for trade facilitation to influence trade costs, and thereby affect the global pattern of trade and production. For instance, WTO (2015) estimates that full implementation of the WTO Trade Facilitation Agreement could generate as much as $3.6 trillion in additional exports globally.

As policy attention has shifted from tariffs to non-tariff measures, including trade facilitation, an empirical literature has developed using gravity models to assess the sensitivity of trade flows and trade costs to particular policies. Wilson et al. (2005) is an early example of the use of a gravity model to analyze trade facilitation. More recently, Saslavsky and Shepherd (2014) opened up the possibility that trade facilitation—measured in their case by the World Bank's Logistics Performance Index—might have different effects on trade in intermediates and final goods, which would imply a potential impact on incentives to engage in international production sharing through GVCs. They found evidence in line with that contention, although the identification of intermediate goods trade relied on an a priori classification that was necessarily approximate. More recently, Kumar and Shepherd (2019) used a structural gravity model combined with MRIO data to show that trade facilitation performance indeed has different effects on trade in final goods and intermediates, this time measured rigorously using intermediate and final demand from the MRIO database. They therefore showed that implementation of the WTO Trade Facilitation Agreement would increase the proportion of intermediates in total trade, which they interpreted as indicating an increase in GVC participation.

While establishing important results, the previous literature falls short of fully incorporating GVC participation in a rigorous modeling framework. The contributions referred to above use single sector gravity models of the Anderson and Van Wincoop (2003) or Eaton and Kortum (2002) variety, which means that they rigorously account for relative price effects, but do not allow for input-output relationships across sectors. Similarly, the approach of modeling intermediates and final goods as separate and unrelated "sectors" necessarily abstracts from the fact that demand for final goods influences demand for intermediates, and thus also the incentive to engage in GVC trade.

A more recent literature has extended the structural gravity framework to incorporate multiple sectors, in addition to multiple countries, with input-output relationships among them. A key contribution is Aichele and Heiland (2018), who extend the multi-sector Ricardian model of Caliendo and Parro (2015) to consider trade in value added in the sense of Koopman et al. (2014). As such, their model makes it possible to examine the consequences of a change in trade policy, captured through a change in iceberg trade costs, on production sharing across sectors and countries. They consider the case of China's WTO Accession, which includes both tariff cuts and changes in non-tariff measures. Using the iceberg assumption to approximate changes in the latter case makes it possible to answer the question of the degree to which China's membership of the WTO led to changes in the extent of GVC trade.

I adopt the Aichele and Heiland (2018) framework in this paper, to look at the related question of the extent to which improvements in trade facilitation over the 2015 to 2019 period resulted in changes in GVC trade. I modify their approach, however, by conceptualizing GVC trade in terms of the fully consistent Wang et al. (2013) decomposition rather than Koopman et al. (2014), as the latter breaks down at a disaggregated level, as Wang et al. (2013) show. Like Aichele and Heiland (2018), I focus on the part of changes in trade facilitation performance that can be assessed in terms of changes in iceberg trade costs by estimating a standard structural gravity model, which is nested within their more general multi-sector general equilibrium framework.[2] I then conduct a counterfactual based on a 2015 baseline, with a shock defined by actual changes in trade facilitation performance between 2015 and 2019 as captured by the OECD's Trade Facilitation Indicators. As a result, I can compare the model's predictions for GVC trade under the counterfactual with observed changes over the sample period, to obtain an indication of the extent to which changes in trade facilitation have caused changes in GVC trade over time. At a global level, the model accounts for over one-third of the total observed increase in GVC trade over the sample period.

Outside policy settings, the existing academic literature on trade facilitation is relatively limited.[3] Early contributions such as Wilson et al. (2005) use proxies that arguably have little to do with the core concept, and the models used do not typically control for unobservables or establish causal relationships. Djankov et al. (2008) use Doing Business data on trade facilitation outcomes—specifically, border crossing times—to show that they are an important determinant of bilateral exports. Although this result has proved influential, the use of outcome variables in a pure cross-country setting is subject to obvious endogeneity concerns, and Hillberry and Zhang (2018) show that outcome measures are in fact more closely associated with general measures of geography, income, and governance than policies specific to trade facilitation. Nonetheless, Volpe Martincus et al. (2015) demonstrate that the qualitative result holds in a more rigorous setting. They use transaction-level data and exploit the conditional random allocation of shipments to different Customs channels based on risk assessment to show that Customs delays negatively impact exports.

[2] This is a standard approach to capturing the effects of changes in non-tariff measures. Walmsley and Minor (2020) take a different approach in a computable general equilibrium (CGE) setting, but do not consider the flow-on effects to GVC trade.

[3] The policy literature on trade facilitation is reviewed in WTO (2015), which summarizes the estimated effects. In addition, Kumar and Shepherd (2019) use a structural gravity model with panel data to analyze the links between trade facilitation and trade in intermediates versus final goods. Their setup, however, does not account for input-output linkages across sectors, and does not fully decompose trade flows into their value added components.

The later literature has emphasized different measures of trade facilitation that more closely track policies rather than outcomes, such as the OECD Trade Facilitation Indicators (TFIs). Beverelli et al. (2015) show that higher performance on this measure is associated with a higher level of product variety in exports. Similarly, Fontagne et al. (2020) show that improvements in trade facilitation as measured by the TFIs have different impacts at a firm level across the size distribution. Finally, Walmsley and Minor (2020) use a CGE model to look at the impacts of implementing the WTO Trade Facilitation Agreement, but conceptualize trade facilitation as an increase in consumers' willingness to pay for imports. Their approach yields smaller GDP effects but larger trade effects than the more standard iceberg approach, but they do not examine the impact of policy changes on GVCs.

Following this literature, I use the OECD TFIs to measure trade facilitation performance. But I extend previous work by estimating the elasticity of trade flows with respect to facilitation performance in a panel data setting rather than a pure cross-country one. As such, I can incorporate current best practice in the use of structural gravity to identify the effects of policy changes, as embodied by Larch et al. (2019). I account for unobservables implied by theory, and also include country-pair fixed effects to control for pair-specific factors that influence bilateral trade. Identification is therefore based on variation over time in TFI scores. In addition, I show that the key policy parameter varies according to end use (final or intermediate), in line with Saslavsky and Shepherd (2014), and Kumar and Shepherd (2019). Further, I conduct simulations based on a model that is calibrated to the data, with only a small number of structural parameters and the trade facilitation elasticities estimated econometrically. Compared with other computational analyses of the impact of trade facilitation, mine has the benefit of focusing on the GVC dimension, and doing so in a parsimonious way that accords with current theory.

Against this background, the paper proceeds as follows. Section 2 presents some basic descriptive analysis supporting the contention that better trade facilitation performance is associated with increased GVC trade. The following section then develops the modeling framework in detail, and discusses data sources. Section 4 presents results, focusing first on structural gravity model estimates, and then on counterfactual simulations using the full general equilibrium framework. The final section concludes and discusses directions for future research.

2 Descriptive Analysis

Yi (2003) argues that an important part of world trade growth in the period of rapid integration of the 1990s and early 2000s was due to an increase in production sharing in goods sectors. However, quantifying this effect is challenging because standard trade data are recorded in gross shipments, not value added, terms. This practice obscures the value added origins of traded goods, and also results in substantial double counting of exports when goods cross borders multiple times during production.

Building on previous insights by Johnson and Noguera (2012) and Koopman et al. (2014), Wang et al. (2013; revised 2018) provide a rigorous methodology to decompose gross exports into their value added components. Their approach combines standard gross value trade data with information from input-output tables, as set out in detail in the Appendix. They distinguish three major aggregates: domestic value added (DVA) sourced in the exporting country; foreign value added (FVA) sourced in other countries; and pure double counting (PDC) resulting from the movement of intermediates across borders multiple times during production. GVC integration is indicated by two components of these aggregates. The proportion of FVA in gross exports is an indicator of backward linkages, that is use of imported intermediates to produce a country's exports. According to Wang et al. (2013), adding FVA and PDC gives an overall indicator of the extent of production sharing in trade; for policy purposes, this indicator shows the extent of GVC integration, and is typically expressed relative to gross exports. In this paper, I refer to the sum of FVA and PDC as "GVC trade" for this reason.

Figure 1 shows the extent of GVC trade based on a Wang et al. (2013) decomposition of gross exports of goods for the 63 countries (including an aggregate rest of the world) in the Asian Development Bank's Multi-Region Input-Output Table (MRIO). Results are aggregated over sectors to give a summary measure of goods market GVC integration at a world level over the 2000-2019 period.

There is a noticeable increase in GVC integration over the sample period. The sum of FVA and PDC was equal to 26.0% of gross exports in 2000, and had increased to 31.2% by 2019. The predominant form of GVC linkage in all periods is FVA, which captures backward linkages, i.e. the use of imported intermediates to produce a country's exports.

But the figure also shows that there are two distinct sub-periods. There is clear growth in the 2000-2008 period, followed by a sharp drop coinciding with the Global Financial Crisis (GFC). Although there is immediate recovery from 2010 onwards, the rate of growth in GVC integration in the post-GFC period is clearly slower than the pre-crisis trend would suggest. From 2009 to 2019, GVC integration grew at an average rate of 0.4 percentage points per year, compared with 0.5 percentage points per year between 2000 and 2008. In dollar terms, the value of GVC trade grew at a rate of 14.1% per year between 2000 and 2008, but slowed to a rate of 6.9% per annum between 2009 and 2019.

Figure 1: GVC integration as a percentage of gross exports of goods, 2000-2019.

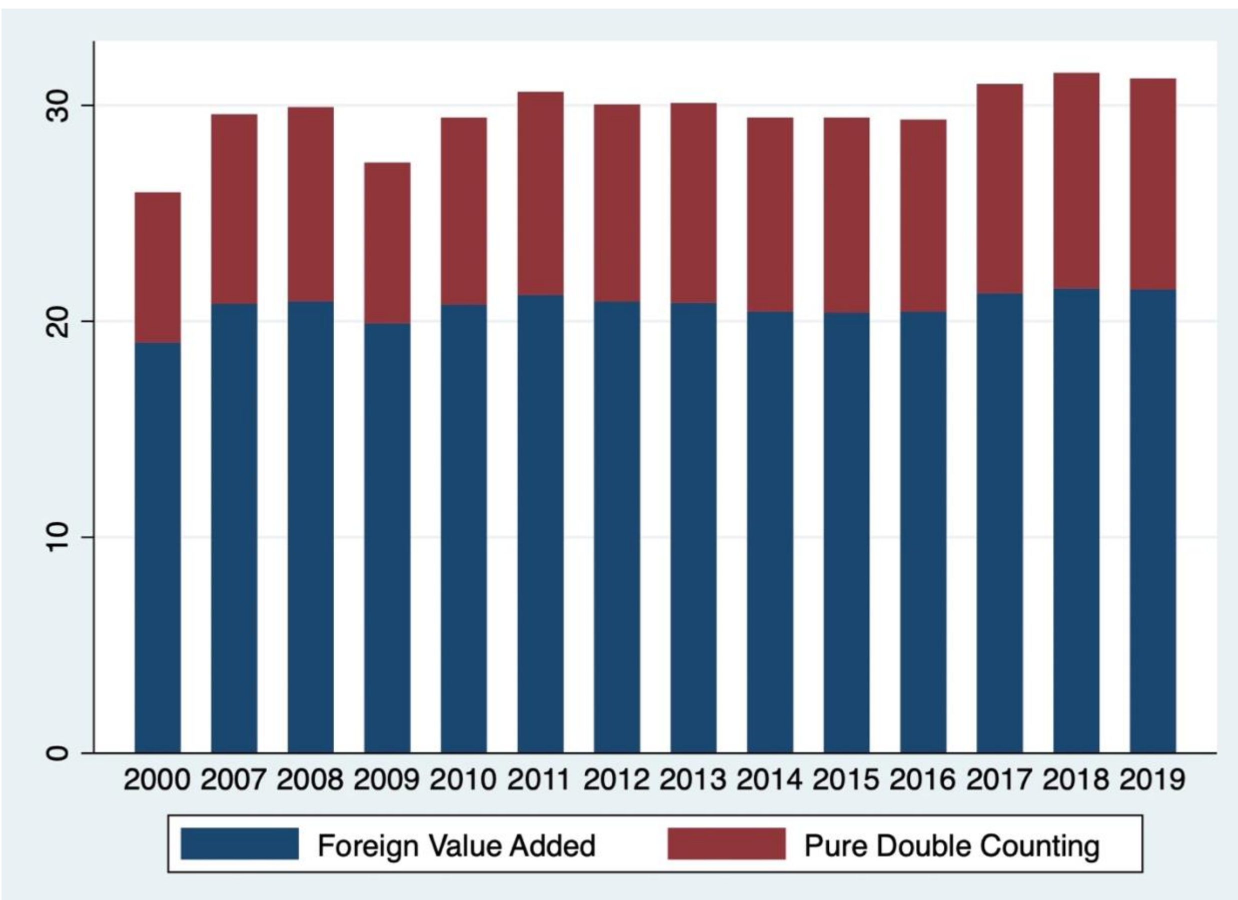
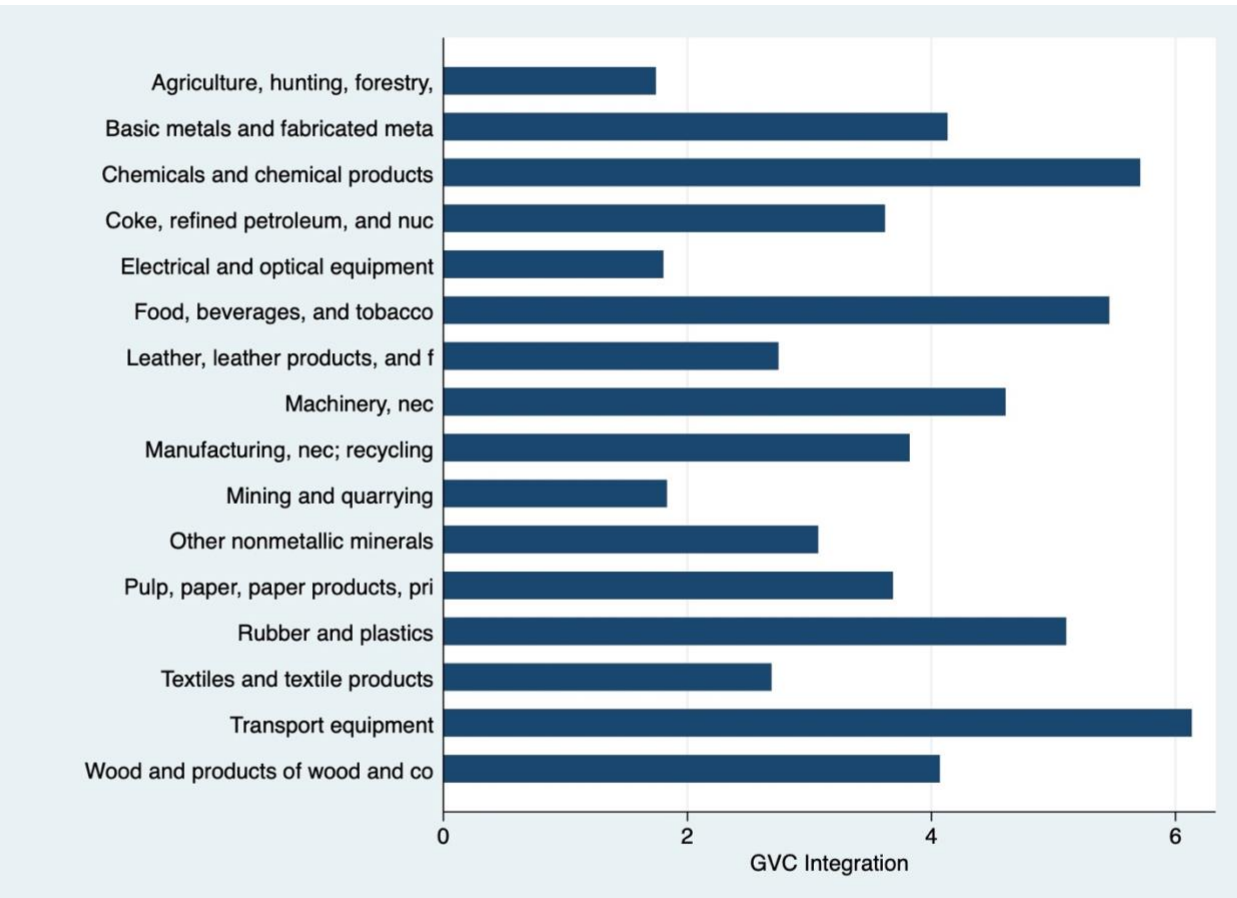


Figure 2 breaks out the data by sector, focusing on changes in total GVC integration (the sum of FVA and PDC relative to gross exports) in percentage point terms between 2009 and 2019. It shows that changes differ substantially at a sectoral level in terms of absolute changes in the indicator. On the one hand, transport equipment—a classic GVC sector—saw an increase in production sharing equal to six percentage points of gross exports over this ten year period. But mining and quarrying only saw an increase of under two percentage points during the same period. While all sectors saw an increase in GVC integration between 2009 and 2019, the extent of that change varies markedly. Sectoral characteristics are therefore very important in determining the way in which economic changes over time translate into different patterns of trade, taking account of input sourcing and end use. Any attempt to model changes in GVC linkages as a result of a change in trade policy would therefore need to pay due attention to these sectoral characteristics, to avoid homogenizing results across disparate sectors.

Figure 2: Changes in backward and forward GVC linkages, percentage points of gross exports, 2009-2019; by sector.



The drivers of increased GVC integration over the last two decades could be multiple. On the one hand, applied tariffs have been at historical lows in most countries. Similarly, regional integration has continued to progress: in 2000 only 7.2% of country pairs shared a regional trade agreement, but by 2019, that number had grown to 13.5% (Mario Larch's RTA Database from Egger and Larch, 2008; 2020 update).

The focus of this paper is on developing a general modeling framework that is well suited to understanding the policy drivers of GVC trade. As an example, I look at improvements in trade facilitation as one possible driver of GVC trade. Various data sources are available to track outcomes related to trade facilitation, such as border crossing times (e.g., Doing Business data as in Freund et al., 2008). However, there is an obvious endogeneity issue inherent in using such data in applied modeling. This paper therefore uses a measure of trade facilitation policies, namely the OECD Trade Facilitation Indicators (TFIs). The TFIs track country-level implementation of particular trade facilitation measures, focused on the operative provisions of the World Trade Organization Trade Facilitation Agreement (WTO TFA). Each measure is scored on a scale from zero (not implemented) to two (fully implemented). I aggregate by taking the simple average across the pillars used by OECD to summarize measures in individual areas, giving a score bounded between zero and two for each country-year combination. The data are available for 2012, 2015, 2017, and 2019.

Figure 3 shows changes in country-level average TFI scores between 2015 and 2019 (2012 is excluded because data coverage is only partial, which reduces sample size unduly). Nearly all countries have 2019 TFI scores that lie above the 45 degree line, which means that they have improved performance over time. In part, this effect is due to ongoing efforts to implement the WTO TFA. But there was an underlying trend towards improving border processes even before the Agreement entered into force. Most countries favor increased integration into the global trading economy, and see improved trade facilitation as one way of bringing that outcome about.

Figure 3: TFI 2019 vs. 2015; index number (0-2).

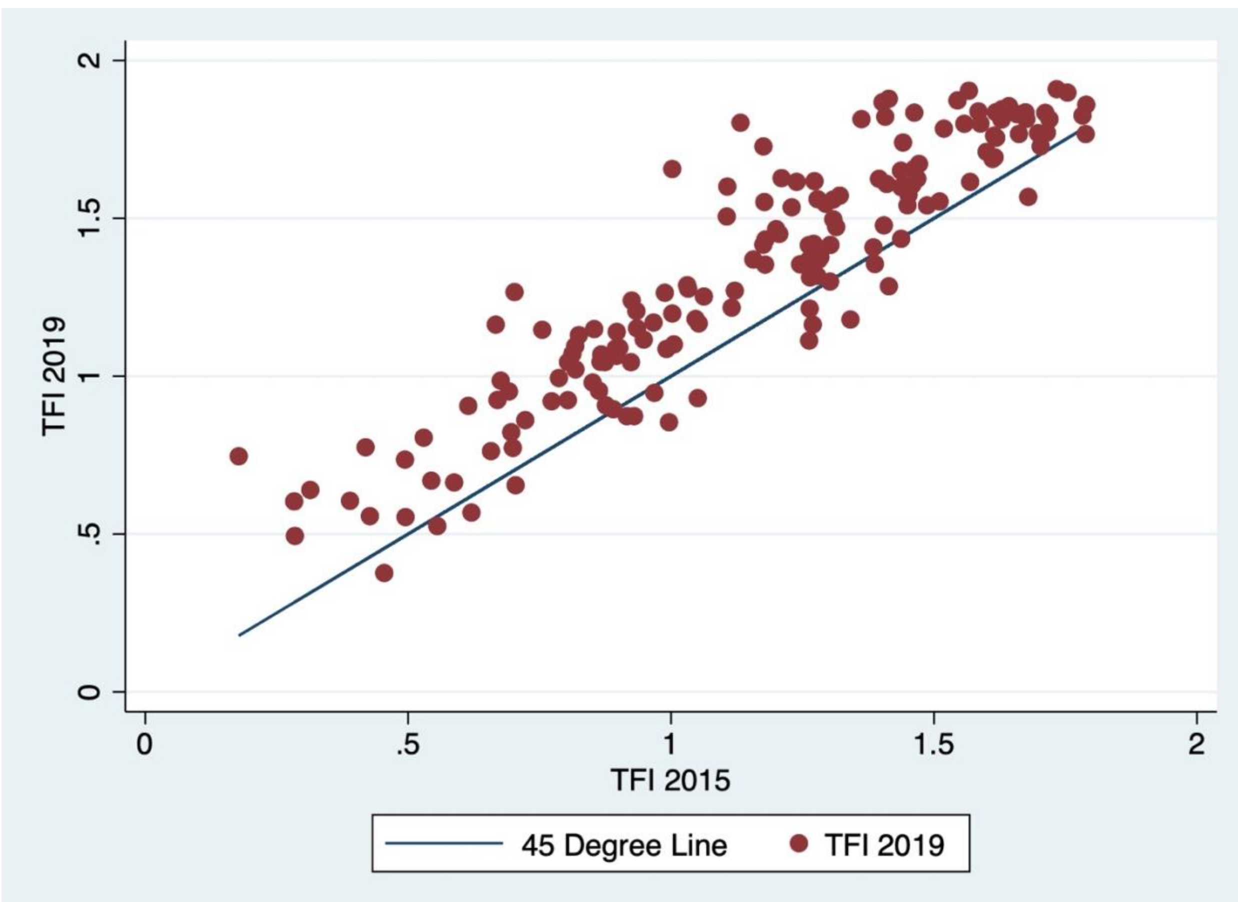
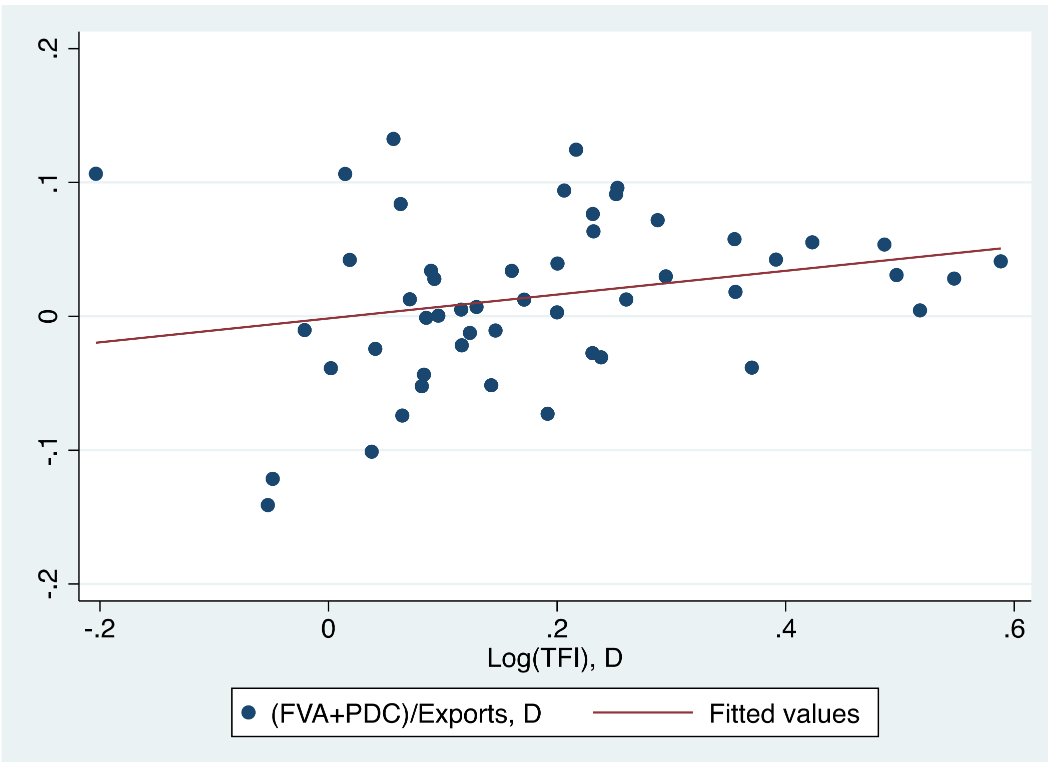


Figure 4 shows the correlation between observed changes in the proportion of GVC trade in gross exports and the relative change in TFI score between 2012 and 2019. There is a clear positive association (rho = 0.25), which provides some preliminary support for the contention that improving trade facilitation, as evidenced by an increase in TFI score, can increase the extent of GVC integration. The evidence is consistent with the econometric models of Saslavsky and Shepherd (2014), and Kumar and Shepherd (2019). Although it is impossible to make a causal claim at this stage—see further below for fully developed models—an initial look at the data suggests that it is plausible that one factor behind the observed increase in GVC integration is changes in trade facilitation policy.

Figure 4: Correlation between the change in production sharing as a proportion of gross exports, and the change in the log of country TFI scores, 2012-2019.



3 MODEL, DATA, AND PARAMETERS

As the discussion above made clear, Aichele and Heiland (2018) provide a general modeling framework that can map changes in iceberg trade costs to patterns of value added trade at a disaggregated level. This section explains in detail how the model works, focusing on intuition, as well as the differences between my model and theirs. Full technical details are in the Appendix.

The general approach falls into the family of "new quantitative trade models" (Ottaviano, 2015), in which trade is governed by a standard structural gravity model, but which also has a full general equilibrium structure with multiple countries, multiple sectors, and input-output relationships across sectors. While CGE models are extensively used in policy settings, new quantitative trade models like the one used here are increasingly finding application in the academic literature as testbeds for exploring policy-relevant questions. Examples include Caliendo and Parro (2015), who examine the trade and welfare impacts of NAFTA, Dhingra et al. (2017) who look at the effect of the UK's exit from the European Union, and Aichele and Heiland (2018) who consider the GVC integration impacts of China's WTO Accession. The key advantage of this class of models over traditional CGE approaches is "a tighter connection between theory and data thanks to more appealing microtheoretical foundations and careful estimation of the structural parameters necessary for counterfactual analysis" (Ottaviano, 2015). In addition, they can work with publicly available data in the form of MRIOs, and are not reliant on proprietary data or specialized software, which in turn aids transparency and replicability. From the standpoint of trade facilitation, a key difference between this paper and Walmsley and Minor (2020) is that my framework is completely consistent with standard trade theory and relies on a small number of precisely-estimated parameters, rather than the thousands of parameters used in standard CGE models. In addition, the use of changes in iceberg trade costs to drive changes in trade flows accords better with the academic literature than a shock to consumer willingness to pay for imports.

The model used in this paper includes multiple countries and multiple sectors. On the consumption side, representative consumers in each country consume the final output of each sector under Cobb Douglas preferences with fixed expenditure shares.

The production side nests the Ricardian model of Eaton and Kortum (2002) in a multi-sector input-output framework. Intermediate goods producers in each sector use labor and a composite intermediate good from all sectors as inputs. They transform inputs into output using constant returns to scale technology and under perfect competition. But countries differ in their underlying level of Ricardian productivity, which determines the technology parameters of intermediate goods production. Production of the composite intermediate—which is incorporated in intermediate goods themselves and also in final goods—uses constant elasticity of substitution technology across a set of intermediate varieties sourced from the lowest cost supplier. Assuming a particular statistical distribution for Ricardian productivity (Fréchet) makes it possible to pin down this input sourcing arrangement for given parameters.

Producers in each country can, in principle, ship their output to any or all of the other countries, as well as domestically to their own country. On each route, including domestically, shipments are subject to iceberg trade costs, composed of tariff and non-tariff components. Following Aichele and Heiland (2018), trade costs vary by end-use, so intermediate shipments can be subject to different trade costs from final goods shipments.

The above set up yields an expression for bilateral trade (including internal shipments) that follows the standard structural gravity framework. Collecting terms gives bilateral trade for an exporter-importer-sector triple in terms of exporter-sector and importer-sector fixed effects, and bilateral trade costs. As in standard structural gravity models, there is a single trade elasticity that governs the sensitivity of bilateral trade to changes in trade costs. The model takes the following form (using equation numbering from the Appendix):

$$(10)\ \pi_{ni}^{jv} = \frac{X_{ni}^{jv}}{X_n^{jv}} = \frac{\lambda_i^j \left[c_i^j \kappa_{ni}^{jv}\right]^{-\theta^j}}{\sum_{h=1}^{N} \lambda_h^j \left[c_h^j \kappa_{nh}^{jv}\right]^{-\theta^j}} = d_i^j d_n^j \kappa_{ni}^{jv^{-\theta^j}}$$

Where: π_{ni}^{jv} is the import share for country n from country i in sector j by end-use v; λ_i^j and θ^j are parameters of the Fréchet distribution; c_i^j is the cost of an input bundle; κ_{ni}^{jv} is iceberg trade costs; d_i^j are exporter-sector fixed effects; and d_n^j are importer-sector fixed effects. As equation (10) makes clear, it is possible to estimate the gravity model consistently while only directly observing trade costs and the trade elasticity.

Standard adding up constraints, with an exogenous trade deficit, close the model. Goods markets clear, and expenditure is set equal to output. National income is then the sum of labor income, rebated tariff income, and the exogenous trade deficit.

From a policy perspective, it is important to examine how the model can be used to look at changes in key economic variables following a shock to trade policies, as captured by iceberg trade costs. Using the exact hat algebra approach of Dekle et al. (2007) makes it possible to specify a shock in terms of a proportional change in iceberg trade costs, and to map it to changes in trade flows through changes in the costs of inputs and final goods prices in consumption, while respecting general equilibrium constraints. The counterfactual solution respects the technological parameters of sectoral input-output relationships, as well as underlying Ricardian technology in the economy. The counterfactual solution yields changes in exports and imports, which can then be used to construct changes in real national income as an indicator of welfare changes. Provided that a policy change can be expressed in terms of a proportional change in iceberg trade costs, the model provides a very flexible framework for understanding its economic implications. Of course, counterfactual simulations are ceteris paribus: the assumption is that there is a proportional change in trade costs, but that no other parameters change. In other words, there are no exogenous shocks to technology or preferences, nor are their exogenous shocks to income.

Building on Aichele and Heiland (2018), it is also possible to take the counterfactual solution methodology a step further. It can be manipulated to yield a full counterfactual input-output table, in addition to the observed one for the baseline. Given that the model has input-output data and trade flows, it is straightforward to use it to produce baseline and counterfactual changes in GVC integration using the Wang et al. (2013) approach discussed above. In other words, it is possible to map a shock to iceberg trade costs not only to standard economic aggregates like trade flows and national income, but also to the proportion of those trade flows that is made up of FVA and PDC, or GVC trade (see discussion above).

To produce this rich set of outputs—with GVC integration an added dimension that is not considered in standard CGE models, nor by Walmsley and Minor (2017)—the model only needs a as inputs a MRIO, estimates of the sectoral trade elasticities, and a vector of shocks to trade costs for intermediate and final goods. This paper uses the ADB MRIO that was already analyzed in the previous section. As an example, the shock to trade costs comes from improvements in trade facilitation, to show kind of policy change that can motivate the model's results. To estimate the structural gravity model that gives the elasticity of trade costs with respect to trade facilitation, the years 2012, 2015, 2017, and 2019 are included (all years for which trade facilitation data are available). For counterfactual simulation, the base year is 2015, with the objective of analyzing counterfactual and observed changes in GVC integration between 2015 and 2019. The ADB data cover 63 countries, including all of the major trading economies, as well as a variety of smaller countries, largely in Asia, along with an aggregate "rest of the world" region (Table 1) The same source also covers 16 goods sectors and 19 services sectors (Table 2).

Table 1: List of countries included in the ADB MRIO.

ISO Code	Country Name
AUS	Australia
AUT	Austria
BEL	Belgium
BGD	Bangladesh
BGR	Bulgaria
BRA	Brazil
BRN	Brunei Darussalam
BTN	Bhutan
CAN	Canada
CHE	Switzerland
CHN	People's Republic of China
CYP	Cyprus
CZE	Czech Republic
DEU	Germany
DNK	Denmark
ESP	Spain
EST	Estonia
FIN	Finland
FJI	Fiji
FRA	France
GBR	United Kingdom
GRC	Greece
HKG	Hong Kong, China
HRV	Croatia
HUN	Hungary
IDN	Indonesia
IND	India
IRL	Ireland
ITA	Italy
JPN	Japan
KAZ	Kazakhstan
KGZ	Kyrgyz Republic
KHM	Cambodia
KOR	Republic of Korea
LAO	Lao People's Democratic Republic
LKA	Sri Lanka
LTU	Lithuania
LUX	Luxembourg
LVA	Latvia
MDV	Maldives
MEX	Mexico
MLT	Malta
MNG	Mongolia
MYS	Malaysia
NLD	Netherlands

NOR	Norway
NPL	Nepal
PAK	Pakistan
PHL	Philippines
POL	Poland
PRT	Portugal
ROM	Romania
ROW	Rest of the World
RUS	Russia
SGP	Singapore
SVK	Slovak Republic
SVN	Slovenia
SWE	Sweden
THA	Thailand
TUR	Turkey
TWN	Taipei, China
USA	United States
VNM	Viet Nam

Table 2: List of sectors included in the ADB MRIO.

Sector
Agriculture, hunting, forestry, and fishing
Mining and quarrying
Food, beverages, and tobacco
Textiles and textile products
Leather, leather products, and footwear
Wood and products of wood and cork
Pulp, paper, paper products, printing, and publishing
Coke, refined petroleum, and nuclear fuel
Chemicals and chemical products
Rubber and plastics
Other nonmetallic minerals
Basic metals and fabricated metal
Machinery, nec
Electrical and optical equipment
Transport equipment
Manufacturing, nec; recycling
Electricity, gas, and water supply
Construction
Sale, maintenance, and repair of motor vehicles and motorcycles; retail sale of fuel
Wholesale trade and commission trade, except of motor vehicles and motorcycles
Retail trade, except of motor vehicles and motorcycles; repair of household goods
Hotels and restaurants
Inland transport
Water transport
Air transport
Other supporting and auxiliary transport activities; activities of travel agencies
Post and telecommunications
Financial intermediation
Real estate activities
Renting of M&Eq and other business activities
Public administration and defense; compulsory social security
Education
Health and social work
Other community, social, and personal services
Private households with employed persons

Estimates of the sectoral trade elasticities come from Egger et al. (2018). Although those authors work with a different data source (the World Input-Output Database), the sectoral aggregation is identical to that used by the ADB MRIO, so their estimates can be used directly without modification. Their approach uses the same general modeling framework as in this paper, so there is no issue of correspondence between estimated and theoretical parameters: they use structural relationships to identify the trade elasticities.

The other key input is a vector of proportional changes in iceberg trade costs. As noted above, trade costs consist of two components: tariffs, and non-tariff measures. Tariffs do not vary in the counterfactual, but data are still required to compute tariff revenues. They are sourced from UNCTAD's TRAINS database, accessed through the World Bank's WITS server. The base year is 2015, and tariffs are based on effectively applied rates that take full account of preferential tariffs.

The OECD TFIs measure trade facilitation performance, but do not map it to iceberg trade costs. To create that mapping, this paper uses the structural gravity model in (10) with a trade costs function specified as follows:

$$(23)\ \log(\kappa_{nit}^{jv}) = \varphi_{ni}^{jv} * t + \rho^{jv}\log(TFI_{nt}) * intl_{ni}$$

The first term is a country-pair dummy interacted with a time trend, following Larch et al. (2019). This approach eliminates all variation by country pair, so that identification needs to be based on time variation within country pairs. The second term is the variable of interest, namely the importing country's average TFI score, as used in the descriptive analysis in the previous section. Following Heid et al. (2021), the TFI score is interacted with a dummy for observations where the exporter and the importer are different countries, which bases identification on observed differences between intra-national and international trade flows, since both are included in the MRIO. Modeling the TFIs as influencing iceberg trade costs is standard in the literature (e.g., Kumar and Shepherd, 2019). I leave to one side the issue of whether the range of costs affected by trade facilitation is broader, potentially including per unit shipping costs (Hummels and Skiba, 2004). The literature does not yet include a fully-specified general equilibrium approach within the family of "new quantitative trade models" that includes per unit shipping costs. But conceptual work by Sorensen (2014) shows that moving to an assumption of per unit shipping costs tends to magnify the gains from trade, so the results in this paper can be considered as a lower bound.

Substituting equation (23) into equation (10) gives a fully-specified structural gravity model that can be taken directly to the data. The next section discusses estimation and results. Table 3 presents summary statistics for the gravity model dataset, while Table 4 presents a correlation matrix of the key variables.

Table 3: Summary statistics, structural gravity dataset, full sample (all sectors pooled).

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Exports (Final)	233,120	252.088	6478.729	0.000	760647.800
Exports (Intermediate)	233,120	594.389	18663.660	0.000	2635580.000
Exports (Total)	233,120	846.477	22997.590	0.000	2682813.000
TFI	233,120	1.502	0.273	0.676	1.909
Intl	233,120	0.984	0.125	0.000	1.000

Table 4: Correlation matrix, structural gravity dataset, full sample (all sectors pooled).

	Exports (Final)	Exports (Intermediate)	Exports (Total)	TFI	Intl
Exports (Final)	1.000				
Exports (Intermediate)	0.573	1.000			

Exports (Total)	0.747	0.973	1.000		
TFI	0.014	0.009	0.011	1.000	
Intl	-0.220	-0.206	-0.229	0.000	1.000

4 RESULTS AND INTERPRETATION

The analysis proceeds in two steps. First, structural gravity models make it possible to obtain an estimate of the elasticity of bilateral trade flows with respect to trade facilitation performance, in a similar way as in most past work on trade facilitation such as WTO (2015), Wilson et al. (2005), and Kumar and Shepherd (2019). With that elasticity, it is straightforward to calculate ad valorem equivalents (AVE) for trade facilitation performance, assuming an iceberg form, under the baseline and counterfactual states. Second, the output from the first stage is used to shock the quantitative trade model, with the objective of recovering counterfactual values for economic aggregates including GVC integration.

4.1 Structural Gravity Models

As noted above, equations (10) and (23) define a standard structural gravity model, where iceberg trade costs are specified as a function of trade facilitation performance and country pair fixed effects that absorb standard gravity variables that do not change over time, such as distance and common geographical and historical features. This approach necessarily assumes that trade facilitation performance translates, at least in part, into changes in iceberg trade costs. Alternative formulations, such as specification of trade costs in per unit terms (Hummels and Skiba, 2004), are left for future work. The iceberg assumption is standard in trade policy modeling, and has been previously in work looking at trade facilitation (e.g., Kumar and Shepherd, 2019; WTO, 2015; Freund et al., 2008).

As is standard, estimation of the structural gravity model is by Poisson Pseudo-Maximum Likelihood (PPML). As Santos Silva and Tenreyro (2006) show, PPML provides consistent estimates under weak assumptions—all that is required is correct specification of the conditional mean—is robust to heteroskedasticity that causes biased coefficient estimates with OLS, and naturally includes observations where exports are equal to zero. Correia et al. (2019) provide a version of the estimator that incorporates high dimensional fixed effects, so it is computationally straightforward to apply in the context of the dataset used here. Given that PPML is a pseudo-maximum likelihood estimator, it does not assume that the dependent variable in fact follows a Poisson distribution at all, and is fully robust to misspecification provided that the conditional mean is correctly specified.

As discussed above, one innovative feature of the model in this paper is that it allows for trade costs to vary by end-use; that is, trade costs can differ between intermediate and final production. From an empirical perspective, this flexibility immediately suggests estimating the model separately for trade in intermediates and trade in final goods, then comparing the results with more standard specifications using total trade (i.e., summed over end-use). Computing intermediate and final goods trade is straightforward from the MRIO. Each model is estimated by sector, so at its most flexible, this approach allows trade facilitation performance to have different trade impacts at a sectoral level for intermediate and final production.

To provide a baseline, Table 5 first provides standard structural gravity estimates by sector for total trade (summing over end uses). Given that trade facilitation only affects goods sectors, services are dropped from the estimation sample. The importing country's TFI score has a positive and statistically significant coefficient in all sectors except mining, which shows that improving trade facilitation can increase bilateral exports in a general sense. Magnitudes vary substantially from sector to sector, being highest in transport equipment and lowest in metals, along with a zero effect for mining. Given that the estimated parameter is the product of the trade cost elasticity of trade facilitation and the trade elasticity, this difference in magnitudes is due potentially to differences in either factor.

Table 5: Structural gravity model estimates, total exports by sector.

	Agriculture, hunting, forestry, and fishing	Mining and quarrying	Food, beverages, and tobacco	Textiles and textile products
Log(TFI)*Intl	0.693 ***	0.244	0.917 ***	1.095 ***
	(0.106)	(0.311)	(0.264)	(0.237)
Obs.	13611	12046	13828	13901
Pseudo-R2	1.000	0.999	0.999	0.999
	Leather, leather products, and footwear	**Wood and products of wood and cork**	**Pulp, paper, paper products, printing, and publishing**	**Coke, refined petroleum, and nuclear fuel**
Log(TFI)*Intl	1.107 ***	0.850 ***	0.837 ***	0.863 **
	(0.268)	(0.101)	(0.139)	(0.352)
Obs.	12407	13066	13596	11940
Pseudo-R2	0.998	0.999	0.999	0.999
	Chemicals and chemical products	**Rubber and plastics**	**Other nonmetallic minerals**	**Basic metals and fabricated metal**
Log(TFI)*Intl	0.965 ***	0.906 ***	0.826 ***	0.433 **
	(0.196)	(0.187)	(0.155)	(0.169)
Obs.	13533	13345	13290	13562
Pseudo-R2	0.999	0.999	0.999	0.999
	Machinery, nec	**Electrical and optical equipment**	**Transport equipment**	**Manufacturing, nec; recycling**
Log(TFI)*Intl	0.852 ***	0.624 **	1.172 ***	1.167 ***
	(0.192)	(0.262)	(0.177)	(0.133)
Obs.	13547	13185	13648	13989

Pseudo-R2	0.999	0.999	0.999	0.998

Note: Dependent variable is exports by sector in all cases. Estimation is by PPML. All models include fixed effects by exporter-year, importer-year, and country pair interacted with a time trend. Standard errors corrected for two-way clustering by country pair and by year are beneath parameter estimates. Statistical significance is as follows: * (10%), ** (5%), and *** (1%).

Thus far, results are in line with previous work, such as Kumar and Shepherd (2019). But an additional contribution of this paper is to examine whether or not the impact of trade facilitation differs systematically depending on whether trade is in intermediates or final goods. The following tables therefore re-estimate the models by sector but taking each end-use separately.

Results for intermediates are in Table 6. The importing country's TFI score has a positive and statistically significant coefficient in all sectors except mining, as in the baseline specification for total trade. In wood products, paper products, machinery, and electrical equipment, the estimated elasticity is higher for intermediates than for total trade, which means that trade flows are more sensitive to improvements in trade facilitation than the estimates in Table 5 would suggest. However, the differences are small in quantitative terms, as is the case for the remaining sectors.

Results for final goods are in Table 7. There are notable differences with Table 5. In addition to mining, electrical equipment and rubber and plastics see no statistically significant impact of trade facilitation on bilateral trade. But 10 of the remaining sectors have coefficients that are larger than those in Table 5, sometimes to an extent that is quantitatively important. Taking results in the three tables together, it is clear that there is some evidence that although improving trade facilitation generally tends to promote bilateral trade, the extent differs somewhat depending on end-use, and significantly by sector. It is therefore important to take account of these differences in policy work.

Table 6: Structural gravity model estimates, exports of intermediates by sector.

	Agriculture, hunting, forestry, and fishing	**Mining and quarrying**	**Food, beverages, and tobacco**	**Textiles and textile products**
Log(TFI)*Intl	0.382 ***	0.422	0.500 ***	0.808 ***
	(0.079)	(0.354)	(0.179)	(0.209)
Obs.	13354	11796	13512	13608
Pseudo-R2	0.999	0.998	0.999	0.999
	Leather, leather products, and footwear	**Wood and products of wood and cork**	**Pulp, paper, paper products, printing, and publishing**	**Coke, refined petroleum, and nuclear fuel**
Log(TFI)*Intl	0.872 ***	0.913 ***	0.869 ***	0.796 **
	(0.173)	(0.121)	(0.172)	(0.381)
Obs.	12276	12833	13364	11734
Pseudo-R2	0.998	0.999	0.999	0.999
	Chemicals and chemical products	**Rubber and plastics**	**Other nonmetallic minerals**	**Basic metals and fabricated metal**
Log(TFI)*Intl	0.876 ***	0.868 ***	0.804 ***	0.419 **
	(0.222)	(0.153)	(0.145)	(0.174)
Obs.	13367	13222	13120	13385
Pseudo-R2	0.999	0.999	0.999	0.999
	Machinery, nec	**Electrical and optical equipment**	**Transport equipment**	**Manufacturing, nec; recycling**
Log(TFI)*Intl	0.933 ***	0.857 ***	1.034 ***	0.994 ***
	(0.204)	(0.305)	(0.190)	(0.179)
Obs.	13386	12915	13261	13719

Pseudo-R2	0.999	0.999	0.999	0.997

Note: Dependent variable is exports of intermediates by sector in all cases. Estimation is by PPML. All models include fixed effects by exporter-year, importer-year, and country pair interacted with a time trend. Standard errors corrected for two-way clustering by country pair and by year are beneath parameter estimates. Statistical significance is as follows: * (10%), ** (5%), and *** (1%).

Table 7: Structural gravity model estimates, exports of final goods by sector.

	Agriculture, hunting, forestry, and fishing	Mining and quarrying	Food, beverages, and tobacco	Textiles and textile products
Log(TFI)*Intl	1.085 ***	0.061	1.090 ***	1.384 ***
	(0.309)	(1.154)	(0.327)	(0.495)
Obs.	13498.000	11689.000	13752.000	13814.000
Pseudo-R2	0.999	0.998	0.999	0.997

	Leather, leather products, and footwear	Wood and products of wood and cork	Pulp, paper, paper products, printing, and publishing	Coke, refined petroleum, and nuclear fuel
Log(TFI)*Intl	1.549 ***	1.349 ***	1.077 ***	0.629 **
	(0.505)	(0.483)	(0.307)	(0.267)
Obs.	12266.000	12838.000	13520.000	11734.000
Pseudo-R2	0.995	0.993	0.998	0.997

	Chemicals and chemical products	Rubber and plastics	Other nonmetallic minerals	Basic metals and fabricated metal
Log(TFI)*Intl	1.385 ***	1.140	1.396 **	0.608 **
	(0.351)	(0.752)	(0.648)	(0.256)
Obs.	13430.000	13259.000	13190.000	13477.000
Pseudo-R2	0.996	0.991	0.991	0.995

	Machinery, nec	Electrical and optical equipment	Transport equipment	Manufacturing, nec; recycling
Log(TFI)*Intl	0.732 ***	0.430	1.169 ***	1.310 ***
	(0.254)	(0.283)	(0.200)	(0.173)
Obs.	13471.000	13123.000	13571.000	13906.000

Pseudo-R2	0.997	0.997	0.998	0.995

Note: Dependent variable is exports of final goods by sector in all cases. Estimation is by PPML. All models include fixed effects by exporter-year, importer-year, and country pair interacted with a time trend. Standard errors corrected for two-way clustering by country pair and by year are beneath parameter estimates. Statistical significance is as follows: * (10%), ** (5%), and *** (1%).

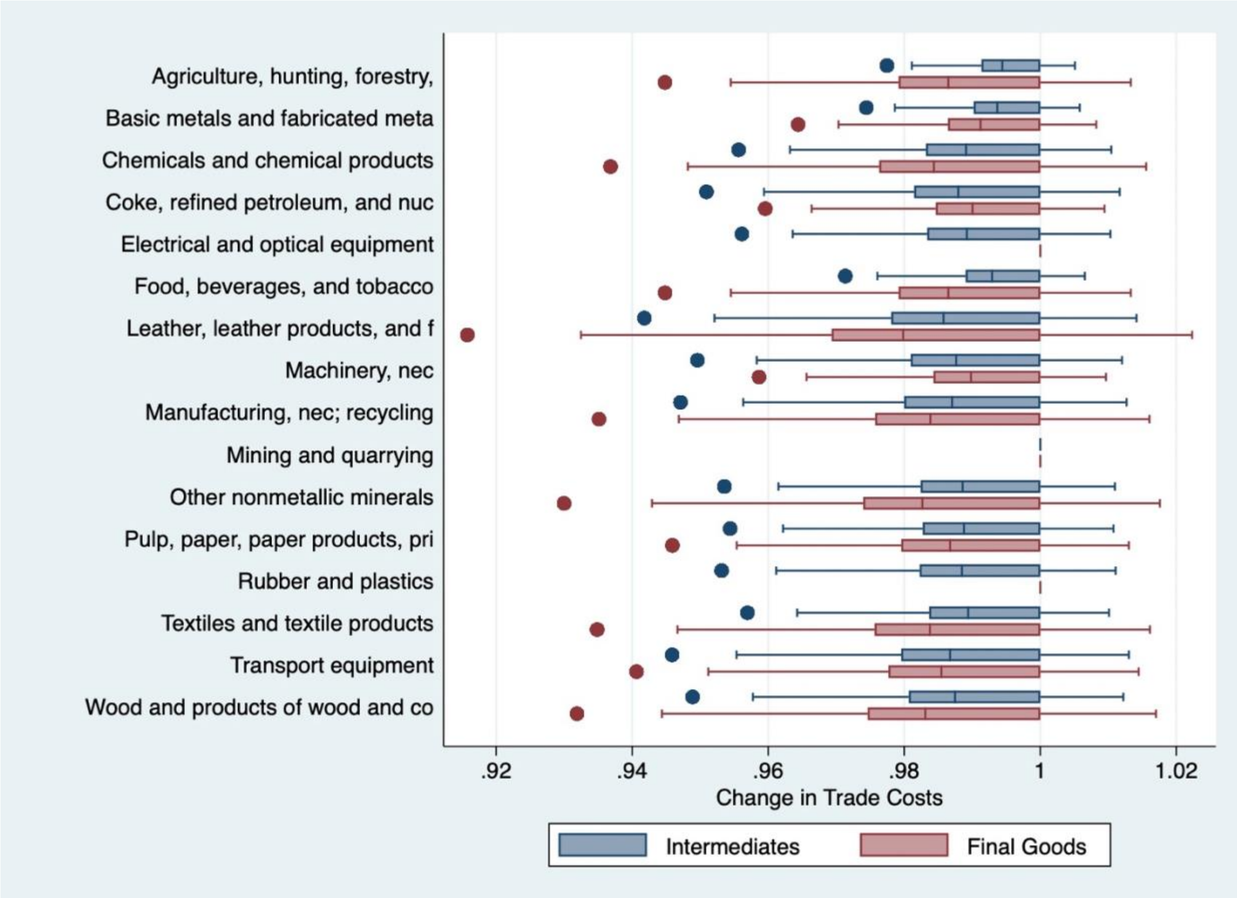
Taking estimates from Tables 6 and 7, it is straightforward to compute changes in iceberg trade costs between 2015 and 2019 (primed) due to observed improvements in trade facilitation:

$$(24)\ \hat{\kappa}_{ni}^{jv} \equiv \frac{\kappa_{ni}^{jv'}}{\kappa_{ni}^{jv}} = \frac{1 + \exp\left(\rho^{jv} \log TFI_n{}'\right)}{1 + \exp(\rho^{jv} * \log TFI_n)}$$

While the notation in equation (24) indicates that iceberg trade costs vary by country pair, in fact the form of the gravity model means that other than for internal trade, the effect is constant across exporters for a given importer. It is therefore possible to summarize results by looking at the distribution of country-level changes within a sector, excluding internal trade (where there is, by assumption, no effect).

Figure 5 takes this approach using standard box plots by sector. While there is a considerable amount of dispersion in trade cost changes within and across sectors, the magnitudes are relatively modest: typically a few percent only, only more than eight percent in one case. Average reductions within sectors are always less than two percent, though as the figure shows, there is considerable dispersion due to different country-level patterns of policy changes. Only three sectors show average reductions in trade costs that are larger for intermediates than for final goods, which is of interest because the difference between the two could potentially impact production sharing. Of course, even if trade costs only fall in final goods trade and not at all in intermediates, there will still be a derived demand effect on trade in intermediates due to input use. But the figure does not immediately suggest that the changes in trade costs are so skewed towards intermediates that they would tend to significantly shift the pattern of trade in favor of GVC integration. Of course, the extent to which that takes place is an empirical question that can only be answered by the solving the structural model.

Figure 5: Changes in iceberg trade costs due to improvements in trade facilitation, 2015-2019; relative change.



4.2 Counterfactual Simulations

This section reports results from a full counterfactual simulation of the model, using the solution technique set out in the Appendix. The trade costs shocks come from the data summarized in Figure 5, with no shocks in services sectors.[4] The baseline for the simulation is 2015, so the counterfactual shows how trade patterns and GVC trade would have changed if trade facilitation performance in that year had been changed to equal the observed level in 2019, and all other factors had remained constant. Comparing counterfactual values with observed changes in key variables between 2015 and 2019 gives an idea of the extent to which changes in trade facilitation policies contributed to observed changes.

Examining the impact on total world exports shows an increase in the counterfactual equal to 40.9% of the observed increase in world exports between 2015 and 2019. This result means two things. First, the model reproduces relatively well this large scale change in the world economy over a four-year period. Second, changes in iceberg trade costs brought about by trade facilitation policies clearly played an important role in driving export growth during this period.

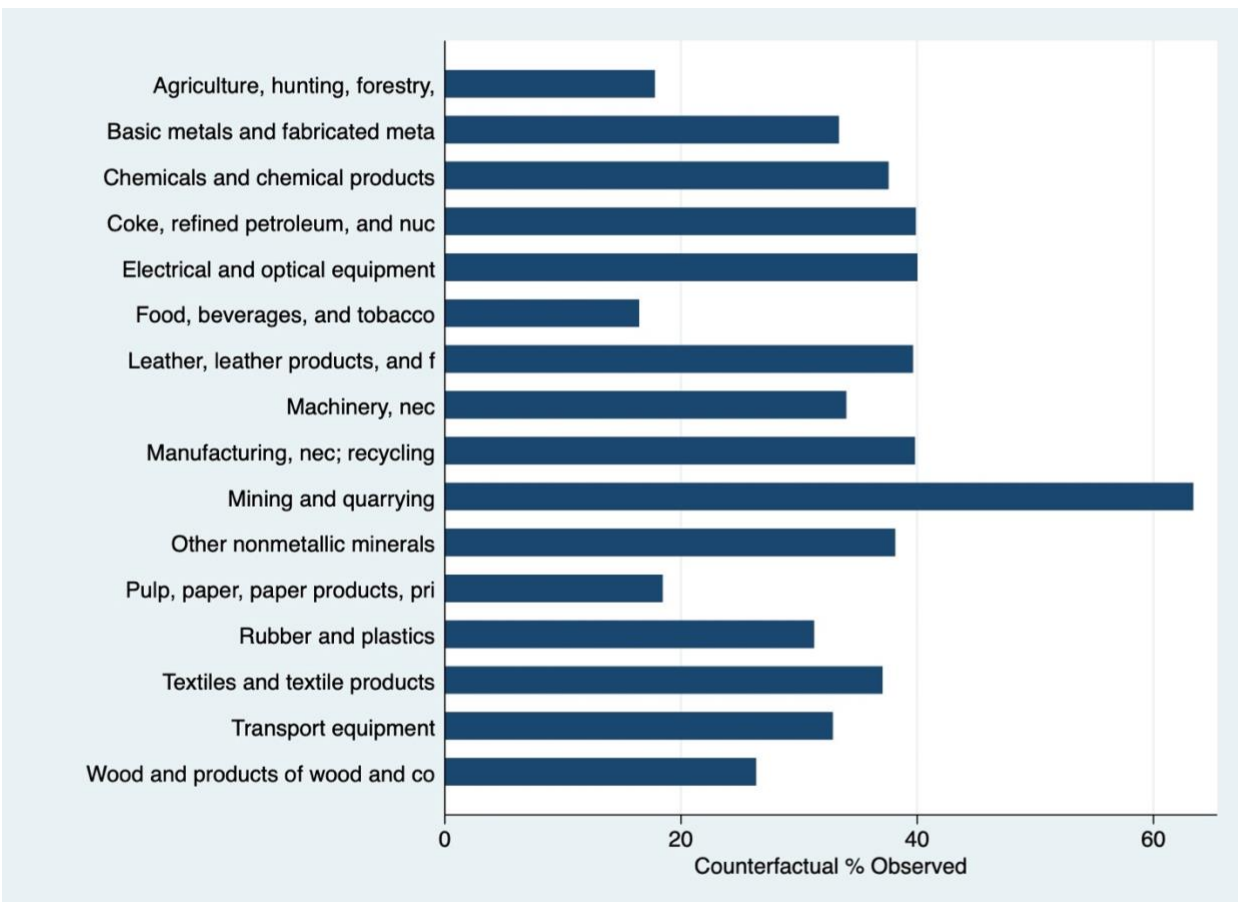
Turning to GVC integration at the world level, simulation results show that growth in GVC trade in the counterfactual is equal to 34.1% of the observed increase in this type of trade during the 2015 to 2019 time period. Again, the model accounts for a significant proportion of observed changes,

[4] Three countries have data in the ADB MRIO but not in the TFIs. Their TFIs are set equal to the world average in both the baseline and counterfactual.

although less than in the case of total trade. But in terms of the proportion of GVC trade in total trade, the counterfactual only accounts for 9.3% of the observed increase. Quantitatively, the increase in GVC integration in the counterfactual is relatively modest, equating to just under half a year's worth of additional integration at the average rate seen between 2009 and 2019. Nonetheless, the model is able to shed some light on the determinants of increasing GVC integration over that time at an aggregate level, and highlights trade facilitation policies as one quantitatively significant factor, albeit in an environment where there were clearly also other factors that were changing at the same time.

Figure 6 breaks results at the world level out by sector. It shows the percentage of the observed change in GVC exports between 2015 and 2019 that is accounted for by the difference between the 2015 baseline and the counterfactual. As is clear, the model has considerable explanatory power for GVC trade, ranging from 17.8% for agriculture to 63.4% for mining, with an average of 34.1%. For typical GVC sectors, results are relatively strong: 40.0% for electrical equipment, 32.9% for transport equipment, and 37.1% for textiles and apparel.

Figure 6: Counterfactual change in GVC trade as a percentage of observed change in GVC trade 2015-2019.

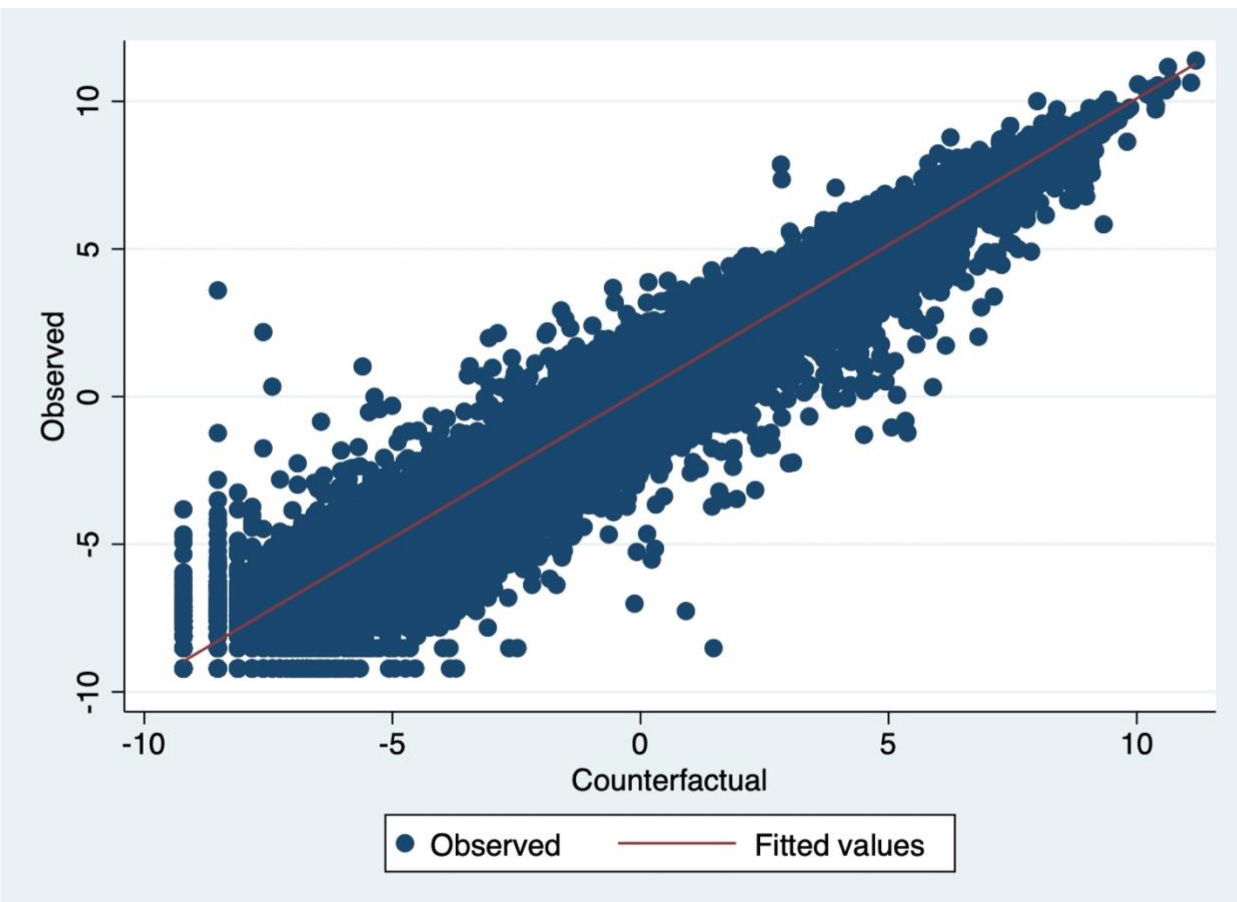


As with the aggregate results, the counterfactual captures a substantial part of the increase in GVC trade, but the ratio of that trade to total exports appears to be subject to a range of other factors. For eight of the 16 goods sectors, the counterfactual shows the same direction of change in terms of the proportion of exports integrated in GVCs as the difference between 2019 and 2015 in the observed data. For those sectors, the model accounts for 13.4% of the change in the ratio of GVC trade to total exports over the sample period. So the model captures an important part of the overall dynamics at play, but also leaves room for the operation of other factors.

At the country level, counterfactual values match the direction of change of observed GVC trade between 2015 and 2019 in 53 of 63 cases. The exceptions are mostly small countries for which there are obvious data concerns, although Canada and South Korea are also in this group. On average, countries saw an increase of 37% in GVC trade between 2015 and 2019; the counterfactual average change is 8%. So the pattern of results at the country level confirms the analysis at the aggregate and sectoral levels, namely that trade facilitation is a significant factor in explaining observed increases in GVC trade, but there are also many other factors at play.

The most disaggregated level at which the model produces results is exporter-importer-sector triples. Some trade values are very small, and so need to be dropped in order to make a meaningful comparison between the observed level of GVC trade in 2019, and the counterfactual level predicted by the model. Figure 7 shows results from this exercise. There is a strong positive correlation (rho = 0.99) between the two series, albeit with considerable dispersion. So at a disaggregated level as well, there is strong evidence that improvements in trade facilitation have been an important determinant of the increase in GVC trade seen over recent years.

Figure 7: GVC trade in logarithms, observed (2019) and counterfactual.



Note: 45 outliers with very small trade values dropped.

5 Conclusion and Directions for Future Research

This paper has motivated and developed a general equilibrium "new quantitative trade model" that is well suited to analyzing the impacts of trade policy changes on GVC trade. Provided that a trade policy change can be approximated as a change in iceberg trade costs, the model can map it to changes in GVC trade at a disaggregated level, in addition to the usual output variables from general equilibrium models. As an example, I have used the case of improvements in trade facilitation between 2015 and 2019, showing that the model gives them substantial explanatory power relative to observed changes in GVC trade over the sample period. shown that intermediate and final goods can respond very differently to changes in trade policy.

Future research could build on this approach and these results in a number of ways. First, trade facilitation is just one policy area where this kind of difference could be quantitatively relevant. Regional integration is another example where the literature currently does not allow for differential impacts based on end-use of goods, but there are features of regional agreements, such as rules of origin, that are explicitly directed at this issue. Adapting the approach here to examine the GVC consequences of regional integration, and taking account of the heterogeneity in the effects of regional agreements noted by Baier et al. (2019), could be a fruitful avenue of research.

Second, structural gravity is a popular way of analyzing the effects of trade policy changes, in particular now that the general equilibrium properties of the gravity system are well understood (Anderson and Van Wincoop, 2003). However, single sector gravity models are inherently limited in their ability to capture forces like production sharing. While they may still give aggregate results that are informative, analyzing GVC trade requires a multi-sector model. Caliendo and Parro (2015) and Aichele and Heiland (2018), which I build on this paper, provide such a framework, in which trade is still governed by a structural gravity model. The potential to build on this framework to examine the impacts of a range of trade policies is very high, provided that those policies can be adequately summarized by standard iceberg trade costs. This paper has taken a first step beyond tariffs to look at trade facilitation, but the concept of trade costs embodies a wide range of other factors (Anderson and Van Wincoop, 2004), many of which could usefully be examined in a context like this one. A more radical extension would be to move from the assumption of iceberg trade costs, which is standard in trade models, to one of per unit shipping costs, as in Hummels and Skiba (2004). As pointed out above, Sorensen (2014) suggests that such a change would result in larger impacts.

From a policy perspective, trade facilitation and GVC trade are both major issues, as indicated by the attention given to the former in WTO (2015), and the latter in publications like World Bank (2020). However, the economics of the links between them is as yet poorly understood. The data constraints in relation to both issues have been loosening, so applied research could helpfully inform policy discussions in this area. I have shown that the two issues are indeed tightly linked in an economic sense, so moving to better understand the ways in which these linkages work at a policy level is also an important question moving forward.

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APPENDIX: MODEL DESCRIPTION

Consumption Side

The consumption side of the model comes from Caliendo and Parro (2015). A measure Ln of representative households in N countries (subscript) maximize Cobb Douglas utility by consuming final goods in J sectors (superscript), with consumption shares α_n^j summing to unity.

$$(1)\ u(C_n) = \prod_{j=1}^{J} \left(C_n^j\right)^{\alpha_n^j}$$

Production Side

The production side of the model also comes from Caliendo and Parro (2015) via Aichele and Heiland (2018), which can be seen as a multi-sector generalization of Eaton and Kortum (2002). As in Aichele and Heiland (2018), there is provision for different shares in intermediate and final consumption

Each sector produces a continuum of intermediate goods $\omega^j \in [0,1]$. Each intermediate good uses labor and composite intermediate goods from all sectors. Intermediate goods producers have production technology as follows:

$$(2)\ q_n^j(\omega^j) = z_n^j(\omega^j)\left[l_n(\omega^j)\right]^{\beta_n^j} \prod_{k=1}^{J} \left[m_n^{k,j}(\omega^j)\right]^{\gamma_n^{k,j}}$$

Where: $z_n^j(\omega^j)$ is the efficiency of producing intermediate good ω^j in country n; $l_n(\omega^j)$ is labor; $m_n^{k,j}(\omega^j)$ are the composite intermediate goods from sector k used for the production of intermediate good ω^j; and β_n^j is the cost share of labor and $(1-\beta_n^j)\gamma_n^{k,j}$ is the cost share of intermediates from sector k used in the production of intermediate good ω^j, with $\sum_{k=1}^{J} \gamma_n^{k,j} = 1$.

Production of intermediate goods exhibits constant returns to scale with perfect competition, so firms price at marginal cost. The cost of an input bundle can therefore be written as follows:

$$(3)\ c_n^j = \Upsilon_n^j w_n^{\beta_n^j} \left(\prod_{k=1}^{J} \left(P_n^{km}\right)^{\gamma_n^{k,j}} \right)^{1-\beta_n^j}$$

Where: P_n^{km} is the price of a composite intermediate good from sector k; w is the wage; and Υ_n^j is a constant.

Producers of composite intermediate goods in country n and sector j supply their output at minimum cost by purchasing intermediates from the lowest cost suppliers across countries, similar to the mechanism in the single sector model of Eaton and Kortum (2002).

Composite intermediate goods from sector j are used in the production of intermediate good ω^k in amount $m_n^{j,k}(\omega^k)$ in all sectors k, as well as final goods in consumption C_n^j. The composite intermediate is produced using CES technology:

$$(4)\ Q_n^j = \left[\int r_n^j(\omega^j)^{1-\frac{1}{\sigma^j}} d\omega^j\right]^{\frac{\sigma^j}{\sigma^j-1}}$$

Where: r is demand from the lowest cost supplier, and σ is the elasticity of substitution across intermediate goods within a sector.

Solving the producer's problem gives an expression for demand:

$$(5)\ r_n^j(\omega^j) = \left(\frac{p_n(\omega^j)}{P_n^j}\right)^{-\sigma^j} Q_n^j$$

Where: $p_n(\omega^j)$ is the lowest price of a given intermediate good across countries; and $P_n^j = \left[\int p_n(\omega^j)^{1-\sigma^j} d\omega^j\right]^{\frac{1}{1-\sigma^j}}$ is the CES price index.

Trade Costs and Equilibrium

Trade costs consist of tariff and NTM components as in Aichele and Heiland (2018), in the standard iceberg formulation for imports by country n from country i, with trade costs potentially differing by end use (intermediate, m, or final, f):

$$(6)\ \kappa_{ni}^{jv} = (1 + t_{ni}^{jv}) * \tilde{t}_{ni}^{jv}, v \ni (m, f)$$

Where t is the ad valorem tariff, and $\tilde{t}$ is NTM-related trade costs, including potentially policy measures but also geographical and historical factors that drive a wedge between producer prices in the exporting country and consumer prices in the importing country (Anderson and Van Wincoop, 2004). Unlike in Caliendo and Parro (2015), I assume that all sectors are tradable; this assumption accords with the reality in our data, where sectors are sufficiently aggregate that trade always takes place, at least to some degree.

With this definition of trade costs, the price of a given intermediate good in country n is:

$$(7)\ p_n^j(\omega^j) = \min_{\mathrm{i}} \frac{c_i^j \kappa_{ni}^{jm}}{z_i^j(\omega^j)}$$

As in Eaton and Kortum (2002), the efficiency of producing ω^j in country n is the realization of a Fréchet distribution with location parameter $\lambda_n^j \geq 0$ and shape parameter $\theta^j > \sigma^j - 1$. The intermediate price index can therefore be rewritten as:

$$(8)\ P_n^{jm} = A^j \left[\sum_{i=1}^{N} \lambda_i^j (c_i^j \kappa_{ni}^{jm})^{-\theta^j}\right]^{-\frac{1}{\theta^j}}$$

Where A^j is a constant.

Then from the utility function, prices are:

$$(9)\ P_n^f = \prod_{j=1}^{N} \left(\frac{P_n^{jf}}{\alpha_n^j} \right)^{\alpha_n^j}$$

Bringing together these ingredients gives a relationship for bilateral trade at the sector level that follows the general form of structural gravity, but developed in an explicitly multi-sectoral framework and with different relations for intermediate and final consumption:

$$(10)\ \pi_{ni}^{jv} = \frac{X_{ni}^{jv}}{X_n^{jv}} = \frac{\lambda_i^j \left[c_i^j \kappa_{ni}^{jv} \right]^{-\theta j}}{\sum_{h=1}^{N} \lambda_h^j \left[c_h^j \kappa_{nh}^{jv} \right]^{-\theta j}}$$

For analytical purposes, a key feature of the gravity model in equation 10 is that the unit costs term depends through equation 3 on trade costs in all sectors and countries. This result is an extension of the multilateral resistance reasoning in Anderson and Van Wincoop (2003) to the case of cross-sectoral linkages.

Goods market equilibrium is defined as follows, where Y is the gross value of production:

$$(11)\ Y_n^j = \sum_{i=1}^{N} \frac{\pi_{in}^{jm}}{1 + t_{in}^{jm}} X_i^{jm} + \sum_{i=1}^{N} \frac{\pi_{in}^{jf}}{1 + t_{in}^{jf}} X_i^{jf}$$

With:

$$(11)\ X_n^{jm} = \sum_{k=1}^{J} \frac{\pi_{in}^{jm}}{1 + t_{in}^{jm}} \gamma_h^{j,k} \left(1 - \beta_h^k\right) Y_h^k$$

$$(12)\ X_n^{jf} = \alpha_n^j I_n$$

National income is the sum of labor income, tariff rebates, and the exogenous trade deficit:

$$(12)\ I_n = w_n L_n + R_n + D_n$$

The model is then closed by setting income equal to expenditure:

$$(13)\ \sum_{j=1}^{J} X_n^{jm} \sum_{i=1}^{N} \frac{\pi_{ni}^{jm}}{1 + t_{ni}^{jm}} + \sum_{j=1}^{J} X_n^{jf} \sum_{i=1}^{N} \frac{\pi_{ni}^{jf}}{1 + t_{ni}^{jf}} - D_n = \sum_{j=1}^{J} Y_n^j$$

Where: I represents final absorption as the sum of labor income, tariff revenue, and the trade deficit; R is tariff revenue, and trade deficits sum to zero globally and to an exogenous constant nationally. So aggregate trade deficits are exogenous, but sectoral deficits are endogenous.

Caliendo and Parro (2015) show that the system defined by equations 3, 8, 10, 11, and 13 can be solved for equilibrium wages and prices, given tariffs and structural parameters.

Counterfactual Simulation

Using exact hat algebra (Dekle et al., 2007), it is simpler to solve the model in relative changes than in levels. This process is equivalent to performing a counterfactual simulation in which a baseline variable

v is shocked to a counterfactual value v', and the relative change is defined as $\hat{v} = \frac{v'}{v}$. Aichele and Heiland (2018) show that counterfactual changes in input costs are given by:

$$(14)\ \hat{c}_n^j = \hat{w}_n^{\beta_n^j} \left(\prod_{k=1}^{J} \hat{P}_n^{km\,\gamma_n^{k,j}} \right)^{1-\beta_n^j}$$

The change in the price index is:

$$(15)\ \hat{P}_n^{jv} = \left[\prod_{i=1}^{N} \pi_{ni}^{jv} \left[\hat{\kappa}_{ni}^{jv} \hat{c}_i^j \right]^{-\theta^j} \right]^{-\frac{1}{\theta^j}}$$

The change in the bilateral trade share is:

$$(16)\ \hat{\pi}_{ni}^{jv} = \left[\frac{\hat{\kappa}_{ni}^{jv} \hat{c}_i^j}{\hat{P}_n^{jv}} \right]^{-\theta^j}$$

Counterfactual intermediate goods and final goods expenditure are given by:

$$(17)\ X_n^{jm'} = \sum_{k=1}^{N} \gamma_n^{j,k} \left(1 - \beta_n^k\right) \left(\sum_{i=1}^{N} X_i^{km'} \frac{\pi_{in}^{km'}}{1 + t_{in}^{km'}} + X_i^{kf'} \frac{\pi_{in}^{kf'}}{1 + t_{in}^{kf'}} \right)$$

With:

$$(18)\ X_n^{jf'} = \alpha_n^j I_n{}'$$

$$(19)\ I_n' = \hat{w}_n w_n L_n + \sum_{j=1}^{J} X_n^{jm'} \left(1 - F_n^{jm'}\right) + \sum_{j=1}^{J} X_n^{jf'} \left(1 - F_n^{jf'}\right) + D_n$$

The trade balance condition requires:

$$(20)\ \sum_{j=1}^{J} F_n^{jm'} X_n^{jm'} + \sum_{j=1}^{J} F_n^{jf'} X_n^{jf'} - D_n = \sum_{j=1}^{J} \sum_{i=1}^{N} X_i^{jm'} \frac{\pi_{in}^{jm'}}{1 + t_{in}^{jm'}} + \sum_{j=1}^{J} \sum_{i=1}^{N} X_i^{jf'} \frac{\pi_{in}^{jf'}}{1 + t_{in}^{jf'}}$$

The change in welfare is given by the change in real income:

$$\hat{W}_n = \frac{\hat{I_n}}{\prod_{j=1}^{J} \left(\hat{p}_n^{jf}\right)^{\alpha_n^j}}$$

The relative change in trade costs is given by the definition of the counterfactual simulation, and in our specification can cover NTMs as well as tariffs. Solving the model using exact hat algebra makes it possible to conduct the counterfactual experiment without data on productivity, and importantly, without trade costs data other than those that are being simulated; due to the multiplicative form of iceberg trade costs, solution in relative changes means that trade cost components, such as geographical and historical factors, which are constant in the baseline and counterfactual simply cancel out. The parameters β_n^j (cost share of labor), $(1-\beta_n^j)\gamma_n^{k,j}$ (cost share of intermediates), and α_n^j (share of each sector in final demand) can be calibrated directly from the baseline data, as can value added ($w_n L_n$). Egger et al. (2018) provide updated estimates of the trade elasticity θ^j at the same level of disaggregation used in our data.

Caliendo and Parro (2015) develop an iterative procedure for solving the model, which I follow here in the modified version developed by Aichele and Heiland (2018).

Trade in Value Added

I follow Aichele and Heiland (2018) in extending the Caliendo and Parro (2015) framework to consider value added trade, which helps identify the proportion of gross value trade that is considered to take place within GVCs. I differ from them, however, in the concept of value added trade that I use. They use Johnson and Noguera (2012) and Koopman et al. (2014), but as Wang et al. (2013) point out, the measures derived in those papers only provide consistent results at an aggregate level; I are interested in a bilateral and sectoral disaggregation, so I follow the same basic approach of Aichele and Heiland (2018) but then apply the key result from Wang et al. (2013) when it comes time to decompose gross value trade into its value added components.

Given the model setup described in the previous subsection, Aichele and Heiland (2018) derive input-output coefficients as follows:

$$(20)\ \left(1+t_{ih}^{km}\right)a_{ih}^{k,j} = \pi_{ih}^{km}\left(1-\beta_h^j\right)\gamma_h^{k,j}$$

Where: a is the input-output coefficient; and $\left(1-\beta_h^j\right)\gamma_h^{k,j}$ is the cost share of intermediates from sector k.

Equation (20) makes clear that if the model dataset includes a baseline input-output table (A), as is necessary, then it is straightforward to calculate a counterfactual input-output matrix (A'), using the outputs of the counterfactual solution defined above.

Wang et al. (2013) show that gross exports can then be fully and consistently decomposed into value added components at the bilateral level as follows (with sectoral superscripts suppressed for readability):

$$(21)\ \pi_{ni}^j = DVA + FVA + PDC$$

$$DVA = \left(V^i B^{ii}\right)' * Y^{ni} + \left(V^i L^{ii}\right)' * \left(A^{ni} B^{nn} Y^{nn}\right)$$
$$+\left(V^i L^{ii}\right)' * \left[A^{ni}\sum_{h\neq n,i}^{N} B^{hn}Y^{hh} + A^{ni}B^{nn}\sum_{h\neq n,i}^{N} Y^{hn} + A^{ni}\sum_{h\neq n,i}^{N} B^{hn}\sum_{k\neq n,i}^{N} Y^{kh}\right]$$
$$+\left(V^i L^{ii}\right)' * \left[A^{ni}B^{nn}Y^{in} + A^{ni}\sum_{h\neq n,i}^{N} B^{hn}Y^{ih} + A^{ni}B^{in}Y^{ii}\right]$$

$$FVA = \left(V^n B^{in}\right)' * Y^{ni} + \left[\left(\sum_{h\neq n,i}^{N} V^h B^{ih}\right)' * Y^{ni}\right]$$

$$+\left(V^n B^{in}\right)' * \left(A^{ni} L^{nn} Y^{nn}\right) + \left(\sum_{h\neq n,i}^{N} V^h B^{ih}\right)' * \left(A^{ni} L^{nn} Y^{nn}\right)$$

$$PDC = \left(V^i L^{ii}\right)' * \left(A^{ni} B^{in} \sum_{h\neq n,i}^{N} Y^{hi}\right) + \left(V^i L^{ii} \sum_{h\neq n,i}^{N} A^{hi} B^{ih}\right)' * \left(A^{ni} X^n\right)$$

$$+\left(V^n B^{in}\right)' * \left(A^{ni} L^{nn} E^{n*}\right) + \left(\sum_{h\neq n,i}^{N} V^h B^{ih}\right)' * \left(A^{ni} L^{nn} E^{n*}\right)$$

Where: E is exports to country n from country i, with a star indicating a country total across all other partners; Y is final demand for country i's output in country n; and DVA, FVA, and PDC are domestic value added, foreign value added, and pure double counting, respectively. A is an input-output matrix, with superscripts used to define sub-matrices by country pair. B is the global Leontief inverse based on A, with superscripts again indicating sub-matrices. V is the matrix of value added shares, calculated directly from A. Y is the matrix of final demand. X is the vector of gross output by country. L is the local Leontief inverse, defined as follows for the three country case (n, i, and k):

$$L = \begin{bmatrix} B_{11}^{nn} & B_{12}^{nn} & 0 & 0 & 0 & 0 \\ B_{21}^{nn} & B_{22}^{nn} & 0 & 0 & 0 & 0 \\ 0 & 0 & B_{11}^{ii} & B_{12}^{ii} & 0 & 0 \\ 0 & 0 & B_{21}^{ii} & B_{22}^{ii} & 0 & 0 \\ 0 & 0 & 0 & 0 & B_{11}^{kk} & B_{12}^{kk} \\ 0 & 0 & 0 & 0 & B_{21}^{kk} & B_{22}^{kk} \end{bmatrix}$$

The above presentation is at the country pair level for simplicity, but Wang et al. (2013) show that it can be extended to the sectoral level. The decomposition can therefore show DVA, FVA, and PDC in, for example, China's exports of electrical equipment to the USA. The sum of FVA and PDC is typically understood as a measure of production sharing, and I adopt that interpretation here.

Our approach to analyzing value added trade is straightforward. The Wang et al. (2013) decomposition for the baseline case can be calculated directly from the observed input-output table. I then use A' as calculated above to conduct a second decomposition for the counterfactual input-output table. The difference between the two shows the extent of changes in GVC trade as a result of the change in trade costs assumed for the counterfactual.