DISS. ETH NO. 28862

# ESSAYS ON GLOBAL VALUE CHAINS

A thesis submitted to attain the degree of

DOCTOR OF SCIENCES

(Dr. sc. ETH Zürich)

presented by

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2022

# Acknowledgements

First and foremost, I want to thank my supervisor Professor Peter Egger for giving me the opportunity to write this thesis and for his invaluable advice, continuous support, and patience during my PhD study. Furthermore, I am deeply grateful to Professor Katharina Erhardt who acted as an unofficial second supervisor. I would also like to thank Professor Gabriel Felbermayr for reviewing and commenting on this thesis. Finally, I would like to express my sincere gratitude to all my colleagues and friends from the Chair of Applied Economics at ETH Zürich and also to those from the EUTIP group.

Finally, I would like to express my gratitude to my parents, Bartomeu and Isabel, and my wife Anna. Without their tremendous understanding and encouragement in the past few years, it would be impossible for me to complete my study.

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# Abstract

This thesis is a collection of three articles that examine the organization of Global Value Chains (GVCs).

In the first chapter, single-authored, I investigate the general structure of Global Value Chains. In particular, I search for trading communities in the world trade network both in final and intermediate goods and then I use a structural gravity model to conduct counterfactual analysis to tease out the main drivers behind such communities. The main findings are twofold (i) global trade is divided into communities broadly corresponding to regional (continental) areas which are driven entirely by bilateral characteristics such as geography, trade policy and cultural similarities; (ii) the original network is significantly less modular than the corresponding random networks which is driven by individual characteristics such as productivity, comparative advantage or size.

In the subsequent two chapters I focus on a particular issue within GVCs, namely, the ownership structure.

In the second chapter (co-authored with Peter Egger and Katharina Erhardt) we seek to understand the forces that determine the pattern of asset ownership in global value chains. We augment a standard model of vertical integration rooted in the property-rights theory and derive four channels of influence for the cross-country and cross-sector pattern of asset ownership: the relative investment intensity of sectors and countries; the relative density of markets; the relative reliance on and importance of supplying and producing country-sectors; and the relative importance of fixed integration costs. Furthermore, we confirm the relevance of these determinants for the observed pattern of asset ownership in a large panel of worldwide directed ownership linkages.

Finally, in the third chapter (co-authored with Peter Egger) we focus on the effect of preferential trade agreements (PTAs) and their depth on firm ownership along Global Value Chains (GVCs). We measure shareholder-affiliate

ownership links at a country-sector-pair level to discern between vertical and horizontal links, and we find that PTAs boost vertical international investment links (both backward and forward) while reducing horizontal investment. Furthermore, the results show that deep PTAs stimulate investment particularly for sector pairs, where a high input specificity prevails.

# Zusammenfassung

Diese Doktorarbeit ist eine Sammlung von drei Beiträgen, die sich mit der Organisation von globalen Wertschöpfungsketten befassen.

Im ersten Kapitel untersuche ich, als alleiniger Autor, die allgemeine Struktur von globalen Wertschöpfungsketten. Im Speziellen suche ich nach Handelsgemeinschaften im Welthandelsnetzwerk mit End- und Zwischenprodukten und ich benutze ein strukturelles Gravitationsmodell zur kontrafaktischen Analyse um die Entstehungsgründe für diese Gemeinschaften zu identifizieren. Meine Untersuchung führen zu zwei Erkenntnissen: (i) der Welthandel ist im Grossen und Ganzen in Ländergemeinschaften geteilt, welche den Weltregionen (Kontinenten) mit ihrer zusammenhängenden Geographie, ihrer gemeinsamen Handelspolitik sowie kultureller Nähe entsprechen; (ii) das ursprüngliche Netzwerk ist signifikant weniger modular als das entsprechende zufällig erstellte Netzwerk, welches von individuellen Eigenschaften wie Produktivität, komparative Vorteile oder Grösse geprägt sind.

In den zwei darauffolgenden Kapiteln fokussiere ich auf den Aspekt der Besitzverhältnisse innerhalb der globalen Wertschöpfungsketten.

Im zweiten Kapitel versuchen wir (in Zusammenarbeit mit Peter Egger und Katharina Erhardt), die Einflussfaktoren zu verstehen, welche die Besitzverflechtungen in globalen Wertschöpfungsketten prägen. Wir erweitern ein Standardmodell der vertikalen Integration, das auf der Theorie der Eigentumsrechte beruht, und leiten daraus vier Einflusskanäle für die länder- und sektorübergreifende Gliederung der Besitzverhältnisse ab: die relative Investitionsintensität von Sektoren und Ländern, die relative Dichte von Märkten, die relative Abhängigkeit von und Bedeutung von Angebots- und Produktionslandessektoren und die relative Bedeutung von fixen Integrationskosten. Darüber hinaus bestätigen wir die Relevanz dieser Determinanten für das beobachtete Muster der Eigentumsverflechtungen in einem großen Panel weltweiter gerichteter Besitzverhältnissen.

Im dritten Kapitel schließlich (gemeinsam mit Peter Egger verfasst) konzentrieren wir uns auf die Auswirkungen von Präferenzhandelsabkommen (PHAs) und deren Umfang auf die Eigentumsverhältnisse von Unternehmen entlang globaler Wertschöpfungsketten. Wir messen Anteilseigentumsverflechtungen auf der Ebene von Länder-Sektor-Paaren, um zwischen vertikaler und horizontaler Verflechtung zu unterscheiden, und wir stellen fest, dass PHAs vertikale internationale Investitionsverflechtungen (sowohl rückwärts als auch vorwärts) begünstigen, während sie horizontale Investitionen reduzieren. Darüber hinaus zeigen die Ergebnisse, dass tiefgreifende PHAs die Investitionstätigkeit vor allem in Sektorenpaaren anregen, in denen eine hohe Inputspezifität vorherrscht.

# Introduction

Production processes have experienced a big revolution during the past two decades. It used to be the case that many goods were produced in a single country or even in a single plant. Nowadays, however, the production is sliced into stages that, in turn, are performed in different plants often located in different regions or countries. Under this new production framework we see an unprecedented increase in the trade of intermediate goods creating so-called Global Value Chains (GVCs). Today, trade in Global Value Chains is the dominant type of international trade (Johnson and Noguera, 2012; Bernard and Fort, 2015; Alfaro et al., 2019).

One particularly interesting question that arises in this context is whether these GVCs are truly global - i.e. production process are sliced and split throughout the world - or, instead, there are several and more regional value chains where intermediate goods do move internationally, but within a geographic cluster.

In the first chapter of this thesis (single-authored), I investigate the overall structure and organization of Global Value Chains. More concretely, I use intermediate goods trade flows from Global Input-Output Tables to generate a network representation of GVCs for every year from 1995 to 2015 and I search for different communities within the network using modularity optimization. I find that there are different communities broadly corresponding to continents - Europe, America and Asia-Africa. Nevertheless, when I compare these results to some random networks I find that these communities are not statistically significant. Overall this suggests that, while there are some regional clusters in GVCs, these clusters are rather weak. Following on this, I create two counterfactual networks to tease out the main drivers of these results. Using a structural gravity model, first, I create a counterfactual network without trade frictions. In this "frictionless world" I find that countries trade much more with each other. Also, modulartity optimization suggests that all countries are grouped in one single and truly global community. The second counterfactual network I create is a frictions only world (a hypothetical network net of individual country characteristics). Modularity optimization in this network suggests that clusters not only exist, but now are statistically significant. All together the first chapter of this thesis suggests that there exists some clustering in GVCs due to trade frictions - i.e. distance between countries, cultural differences, etc. - but thanks to countries' individual characteristics - i.e. comparative advantage, productivity, etc. - these clusters are weak.

Global Value Chains brought new production strategies and more specialization. Also they brought new and important decisions by the firms that participate in them. Once a firm decides to slice its production process and perform different stages at different facilities, a key point arises, namely, the ownership of assets. Should different facilities be vertically integrated into a single company? Should they remain independent, instead, and operate at arm's length? If integrated, who should be the final owner of the assets?

In the second and third chapter of this thesis, hence, I focus on these important questions and I focus on the ownership structure along GVCs.

In chapter 2 (joint work with Peter Egger and Katharina Erhardt) we seek to understand the forces that determine the pattern of asset ownership in global value chains. We start with a parsimonious model of vertical integration where a supplier and a producer bargain for asset ownership within their relation. We find that there are four channels of influence for the cross-country and cross-sector pattern of asset ownership: the relative investment intensity of sectors and countries; the relative density of markets; the relative reliance on and importance of supplying and producing country-sectors; and the relative importance of fixed integration costs. Moreover, we test our theoretical predictions in a novel firm ownership dataset. More concretely, we use the Orbis Database published by Bureau van Dijk, which contains worldwide ownership information at the firm level. Building on this, we count the number of ownership links between country pairs (across more than 200 countries) and sector pairs (across 38 sectors). This dataset allows us to work with ownership relations in country-and-sector-pair cells. Moreover, with this structure we can use (global) input-output tables to distinguish vertical forward links (where the shareholder is up the stream of an affiliate); vertical backward links (where the shareholder is down the stream of the affiliate); and horizontal links. Overall, all the theoretical predictions of our model are confirmed and are robust to different specifications.

Finally, in the last chapter (coauthored with Peter Egger) we turn our attention to one of the key policy instruments to influence international economic relations, namely Preferential Trade Agreements (PTAs). PTAs have a long history among international agreements. This type of agreement, traditionally, was geared towards decreasing tariffs on all the goods (or a particular subset) traded between the signatory countries. Nevertheless, PTAs evolved with time, they became deeper and, nowadays, they are not only about tariffs. In fact, contemporaneous PTAs cover many different aspects such as services trade, labour rights, environmental issues, or, and particularly interesting for us, international investment. It is long being hypothesized by theoritcal economists that while PTAs should reduce the propensity of horizontal ownership, they should increase the propensity of vertical ownership (in both the forward and backward direction). However, up to now, it was difficult to corroborate such predictions due to the lack of a sectoral disaggregation in cross-border investment data. In this chapter, therefore, we use our novel firm ownership dataset, and we tease out the impact of new PTAs coming into force during 2007 to 2015 on firm ownership and, in particular, on those links along GVCs. Overall, we find that PTAs promote foreign ownership. Also we corroborate the existing theory and find that the positive effect concentrates on vertical integration links. Moreover, we acknowledge the intrinsic heterogeneity of PTAs and create several depth measures to account for it. Overall, we find that deeper PTAs - those that cover more areas- have a higher impact.

Overall this thesis does not pretend to be an exhaustive work on Global Value Chains, but a glimpse on this huge and important topic for international trade by, first, investigating the general structure of GVCs and, then, focusing on a particularly key issue, such as, the ownership structure.

# Chapter 1

# Trading Communities in the Global Value Chain Network.

## 1.1 Introduction

Production processes are increasingly organized in international production networks. These networks usually consist of one or different firms slicing their production process in a sequential manner and performing every given step in different facilities potentially located in different countries. Following this pattern, intermediate goods flow from one country to another following the firm's chain of value and generating so-called Global Value Chains (GVCs). GVCs are a major source of international trade (Johnson and Noguera, 2012).

In this paper I search for trading communities in GVCs and final goods trade using network analysis techniques. The idea is to find groups of countries that trade a lot with other countries withing their community and little with countries from other communities. Furthermore I use a structural gravity framework to identify the source of trade modularity (i.e, the strength of communities) and conduct counterfactual analyses and examine how trading communities differ when trade costs change.

Using World Input-Output Table data from the EORA Database for the years 1995 to 2015 I search for trading communities maximizing the modularity of both the final and the intermediate goods network. Overall I find that world trade has three communities broadly corresponding to big regional areas (Asia, Europe and the Americas). When comparing these results to those of some random trade networks, however, I find that these communities are "weak" in the sense that, in line with Piccardi and Tajoli (2012), they are not statistically significant.

To find the main mechanisms behind this particular modular structure I use counterfactual analysis and look at a frictionless world (the hypothetical network if there would be no trade frictions). I find, that in a such a world all the countries trade intensively with each other in one single truly global community. Finally, I also look at a frictions only world (a hypothetical network net of all individual country characteristics). In this counterfactual, not only communities keep existing, but they are statistically significant. Hence, county characteristics mitigate the modular structure present in the trade friction on the globe.

This paper contributes at several fronts. First, it contributes to the GVCs literature in particular and international trade in general as it is one of the few papers that presents a systematic search for trading communities and their time evolution for intermediate and final goods. Also, up to my knowledge, it it the first paper that disentangles the mechanisms behind such communities using counterfactual analysis.

Finally, the paper also contributes to the network analysis literature as it finds that trade networks are less modular than their random counterparts, which is a highly unusual characteristic of notworks of any kind.

## 1.2 Literature Review

This paper lies at the intersection between two distinct fields of knowledge: international trade (in particular GVC) and network analysis (particularly community detection). Studies on both topics are abundant.

**GVC in the economics literature**

The majority of international trade flows can be traced to happen within Global Value Chains (Borino and Mancini, 2019) and, consequently, GVCs related research has an important place within the international trade literature. At a theoretical level, one can distinguish two main approaches to GVCs (Antràs and Chor, 2021). The first one focuses on a macro scale where the analysis is at the country or country-sector unit. Among these, the framework of Caliendo and Parro (2014) became the benchmark model in field. While most existing work falls into this first approach, there exists a second approach that focuses on a micro scale where the unit of analysis are individual firms. Some relevant studies are Alfaro et al. (2019); Antràs and de Gortari (2020) that focus on the firm's production as a sequential process. In any case the literature of theoretical models for GVC is vast (see Antràs and Chor (2021) for a detailed review).

The most relevant part of the GVC literature for the purpose of this paper, however, is the empirical work. Obtaining data on Global Value Chains is not easy as customs data do not record information on how goods were produced (Antràs, 2020). To overcome this problems there are some initiatives that combine customs data with national input-output tables to create World Intput-Ouput Tables (WIOT). These tables present a detailed decomposition of international trade flows between finished goods (those that are used by the public) and intermediate goods (those that are used by firms in their production) as well as a clear tracking of the origin (country-sector) and destination (country-sector) of the flow. The analysis of such tables still relies on the seminal work by Leontief (1936) to calculate direct and total requirements. Building on Leontieff's work, Antràs and Chor (2013) have developed an "upstreamness" and "downstreamness" measure to identify those country-sectors that are closer to the edges of the chain. In this context an "upstream" unit would be closer to the beginning of the chain (i.e. a raw material producer), while a "downstream" unit will be closer to the end of the chain (i.e. a retailer). Surprisingly enough, there are few studies in the economics literature that use the inherent network structure of GVC.

**Community detection in the network literature**

One of the most interesting and active areas in network analysis is community and structure detection. Separating nodes into different groups is not an easy task, yet there exist many different methods to do so (Fortunato, 2010; Fortunato and Hric, 2016).

Probably the most used method to detect communities is based on modularity (Newman and Girvan, 2004). The modularity score asseses how well a network can be divided into different communities or modules, where the nodes have many relations (edges) within the module and few relations between modules. Optimization of modularity is one of the most studied community detection approaches. It has been generalized to directed (Arenas et al., 2007) and to bipartite networks (Malliaros and Vazirgiannis, 2013; Guimerà et al., 2007; Barber, 2007; Arenas et al., 2008). As well as this, some research has focused on generating fast heuristics to use the method in large and complex networks (Blondel et al., 2008).

**Network analysis of trade data**

There are some studies where the network structure of international trade data is analyzed. The majority of this literature focuses on overall trade given the difficulties aforementioned on decomposing intermediate and final goods. Following Mariani et al. (2019), it is possible to separate the studies between those that focus on country-country trade data and those that focus on country-sector data.

In country-country networks each node is a country and there is an edge between two nodes if there is some trade between the two countries. This type of networks where all the node are the same category are unipartite networks. Benedictis and Tajoli (2011) are one of the first to apply network analysis to country-country trade data. In this paper, they study the temporal dynamics of world trade and show that the world has become more interconnected over the years yet it is still far from complete. Other studies have shown the differences between representing the world trade network in a binary form (Squartini et al., 2011a) and a weighted format (Squartini et al., 2011b). There are some studies focusing on community detection using a modularity approach (Zhu et al., 2014), as well as nestedness detection (König et al., 2014). Particularly, König et al. (2014) develop a dynamic network formation model that can explain the observed nestedness in real-world networks.

Also, Piccardi and Tajoli (2012) search for communities in the world trade network using International Monetary Found (IMF) and United Nation (UN) data from 1962 to 2008. They use four different approaches for community detection: modularity optimization, cluster analysis, stability functions, and persistence probabilities. The main finding is that the communities found are very weak and not statistically significant.

Country-sector networks are bipartite networks were there is a first group of nodes corresponding to countries and a second group of nodes corresponding to sectors. These bipartite networks have edges between groups if a given country trades in a given sector and have no edges within groups. There some studies that focus on this representation of the world trade (Saracco et al., 2015a; Hausmann and Hidalgo, 2011; Saracco et al., 2015b). Bustos et al. (2012) investigate the nested structure of these type of networks. Servedio et al. (2018) use these networks to create a measure of complexity of products and fitness of countries. One of the main features of this literature is that it mainly focuses on networks of exported products, while it ignores imports (one relevant exception is Ermann and Shepelyansky (2013)).

From this previous literature two important facts arise. One is that virtually all previous studies only consider trade flows, while it may be important to account for the differences between intermediate and final goods. Second, both the unipartite (country-country) and the bipartite (country-sector) approach are useful simplifications of world trade, yet they neglect important information when compared to a country-sector-to-country-sector network.

The first challenge is more or less easy to fix using data form World Input-Output Tables. This is the approach taken by McNerney et al. (2013); Xiao et al. (2017) and Tsekeris (2017). Regarding this literature, there are two main considerations to keep in mind. First, it is not very extensive and, up to my knowledge, there are still some relevant questions unanswered e.g. whether there exists a statistically significant difference between the intermediate goods and final goods networks or whether they present different structures. Second, many of the existing works do not consider a country-sector-to-country-sector network.

The second challenge is not as easy to tackle. Indeed some studies have tried alternative representations of the World Input-Output Tables. Alves et al. (2018) experiment with single-layer, multiplex, and multi-layer networks to represent WIOT and conclude that the more complex representations such as multi-layer networks are the most appropriate. Within multi-layer representations, Ren et al. (2020) use a multiplex network where each layer is a different sector and the nodes represent countries. They find a clearly nested structure of the multiplex network, however, they miss all the trade between sectors due to their multiplex representation. Finally, there is only paper that studies the nested structure of a multi-layer network (Alves et al., 2019) representing all the trade flows at a country-sector-to-country-sector level. This study finds that this particular network indeed exhibits a nested structure, however, they use an unweighted network and they ignore other potential structures such as modularity.

## 1.3 Data

### 1.3.1 Global Value Chain

The key database this analysis rests upon is the World Input-Output Table (WIOT) as published in the EORA Multi-Region Input-Output table (MRIO). In particular, this dataset distinguishes between 26 two-digit (primary production, manufacturing, and services) sectors and 189 countries, and contains annual data for all the years of the period 1995-2015.

For a more formal account of the WIOT-data construction for my purposes, let me closely follow the notation in Antràs and Chor (2018) and define a world economy with $J$ countries (indexed by $i$ or $j$) and $S$ sectors (indexed by $r$ or

$s$). This structure is represented by the stylized global input-output table for a generic year in Figure 1.1. The data in the figure are first sorted by country (slow index) and then by sector (fast index) in both rows and columns. This generic global input-output table has five distinct data blocks. First, a $JS \times JS$ block in the upper left of the table contains intermediate (goods or services) input-output purchases of the country-sector pairs in the columns (users) from the country-sector pairs in the rows (suppliers). The row blocks of this sub-matrix are labelled "*Intermediate inputs supply*", and the column blocks are labelled "*Inputs use.*" Let me call this matrix $Z$ and refer to its typical element by $Z_{ij}^{rs}$. Second, there is a $JS \times J$ block just to the right of this block, whose columns are jointly labelled "*Final use.*" I will call this matrix $F$ and refer to a typical element by $F_{ij}^{r}$. Third, the outer-right column of the first $JS$ rows, a $JS \times 1$ vector, is labelled "*Total use*" and contains the sum across the $2JS$ elements in each one of the first $JS$ rows of the matrix (the sum of output in a country-sector row used either as an input or for final consumption). Finally, there are two row vectors of dimension $1 \times JS$, which contain the "*Value added*" (output minus intermediate inputs) and "*Gross output*" (value added plus intermediate input) of each using country-sector pair.

Table 1.1: World Input-output Table.

| | | | Input use & value added | | | | | | | Final use | | | Total use |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Country | | 1 | … | 1 | … | J | … | J | J | … | J | |
| | | Industry | 1 | … | S | … | 1 | … | S | | | | |
| Intermediate | 1 | 1 | $Z_{11}^{11}$ | … | $Z_{11}^{1S}$ | … | $Z_{1J}^{11}$ | … | $Z_{1J}^{1S}$ | $F_{11}^{1}$ | … | $F_{1J}^{1}$ | $Y_1^1$ |
| | ⋮ | ⋮ | ⋮ | $Z_{11}^{rs}$ | ⋮ | ⋮ | ⋮ | $Z_{1J}^{rs}$ | ⋮ | ⋮ | $F_{1j}^{r}$ | ⋮ | ⋮ |
| | 1 | S | $Z_{11}^{S1}$ | … | $Z_{11}^{SS}$ | … | $Z_{1J}^{S1}$ | … | $Z_{1J}^{SS}$ | $F_{11}^{S}$ | … | $F_{1J}^{S}$ | $Y_1^S$ |
| input | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | $Z_{ij}^{rs}$ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| | J | 1 | $Z_{J1}^{11}$ | … | $Z_{J1}^{1S}$ | … | $Z_{JJ}^{11}$ | … | $Z_{JJ}^{1S}$ | $F_{J1}^{1}$ | … | $F_{JJ}^{1}$ | $Y_J^1$ |
| supply | ⋮ | ⋮ | ⋮ | $Z_{J1}^{rs}$ | ⋮ | ⋮ | ⋮ | $Z_{JJ}^{rs}$ | ⋮ | ⋮ | $F_{Jj}^{r}$ | ⋮ | ⋮ |
| | J | S | $Z_{J1}^{S1}$ | … | $Z_{J1}^{SS}$ | … | $Z_{JJ}^{S1}$ | … | $Z_{JJ}^{SS}$ | $F_{J1}^{S}$ | … | $F_{JJ}^{S}$ | $Y_J^S$ |
| Value added | | | $V_1^1$ | … | $V_1^S$ | $V_j^s$ | $V_J^1$ | … | $V_J^S$ | | | | |
| Gross output | | | $Y_1^1$ | … | $Y_1^S$ | $Y_j^s$ | $Y_J^1$ | … | $Y_J^S$ | | | | |

For the rest of the paper I will mainly use the matrices $Z$ and $F$ at different levels of aggregation. To be more concrete I will focus my attention in the analysis of three different matrices.

The $Z$ matrix collects country-sector-to-country-sector intermediate goods trade. It has dimensions $JS \times JS$ and its typical element is $Z^{rs}_{ij,t}$.

The $\hat{Z}$ matrix collects country-to-country intermediate goods trade. It has dimensions $J \times J$ and its typical element is $\sum_{r=1}^{S}\sum_{s=1}^{S} Z^{rs}_{ij,t}$.

The $\hat{F}$ matrix collects country-to-country final goods trade. It has dimensions $J \times J$ and its typical element is $\sum_{r=1}^{S} F^{r}_{ij,t}$.

### 1.3.2 Network representation

Any of the aforementioned matrices can be trivially represented in a network format. It suffices to note that these matrices are, in fact, adjacency matrices of a directed and weighted graph. Thus, for the rest of the paper I will define a generic graph $\mathcal{G}$ whose adjacency can be represented by either of the matrices $Z$, $\hat{Z}$ or $\hat{F}$ without loss of generality. Note that while in this section I can report some descriptive statistics for the $Z$, due to computational issues for all the other analysis of the paper I can only focus on $\hat{Z}$ or $\hat{F}$.

The directed and weighed graph, $\mathcal{G}$, contains $N$ nodes (indexed by $n$ or $m$)[1] and $L$ edges that represent the trade flows in thousands of dollars between two nodes $n$ and $m$ denoted by $w_{nm}$. Finally, note that the original WIOT data also collects information on domestic trade, in my network representation this data would take the form of self-loops. However, the presence of self-loop complicates some of the methods used, specially if the weight of these is various orders of magnitude higher than that of between nodes, as is the case with trade data. Therefore, I set all domestic trade to 0 i.e. I set $w_{n=m} = 0$

From my directed and weighed graph, $\mathcal{G}$, I can define in-strength as $s_n^{in} = \sum_{m=1}^{N} w_{nm}$ which measures the total amount of imports for country $n$; out-strength as $s_n^{out} = \sum_{n=1}^{N} w_{nm}$ which measures the total amount of exports for country $n$; and total-strength as $s_n^{total} = s_n^{out} + s_n^{in}$. As well as this, it is useful to define a measure to capture the mere existence of edges regardless of their weight, $a_{nm} = 1$ if $w_{nm} > 0$. Following this notation, I define in-degree as $d_n^{in} = \sum_{m=1}^{N} a_{nm}$; out-degree as $d_n^{out} = \sum_{n=1}^{N} a_{nm}$; and total degree as $d_n^{total} = d_n^{out} + d_n^{in}$.

In table 1.2 I provide descriptive statistics for my three networks in the first and last year of the sample.

The first thing that stands out of Table 1.2 is that both networks at the country level, $\hat{Z}$ and $\hat{F}$, are a complete graph with $J = 189$ nodes ($K_{189}$) showing that already in 1995 every country had already some positive amount

[1] $N = J$ for the graph representing $\hat{Z}$ or $\hat{F}$ and $N = J \times S$ for the graph representing $Z$.

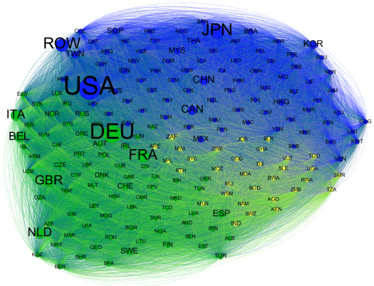
Table 1.2: Descriptive Statistics

| | Country-Sector intermediate goods ($Z$) | | Country intermediate goods ($\hat{Z}$) | | Country Final goods ($\hat{F}$) | |
|---|---|---|---|---|---|---|
| Metric | 1995 | 2015 | 1995 | 2015 | 1995 | 2015 |
| Nodes (N) | 4,889 | 4,889 | 189 | 189 | 189 | 189 |
| | (-) | (-) | (-) | (-) | (-) | (-) |
| Mean $d^{in}$ | 4,859 | 4,860 | 188 | 188 | 188 | 188 |
| | (107) | (98) | (-) | (-) | (-) | (-) |
| Mean $d^{out}$ | 4,859 | 4,860 | 188 | 188 | 188 | 188 |
| | (72) | (69) | (-) | (-) | (-) | (-) |
| Mean $d^{total}$ | 9,718 | 9,720 | 376 | 376 | 376 | 376 |
| | (167) | (155) | (-) | (-) | (-) | (-) |
| Mean $s^{in}$ | 864 | 2,878 | 22,369 | 74,451 | 10,524 | 37,519 |
| | (5,398) | (14,243) | (61,624) | (200,901) | (34,205) | (107,205) |
| Mean $s^{out}$ | 864 | 2,878 | 22,369 | 74,451 | 10,524 | 37,519 |
| | (6,103) | (16,515) | (68,707) | (191,628) | (33,114) | (110,756) |
| Mean $s^{total}$ | 1,729 | 5,756 | 44,739 | 148,902 | 21,049 | 75,039 |
| | (1,119) | (29,586) | (129,800) | (390,288) | (65,844) | (207,210) |

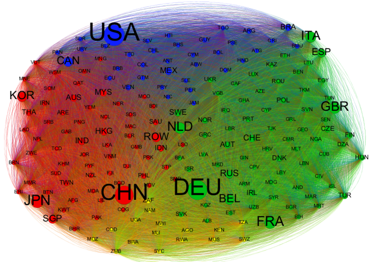
Note: The strengths values are in millions of US dollars. Standard deviations in parentheses.

of trade with every other country in the world, both in intermediate and final goods. Secondly, the strength metrics show that trade in intermediate goods is twice as large as trade in final goods and that both have tripled over the period studied[2]. Finally, it is important to note that the standard deviation of the strength metrics is quite higher than the mean. This suggests that there is a lot of heterogeneity in the trade flows of different countries. As an example, in 2015 the United States had a combined value of exports and imports of 2,784,850 million dollars in intermediate inputs; while Somalia had merely 124 million.

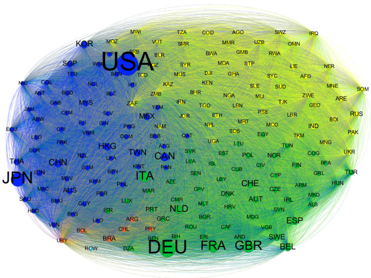
[2]The increase in time is due to both increase in products traded as well as increase in price of these products.



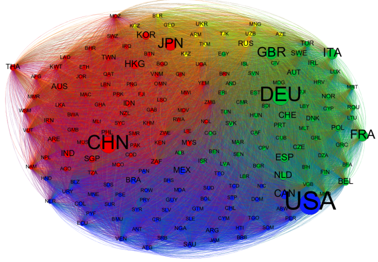

(a) Intermediate goods in 1995.




(b) Intermediate goods in 2015.




(c) Final goods in 1995.




(d) Final goods in 2015.

Figure 1.1: Network visualization.
Note: The size of the node is proportional to the total strength and color according to communities found based on modularity.

# 1.4 Communities in the World Trade Network

## 1.4.1 Modularity

In this section I examine the mesoscale structure of the different networks. To do so I will identify the best way to divide the network in communities based on modularity. The main idea behind this method is to group nodes such that the interactions with nodes within the group are higher than the interaction with node from other groups.

The most popular way to find partitions is based on the work of Newman and Girvan (2004) and its weighted generalization (Newman, 2004a). More concretely the method consists on the optimization of a function $Q$:

$$Q = \frac{1}{\omega} \sum_{n=1}^{N} \sum_{m=1}^{N} \left( w_{nm} - \frac{s_n^{out} s_m^{in}}{\omega} \right) \delta(C_n, C_m), \tag{1.1}$$

where $\omega = \sum_{nm} w_{nm}$ and $\delta(C_n, C_m)$ is the Kronecker delta that equals one if nodes $n$ and $m$ belong to the same community and zero otherwise. The best partition, therefore, is the one that has $Q = Q_{max}$. To find such a solution it is required to carry an exhaustive search that, even in very small networks, is computationally very demanding. It is for this reason that several authors have created different heuristics that find (maybe sub)optimal partitions efficiently. In this paper I use the Louvain algorithm by Blondel et al. (2008) and the fast-algorithm by Newman (2004b).

Figure 1.2 shows the evolution of the number of communities for the two networks that I examine in this paper. Clearly, the number of communities remains quite stable over time being around 3-4 for the network of intermediate goods and around 5 for the network of final goods.

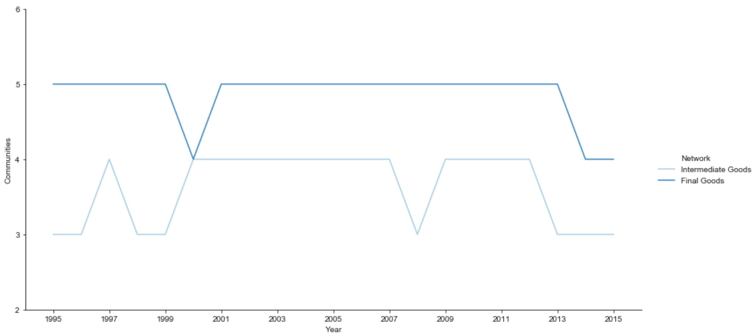



Figure 1.2: Number of communities detected.

Regarding the composition of the communities, Figure 1.1 shows that countries tend to form stronger ties with other countries from their proximity confirming the well-established gravity theory of international trade. Regarding the evolution over time it is very interesting to see how at the beginning of the sample, in 1995, there were two main communities for each two main blocks in the international world order at the time, Europe and America, with Germany and the USA as the principal node. Interestingly, in the final goods there is also a quite relevant African community. However, the most relevant finding is the emergence of the Asian community over time. While in 1995 the majority of Asia and Oceania countries were integrated in the American community; in 2015 they have formed their own community, with China as the most relevant node. As well as the Asian community, in 2015, there still exist an European community with Germany as a leader and an American community with the USA at the front. The latter, however, has experienced a big drop in members from 76 to 36 in the intermediate goods trade. Also, the Asian community has absorbed almost the entire African community in both, final and intermediate goods, showing a clear interest and strong ties between China and African countries. All these results are consistent with previous literature on community detection in trade flows networks (Barigozzi et al., 2011; Piccardi and Tajoli, 2012).

### 1.4.2 Randomizations

One of the main problems that appears when finding the best partition by the optimization of (1.1) is that the $Q$ value alone cannot be used to assess the statistical significance of a given partition. In this case, the normal procedure consists on creating several random graphs, preserving some properties of the original network, and applying the modularity optimization on them. The main idea is then, to compare the $Q$ value for the random graphs to that of the original network and assess if they are statistically different.

To be more formal, I create one hundred random graphs, $\mathcal{G}'_i$ with $i = [1, 100]$, for each network and I find the corresponding value $Q'_i$ optimizing (1.1). Then I compute $\bar{Q}'$ as the average value of $Q'_i$ and $\sigma(Q')$ as the standard deviation. Using this and letting $Q^{org}$ be the $Q$ value for the original network it is straightforward to compute the score $z = \frac{Q^{org} - \bar{Q}'}{\sigma(Q')}$. A value far from 0 indicates statistical significance of the partition found in the original network.

In the case of directed and weighted graphs finding suitable randomization is not an easy task. In this paper I have used three different algorithms each preserving different features of the original network.

The **in-strength preserving randomization** conducts random permutations to the columns of the adjacency matrix, in this fashion the column sum remains equal to the one of the original matrix, yet the row total changes. In other words, this algorithm pretends that countries buy a given amount of goods and randomly assign from whom this goods come from.

The **out-strength preserving randomization** conducts random permutations to the rows of the adjacency matrix, in this fashion the row sum remains equal to the one of the original matrix, yet the column total changes. In other words, this algorithm pretends that countries sell a given amount of goods and randomly assign whom they sell to.

The **full randomization** conducts random permutations to the rows and columns of the adjacency matrix. Neither the row nor the column total remains equal to the one of the original matrix. In other words, this algorithm only fixes the total amount of trade world-wide, yet the trading partners are fully randomized.

In Table 1.3 I present the result of these three randomization on the country level intermediate and final goods networks respectively.

Table 1.3: Randomization statistics for the World Trade Network

| | Intermediate Goods | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | in-strength preserving | | | | out-strength preserving | | | | full randomization | | | |
| Year | $Q'$ | $\sigma(Q')$ | $Q^{org}$ | $z$ | $Q'$ | $\sigma(Q')$ | $Q^{org}$ | $z$ | $Q'$ | $\sigma(Q')$ | $Q^{org}$ | $z$ |
| 1995 | 0.408 | 0.017 | 0.276 | -7.605 | 0.435 | 0.016 | 0.276 | -10.079 | 0.555 | 0.007 | 0.276 | -41.895 |
| 2000 | 0.423 | 0.016 | 0.267 | -9.477 | 0.422 | 0.017 | 0.267 | -8.978 | 0.547 | 0.006 | 0.267 | -46.122 |
| 2005 | 0.419 | 0.017 | 0.283 | -7.908 | 0.415 | 0.014 | 0.283 | -9.201 | 0.538 | 0.006 | 0.283 | -39.764 |
| 2010 | 0.392 | 0.014 | 0.282 | -7.758 | 0.392 | 0.013 | 0.282 | -8.211 | 0.510 | 0.006 | 0.282 | -39.228 |
| 2015 | 0.364 | 0.017 | 0.277 | -5.229 | 0.379 | 0.014 | 0.277 | -7.036 | 0.490 | 0.006 | 0.277 | -37.408 |

| | Final Goods | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | in-strength preserving | | | | out-strength preserving | | | | full randomization | | | |
| Year | $Q'$ | $\sigma(Q')$ | $Q^{org}$ | $z$ | $Q'$ | $\sigma(Q')$ | $Q^{org}$ | $z$ | $Q'$ | $\sigma(Q')$ | $Q^{org}$ | $z$ |
| 1995 | 0.469 | 0.012 | 0.247 | -18.897 | 0.469 | 0.014 | 0.247 | -15.922 | 0.565 | 0.007 | 0.247 | -43.356 |
| 2000 | 0.508 | 0.011 | 0.239 | -23.979 | 0.464 | 0.015 | 0.239 | -14.526 | 0.589 | 0.007 | 0.239 | -49.278 |
| 2005 | 0.472 | 0.011 | 0.251 | -20.397 | 0.448 | 0.013 | 0.251 | -15.511 | 0.555 | 0.006 | 0.251 | -46.790 |
| 2010 | 0.431 | 0.010 | 0.259 | -16.301 | 0.431 | 0.011 | 0.259 | -15.854 | 0.509 | 0.005 | 0.259 | -45.712 |
| 2015 | 0.418 | 0.010 | 0.258 | -15.370 | 0.426 | 0.010 | 0.258 | -17.046 | 0.501 | 0.006 | 0.258 | -43.693 |

A very particular result arises from Table 1.3 as it seems to suggest that the original networks exhibit (very) significantly less $Q$ than the random graphs. This result holds for the three randomization methods and for intermediate as well as, final goods.

The high significance of the z-scores indicates that not only the original network communities are "weak" (as found in Piccardi and Tajoli (2012) or Piccardi and Tajoli (2015)), but also that the relations in it are made such that modularity is minimized. Up to my knowledge, these networks are the first to be found that exhibit such a behaviour.

Taken together, the results so far seem to suggest that two facts stand out in the World Trade Network:

- **RESULT 1**: the world exhibits some modularity and it is divided into communities;

- **RESULT 2**: the world is less modular that its corresponding randomizations.

In what follows I will create several counterfactual networks where I can freely change some important factors, such as geography, culture and trade policy in order to understand the drivers of the trade network features.

## 1.5 Counterfactuals

In this section I describe a general framework to create counterfactuals using a structural gravity model. First, I layout the full theoretical framework and, later, I outline a practical implementation in three simple steps. Finally I define different counterfactual scenarios.

### 1.5.1 Theoretical framework

A customary gravity model in (very) generic form for a cross section of bilateral exports, $X_{ij}$, with $i$ being the exporter and $j$ being the importer can be defined as follows:

$$\begin{aligned}
X_{ij} &= A_i B_{ij} C_j, \\
C_j &= \frac{E_j}{\sum_{i=1}^{J} A_i B_{ij}}, \\
E_j &= \sum_{i=1}^{J} X_{ij} = \phi_j Y_j, \\
Y_i &= \sum_{j=1}^{J} X_{ij}, \\
B_{ij} &= T_{ij}^{\alpha},
\end{aligned} \tag{1.2}$$

where, $A_i$ and $C_j$ are the individual characteristics for exporters and importers respectively, $T_{ij} \geq 1$ are the iceberg trade costs, $\alpha$ is the trade elasticity parameter (e.g., $1 - \sigma$), $E_j$ is expenditure of $j$, $Y_i$ is the sales value of $i$, and $\phi_j$ is an importer-country-specific parameter scaling the degree of the trade imbalance. If $\phi_j = 1$ for all $j$, we have $Y_i = E_i$ for all $i$.

Note that all the parameters $A_i$, $B_{ij}$, $C_j$, $E_j$, $Y_i$ and $\phi_j$ can be estimated and, thus, are known (see step 1 of the practical implementation).

Also, let me define $V'$ as the counterfactual value of any variable/parameter $V$ and $\dot{V} = V'/V$. I can substitute $V' = \dot{V}V$, where $V$ is known (or estimated) and $\dot{V}$ is unknown. Moreover, in this class of models, it is the case that $\dot{A} = \dot{Y}^{\alpha}$.

Next, let me rewrite the system in (1.2) for a counterfactual trade network as

$$Y'_i = A'_i \sum_{j=1}^{J} B'_{ij} \frac{\phi_j Y'_j}{\sum_{i=1}^{J} A'_i B'_{ij}}. \tag{1.3}$$

Now it is useful to substitute $Y_i \dot{Y}_i = Y'_i$ and $A_i \dot{Y}_i^{\alpha} = A'_i$. This leads to

$$\dot{Y}_i = \frac{A_i}{Y_i} \dot{Y}_i^{\alpha} \sum_{j=1}^{J} B'_{ij} \frac{\phi_j Y_j \dot{Y}_j}{\sum_{i=1}^{J} A_k \dot{Y}_i^{\alpha} B'_{ij}}. \tag{1.4}$$

Note that $A_i$ is known for all $i$ and $\alpha$, $Y_i$, and $\phi_j$ are also known. $B'_{ij}$ is the counterfactual trade friction parameter and it can be freely set (see step 2 of of the practical implementation). The only thing unknown, therefore, is $\dot{Y}_i$, that can be solved iteratively (see step 3 of the practical implementation).

### 1.5.2 Practical implementation

In a similar fashion as Yotov et al. (2017), the above theoretical framework can be implemented using three practical steps.

**Step 1: Estimation of the baseline parameters.**

The first step to implement the counterfactual model described above consists of estimating the baseline parameters. Building on Arvis and Shepherd (2013) and Fally (2015) equation (1.2) can be estimated using the Pseudo Poisson Maximum Likelihood estimator with importer ($\xi_j$) and exporter ($\pi_i$) fixed effects:

$$X_{ij} = \exp\left[\pi_i + \xi_j + ln(B_{ij})\right] \epsilon_{ij}, \tag{1.5}$$

where

$$\begin{aligned} ln(B_{ij}) = T_{ij}\beta &= lnDIST_{ij}\beta_1 + CONTIG_{ij}\beta_2 + BRDR_{ij}\beta_3 \\ &+ COMLANG_{ij}\beta_4 + COMCOL_{ij}\beta_5 + RTA_{ij}\beta_6 + WTO_{ij}\beta_7 \end{aligned} \tag{1.6}$$

and $lnDIST_{ij}$ is the logarithm of bilateral distance; $CONTIG_{ij}$ an indicator variable for contiguity; $BRDR_{ij}$ is an indicator variable for international borders; $COMLANG_{ij}$ and $COMCOL_{ij}$ are indicators for common language and colonizer, respectively; $RTA_{ij}$ indicate whether there is a trade agreement between the trade partners; and $WTO_{ij}$ is an indicator for common membership to the WTO.

Note that to estimate equation (1.5) it is needed to suppress the constant and leave one fixed effect out of the regression. Setting $\pi_1 = 0$ I define exporter 1 as the reference category. See Table 1.A.1 in section 1.A of the Appendix for the estimated coefficients of equation (1.5).

After estimation of equation (1.5) one can see that:

$$
\begin{aligned}
E_j &= \sum_{i=1}^{J} X_{ij}, \\
Y_i &= \sum_{j=1}^{J} X_{ij}, \\
\phi_j &= E_j / Y_j, \\
C_j &= \exp[\hat{\xi}_j], \\
A_i &= \exp[\hat{\pi}_i], \\
B_{ij} &= \exp[T_{ij}\hat{\beta}]
\end{aligned}
\tag{1.7}
$$

**Step 2: Define a counterfactual scenario.**

The second step involves defining counterfactual scenarios. In this framework the counterfactuals are created by manipulating the parameter $B_{ij}$.

More concretely, one can freely change any of the variables that inform $T_{ij}$ to create the desired counterfactuals. As example, if one would be interested in a world without distance, it suffices to create $T'_{ij} = T_{ij}\beta - lnDIST_{ij}\beta_1$ setting $lnDIST_{ij} = 0$ for all pairs and then create $B'_{ij} = \exp[T'_{ij}\hat{\beta}]$.

**Step 3: Solve the system iteratively.**

For solving equation (1.4), two things are helpful. First, it is only possible to solve the system up to a scalar, this means that only $J - 1$ values (or the variation but not the level) of $\dot{Y}_i$ are determined. It is customary to fix $\dot{Y}_1 = 1$ and solve for the remaining $J - 1$ values $(\dot{Y}_2, ..., \dot{Y}_J)$.

Second it is useful to see the above problem as one that has $J-1$ rows and $J$ columns. For this purpose, let me divide (1.4) by $\dot{Y}^{\alpha}$ and separate its right hand side into its numerator and its denominator. Therefore, let's define a $(J-1)\times J$ matrix $N$ (for the numerator), whose $ij$th element is

$$N_{ij} = \frac{A_i}{Y_i} B'_{ij}\phi_j Y_j = \frac{A_i}{Y_i} B'_{ij} E_j. \tag{1.8}$$

and a $J \times 1$ vector $D$ (for the denominator)

$$D_j = \sum_{i=1}^{J} A_i B'_{ij} \dot{Y}_i = A_1 B'_{1j} + \sum_{i=2}^{J} A_i B'_{ij} \dot{Y}_i^{\alpha}. \tag{1.9}$$

where $\dot{Y}_1^{\alpha} = 1$ by definition.

For implementation, it is convenient to solve $\dot{Y}_i$ iteratively in steps. Let me refer to the initial values or step-0 values of $\dot{Y}_i$ by $\dot{Y}_{i,0} = 1$. Note that $\dot{Y}_{i,0} = 1$ for all countries $i$. In the same step 0, I then can compute step-1 outcome for all exports $i > 1$ from

$$\dot{Y}_{i,1}^{1-\alpha} \quad = \quad \sum_{j=1}^{J} \frac{N_{ij}}{D_{j,0}}, \tag{1.10}$$

and solve for $\dot{Y}_{i,1}$ that will be used to update equation (1.9) and obtain for every step $s$:

$$\dot{Y}_{i,s+1}^{1-\alpha} \quad = \quad \sum_{j=1}^{J} \frac{N_{ij}\dot{Y}_{j,s}}{D_{j,s}}. \tag{1.11}$$

The latter can be iterated until ($\dot{Y}_{i,s+1} - \dot{Y}_{i,s} < \epsilon$), where $\epsilon$ is a pre-selected criterion value.

In section 1.B of Appendix I provide a simple STATA code to implement the whole procedure.

### 1.5.3 Counterfactual analysis

In this subsection I define different counterfactual scenarios that will help clarify (i) why there are communities in the trade network, (ii) why the the modular structure is more intense in the random networks.

**A world without trade frictions - Explaining Result 1.**

The first counterfactual consists of creating a world without trade frictions. Trade frictions can influence modularity in several ways. Geographic frictions, such as distance between countries, can increase the modularity of the network by making close countries trade more between them and less with further away countries. Trade policy, on the other hand, could reduce modularity by creating incentives to trade with more and more diverse partners. Before analysing different frictions individually, I first eliminate all trade frictions, i.e. I set $T_{ij}$ in equation (1.6) to 0, which is equivalent to set $B'_{ij} = 1$ and, thus, leaving only the individual characteristics for exporters and importers in the first line of equation (1.2), this produces $\hat{X}_{ij}^{NF}$ as the non-frictions trade between country $i$ and $j$.

Table 1.4: Randomization statistics for the No Frictions Counterfactual Network

Intermediate Goods

| Year | in-strength preserving $\bar{Q}'^{NF}$ | $\sigma(Q'^{NF})$ | $Q^{NF}$ | $z$ | out-strength preserving $\bar{Q}'^{NF}$ | $\sigma(Q'^{NF})$ | $Q^{NF}$ | $z$ | full randomization $\bar{Q}'^{NF}$ | $\sigma(Q'^{NF})$ | $Q^{NF}$ | $z$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1995 | 0.311 | 0.007 | -0.0 | -46.202 | 0.238 | 0.007 | -0.0 | -33.754 | 0.351 | 0.004 | -0.0 | -81.044 |
| 2000 | 0.331 | 0.006 | 0.0 | -51.944 | 0.250 | 0.008 | 0.0 | -33.290 | 0.372 | 0.004 | 0.0 | -92.688 |
| 2005 | 0.323 | 0.007 | 0.0 | -45.938 | 0.272 | 0.008 | 0.0 | -35.732 | 0.380 | 0.004 | 0.0 | -92.592 |
| 2010 | 0.321 | 0.007 | 0.0 | -44.682 | 0.281 | 0.008 | 0.0 | -35.096 | 0.383 | 0.004 | 0.0 | -96.972 |
| 2015 | 0.296 | 0.006 | 0.0 | -49.692 | 0.229 | 0.007 | 0.0 | -33.208 | 0.336 | 0.004 | 0.0 | -87.243 |

Final Goods

| Year | in-strength preserving $\bar{Q}'^{NF}$ | $\sigma(Q'^{NF})$ | $Q^{NF}$ | $z$ | out-strength preserving $\bar{Q}'^{NF}$ | $\sigma(Q'^{NF})$ | $Q^{NF}$ | $z$ | full randomization $\bar{Q}'^{NF}$ | $\sigma(Q'^{NF})$ | $Q^{NF}$ | $z$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1995 | 0.282 | 0.008 | -0.0 | -34.778 | 0.223 | 0.009 | -0.0 | -24.290 | 0.307 | 0.007 | -0.0 | -41.835 |
| 2000 | 0.319 | 0.011 | 0.0 | -28.031 | 0.266 | 0.013 | 0.0 | -20.803 | 0.365 | 0.008 | 0.0 | -44.352 |
| 2005 | 0.265 | 0.008 | 0.0 | -33.127 | 0.209 | 0.008 | 0.0 | -27.679 | 0.295 | 0.007 | 0.0 | -43.181 |
| 2010 | 0.250 | 0.009 | 0.0 | -28.317 | 0.207 | 0.008 | 0.0 | -25.426 | 0.278 | 0.008 | 0.0 | -36.275 |
| 2015 | 0.231 | 0.007 | 0.0 | -32.013 | 0.183 | 0.009 | 0.0 | -21.114 | 0.254 | 0.007 | 0.0 | -35.524 |

In Table 1.4 I provide the results for $Q^{NF}$ corresponding to the Q value of the counterfactual No-Friction network and the corresponding $\bar{Q}'^{NF}$ for its randomization.

What clearly stands out in table 1.4 is that result 1 is entirely driven by trade costs. To see why, it is important to note the value of $Q^{NF}$ is 0 suggesting that a world without trade frictions would be not modular at all. In this counterfactual, indeed, there exists only one community and all countries trade intensively with each other.

Furthermore, when comparing $Q^{NF}$ with $\bar{Q}'^{NF}$ Table 1.4 shows that the corresponding randomizations of the No-Friction network still appear to be more modular. This suggests that the driver of result 2 is not the bilateral part of the first line of equation (1.2).

In Table 1.5 I present the disaggregation of trade frictions into its three components - geography, culture and trade policy.

Table 1.5: Randomization statistics for the Intermediate Goods No Frictions Network - Disaggregation

| | No geographic frictions | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | in-strength preserving | | | | out-strength preserving | | | | full randomization | | | |
| Year | $\bar{Q}'^{NF}$ | $\sigma(Q'^{NF})$ | $Q^{NF}$ | $z$ | $\bar{Q}'^{NF}$ | $\sigma(Q'^{NF})$ | $Q^{NF}$ | $z$ | $\bar{Q}'^{NF}$ | $\sigma(Q'^{NF})$ | $Q^{NF}$ | $z$ |
| 1995 | 0.328 | 0.007 | 0.069 | -39.071 | 0.253 | 0.008 | 0.069 | -23.457 | 0.368 | 0.004 | 0.069 | -76.744 |
| 2000 | 0.329 | 0.005 | 0.046 | -53.658 | 0.244 | 0.008 | 0.046 | -25.239 | 0.367 | 0.004 | 0.046 | -79.767 |
| 2005 | 0.319 | 0.005 | 0.056 | -47.913 | 0.248 | 0.008 | 0.056 | -25.166 | 0.360 | 0.004 | 0.056 | -68.871 |
| 2010 | 0.315 | 0.007 | 0.063 | -34.908 | 0.247 | 0.006 | 0.063 | -28.479 | 0.355 | 0.004 | 0.063 | -70.985 |
| 2015 | 0.309 | 0.007 | 0.068 | -36.917 | 0.244 | 0.007 | 0.068 | -26.533 | 0.349 | 0.004 | 0.068 | -71.599 |

| | No cultural frictions | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | in-strength preserving | | | | out-strength preserving | | | | full randomization | | | |
| Year | $\bar{Q}'^{NF}$ | $\sigma(Q'^{NF})$ | $Q^{NF}$ | $z$ | $\bar{Q}'^{NF}$ | $\sigma(Q'^{NF})$ | $Q^{NF}$ | $z$ | $\bar{Q}'^{NF}$ | $\sigma(Q'^{NF})$ | $Q^{NF}$ | $z$ |
| 1995 | 0.303 | 0.006 | 0.249 | -9.193 | 0.309 | 0.007 | 0.249 | -8.293 | 0.360 | 0.004 | 0.249 | -30.420 |
| 2000 | 0.312 | 0.007 | 0.258 | -7.510 | 0.309 | 0.007 | 0.258 | -7.482 | 0.365 | 0.004 | 0.258 | -25.380 |
| 2005 | 0.322 | 0.008 | 0.264 | -7.445 | 0.318 | 0.006 | 0.264 | -9.159 | 0.376 | 0.004 | 0.264 | -25.456 |
| 2010 | 0.305 | 0.006 | 0.276 | -5.283 | 0.300 | 0.006 | 0.276 | -3.965 | 0.355 | 0.003 | 0.276 | -22.809 |
| 2015 | 0.284 | 0.005 | 0.261 | -4.605 | 0.282 | 0.005 | 0.261 | -3.908 | 0.332 | 0.004 | 0.261 | -18.904 |

| | No trade policy | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | in-strength preserving | | | | out-strength preserving | | | | full randomization | | | |
| Year | $\bar{Q}'^{NF}$ | $\sigma(Q'^{NF})$ | $Q^{NF}$ | $z$ | $\bar{Q}'^{NF}$ | $\sigma(Q'^{NF})$ | $Q^{NF}$ | $z$ | $\bar{Q}'^{NF}$ | $\sigma(Q'^{NF})$ | $Q^{NF}$ | $z$ |
| 1995 | 0.250 | 0.005 | 0.172 | -14.619 | 0.252 | 0.006 | 0.172 | -14.488 | 0.302 | 0.003 | 0.172 | -37.440 |
| 2000 | 0.274 | 0.006 | 0.189 | -14.491 | 0.272 | 0.005 | 0.189 | -15.755 | 0.329 | 0.003 | 0.189 | -43.999 |
| 2005 | 0.290 | 0.006 | 0.151 | -21.585 | 0.292 | 0.007 | 0.151 | -19.664 | 0.357 | 0.004 | 0.151 | -57.208 |
| 2010 | 0.282 | 0.006 | 0.158 | -20.213 | 0.296 | 0.007 | 0.158 | -19.638 | 0.357 | 0.004 | 0.158 | -50.431 |
| 2015 | 0.242 | 0.005 | 0.167 | -13.800 | 0.232 | 0.006 | 0.167 | -10.810 | 0.288 | 0.003 | 0.167 | -36.730 |

Clearly, Table 1.5 shows that geographic frictions matter the most when explaining the modularity found in the world trade network. More concretely, when I eliminate all geographic frictions the value of $Q$ for the counterfactual network drop to around 0.05 compared to the 0.27 of the original $\hat{Z}$ network.

Eliminating all trade policy (trade agreement and WTO membership), surprisingly, also reduces the value of $Q$, but only to around 0.16. This results suggests that trade agreements actually increase modularity (as its elimination, reduces it). Finally, eliminating all cultural frictions has virtually no effect on the $Q$ value as compared to the original network.

**Only frictions network - Explaining Result 2.**

In this counterfactual I build a network that only rests on the bilateral trade frictions. This exercise is useful as this would be a network net of individual country characteristics. These individual features, such as size, productivity or comparative advantage can play an important role in community creation or its lack. To compute this counterfactual I use:

Table 1.6: Randomization statistics for the Final Goods No Frictions Network - Disaggregation

| | No geographic frictions | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | in-strength preserving | | | | out-strength preserving | | | | full randomization | | | |
| Year | $\bar{Q}'^{NF}$ | $\sigma(Q'^{NF})$ | $Q^{NF}$ | $z$ | $\bar{Q}'^{NF}$ | $\sigma(Q'^{NF})$ | $Q^{NF}$ | $z$ | $\bar{Q}'^{NF}$ | $\sigma(Q'^{NF})$ | $Q^{NF}$ | $z$ |
| 1995 | 0.298 | 0.009 | 0.048 | -27.146 | 0.242 | 0.009 | 0.048 | -20.462 | 0.324 | 0.007 | 0.048 | -39.231 |
| 2000 | 0.305 | 0.010 | 0.036 | -26.592 | 0.237 | 0.009 | 0.036 | -22.161 | 0.332 | 0.008 | 0.036 | -36.063 |
| 2005 | 0.292 | 0.010 | 0.031 | -27.350 | 0.244 | 0.010 | 0.031 | -21.900 | 0.324 | 0.007 | 0.031 | -42.542 |
| 2010 | 0.268 | 0.009 | 0.042 | -26.078 | 0.227 | 0.010 | 0.042 | -18.017 | 0.300 | 0.007 | 0.042 | -37.534 |
| 2015 | 0.256 | 0.009 | 0.058 | -21.301 | 0.218 | 0.009 | 0.058 | -18.360 | 0.285 | 0.007 | 0.058 | -34.721 |

| | No cultural frictions | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | in-strength preserving | | | | out-strength preserving | | | | full randomization | | | |
| Year | $\bar{Q}'^{NF}$ | $\sigma(Q'^{NF})$ | $Q^{NF}$ | $z$ | $\bar{Q}'^{NF}$ | $\sigma(Q'^{NF})$ | $Q^{NF}$ | $z$ | $\bar{Q}'^{NF}$ | $\sigma(Q'^{NF})$ | $Q^{NF}$ | $z$ |
| 1995 | 0.258 | 0.009 | 0.209 | -5.436 | 0.258 | 0.009 | 0.209 | -5.750 | 0.293 | 0.007 | 0.209 | -12.348 |
| 2000 | 0.292 | 0.010 | 0.221 | -7.295 | 0.266 | 0.010 | 0.221 | -4.480 | 0.323 | 0.007 | 0.221 | -15.513 |
| 2005 | 0.294 | 0.009 | 0.232 | -6.537 | 0.275 | 0.009 | 0.232 | -4.663 | 0.328 | 0.007 | 0.232 | -12.878 |
| 2010 | 0.260 | 0.008 | 0.249 | -1.303 | 0.256 | 0.009 | 0.249 | -0.745 | 0.294 | 0.006 | 0.249 | -7.167 |
| 2015 | 0.242 | 0.008 | 0.238 | -0.488 | 0.244 | 0.007 | 0.238 | -0.825 | 0.277 | 0.006 | 0.238 | -6.825 |

| | No trade policy | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | in-strength preserving | | | | out-strength preserving | | | | full randomization | | | |
| Year | $\bar{Q}'^{NF}$ | $\sigma(Q'^{NF})$ | $Q^{NF}$ | $z$ | $\bar{Q}'^{NF}$ | $\sigma(Q'^{NF})$ | $Q^{NF}$ | $z$ | $\bar{Q}'^{NF}$ | $\sigma(Q'^{NF})$ | $Q^{NF}$ | $z$ |
| 1995 | 0.231 | 0.008 | 0.161 | -8.951 | 0.226 | 0.008 | 0.161 | -7.888 | 0.265 | 0.006 | 0.161 | -16.991 |
| 2000 | 0.282 | 0.010 | 0.171 | -11.143 | 0.266 | 0.009 | 0.171 | -10.422 | 0.328 | 0.008 | 0.171 | -19.549 |
| 2005 | 0.254 | 0.008 | 0.165 | -10.481 | 0.226 | 0.008 | 0.165 | -7.467 | 0.285 | 0.006 | 0.165 | -18.867 |
| 2010 | 0.225 | 0.007 | 0.172 | -7.559 | 0.219 | 0.007 | 0.172 | -6.445 | 0.259 | 0.007 | 0.172 | -13.285 |
| 2015 | 0.204 | 0.006 | 0.168 | -6.265 | 0.192 | 0.007 | 0.168 | -3.607 | 0.231 | 0.005 | 0.168 | -12.724 |

$$\hat{X}_{ij}^{FO} = \frac{X_{ij}}{\hat{X}_{ij}^{NF}}, \tag{1.12}$$

where $X_{ij}$ are the original trade flows, $\hat{X}_{ij}^{NF}$ are the non-friction trade flows and $\hat{X}_{ij}^{FO}$ are the frictions only part of $X_{ij}$.

In Table 1.7 I provide the results for the $Q^{FO}$ corresponding to the Q value of the counterfactual Frictions Only network and the corresponding $\bar{Q}'^{FO}$ for its randomization.

Table 1.7 shows a high vale for $Q^{FO}$ suggesting that the modularity of the original trade network originates only at a bilateral level and it is not affected by countries' individual characteristics.

What is more interesting is that Table 1.7 shows a clearly significant and positive $z$ score. This indicates that the corresponding Frictions Only network randomizations are less modular than the original Frictions Only network. In other words, result 2 found in Table 1.3 is not present in the Frictions Only networks.

This finding suggests that the lack of modularity (compared to its randomizations) of the original world trade originates in the individual countries' characteristics.

Table 1.7: Randomization statistics for the Frictions Only Counterfactual Network

| | Intermediate Goods | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | in-strength preserving | | | | out-strength preserving | | | | full randomization | | | |
| Year | $\bar{Q}'^{FO}$ | $\sigma(Q'^{FO})$ | $Q^{FO}$ | $z$ | $\bar{Q}'^{FO}$ | $\sigma(Q'^{FO})$ | $Q^{FO}$ | $z$ | $\bar{Q}'^{FO}$ | $\sigma(Q'^{FO})$ | $Q^{FO}$ | $z$ |
| 1995 | 0.262 | 0.006 | 0.371 | 19.031 | 0.295 | 0.004 | 0.371 | 18.388 | 0.318 | 0.003 | 0.371 | 17.261 |
| 2000 | 0.260 | 0.005 | 0.378 | 22.335 | 0.264 | 0.004 | 0.378 | 26.205 | 0.301 | 0.003 | 0.378 | 22.567 |
| 2005 | 0.241 | 0.005 | 0.381 | 28.021 | 0.257 | 0.004 | 0.381 | 33.555 | 0.277 | 0.003 | 0.381 | 29.832 |
| 2010 | 0.236 | 0.005 | 0.374 | 27.214 | 0.248 | 0.004 | 0.374 | 33.252 | 0.269 | 0.004 | 0.374 | 27.681 |
| 2015 | 0.235 | 0.005 | 0.380 | 30.297 | 0.268 | 0.003 | 0.380 | 33.433 | 0.277 | 0.003 | 0.380 | 33.090 |

| | Final Goods | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | in-strength preserving | | | | out-strength preserving | | | | full randomization | | | |
| Year | $\bar{Q}'^{FO}$ | $\sigma(Q'^{FO})$ | $Q^{FO}$ | $z$ | $\bar{Q}'^{FO}$ | $\sigma(Q'^{FO})$ | $Q^{FO}$ | $z$ | $\bar{Q}'^{FO}$ | $\sigma(Q'^{FO})$ | $Q^{FO}$ | $z$ |
| 1995 | 0.274 | 0.010 | 0.361 | 8.689 | 0.307 | 0.007 | 0.361 | 7.986 | 0.368 | 0.003 | 0.361 | -2.107 |
| 2000 | 0.243 | 0.008 | 0.360 | 14.665 | 0.254 | 0.006 | 0.360 | 17.538 | 0.313 | 0.004 | 0.360 | 12.001 |
| 2005 | 0.255 | 0.008 | 0.372 | 14.202 | 0.304 | 0.007 | 0.372 | 10.417 | 0.356 | 0.004 | 0.372 | 3.552 |
| 2010 | 0.234 | 0.008 | 0.351 | 15.378 | 0.324 | 0.007 | 0.351 | 3.822 | 0.372 | 0.004 | 0.351 | -5.120 |
| 2015 | 0.283 | 0.009 | 0.364 | 9.076 | 0.351 | 0.009 | 0.364 | 1.543 | 0.403 | 0.005 | 0.364 | -8.523 |

## 1.6 Conclusion

In this paper I have explored the structure of world trade network in final and intermediate goods focusing in its mesoscale structure.

I find that, when optimizing modularity, countries organize in broad communities corresponding to continents (or regional trade blocks) namely Asia, Europe and America. Moreover, I use three different randomization algorithms (in-strength preserving, out-strength preserving and full randomization) and I produce 100 random network for each algorithm. I find that the random networks are actually more modular than the original network. The world trade network is, up to my knowledge, the first to be found with this property. These result holds for both the final goods and the intermediate goods network.

To better understand the mechanisms behind these results I use counterfactual analyses to create hypothetical networks. In my first counterfactual I eliminate all trade frictions originating at a bilateral level (geographic, cultural and trade policy frictions). As a result I find that a frictionless world would have a much smaller modularity and all countries would be grouped in one single community. Also, when I disaggregate bilateral frictions into different components I find that geographic barriers are the ones that matter the most to explain the modularity of the world trade network.

In general all counterfactuals that change bilateral characteristics, however, still present more modular randomizations. In my second counterfactual, therefore, I generate a frictions only world which is net of individual countries characteristics. Eventually, the randomizations associated with this counterfactual are less modular.

# Appendix

## 1.A Regression results

Table 1.A.1: estimated coefficient for equation (1.5)

| | Intermediate Goods | | | | | | |
|---|---|---|---|---|---|---|---|
| Year | ln(Dist) | CONTING | BRDR | COMLANG | COMCOL | RTA | WTO |
| 1995 | -0.532 | 0.516 | -4.289 | 0.257 | -0.361 | 0.619 | 1.065 |
| | (0.04) | (0.098) | (0.149) | (0.082) | (0.288) | (0.085) | (0.205) |
| 2000 | -0.561 | 0.602 | -4.095 | 0.186 | -0.351 | 0.539 | 0.771 |
| | (0.042) | (0.114) | (0.152) | (0.09) | (0.269) | (0.083) | (0.215) |
| 2005 | -0.564 | 0.611 | -4.023 | 0.165 | -0.22 | 0.497 | 2.541 |
| | (0.048) | (0.108) | (0.167) | (0.093) | (0.267) | (0.085) | (0.169) |
| 2010 | -0.596 | 0.492 | -4.007 | 0.243 | -0.212 | 0.558 | 2.317 |
| | (0.052) | (0.122) | (0.174) | (0.1) | (0.276) | (0.08) | (0.188) |
| 2015 | -0.569 | 0.446 | -4.219 | 0.351 | -0.155 | 0.666 | 2.722 |
| | (0.049) | (0.125) | (0.167) | (0.097) | (0.27) | (0.075) | (0.176) |

| | Final Goods Goods | | | | | | |
|---|---|---|---|---|---|---|---|
| Year | ln(Dist) | CONTING | BRDR | COMLANG | COMCOL | RTA | WTO |
| 1995 | -0.504 | 0.518 | -5.177 | 0.289 | -0.533 | 0.397 | 1.26 |
| | (0.042) | (0.12) | (0.171) | (0.098) | (0.202) | (0.105) | (0.243) |
| 2000 | -0.54 | 0.631 | -5.07 | 0.242 | -0.614 | 0.349 | 1.101 |
| | (0.047) | (0.143) | (0.182) | (0.112) | (0.192) | (0.107) | (0.259) |
| 2005 | -0.574 | 0.6 | -4.91 | 0.174 | -0.365 | 0.305 | 3.208 |
| | (0.052) | (0.128) | (0.183) | (0.102) | (0.181) | (0.092) | (0.173) |
| 2010 | -0.606 | 0.512 | -4.877 | 0.179 | -0.257 | 0.379 | 3.215 |
| | (0.053) | (0.131) | (0.191) | (0.097) | (0.181) | (0.088) | (0.187) |
| 2015 | -0.566 | 0.475 | -5.094 | 0.276 | -0.243 | 0.561 | 3.477 |
| | (0.05) | (0.136) | (0.183) | (0.092) | (0.172) | (0.085) | (0.17) |

Standard errors reported in parentheses.

## 1.B Stata code

In this section I provide the Stata code to implement a "No distance" counterfactual.

```
*****************************
* Step 1: Estimate Baseline *
*****************************

* Create variables for output and expenditure
bysort exporter: egen Y = sum(trade)
bysort importer: egen E = sum(trade)
gen phi=E/Y

*Generate dummies for the FE
qui tab exporter, gen(exp_fe_)
qui tab importer, gen(imp_fe_)
local NoC=r(r)

/* Estimate the gravity model with the PPML estimator
leaving the the first exporter FE and the constant out.*/

ppml trade ln_dist contig bordr comlang_off comcol rta wto ///
exp_fe_2-exp_fe_`=`NoC''imp_fe_1-imp_fe_`=`NoC'', noconstant

*Save predicted trade.
predict tradehat_BLN, mu


* Construct the variables for export- and import-fixed effects
forvalues i = 2 (1) `=`NoC'' {
qui replace exp_fe_`i'=exp_fe_`i'*exp(_b[exp_fe_`i'])
qui replace imp_fe_`i'=imp_fe_`i'*exp(_b[imp_fe_`i'])
}
replace imp_fe_1=imp_fe_1*exp(_b[imp_fe_1])


*Create parameter A and C
egen A = rowtotal(exp_fe_1-exp_fe_`=`NoC'')
egen C = rowtotal(imp_fe_1-imp_fe_`=`NoC'')

drop exp_fe_* imp_fe_*
```

```
* Compute the variables of bilateral trade costs
generate B_BLN = exp(_b[ln_dist] * ln_dist + _b[contig] * contig ///
+ _b[bordr] * bordr + _b[comlang_off] * comlang_off + _b[comcol] *
    comcol ///
+ _b[rta] * rta+ _b[wto] * wto)



*********************************
* Step 2: Define Counterfactual *
*********************************


*Set ln_dist to 0 and create B'
generate B_CFL =exp(_b[ln_dist] * ln_dist *0+ _b[contig] * contig ///
+ _b[bordr] * bordr + _b[comlang_off] * comlang_off + _b[comcol] *
    comcol ///
+ _b[rta] * rta+ _b[wto] * wto)


*****************************
* Step 3: Solve iteratively *
*****************************

*Define sigma and alpha and initial vector of ones for Ydot and Ydotj
scalar sigma=5
scalar alpha=1-sigma
generate Ydot_0=1
generate tempYdotj_0 = Ydot_0 if exporter == importer
bysort importer: egen Ydotj_0 = mean(tempYdotj_0)


*Equation 11
generate N=(A/Y)*B_CFL*E

*We eliminate the first row
replace N=. if A==1

*Equation 12
generate D=A*B_CFL
generate temp_H_0=D*Ydot_0
bysort importer: egen H_0=sum(temp_H_0)
```

```
*Equation 13
gen temp_Ydot_malpha_1=N/H_0
bysort exporter: egen Ydot_malpha_1=sum(temp_Ydot_malpha_1)
gen Ydot_1=Ydot_malpha_1^(1/(1-alpha))
replace Ydot_1=1 if N==.



*generate Ydot_j
generate tempYdotj_1 = Ydot_1 if exporter == importer
bysort importer: egen Ydotj_1 = mean(tempYdotj_1)



 ***** Start the loop *****

local s=1
generate dif_Ydot_1 = Ydot_1-Ydot_0
summarize dif_Ydot_1
local sd_dif_Ydot = r(sd)
local mean_dif_Ydot = abs(r(mean))

while (`sd_dif_Ydot' > 0.001) | (`mean_dif_Ydot' > 0.001) {

*Update Equation 12
generate temp_H_`s'=D*((Ydot_`s')^alpha)
bysort importer: egen H_`s'=sum(temp_H_`s')

*Update Equation 13
gen temp_Ydot_malpha_`=`s'+1'=N*Ydotj_`s'/H_`s'
bysort exporter: egen Ydot_malpha_`=`s'+1'=sum(temp_Ydot_malpha_`=`s
    '+1')

gen Ydot_`=`s'+1'=Ydot_malpha_`=`s'+1'^(1/(1-alpha))
replace Ydot_`=`s'+1'=1 if N==.
generate tempYdotj_`=`s'+1' = Ydot_`=`s'+1' if exporter == importer
bysort importer: egen Ydotj_`=`s'+1' = mean(tempYdotj_`=`s'+1')


*Set stopping criterion
local dif_Ydot = abs(Ydot_`=`s'+1'-Ydot_`s')
```

```
generate dif_Ydot_`=`s'+1' = Ydot_`=`s'+1'-Ydot_`s'
summarize dif_Ydot_`=`s'+1'
local sd_dif_Ydot = r(sd)
local mean_dif_Ydot = abs(r(mean))

local s=`s'+1
}

local S=`s'

* Compute X_prime

generate N_prime=A*Ydot_`S'*B_CFL*E*Ydotj_`S'
generate D_prime=A*B_CFL*Ydot_`S'
bysort importer: egen H_prime=sum(D_prime)
gen X_prime=N_prime/H_prime
```

# Chapter 2

# Backward versus Forward Integration of Firms in Global Value Chains

## 2.1 Introduction

Modern production entertains the mechanics of comparative advantage to an unprecedented degree. This becomes evident in the specialization of production facilities on ever-thinner slices of their products' value chains, in their sourcing of inputs from suppliers at home as well as abroad, and in their supply to customers there. Today, trade in global value chains is the dominant type of international trade (Johnson and Noguera, 2012; Bernard and Fort, 2015; Alfaro et al., 2019). Global production networks also lead to more complex organization structures observed in internationally operating firms that source and supply inputs within and outside the boundaries of the firm.

The international division of production in tandem with firm boundaries that reach beyond national borders has important implications for the pattern of asset ownership. While this is unsurprising at first glance, it is important to emphasize that this pattern might not only be distinct from the one of production, but also be subject to different forces. Relative to the pattern of international production, however, the pattern of asset ownership in global value chains is far less well studied. This paper aims at filling this gap and seeks to understand the forces that determine the pattern of asset ownership in global value chains.[1]

To that end, we provide a systematic picture of the value-chain coordinates (upstream versus downstream) and directional ownership characteristics (owner versus owned) in the largest possible dataset of worldwide shareholder-affiliate-ownership links among 1,565,167 firms which we observe annually over the period 2007-2013. The combination of country-sector with country-sector input-output links from World Input-Output Tables (WIOT) and of the country-sector firm affiliations in the firm data permits distinguishing between forward integration (the owner is up the stream of the affiliate in the value chain), backward integration (the owner is down the stream of the affiliate in the value chain), and independence (no integration whatsoever).

In order to understand the country-sector-specific drivers of ownership patterns around the world, we aggregate firm-to-firm links into country-sector-to-country-sector directed-ownership-frequency cells in each year and obtain a distribution of frequencies of integration links across country-sector pairs and time periods.[2] With 199 countries and 38 sectors, the aggregated dataset of country-sector-pair ownership links represents the universe of potential network links ($199^2 \times 38^2$ observations in the cross section) while the frequency of integration within cells is informative of the extensive margin forces of ownership between pairs of country-sector dyads. The aggregated dataset permits exploiting the variation in country-sector characteristics of the shareholder as well as the affiliate to assess hypotheses regarding the likelihood of backward versus forward ownership directions with a focus on theoretically motivated observables but conditional on a rich set of fixed effects. The latter permits focusing on ownership-frequency and -direction responses to *changes* in fundamentals. This is an important step towards an identification of the mechanisms at work.

We will document that both forward and backward directions of ownership are important. They even account for very similar shares in the large cross-country and cross-sector ownership dataset we use. In deriving empirical predictions about the country-sector determinants of international ownership patterns, we build upon earlier work that has shown that (vertical) integration decisions of individual firms can be rationalized in models in the spirit

[1]In that sense, this paper takes as given the location of production and assesses the determinants of the pattern of asset ownership within this pre-determined production network. For an example of a model that features both an endogenous pattern of production as well as one of ownership see, e.g., Garetto (2013).

[2]Econometric work on individual choice problems suggests that if choices depend on variables and parameters that can be grouped (e.g., into country-sector pairs, here) they can be aggregated and analyzed in terms of frequency of occurrence (see Schmidheiny and Brülhart, 2011).

of a property-rights framework (Grossman and Hart, 1986; Hart and Moore, 1990). The underlying theory emphasizes the importance of ownership rights as a source of power, when contracts are incomplete. Ownership of assets determines the distribution of surplus between parties. The core insight of this literature is that residual rights of control should be assigned to the party whose investment contributes most to the value of the final output (see also Whinston, 2001). We take this mechanism as given and test if variations in the institutional and economic environment across countries and sectors related to some deep parameters of the underlying model are informative in understanding (i) the pattern of international asset ownership and (ii) its response to changes in the drivers.

Specifically, we build on Acemoglu et al. (2010) and modify their framework slightly to explicitly account for the role of fixed costs of integration whose reduction is the primary goal of international investment agreements. Incorporating this additional aspect, the augmented model suggests four channels of influence on the pattern of asset ownership: the relative investment intensity of sectors and countries; the relative density of markets; the relative reliance on and importance of supplying and producing country-sectors; and the relative importance of fixed integration costs.

Empirically, we measure the deep parameters of the model using country-sector-pair-specific proxies. We associate the investment intensity of sectors with their intensity in research and development. We measure market thickness and the relative importance of the upstream country and sector for the downstream country and sector (and vice versa) directly from the firm-to-firm-links and WIOT data in conjunction with typical products supplied by a sector according to the Rauch (1999) classification, respectively. Finally, we approximate (inverse) foreign-integration fixed costs with the existence of bilateral investment treaties (BITs). The latter are designed to reduce inter alia expected costs of integration across national borders over time.[3]

The results quite strongly support the four theoretical findings. Sectors with a relatively high investment intensity have a larger propensity to host owners of affiliates in sectors with a lower intensity on average, a greater market thickness reduces and investment-agreement membership increases this propensity, and a stronger input reliance also increases the propensity of shareholder-affiliate ownership. We also find support of the interaction effect between market thickness and fixed integration costs for the magnitude and the sector-country-pair direction of ownership.

[3]The United Nations Conference of Trade and Development (UNCTAD) provides a collection of all important international investment agreements (IIAs), including the signatory parties as well as the dates of signature and entry into force.

The firm-level behavior underlying the property-rights framework which we take as given in our work has been studied and confirmed in earlier work. Still, one interesting feature stands out in previous work on vertical integration: the focus is almost entirely on the integration of input suppliers by and up the stream of a final-goods producer (Grossman and Helpman, 2003, 2005; Antràs, 2003, 2005; Feenstra and Hanson, 2005; Nunn and Trefler, 2008; Alfaro et al., 2019). As has been noted by Del Prete and Rungi (2017), this focus is unwarranted from the perspective of the data which appear to feature both backward and forward integration. We document this fact also in the present paper in the largest-possible international dataset for this purpose we know of.

There are a few exceptions of papers that do assess both forward and backward integration decisions of individual firms through the lens of the property-rights framework (Acemoglu et al., 2010; Lileeva and van Biesebroeck, 2013; Liu, 2021). However, the data neither of Acemoglu et al. (2010) nor of Lileeva and van Biesebroeck (2013) permit separating forward and backward integration. Acemoglu et al. (2010) assume that backward integration is the dominant form of integration, and under this assumption they obtain that the marginal effects of buyer and supplier investment intensities are unambiguous (and opposite) for the attractiveness of integrated versus arm's-length transactions to the producer. Provided this assumption holds, they find support for their results in the data. In contrast, Lileeva and van Biesebroeck (2013) explicitly allow for forward integration to exist as well. They look for an effect of the difference in investments between producer and supplier. If this difference were large enough, the more investment-intensive party should be given control and integrate the other one. They find support for this hypothesis, but, as said, cannot explicitly check whether indeed forward and backward integration occur, where the model predicts them to do. Both Acemoglu et al. (2010) and Lileeva and van Biesebroeck (2013) focus on shareholder firms in a single country, Britain with Acemoglu et al. (2010) and Canada with Lileeva and van Biesebroeck (2013). Liu (2021) proposes a model, where she augments the standard property-rights framework to feature forward, backward, and no integration with heterogeneous firms. In contrast to Acemoglu et al. (2010) and Lileeva and van Biesebroeck (2013), Liu (2021) can indeed distinguish between forward and backward integration as well as firms operating at arm's length in a dataset covering international firm-to-firm linkages. Her empirical analysis confirms that relationship-specific investments of individual firms are relevant for integration outcomes.

The primary focus of the aforementioned work is testing the role of relative investment intensities between buyers and suppliers for integration outcomes in order to confirm that the property-rights framework with that core prediction is indeed the relevant one to think about firms' integration choices.[4] By contrast, our empirical work takes the property-rights framework as given – even though we confirm that it is relevant also in our context – and relates the deep parameters of the model to variations in the market environment across sectors and countries in order to understand whether and how they shape the pattern of asset ownership across country and sector pairs. In order to assess this properly, it is important to examine the extensive margin of ownership, taking into account the full potential choice set of linkages across countries and sectors including services.

With the adopted empirical approach, this paper improves on two potential drawbacks of earlier work. First, it takes into account the full set of ownership choices and input-output linkages consistent with global-value-chain tables and a notion of inputs that is broader than in most empirical work on GVCs, in particular, by taking into account services. Second, the use of time variation in the data in conjunction with high-dimensional fixed effects helps reducing the potential bias from omitted drivers of firm ownership and improves on the identification of causal effects.

Among the results we provide the one regarding BITs as an inverse measure of investment costs is particularly interesting and novel. On the one hand, we show that BITs indeed induce integration in both the forward and backward direction. On the other hand, we demonstrate that the strength of these effects depends systematically on other deep parameters of the model. In particular – consistent with the theoretical hypotheses – we find that a better marketability of inputs increases the impact of implementing a BIT on forward integration, while it reduces it on backward integration.

## 2.2 Conceptual Framework

We consider a model of vertical integration that is rooted in the property-rights theory advanced by Grossman and Hart (1986) and Hart and Moore (1990). In this model, two firms can decide to integrate backwards or forward or to stay independent. The respective outcome depends on the relative in-

[4]To that end, all of the aforementioned works' outcomes of interest are obtained from already established integration and value-chain-linkage choices. In validating the theoretical framework, these papers associate variations in investment-intensities between two firms linked in the value chain with the incidence of theses firms being integrated or operating at arm's length. Most of the literature including the mentioned work as well as the present paper focuses on the use of a single input. van Biesebroeck and Zhang (2014) consider several inputs and demonstrate that intricate interdependencies may emerge between them.

vestment intensity of the partners. Since the general setup of the model is well established in the literature, we refer the reader to Appendix 2.A for technical details and focus on the general intuition and main empirical predictions in the main text. We closely follow Acemoglu et al. (2010), but extend their model by introducing fixed costs of firm integration. The latter permits deriving further empirical predictions. In contrast to Acemoglu et al. (2010), when assessing these predictions, we will specifically address backward versus forward integration explicitly.

In the model, two parties, a supplier $S$ and a producer $P$, are collaborating along the value chain, with $\varphi \in (0, 1)$ indicating to which extent the final output of the producer relies on the provision of the customized input by the supplier. The output generated from this relationship depends on the investment undertaken by both parties. Assuming that contracts conditioning on investment or output levels are not available, investment incentives can be aligned through the allocation of property rights. In particular, the two parties can either decide to stay independent ($I$), or to integrate either backward ($Bwd$) or forward ($Fwd$). We assume that integration is subject to a fixed cost $F$ paid by the owning party (the shareholder).

Knowing equilibrium investment levels under independence relative to each form of integration is key for the equilibrium choice of integration and, hence, the model mechanics: since, in equilibrium, any party invests most under that organizational form where the party is the owner of all assets, the optimal organizational form depends on the importance of the producer's investment $p$ relative to the supplier's investment $s$ for total output. Given $p$ and $s$, the attractiveness of the independence option is, on the one hand, governed by the supplier's outside option of selling the customized input to a different producer. We denote this marketability of the customized input by $\theta$. The higher is $\theta$, the higher are the incentives for the supplier to invest even under independence, because in the event of disagreement, a large share of the benefits generated by the investment can then be collected. This reduces the need to use integration as a tool to align incentives between the parties. On the other hand, the incentive for the producer to invest into the joint output under non-integration is decreasing in $\varphi$, as this parameter governs the relative importance of the customized input for final output. Since the input would not be provided in the event of disagreement, if the parties were independent, the need to integrate increases in the relative importance of the customized input.

The organizational form chosen in equilibrium will be the one that maximizes total surplus and can be expressed in terms of the relative returns to investment for the producer $p$ and supplier $s$, respectively. In particular, we can derive two loci as a function of $p$ and $s$, $\Delta^{Fwd}$ and $\Delta^{Bwd}$, which represent

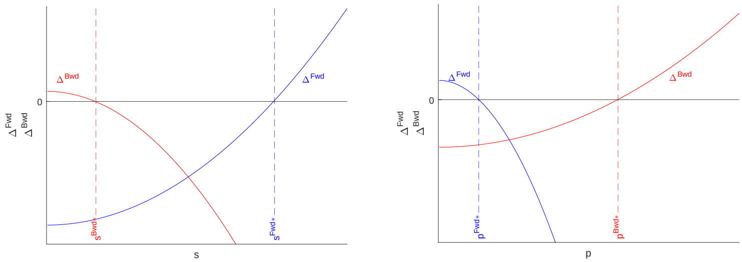



Figure 2.2.1: Graphical representation of the equilibrium organizational form as a function of the returns to investment for the supplier $s$ and as a function of returns to investment for the producer $p$.

the additional surplus generated by forward integration compared to independence and by backward integration compared to independence, respectively (see Equations (2.15) and (2.16) in the Appendix). Figure 2.2.1 depicts the net profitability and optimal choice of an organizational form as a function of $s$ (left panel) and $p$ (right panel), respectively. In the support of $s$, $\Delta^{Fwd}$ is strictly increasing, while $\Delta^{Bwd}$ is strictly decreasing. Vice versa, in the support of $p$, $\Delta^{Fwd}$ is strictly decreasing, while $\Delta^{Bwd}$ is strictly increasing. Taken together, these two graphs establish a well-defined ranking of the equilibrium organizational forms depending on $p$ and $s$. The intersection of the respective loci with the horizontal axis determines four threshold values for $p$ and $s$, $p^{Fwd*}$, $p^{Bwd*}$, $s^{Fwd*}$, and $s^{Bwd*}$, such that the equilibrium organizational form is **forward integration** – holding $p$ constant – for any $s > s^{Fwd*}$ or – holding $s$ constant – for any $p < p^{Fwd*}$. The equilibrium organizational form is **backward integration** – holding $p$ constant – for any $s < s^{Bwd*}$ or – holding $s$ constant – for any $p > p^{Bwd*}$. Forward integration is more desirable as the returns to investment by the supplier are relatively high, while the opposite holds for backward integration. Since fixed costs have to be incurred for both forms of integration but not for independence, the level of fixed costs acts as a shifter for both loci. If none of the inequalities holds, the two parties will choose to stay **independent**.[5]

The intercepts of $\Delta^{Fwd}$ and $\Delta^{Bwd}$ with respect to $s$ depend on $\varphi$ and $p$. Clearly, with higher $p$, forward integration is less desirable and $\Delta^{Fwd}$ with

[5]Technically, there might arise situations where integration is always preferred to independence. For the design of Figure 2.2.1 and throughout the subsequent analysis, we assume, consistent with the data, that a parameter configuration prevails, where any one of the three possible forms of integration are preferable for some values of $p$ and $s$.

respect to $s$ shifts downwards, while backward integration becomes more profitable and $\Delta^{Bwd}$ with respect to $s$ shifts upwards. With higher $\varphi$, the intercepts of both $\Delta^{Bwd}$ with respect to $s$ and $\Delta^{Fwd}$ with respect to $s$ shift upwards – this is because the producer's investment under independence is lower the more important the input is for total output (higher $\varphi$), making any form of integration more desirable. However, $\varphi$ also governs the slope of $\Delta^{Fwd}$ and $\Delta^{Bwd}$ with respect to $s$, as it governs the importance of the supplier's investment for overall surplus and, hence, makes both slopes steeper: a given increase in $s$ makes backward integration less profitable, if the input is more important for the final output, while a given increase in $s$ makes forward integration more profitable, if the input is more important for the final output. Both slopes are also affected by $\theta$, which determines the level of supplier investment under independence. A higher level of $\theta$ increases supplier investment under independence and, hence, increases surplus under independence vis-a-vis both backward and forward integration. Therefore – with respect to $s$ – $\Delta^{Fwd}$ becomes flatter and turns positive at a higher level of $s$, while $\Delta^{Bwd}$ becomes steeper, and the cutoff level of $s$ for independence relative to backward integration is reached at a lower value of $s$. Overall, the range of $s$ for which independence is most profitable increases.

The intercepts of $\Delta^{Fwd}$ and $\Delta^{Bwd}$ with respect to $p$ depend on $s$, $\varphi$, and $\theta$. Conversely to before, with higher $s$, forward integration gets more desirable and $\Delta^{Fwd}$ with respect to $p$ shifts upwards, while backward integration becomes less profitable and $\Delta^{Bwd}$ with respect to $p$ shifts downwards. Given $s$ and $p$, the supplier invests more under independence the better the outside option, $\theta$, is, shifting both loci $\Delta^{Fwd}$ and $\Delta^{Bwd}$ with respect to $p$ downwards. Moreover, given $s$, $\varphi$ scales the impact of any investment by the supplier on total output. Since the supplier's investment level is ceteris paribus always higher under forward integration than under independence, a higher level of $\varphi$ shifts $\Delta^{Fwd}$ with respect to $p$ upwards, while it shifts $\Delta^{Bwd}$ with respect to $p$ downwards, as the supplier's investment level under independence is higher than under backward integration. The impact of $\varphi$ on the slope of $\Delta^{Fwd}$ and $\Delta^{Bwd}$ with respect to $p$ is analogous to the effect of $\theta$ on the slope of $\Delta^{Fwd}$ and $\Delta^{Bwd}$ with respect to $s$. Since $\varphi$ affects the producer's investment level under independence and, in this case, lowers surplus under independence vis-a-vis both backward and forward integration, this leads to a steeper slope of $\Delta^{Bwd}$ with respect to $p$ and a flatter slope of $\Delta^{Fwd}$ with respect to $p$.

### 2.2.1 Model Implications and Testable Predictions

The model at hand allows us to derive testable predictions regarding the role of the various determinants of (international) firm integration along the value chain. The aim of this section is twofold. First, we present and discuss the comparative statics of the formal model with respect to these determinants (Results 1–4). Second, we translate these implications into testable predictions taking into account the specific nature of our data and the empirical specification following from it (Predictions 1–4).

In particular, the theoretical model generates empirical predictions regarding the integration choice of a *given* supplier-producer pair. This setting is, however, stylized as modern production is substantially more complex, involving many intermediate steps along the value chain. Moreover, in the dataset of firm-level ownership relationships that we are going to employ, at any given time we observe only the already realized outcome of integration between a given producer and a given supplier but not the latent gains behind these choices. As has been shown by, e.g., Schmidheiny and Brülhart (2011) such micro-level choice problems can be analyzed by counting the number of firms within cells – here, we will consider shareholder-country-sector-to-affiliate-country-sector cells – and compare the counts across these cells using a Poisson regression analysis. Clearly, as we count the number of firms for all possible combinations of shareholder-country-sectors and affiliate-country-sectors over time, the empirical measurement of parameters of interest such as $\{p, s, \theta, \varphi, F\}$ can at most vary at the (shareholder)-sector-country-(affiliate)-sector-country-year level but not the firm level.

Our left-hand-side variable will be a variable that measures the frequency of directed shareholder-affiliate relationships across country-industry pairs. Based on information from input-output tables, any combination of shareholders and affiliates can be classified as backward, forward, or none of the two. We will use this classification and interact it with the fundamental parameters of interest that, according to the model, should determine firm integration. This serves two purposes. First, in some cases the qualitative predictions regarding the parameters of interest vary with the mode of integration. Second, even for those cases where qualitative predictions do not vary with respect to the type of integration, they might vary quantitatively. Therefore, it is meaningful to see, on the one hand, if the qualitative predictions hold for either form of integration and, on the other hand, how they differ quantitatively. As discussed earlier, the literature has mainly focused on backward integration. While some of the results – in particular, Result 1 – have been tested and confirmed empirically, the evidence regarding their (quantitative and qualitative) importance for forward integration is scarce. We will discuss each of the results and the ensuing predictions in what follows.

The main mechanism of the model operates through the marginal returns to investment for the producer and the supplier, respectively. Hence, we expect forward integration to be more profitable – and, eventually, be the dominant mode of integration – as the supplier becomes more investment relative to the producer. Vice versa, we expect backward integration to be more profitable – and, eventually, be the dominant mode of integration – as the producer becomes more investment intensive relative to the supplier. These relationships are obvious from the slopes of the two differential-profit schedules for forward and backward integration in Figure 2.2.1. The figure clearly shows that the differential profitability of backward integration, $\Delta^{Bwd}$, rises with $p$ and falls with $s$, whereas the differential profitability of forward integration, $\Delta^{Fwd}$, rises with $s$ and declines with $p$.[6] This is the core idea behind the Grossman-Hart-Moore property-rights framework: residual rights of control should be assigned to the party whose investment contributes most to the value of the final output.

**Result 1**: $\frac{\partial\Delta^{Fwd}}{\partial s} > 0, \frac{\partial\Delta^{Fwd}}{\partial p} < 0$ and $\frac{\partial\Delta^{Bwd}}{\partial s} < 0, \frac{\partial\Delta^{Bwd}}{\partial p} > 0.$

The way we translate this prediction into our empirical setting is simple: according to the model, firms that have ceteris paribus low returns to investment will be owned by firms that have ceteris paribus high returns to investment. This predictions holds both for supplier-buyer relationships that are classified as forward and those that are classified as backward. Therefore, when counting the number of firms that have low returns to investment and are owned by firms with high returns to investment, we expect a higher count than vice versa.[7]

PREDICTION 1: *Any (shareholder)-sector-country-(affiliate)-sector-country*

[6]Below, we will speak of one or the other integration choice to be more likely, if the associated profitability is higher. The latter builds on the idea that in the data there will be stochastic shocks which lead to some gap between latent deterministic profitabilities and firms' choices.

[7]While this prediction has been tested in previous work (see, in particular, Liu (2021) who has tested the prediction for both forward and backward integration), confirming this key mechanism of the theoretical model using the data set at hand and within the empirical setting employed in this paper seems important as all other predictions hinge on this mechanism. Moreover, we aim at corroborating existing findings based on different data and in a distinct setting as we focus on the extensive margin and changes in ownership over time.

*combination that features a high investment intensity of the shareholder relative to that of the affiliate should contain a high count of integrated firms. This result holds for either form of integration.*

In the property-rights framework, the organizational form chosen depends on the marketability of the input, $\theta$, and the importance of the input for final production, $\varphi$, as these parameters determine the equilibrium investment levels under independence and, hence, the need to use integration to align incentives. Generally, integration becomes less likely, the higher the joint surplus is under independence. In particular, backward integration and taking control of the supplier is less likely the better the marketability of the customized input because the supplier's incentives to invest are high even under independence. Similarly, the incentives of the producer to invest under independence are higher the lower $\varphi$, the relative importance of the customized input for the final product. Hence, forward integration becomes more likely for higher levels of $\varphi$ since integration allows the supplier to incentivize appropriate investment of the producer.

**Result 2**: $\frac{\partial s^{Fwd*}}{\partial \theta} > 0$, $\frac{\partial p^{Fwd*}}{\partial \theta} < 0$ and $\frac{\partial s^{Fwd*}}{\partial \varphi} < 0$, $\frac{\partial p^{Fwd*}}{\partial \varphi} > 0$. Furthermore, $\frac{\partial s^{Bwd*}}{\partial \theta} < 0$, $\frac{\partial p^{Bwd*}}{\partial \theta} > 0$ and $\frac{\partial s^{Bwd*}}{\partial \varphi} > 0$, $\frac{\partial p^{Bwd*}}{\partial \varphi} < 0$.

Note that the respective effect sizes might vary across directions of integration. Shedding light on these differences is a main objective of the empirical exercise and goes beyond previous work. In light of our empirical specification, Result 2 leads to the following predictions.

PREDICTION 2: *Any (shareholder)-sector-country-(affiliate)-sector-country combination that features a high marketability of the respective input sector should contain a lower count of integrated firms. Furthermore, any (shareholder)-sector-country-(affiliate)-sector-country combination that features a high importance of the respective input sector should contain a higher count of firms.*

We extend the existing models of firms' integration decisions in global value chains by introducing fixed costs of integration. These fixed costs have a direct impact on integration (Result 3) but also more subtle implications regarding their interaction with the supplier's outside option (Result 4). Since reducing fixed costs of (international) firm integration is a widely discussed strategy, it is not only important to understand and quantify their direct implications for firm integration decisions but also important to see how other parameters affect their impact on integration. Moreover, it is insightful to understand if the implications vary across organizational forms. Formally, in Figure 2.2.1, an increase in fixed costs will shift both $\Delta^{Bwd}$ and $\Delta^{Fwd}$ downwards. Clearly, since integration is costly, any reduction in these costs will foster integration.

**Result 3**: $\frac{\partial s^{Fwd*}}{\partial F} > 0, \frac{\partial p^{Fwd*}}{\partial F} < 0$ and $\frac{\partial s^{Bwd*}}{\partial F} < 0, \frac{\partial p^{Bwd*}}{\partial F} > 0.$

In our data, we will test the following prediction.

PREDICTION 3: *Any (shareholder)-sector-country-(affiliate)-sector-country combination that features low costs of integration should contain a higher count of integrated firms. This result holds for either form of integration.*

A more subtle prediction of the model relates to second-order derivatives regarding parameters of interest. We are particularly interested how changing fixed costs affect integration differently depending on other core parameters of the model.

Consider $\Delta^{Fwd}$ and $\Delta^{Bwd}$ with respect to $s$. As laid out in the description of Figure 2.2.1, the marketability of the input, $\theta$, affects the slope of both $\Delta^{Fwd}$ and $\Delta^{Bwd}$ with respect to $s$. A higher level of $\theta$ increases supplier investment under independence and, hence, increases surplus under independence relative to both backward and forward integration. Therefore – with respect to $s$ – $\Delta^{Fwd}$ becomes flatter and turns positive at a higher level of $s$, while $\Delta^{Bwd}$ becomes steeper. Given the different slopes for different values of $\theta$, a given change in fixed costs affects the cutoff values differentially. As higher levels of $\theta$ make $\Delta^{Fwd}$ flatter, a given change in fixed costs will lead to a larger increase in the cutoff value $s^{Fwd*}$. As higher levels of $\theta$ make $\Delta^{Bwd}$ steeper, a given increase in fixed costs (downward shift of $\Delta^{Bwd}$) induces a smaller shift of the threshold level $s^{Bwd*}$. The economic rationale of the different responses is as follows: optimal investment under independence and, hence, total output – given $s$ – is increasing in $\theta$. Since supplier investment is always highest under forward integration and lowest under backward integration, an increase in $\theta$ shrinks the difference in optimal supplier investment between forward integration and independence, but increases the difference in optimal supplier investment between backward integration and independence. These differences become more pronounced as $s$ increases. As the cutoff level $s^{Bwd*}$ is always smaller for higher levels of $\theta$, the marginal change in the cutoff given a change in fixed costs which is governed by this slope will be smaller. This is illustrated in the left Panel of Figure 2.2.2. The opposite logic applies to the cutoff $s^{Fwd*}$ as the slope of $\Delta^{Fwd}$ becomes flatter.

Consider $\Delta^{Fwd}$ and $\Delta^{Bwd}$ with respect to $p$. $\theta$ affects the intercept as it increases surplus under independence making any form of integration less desirable. Therefore, both $\Delta^{Fwd}$ and $\Delta^{Bwd}$ are shifted downwards for higher levels of $\theta$. Note also that $\Delta^{Fwd}$ is concave in $p$, while $\Delta^{Bwd}$ is convex in $p$. Hence, inevitably, increasing $F$ and, hence, shifting $\Delta^{Fwd}$ and $\Delta^{Bwd}$ downwards will affect $p^{Fwd*}$ to be situated, where $\Delta^{Fwd}$ is more elastic (flatter). Increasing $F$ gradually by the same magnitude will, hence, reduce $p^{Fwd*}$ by an ever larger magnitude. Since increasing $\theta$ shifts $\Delta^{Fwd}$ downwards akin to increasing $F$, the marginal effect of $F$ on $p^{Fwd*}$ will become ever larger, if $\theta$ is increased. Economically, the difference in surplus between forward integration and independence decreases more rapidly as we move to the right. This is because the investment level of the producer is strictly higher under independence. The more important the producer's contribution to the overall surplus becomes as $p$ rises, the more rapidly decreases the overall advantage of forward integration over independence. In a supplier-producer relationship that processes an input with a high marketability, the investment level of the supplier is relatively high even under independence, thus making the differential surplus under forward integration generally quite small. At this point changing the fixed costs of integration by a given amount makes it profitable to integrate forward for a smaller range of $p$ compared to a situation with low $\theta$. This is illustrated in the right Panel of Figure 2.2.2. The opposite is true for $\Delta^{Bwd}$. The latter is also shifted downwards by an increase in $F$. In response, $p^{Bwd*}$ will move rightwards and be situated at a point where $\Delta^{Bwd}$ is now less elastic (steeper). Hence, increasing $F$ subsequently by the same amount will induce smaller and smaller effects on $p^{Bwd*}$. By the same token, an increase in $\theta$, which entails a downward shift of $\Delta^{Bwd}$, like increasing $F$, will reduce the marginal effect of an increased $F$ on $p^{Bwd*}$. Economically, as before, the change in slope as $p$ increases comes from the fact that – with producer investment under backward integration being strictly larger than under independence – the differential surplus of backward integration as we move along the horizontal axis increases disproportionately.

Overall, a better marketability of inputs will increase the policy impact of reduced fixed costs on forward integration, while it will reduce it on backward

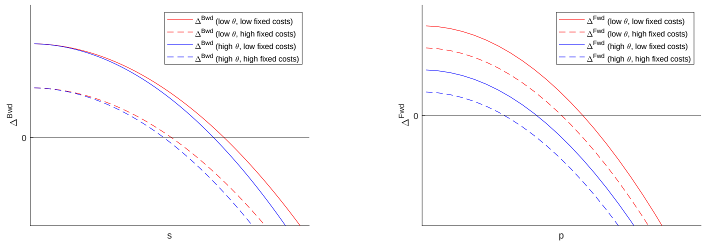



Figure 2.2.2: Illustration of Result 4 – Different slopes at cutoff values for varying levels of $\theta$ lead to different elasticities of thresholds values as fixed costs are rising.

integration.[8]

**Result 4**: $\frac{\partial^2 s^{Fwd*}}{\partial F \partial \theta} > 0$, $\frac{\partial^2 p^{Fwd*}}{\partial F \partial \theta} < 0$ and $\frac{\partial^2 s^{Bwd*}}{\partial F \partial \theta} > 0$, $\frac{\partial^2 p^{Bwd*}}{\partial F \partial \theta} < 0$.

PREDICTION 4: *Any (shareholder)-sector-country-(affiliate)-sector-country cell that experienced a change in fixed integration costs should see a larger effect on the frequency of forward integration with a better marketability of the input. In contrast, any (shareholder)-sector-country-(affiliate)-sector-country cell that experienced a change in fixed integration costs should see a smaller effect on the frequency of backward integration with a better marketability of the input.*

Table 2.2.1 summarizes the comparative static results regarding the direction of firm integration based on the model parameters $\{\theta, \varphi, F\}$ as well as the testable predictions in light of the data and the implied empirical setting that we will introduce in the following sections.

[8] By contrast, the role of $\varphi$ is less straightforward. $\varphi$ affects the loci of $\Delta^{Bwd}$ and $\Delta^{Fwd}$ through two mechanisms. First, it determines the producer's investment level under independence (a role comparable to the effect of $\theta$ on outcomes). Second, $\varphi$ also affects the relative importance of the producer's investment for differences in surpluses across organizational forms. Graphically, this affects the position of the intercept and determines the relative importance of slope versus intercept effects for the overall effect such that the overall effect of $\varphi$ remains ambiguous.

Table 2.2.1: Implications for the direction of integration based on Results 2–4

| | Derivatives ($p$) | Derivatives ($s$) | Implications for integration forces |
|---|---|---|---|
| **Backward** | | | |
| | $\frac{\partial p^{Bwd*}}{\partial \theta} > 0$ | $\frac{\partial s^{Bwd*}}{\partial \theta} < 0$ | - |
| | $\frac{\partial p^{Bwd*}}{\partial \varphi} < 0$ | $\frac{\partial s^{Bwd*}}{\partial \varphi} > 0$ | + |
| | $\frac{\partial p^{Bwd*}}{\partial F} > 0$ | $\frac{\partial s^{Bwd*}}{\partial F} < 0$ | - |
| | $\frac{\partial^2 p^{Bwd*}}{\partial F \partial \theta} < 0$ | $\frac{\partial^2 s^{Bwd*}}{\partial F \partial \theta} > 0$ | - |
| **Forward** | | | |
| | $\frac{\partial p^{Fwd*}}{\partial \theta} < 0$ | $\frac{\partial s^{Fwd*}}{\partial \theta} > 0$ | - |
| | $\frac{\partial p^{Fwd*}}{\partial \varphi} > 0$ | $\frac{\partial s^{Fwd*}}{\partial \varphi} < 0$ | + |
| | $\frac{\partial p^{Fwd*}}{\partial F} < 0$ | $\frac{\partial s^{Fwd*}}{\partial F} > 0$ | - |
| | $\frac{\partial^2 p^{Fwd*}}{\partial F \partial \theta} < 0$ | $\frac{\partial^2 s^{Fwd*}}{\partial F \partial \theta} > 0$ | + |

## 2.3 Data

The empirical analysis of this paper relies on a combination of two datasets. First, we use annual data on the global ownership of all firms contained in Bureau van Dijk's ORBIS Database between 2007 and 2013. Second, we rely on the World Input Output Tables (WIOT) for the years covered. The latter contain information on the country-sector-to-country-sector input-output links of 43 economies and 56 sectors in each year over the period 2000-2014.

### 2.3.1 Firm-ownership Data

ORBIS is a large compilation of firm data that allows us to identify ownership relations. For any shareholder (owner) firm, we know in any year $t$ the country of residence (incorporation) which we index by $j$ and its main sector of operation which we index by $s$. Moreover, we know for the latter firm all of its affiliates as well as their country of residence $i$ and sector $r$ in the same year. Note that $i$ and $j$ as well as $r$ and $s$ may be the same or not. In the raw data, the coverage of firm-to-firm relationships increases over time. In order to exclude the possibility of any changes in ownership stemming from changes in data coverage over time and countries, we use only those shareholders and affiliates in our analysis that are observed over the entire period from 2007-2013.

Imposing those restrictions, we observe 571,636 unique shareholders and 993,531 unique affiliates across all years in 2007-2013.[9] The number of shareholder-

[9] Clearly, we can only include those firms of which the country of location and the main

affiliate links amounts to 12,229,737.

Since we are interested in the extensive margin of firm-ownership links across countries and sectors, we aggregate the firm-to-firm ownership data up to the country-and-sector-pair level. We construct an $\{ij, rs, t\}$-indexed dataset where the dependent variable, $(CF_{ij,t}^{rs})$, measures the number of shareholder affiliate links from country-sector $js$ in country-sector $ir$ and year $t$. With 199 countries $\{i, j\}$ and 38 (ISIC Rev. 4) one-digit (two-digit for manufacturing) sectors, we end up with a $199^2 \cdot 38^2 = 57,183,844$ country-sector-pair cells of potential ownership links which are non-negative integers (and, hence, may be zero in absence of any such links). With annual data in the period 2007-2013 this yields a panel dataset of 400,286,908 observations.

In order to guard against a host of possible factors of influence on firm-to-firm integration choices beyond the ones in our focus, we employ a high-dimensional set of fixed effects. Doing so entails that only a subset of the data where links vary sufficiently across country and sector pairs as well as over time will inform the identification of the parameters of interest.[10]

### 2.3.2 Global-value-chain Data

The second key database our analysis rests upon are international (global) input-output-data coefficients as published in the World Input-Output Tables (WIOT). In particular, we use data from the 2016 release of WIOT, which distinguishes between 56 (ISIC Rev. 4) two-digit sectors and 43 countries, and which contains annual data for all the years of interest (2007-2013). Since we are constrained in terms of dimensionality – the final dataset will consist of $199^2 \cdot (\text{Number of Sectors})^2 \cdot 7$ observations – but at the same time want to keep the richness of the WIOT data for the value chain relationships across manufacturing sector, we combine all non-manufacturing sectors at the one-digit level but keep the original two-digit level for all manufacturing sectors. Hence, we aggregate the 56 WIOT sectors up to 38 sectors. The sectors used in the analysis are presented in Table 2.C.1 in the Appendix. We will later describe a robustness exercise in which we use a finer-grained sector classification for same-(aggregated-)sector pairs.[11]

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sector of operation are known.

[10]The discarded units of observation will all lack variation in ownership links within the dimension of one or more of the included types of fixed effects.

[11]Moreover, we impute WIOT coefficients for the countries contained in ORBIS but not in WIOT as follows. First, we group the 43 WIOT countries into 22 major world regions according to the detailed geoscheme of the United Nations (Northern America, Central America, Caribbean, South America, Northern Africa, Western Africa, Middle Africa, Eastern Africa, Southern Africa, Southern Europe, Western Europe, Northern Europe, Eastern

For the construction of any variable that describes the value chain relationships of any (shareholder)-sector-country-(affiliate)-sector-country combination let us closely follow the notation in (Antràs and Chor, 2018) and define a world economy with $J$ countries (indexed by $i$ or $j$) and $S$ sectors (indexed by $r$ or $s$). Let us refer to the total value of inputs used by country $j$'s sector $s$ that stems from country $i$'s sector $r$ in year $t$ as $Z^{rs}_{ij,t}$.

**Input coefficient.** The intermediate input-output linkages, $Z^{rs}_{ij,t}$, are measured in U.S. dollars. We can define a measure-free input coefficient $a^{rs}_{ij,t} = Z^{rs}_{ij,t}/Y^{s}_{j,t}$, where $Y^{s}_{j,t}$ is the gross output of sector $s$ in country $j$ at year $t$.[12] Based on $a^{rs}_{ij,t}$, we can aggregate across supplying countries to obtain

$$a^{rs}_{j,t} = \sum_{i=1}^{J} a^{rs}_{ij,t} = \frac{\sum_{i=1}^{J} Z^{rs}_{ij,t}}{Y^{s}_{j,t}} \tag{2.1}$$

as a sector-pair-country-of-use input coefficient. The latter measures the normalized inputs of sector-$r$ output (regardless of its geographic origin) as used by country $j$ in its production of sector-$s$ output in year $t$.

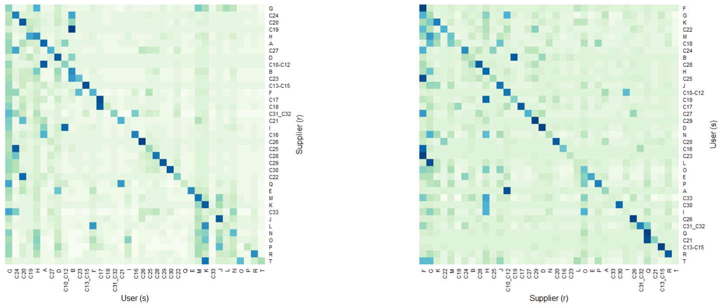
**Output coefficient.** Following the same logic, we can define $b^{rs}_{ij,t} = Z^{rs}_{ij,t}/Y^{r}_{i,t}$ as a measure-free (country-$i$-normalized) output of country $i$'s sector $r$ used by country $j$'s sector $s$. This can be aggregated across using countries $j$ to obtain

$$b^{rs}_{i,t} = \sum_{j=1}^{J} b^{rs}_{ij,t} = \frac{\sum_{j=1}^{J} Z^{rs}_{ij,t}}{Y^{r}_{i,t}} \tag{2.2}$$

as a sector-pair-country-of-supply output coefficient. The latter measures which sectors (regardless of the country) are the main users for country $i$'s sector-$r$ output at year $t$.

Europe, Western Asia, Central Asia, Southern Asia, Eastern Asia, Southeaster Asia, Australia and New Zealand, Micronesia, Polynesia, and Melanesia) and substitute coefficients for those countries in ORBIS which are not specifically contained in the WIOT by the respective annual average of the group they belong in. We will present sensitivity checks, where we focus only on those countries for which data are explicitly reported in the WIOT. As the WIOT do not contain any country from Africa, we impute the subsequent input-output measures for every African country in ORBIS by assigning it the WIOT "Rest of the World" average.

[12]The WIOT distinguish three components of gross output – namely intermediate uses, final uses, and net inventories – instead of just two (intermediate and final uses). Therefore, we follow Antràs et al. (2012) in applying a "net inventory" correction.



(a) Average input coefficients ($a^{rs}$) (b) Average output coefficients ($b^{rs}$)

Figure 2.3.1: Input and output coefficients (averages across countries and years).
Note: Sectors ordered by eigenvector centrality.

In Figure 2.3.1 we illustrate input and output coefficients averaged across countries and years by way of heat maps. There are some positive input-output relations for every sector pair. Nevertheless, there is a large overall degree of variation in the coefficients, and for many sector pairs the coefficients are close to zero. Hence, the variation is dominated by extreme values. For this reason, we will not use the information contained in input and output coefficients at face value but define binary indicators based on the average of $(a_j^{\tilde{r}s}, b_i^{\tilde{r}s})$ over years, which indicate if a given sector $r$ is a major input or output sector for country $j$'s sector $s$. Specifically, we define one indicator stating whether sector $r$ is among the top-5 input-supplying sectors to country $j$ and sector $s$ which proxies backward integration:

$$\text{Backward}_j^{rs} = \begin{cases} 1 & \text{if } a_j^{\tilde{r}s} \in \{\text{Top-5 } a_j^{\tilde{r}s} \text{ for js}\}, \\ 0 & \text{otherwise.} \end{cases}$$

Analogously, we define another indicator stating whether sector $r$ is among the top-5 using sectors of output from country $j$ and sector $s$ which proxies forward integration:[13]

$$\text{Forward}_j^{rs} = \begin{cases} 1 & \text{if } b_j^{\tilde{r}s} \in \{\text{Top-5 } b_j^{\tilde{r}s} \text{ for sj}\}, \\ 0 & \text{otherwise.} \end{cases}$$

It should be noted that with this definition the variables $\text{Backward}_j^{rs}$ and

[13]It will become clear immediately in the next paragraph, why we administer a slight change in the use of indices here.

$\text{Forward}_j^{rs}$ only account for the magnitude of direct (or first-order) input-use relationships. They do not take indirect (or higher-order) links into account.

To proxy for backward and forward integration we are interested in the shareholder's suppliers of inputs as well as the shareholder's buyers of its output. Recall that, in a generic year, the dependent variable in the analysis is $CF_{ij}^{rs}$, where $sj$ pertains to (potential) shareholders whereas $ri$ pertains to (potential) affiliates. In matching the information on input and output coefficients onto these data, we will use $\text{Backward}_j^{rs}$ to indicate whether sector $r$ of the affiliates is among the top-5 supplying sectors of shareholders in $j$ and $s$. This variable will indicate that $r$ is in the upstream direction of the value chain relative to $s$ and $j$ and associated shareholder-affiliate links would reflect a backward integration. Similarly, we will use $\text{Forward}_j^{rs}$ to indicate a shareholder's top-5 using (or purchasing) industries $r$. This variable will indicate if $s$ is in the downstream direction of the value chain and associated shareholder-affiliate links would reflect a forward integration.

### 2.3.3 Other Data

We will use firm-level accounting data contained in ORBIS to construct measurements for the explanatory variables discussed in the theoretical model.

#### R&D intensity as a measure of technology intensity ($p$ and $s$)

In the stylized model, $p$ and $s$ reflect the productivity of investment of the producer (or input user, $P$) relative to the input supplier ($S$). With sector-level data, the latter would be the relative productivity of the using and supplying country-sector pairs. This is not directly observable, but we conjecture that the R&D intensity (the share of expenditure on research and development in total revenues of a firm) is closely associated with this productivity. We measure the average R&D intensity of the firms in a sector as the year-2006, pre-sample average across all firms between the second and the 99th percentile of the distribution to avoid outliers, using the information contained in the ORBIS balance-sheet dataset. It will turn out useful to distinguish between the R&D intensity of the shareholder, $\text{InvShare}^s$, and that of the affiliate, $\text{InvAff}^r$. Note that by the organization of the data shareholders are always located in sector $s$, whereas affiliates always belong in sector $r$. What is key here is that looking at the data from the viewpoint of shareholder-affiliate ownership is conceptually different from looking at them through the lens of input supply versus production. In the empirical analysis, we aim at providing a synthesis of those two dimensions of variation.

Recall that we saw that, from a theoretical point of view, any form of integration was more likely between two firms the higher the investment intensity ($p$ for the producer and $s$ for the supplier) was for a potential shareholder relative to a potential affiliate. Therefore, it is useful to introduce two indicator functions utilizing the information contained in $\text{InvShare}^s$ (where the shareholder could be either a supplier or a producer to the other party) and $\text{InvAff}^r$ (where the affiliate could be either a supplier or a producer). Let us define these indicator functions as:

$$\mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r) = \begin{cases} 1 & \text{if R\&D intensity shareholder-sector } s \geq \\ & \text{R\&D intensity affiliate-sector } r)^{rs}, \\ 0 & \text{otherwise.} \end{cases}$$

If both $\text{InvShare}^s \geq \text{InvAff}^r$ and the shareholder is up the stream of the affiliate indicates that the shareholder is a supplier and the affiliate is a producer (forward integration). Accordingly, we would expect the impact of a variable $\text{Forward}_j^{r,s} \times \mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$ to be positive on the propensity and frequency of forward integration. Conversely, if both $\text{InvShare}^s \geq \text{InvAff}^r$ and the shareholder is down the stream of the affiliate indicates that the shareholder is a producer and the affiliate is a supplier (backward integration). Accordingly, we would expect the impact of a variable $\text{Backward}_j^{r,s} \times \mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$ to be positive on the propensity and frequency of backward integration.[14]

**Shareholder and affiliate relative densities in a market as a measure of competition ($\theta$)**

In the theoretical model, $\theta$ measures the marketability of inputs outside of a particular relationship between two firms. Hence, we interpret it as a measure of competition or the availability of outside options. Again, this parameter cannot be directly observed. However, we follow Acemoglu et al. (2010) and measure it as the ratio of the total number of firms in (the shareholder) country $j$ and sector $s$ over the total number of firms in (the affiliate) country $i$ and sector $r$ for backward integration and the inverse of that for forward

[14] In the Appendix, we present a table, where we use $\text{Forward}_j^{r,s} \times \text{InvShare}^s$ instead of $\text{Backward}_j^{r,s} \times \mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$ and $\text{Forward}_j^{r,s} \times \text{InvShare}^s$ instead of $\text{Backward}_j^{r,s} \times \mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$. The results turn out to be robust to this alternative specification.

integration:

$$\theta^{rs}_{ij,t} = \begin{cases} \theta^{Bwd^{rs}}_{ij,t} = \frac{\#firms^{s}_{j,t}}{\#firms^{r}_{i,t}} & \text{for backward integration,} \\ \\ \theta^{Fwd^{rs}}_{ij,t} = \frac{\#firms^{r}_{i,t}}{\#firms^{s}_{j,t}} & \text{for forward integration.} \end{cases}$$

**Total input consumption and specificity as a measure of reliance on customized inputs ($\varphi$)**

The third important parameter in the model is the one reflecting the reliance on customized inputs, $\varphi$. A greater reliance on such inputs reduces the intervals $[s^{Bwd*}, s^{Fwd*}]$ and $[p^{Fwd*}, p^{Bwd*}]$ in Figure 1, making any form of firm integration ceteris paribus more likely. To measure $\varphi$, we need to account for how important an input is for the producer. Such importance should be reflected, on the one hand, in the share of expenses for an input and also, on the other hand, in the degree to which inputs are specific and customized.

We measure the share of expenses by the producer by the input coefficient for the producer, $a^{rs}_{j,t}$, obtained from the WIOT. Moreover, we measure the degree of specificity of the input by the differentiation of the inputs supplied according to the Rauch (1999) classification. More concretely, for every sector, we measure its degree of input differentiation by its input use of differentiated products and we define $\delta^s_t$ and $\delta^r_t$, which measures the degree of differentiation, respectively, for the inputs used by the shareholder-producers and the affiliate-producers.

The resulting measure of $\varphi$, therefore, is the input dependence for the shareholder (superscript $s$), who the producer in case of backward integration, and it is the input dependence of the affiliate (superscript $r$), who is the producer in case of forward integration. In both cases, $\varphi$ is the differentiation-weighted sum of input coefficients across supplying sectors serving the producer firms:

$$\varphi^{Bwd^s}_{j} = \sum_r a^{rs}_j \delta^r \qquad \varphi^{Fwd^r}_{i} = \sum_s a^{rs}_i \delta^s.$$

There are two measures of input differentiation, $\varphi^{Bwd,s}_j$ and $\varphi^{Bwd,r}_i$, because producers can be shareholders (backward integration) or affiliates (forward integration).

**Bilateral-investment-treaty (BIT) membership as a measure of inverse fixed costs ($F^{-1}$)**

One particular concern with the ownership of firms in foreign countries is legal certainty and, hence, a ceteris paribus higher level of fixed integration costs than of comparable domestic integration. An important instrument to reduce such risk and associated incremental fixed costs of integration are bilateral investment treaties (BITs), which are signed and put into force between many industrialized countries and the major potential host economies of their foreign affiliates.

The United Nations Conference of Trade and Development (UNCTAD) provides a collection of all important international investment agreements (IIAs), including the signatory parties as well as the dates of signature and entry into force. We use the incidence of such agreements as an inverse measure of fixed costs of integration between two countries:[15]

$$F_{ij,t}^{-1} \propto BIT_{ij,t} = \begin{cases} 1 & \text{if a BIT is in force between } i \text{ and } j \text{ at year } t, \\ 0 & \text{otherwise.} \end{cases}$$

BITs only pertain to cross-border investments. Unfortunately, we do not have comparable measures which reflect the costs of domestic integration across countries. In order to control for such costs – without being able to address them explicitly – we will include in the empirical models binary indicators which index domestic relationships. We will allow those indicators to carry year-specific coefficients in order for fixed integration costs and other drivers of domestic integration to be allowed to change over time.

$$F_{ii}^{-1} \propto \text{Domestic}_{ii} = \begin{cases} 1 & \text{if for } i = j, \\ 0 & \text{otherwise.} \end{cases}$$

### 2.3.4 Descriptive Statistics

We present summary statistics of the dependent variable and the explanatory variables in Table 2.3.1. The dependent variable of our analysis, the number of links between shareholders in sector $r$ and country $i$ with affiliates in sector $s$ and country $j$ in year $t$, $CF_{ij,t}^{rs}$, takes on a value of less than unity on average, and it displays a very large standard deviation. The reason for the small average value is that for a number of country-sector pairs there are no ownership links in the average year. This is one of the reasons for why we feel compelled to use count-data methods for the analysis.

[15] The most important forms of IIAs are BITs and chapters on investment in preferential trade agreements (PTAs). We control for PTA membership separately. Moreover, we will control for all time-invariant country-pair-specific characteristics by way of respective fixed effects. To identify a reduction in fixed costs of integration we focus on BITs, here.

One aspect that is key to the motivation of this paper is the relative importance of forward versus backward integration as measured by ownership shares in the data. In this regard, our data reveal that 52% of the firm-to-firm links are ones, where the affiliate operates in one of the five most-important supplying sectors of the shareholder's sector and country. This backward ownership structure – which is the default ownership structure in most existing work on ownership in value chains – is, hence, quantitatively important. However, in 52% of the cases the affiliate operates in a sector which is among the five most important buying ones of the shareholder's sector and country. Clearly, these numbers reflect to some extent an overlap between the top buying and supplying sectors. But even when considering only those sectors that are either a top supplying or a top buying sector but not both, backward and forward integration amount to 13% each and are equally likely. Overall, this calls for a more comprehensive examination of the location of ownership in international value chains beyond the traditional lens of backward integration only.

The cross-sectional binary variables $\text{Backward}_j^{rs}$ and $\text{Forward}_j^{rs}$ indicating whether $r$ is a top-5 supplying or using sector, respectively take on values of about 0.15 each, indicating that about 15 percent of the sector pairs imply some backward or forward vertical structure. The two are not completely identically frequent, because the data are not balanced. This is also reflected in the shareholder sector exhibiting at least as high an R&D intensity as the affiliate sector in slightly more than 50% of the cases.

The relative importance of inputs (the input coefficient) is approximately the same for the shareholder as for the affiliate sectors and countries in the data. The market thickness variable for the shareholder relative to the affiliate sector and the inverse of it can reach large values, as they are measured as a ratio of firm numbers each.

For about 38% of the country-pair-sector-pair-year observations in the data, the BIT indicator is unity (i.e., a BIT is in force). Of the 199 countries in the data, 174 have at least one BIT in force. In 2006, the year prior to the sample period, there were 1,774 BITs in force among the 39,601 country pairs in the data. During the sample period, between 2007 and 2013, 314 new BITs came into force among the covered economies. Hence, the effect of BITs on the frequency of shareholder-affiliate ownership links can be identified within the sample period conditional on country-pair fixed effects.

Finally, in about 42% of the country-sector-pair observations a PTA is in force.[16]

[16] Note that the deep parameters reported in Table 2.3.1 vary systematically, e.g., between developed and less developed countries and also manufactures versus services. These variations could explain heterogeneous responses to policy changes across countries and sectors.

Table 2.3.1: Summary Statistics of Variables for the Regression Sample

| **Variable** | **Mean** | **Std. Dev.** |
|---|---|---|
| Number of firm-to-firm connections ($CF_{ij,t}^{rs}$) | 0.430 | 69.523 |
| $\text{Backward}_j^{rs}$ | 0.153 | 0.360 |
| $\text{Forward}_j^{rs}$ | 0.146 | 0.353 |
| Rel. high shareholder R&D intensity ($\mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$) | 0.516 | 0.500 |
| BIT ($F_{ij,t}^{-1}$) | 0.377 | 0.485 |
| Rel. importance of inputs for shareholder ($\varphi^{Bwd}{}^{rs}_{j,t}$) | 0.301 | 0.098 |
| Rel. importance of inputs for affiliate ($\varphi^{Fwd}{}^{rs}_{i,t}$) | 0.299 | 0.100 |
| Market thickness of shareholder industry rel. to affiliate industry ($\theta^{Bwd}{}^{rs}_{ij,t}$) | 77.068 | 1382.147 |
| Market thickness of affiliate industry rel. to shareholder industry ($\theta^{Fwd}{}^{rs}_{ij,t}$) | 351.908 | 3391.981 |
| $\text{PTA}_{ij,t}$ | 0.416 | 0.493 |

Note: The regression sample refers to those observations that are not absorbed by fixed effects in the regression presented in Column (3) of Table 2.4.5 which contains all parameters. In particular, any shareholder-sector-country to affiliate-sector-country combination that experience no changes over the period are absorbed by fixed effects. These are mainly shareholder-sector-country to affiliate-sector-country combinations, where the number of firm-to-firm connections is zero throughout the sample period.

## 2.4 Empirical Analysis

In this section, we estimate parameters in order to see to which extent the data on shareholder-affiliate links and value-chain relations support or reject some the key predictions of the model on firm integration. As the dependent variable in our analysis, $CF_{ij,t}^{rs}$, is a country-sector-to-country-sector count of firm-to-firm links, we use a Poisson model to estimate the parameters on the observables which are motivated by the model underlying our conceptual framework outlined above. Akin to the dependent variable, most explanatory variables introduced in the previous section vary across sectors or sector pairs and countries or country pairs as well as time.

In the empirical model, the parameters on variables measuring the backwardness ($\text{Backward}_j^{rs}$) versus the forwardness ($\text{Forward}_j^{rs}$) of the affiliates' country-sectors relative to the shareholders' and their interactions with variables capturing the essence of $\{p, s, \varphi, \theta, F\}$ are in the limelight. The latter

However, a distinction between such categories of the data lies beyond of the scope of the present paper.

will be represented by what we call

$$Parameter^{Bwd} = \begin{cases} \mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r) & \text{Technology Intensity Down/Upstream,} \\ BIT_{ij,t} & \text{Fixed Integration Cost,} \\ \theta^{Bwd^{rs}}_{ij,t} & \text{Competition of Shareholders/Affiliates,} \\ \varphi^{Bwd^{rs}}_{j,t} & \text{Input Dependence of Shareholders,} \end{cases}$$

for backward or upstream and

$$Parameter^{Fwd} = \begin{cases} \mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r) & \text{for Technology Intensity Down/Upstream,} \\ BIT_{ij,t} & \text{Fixed Integration Cost,} \\ \theta^{Fwd^{rs}}_{ij,t} & \text{Competition of Affiliates/Shareholders,} \\ \varphi^{Fwd^{rs}}_{i,t} & \text{Input Dependence of Affiliates,} \end{cases}$$

for forward or downstream integration directions. Hence, the proposed model reads

$$\begin{aligned} CF^{rs}_{ij,t} = exp(&\beta_{Parameter^{Bwd}}\text{Parameter}^{Bwd} + \\ &+ \beta_{Bwd}\text{Backward}^{rs}_j + \beta_{Bwd\times Par.}(\text{Backward}^{rs}_j \times \text{Parameter}^{Bwd}) \\ &+ \beta_{Parameter^{Fwd}}\text{Parameter}^{Fwd} + \\ &+ \beta_{Fwd}\text{Forward}^{rs}_j + \beta_{Fwd\times Par.}(\text{Forward}^{rs}_j \times \text{Parameter}^{Fwd}) \\ &+ \beta_{PTA}PTA_{ij,t} + \sum_{t=2007}^{2013} \beta_{Domestic,t}\text{Domestic}_{ij} + \eta_{ij} + \omega^r_{i,t} + \nu^s_{j,t} + \epsilon^{rs}_{ij,t}) \end{aligned} \tag{2.3}$$

where $\{\eta_{ij}, \omega^r_{i,t}, \nu^s_{j,t}\}$ are country-pair, owner-sector-country-time, and affiliate-country-sector-time fixed effects, respectively, and $\beta_{Domestic,t}$ measure fixed-type effects for domestic links in every individual year covered. The parameter $\epsilon^{rs}_{ij,t}$ is a remainder error term.

The indicators $\text{Backward}^{rs}_j$ and $\text{Forward}^{rs}_j$ are the respective measures for the backwardness (indexed as Bwd) and the forwardness (indexed as Fwd), respectively, of the shareholders' country-sector $sj$ relative to the affiliates' $ri$. Recall that these measures are based on top-5 sectors as defined above.

The parameters $\beta_{Bwd}$ and $\beta_{Fwd}$ measure the baseline effects of backwardness or upstreamness and forwardness or downstreamness, respectively. We include the main effects and estimate these parameters only to make sure that the interaction effects we are ultimately interested in do not pick up effects that should not be attributed to them. We will also abstain from interpreting the coefficients $\beta_{PTA}$ and $\beta_{Domestic,t}$ as the corresponding variables on which they are estimated are only included to absorb otherwise omitted effects.

Clearly, in view of the model predictions from Section 2, the coefficients $\{\beta_{Parameter^{Bwd}},\ \beta_{Parameter^{Fwd}}\}$ and $\{\beta_{Bwd\times Par}, \beta_{Fwd\times Par}\}$ are the ones of key interest here, and Parameter$^{Bwd}$ and Parameter$^{Fwd}$ have been defined above. The interpretation of these coefficients is one of average treatment effects.

We will present the results in a way, where we consider first the effect of one parameter of interest $(\mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r), \theta, \varphi, F)$ at a time. We will turn to a more comprehensive analysis later, where we condition on all relevant parameters simultaneously. The latter analysis will suggest that the degree of collinearity between the respective measures used to capture the parameters of interest is small enough so that leaving out some measures of interest at first does not invalidate the conclusions.

Changing the parameter $\mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$ given the other parameters will move us along the loci indicating the profitability of forward ($\Delta^{Fwd}$) or backward integration ($\Delta^{Bwd}$). In that sense, altering $\mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$ is telling about which **direction of integration** to expect. We will focus on this point, i.e., an assessment of Prediction 1, first. Then, we will consider effects of variables capturing parameters which affect the intercept and slope of the integration-profitability loci $(\mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r), \theta, \varphi, F)$. These parameters will determine the **strength of integration forces**.

Before turning to the empirical results, a word of caution is in order. In the theoretical model, there are only two players, one an input supplier and the other one an input user. Hence, the technological relationship is one-way. Empirically, this is not the case at the level of sector pairs nor is it true for country-sector pairs. To some extent, this is an outcome of aggregation. However, empirically it is not even true for firm-to-firm relations: a car manufacturer may purchase tires from a tire producer and the latter might transport the tires with the car producer's trucks (those would be classified as within-sector transactions with the chosen sector aggregation); the same car manufacturer may purchase LED bulbs for beamers from a bulb producer and the latter might transport the light bulbs with the car producer's trucks (those would be classified as between-sector transactions with the chosen sector aggregation). Hence, empirically, there may be a co-existence of shareholders in

$sj$ and their affiliates in $ri$ and shareholders in $ri$ and their affiliates in $sj$.

### 2.4.1 Investment Intensity ($\mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$). Assessing Prediction 1

In this first subsection we discuss the empirical results of Prediction 1, which states that shareholders are expected to be relatively more investment intensive compared to affiliates. As said before, this prediction is crucial, as it addresses the possibility and profitability of not only backward but also of forward integration. In that sense, the remaining predictions are interesting mainly after documenting that an increase in the relative investment intensity on a potential shareholder's part (who could be a producer or a supplier) stimulates integration (backward or forward). Table 2.4.1 reports the estimates corresponding to an assessment of this prediction.

We present the results in three columns numbered (1)-(3). Whereas we focus on the prediction regarding backward integration in Column (1) and regarding forward integration in Column (2), we consider both of those integration directions together in Column (3). In general, note that the number of (country-sector-pair-time) observations utilized to estimate the parameters on the variables of interest in this table is some 28 million. The explanatory power of the model is quite large, but much of the variance is clearly explained by the fixed effects.

However, what is comforting to see is that the coefficient signs do not change between Columns (1) and (2) on the one hand and Column (3) on the other hand. The main effect of the investment-intensity variable $\mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$ is positive and so are the forward- and backward-relations interaction effects. The overall effect of the investment intensity is, hence, positive in any direction of integration, which is consistent with Prediction 1. The effect estimates suggest that, on average, slightly larger in the backward-integration than the forward-integration direction, according to Column (3). However, the effect difference is minor relative to the large size of either average treatment effect (which corresponds to the sum of the main effect and the respective interaction effect of $\mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$). Regarding the large treatment effect it should be borne in mind that, on average, the country-sector-pair counts measured by the dependent variable are relatively small. Hence, large effects in percent still mean small effects in terms of numbers.

Table 2.4.1: R&D Investment Intensity

| Number of Firm-to-Firm Connections ($CF^{rs}_{ij,t}$) | (1) | (2) | (3) |
|---|---|---|---|
| Rel. high shareholder R&D intensity ($\mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$) | 0.656*** | 0.704*** | 0.502*** |
| | (0.070) | (0.076) | (0.070) |
| $\text{Backward}^{rs}_j$ | 0.338*** | | 0.371*** |
| | (0.062) | | (0.065) |
| $\text{Backward}^{rs}_j \times \mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$ | 0.579*** | | 0.342*** |
| | (0.078) | | (0.084) |
| $\text{Forward}^{rs}_j$ | | 0.299*** | 0.322*** |
| | | (0.053) | (0.058) |
| $\text{Forward}^{rs}_j \times \mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$ | | 0.532*** | 0.262*** |
| | | (0.059) | (0.071) |
| $\text{PTA}_{ij,t}$ | 0.038*** | 0.036*** | 0.037*** |
| | (0.009) | (0.009) | (0.009) |
| Country-pair FE | ✓ | ✓ | ✓ |
| Shareholder-country-industry-year FE | ✓ | ✓ | ✓ |
| affiliate-country-industry-year FE | ✓ | ✓ | ✓ |
| Domestic-year FE | ✓ | ✓ | ✓ |
| Obs. | 28,437,671 | 28,437,671 | 28,437,671 |
| $R^2$ | 0.92827 | 0.92763 | 0.92986 |

Standard errors are clustered at country-industry pairs level and reported in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Prediction 1 suggests that the parameters on the main effects plus the ones on the two interaction terms with $\mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$ should be positive.

### 2.4.2 Competition and Input-specificity Effects ($\theta, \varphi$). Assessing Prediction 2

In this subsection, we assess Prediction 2 which suggests that a better marketability of the customized input which corresponds to a thicker market and increased competition ($\theta$) increases the size of the non-integration subdomain in investment-intensity space in the model. Hence, as the outside option of at least one of the parties improves, any form of integration becomes less likely. Moreover, the same prediction states that integration becomes more likely, the more crucial the input is ($\varphi$) and production of the downstream output depends on the customized input.

In Table 2.4.2 we present the results for the model when using ($\theta^{Bwd}, \theta^{Fwd}$) for market competition. Recall that for forward integration $\theta^{Fwd}$ is defined as the number of firms in affiliate-sector-country $ri$ over the number of firms in shareholder-sector-country $sj$. Then $ri$ is upstream and $sj$ is downstream. For backward integration $\theta^{Bwd}$ is inversely defined and $ri$ is downstream whereas $js$ is upstream. In view of Prediction 2 we would expect a negative coefficient on both $\theta^{Bwd}$ and $\theta^{Fwd}$. In the table, the prediction needs to be assessed not from the main effect of ($\theta^{Bwd}, \theta^{Fwd}$) but from the interaction effects ($\text{Backward} \times \theta^{Bwd}, \text{Forward} \times \theta^{Fwd}$) or at least from the sum of the coefficients

Table 2.4.2: Competition Effects

| Number of Firm-to-Firm Connections ($CF_{ij,t}^{rs}$) | (1) | (2) | (3) |
|---|---|---|---|
| Market thickness of shareholder industry rel. to affiliate industry ($\theta^{Bwd}{}_{ij,t}^{rs}$) | −0.023*** | | −0.013*** |
| | (0.004) | | (0.003) |
| Backward$_j^{rs}$ | 0.916*** | | 0.766*** |
| | (0.054) | | (0.046) |
| Backward$_j^{rs}$ × $\theta^{Bwd}{}_{ij,t}^{rs}$ | −0.219*** | | −0.250*** |
| | (0.042) | | (0.046) |
| Market thickness of affiliate industry rel. to shareholder industry ($\theta^{Fwd}{}_{ij,t}^{rs}$) | | 0.012*** | 0.014*** |
| | | (0.002) | (0.002) |
| Forward$_j^{rs}$ | | 0.803*** | 0.624*** |
| | | (0.058) | (0.052) |
| Forward$_j^{rs}$ × $\theta^{Fwd}{}_{ij,t}^{rs}$ | | −0.023*** | −0.027*** |
| | | (0.006) | (0.007) |
| PTA | 0.038*** | 0.037*** | 0.037*** |
| | (0.009) | (0.009) | (0.009) |
| Country-pair FE | ✓ | ✓ | ✓ |
| Shareholder-country-industry-year FE | ✓ | ✓ | ✓ |
| affiliate-country-industry-year FE | ✓ | ✓ | ✓ |
| Domestic-year FE | ✓ | ✓ | ✓ |
| Obs. | 28,553,898 | 28,553,898 | 28,553,898 |
| $R^2$ | 0.92437 | 0.92320 | 0.92719 |

Standard errors are clustered at country-industry pairs level and reported in parentheses.
For better readability $\theta^{Bwd}{}_{ij,t}^{rs}$ and $\theta^{Fwd}{}_{ij,t}^{rs}$ have been scaled by $10^{-3}$.
Column (3) also includes Output coef. × $\theta^{Bwd}$ and Input coef. × $\theta^{Fwd}$ as controls.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Prediction 2 suggests that the two interaction terms should be negative.

on the main and interaction effects.

Again, we present results first separately for forward integration in Column (1) and backward integration in Column (2) and then jointly in Column (3). Indeed, the reported coefficients suggest that the data support the hypothesis regarding competition and market thickness for the propensity of integration in either the backward or the forward direction in the value chain. Note that for better readability of the results the coefficients on $\theta$ as well as coefficients on interactions involving $\theta$ have been scaled by $10^{-3}$.

We summarize the results regarding input dependence in Table 2.4.3 in an analogous way. As with market thickness $\theta$, we define $\varphi$ separately for when the affiliate-sector-country $ri$ is up the stream (backward) or down the stream (forward) of the shareholder-sector-country $sj$ as $(\varphi^{Bwd}, \varphi^{Fwd})$. In view of Prediction 2 we would expect the parameters on the country-sector-pair-year-variant (Backward$\times\varphi^{Bwd}$, Forward$\times\varphi^{Fwd}$) to be positive, as the propensity of integration should increase with greater input dependence. Again, we present results for the separate focus on backward and forward integration in Columns (1) and (2) and we consider them jointly in Column (3). The coefficients of interest in Table 2.4.3 are unequivocally aligned with our expectations from Prediction 2, irrespective of which column of results we consider.

Table 2.4.3: Input-specificity Effects

| Number of Firm-to-Firm Connections ($CF^{rs}_{ij,t}$) | (1) | (2) | (3) |
|---|---|---|---|
| $\text{Backward}^{rs}_{j}$ | 0.215 | | 0.086 |
| | (0.159) | | (0.153) |
| $\text{Backward}^{rs}_{j}$ × Rel. importance of inputs for shareholder ($\varphi^{Bwd^{s}_{j}}$) | 2.346*** | | 2.284*** |
| | (0.480) | | (0.471) |
| $\text{Forward}^{rs}_{j}$ | | 0.134 | −0.109 |
| | | (0.186) | (0.176) |
| $\text{Forward}^{rs}_{j}$ × Rel. importance of inputs for affiliate ($\varphi^{Fwd^{r}_{i}}$) | | 2.280*** | 2.490*** |
| | | (0.599) | (0.564) |
| $\text{PTA}_{ij,t}$ | 0.039*** | 0.037*** | 0.037*** |
| | (0.009) | (0.009) | (0.009) |
| Country-pair FE | ✓ | ✓ | ✓ |
| Shareholder-country-industry-year FE | ✓ | ✓ | ✓ |
| affiliate-country-industry-year FE | ✓ | ✓ | ✓ |
| Domestic-year FE | ✓ | ✓ | ✓ |
| Obs. | 28,579,070 | 28,566,322 | 28,545,311 |
| $R^2$ | 0.92461 | 0.92338 | 0.92770 |

Standard errors are clustered at country-industry pairs level and reported in parentheses.
Column (3) also includes Output coef. × $\varphi^{Bwd}$ and Input coef. × $\varphi^{Fwd}$ as controls.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Prediction 2 suggests that the parameters on the two interaction terms should be positive.

### 2.4.3 Fixed Integration Costs. Assessing Prediction 3

Prediction 3 states that a reduction in fixed integration costs should increase the inclination towards integration. Recall that we use two types of variables to account for the inverse of fixed integration costs: binary indicators for domestic integration and BIT for foreign integration. We do not present the time-specific parameters on the domestic indicators, but it should be noted that those are positive, and they reflect that the propensity of domestic ownership is particularly high in the data. Hence, we focus on BITs as a measure of inverse fixed foreign integration costs.

We understand that BITs help firms to invest abroad as they reduce fixed integration costs ceteris paribus through provisions pertaining to the "national treatment" or the "fair and equitable treatment" of foreign establishments. They also reduce the risk of expropriation through clauses against any kind of expropriation and the inclusion of reliable and efficient enforcement mechanisms such as arbitration courts.

In view of Prediction 3, we would expect a positive coefficient on BITs both for forward and backward integration. Again we would expect this to be revealed from the interaction effects $\{\text{Backward} \times F^{-1}_{ij,t}, \text{Forward} \times F^{-1}_{ij,t}\}$ as well as from the sum of the interaction-term coefficients and the main effect of BITs.

Table 2.4.4: Fixed-cost Effects

| Number of Firm-to-firm Connections ($CF_{ij,t}^{rs}$) | (1) | (2) | (3) |
|---|---|---|---|
| BIT ($F_{ij,t}^{-1}$) | −0.036 | −0.005 | −0.053 |
| | (0.030) | (0.031) | (0.034) |
| $\text{Backward}_j^{rs}$ | 0.901*** | | 0.753*** |
| | (0.056) | | (0.048) |
| $\text{Backward}_j^{rs} \times F_{ij,t}^{-1}$ | 0.268*** | | 0.207*** |
| | (0.047) | | (0.044) |
| $\text{Forward}_j^{rs}$ | | 0.792*** | 0.615*** |
| | | (0.059) | (0.053) |
| $\text{Forward}_j^{rs} \times F_{ij,t}^{-1}$ | | 0.173*** | 0.096** |
| | | (0.048) | (0.045) |
| $\text{PTA}_{ij,t}$ | 0.038*** | 0.037*** | 0.037*** |
| | (0.009) | (0.009) | (0.009) |
| Country-pair FE | ✓ | ✓ | ✓ |
| Shareholder-country-industry-year FE | ✓ | ✓ | ✓ |
| affiliate-country-industry-year FE | ✓ | ✓ | ✓ |
| Domestic-year FE | ✓ | ✓ | ✓ |
| Obs. | 28,553,898 | 28,553,898 | 28,553,898 |
| $R^2$ | 0.92438 | 0.92319 | 0.92717 |

Standard errors are clustered at country-industry pairs level and reported in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Prediction 3 suggests that the parameters on the two interaction terms should be positive.

We summarize the results focused on (inverse) fixed integration costs in Table 2.4.4. As before, we consider the effects on backward and forward integration separately in Columns (1) and (2) and pool them in Column (3). The results are unequivocally aligned with Prediction 3.

### 2.4.4 Conditioning on All Parameters. Assessing Predictions 1-3

In the previous subsections, we provided evidence regarding Predictions 1 to 3, separately. In this subsection, we provide the results of estimating (2.4) conditioning on all the parameters simultaneously. These results are presented in Table 2.4.5, where the effects on backward and forward integration are presented in Columns (1) and (2), respectively, and then jointly in Column (3). See that the $R^2$ of the model is quite large, but much of the variance is explained by the fixed effects.[17] All of the corresponding results are clearly

[17] A regression of the dependent variable on the fixed effects only results in an $R^2$ of 91.83%. A regression of the dependent variable on the covariates as in Column (3) in Table

supportive of our model.

Quantitatively, the results in the last column of Table 2.4.5 suggest the following effects when increasing each fundamental variable of interest by one standard deviation of the value as reported in Table 2.4.5.[18] In computing effects, note that we account for main- as well as interaction-effects parameters. First, raising the measure of $\mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$ by one standard deviation raises any form of integration by about 27%. What is mainly interesting, though, is by how much $\mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$ changes the main effect in a particular direction of ownership. There, we can conclude that the results suggest an additional increase (beyond the baseline) in the backward integration direction by about 21 percentage points and one in the forward direction by about 23 percentage points.

A standardized shock in ${\theta^{Bwd}}^{rs}_{ij,t}$ reduces the main effect in the backward-integration direction by about 27 percentage points and one in ${\theta^{Fwd}}^{rs}_{ij,t}$ reduces forward-integration by about 8 percentage points. A similar standardized shock of ${\varphi^{Bwd}}^{rs}_{j,t}$ and ${\varphi^{Fwd}}^{rs}_{i,t}$ leads to a marginal increase in the backward and forward integration directions by about 13 and 40 percentage points, respectively. Raising BIT $(F^{-1}_{ij,t})$ by one standard deviation raises backward integration marginally by about 12 percentage points and forward integration by about 8 percentage points beyond the baseline effect.

Overall, the considered shocks appear to have consistently larger effects in the backward- than in the forward-integration direction except for $\varphi$.

Providing quantitative evidence on these relative responses of forward versus backward integration to changes in fundamental parameters in a large data-set as this one is a novel element of the present paper.

### 2.4.5 Cross Effects of Relevant Parameters. Assessing Prediction 4

In a final step, we integrate all results from before and add two further ones which entail the cross-derivative in Prediction 4. The latter terms ask how the impact of input marketability and fixed integration costs interact with each other and, in terms of the empirical model, require the inclusion of triple-

7 without the fixed effects results in an $R^2$ of 10.52%. Note that these $R^2$ values do not add up to the value in Column (3) of Table 7 (93.05%) due to a lack of orthogonality between the covariates and the fixed effects. However, the relative magnitudes of the aforementioned $R^2$ values give an idea about the relative contributions of these components.

[18] Of course, binary variables can not change in a non-binary way in reality. However, considering one-standard-deviation shocks throughout permits inspecting the importance of the different fundamentals relative to each other.

Table 2.4.5: All parameters

| Number of Firm-to-Firm Connections ($CF^{rs}_{ij,t}$) | (1) | (2) | (3) |
|---|---|---|---|
| Rel. high shareholder R&D intensity ($\mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$) | 0.662*** | 0.667*** | 0.479*** |
| | (0.070) | (0.079) | (0.072) |
| BIT ($F^{-1}_{ij,t}$) | −0.0519* | −0.045 | −0.098*** |
| | (0.030) | (0.032) | (0.034) |
| Market thickness of shareholder-to-affiliate industry ($\theta^{Bwd^{rs}}_{ij,t}$) | −0.019*** | | −0.0126*** |
| | (0.005) | | (0.004) |
| $\text{Backward}^{rs}_j$ | −0.042 | | 0.018 |
| | (0.142) | | (0.142) |
| $\text{Backward}^{rs}_j \times \mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$ | 0.547*** | | 0.304*** |
| | (0.080) | | (0.085) |
| $\text{Backward}^{rs}_j \times F^{-1}_{ij,t}$ | 0.305*** | | 0.236*** |
| | (0.047) | | (0.045) |
| $\text{Backward}^{rs}_j \times$ Rel. importance of inputs for shareholder ($\varphi^{Bwd^s_j}$) | 1.308*** | | 1.220*** |
| | (0.450) | | (0.457) |
| $\text{Backward}^{rs}_j \times \theta^{Bwd^{rs}}_{ij,t}$ | −0.218*** | | −0.231*** |
| | (0.043) | | (0.046) |
| Market thickness of affiliate-to-shareholder industry ($\theta^{Fwd^{rs}}_{ij,t}$) | | 0.013*** | 0.013*** |
| | | (0.002) | (0.002) |
| $\text{Forward}^{rs}_j$ | | −0.808*** | −0.690*** |
| | | (0.208) | (0.191) |
| $\text{Forward}^{rs}_j \times \mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$ | | 0.622*** | 0.337*** |
| | | (0.059) | (0.070) |
| $\text{Forward}^{rs}_j \times F^{-1}_{ij,t}$ | | 0.271*** | 0.169*** |
| | | (0.049) | (0.047) |
| $\text{Forward}^{rs}_j \times$ Rel. importance of inputs for affiliate ($\varphi^{Fwd^r_i}$) | | 3.582*** | 3.316*** |
| | | (0.663) | (0.598) |
| $\text{Forward}^{rs}_j \times \theta^{Fwd^{rs}}_{ij,t}$ | | −0.025*** | −0.027*** |
| | | (0.007) | (0.007) |
| $\text{PTA}_{ij,t}$ | 0.038*** | 0.036*** | 0.037*** |
| | (0.009) | (0.009) | (0.0091) |
| Country-pair FE | ✓ | ✓ | ✓ |
| Shareholder-country-industry-year FE | ✓ | ✓ | ✓ |
| Affiliate-country-industry-year FE | ✓ | ✓ | ✓ |
| Domestic-year FE | ✓ | ✓ | ✓ |
| Obs. | 28,416,704 | 28,404,014 | 28,383,055 |
| $R^2$ | 0.92844 | 0.92822 | 0.93054 |

Standard errors are clustered at country-industry-pair level and reported in parentheses.
For better readability $\theta^{Bwd^{rs}}_{ij,t}$ and $\theta^{Fwd^{rs}}_{ij,t}$ have been scaled by $10^{-3}$.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

interaction terms in the specification. This analysis is particularly important as it sheds light on heterogeneous responses to changes in policy across country-sector-pair characteristics. One can show for instance that measures of input marketability vary substantially across countries and sectors. We should, hence, expect distinct sensitivities to policy changes not only across forms of integration but also across sector-country pairs.

We present the corresponding results in Table 2.4.6, which has a similar organization as the previous tables. Prediction 4 states that the effect size of any change in fixed costs should be increasing in $\theta$ for forward integration but should be decreasing in $\theta$ for backward integration.

Again, Columns (1) and (2) focus on backward and forward integration separately, while we pool the estimates in Column (3). The corresponding estimates in the third column are supportive of Prediction 4: the point estimate on the backward-integration term $\text{Backward}_j^{rs} \times F^{-1} \times \theta$ is negative as expected, and the estimate on the forward-integration term $\text{Forward}_j^{rs} \times F^{-1} \times \theta$ is positive as expected though not statistically significant. Most of the coefficients can be estimated at what is deemed to be a sufficient degree of precision by conventional standards. This is remarkable as the simultaneous identification of main, interaction and triple-interaction tends to be difficult even with large data.

## 2.5 Robustness

In this section we perform several robustness checks. First, we change the originally-adopted definition of how to classify forward and backward relations by creating Top-H $\text{Input}_j^{rs}$ and Top-H $\text{Output}_j^{rs}$ with $H$ measuring whether a sector is among the $H$ most-important ones with $H \in \{1, ..., 10\}$. Second, we use a different measure of investment intensity. Third, we run the regressions for a subsample of countries for which we are not required to impute input-output linkages. Fourth, we use a finer-grained input-output table for same-industry connections. Finally, we run separate regressions for backward and forward integration.

### 2.5.1 Different Definitions of Forward/Backward

In our first robustness check we change the definition for forward and backward integration. In Section 3.2 we defined $\text{Backward}_j^{rs}$ as an indicator variable consisting on whether sector $r$ of the affiliates is among the top-5 supplying sectors of shareholders in $j$ and $s$. Respectively we defined $\text{Forward}_j^{rs}$ to indicate a

Table 2.4.6: Competition and Fixed-cost Effects

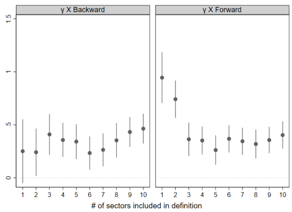
| Number of Firm-to-Firm Connections ($CF^{rs}_{ij,t}$) | (1) | (2) | (3) |
|---|---|---|---|
| BIT ($F^{-1}_{ij,t}$) | $-0.048$ | $-0.026$ | $-0.074^{**}$ |
| | (0.030) | (0.031) | (0.033) |
| Rel. high shareholder R&D intensity ($\mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$) | $0.656^{***}$ | $0.704^{***}$ | $0.501^{***}$ |
| | (0.070) | (0.076) | (0.070) |
| Market thickness of shareholder industry rel. to affiliate industry ($\theta^{Bwd}{}^{rs}_{ij,t}$) | $-0.013^{**}$ | | $-0.006$ |
| | (0.006) | | (0.005) |
| $\text{Backward}^{rs}_j$ | $0.324^{***}$ | | $0.362^{***}$ |
| | (0.063) | | (0.063) |
| $\text{Backward}^{rs}_j \times \mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$ | $0.579^{***}$ | | $0.340^{***}$ |
| | (0.078) | | (0.083) |
| $\text{Backward}^{rs}_j \times \theta^{Bwd}{}^{rs}_{ij,t}$ | $-0.150^{***}$ | | $-0.184^{***}$ |
| | (0.048) | | (0.054) |
| $\text{Backward}^{rs}_j \times F^{-1}_{ij,t}$ | $0.316^{***}$ | | $0.243^{***}$ |
| | (0.048) | | (0.047) |
| $F^{-1}_{ij,t} \times \theta^{Bwd}{}^{rs}_{ij,t}$ | $-0.013^{**}$ | | $-0.013^{***}$ |
| | (0.006) | | (0.005) |
| $\text{Backward}^{rs}_j \times F^{-1}_{ij,t} \times \theta^{Bwd}{}^{rs}_{ij,t}$ | $-0.185^{***}$ | | $-0.192^{**}$ |
| | (0.070) | | (0.078) |
| Market thickness of affiliate industry rel. to shareholder industry ($\theta^{Fwd}{}^{rs}_{ij,t}$) | | $0.012^{***}$ | $0.012^{***}$ |
| | | (0.003) | (0.003) |
| $\text{Forward}^{rs}_j$ | | $0.292^{***}$ | $0.318^{***}$ |
| | | (0.054) | (0.060) |
| $\text{Forward}^{rs}_j \times \mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$ | | $0.534^{***}$ | $0.265^{***}$ |
| | | (0.059) | (0.071) |
| $\text{Forward}^{rs}_j \times \theta^{Fwd}{}^{rs}_{ij,t}$ | | $-0.038^{**}$ | $-0.036^{**}$ |
| | | (0.018) | (0.017) |
| $\text{Forward}^{rs}_j \times F^{-1}_{ij,t}$ | | $0.221^{***}$ | $0.128^{***}$ |
| | | (0.048) | (0.047) |
| $F^{-1}_{ij,t} \times \theta^{Fwd}{}^{rs}_{ij,t}$ | | 0.003 | 0.003 |
| | | (0.003) | (0.003) |
| $\text{Forward}^{rs}_j \times F^{-1}_{ij,t} \times \theta^{Fwd}{}^{rs}_{ij,t}$ | | 0.026 | 0.023 |
| | | (0.018) | (0.017) |
| $\text{PTA}_{ij,t}$ | $0.038^{***}$ | $0.036^{***}$ | $0.037^{***}$ |
| | (0.009) | (0.009) | (0.009) |
| Country-pair FE | ✓ | ✓ | ✓ |
| Shareholder-country-industry-year FE | ✓ | ✓ | ✓ |
| affiliate-country-industry-year FE | ✓ | ✓ | ✓ |
| Domestic-year FE | ✓ | ✓ | ✓ |
| Obs. | 28,437,671 | 28,437,671 | 28,437,671 |
| $R^2$ | 0.92833 | 0.92768 | 0.92995 |

Standard errors are clustered at country-industry pairs level and reported in parentheses.
For better readability $\theta^{Bwd}{}^{rs}_{ij,t}$ and $\theta^{Fwd}{}^{rs}_{ij,t}$ have been scaled by $10^{-3}$.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

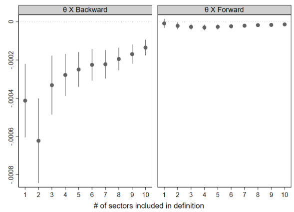
Note: Prediction 4 suggests that the parameter on the triple interaction should be negative.

shareholder's top-5 using (or purchasing) industries $r$. The election of the top-5 supplying and top-5 using industries was somehow arbitrary. In this section we consider the top-H supplying and top-H using, where $H \in \{1, ..., 10\}$

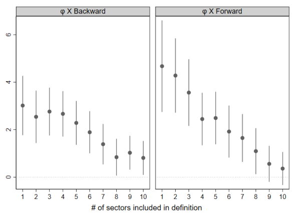
In Figure 2.5.1, we present the estimates of the interaction-term parameters as in Column (3) of Tables 2.4.1, 2.4.2, 2.4.3, and 2.4.4 for the alternative definitions of forward and backward, respectively. This figure documents the robustness to using a different number of sectors in determining importance as input suppliers or customers.



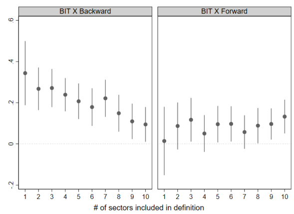

(a) Investment intensity




(b) Competition effects




(c) Input-specificity effects




(d) Fixed integration costs

Figure 2.5.1: Robustness check using different definitions of Forward/Backward.

Note: We present the estimates of the interaction-term parameters as in Column (3) of Tables 2.4.1, 2.4.2, 2.4.3, and 2.4.4 for the alternative definitions of forward and backward. The positioning along the x-axis indicates the number of sectors used to define top input and top output sectors, respectively.

### 2.5.2 Different Measures of Investment Intensity ($\mathbb{1}(\textbf{InvShare}^s \geq \textbf{InvAff}^r)$)

Our next robustness check employs an alternative measure of investment intensity at the sector level. While R&D intensity is our preferred measure for investment intensity, it is possible that R&D expenditures are not homogeneously reported for all types of firms. For this reason, we provide estimates for an alternative measure of investment intensity, namely the physical-capital investment intensity.

To construct this measure we divide physical-capital investment expenditures[19] by total sales and create $\mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)'$ as the physical-capital-investment equivalent of $\mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$.

Table 2.5.1: Physical-capital Investment Intensity

| Number of Firm-to-Firm Connections ($CF^{rs}_{ij,t}$) | (1) | (2) | (3) |
|---|---|---|---|
| Rel.-high shareholder phys.-cap. investment intensity ($\mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)'$) | 0.753*** | 0.904*** | 0.595*** |
| | (0.087) | (0.072) | (0.085) |
| $\text{Backward}^{rs}_j$ | 0.529*** | | 0.479*** |
| | (0.061) | | (0.064) |
| $\text{Backward}^{rs}_j \times \mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)'$ | 0.289*** | | 0.144* |
| | (0.078) | | (0.077) |
| $\text{Forward}^{rs}_j$ | | 0.471*** | 0.334*** |
| | | (0.061) | (0.065) |
| $\text{Forward}^{rs}_j \times \mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)'$ | | 0.414*** | 0.416*** |
| | | (0.084) | (0.088) |
| $\text{PTA}_{ij,t}$ | 0.037*** | 0.036*** | 0.036*** |
| | (0.009) | (0.009) | (0.009) |
| Country-pair FE | ✓ | ✓ | ✓ |
| Shareholder-country-industry-year FE | ✓ | ✓ | ✓ |
| affiliate-country-industry-year FE | ✓ | ✓ | ✓ |
| Domestic-year FE | ✓ | ✓ | ✓ |
| Obs. | 28,600,089 | 28,600,089 | 28,600,089 |
| $R^2$ | 0.92733 | 0.92823 | 0.93021 |

Standard errors are clustered at country-industry pairs level and reported in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The model in Section 2 suggests that the two interaction terms should be positive.

The results associated with using the alternative measure $\mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)'$ lead to similar qualitative conclusions as the ones using the original $\mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$.

### 2.5.3 Separate regressions for R&D investment intensity as a continuous measure

In this subsection we introduce the continuous measure of R&D investment of the shareholder as described in Subsection 3.3. In Table 2.5.2 we present the results for this robustness test. It is important to note that the baseline effects of R&D$^s$ and R&D$^s$ are absorbed by the included fixed effects. Moreover, it is useful to remember that in the case of backward integration the R&D intensity of the shareholder (InvShare$^s$) corresponds to the model parameter $p$, while for the case of forward integration it corresponds to model parameter $s$.

[19] We define this as the difference between fixed tangible assets in year $t$ minus those in $t-1$ plus the recorded depreciation in year $t$.

Table 2.5.2: Separate regressions for R&D investment intensity as a continuous measure

| Number of Firm-to-Firm Connections ($CF_{ij,t}^{rs}$) | (1) | (2) | (3) |
|---|---|---|---|
| Backward$_j^{rs}$ | 0.811*** | | 0.723*** |
| | (0.059) | | (0.053) |
| Backward$_j^{rs}$ $\times$ $p^s$ | 48.800*** | | 20.500* |
| | (11.176) | | (12.141) |
| Forward$_j^{rs}$ | | 0.727*** | 0.551*** |
| | | (0.062) | (0.057) |
| Forward$_j^{rs}$ $\times$ $s^s$ | | 34.017*** | 28.134** |
| | | (11.772) | (12.947) |
| PTA$_{ij,t}$ | 0.039*** | 0.037*** | 0.038*** |
| | (0.009) | (0.009) | (0.009) |
| Country-pair FE | ✓ | ✓ | ✓ |
| Shareholder-country-industry-year FE | ✓ | ✓ | ✓ |
| affiliate-country-industry-year FE | ✓ | ✓ | ✓ |
| Domestic-year FE | ✓ | ✓ | ✓ |
| Obs. | 28,533,054 | 28,533,054 | 28,533,054 |
| $R^2$ | 0.92451 | 0.92322 | 0.92723 |

Standard errors are clustered at country-industry pairs level and reported in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The model in Section 2 suggests that the two interaction terms should be positive.

Overall, Table 2.5.2 confirms the previous results and shows that a higher R&D investment intensity by the shareholder leads to more firm-to-firm integration in both the forward and the backward integration directions.

### 2.5.4 Using Only Countries Covered in the WIOT

Our fourth robustness check bases the original analysis on the subsample of countries that are explicitly included in the WIOT, so that we use direct and not any imputed measures of their input and output coefficients. It turns out that the imputation for countries outside the WIOT does not have any qualitative impact on our findings. The results are shown in Table 2.5.3.

### 2.5.5 Using the Fine-grained U.S. Input-output Table to Disentangle Same-industry Connections

One concern of the previous analysis could be that there exists some overlap between those sector pairs classified as backward integration and those classified as forward integration. Furthermore, in light of Figure 2.3.1 this could be particularly the case for the cells in the diagonal of the input-output table

Table 2.5.3: Only WIOD countries

| Number of Firm-to-Firm Connections ($CF^{rs}_{ij,t}$) | (1) | (2) | (3) |
|---|---|---|---|
| Rel. high shareholder R&D intensity ($\mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$) | 0.661*** | 0.666*** | 0.480*** |
| | (0.074) | (0.083) | (0.076) |
| BIT ($F^{-1}_{ij,t}$) | −0.079** | −0.064* | −0.141*** |
| | (0.036) | (0.037) | (0.040) |
| Market thickness of shareholder-to-affiliate industry ($\theta^{Bwd}{}^{rs}_{ij,t}$) | −0.052*** | | −0.029** |
| | (0.020) | | (0.014) |
| $\text{Backward}^{rs}_j$ | −0.064 | | −0.015 |
| | (0.162) | | (0.163) |
| $\text{Backward}^{rs}_j \times \mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$ | 0.535*** | | 0.2877*** |
| | (0.086) | | (0.092) |
| $\text{Backward}^{rs}_j \times F^{-1}_{ij,t}$ | 0.417*** | | 0.324*** |
| | (0.055) | | (0.053) |
| $\text{Backward}^{rs}_j \times$ Rel. importance of inputs for shareholder ($\varphi^{Bwd}{}^s_j$) | 1.44*** | | 1.410*** |
| | (0.510) | | (0.518) |
| $\text{Backward}^{rs}_j \times \theta^{Bwd}{}^{rs}_{ij,t}$ | −1.197*** | | −1.284*** |
| | (0.210) | | (0.226) |
| Market thickness of affiliate-to-shareholder industry ($\theta^{Fwd}{}^{rs}_{ij,t}$) | | 0.019*** | 0.019*** |
| | | (0.003) | (0.003) |
| $\text{Forward}^{rs}_j$ | | −0.736*** | −0.624*** |
| | | (0.237) | (0.219) |
| $\text{Forward}^{rs}_j \times \mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$ | | 0.612*** | 0.329*** |
| | | (0.062) | (0.074) |
| $\text{Forward}^{rs}_j \times F^{-1}_{ij,t}$ | | 0.347*** | 0.227*** |
| | | (0.056) | (0.053) |
| $\text{Forward}^{rs}_j \times$ Rel. importance of inputs for affiliate ($\varphi^{Fwd}{}^r_i$) | | 3.379*** | 3.136*** |
| | | (0.751) | (0.680) |
| $\text{Forward}^{rs}_j \times \theta^{Fwd}{}^{rs}_{ij,t}$ | | −0.048* | −0.044* |
| | | (0.025) | (0.024) |
| $\text{PTA}_{ij,t}$ | 0.039*** | 0.036*** | 0.037*** |
| | (0.010) | (0.010) | (0.010) |
| Country-pair FE | ✓ | ✓ | ✓ |
| Shareholder-country-industry-year FE | ✓ | ✓ | ✓ |
| Affiliate-country-industry-year FE | ✓ | ✓ | ✓ |
| Domestic-year FE | ✓ | ✓ | ✓ |
| Obs. | 12,514,470 | 12,514,470 | 12,514,470 |
| $R^2$ | 0.93116 | 0.93084 | 0.93341 |

Standard errors are clustered at country-industry-pair level and reported in parentheses.
For better readability $\theta^{Bwd}{}^{rs}_{ij,t}$ and $\theta^{Fwd}{}^{rs}_{ij,t}$ have been scaled by $10^{-3}$.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

(same industry connections).

To address this problem, in this robustness test, we use the 4-digit US input-output table to zoom-in on these same industry connections and disentangle which connections are backward, forward, or neither.

Particularly, note that every within-2-digit-sector relationship is made up of several underlying 4-digit-sector connections, which, in turn, can be classified according to their integration directions. It is, therefore, possible to divide same industry connections into three configurations: one where ownership is in the backward direction in terms of the underlying 4-digit sector pairs within the same 2-digit sector (where the 4-digit level input coefficient is higher than the output coefficient); one where ownership is in the forward direction in terms of the underlying 4-digit sector pairs within the same 2-digit sector (where the 4-digit level output coefficient is higher than the input coefficient); and one where ownership is not clear-cut forward or backward (where the 4-digit level input coefficient is equal to the output coefficient or they are missing). In Table 2.5.4 we present the results after disentangling the same industry connections. An inspection of Table 2.5.4 revels that our results remain robust to this specification.

### 2.5.6 Running Separate Regressions for Backward and Forward Integration

In our final robustness test, we run separate regression for backward versus independent connections (omitting the forward) and forward versus independent connections (omitting the backward).

In Table 2.5.5 we present the results for this robustness test. The main findings all remain qualitatively the same as for our main specification. However, we do not advertise this analysis as the preferable one in the present context. The reason is that, from a stochastic point of view, one might find it problematic due to selection of the subsample data on a variable that is endogenous to the analysis, namely the direction of ownership. The latter might impact at least the quantitative conclusions regarding the estimated coefficients. However, the qualitative robustness of the key findings in the subsample analysis with backward-integrated and independent versus forward-integrated and independent ownership in comparison to the full-sample analysis is comforting.

Table 2.5.4: Using the Fine-grained U.S. Input-output Table to Disentangle Same-industry Connections

| Number of Firm-to-Firm Connections ($CF^{rs}_{ij,t}$) | (1) | (2) | (3) |
|---|---|---|---|
| Rel. high shareholder R&D intensity[†] ($\mathbb{1}(\text{InvShare}^s > \text{InvAff}^r)$) | $-0.503^{***}$ | $-0.499^{***}$ | $-0.611^{***}$ |
| | (0.082) | (0.072) | (0.084) |
| BIT ($F^{-1}_{ij,t}$) | $-0.012$ | $-0.007$ | $-0.075^{**}$ |
| | (0.032) | (0.030) | (0.036) |
| Market thickness of shareholder-to-affiliate industry ($\theta^{Bwd^{rs}}_{ij,t}$) | $-0.018^{***}$ | | $-0.016^{***}$ |
| | (0.005) | | (0.005) |
| $\text{Backward}^{rs}_j$ | $-0.267$ | | $-0.295$ |
| | (0.215) | | (0.227) |
| $\text{Backward}^{rs}_j \times \mathbb{1}(\text{InvShare}^s > \text{InvAff}^r)$ | $0.585^{***}$ | | $0.538^{***}$ |
| | (0.192) | | (0.202) |
| $\text{Backward}^{rs}_j \times F^{-1}_{ij,t}$ | $0.345^{***}$ | | $0.320^{***}$ |
| | (0.111) | | (0.109) |
| $\text{Backward}^{rs}_j \times$ Rel. importance of inputs for shareholder ($\varphi^{Bwd^s}_j$) | 0.0561 | | 0.135 |
| | (0.959) | | (0.961) |
| $\text{Backward}^{rs}_j \times \theta^{Bwd^{rs}}_{ij,t}$ | $-0.061^{**}$ | | $-0.061^{*}$ |
| | (0.030) | | (0.032) |
| Market thickness of affiliate-to-shareholder industry ($\theta^{Fwd^{rs}}_{ij,t}$) | | $0.010^{***}$ | $0.008^{***}$ |
| | | (0.002) | (0.002) |
| $\text{Forward}^{rs}_j$ | | $-0.542^{**}$ | $-0.701^{**}$ |
| | | (0.264) | (0.309) |
| $\text{Forward}^{rs}_j \times \mathbb{1}(\text{InvShare}^s > \text{InvAff}^r)$ | | $0.371^{***}$ | $0.330^{***}$ |
| | | (0.100) | (0.116) |
| $\text{Forward}^{rs}_j \times F^{-1}_{ij,t}$ | | $0.254^{***}$ | $0.256^{***}$ |
| | | (0.061) | (0.060) |
| $\text{Forward}^{rs}_j \times$ Rel. importance of inputs for affiliate ($\varphi^{Fwd^r}_i$) | | $1.898^{***}$ | $2.256^{***}$ |
| | | (0.720) | (0.787) |
| $\text{Forward}^{rs}_j \times \theta^{Fwd^{rs}}_{ij,t}$ | | $-0.010^{***}$ | $-0.009^{**}$ |
| | | (0.004) | (0.004) |
| $\text{PTA}_{ij,t}$ | $0.026^{***}$ | $0.026^{***}$ | $0.026^{***}$ |
| | (0.009) | (0.009) | (0.009) |
| Country-pair FE | ✓ | ✓ | ✓ |
| Shareholder-country-industry-year FE | ✓ | ✓ | ✓ |
| Affiliate-country-industry-year FE | ✓ | ✓ | ✓ |
| Domestic-year FE | ✓ | ✓ | ✓ |
| Obs. | 28,624,843 | 28,613,114 | 28,591,190 |
| $R^2$ | 0.91401 | 0.91373 | 0.91451 |

[†] $\mathbb{1}(\text{InvShare}^s > \text{InvAff}^r)$ is used with strict inequality in this setting.
Standard errors are clustered at country-industry-pair level and reported in parentheses.
For better readability $\theta^{Bwd^{rs}}_{ij,t}$ and $\theta^{Fwd^{rs}}_{ij,t}$ have been scaled by $10^{-3}$.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.5.5: Running Separate Regressions for Backward and Forward Integration

| Number of Firm-to-Firm Connections ($CF^{rs}_{ij,t}$) | (1) | (2) |
|---|---|---|
| Rel. high shareholder R&D intensity ($\mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$) | 0.749*** | 0.816*** |
| | (0.082) | (0.083) |
| BIT ($F^{-1}_{ij,t}$) | −0.055 | −0.105*** |
| | (0.034) | (0.036) |
| Market thickness of shareholder-to-affiliate industry ($\theta^{Bwd}{}^{rs}_{ij,t}$) | −0.006 | |
| | (0.004) | |
| $\text{Backward}^{rs}_j$ | 0.228 | |
| | (0.143) | |
| $\text{Backward}^{rs}_j \times \mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$ | 0.588*** | |
| | (0.076) | |
| $\text{Backward}^{rs}_j \times F^{-1}_{ij,t}$ | 0.270*** | |
| | (0.047) | |
| $\text{Backward}^{rs}_j \times$ Rel. importance of inputs for shareholder ($\varphi^{Bwd}{}^s_j$) | 1.411*** | |
| | (0.438) | |
| $\text{Backward}^{rs}_j \times \theta^{Bwd}{}^{rs}_{ij,t}$ | −0.198*** | |
| | (0.040) | |
| Market thickness of affiliate-to-shareholder industry ($\theta^{Fwd}{}^{rs}_{ij,t}$) | | 0.015*** |
| | | (0.002) |
| $\text{Forward}^{rs}_j$ | | −0.760*** |
| | | (0.220) |
| $\text{Forward}^{rs}_j \times \mathbb{1}(\text{InvShare}^s \geq \text{InvAff}^r)$ | | 0.594*** |
| | | (0.059) |
| $\text{Forward}^{rs}_j \times F^{-1}_{ij,t}$ | | 0.361*** |
| | | (0.054) |
| $\text{Forward}^{rs}_j \times$ Rel. importance of inputs for affiliate ($\varphi^{Fwd}{}^r_i$) | | 4.221*** |
| | | (0.678) |
| $\text{Forward}^{rs}_j \times \theta^{Fwd}{}^{rs}_{ij,t}$ | | −0.022*** |
| | | (0.006) |
| $\text{PTA}_{ij,t}$ | 0.035*** | 0.037*** |
| | (0.010) | (0.010) |
| Obs. | 25,319,018 | 24,628,430 |
| $R^2$ | 0.92848 | 0.93095 |

Standard errors are clustered at country-industry-pair level and reported in parentheses.
For better readability $\theta^{Bwd}{}^{rs}_{ij,t}$ and $\theta^{Fwd}{}^{rs}_{ij,t}$ have been scaled by $10^{-3}$.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

## 2.6 Conclusions

Production processes are increasingly organized in international value chains. Firms involved in such chains can be operating at arm's length or be vertically integrated. Incidence of integration as well as its direction (upward or downward) depend on specific characteristics of the economic and institutional environment firms are operating in. We propose a simple model of vertical integration in a supplier-producer relationship that is rooted in the property-rights theory. Generally, the direction of integration – backward versus forward – depends on the relative investment intensity of producing and supplying sector, respectively, so as to align investment incentives and maximize joint surplus. Moreover, the organizational form depends on the market environment in the input market as well as the relative importance of the specific input for the final output.

We take a set of hypotheses derived from this model to a large dataset on firms, where two crucial ingredients are known for firms and years: (i) the sectoral affiliation of firms and, in conjunction with global input-output tables, the upstream versus downstream positioning of two firms, and (ii) firm-to-firm ownership. The combination of these two ingredients together permit identifying responses in the backward (upstream) versus forward (downstream) ownership characteristics between linked pairs of firms on the relative frequency of firm-to-firm ownership linkages between pairs of both sectors and countries over a time span of seven years between 2007 and 2013.

The data support a number of predictions of the model, in particular, ones related to the impact of competition, the relative technological intensity of the upstream and downstream sectors the firms in a pair of sectors and countries, and the fixed costs which we parameterize by the countries' membership in a bilateral investment treaty, BIT, which we argue is inversely related to fixed costs.

# Appendix

## 2.A Model

### 2.A.1 Outline

We propose a model of vertical integration that is rooted in the property-rights theory advanced by Grossman and Hart (1986) and Hart and Moore (1990). In this model, two firms can decide to integrate backwards or forward but also to stay independent. The respective outcome depends on the relative investment intensity of the partners. We closely follow Acemoglu et al. (2010) but extend their model by introducing fixed costs of firm integration. The latter permits deriving further empirical predictions. In contrast to Acemoglu et al. (2010), when assessing these predictions, we will specifically address backward versus forward integration explicitly.

The two parties, a supplier $S$ and a producer $P$, are collaborating along the value chain. The output generated from this relationship depends on the investment undertaken by both parties. Assuming that contracts conditioning on investment or output levels are not available, investment incentives can be aligned through the allocation of property rights. In particular, the two parties can either decide to stay independent ($I$), or to integrate either backward ($Bwd$) or forward ($Fwd$). We assume the following timing:

1. The producer $P$ offers an organizational form $o \in \{Fwd, I, Bwd\}$ and corresponding transfers, $T_P^o$ and $T_S^o$, such that $T_P^o + T_S^o = 0$.[20]

2. The supplier $S$ decides whether she accepts the offer to integrate or not.

3. The supplier $S$ and producer $P$ simultaneously decide on their investment levels $e_P^o \geq 0, e_S^o \geq 0$.

[20] We assume that there are no financial constraints such that transfers can be negative.

4. After investments are realized, the supplier and producer bargain over revenues according to Nash bargaining.

Producing the final output $Y(\cdot)$ involves, apart from the aforementioned investments $e_P^o$ and $e_S^o$, a customized input provided by the supplier, $x_S \in (0,1)$. Specifically, we will assume the production technology of the final output to be

$$Y(x_S, e_P^o, e_S^o) = \varphi x_S(pe_P^o + se_S^o + 1) + (1-\varphi)(pe_P^o + 1), \tag{2.4}$$

where $p > 0$ and $s > 0$ are two parameters governing the marginal product of investments by the producer and the supplier, respectively, and $\varphi \in (0,1)$ indicates to which extent the final output relies on the provision of the customized input.

Following Acemoglu et al. (2010), we consider a simple quadratic form for the costs of investments:[21]

$$C_p(e_P^o) = \frac{1}{2}\left(e_P^o\right)^2 \text{ and } C_S(e_S^o) = \frac{1}{2}\varphi\left(e_S^o\right)^2. \tag{2.5}$$

Before determining the outcome of the Nash bargaining, we have to define the respective outside options $V_i^o$ in case of disagreement for player $i$ under each organizational form $o$. In the case of forward integration the supplier owns all assets and will keep the output generated. However, the producer can retain a fraction $\lambda^P$ of her investment in case of disagreement. The respective outside options in the case of **forward integration** amount therefore to:

$$\begin{aligned} V_S^{Fwd} &= Y(x_S = 1, (1-\lambda^P)e_P^{Fwd}, e_S^{Fwd}), \\ V_P^{Fwd} &= 0. \end{aligned} \tag{2.6}$$

If the two parties are not integrated but independent, every firm legally owns its assets. The supplier will, however, not supply the customized input to the producer in case of disagreement but sell it on the market. The marketability of the customized input is measured by $\theta$ which depends on both the specificity of the customized input and the competition in the market. Hence, outside options under **independence** are given by:

$$\begin{aligned} V_S^I &= \theta\varphi(se_S^I + 1), \\ V_P^I &= Y(x_S = 0, e_P^I, 0). \end{aligned} \tag{2.7}$$

[21] Note that including $\varphi$ avoids implicit economies of scale. See Acemoglu et al. (2010) for a discussion of that assumption.

Finally, under backward integration all assets belong to the producer and she will keep the entire output. As before, we assume that the supplier can retain a fraction $\lambda^S$ of her investment. The respective outside options under **backward integration** are given by:

$$\begin{aligned} V_S^{Bwd} &= 0, \\ V_P^{Bwd} &= Y(x_S = 1, e_P^{Bwd}, (1-\lambda^S)e_S^{Bwd}). \end{aligned} \tag{2.8}$$

The gross revenue accruing to each party under each organizational form, $y_i^o$, is determined by Nash bargaining:

$$\arg\max_{y_P^o}\{(y_P^o - V_P^o)(y_S^o - V_S^o)\} \quad s.t.\ y_S^o = Y(x_S = 1, e_P^o, e_S^o) - y_P^o \tag{2.9}$$

The equilibrium gross revenue for any party $i$ is therefore

$$y_i^o(e_P^o, e_S^o) = V_i^o + \frac{1}{2}\left(Y(x_S = 1, e_P^o, e_S^o) - V_S^o - V_P^o\right). \tag{2.10}$$

Profits are obtained by taking into account the cost of investment and integration as well as transfers:

$$\pi_i^o = y_i^o - C_i(e_i^o) - F_i^o + T_i^o, \tag{2.11}$$

where $F_i^o$ denote fixed costs of integration paid by the owning party (the shareholder), with[22]

$$\begin{aligned} &F_S^{Fwd} = F > 0,\ F_P^{Fwd} = 0 \\ &F_S^I = F_P^I = 0 \\ &F_S^{Bwd} = 0,\ F_P^{Bwd} = F > 0. \end{aligned}$$

Each party chooses its investment levels conditional on the chosen organizational form to maximize its profits (2.11):

$$e_S^{Fwd*} = s, \qquad e_P^{Fwd*} = \frac{\lambda^P}{2}p \tag{2.12}$$

$$e_S^{I*} = \frac{1+\theta}{2}s, \qquad e_P^{I*} = (1 - \frac{\varphi}{2})p \tag{2.13}$$

$$e_S^{Bwd*} = \frac{\lambda^S}{2}s, \qquad e_P^{Bwd*} = p. \tag{2.14}$$

[22] Note that we assume that $F > 0$ and, hence, just as for $p$ and $s$, there is no upper bound for the level of fixed costs. The importance of the size of fixed costs is only meaningful in relation to $p$ and $s$ since these levels determine their size relative to returns to investments under various regimes.

Since we assume that there are no credit constraints and we allow for transfers, the organizational form chosen in equilibrium will be the one that maximizes total surplus, $S^o = \pi_S^o + \pi_P^o$. We can derive two loci as a function of $p$ and $s$ – the returns to investment for the producer and supplier, respectively – $\Delta^{Fwd}$ and $\Delta^{Bwd}$, which represent the additional surplus generated by forward integration compared to independence and the additional surplus generated by backward integration compared to independence, respectively:

$$\Delta^{Fwd} = (1-\theta)^2 \frac{s^2}{8}\varphi - \left(\left(2-\lambda^P\right)^2 - \varphi^2\right)\frac{1}{8}p^2 - F, \tag{2.15}$$

$$\Delta^{Bwd} = \left(\frac{\varphi^2}{8}\right)p^2 - (1+\theta-\lambda^S)(3-\theta-\lambda^S)\frac{\varphi s^2}{8} - F. \tag{2.16}$$

Hence, given $p$, the equilibrium organizational form is **forward integration** for any $s > s^{Fwd*}$, where

$$s^{Fwd*} = \sqrt{\frac{\left(\left(2-\lambda^P\right)^2 - \varphi^2\right)p^2 + 8F}{\left(1-\theta\right)^2\varphi}}. \tag{2.17}$$

Vice versa, holding $s$ fixed, the equilibrium organizational form is **forward integration** for any $p < p^{Fwd*}$, where

$$p^{Fwd*} = \sqrt{\frac{\left(1-\theta\right)^2 s^2\varphi - 8F}{\left(\left(2-\lambda^P\right)^2 - \varphi^2\right)}}. \tag{2.18}$$

On the other hand, given $p$, the equilibrium organizational form is **backward integration** for any $s < s^{Bwd*}$, where

$$s^{Bwd*} = \sqrt{\frac{\varphi^2 p^2 - 8F}{(1+\theta-\lambda^S)(3-\theta-\lambda^S)\varphi}}. \tag{2.19}$$

Vice versa, holding $s$ fixed, the equilibrium organizational form is **backward integration** for any $p > p^{Bwd*}$, where

$$p^{Bwd*} = \sqrt{\frac{(1+\theta-\lambda^S)(3-\theta-\lambda^S)\varphi s^2 + 8F}{\varphi^2}}. \tag{2.20}$$

If none of the inequalities holds, the two parties will choose to stay **independent**.[23]

[23]Technically, there might arise situations where integration is always preferred to in-

## 2.B Mathematical Derivations

### 2.B.1 Optimal Investment Levels

Equilibrium investment levels depend on the particular organizational form and are chosen while taking the other party's investment as given:

$$e_S^{o*} = \arg\max_{e_S}\{y_S^o(e_P^{o*}, e_S^o) - C_S(e_S^o) - F_S^o + T_S^o\} \tag{2.21}$$

$$e_P^{o*} = \arg\max_{e_P}\{y_P^o(e_P^o, e_S^{o*}) - C_P(e_P^o) - F_P^o + T_P^o\} \tag{2.22}$$

#### Forward Integration

$$\begin{aligned}
&\max_{e_S}\{y_S^{Fwd}(e_P^{Fwd*}, e_S^{Fwd}) - C_S(e_S^{Fwd}) - F_S^{Fwd} + T_S^{Fwd}\}\\
&\varphi s + \frac{1}{2}(\varphi s - \varphi s) - \varphi e_S^{Fwd} = 0\\
&e_S^{Fwd*} = s\\
&\max_{e_P}\{y_P^{Fwd}(e_P^{Fwd}, e_S^{Fwd*}) - C_P(e_P^{Fwd}) - F_P^{Fwd} + T_P^{Fwd}\}\\
&\frac{1}{2}(\varphi p + (1-\varphi)p - \varphi p(1-\lambda^P) - (1-\varphi)p(1-\lambda^P)) - e_P^{Fwd} = 0\\
&e_P^{Fwd*} = \frac{\lambda^P}{2}p
\end{aligned}$$

dependence. In this case, backward integration is always preferred to forward integration when $s < s^{BF*}$, where, given $p$, $s^{BF*} = \sqrt{\frac{(2-\lambda^P)^2 p^2}{(2-\lambda^S)^2\varphi}}$ or, given $s$, $p > p^{BF*}$, $p^{BF*} = \sqrt{\frac{(2-\lambda^S)^2\varphi s^2}{(2-\lambda^P)^2}}$.

**Independence**

$$\max_{e_S}\{y_S^I(e_P^{I*}, e_S^I) - C_S(e_S^I) - F_S^I + T_S^I\}$$
$$\theta\varphi s + \frac{1}{2}\varphi s - \frac{1}{2}\theta\varphi s - \varphi e_S^I = 0$$
$$e_S^{I*} = \frac{1+\theta}{2}s$$
$$\max_{e_P}\{y_P^I(e_P^I, e_S^{I*}) - C_P(e_P^I) - F_P^I + T_P^I\}$$
$$(1-\varphi)p + \frac{1}{2}\left(\varphi p + (1-\varphi)p - (1-\varphi)p\right) - e_P^I = 0$$
$$e_P^{I*} = (1 - \frac{\varphi}{2})p$$

**Backward Integration**

$$\max_{e_S}\{y_S^{Bwd}(e_P^{Bwd*}, e_S^{Bwd}) - C_S(e_S^{Bwd}) - F_S^{Bwd} + T_S^{Bwd}\}$$
$$\frac{1}{2}\left(\varphi s - \varphi s(1-\lambda^S)\right) - \varphi e_S^{Bwd} = 0$$
$$e_S^{Bwd*} = \frac{\lambda^S}{2}s$$
$$\max_{e_P}\{y_P^{Bwd}(e_P^{Bwd}, e_S^{Bwd*}) - C_P(e_P^{Bwd}) - F_P^{Bwd} + T_P^{Bwd}\}$$
$$\varphi p + (1-\varphi)p + \frac{1}{2}\left(\varphi p + (1-\varphi)p - \varphi p - (1-\varphi)p\right) - e_P^{Bwd} = 0$$
$$e_P^{Bwd*} = p$$

## 2.B.2 Equilibrium Organizational Form

Before deriving the equilibrium organizational form, we have to characterize the joint surplus under each organization form, $S^o = \pi_S^o + \pi_P^o$.

**Forward Integration**

$$S^{Fwd} = \frac{1}{2}\varphi s^2 + \frac{\lambda^P}{2}\left(1 - \frac{\lambda^P}{4}\right)p^2 + 1 - F$$

**Independence**

$$S^I = 1 + \frac{1+\theta}{2}\varphi\left(1 - \left(\frac{1+\theta}{4}\right)\right)s^2 + \left(1 - \frac{\varphi}{2}\right)\left(\frac{1}{2} + \frac{\varphi}{4}\right)p^2$$

**Backward Integration**

$$S^{Bwd} = \frac{1}{2}p^2 + 1 + \varphi\frac{\lambda^S}{2}\left(1 - \frac{\lambda^S}{4}\right)s^2 - F$$

Now, we can conduct a pairwise comparison of the surplus under each organizational form.

**Forward Integration versus Independence**

$$\begin{aligned}
\Delta^{Fwd} &= S^{Fwd} - S^I \\
\Delta^{Fwd} &= \frac{1}{2}\varphi s^2 + \frac{\lambda^P}{2}\left(1 - \frac{\lambda^P}{4}\right)p^2 + 1 - F - \\
&- \left(1 + \frac{1+\theta}{2}\varphi\left(1 - \left(\frac{1+\theta}{4}\right)\right)s^2 + \left(1 - \frac{\varphi}{2}\right)\left(\frac{1}{2} + \frac{\varphi}{4}\right)p^2\right) \\
\Delta^{Fwd} &= (1-\theta)^2\frac{s^2}{8}\varphi - \left(\left(2-\lambda^P\right)^2 - \varphi^2\right)\frac{1}{8}p^2 - F,
\end{aligned}$$

where $\left(\left(2-\lambda^P\right)^2 - \varphi^2\right) > 0$. We can show that, given $p$, $\Delta^{Fwd} > 0$ as long as $s > s^{Fwd*}$, where

$$s^{Fwd*} = \sqrt{\frac{\left(\left(2-\lambda^P\right)^2 - \varphi^2\right)p^2 + 8F}{(1-\theta)^2\varphi}}$$

and, holding $s$ fixed, $\Delta^{Fwd} > 0$ as long as $p < p^{Fwd*}$, where

$$p^{Fwd*} = \sqrt{\frac{(1-\theta)^2 s^2\varphi - 8F}{\left(\left(2-\lambda^P\right)^2 - \varphi^2\right)}}.$$

**Backward Integration versus Independence**

$$\Delta^{Bwd} = S^{Bwd} - S^{I}$$

$$\Delta^{Bwd} = \frac{1}{2}p^2 + 1 + \varphi\frac{\lambda^S}{2}\left(1 - \frac{\lambda^S}{4}\right)s^2 - F -$$

$$-\left(1 + \frac{1+\theta}{2}\varphi\left(1 - \left(\frac{1+\theta}{4}\right)\right)s^2 + \left(1 - \frac{\varphi}{2}\right)\left(\frac{1}{2} + \frac{\varphi}{4}\right)p^2\right)$$

$$\Delta^{Bwd} = \left(\frac{\varphi^2}{8}\right)p^2 - (1+\theta-\lambda^S)(3-\theta-\lambda^S)\frac{\varphi s^2}{8} - F,$$

where $(1+\theta-\lambda^S)(3-\theta-\lambda^S) > 0$. We can show that, given $p$, $\Delta^{Bwd} > 0$ as long as $s < s^{Bwd*}$, where

$$s^{Bwd*} = \sqrt{\frac{\varphi^2 p^2 - 8F}{(1+\theta-\lambda^S)(3-\theta-\lambda^S)\varphi}}$$

and, holding $s$ fixed, $\Delta^{Bwd} > 0$ as long as $p > p^{Bwd*}$, where

$$p^{Bwd*} = \sqrt{\frac{(1+\theta-\lambda^S)(3-\theta-\lambda^S)\varphi s^2 + 8F}{\varphi^2}}.$$

**Backward Integration versus Forward Integration**

$$\Delta^{BF} = S^{Bwd} - S^{Fwd}$$

$$\Delta^{BF} = \frac{1}{2}p^2 + \varphi\frac{\lambda^S}{2}\left(1 - \frac{\lambda^S}{4}\right)s^2 - \frac{1}{2}\varphi s^2 - \frac{\lambda^P}{2}\left(1 - \frac{\lambda^P}{4}\right)p^2$$

$$\Delta^{BF} = \left(\lambda^P - 2\right)^2\frac{1}{8}p^2 + \left(\lambda^S - 2\right)^2\frac{1}{8}\varphi s^2$$

We can show that $\Delta^{BF} > 0$ as long as $s < s^{BF*}$, where, given $p$,

$$s^{BF*} = \sqrt{\frac{\left(2-\lambda^P\right)^2 p^2}{\left(2-\lambda^S\right)^2\varphi}}$$

or, given $s$, $p > p^{BF*}$

$$p^{BF*} = \sqrt{\frac{\left(2-\lambda^S\right)^2\varphi s^2}{\left(2-\lambda^P\right)^2}}.$$

### 2.B.3 Comparative Statics

$$\frac{\partial s^{Fwd*}}{\partial\theta}=\frac{1}{2}\left(\frac{\left(\left(2-\lambda^{P}\right)^{2}-\varphi^{2}\right)p^{2}+8F}{(1-\theta)^{2}\varphi}\right)^{-1/2}\frac{\left(\left(\left(2-\lambda^{P}\right)^{2}-\varphi^{2}\right)p^{2}+8F\right)\left(2\left(1-\theta\right)\varphi\right)}{\left((1-\theta)^{2}\varphi\right)^{2}}>0.$$

$$\frac{\partial p^{Fwd*}}{\partial\theta}=\frac{1}{2}\left(\frac{(1-\theta)^{2}s^{2}\varphi-8F}{((2-\lambda^{P})^{2}-\varphi^{2})}\right)^{-1/2}\frac{-\left(\left(2-\lambda^{P}\right)^{2}-\varphi^{2}\right)2\left(1-\theta\right)s^{2}\varphi}{\left((2-\lambda^{P})^{2}-\varphi^{2}\right)^{2}}<0.$$

$$\frac{\partial s^{Fwd*}}{\partial\varphi}=-\frac{1}{2}\left(\frac{\left(\left(2-\lambda^{P}\right)^{2}-\varphi^{2}\right)p^{2}+8F}{(1-\theta)^{2}\varphi}\right)^{-1/2}\frac{(1-\theta)^{2}}{\left((1-\theta)^{2}\varphi\right)^{2}}\left(2\varphi^{2}p^{2}+\left(\left(\left(2-\lambda^{P}\right)^{2}-\varphi^{2}\right)p^{2}+8F\right)\right)<0.$$

$$\frac{\partial p^{Fwd*}}{\partial\varphi}=\frac{1}{2}\left(\frac{(1-\theta)^{2}s^{2}\varphi-8F}{((2-\lambda^{P})^{2}-\varphi^{2})}\right)^{-1/2}\frac{\left(\left(2-\lambda^{P}\right)^{2}-\varphi^{2}\right)(1-\theta)^{2}s^{2}+\left((1-\theta)^{2}s^{2}\varphi-8F\right)2\varphi}{\left((2-\lambda^{P})^{2}-\varphi^{2}\right)^{2}}>0.$$

$$\frac{\partial s^{Bwd*}}{\partial\theta}=\frac{1}{2}\left(\frac{\varphi^{2}p^{2}-8F}{(1+\theta-\lambda^{S})(3-\theta-\lambda^{S})\varphi}\right)^{-1/2}\frac{-\left(\varphi^{2}p^{2}-8F\right)2\varphi\left(1-\theta\right)}{((1+\theta-\lambda^{S})(3-\theta-\lambda^{S})\varphi)^{2}}<0.$$

$$\frac{\partial p^{Bwd*}}{\partial\theta}=\frac{1}{2}\left(\frac{(1+\theta-\lambda^{S})(3-\theta-\lambda^{S})\varphi s^{2}+8F}{\varphi^{2}}\right)^{-1/2}\frac{\varphi^{3}s^{2}2\left(1-\theta\right)}{(\varphi^{2})^{2}}>0.$$

$$\frac{\partial s^{Bwd*}}{\partial\varphi}=\frac{1}{2}\left(\frac{\varphi^{2}p^{2}-8F}{(1+\theta-\lambda^{S})(3-\theta-\lambda^{S})\varphi}\right)^{-1/2}(1+\theta-\lambda^{S})(3-\theta-\lambda^{S})\frac{\varphi^{2}p^{2}+8F}{((1+\theta-\lambda^{S})(3-\theta-\lambda^{S})\varphi)^{2}}>0.$$

$$\frac{\partial p^{Bwd*}}{\partial\varphi}=\left(\frac{(1+\theta-\lambda^{S})(3-\theta-\lambda^{S})\varphi s^{2}+8F}{\varphi^{2}}\right)^{-1/2}\frac{(1+\theta-\lambda^{S})(3-\theta-\lambda^{S})\varphi^{2}s^{2}+16F\varphi}{(\varphi^{2})^{2}}(-1)<0.$$

$$\frac{\partial s^{Fwd*}}{\partial F}=\frac{1}{2}\left(\frac{\left(\left(2-\lambda^{P}\right)^{2}-\varphi^{2}\right)p^{2}+8F}{(1-\theta)^{2}\varphi}\right)^{-1/2}\frac{8}{(1-\theta)^{2}\varphi}>0.$$

$$\frac{\partial p^{Fwd*}}{\partial F}=\frac{1}{2}\left(\frac{(1-\theta)^{2}s^{2}\varphi-8F}{((2-\lambda^{P})^{2}-\varphi^{2})}\right)^{-1/2}\frac{-8}{((2-\lambda^{P})^{2}-\varphi^{2})}<0.$$

$$\frac{\partial s^{Bwd*}}{\partial F} = \frac{1}{2}\left(\frac{\varphi^2 p^2 - 8F}{(1+\theta-\lambda^S)(3-\theta-\lambda^S)\varphi}\right)^{-1/2} \frac{-8}{(1+\theta-\lambda^S)(3-\theta-\lambda^S)\varphi} < 0.$$

$$\frac{\partial p^{Bwd*}}{\partial F} = \frac{1}{2}\left(\frac{(1+\theta-\lambda^S)(3-\theta-\lambda^S)\varphi s^2 + 8F}{\varphi^2}\right)^{-1/2} \frac{8}{\varphi^2} > 0.$$

$$\frac{\partial^2 s^{Fwd*}}{\partial F \partial \theta} = \frac{\left(\left(\left(2-\lambda^P\right)^2 - \varphi^2\right) p^2 + 8F\right)^{-1/2} 4\left(1-\theta\right)\varphi^{1/2}}{\left(\left(1-\theta\right)\varphi^{1/2}\right)^2} > 0.$$

$$\frac{\partial^2 p^{Fwd*}}{\partial F \partial \theta} = \frac{-\left(\left(2-\lambda^P\right)^2 - \varphi^2\right)^{1/2} 2\left(\left(1-\theta\right)^2 s^2\varphi - 8F\right)^{-3/2} 2\left(1-\theta\right) s^2\varphi}{\left((2-\lambda^P)^2 - \varphi^2\right)} < 0.$$

$$\frac{\partial^2 s^{Bwd*}}{\partial F \partial \theta} = \frac{2\left(\varphi^2 p^2 - 8F\right)^{-1/2}\left((1+\theta-\lambda^S)(3-\theta-\lambda^S)\varphi\right)^{-1/2} 2\varphi\left(1-\theta\right)}{((1+\theta-\lambda^S)(3-\theta-\lambda^S)\varphi)} > 0.$$

$$\frac{\partial^2 p^{Bwd*}}{\partial F \partial \theta} = -\frac{2}{\varphi}\left((1+\theta-\lambda^S)(3-\theta-\lambda^S)\varphi s^2 + 8F\right)^{-3/2}\varphi s^2 2\left(1-\theta\right) < 0.$$

# 2.C Sector Description

Table 2.C.1: Sector Description

| Section | Division | Description |
|---|---|---|
| A | 01-03 | Agriculture, forestry and fishing |
| B | 05-09 | Mining and quarrying |
| C | 10-12 | Manufacture of food products, beverages and tobacco products |
| C | 13-15 | Manufacture of textiles, wearing apparel and leather products |
| C | 16 | Manufacture of wood and of products of wood and cork, except furniture; etc. |
| C | 17 | Manufacture of paper and paper products |
| C | 18 | Printing and reproduction of recorded media |
| C | 19 | Manufacture of coke and refined petroleum products |
| C | 20 | Manufacture of chemicals and chemical products |
| C | 21 | Manufacture of basic pharmaceutical products and pharmaceutical preparations |
| C | 22 | Manufacture of rubber and plastic products |
| C | 23 | Manufacture of other non-metallic mineral products |
| C | 24 | Manufacture of basic metals |
| C | 25 | Manufacture of fabricated metal products, except machinery and equipment |
| C | 26 | Manufacture of computer, electronic and optical products |
| C | 27 | Manufacture of electrical equipment |
| C | 28 | Manufacture of machinery and equipment n.e.c. |
| C | 29 | Manufacture of motor vehicles, trailers and semi-trailers |
| C | 30 | Manufacture of other transport equipment |
| C | 31-32 | Manufacture of furniture; other manufacturing |
| C | 33 | Repair and installation of machinery and equipment |
| D | 35 | Electricity, gas, steam and air conditioning supply |
| E | 36-39 | Water supply; sewerage, waste management and remediation activities |
| F | 41-43 | Construction |
| G | 45-47 | Wholesale and retail trade; repair of motor vehicles and motorcycles |
| H | 49-53 | Transportation and storage |
| I | 55-56 | Accommodation and food service activities |
| J | 58-63 | Information and communication |
| K | 64-66 | Financial and insurance activities |
| L | 68 | Real estate activities |
| M | 69-75 | Professional, scientific and technical activities |
| N | 77-82 | Administrative and support service activities |
| O | 84 | Public administration and defense; compulsory social security |
| P | 85 | Education |
| Q | 86-88 | Human health and social work activities |
| R-S | 90-96 | Arts, entertainment and recreation |
| T | 97-98 | Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use |
| U | 99 | Activities of extraterritorial organizations and bodies |

# Chapter 3

# Deep trade agreements and firm ownership in GVC

## 3.1 Introduction

Preferential Trade Agreements (PTAs) are a key instrument to conduct trade policy and the main one to extend a preferential treatment to trading partners in the long run. The proliferation of PTAs, particularly since the 1990s has been well documented (Hofmann et al., 2017).

Naturally, this led to a vast literature about the effects of such agreements. Primarily, these studies focus on the tariff-reduction effect of PTAs and find a positive association between PTAs and trade flows (Baier and Bergstrand, 2009; Egger et al., 2011; Caliendo and Parro, 2014; Anderson and Yotov, 2016).

An eminent literature has studied normative as well as positive aspects of PTAs as preferential tariff agreements. However, in particular the rising importance of services – where tariffs do not apply and only non-tariff barriers (NTBs) – and the efforts to standardize provisions around, declarations of, and the measurement of NTBs at the time of the Uruguay Round at the World Trade Organization have put non-tariff aspects in PTAs into the limelight. This could be seen as the wake of research around non-tariff aspects in PTAs and the literature on the depth of PTAs.

Work on the depth of PTAs is much younger than the one on exclusively-tariff-reducing PTAs. A small body of theoretical work established normative insights into deep PTAs (Bagwell and Staiger, 2001; Maggi and Ossa, 2021; Grossman et al., 2021; Parenti and Vannoorenberghe, 2022).

In parallel to the emergence of theoretical work, substantial efforts were made to delineate the key non-tariff and non-trade provisions in PTAs (see, e.g., Hofmann et al., 2017). The measurement of PTA content led to new empirical work on the determinants and effects of PTAs which essentially meant parting with their binary characterization. Hence, data on the depth of PTAs enabled research to look into their heterogeneous effects beyond tariff reductions (see the various chapters in Mattoo et al., 2020).

While non-goods-trade provisions in "new" PTAs, namely ones that were signed since the 1990s, are frequent and key, much of the work on the consequences of PTAs still focuses on heterogeneous depth-related effects of PTAs on goods trade (see Egger and Nigai, 2015; Aichele et al., 2016; Mulabdic et al., 2017; Mattoo et al., 2022). Some other work focuses on services trade (see Egger and Wamser, 2013a; Gootiiz et al., 2020; Borchert and Di Ubaldo, 2021), global value chains (see Bruhn, 2014; Orefice and Rocha, 2014; Berger et al., 2016; Ruta, 2017; Laget et al., 2020), and foreign direct investment (see Egger and Wamser, 2013b; Osnago et al., 2017, 2019; Kox and Rojas-Romagosa, 2020).

This paper contributes to the literature on the effect of deep PTAs on firm-to-firm ownership at the country-and-sector-pair level. Accordingly, it addresses effects at the interface of ones on direct investment as well as global value chains (GVCs). Specifically, we analyze effects of entering deep PTAs in a unique data-set on the frequency of shareholder-affiliate links across all pairs of 209 countries and 38 sectors over 9 years between 2007 and 2015.

Global input-output tables permit assigning to every shareholder sector and country whether it is up the stream or down the stream of an affiliate sector and country. Hence, every shareholder-affiliate link can be classified as horizontal (within the same sector) or vertical and then forward (the shareholder being up the stream of the affiliate) or backward (the shareholder being down the stream of the affiliate).

Theoretical work on the activity of multinational firms provides guidance as to the expected effect of PTA membership on foreign ownership (see Markusen, 2002; Egger et al., 2007): whereas lower preferential tariffs should reduce the propensity horizontal ownership, they should increase the propensity of vertical ownership (in both the forward and backward direction). On average, positive effects of PTAs on foreign direct investment appear to dominate (Orefice and Rocha, 2014; Osnago et al., 2017; Kox and Rojas-Romagosa, 2020; Laget et al., 2020). This points to a relative dominance of vertical ownership links, consistent with the findings of Alfaro and Charlton (2009). However, the evidence is implicit only, because, as Kox and Rojas-Romagosa (2020) put it, "*we cannot separate the FDI data between horizontal and vertical FDI*".

In the light of the latter, the present study provides three innovations. First, it provides a new measurement by focusing on the extensive margin of investment in terms of shareholder-affiliate ownership links. Second, it differentiates those links as to be horizontal versus vertical (and then forward versus backward) in terms in the light of GVC data. Third, it identifies parameters and provides insights based on a very large panel data-set covering all pairs among 209 countries and 38 sectors over a period of 9 years. The latter permits conditioning on a host of unobservable factors in a high-dimensional fixed-effects design. The latter ensures that the effects of PTAs ad their depth can be identifies from the time variation in the data – i.e., the new membership in PTAs – only.

The key insights from our study are the following. First, entering a PTA raises the number of new foreign ownership links. Second, the latter is completely driven by vertical links, i.e., ones in the forward or backward integration direction. The effects tend to be somewhat stronger in the forward than in the backward direction. The propensity of horizontal ownership links declines with the formation of PTAs. The effects of PTAs on vertical ownership links increase with a higher PTA depth. Finally, PTA effects on vertical investment are stronger, if the specificity of inputs for a sector pair the shareholder and the affiliate belong in is higher on average.

## 3.2 Data

In this paper we use a unique combination of datasets that allow us to explore the effects of PTA on firm ownership.

Firstly, we obtain the data on firm ownership from the Bureau van Dijk's ORBIS dataset. Our main explanatory variable -PTAs- comes from the Deep Trade Agreement Dataset prepared by the World Bank which also includes a detailed text analysis of every treaty's content. Finally we use World Input-Output Tables from the WIOD to obtain different measures of GVCs organization.

### 3.2.1 Firm-ownership Data

The ORBIS dataset extensively complies firm level data such as annual accounts and ownership structure for the period 2007-2018. For the purpose of this analysis the most relevant information is the ownership structure. In this data set a link is defined as an ownership relation of any kind (regardless of the share of ownership) between a parent firm located in country $j$ and sector $s$ and an affiliate located a country $i$ and sector $r$.

To clean the dataset we drop the duplicated entries and also those observation with relevant information missing such as country or sector. Furthermore, we keep a panel of incumbents (observed during the full sample) and entrants (firms born during the sample).

Finally, we aggregate these data at the country-sector-to-country-sector level and fill in the 0s. In the process we create a new variable called number of connected firms ($CF^{rs}_{ij,t}$), that counts the number of firms in country $i$ and sector $r$ that are owned by firms from sector $s$ in country $j$.

Note that given the number of countries (209) and sectors (38) this dataset is huge. More concretely, we have $209 \times 209 \times 38 \times 38 = 63$ million observations per year, which represent almost 600 million observations in total.

Given the size of the sample and to avoid computational problems we have to focus separately on the frequency and the propensity of any ownership as two types of extensive foreign investment margins. First, we focus on the (non-zero) ownership counts and use $\log(CF^{rs}_{ij})$. Moreover, use a binary variable indicating the existence or not of any ownership link, $\mathbb{1}(CF^{rs}_{ij,t})$ as a dependent variable.

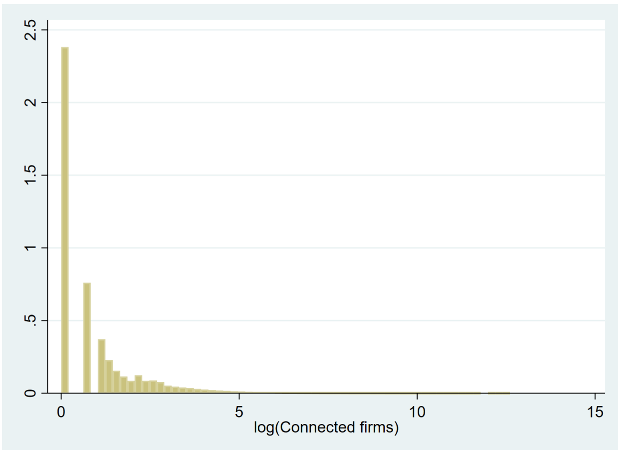



Figure 3.2.1: Log of Number of Connected Firms.

### 3.2.2 PTA Data

Deep Trade Agreement Dataset of the World Bank is the most comprehensive database of PTAs. It includes 279 treaties from 1958 to 2015. Even more interestingly, this database also includes a full text analysis of each treaty and a detailed codification on the inclusion of 52 different provision.

Given our empirical specification, which will include country pair fixed effects, we can only identify the effects of those treaties that come into force during the period 2007-2015. Nevertheless, it is the case that this includes almost half of the treaties (112 new treaties) that generate around 4,000 new dyadic relations (see table 3.2.1) that involve a rich variety of countries (see table 3.2.2).

Table 3.2.1: PTAs coming into force 2007-2015.

| Year | PTAs | Total depth | Core depth | WTO-X depth |
|---|---|---|---|---|
| 2007 | 11 | 0.415 | 0.833 | 0.193 |
| 2008 | 17 | 0.354 | 0.784 | 0.126 |
| 2009 | 18 | 0.366 | 0.809 | 0.132 |
| 2010 | 12 | 0.359 | 0.801 | 0.125 |
| 2011 | 11 | 0.423 | 0.808 | 0.219 |
| 2012 | 15 | 0.390 | 0.763 | 0.192 |
| 2013 | 12 | 0.466 | 0.801 | 0.289 |
| 2014 | 10 | 0.508 | 0.844 | 0.329 |
| 2015 | 6 | 0.455 | 0.852 | 0.245 |

In our empirical analysis, we define different measures to account for PTAs. One measure is simply an indicator variable, $PTA_{ij,t}$, that equals 1 if there is a PTA in force between countries $i$ and $j$ at year $t$. This measure of PTAs is, however, too broad and does not take into consideration the intrinsic heterogeneities between different treaties.

To account for differences between treaties, therefore, we make use of the rich set of provisions coded in the database and define various variables to measure the depth of every PTA.

More concretely, it is possible to classify the different provision into 2 groups: (i) WTO+ which includes provisions already covered by the WTO (14 provisions) and (ii) WTO-X which includes those provisions that go beyond the current WTO mandate (38 provisions). Moreover, there are some provision that have been recognized in previous studies (Baldwin, 2008; Damuri et al., 2012) as being more relevant than others. This group of provisions are named

”core” and include WTO+ plus competition policy, investment, movement of capital and intellectual property rights (18 provisions). Hence, we define three different depth measures:

$$
\begin{aligned}
\text{Total Depth} &= \frac{\sum_{p=1}^{52} \text{Provision}_p}{52} \\
\text{Core Depth} &= \frac{\sum_{c=1}^{18} \text{Provision}_c}{18} \\
\text{WTO-X Depth} &= \frac{\sum_{x=1}^{34} \text{Provision}_x}{34}
\end{aligned} \tag{3.1}
$$

where Provision indicates in a binary way whether a given provision is included in the agreement or not.

Table 3.2.2: New dyadic PTA relations by country in period 2007-2015 (top 15 countries of 122).

| Country | New dyadic relations | Total depth | Core depth | WTO-X depth |
|---|---|---|---|---|
| Romania | 95 | 0.577 | 0.905 | 0.403 |
| Bulgaria | 95 | 0.577 | 0.905 | 0.403 |
| Rest of EU (each country) | 87 | 0.602 | 0.907 | 0.441 |
| Moldova | 46 | 0.641 | 0.804 | 0.555 |
| Croatia | 44 | 0.629 | 0.933 | 0.469 |
| South Korea | 43 | 0.440 | 0.903 | 0.195 |
| Peru | 43 | 0.620 | 0.926 | 0.458 |
| Montenegro | 41 | 0.274 | 0.775 | 0.009 |
| Yugoslavia | 40 | 0.259 | 0.704 | 0.024 |
| Bosnia and Herzegovina | 39 | 0.253 | 0.702 | 0.015 |
| Colombia | 39 | 0.642 | 0.922 | 0.494 |
| Costa Rica | 38 | 0.753 | 0.939 | 0.654 |
| Honduras | 37 | 0.758 | 0.913 | 0.676 |
| El Salvador | 34 | 0.788 | 0.920 | 0.719 |
| Guatemala | 34 | 0.784 | 0.923 | 0.710 |

### 3.2.3 Global Value Chains Data

The WIOD dataset is a widly use Global input-output tables source. We use the the information contained in the 2016 release which covers 43 countries and 56 ISIC Rev. 4 two-digit (primary production, manufacturing, and services). In order to match the WIOT data with the information contained in ORBIS, we aggregate the 56 sectors up so as to obtain 38 sectors. Moreover, we group the countries in 22 major world regions[1] according to the detailed United

[1]Northern America, Central America, Caribbean, South America, Northern Africa, Western Africa, Middle Africa, Eastern Africa, Southern Africa, Southern Europe, West-

Nations geoscheme and substitute coefficients for those countries in ORBIS which are not specifically contained in WIOT by the respective annual group average.

For a more formal account of the WIOT-data construction for our purpose, let us closely follow the notation in (Antràs and Chor, 2018) and define a world economy with $J$ countries (indexed by $i$ or $j$) and $S$ sectors (indexed by $r$ or $s$). Also let us use $Z^{rs}_{ij,t}$ as total value of inputs used by country $j$'s sector $s$ originating from country $i$'s sector $r$ in year $t$; $F^{r}_{i,t}$ and $Y^{r}_{i,t}$ as the total value of the final goods sold and the gross output by industry $r$ in country $j$, respectively.

These basic definitions serve to define three measures which are informed by and reflective of a country-sector pair's positioning in the global value chain. These measures are the following.

**Input coefficient.** Given that $Z^{rs}_{ij,t}$ is measured in U.S. dollars. It is useful to define a currency-free input coefficient $a^{rs}_{ij,t} = Z^{rs}_{ij,t}/Y^{s}_{j,t}$. Moreover we can aggregate $a^{rs}_{ij,t}$ across supplying countries to obtain

$$a^{rs}_{j,t} = \sum_{i=1}^{J} a^{rs}_{ij,t} = \frac{\sum_{i=1}^{J} Z^{rs}_{ij,t}}{Y^{s}_{j,t}} \tag{3.2}$$

The latter measures the normalized inputs used by sector-$s$ of country $j$ in its production sourced from sector-$r$ output (regardless of its geographic origin) in year $t$. In what follows we associate a high input coefficient of the parent firm to backward integration.

**Output coefficient.** By the same toke, we can define $b^{rs}_{ij,t} = Z^{rs}_{ij,t}/Y^{r}_{i,t}$ as a currency-free output coefficient. In turn, this can also be aggregated across using countries $j$ to obtain

$$b^{rs}_{i,t} = \sum_{j=1}^{J} b^{rs}_{ij,t} = \frac{\sum_{j=1}^{J} Z^{rs}_{ij,t}}{Y^{r}_{i,t}} \tag{3.3}$$

The latter measures the normalized output sold by country $i$'s sector-$r$ geared toward sector-$r$ (regardless of the country) at year $t$. In what follows we associate a high output coefficient of the parent firm to forward integration.

**Upstreamness.** While the previous two measures provide information about the connectedness of two sectors for a given (making or using) country,

ern Europe, Northern Europe, Eastern Europe, Western Asia, Central Asia, Southern Asia, Eastern Asia, Southeaster Asia, Australia and New Zealand, Micronesia, Polynesia, Melanesia they are not immediately informative about the overall relative positioning of any sector and country or any sector-to-sector link and country in the global value chain. To determine the general upstreamness of a country-sector pair, we can iteratively make use of $a^{rs}_{ij,t}$ to obtain:

$$Y^r_{i,t} = F^r_{i,t} + \sum_{s=1}^{S}\sum_{j=1}^{J} a^{rs}_{ij,t}F^s_{j,t} + \sum_{s=1}^{S}\sum_{j=1}^{J}\sum_{t=1}^{S}\sum_{k=1}^{J} a^{rs}_{ij,t}a^{st}_{jk,t}F^t_{k,t} + ... \tag{3.4}$$

This equations shows that the output of a country-sector can be expressed as that supplied directly for final consumption, plus that supplied in the production for final consumption in all country-sectors, plus that supplied to a supplier for final consumption in all country-sectors, etc. From equation 3.4 we can define a measure of upstreamness as:

$$U^r_{i,t} = 1\times\frac{F^r_{i,t}}{Y^r_{i,t}} + 2\times\frac{\sum_{s=1}^{S}\sum_{j=1}^{J} a^{rs}_{ij,t}F^s_j}{Y^r_{i,t}} + 3\times\frac{\sum_{s=1}^{S}\sum_{j=1}^{J}\sum_{t=1}^{S}\sum_{k=1}^{J} a^{rs}_{ij,t}a^{st}_{jk,t}F^t_{k,t}}{Y^r_{i,t}} + ... > 1 \tag{3.5}$$

Higher values of $U^r_i$ represent a larger degree of upstreamness.

When defining the $JS \times 1$ vectors $\mathbf{U}$ and $\mathbf{Y}$ which have typical elements $U^r_{i,t}$ and $Y^r_{i,t}$, respectively, as well as the $JS \times JS$ matrix $\mathbf{A}$ which has typical elements $a^{rs}_{ij,t}$, and the $JS \times JS$ identity matrix $\mathbf{I}$, the vector of upstreamness can be elegantly obtain as

$$\mathbf{U} = [\mathbf{I} - \mathbf{A}]^{-1}\mathbf{Y} \oslash \mathbf{Y}, \tag{3.6}$$

where $\oslash$ indicates an elementwise division.

**Downstreamness.** Analogously, using $b^{rs}_{ij,t}$ and $VA^r_{i,t}$ as the value added created by sector $r$ in country $i$ we can define a measure that measure the general downstreamness of a country-sector pair:

$$D^r_{i,t} = 1\times\frac{VA^r_{i,t}}{Y^r_{i,t}} + 2\times\frac{\sum_{s=1}^{S}\sum_{j=1}^{J} b^{rs}_{ij,t}VA^s_j}{Y^r_{i,t}} + 3\times\frac{\sum_{s=1}^{S}\sum_{j=1}^{J}\sum_{t=1}^{S}\sum_{k=1}^{J} b^{rs}_{ij,t}b^{st}_{jk,t}VA^t_{k,t}}{Y^r_{i,t}} + ... > 1 \tag{3.7}$$

Higher values of $D^r_i$ represent a larger degree of downstreamness.

For the analysis at hand, we compute $(a^{rs}_{j,t}, b^{rs}_{i,t}, U^r_{i,t}, , D^r_{i,t})$ for all years in the WIOD and we take the average.[2]

[2]The WIOT distinguishes three components of gross output – namely intermediate uses, final uses, and net inventories – instead of just two (intermediate and final uses). Therefore, we follow Antràs et al. (2012) in applying a "net inventory" correction.

Table 3.2.3: Descriptive Statistics

| Variable | Positive Ownership-link Sample Mean | Positive Ownership-link Sample Standard Deviation | Ownership Propensity Sample Mean | Ownership Propensity Sample Standard Deviation |
|---|---|---|---|---|
| $\log(CF^{rs}_{ij,t})$ | 0.896 | 1.277 | 0.009 | 0.094 |
| $\text{PTA}_{ij,t}$ | 0.457 | 0.498 | 0.303 | 0.459 |
| $\text{TotalDepth}_{ij,t}$ | 0.310 | 0.363 | 0.163 | 0.283 |
| $\text{CoreDepth}_{ij,t}$ | 0.421 | 0.474 | 0.24 | 0.391 |
| $\text{WTO-XDepth}_{ij,t}$ | 0.251 | 0.314 | 0.122 | 0.241 |
| $\text{Downstreamnes}^r_i$ (affiliate) | 2.173 | 0.456 | 2.293 | 0.558 |
| $\text{Downstreamnes}^s_j$ (parent) | 2.131 | 0.437 | 2.269 | 0.542 |
| $\text{Upstreamnes}^r_i$ (affiliate) | 2.337 | 0.633 | 2.262 | 0.772 |
| $\text{Upstreamnes}^s_j$ (parent) | 2.344 | 0.623 | 2.252 | 0.763 |
| $\text{Backward}(a^{rs}_{j,t})$ | 0.039 | 0.065 | 0.014 | 0.036 |
| $\text{Forward}(b^{rs}_{i,t})$ | 0.039 | 0.067 | 0.014 | 0.04 |
| Input specificity$^r$(affiliate) | 0.612 | 0.152 | 0.571 | 0.161 |
| Input specificity$^s$(parent) | 0.626 | 0.150 | 0.571 | 0.161 |
| $\text{BIT}_{ij,t}$ | 0.288 | 0.453 | 0.331 | 0.471 |

## 3.3 Empirical Analysis: PTA Effects on Firm-to-Firm Ownership in GVCs

In this section we explain our empirical strategy and present the main results of the analysis. It will be useful to introduce the generic dependent variable $Y^{rs}_{ij,t} \in \{log(CF^{rs}_{ij,t}, \mathbb{1}(CF^{rs}_{ij,t} > 0)\}$, where $log(CF^{rs}_{ij,t}$ is defined only for positive ownership counts for each observation, and $\mathbb{1}(CF^{rs}_{ij,t} > 0)\}$ is a binary indicator, which is unity for (any) positive ownership counts and zero else. We will refer to the variation in $log(CF^{rs}_{ij,t}$ and $\mathbb{1}(CF^{rs}_{ij,t} > 0)\}$ as to be informative about the positive count (the extent) and the propensity of any foreign ownership, respectively.

Note that in the data the count of all observations $\{rs, ij, t\}$ is $100,828,240$. Of the latter, positive firm-to-firm ownership counts exist for only $985,731$ observations. In the interest of computational feasibility, we will employ $Y^{rs}_{ij,t}$ generally in linear regressions, irrespective of whether we focus on the positive counts or the propensity of any firm-to-firm ownership. In what follows, we will report on the result based on regressions of the form

$$\begin{aligned} Y^{rs}_{ij,t} &= \text{PTA-Measures}_{ij,t}\beta_{\text{PTA-Measures}} + \text{GVC-Measures}^{rs}_{i,t}\beta_{\text{GVC-Measures}} \\ &+ \text{PTA-Measures}_{ij,t} \times \text{GVC-Measures}^{rs}_{i,t}\beta_{\text{Interact}} + \beta_{\text{BIT}}\text{BIT}_{ij,t} \\ &+ \sum_{t=2007}^{2015} \beta_{\text{Domestic},t}\text{Domestic}_{ij,t} + \eta_{ij} + \gamma^{rs} + \omega^r_{i,t} + \nu^s_{j,t} + \epsilon^{rs}_{ij,t}, \end{aligned} \quad (3.8)$$

where $PTA - Measures_{ij,t}$ is a vector of various measures on PTAs as introduced above and depending on the specification, $GVC - Measures^{rs}_{ij,t}$ is a vector of GVC measures of upstreamness/downstreamness or input-output coefficients, $BIT_{ij,t}$ is the binary indicator for the presence of a ratified BIT between countries $i$ and $j$, and Domestic$_{ij,t}$ is an indicator which is unity whenever $i = j$ in year $t$. All parameters $\beta$ are regression coefficients, $\{\eta_{ij}, \gamma^{rs}, \omega^{r}_{i,t}, \nu^{s}_{j,t}\}$ are fixed effects, and $\epsilon^{rs}_{ij,t}$ is a disturbance term. We will generally only report on the parameters $\beta$, and they will always be identified using the high-dimensional set of fixed effects mentioned above.

### 3.3.1 PTAs and Upstream versus Downstream Ownership in GVCs

In this subsection, we employ the aforementioned measures of upstreamness and downstreamness in GVC-Measures$^{rs}_{j,t}$. Note that these measures of the positioning of a shareholder or an affiliate in GVCs are country-sector-indexed each. Hence, we measure for every shareholder and affiliate country and sector its degree of upstreamness as well as downstreamness. Due to the country-sector variation of the aforementioned measures, their main effects will be absorbed by the country-sector-time fixed effects. However, their interaction effects with PTA-Measures$_{ij,t}$ can be identified.

As indicated above, we will present results regarding the firm-to-firm ownership at two types of extensive margins: the frequency of ownership links and the propensity of any ownership link. Table 3.3.1 presents the results for the ownership-link frequency. In the first column, we employ a binary indicator for PTA membership, while in the remaining columns we employ alternative measures of PTA depth. Clearly, the results suggest that PTAs have a positive and stronger effect on vertical ownership links (that is, if either the shareholder or the affiliate are situated up or down the stream of the value chain of each other). The effects appear to be bigger for upstream ownership links, which is possible, because ownership may be more or less concentrated.[3] The positive effects on vertical ownership tend to be bigger with deeper the PTAs. However, there is one exception with regard to the latter: deep PTAs appear to have a weaker effect on the acquisition of upstream affiliates.

[3]Several shareholders may be involved in one affiliate. Conversely, One shareholder my hold ownership in several affiliates, etc.)

Table 3.3.1: Frequency of Ownership Links: Upstreamness and Downstreamness within GVCs

| log(Number of Firm-to-Firm Connections ($CF^{rs}_{ij,t}$)) | PTA | Total depth | Core depth | WTO-X depth |
|---|---|---|---|---|
| PTA-Measures$_{ij,t}$ | $-1.338^{***}$ | $-1.917^{***}$ | $-1.442^{***}$ | $-2.122^{***}$ |
| | (0.047) | (0.072) | (0.052) | (0.085) |
| PTA-Measures$_{ij,t}$ × upstreamness affiliate$^r_i$ | $0.025^{***}$ | 0.022 | $0.020^{*}$ | 0.024 |
| | (0.009) | (0.014) | (0.01) | (0.017) |
| PTA-Measures$_{ij,t}$ × upstreamness parent$^s_j$ | $0.045^{***}$ | $0.072^{***}$ | $0.051^{***}$ | $0.087^{***}$ |
| | (0.009) | (0.013) | (0.009) | (0.015) |
| PTA-Measures$_{ij,t}$ × downstreamness affiliate$^r_i$ | $0.230^{***}$ | $0.375^{***}$ | $0.263^{***}$ | $0.435^{***}$ |
| | (0.013) | (0.021) | (0.015) | (0.025) |
| PTA-Measures$_{ij,t}$ × downstreamness parent$^s_j$ | $0.313^{***}$ | $0.429^{***}$ | $0.324^{***}$ | $0.479^{***}$ |
| | (0.013) | (0.02) | (0.014) | (0.023) |
| BIT$_{ij,t}$ | $0.018^{*}$ | $0.018^{*}$ | 0.018 | $0.018^{*}$ |
| | (0.011) | (0.011) | (0.011) | (0.011) |
| Country-pair FE | ✓ | ✓ | ✓ | ✓ |
| Industry-pair FE | ✓ | ✓ | ✓ | ✓ |
| Shareholder-country-industry-year FE | ✓ | ✓ | ✓ | ✓ |
| Subsidiary-country-industry-year FE | ✓ | ✓ | ✓ | ✓ |
| Domestic-year FE | ✓ | ✓ | ✓ | ✓ |
| Obs. | 985,731 | 985,731 | 985,731 | 985,731 |
| $R^2$ | 0.568 | 0.568 | 0.568 | 0.568 |

Standard errors are clustered at country-industry pairs level and reported in parentheses.
Downstreamness have been scaled by $10^{-3}$
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

In Table 3.3.2 we use the same structure as in Table 3.3.1 but now focus on the propensity of any ownership links from one country-sector pair to another one. Table 3.3.2 suggests that firms located up the stream of the chain tend to integrate more likely when a PTA comes into force. The opposite appears to be true for firms down the stream of the value chain. Both of these results appear to be intensified by the depth of the PTA, ie. a deeper PTA increases more integration up the stream and decreases more integration down the stream of the chain vis-a-vis a shallower PTA.

Table 3.3.2: Ownership Propensity: Upstreamness and Downstreamness within GVCs

| $\mathbb{1}$(Number of Firm-to-Firm Connections ($CF^{rs}_{ij,t}$)) | PTA | Total depth | Core depth | WTO-X depth |
|---|---|---|---|---|
| PTA-Measures$_{ij,t}$ | $0.007^{***}$ | $0.019^{***}$ | $0.012^{***}$ | $0.023^{***}$ |
| | (0.000) | (0.001) | (0.000) | (0.001) |
| PTA-Measures$_{ij,t}$ × upstreamness affiliate$^r_i$ | $0.002^{***}$ | $0.005^{***}$ | $0.003^{***}$ | $0.007^{***}$ |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| PTA-Measures$_{ij,t}$ × upstreamness parent$^s_j$ | $0.003^{***}$ | $0.008^{***}$ | $0.005^{***}$ | $0.009^{***}$ |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| PTA-Measures$_{ij,t}$ × downstreamness affiliate$^r_i$ | $-0.003^{***}$ | $-0.009^{***}$ | $-0.005^{***}$ | $-0.011^{***}$ |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| PTA-Measures$_{ij,t}$ × downstreamness parent$^s_j$ | $-0.005^{***}$ | $-0.013^{***}$ | $-0.008^{***}$ | $-0.015^{***}$ |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| BIT$_{ij,t}$ | $-0.001^{***}$ | $-0.001^{***}$ | $-0.001^{***}$ | $-0.001^{***}$ |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Country-pair FE | ✓ | ✓ | ✓ | ✓ |
| Industry-pair FE | ✓ | ✓ | ✓ | ✓ |
| Shareholder-country-industry-year FE | ✓ | ✓ | ✓ | ✓ |
| Subsidiary-country-industry-year FE | ✓ | ✓ | ✓ | ✓ |
| Domestic-year FE | ✓ | ✓ | ✓ | ✓ |
| Obs. | 102,828,240 | 102,828,240 | 102,828,240 | 102,828,240 |
| $R^2$ | 0.200 | 0.200 | 0.200 | 0.200 |

Standard errors are clustered at country-industry pairs level and reported in parentheses.
Downstreamness have been scaled by $10^{-6}$
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

## 3.3.2 PTAs and Vertical Integration Effects on Ownership in GVCs

In this subsection, we employ the variation in input and output coefficients for each country pair and sector. Hence, in contrast to the country-sector-variant measures of upstreamness and downstreamness above, we utilize country-sector-to-sector data on the relative input and output dependence in this subsection. Recall that a higher input coefficient indicates a larger degree of backward integration (as the affiliate is a bigger supplier to the parent), while a higher output coefficient indicates a larger degree of forward integration (the affiliate is a bigger user of the parent). We can identify the main effect on the respective input and output coefficients apart from their interaction effects with PTA-Measures$_{ij,t}$.

Again, we will present effects on the positive counts and the propensity of any firm-to-firm ownership in separate tables.

Table 3.3.3: Positive Ownership Counts: Vertical integration in Global Value Chains

| log(Number of Firm-to-Firm Connections ($CF^{rs}_{ij,t}$)) | PTA | Total depth | Core depth | WTO-X depth |
|---|---|---|---|---|
| Backward$^{rs}_j$ ($a^{rs}_{j,t}$) | 0.017 | −0.031 | −0.013 | −0.046 |
| | (0.104) | (0.102) | (0.103) | (0.101) |
| Forward$^{rs}_j$ ($b^{rs}_{j,t}$) | 0.448*** | 0.407*** | 0.420*** | 0.406*** |
| | (0.111) | (0.109) | (0.110) | (0.108) |
| PTA-Measures$_{ij,t}$ | 0.022** | 0.045** | 0.019* | 0.065** |
| | (0.010) | (0.021) | (0.012) | (0.031) |
| PTA-Measures$_{ij,t}$ × Backward$^{rs}_j$ | −0.175* | −0.138 | −0.135 | −0.122 |
| | (0.100) | (0.136) | (0.106) | (0.155) |
| PTA-Measures$_{ij,t}$ × Forward$^{rs}_j$ | 0.161* | 0.372*** | 0.243** | 0.467*** |
| | (0.095) | (0.130) | (0.101) | (0.149) |
| BIT$_{ij,t}$ | 0.013 | 0.013 | 0.013 | 0.013 |
| | (0.011) | (0.011) | (0.011) | (0.011) |
| Country-pair FE | ✓ | ✓ | ✓ | ✓ |
| Industry-pair FE | ✓ | ✓ | ✓ | ✓ |
| Shareholder-country-industry-year FE | ✓ | ✓ | ✓ | ✓ |
| Subsidiary-country-industry-year FE | ✓ | ✓ | ✓ | ✓ |
| Domestic-year FE | ✓ | ✓ | ✓ | ✓ |
| Obs. | 990,033 | 990,033 | 990,033 | 990,033 |
| $R^2$ | 0.564 | 0.564 | 0.564 | 0.564 |

Standard errors are clustered at country-industry pairs level and reported in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3.3 reports on the ownership-count effects of PTA-Measures$_{ij,t}$ as such and interacted with the vertical-integration measures. The table is horizontally organized in four columns of results, where the first column is devoted to the binary measure of PTA and the rest to their depth.

The binary PTA indicator carries a positive (semi-elasticity) coefficient, and bigger interdependence in the forward integration direction also boosts the number of ownership links. However, we do not find evidence of a strong and robust evidence of the interaction between PTA membership and the backward integration direction.

Whereas the first column of Table 3.3.3 did not acknowledge the heterogeneity of PTAs depending on their depth, we will do so in the columns 2 to 4 by defining PTA-Measures$_{ij,t}$ as to contain one of the elements in $\{\text{Total depth}_{ij,t}, \text{Core depth}_{ij,t}, \text{WTO-X depth}_{ij,t}\}$, always used in the main effects as well as in the interactions with the GVC measures. These results suggest that PTA membership raises the number of ownership links, in particular, in the forward-integration direction. Moreover, forward integration becomes more attractive with deeper PTAs.

Next, we turn to the results regarding the propensity of any ownership links being formed where there were none prior to a PTA.

Table 3.3.4 is structured in the same way as Table 3.3.3, but it involves the binary ownership indicator as a dependent variable. The results suggest a relatively stronger influence of backward integration than of forward integration for the propensity of any ownership. When taking the main effects and the interaction terms together and evaluating the increase of GVC-Measures$_{i,t}^{rs}$ in one standard deviation, the overall effect of PTAs is positive.

Interestingly, conditional on PTA membership, BITs tend to reduce the propensity of any ownership in this table.

Table 3.3.4: Ownership Propensity: Vertical integration in Global Value Chains

| $\mathbb{1}$(Number of Firm-to-Firm Connections ($CF_{ij,t}^{rs}$)) | PTA | Total depth | Core depth | WTO-X depth |
|---|---|---|---|---|
| Backward$_j^{rs}$ ($a_{j,t}^{rs}$ | −0.006*** | −0.017*** | −0.015*** | −0.013*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Forward$_j^{rs}$ ($b_{j,t}^{rs}$) | 0.039*** | 0.034*** | 0.035*** | 0.037*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| PTA-Measures$_{ij,t}$ | −0.004*** | −0.008*** | −0.005*** | −0.009*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| PTA-Measures$_{ij,t}$ × Backward$_j^{rs}$ | 0.120*** | 0.287*** | 0.190*** | 0.343*** |
| | (0.003) | (0.005) | (0.004) | (0.007) |
| PTA-Measures$_{ij,t}$ × Forward$_j^{rs}$ | 0.085*** | 0.202*** | 0.131*** | 0.244*** |
| | (0.002) | (0.004) | (0.003) | (0.006) |
| BIT$_{ij,t}$ | −0.001*** | −0.001*** | −0.001*** | −0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Country-pair FE | ✓ | ✓ | ✓ | ✓ |
| Industry-pair FE | ✓ | ✓ | ✓ | ✓ |
| Shareholder-country-industry-year FE | ✓ | ✓ | ✓ | ✓ |
| Subsidiary-country-industry-year FE | ✓ | ✓ | ✓ | ✓ |
| Domestic-year FE | ✓ | ✓ | ✓ | ✓ |
| Obs. | 111,505,680 | 111,505,680 | 111,505,680 | 111,505,680 |
| $R^2$ | 0.193 | 0.194 | 0.194 | 0.194 |

Standard errors are clustered at country-industry pairs level and reported in parentheses.

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

Table 3.3.4 suggests that, across all three measures of PTA depth, the propensity of any ownership link being present rises, and more strongly so in the backward rather than the forward-integration direction.

In Tables 3.3.5 and 3.3.6 we further scrutinize on the ownership margin results, using triple interaction terms between the PTA-depth measures, the GVC measures, and a measure of the specificity of inputs. The latter reflects the degree to which inputs are customized and cannot be easily substituted for when traded between firms, and it is defined by following Rauch (1999) in classifying the average products belonging to a supplying sector at stake.[4]

In discussing the results, we focus on the coefficient on the interaction effect between PTA depth and input specificity and the triple-interaction terms.

We start presenting the results where the dependent variable is the log($CF_{ij,t}^{rs}$), i.e., the ownership count, in Table 3.3.5. This table suggests that a high specificity of inputs – which are supplied by the shareholder or the affiliate, depending on the direction of ownership – increases the integration frequency in the forward direction, while it reduces it in the backward direction.

Table 3.3.5: Positive Ownership Counts: Vertical Integration in GVCs and Input Specificity

| log(Number of Firm-to-Firm Connections ($CF_{ij,t}^{rs}$)) | PTA | Total depth | Core depth | WTO-X depth |
|---|---|---|---|---|
| Backward$_j^{rs}$ ($a_{j,t}^{rs}$ | 1.035*** | 0.962*** | 1.014*** | 0.944*** |
| | (0.362) | (0.355) | (0.358) | (0.352) |
| Forward$_j^{rs}$ ($b_{j,t}^{rs}$) | −0.293 | −0.461 | −0.408 | −0.531 |
| | (0.381) | (0.376) | (0.379) | (0.373) |
| Specificity affiliate × intput coefficient | 1.093* | 1.317** | 1.249** | 1.435** |
| | (0.631) | (0.621) | (0.626) | (0.613) |
| Specificity parent × output coefficient | −1.464** | −1.449** | −1.495** | −1.459** |
| | (0.61) | (0.598) | (0.603) | (0.590) |
| PTA-Measures$_{ij,t}$ | 0.532*** | 0.744*** | 0.540*** | 0.856*** |
| | (0.036) | (0.055) | (0.039) | (0.067) |
| PTA-Measures$_{ij,t}$ × Backward$_j^{rs}$ | 0.528 | 0.982** | 0.617* | 1.259** |
| | (0.346) | (0.476) | (0.369) | (0.544) |
| PTA-Measures$_{ij,t}$ × Forward$_j^{rs}$ | −1.566*** | −1.974*** | −1.485*** | −2.249*** |
| | (0.34) | (0.471) | (0.361) | (0.541) |
| PTA-Measures$_{ij,t}$ × Input specificity affiliate$^r$ | −0.218*** | −0.354*** | −0.249*** | −0.416*** |
| | (0.039) | (0.058) | (0.043) | (0.068) |
| PTA-Measures$_{ij,t}$ × Inputspecificity parent$^s$ | −0.583*** | −0.753*** | −0.571*** | −0.843*** |
| | (0.038) | (0.055) | (0.041) | (0.065) |
| PTA-Measures$_{ij,t}$ × Input specificity affiliate$^r$ × Backward$_j^{rs}$ | −1.474** | −2.197*** | −1.532** | −2.649*** |
| | (0.614) | (0.839) | (0.651) | (0.955) |
| PTA-Measures$_{ij,t}$ × Input specificity parent$^s$ × Forward$_j^{rs}$ | 3.020*** | 4.054*** | 3.004*** | 4.682*** |
| | (0.62) | (0.859) | (0.658) | (0.983) |
| BIT$_{ij,t}$ | 0.013 | 0.013 | 0.013 | 0.012 |
| | (0.011) | (0.011) | (0.011) | (0.011) |
| Country-pair FE | ✓ | ✓ | ✓ | ✓ |
| Industry-pair FE | ✓ | ✓ | ✓ | ✓ |
| Shareholder-country-industry-year FE | ✓ | ✓ | ✓ | ✓ |
| Subsidiary-country-industry-year FE | ✓ | ✓ | ✓ | ✓ |
| Domestic-year FE | ✓ | ✓ | ✓ | ✓ |
| Obs. | 990,033 | 990,033 | 990,033 | 990,033 |
| $R^2$ | 0.565 | 0.565 | 0.565 | 0.565 |

Standard errors are clustered at country-industry pairs level and reported in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3.6 indicates that a higher input specificity raises the marginal effect of any PTA membership and of PTA depth for the propensity of there being any ownership links. The effect tends to be generally bigger in the forward than in the backward integration direction.

Hence, overall, PTAs – and particularly deep ones – raise the propensity of any firm integration, specifically in the forward integration direction, and even more so, when the inputs supplied by the parent to the affiliate are more specific and customized than otherwise.

[4] Rauch (1999) product classification is based on the SITC 5-digit level. The association between 5-digit SITC-product categories and 2-digit ISIC sectors as used to cluster firms follows the concordance tables provided by UNCTAD.

Table 3.3.6: Ownership Propensity: Vertical Integration in GVCs and Input Specificity

| $\mathbb{1}$(Number of Firm-to-Firm Connections ($CF_{ij,t}^{rs}$)) | PTA | Total depth | Core depth | WTO-X depth |
|---|---|---|---|---|
| Backward$_j^{rs}$ ($a_{j,t}^{rs}$ | 0.022*** | 0.025*** | 0.023*** | 0.026*** |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| Forward$_j^{rs}$ ($b_{j,t}^{rs}$) | −0.006 | −0.003 | −0.003 | −0.005 |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| Specificity affiliate × intput coefficient | −0.058*** | −0.086*** | −0.078*** | −0.081*** |
| | (0.011) | (0.011) | (0.011) | (0.011) |
| Specificity parent × output coefficient | 0.079*** | 0.064*** | 0.066*** | 0.073*** |
| | (0.013) | (0.013) | (0.013) | (0.013) |
| PTA-Measures$_{ij,t}$ | −0.018*** | −0.043*** | −0.027*** | −0.052*** |
| | (0.000) | (0.001) | (0.000) | (0.001) |
| PTA-Measures$_{ij,t}$ × Backward$_j^{rs}$ | −0.002 | 0.026 | 0.010 | 0.035* |
| | (0.008) | (0.016) | (0.011) | (0.020) |
| PTA-Measures$_{ij,t}$ × Forward$_j^{rs}$ | −0.022** | −0.084*** | −0.058*** | −0.091*** |
| | (0.009) | (0.018) | (0.012) | (0.022) |
| PTA-Measures$_{ij,t}$ × Input specificity affiliate$^r$ | 0.008*** | 0.021*** | 0.012*** | 0.027*** |
| | (0.000) | (0.001) | (0.000) | (0.001) |
| PTA-Measures$_{ij,t}$ × Inputspecificity parent$^s$ | 0.017*** | 0.040*** | 0.026*** | 0.048*** |
| | (0.000) | (0.001) | (0.001) | (0.001) |
| PTA-Measures$_{ij,t}$ × Input specificity affiliate$^r$ × Backward$_j^{rs}$ | 0.232*** | 0.489*** | 0.338*** | 0.574*** |
| | (0.016) | (0.033) | (0.022) | (0.040) |
| PTA-Measures$_{ij,t}$ × Input specificity parent$^s$ × Forward$_j^{rs}$ | 0.205*** | 0.556*** | 0.369*** | 0.651*** |
| | (0.018) | (0.037) | (0.024) | (0.045) |
| BIT$_{ij,t}$ | −0.001*** | −0.001*** | −0.001*** | −0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Country-pair FE | ✓ | ✓ | ✓ | ✓ |
| Industry-pair FE | ✓ | ✓ | ✓ | ✓ |
| Shareholdert-country-industry-year FE | ✓ | ✓ | ✓ | ✓ |
| Subsidiary-country-industry-year FE | ✓ | ✓ | ✓ | ✓ |
| Domestic-year FE | ✓ | ✓ | ✓ | ✓ |
| Obs. | 111,505,680 | 111,505,680 | 111,505,680 | 111,505,680 |
| $R^2$ | 0.194 | 0.195 | 0.195 | 0.195 |

Standard errors are clustered at country-industry pairs level and reported in parentheses.

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

## 3.4 Conclusion

In this paper we investigate the effects of PTAs (and their depth) on firm ownership. Thanks to a unique and novel dataset that measures counts of ownership links at a country and sector pair level, we can uncover interesting heterogenities arising when a PTA comes into force. In particular, given the structure of our data, we are the first to look at sector-specific characteristics when it comes to ownership along the value chain.

Overall, we find a positive effect of PTAs (and their depth) on firm foreign ownership both for the frequency as well as the propensity of any ownership. Moreover, for the downstream ownership frequency is increased by more than the upstream one. On the other hand, the propensity of there being any upstream ownership at all increases by more with PTAs than the propensity of any downstream ownership does.

A second set of results is related to the direction of integration within GVCs. More concretely, after combining our ownership data with input-output coefficients from input-output tables, we are able to differentiate between horizontal and vertical and, for the latter, between forward versus backward investment. Regarding positive ownership links, we only find a mild positive effect of PTAs on horizontal and vertical forward integration. The strongest effects materialize for the propensity of any ownership. At this margin, we find a clear negative impact of PTAs on horizontal integration and a positive effect on vertical integration in both the forward and backward directions.

Finally, we shed light on the role of the specificity of inputs in conjunction with PTA membership for vertical integration. We find that a higher input specificity induces a larger positive effect of PTAs on the frequency of forward integration, while the opposite is true for backward integration. A higher input specificity raises the propensity of any integration in both the forward and the backward direction.

# Appendix

## 3.A Sector Description

Table 3.A.1: Sector Description

| Section | Division | Description |
|---|---|---|
| A | 01-03 | Agriculture, forestry and fishing |
| B | 05-09 | Mining and quarrying |
| C | 10-12 | Manufacture of food products, beverages and tobacco products |
| C | 13-15 | Manufacture of textiles, wearing apparel and leather products |
| C | 16 | Manufacture of wood and of products of wood and cork, except furniture; etc. |
| C | 17 | Manufacture of paper and paper products |
| C | 18 | Printing and reproduction of recorded media |
| C | 19 | Manufacture of coke and refined petroleum products |
| C | 20 | Manufacture of chemicals and chemical products |
| C | 21 | Manufacture of basic pharmaceutical products and pharmaceutical preparations |
| C | 22 | Manufacture of rubber and plastic products |
| C | 23 | Manufacture of other non-metallic mineral products |
| C | 24 | Manufacture of basic metals |
| C | 25 | Manufacture of fabricated metal products, except machinery and equipment |
| C | 26 | Manufacture of computer, electronic and optical products |
| C | 27 | Manufacture of electrical equipment |
| C | 28 | Manufacture of machinery and equipment n.e.c. |
| C | 29 | Manufacture of motor vehicles, trailers and semi-trailers |
| C | 30 | Manufacture of other transport equipment |
| C | 31-32 | Manufacture of furniture; other manufacturing |
| C | 33 | Repair and installation of machinery and equipment |
| D | 35 | Electricity, gas, steam and air conditioning supply |
| E | 36-39 | Water supply; sewerage, waste management and remediation activities |
| F | 41-43 | Construction |
| G | 45-47 | Wholesale and retail trade; repair of motor vehicles and motorcycles |
| H | 49-53 | Transportation and storage |
| I | 55-56 | Accommodation and food service activities |
| J | 58-63 | Information and communication |
| K | 64-66 | Financial and insurance activities |
| L | 68 | Real estate activities |
| M | 69-75 | Professional, scientific and technical activities |
| N | 77-82 | Administrative and support service activities |
| O | 84 | Public administration and defense; compulsory social security |
| P | 85 | Education |
| Q | 86-88 | Human health and social work activities |
| R-S | 90-96 | Arts, entertainment and recreation |
| T | 97-98 | Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use |
| U | 99 | Activities of extraterritorial organizations and bodies |

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