Why GVCs Matter

Exploring the complex interrelationships between Global Value Chains and Trade Policy

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Abstracts

Abstract English
Global Value Chains (GVCs) are a key feature of today‘s global economy. Countries, industries, and firms are connected worldwide through shared production processes. Although these global interdependencies have altered most industrialized and emerging economies substantively, the political economy literature only recently started to integrate GVCs in its research agenda. My thesis contributes to this development and tackles some key questions related to the causes and consequences of the globalization of production: What role can international trade policy play in shaping GVCs? How do GVCs alter the distributional consequences of trade liberalization? What effect do GVCs have on trade preferences and policy outcomes?

I argue that these interrelationships are rather complex. The causal mechanisms connecting my key concepts are rarely straightforward: Findings show that GVC participation leads to more support for liberal trade policy in general - but not in all countries and not in all industries. Strong involvement of multinational corporations in cross-border investments can influence trade policy in the form of faster and higher tariff cuts between the countries involved - but not for all products. Trade policy can alter investment patterns and therefore GVCs - but not all provisions have the same effect.

By using several different measures of GVC integration, based on the firm- and the industry-level, I am able to capture various aspects of these complex interrelationships between global value chains and trade preferences, as well as policy outcomes.

Theoretically, I advance the debate by showing that GVC integration has the potential to broaden the coalition supporting free trade - but not under all circumstances. Additionally, the thesis shows that trade policy can shape GVCs in surprising ways. My main empirical contribution is an original data set, covering trade preferences from over a thousand interest groups worldwide. This data allows me to analyze the effects of GVC integration on key trade policy actors: business groups. Using social media data to measure trade preferences is a new approach, with various advantages and much potential to inspire future research in different fields, far beyond interest group topics. My findings show, that including GVCs in a political economy research agenda allows for a more nuanced analysis of well-established causal relationships.

Abstract Deutsch

Globale Warenketten (global value chains, GVCs) prägen unsere Weltwirtschaft seit Jahrzehnten. Unternehmen, Industriezweige und ganze Staaten sind durch gemeinsame Produktionsprozesse miteinander verbunden. Obwohl diese internationalen wirtschaftlichen Interdependenzen die meisten Industrie- und Schwellenländer nachhaltig beeinflussen, hat die Disziplin der internationalen politischen Ökonomie erst in den letzten Jahren damit begonnen, GVCs in ihre Analysen miteinzubeziehen.

Die zentralen Forschungsfragen in dieser Dissertation tragen zu dieser Entwicklung bei: Inwieweit und in welcher Weise kann internationale Handelspolitik globale Warenketten beeinflussen? Welche Verteilungseffekte haben GVCs? Wie wirken sich diese globalen ökonomischen Interdependenzen auf Präferenzen bezüglich Handelspolitik aus? Globale Warenketten werden hier sowohl als abhängige als auch als unabhängige Variable beleuchtet.

Die kausalen Beziehungen, die zwischen meinen zentralen Konzepten (GVCs, Handelspräferenzen, Handelspolitik) wirken, sind in den meisten Fällen komplexer als sie auf den ersten Blick erscheinen. Die Teilnahme an GVCs führt zwar oft zu liberaleren Handelspräferenzen, jedoch weder in jedem Staat noch in jedem Industriezweig in gleicher Weise. Ähnliches gilt für den Einfluss von multinationalen Konzernen (MNCs) auf Handelspolitik: Ergebnisse deuten darauf hin, dass starke grenzüberschreitende Aktivitäten von MNCs zu schnelleren und stärkeren Zollsenkungen führen - jedoch nicht für alle Produktgruppen gleichermaßen. Ebenso vielschichtig stellt sich die umgekehrte kausale Beziehung dar: Handelspolitik (in Form von internationalen Handelsverträgen) wirkt sich auf Investitionen, und damit auf GVCs, aus. Allerdings ist dieser Effekt von dem genauen Inhalt der Verträge abhängig. Manche Bestimmung erhöhen internationale Investitionen, andere hemmen sie.

Die Intensität der Teilnahme an GVCs wird in dieser Arbeit auf unterschiedliche Weise gemessen. Sowohl die Datenquellen variieren, als auch die Aggregationsebene: neben GVC-Indikatoren für einzelne Industriezweige werden auch Daten auf Firmenebene miteinbezogen. Diese Strategie erlaubt es mir, unterschiedliche Aspekte der komplexen kausalen Beziehungen zwischen GVCs und Handelspräferenzen, sowie Policies, zu beleuchten.

Mein wichtigster empirischer Beitrag zur Forschung stellt ein neuer Datensatz dar, der Handelspräferenzen von wirtschaftlichen Interessensgruppen misst. Die Daten basieren auf knapp hunderttausend Tweets, verfasst von über tausend Gruppen weltweit. Obwohl Social Media in den Sozialwissenschaften immer häufiger als Quelle genutzt wird, gibt es bisher – meines Wissens – noch keine vergleichbaren Studien, die mithilfe von machine learning Handelspräferenzen aus Tweets ableiten.

Die Ergebnisse dieser Dissertation zeigen, dass sich durch die Einbeziehung von globalen Warenketten in etablierte Theorien spannende neue Facetten im Forschungsfeld der politischen Ökonomie ergeben können.

Abbreviations

AMNE	Activity of Multinational Enterprises Database
API	Application Programming Interface
ASEAN	Association of Southeast Asian Nations
CETA	Comprehensive Economic and Trade Agreement
DESTA	Design of Trade Agreements Database
EU	European Union
FDI	Foreign Direct Investment
G20	Group of Twenty
GATT	General Agreement on Tariffs and Trade
GDP	Gross Domestic Product
GVC	Global Value Chain
HO	Heckscher-Ohlin
HS	Harmonized Commodity Description and Coding System
IG	Interest Group
IPR	Intellectual Property Rights
MFN	Most-favored-nation
MNC	Multinational Corporation
NAFTA	North American Free Trade Agreement
NGO	Non-Governmental Organization
OECD	Organisation for Economic Co-operation and Development
PTA	Preferential Trade Agreement
RV	Ricardo-Viner
TiVA	Trade in Value Added Database
TTIP	Transatlantic Trade and Investment Partnership
US	United States of America
WITS	World Integrated Trade Solutions
WTO	World Trade Organization

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Chapter 1

Introduction

Global Value Chains (GVCs) have transformed our economy for the last few decades. Whereas before, goods and services have been produced in one, maybe two countries, the way we produce today (especially in highly industrialized countries) is much more fragmented. Goods are increasingly made by combining foreign and domestic inputs via shared production networks, spanning across multiple countries and often even continents (Blanchard et al., 2016a). In many industries, GVCs have become the norm for the production of most goods and services (Amador and di Mauro, 2015) - “more intermediate goods are traded across borders, and more imported parts and components are embodied in exports” (Gereffi, 2019, p. 329). Economic activity has therefore become more interconnected and complex, with important implications for numerous actors and policy fields (Kowalski et al., 2015).

Although the political economy literature has started to integrate the globalization of production into their research agenda in the last few years, many aspects of the interrelationship between GVCs and trade policy remain unclear (e.g., Baccini and Dür, 2018; Baccini et al., 2018; Kim and Osgood, 2019). This dissertation addresses various gaps in this relatively new research agenda, by focusing on both the causes and consequences of GVCs.

The participation and integration in GVCs can alter opportunities and preferences of various economic actors - especially firms. GVCs can increase the potential to engage (further) internationally, but can also intensify competitive pressures. Both effects can influence their trade preferences, leading either to support for more liberal, or more protectionist policies. This opens up various questions: In which ways can GVC integration shape trade preferences? Does more engagement in international production processes automatically lead to more support for further trade liberalization? Which country- or industry-level characteristics play a role in this relationship? Most research on trade preferences focuses on explaining individuals' positions on trade issues, while other actors are rather neglected. By investigating the trade policy preferences of firms and especially interest groups, this thesis broadens our understanding of these aggregated actors.

If GVCs can alter trade *preferences*, they also have the potential to affect trade *policy*. Understanding specific policy decisions, somewhere between tight protectionism and unconditional free trade - always include (at least implicitly) a theory of key trade policy actors' preferences. This is based on the assumption that decision-makers are receptive to lobbying efforts and design trade policy that benefits the most influential economic actors. If those actors' preferences are shaped by GVCs, then we could also be able to see a relationship between GVC integration and trade policy outcomes. If this is indeed the case, does that mean that GVC integration leads to even more trade liberalization, or do we see a backlash towards more protectionist policies? Which actors are most influential in this process? Are there any country- or industry-level differences? Maybe GVC integration is only influencing trade policy in certain industries or for specific products. Maybe only particular countries are affected. Theoretically, differences like these would be plausible. Empirically, we simply do not know (yet) if they exist.

The interrelationship between GVCs and trade policy goes both ways: GVC integration can influence trade preferences and policy, but specific policies might also have the potential to shape GVCs. Changing the perspective - from analyzing the *consequences* of GVCs to focusing on their *causes* - opens up a different set of promising research questions. In what way can trade policy influence the establishment, shape, and governance of GVCs? Does trade liberalization always lead to more GVC integration? Which trade policy provisions have the strongest effect on GVCs, and why? Again, these relationships might also depend on country- or industry-level characteristics.

Explaining trade preferences and policy outcomes have been prominent research topics for decades, with several different theories contrasting and complementing each other. Research on GVCs, on the other hand, is a comparatively new subject. Its multi-disciplinary nature offers diverse theoretical and empirical approaches. Combining these two fields has the potential to improve our understanding of some of the complex interdependent relationships in the contemporary economic world. I contribute to this knowledge both theoretically and empirically, targeting the issue from different angles and on different levels of aggregation.

This introductory chapter will continue with a brief overview of what constitutes global value chains, as well as a first glimpse at their relevance for political economy research. Some basic definitions and distinctions are also provided concerning the other two main concepts used throughout the thesis: trade policy and trade preferences. After this, I discuss the state of the art concerning causes and consequences of GVCs, again with a focus on trade preferences and trade policy. Gaps in existing research are highlighted, which relates directly to the next part: the specific research agenda guiding my dissertation. Given that a key contribution of my work is based on a new way of measuring trade preferences, I will also provide a comprehensive overview of the most important concepts, variables, and data sources used throughout the chapters. A brief introduction of my new data set is also included. Potential contributions to broader debates, as well as an overview of the specific research papers constituting this cumulative dissertation conclude the introductory chapter.

1.1 Global Value Chains and Trade: The Basics

A major characteristic of our contemporary economic system is the globalization of production, with the emergence of *global value chains* (GVCs) as one of the most obvious manifestation of international interdependencies (National Board of Trade, 2015). A value chain is defined as "the full range of activities that firms and workers perform to bring a product from its conception to end use and beyond" (Gereffi and Fernandez-Stark, 2016, p. 7). If value is added to a product in multiple steps, crossing international borders, then the value chain is called global. In other words: “Global value chains (GVCs) can be thought of as factories that cross international borders” (Taglioni and Winkler, 2016, p. 11). A “Factory World” (Los et al., 2015) is emerging.

International production processes can take on many forms. They can look like ‘snakes’, with sequential production stages, where intermediate goods (i.e. goods that are not finished, but rather used for production of other intermediates or final goods) are shipped from one country to the next, until the final product is sold. ‘Spiders’ are also widespread, where individual parts from different countries are imported to a single location for final assembly (Amador and di Mauro, 2015; Kowalski et al., 2015). Most GVCs resemble some complex mixture of the two ideal types (Timmer et al., 2014) - with one crucial feature uniting all different patterns: each step in the production process *adds value* to the product. Although this might be an obvious statement, its implications are not straightforward. International trade can be measured with traditional import- and export-data (gross trade flows) or in value-added terms (Johnson, 2014). Gross trade data can be very misleading when the goal is to capture links in GVC-integrated countries and industries. Consider an example of trade flows between Mexico and the US in the automobile industry (Ravikumar and Reinbold, 2020): although a production site is situated in Mexico, about 70 % of a vehicle’s value comes from foreign components, and only 30% stems from Mexican parts and labor. Most of the foreign value, in this case, comes from the US itself. When the US imports this vehicle (again), the entire costs (including the cost of all the parts and assembly, no matter where they originated) is included in the export value. This leads to an increase of the US trade deficit with Mexico - in gross trade terms. The dependence on Mexican imports can therefore be highly overestimated when only looking at traditional trade data (Johnson, 2014). *Value added trade data*, on the other hand, allows us to uncover a much more detailed picture, and shows that the trade deficit with Mexico is actually much smaller than previously thought - since much of the value imported into the US has actually been created and added to the product in the US itself. For the year 2015, for example, the gross trade deficit ran at 79 billion US-dollars, whereas the value-added deficit is only roughly half as big, with 40 billion US-dollars (Ravikumar and Reinbold, 2020). Ways of addressing this bias are discussed further below, in the section ’Capturing Key Concepts’.

GVCs do not exist in a vacuum - they are intricately connected to international *trade policy.* Policy provisions provide the legal framework for international trade and investment flows - the very foundation of GVCs. Trade policy includes all instruments regulating trade flows between countries, ranging from free trade (no restrictions on imports and exports) to protectionism (many trade barriers to protect domestic markets), with numerous nuances in between. Governments use many different policies targeting imports, from the most straight-forward one - ad valorem import tariffs - to “dozens if not hundreds of eclectic instruments that are more complex and less transparent” (Bown, 2015, p. 57). Before the formation of the current multilateral trading system, tariffs and non-tariff barriers to trade were relatively high. The creation of the GATT (General Agreement on Tariffs and Trade, 1947) and then the WTO (World Trade Organization, 1994) was aimed at lowering these barriers and negotiate nondiscriminatory (or most-favored-nation, MFN[1]) trade policies among all member states. One crucial exception to the MFN principle is the possibility to form preferential free trade agreements and customs unions, where partner countries liberalize trade relations between them, going beyond GATT/WTO principles. Although preferential trade agreements (PTAs) have been in use since 1948, it was not until decades later that this form of trade policy became increasingly widespread, with a sharp rise in PTAs in force since the 1990s. Given the importance of PTAs in today’s global economic relations, I decided to focus on them, excluding all other forms of international trade policy tools in my analyses. Additional information on the operationalization of trade agreements and their contents is provided in the data section below, as well as in the respective chapters throughout the thesis.

Another essential concept in this thesis concerns *trade preferences.* Generally, they can be defined as the preferences towards trade policy (as described above). At the most basic form, it is about the question whether someone (citizens, groups, firms, industries, government officials, organizations, etc.) prefers protectionist measures or free trade. Of course, trade policy is not a binary variable. Many actors hold complex views towards trade liberalization, support some

[1] This key WTO principle states that countries cannot (normally) discriminate between their trading partners. Granting one country special privileges (e.g. lower tariffs) means all other WTO members must be given the same treatment.

restrictions, but oppose others. Every operationalization of trade preferences will therefore inevitably omit some of these nuances. I approach the measurement of these preferences in a novel way - which is discussed in more detail in the data section below.

The three main concepts defined above - *GVCs, trade policy, and trade preferences* - are intricately linked in ways we do not yet fully understand. The following section serves as an overview of the state of the art on these topics. To structure this interdisciplinary literature, I decided to differentiate between the causes and the consequences of global value chain integration. This distinction will be relevant for all following chapters of the thesis.

1.2 State of the Art: Causes and Consequences of GVCs

Research on GVCs has been carried out in various different disciplines, from business studies, to international economics, regional and development studies, sociology, economic geography, and many more (Kano et al., 2020). Many studies strongly focus on mapping, measuring, and describing the nature of these cross-border processes (Ponte et al., 2019), with many highlighting the role of multinational companies shaping and controlling GVCs (Cadestin et al., 2018b). Theoretical and conceptual work (e.g., Buckley, 2011; Gereffi et al., 2005; Levy, 2008; Strange and Newton, 2006) is complemented by various case studies (e.g., Hatani, 2009; He et al., 2018; Miroudot et al., 2013; Sturgeon et al., 2008) and some quantitative research (e.g., Amendolagine et al., 2019; Carnovale and Yeniyurt, 2014; Fortanier et al., 2020).

In the past few years, this multi-disciplinary literature has been growing rapidly, leading to many new research agendas (see Kano et al., 2020, for an excellent overview). Although political science scholars were not among the first to include GVCs in their field, multiple recent contributions (e.g., Baccini and Dür, 2018; Behuria, 2020; Eckhardt and Poletti, 2016; Kim and Osgood, 2019; Laget et al., 2019; Mayer et al., 2017; Osgood, 2018; Yildirim et al., 2018) have been focusing on the topic and advancing our knowledge of the causes and consequences of globalized production processes in a political economy framework. Despite this work, there are still a lot of blind spots and open questions surrounding this topic - which is why most scholars mentioned above emphasize the need for further research.

The following two sections focus on existing studies, point out relevant research gaps concerning GVCs as a dependent and as an independent variable, and show how this thesis is related to this state of the art. First, research on some of the various *effects* of GVCs - specifically the consequences for trade preferences and trade policy outcomes - are discussed. The second section deals with the *causes* of ‘going global’, with special attention on multinational companies, and how trade policy might influence their investment decisions and therefore the shape of GVCs.

1.2.1 Consequences of GVCs: Explaining Trade Preferences and Policy Outcomes in a Globalized Economy

The globalization of production has a myriad of direct and indirect effects, ranging from areas like economic growth (Jangam and Rath, 2021), innovation and productivity (Fagerberg et al., 2018; Formai and Vergara Caffarelli, 2015), employment (Banga, 2016; Ma et al., 2019), food security (Greenville and Kawasaki, 2018; Narula and Wahed, 2017), to pollution (Duan et al., 2021), and other environmental issues (Rodil-Marzábal and Campos-Romero, 2021; Wang et al., 2019). The multi-disciplinary nature of GVCs allows for many different research questions and empirical approaches, which makes it a very versatile and exciting topic. At the same time, it increases the need to zero in on specific issues, rather than exploring more general effects and trends concerning GVCs.

In the political economy literature, two prominent areas potentially related to GVCs are trade preferences and trade policy outcomes. Both have been studied extensively for decades, but the role of GVCs has mostly been neglected so far (with some notable exceptions mentioned below). This indicates two things: First, both topics are highly relevant for the political economy literature. But, secondly, their relationship with a crucial and defining feature of our contemporary economic system, global value chains, is still not fully understood.

Based on the assumption that policymakers react to the preferences and lobbying efforts of key trade policy actors (business groups, MNCs, trade unions, etc.), explaining policy outcomes must always (at least implicitly) include a theory of trade preference formation. This includes questions like: Who holds which preferences on trade policy and why? How are these preferences aggregated and communicated? Whose positions influence policy outcomes the most? Consequently, the next part of this section will rely heavily on the literature about the determinants of trade preferences, but is equally important for questions concerning policy outcomes.

Explaining Trade Preferences

Theories explaining preferences about trade liberalization are usually set in a rational framework: Actors who potentially gain from fewer restrictions on trade will support liberalization, whereas groups who are disadvantaged by liberal policies, prefer protectionist measures (Stolper and Samuelson, 1941). Assumptions about the distributional consequences of trade policy are therefore at the heart of most research on trade preferences. So, the question becomes: Who wins and who loses from trade liberalization?

Earlier work on these questions was mostly based on the two workhorse models of Standard Trade Theory (the Heckscher-Ohlin and the Ricardo-Viner framework - see Baldwin (2008) for an overview). In the 1980s, New Trade Theory (Krugman, 1980) refined these standard frameworks and shifted the level of analysis from the country to the industry level (Ciuriak et al., 2015), enabling researchers to explain much more phenomena in international trade, leading to new insights concerning trade preferences.

The early 2000s have brought on another development: the integration of firm-level heterogeneity. Only a minority of firms engage in international trade (Bernard et al., 2007) and only a handful of “Superstar Exporters” (Osgood et al., 2017) dominate export-markets. The New New Trade Theory (based on Melitz, 2003) is accounting for these firm-level differences and can be used to explain which firms (successfully) engage in international trade and will therefore support trade liberalization: Size and productivity are among the most important determinants explaining support for liberal trade policies (Kim and Osgood, 2019).

In recent years, researchers have begun to push for another improvement in this area: multiple contributions (e.g., Eckhardt and Poletti, 2016; Kim, 2017; Kim and Osgood, 2019; National

Board of Trade, 2015; Osgood et al., 2017; Yildirim et al., 2018) argue that we have to adjust our well-established theories to the realities of a globalized world. Simply put: Without accounting for GVCs, these theories cannot accurately explain preference formation anymore.

For a long time, research was based on a rather simple distinction: Exporting industries, on the one side, are supposed to support trade liberalization because they have much to gain from foreign market access. Import-competing industries, on the other side, should oppose trade liberalization because they are threatened by foreign competition. In a globalized world, the distinction between these two groups is far less clear-cut than the theory would suggest. The distributional consequences of trade liberalization become more complex, making it harder to explain who holds which preferences and why. The next section shows how some scholars have started to address this issue from different angles.

Uncovering the Role of GVCs in Trade Policy Research

Several new studies already started to tackle this promising research agenda, addressing questions concerning trade preferences, policy outcomes and several other topics. Zeng et al. (2020) show, for example, that US companies with a higher level of GVC integration tend to lobby more for trade liberalization - which indicates that participating in GVCs leads to more liberal trade preferences. Other research reaches similar conclusions: Blanchard and Matschke (2015) also find a significant correlation between offshoring and the support for trade liberalization, and Kim and Osgood (2019) show how the degree of a firm's involvement in GVCs can shape their trade preferences.

Most studies like these only include one or a few countries (with a majority working with data from the US). Although the US is undeniably a major economic player, it seems unlikely that the impact of GVC integration is the same for each country worldwide. A wider geographical focus, allowing for comparative analyses, could provide valuable insights. With data on GVC integration and trade preferences covering 42 countries worldwide, this thesis takes a first step towards this goal.

Another promising approach can be to focus on different actors. Although firms can be influential in the trade policy making process, there are various other crucial actors whose preferences should also be affected by GVCs, but have been neglected by the literature so far. Interest groups are one example: especially business groups, representing industry-level preferences. They are among the most active and influential actors in trade politics (Dür et al., 2015; Dür and De Bièvre, 2007; Gilligan, 1997a; Grossman and Helpman, 2002), yet we do not know much about their specific trade preferences, let alone the impact of GVCs on them. This research gap is addressed in this thesis by using a novel approach at measuring interest group preferences.

A closely related topic - GVC effects on trade policy outcomes - has also sparked attention in recent years (Bown et al., 2020): Orefice and Rocha (2014) find that higher GVC integration can lead to deeper trade agreements, Blanchard et al. (2016a) show that governments set lower tariffs and use fewer temporary trade protection measures towards important GVC partner countries, and Ludema et al. (2019) explain how GVC integration reduces a governments' incentives to apply trade protection. Yildirim et al. (2018) investigate how GVC integration can influence the compliance with WTO dispute settlement rulings, and uncover that trade liberalization becomes more likely when highly integrated sectors are targeted. These studies already address important questions and build a solid foundation for more research. Many different aspects on both sides of the proposed causal relationship can be explored further - this thesis addresses several of them.

1.2.2 Reasons for "Going Global": Multinational Corporations and the Role of Trade Policy

As mentioned above, the relationship between GVCs and trade policy goes both ways. GVC linkages affect trade preferences and policies, but specific trade policy provisions can also influence the establishment, shape, strength, and governance of GVCs. Exploring the interrelationship between GVCs and trade can therefore benefit from both perspectives - GVCs as an independent variable (as discussed in the section above), but also as a dependent variable (following below).

Explaining the emergence, shape, and development of GVCs (i.e. working with value chains as a dependent variable) is inevitably closely related to the economic actors driving international trade relationships. Private firms, especially big multinational corporations, are among the most powerful and influential architects of GVCs (Cadestin et al., 2018b). Their trade and investment decisions create the cross-border linkages that make up the global value chain network (Baldwin, 2014).

The international trade and investment literature is vast and involves several different disciplines, which makes it unfeasible to discuss here in detail. Instead, I will focus on the specific aspect of international investment activities that is most important for this thesis: foreign direct investments (FDI). The determinants of FDI has been a popular research topic (e.g. Bénassy-Quéré et al., 2007; Blonigen and Piger, 2014; Dunning, 1998; Faeth, 2009; Hosseini, 2005). Scholars focus on different economic, geographical, and political reasons for firms to engage internationally via cross-border investments. One important and often discussed political factor is the membership in preferential trade agreements (PTAs) (Büthe and Milner, 2014).

PTA-effects on FDI can take different static and dynamic forms (Blomström and Kokko, 1999), and depend on numerous factors mediating the relationship (Baltagi et al., 2008). One often mentioned reason for an increase of FDI flows in PTA partner countries is the idea that a trade agreement can serve as a credible commitment device, signaling the intention to implement long-term liberal trade reforms. Trade agreements can create a more stable and predictable environment for potential investors, since economic reforms are locked-in through the international agreement, and the risk of short-term policy changes is minimized. This effect should be strongest for developing countries, where political risks often limit investment inflows (Büthe and Milner, 2008; Medvedev, 2012). Other explanations for the empirical relationship between PTAs and FDI have been proposed for both developing and industrialized countries (Baltagi et al., 2008; MacDermott, 2007), with some ambiguous findings concerning the exact causal mechanisms between them (Kenyon and Margalit, 2014; Osnago et al., 2019). One reason for the difficulties in grasping this complex relationship might be related to the operationalization of the independent variable: PTAs.

Trade agreement design varies considerably, both in terms of provisions included and scope thereof. Although some studies have begun to account for this variation (e.g., Büthe and Milner, 2014; Osnago et al., 2019; Rodrik, 2018), much more work is needed to fully understand the impact of specific PTA provisions on investment decisions and, as a consequence, on GVCs. This concerns more obvious topics like investment or dispute settlement provisions, but also issues like environmental and social standards, or intellectual property rights. All provisions included in PTAs could theoretically influence costs and benefits for MNCs' investment and trading partner choices. This also implies that trade policy has the potential to shape the international economic systems in nuanced ways - many of which have not yet been uncovered. This thesis sheds some light on the effect of specific PTA provisions on foreign investments, and therefore on the relationship between trade policy and GVC integration.

1.3 The Interrelationship between GVCs and Trade Policy: A Research Agenda

In this dissertation, I approach the connections between GVCs and trade policy in three different ways: First, I investigate the effect of GVC integration on trade *preferences*. Secondly, and closely related, I go one step further along the causal chain and analyze the impact of GVCs on trade policy *outcomes*. Finally, I focus on the reverse relationship: the influence of trade policy on GVCs. Therefore, three key questions structure my research agenda:

How does GVC Integration affect Trade Preferences?

The globalization of production creates new winners and losers of trade liberalization – leading to new cleavages, new conflicts, and new alliances in trade politics. Winners include highly integrated industries (Yildirim et al., 2018), meaning firms and whole sectors that offshore production, import intermediates and also supply downstream industries in their own country, which then in turn export their own products (Osgood, 2018). Large and highly productive corporations with opportunities to multinationalize even further are among the chief beneficiaries of trade liberalization (Blanchard and Matschke, 2015). Losers, on the other hand, are small and less productive firms and industries (Kim and Osgood, 2019) in countries with only weak GVC integration.

Following this distinction, we should see higher levels of support for trade liberalization among actors who are integrated in GVCs. Assessing this hypothesis will be one of the key research goals of this thesis. Additionally, I will focus on country- and industry-level differences, since there is considerable heterogeneity in both aspects. Some countries are highly integrated into complex GVCs, hosting the headquarters of big multinational corporations controlling considerable parts of the production process. Other countries might participate in GVCs, but mostly as highly dependent suppliers (Gereffi et al., 2005), or they do not participate in GVCs in any substantive way at all. Differences between industries (meaning different industries in one country, as well as the same industry in different countries) are similarly large and also have the potential to influence the relationship between GVC integration and trade preferences. Not all industries inevitably react the same way to participation in GVCs - finding and explaining these differences will be the second main goal of this thesis.

How does GVC Integration affect Trade Policy?

If GVC integration has (differential) effects on trade preferences of important economic actors, we should also be able to observe an effect on trade policy outcomes.

Both topics - trade preferences and trade policy - are closely related, since the preferences of different influential actors ultimately shape policy outcomes. This connection is built on the idea that decision makers in trade policy want to secure support from the most important economic actors, like large firms, business groups, labor unions, and so on. Hence, their decisions will be guided by what benefits these groups the most. These actors are usually not secretive about their positions - quite on the contrary, they often lobby extensively for their preferred policies. Trade policy outcomes can therefore be viewed as a manifestation of powerful actors' trade preferences. It follows that explaining trade *policy* should always include and be based on explaining trade *preferences.*

Whether liberal or protectionist trade policies are implemented is not only dependent on the number of respective supporters, but rather on their political clout (Cornick et al., 2019). Explaining the relationship between GVCs and trade policy outcomes must therefore also include a theory about power: Which actors are able to influence trade policy makers? In this thesis I will focus on two - potentially very influential - ones: multinational corporations and business groups.

How does Trade Policy affect GVCs?

The causal connections between GVCs and trade preferences (and policies) are not unidirectional. While GVCs have the potential to influence trade policy outcomes in various ways, the effect can also go the other way: Policies can shape GVCs. Therefore, I will not only investigate the role of GVCs as an explanatory variable, but also as a dependent one. In order to do so, I decided to focus on the direct effect trade policy can have on the decisions of specific economic actors: multinational corporations (MNCs).

Global Value Chains are not established randomly - they are the product of many individual decisions, often made by large MNCs. These firms outsource parts of their production process to foreign partners and thereby build international linkages and - sometimes highly asymmetrical (Gereffi et al., 2005) - networks. Lead firms are therefore often able to shape and govern considerable parts of GVCs via different mechanisms (Kano, 2018), with specific trade and investment decisions being one of the most obvious and powerful tools. If a firm decides to 'go global', they can either trade with independent partners ('at arm's-length') or integrate foreign subsidiaries into their corporate structure, retaining some degree of control over the production steps carried out abroad (Osnago et al., 2019).

Different theoretical approaches have been established to analyze companies' motives for engaging internationally (Dunning, 1998; Faeth, 2009), focusing on various aspects of costs and benefits related to MNCs' investment and trade strategies. These decisions - whether to outsource or produce domestically, where to invest, who to trade with - are made based on multiple different economic, geographical, and political factors. International trade policy can influence these factors to a certain degree - and therefore also indirectly shape GVCs. Studies show, for example, that preferential trade agreements (PTAs) can boost foreign direct investments (Büthe and Milner, 2014), which should consequently influence the creation, form, and strength of global production networks.

I focus on two specific aspects of both trade policy and GVCs, and tackle the question of how trade agreement design can influence investment decisions. This allows me to zero in on the causal mechanism between two very large concepts (trade policy and GVCs) by only focusing on specific manifestations of them. Although this approach limits the generalizability of my findings, they nevertheless can contribute to a better understanding of how trade policy can shape GVCs.

1.4 Capturing Key Concepts

This thesis includes several different concepts of GVCs, trade policies and trade preferences. In order to get a better idea of the definitions, operationalizations and data sources used throughout the chapters, this section provides a detailed overview. First, the two main approaches to measuring GVCs (using value-added trade and firm-level indicators) are discussed, then trade policy, and finally trade preferences.

1.4.1 GVC Integration

Value Added Trade Flows

International trade can be measured with traditional gross trade data or in value-added terms (Johnson, 2014). The distinction between gross and value added trade flows, is not just relevant for the evaluation of trade balances (see discussion above). National trade accounts "contain no information on how exports are used abroad, and they do not tell us anything about how imported goods are produced" (Johnson, 2018, p. 208). They only capture the relationship between pairs of countries, which can be problematic, since the very nature of GVCs is that they connect multiple countries across various borders or even continents.

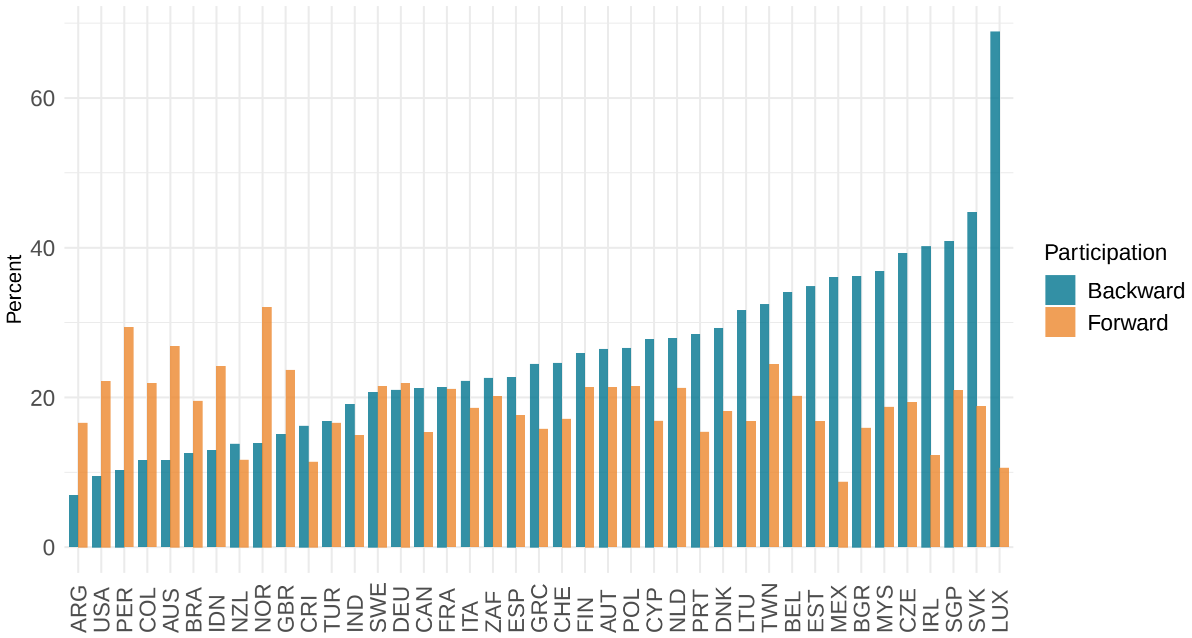
To address these problems, the concept of *value-added trade* has been established in the literature (e.g., Daudin et al., 2011; Johnson, 2014; Johnson and Noguera, 2012; Koopman et al., 2010), although the exact measurement and specific indicators vary. One widely used resource for value-added trade data is the OECD's Trade in Value Added (TiVA) Database (OECD, 2020b): Indicators are available for over sixty countries (OECD, EU, G20, several East/South-east Asian and some South American countries)[2]. The database offers many different indicators, covering multiple aspects of GVC integration.

Roughly speaking, GVCs can be captured using two different perspectives: forward and backward participation in value chains. *Forward participation* indicators are based on the "extent to which a given country's exports are used by firms in partner countries as inputs into their own exports" (Kowalski et al., 2015, p. 14), available for both the country and the industry level (OECD, 2019). *Backward participation* indicators capture the "extent to which domestic firms use foreign intermediate value added for exporting" (Kowalski et al., 2015, p. 14). Both perspectives can be used to assess a country's or industry's degree of integration into global production processes, with backward indicators capturing the role of a country or industry in relation to the upstream part of production, and forward indicators focusing on relationships concerning downstream activities. Which indicator is best suited to measure GVC integration depends on the specific research interest.

Figure 1.1 shows the backward and forward GVC participation for each country in the TiVA database. Some countries have a strong backward integration, but their forward integration is rather low (examples would be Luxembourg or Mexico). This means that there is a lot of foreign value added in their exports, but not much domestic value added in exports of other countries, further downstream. Other countries (like France) are integrated rather evenly, with both indicators at around 20 percent. The main reason this plot is important, is that there is no obvious relationship between forward and backward participation. Both indicate that a country is participating in GVCs, but the nature of this participation varies considerably between countries. TiVA also offers industry-level data (forward and backward perspective), which allow for a much more detailed analysis of the causes and consequences of GVCs.

[2]The full list of countries can be accessed here: `https://www.oecd.org/industry/ind/tiva-2018-countries-regions.pdf` (30 November 2020)

Figure 1.1: Forward and Backward GVC participation (TiVA), country-level comparison



International Investment Flows and the Role of MNCs

Although country- and industry-level value-added trade flows are crucial to map, measure, and analyze GVCs, they inevitably represent very aggregated relationships. Depending on the respective research agenda, this might not be enough. As we know from the extensive firm heterogeneity literature (Melitz and Redding, 2012), firms differ significantly in terms of size, productivity, international engagement, and many other factors. These differences can be relevant for various GVC-related research questions, which go beyond country- or industry-level explanations and focus on the role of firms in GVCs. Especially the activities of multinational corporations (MNCs) are central to understanding global production networks (Hatch et al., 2015). These actors control considerable parts of GVCs and are often very actively participating in the trade policy making process. Measuring MNC activity can be approached in different ways - two of which are used in this dissertation: foreign direct investments and outputs of foreign affiliates.

Foreign direct investments (FDI) are one way of retaining control over the production process while simultaneously exploiting the economic advantages of offshoring. It can be seen as an "investment in control of productive facilities overseas" (Sobel, 2006, p. 805). Operations can be built from the ground up (i.e. greenfield investments) or as a merger with or an acquisition of a foreign company. These investment decisions can create, shape, and influence the form of GVCs. MNCs with control over many foreign affiliates can govern (part of) a value chain, altering the power dynamics between all parties involved (e.g. dictate prices, lock in specific technologies, etc.). Understanding what drives these decisions (and which influence specific trade policy issues might have) is the one key research goal of this dissertation.

Using firm-level data from the Thomson Reuters Mergers and Acquisitions Database (Thomson Reuters, 2020b), which offers information on over one million cross-border M&As (mergers and acquisitions) since the 1970s, makes it possible to compare investment strategies of firms between country-pairs, as well as across time. This approach allows to trace the effect of specific trade policy provisions on investment decisions, and therefore, on the creation and development of GVCs.

FDI are by far not the only firm-level manifestation of the internationalization of production. The OECD has developed a comprehensive collection of *MNC activities* across countries and industries, the analytical AMNE (activities of MNEs[3]) database (OECD, 2020a). It enables researchers to quantify the links between MNC headquarters and their foreign subsidiaries. Relationships like these are characteristic for GVC-integrated industries, and could have many different implications for trade preferences and trade policy outcomes. One chapter in this dissertation shows how these MNC connections can influence trade policy in the form of tariff cuts.

Even though these two concepts only capture specific parts of global production linkages, explaining the causes and consequences of these aspects can help us understand the intricacies of GVCs in more detail. In combination with the TiVA data described above, this dissertation can therefore contribute to the GVC-literature on three different levels of aggregation: the firm-,

[3]The OECD uses the term MNE (multinational enterprise), instead of MNC - both describe the same corporate construct and are used interchangeably in the literature.

the industry-, and the country-level.

1.4.2 International Trade Policy

International trade policy includes many different tools (Bown, 2015), and their respective importance has changed over time. In recent decades, preferential trade agreements have seen a sharp increase both in their number and in their scope. Agreements differ in at least five categories (Johns and Peritz, 2015): depth (the extent to which a PTA constrains state behavior), scope (the number of issue areas covered by the agreement), membership (how many partner countries are included, and whether they are more regional or global), rigidity (the degree of flexibility in violating or temporarily escaping obligations), and institutionalization (this can range from simple goals for cooperation to complex bureaucracies). Capturing (parts of) these design differences is not an easy task, since it means dealing with huge amounts of text data from increasingly complex agreements. The DESTA (Design of Trade Agreements) project team (Dür et al., 2014) took on this challenge and now provide manually coded data on a large set of design features for more than 700 agreements.

Parts of this thesis are (at least indirectly) based on this project, with trade policy being measured in two different ways: First, data from Baccini et al. (2018) is used to capture the most straightforward manifestation of trade liberalization: tariff cuts. The authors drew a sample of PTAs from the DESTA database, covering agreements with major trading powers. They collected detailed tariff schedules from the World Integrated Trade Solutions (WITS) dataset (i.e. tariffs on which goods are reduced at which rate, between country-dyads), containing thousands of tariff lines. This dataset captures detailed information for specific goods at the Harmonized Commodity Description and Coding System (HS) six-digit level, which means that we know, for example, at which rate country A is reducing its tariffs on goods like cocoa powder or sewing machine needles, vis-à-vis country B. Using data at this level of aggregation allows for a very nuanced analysis of the determinants of trade policy outcomes. The second way of measuring trade policy focuses on specific non-tariff provisions included in many contemporary PTAs: intellectual property rights (IPRs), which provide a regulatory framework to protect owners and producers of intellectual property. Using an innovative new data set from Mödlhamer (2020) (which is based on the DESTA project as well), makes it possible to capture not only whether a PTA contains such provisions, but also the strength of IPR protection. Rather than a binary variable, this data provides a much more sophisticated measure of IPR protection, using a dictionary-based quantitative text analysis to construct an IPR-strength index. This makes it possible to assess not only the effect of IPR provisions in general, but the differential impact of various degrees of IPR protection strength.

Including both approaches to measuring trade policy - one focusing on the most general and straightforward instrument to liberalize trade (tariffs), and one highlighting a very specific provision (IPRs) - allows me to capture different aspects in the interrelationship between GVCs and trade policy.

1.4.3 Trade Preferences

In a nutshell, trade preferences capture an actor's preferences concerning trade policies. That sounds rather simple, but trade policy is a vast and complex field. Depending on the specific research interest, it can be sufficient to simply distinguish between the preference for free trade vs. protectionism. Given that trade policy provisions include so much more than these dichotomous categories (see section above), this strategy can be an oversimplification of the many different possible positions an actor may have on issues like investments, intellectual property protection, or many other provisions that make up modern trade policies. For the scope of this thesis, I differentiate between a critical, a neutral, and a positive stance towards trade liberalization. Given that my theoretical arguments also only distinguish between supporters and opponents of liberal trade policies, this rather simple classification should suffice.

Many different actors can hold distinct trade preferences. Existing research includes studies on individuals (Rho and Tomz, 2017; Schaffer and Spilker, 2019; Scheve and Slaughter, 2001), firms (Osgood et al., 2017; Plouffe, 2015), industries (Curran and Nadvi, 2015), and countries or whole regions (Collier and Venables, 2007; Persson and Wilhelmsson, 2016). I mainly focus on interest groups - more specifically, business groups. Not because other groups are not interested in international trade issues (many indeed are), but mostly because their influence is often rather limited (De Bièvre, 2014; Poletti et al., 2016). I want to restrict my analysis to actors with clear preferences *and* the potential to advocate somewhat successfully.

Measuring preferences can be approached in different ways: A researcher can either use interviews or surveys to directly ask the actors of interest about their opinions, or infer preferences from their behavior (e.g. voting patterns, official statements, policy documents, etc.). This thesis takes the latter approach and uses social media data to quantitatively measure preferences of specific trade policy actors. The following section discusses this choice in detail.

1.5 From Tweets to Preferences

Although this thesis covers a variety of different data sources, the most innovative one is the collection of interest group tweets and their machine learning-based classification into different categories, capturing the authors' preferences concerning trade policy. Given the importance of the data set for my work, a more detailed introduction seems useful. I will start with discussing the use of text as data in general and the possible chances and pitfalls of working with twitter data in particular. Then, the data collection process is described, and some basic approaches for statistical analyses for this kind of data are presented. Finally, my original data set is briefly introduced.

1.5.1 Text as Data: Working with Twitter Data

Monroe and Schrodt (2008, p. 351) consider text as "the most pervasive - and certainly the most persistent - artifact of political behavior". In the political science literature, there is a "long tradition of analyzing texts to gain information about the actors who produced them" (Benoit, 2020, p. 462). Methods range from quantitative content analysis (Krippendorff, 2018) using human coders, to more qualitative approaches like discourse analysis (Van Dijk et al., 1997). In the past two decades, the focus somewhat shifted "to treating text as something not to be read, digested and summarised, but rather as inputs to more automated methods where the text is treated as data to be processed and analysed using the tools of quantitative analysis, even without necessarily being read at all" (Benoit, 2020, p. 463). Both the availability of a rapidly growing amount of text data as well as advances in computational social science methods have pushed this development forward.

Chances and possible pitfalls

Out of the many social media platforms, Twitter is especially suited for social science research, for several reasons: It is an increasingly popular forum for political debates (with many societal actors actively participating), and most tweets are publicly accessible, since only a minority of users decide to make their account private. Twitter data offers a very high degree of granularity, in spatial as well as temporal terms. This allows for research at a low level of aggregation (e.g. individual political preferences), but also at a more comparative macro scale. The number of characters per text unit is limited (in contrast to many Facebook posts, for example), which makes it easier to compare different tweets with each other. The information is text-based (unlike mostly visual content on platforms like Instagram) and therefore much easier to analyze both manually and computationally. One of the biggest advantages is the comparatively easy data access via Twitter's own developer environment.

Working with social media data also has its limitations (Barberá and Steinert-Threlkeld, 2020): One of the most often discussed potential pitfalls concerns the representativeness of samples obtained from social media (Nyhuis, 2020). The severity of this problem is closely related to the population of interest: individual twitter users' opinions can probably not directly be generalized to all citizens (Mellon and Prosser, 2017). For other populations, this critique is less valid: more than 85 percent of leading politicians have active Twitter (or Facebook) accounts (Barberá and Zeitzoff, 2018), for example.

Another limitation of working with social media data is replicability. Sharing the raw text data is restricted: Twitter only allows an individual to share a limited number of tweets per day. Also, "replication requires programming skills that many replicators may not possess" (Barberá and Steinert-Threlkeld, 2020, p. 408)[4]. The third reason social media data analyses are only partly replicable is 'post rot' (Timoneda, 2018): if a user deletes a tweet or an entire account, the

[4]Note: The data collection process is described in the next section.

data is not available anymore. A related issue is the limitation of posts that can be downloaded for a specific timeline: only a limited amount of tweets per user is available - which inevitably changes quite quickly. Despite these limitations, researchers emphasize the "immense and still largely untapped potential of social media as data generators" (Barberá and Steinert-Threlkeld, 2020, p. 417).

The data collection process

As mentioned above, the data collection process for social media data can be a little challenging for researchers without any programming skills. Fortunately, the R- and Python-communities offer many useful free tutorials, scripts, packages and libraries to make this work more accessible.

Many websites offer data access via APIs (application programming interfaces), allowing to retrieve information in a structured manner. Twitter provides this option via their developer's account.

Quantitative data analysis

After the sometimes tricky data collection process, the large amount of potentially interesting texts can be cleaned and analyzed. In order to work with text as data in quantitative analyses, the 'unstructured' form of natural language has to be transformed into more structured, quantitative data. The most common approach to achieve this is to first pre-process the selected text corpus (remove very common words, remove punctuation, etc.), and then extract features and summarize their counts: this is called the document-feature matrix. Features can be *unigrams* (single words), or - if word order has to be preserved - *bi-* and *n-grams* (two or more words, respectively). A simple list of words (unigrams) and their counts (i.e. how often they appear in a selected corpus) is often sufficient to convey the general meaning of a text (Grimmer and Stewart, 2013). Whether word order is essential, mostly depends on the complexity of the sentences - with the simple and straightforward communication style used in tweets, this is most likely not an issue.

Once the text is converted into data, several tools are available to extract information from it. Among the many different methodological approaches available to carry out automated content analyses (Benoit, 2020), three broad categories can be distinguished: statistical summaries, dictionary approaches, and machine learning methods (supervised or unsupervised).

Statistical summaries are used to describe the characteristics of a text corpus, based on some specific indicator. In its most basic form, this could mean identifying the most frequently used words, and use frequency distributions to extract meaning from the text (Benoit, 2020). More sophisticated approaches include statistical association methods or measures of similarity and distance (Einspänner et al., 2014). The second category, *dictionary-based approaches*, can be an easy way to classify large text corpora into pre-defined categories, simply based on the words used in the respective text units (Haselmayer and Jenny, 2017; Kleinnijenhuis et al., 2013). Dictionaries can be pre-existing (included in python-libraries or R-packages, for example) or defined by the researcher. For Benoit (2020), dictionary analysis is therefore a hybrid approach combining qualitative content analysis and fully automated methods. A major weakness of dictionary-based approaches is the difficulty in dealing with context-specific language and nuanced expressions, like ironic statements. Ceron et al. (2014, p. 343) illustrate this problem with the example "What a nice rip-off!" This is clearly a negative statement, but a dictionary-based approach would most likely categorize it as positive, based on the use of the word 'nice'. Similar problems arise with very specific or technical language, which is rarely covered in pre-existing dictionaries. A much more nuanced analysis is possible with the third category of automated text analysis tools - *machine learning* techniques. *Supervised* machine learning "is based on the idea that a procedure will 'learn' from texts about which the analyst declares some external knowledge, and the results of this learning are then mapped onto texts for which the analyst lacks this knowledge" (Benoit, 2020, p. 474). This process starts with hand-coding a small sample of the text into defined categories, which is then used to train an algorithm to classify the remaining texts, based on the patterns of the pre-coded training data. Various different algorithms are available for this task. Machine learning tools can also be used to discover new ways of organizing texts (Grimmer and Stewart, 2013), utilizing *unsupervised* methods, like clustering texts into topics or estimating latent traits (such as ideology) (Olivella and Shoub, 2020). The key difference between supervised and unsupervised machine learning approaches it that there is no separate learning step included in unsupervised techniques.

1.5.2 Interest Group Trade Preferences: Introducing a New Data Set

Using the Twitter REST API, I collected millions of interest group tweets, and then carried out a supervised sentiment analysis to classify all trade-related statements. The result is a data set with 95,600 tweets discussing trade issues, posted by more than one thousand groups from 42 countries, between 2009 and 2021. Each collected tweet can be either positive, neutral, or critical towards free trade. Figure 1.2 captures the country-level average percentage of positive and critical statements found in the sample. Both maps show geographical differences, although the share of positive tweets varies across a wider range than the share of critical statements. Since this dissertation is heavily guided by the question of whether and how GVCs influence trade preferences, I decided to restrict my analysis to industry-level business groups[5]. These IGs are likely to have distinct trade preferences, since they represent actors directly affected by trade policies: firms and whole industries.

Figure 1.3 shows the number of groups per industry (bars) and the average number of tweets per group, representing the respective industry. The data set is unbalanced in multiple ways. First, the overall share of critical tweets is only 10 percent. On the one hand, this is to be expected, since business groups are typically rather supportive of free trade. On the other hand, this creates challenges for the data analysis and the generalizability of the findings. Another source of possible bias is the highly skewed distribution of groups and tweets across industries and countries. Agricultural industries and food products are disproportionately well represented, while I was only able to find a handful of groups in many other industries. Non-OECD countries are also underrepresented (see Table A.1). Although both issues constrain the possible research questions that can be answered with this data set, being cautious in the analysis and interpretation nevertheless allows me to uncover several interesting relationships.

[5]In order to assess the impact of GVCs on IG trade preferences, groups have been selected based on the same industry list as the available GVC data. An overview of all industries included in the sample, as well as the respective number of groups, is provided in Table A.1 in the appendix

Figure 1.2: Country percentages of positive and critical business group tweets

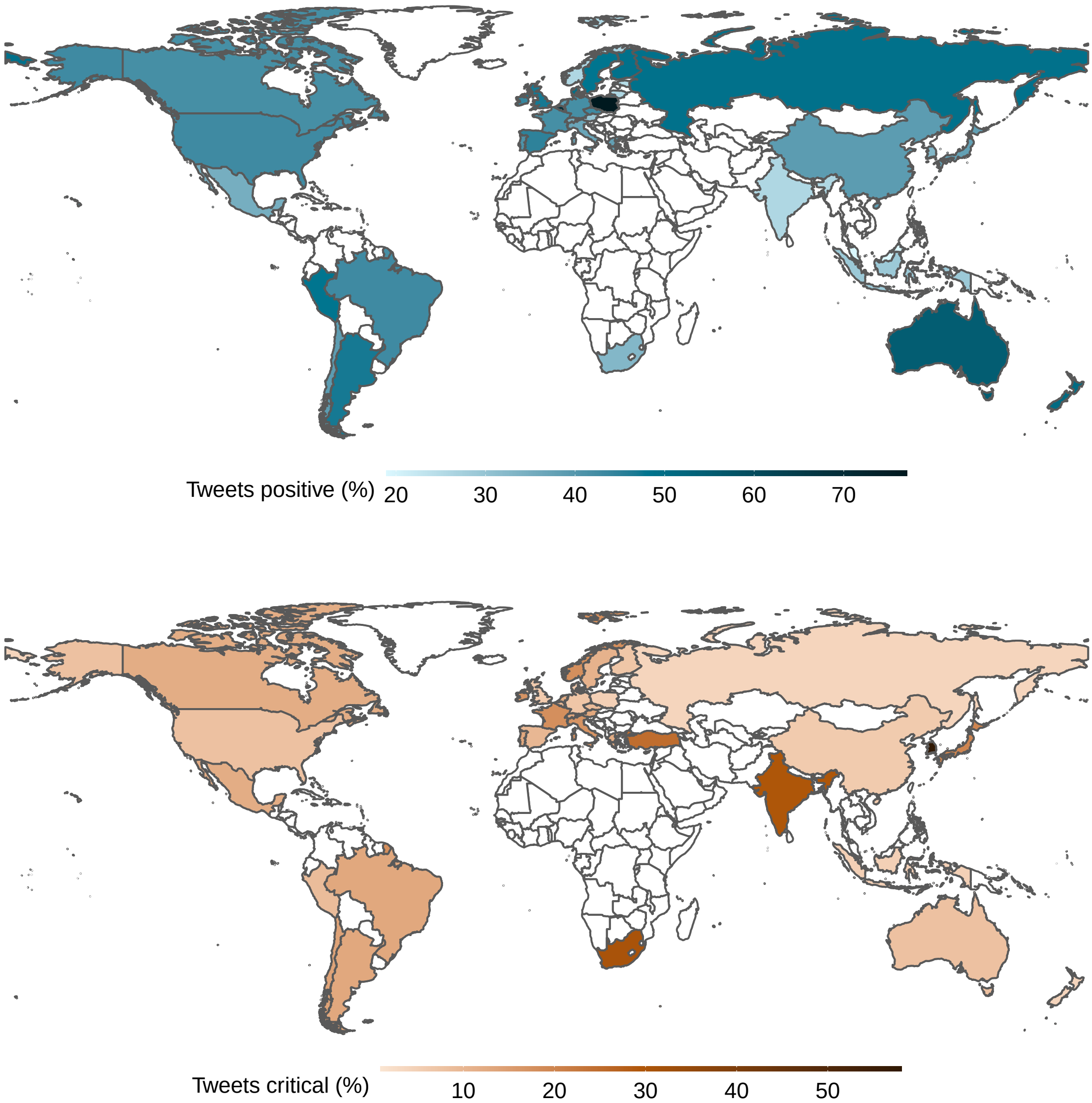
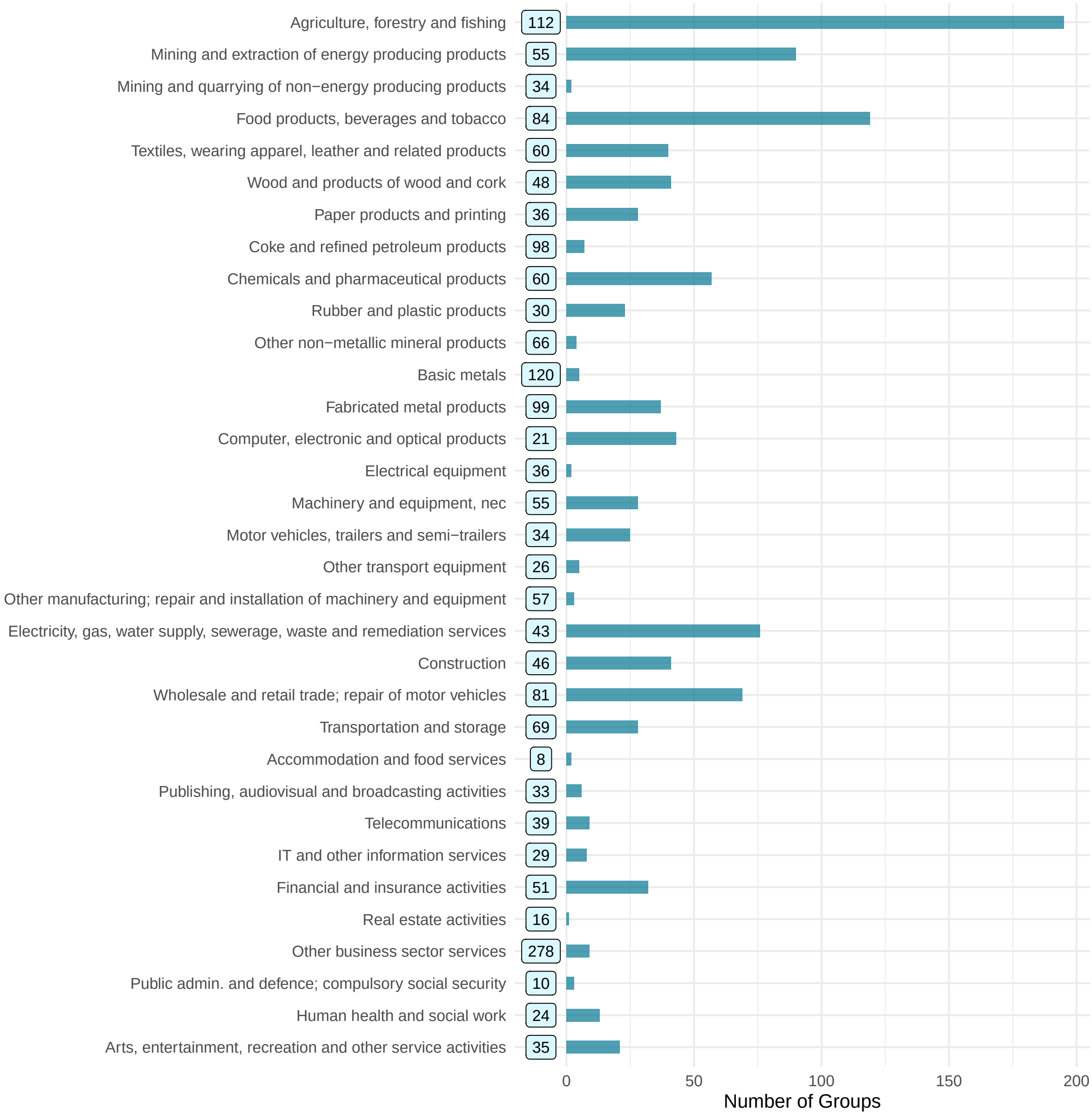


Figure 1.3: Number of groups per industry and average number of trade-related tweets per group



1.6 Contributions to Broader Debates

This thesis explores some specific aspects concerning the causes and consequences of GVCs in a political economy framework. Findings show, that the relationship between the globalization of production and trade preferences, as well as trade policy, is not as straightforward as often suggested, but rather dependent on various intermediate factors. Apart from the very diverse and multidisciplinary literature on GVCs, this thesis can also contribute to discussions in fields like the political economy of trade, design of political institutions (especially trade agreements), economic development, and computational social sciences.

The Political Economy of Trade

The political economy of trade policy has sparked interest among scholars for a long time (Baldwin, 2008). Explaining the way international trade is organized - on the spectrum between free trade and protectionism - has been guided by various different theories, some of them contradicting, others complementing each other. One uniting factor of all rational explanations lies in the assumption that trade has distributive consequences, with winners supporting further liberalization, and losers preferring protectionist policies. "Understanding trade policy, therefore, requires an analysis of the constellation of actors - both public and private - who participate in the making of trade policy, their interests, and the nature of the making of policy institutions involved" (Cornick et al., 2019, p. 117). The papers in this thesis add to our understanding of crucial trade policy actors: business groups, and multinational corporations. Findings show that GVCs can alter these actors' preferences, as well as subsequent policy outcomes. Recent studies have urged scholars to integrate global value chains into the political economy framework of trade policy (Baccini and Dür, 2018; Kim and Osgood, 2019; Yildirim et al., 2018) - this thesis can be seen as one step in this direction.

Institutional Design: PTAs

Another link between this thesis and some broader debates can be drawn to the institutional design literature (Koremenos et al., 2001; Rosendorff and Milner, 2001), which seeks to explain the considerable variation found in different forms of institutionalized cooperation. Trade agreements have been studied extensively in this framework (see Baccini, 2019, for a comprehensive overview). Early research started with explaining the formation of PTAs and their impact on a very aggregated level, focusing on agreements in general, and country-level factors. Advancements in the measurement of trade agreement design (Dür et al., 2014) made it possible to include specific provisions in the research agenda, either as an explanatory or a dependent variable. Two papers in this dissertation directly relate to this development: one shows that GVC integration can influence the extent and the speed of tariff liberalization included in PTAs, and another sheds light on the impact of specific design provisions. Both contributions show, that including GVCs in the PTA research agenda can help uncover new aspects of established causal connections.

Economic Development

The questions of whether, how, and under which conditions the participation in GVCs can boost economic development have been addressed in many recent studies. Some are more optimistic, seeing GVC integration as a "vital condition for development" (Gereffi and Fernandez-Stark, 2016, p. 6), others show considerable variation in effects of GVC participation for different countries (Horner, 2016), with various possible socio-economic development patterns (Carballa Smichowski et al., 2021). Many scholars emphasize that the positive impact of GVCs depends how well the local economy is able to participate directly, via "creating and strengthening links with domestic firms and ensuring that the host country benefits from technology transfers, knowledge spill-overs, and increased value addition" (Taglioni and Winkler, 2016, p. 2). This is where trade policy can play a role: as I show in this thesis, specific trade agreement provisions can influence MNCs' investment decisions, and therefore the creation, shape, and governance of GVCs. Including PTAs in a nuanced way, accounting for their diverse scope, could prove beneficial for researchers trying to 'make global value chains work for development' (Taglioni and Winkler, 2016).

Computational Social Science

We arguably live in a "golden age of data", where "scores of data on every conceivable subject are often just one click away” (Nyhuis, 2020, p. 387). This brought on a very divers set of new research fields, often summarized as ‘computational social science’ (De Marchi and Page, 2016; Edelmann et al., 2020). Typical characteristics are new forms of data collection (Nyhuis, 2020), working with large amounts of unstructured (text) data (Benoit, 2020), and employing machine learning techniques (Curini and Fahey, 2020; Grimmer et al., 2021). Whereas this dissertation is clearly not providing any conceptual or methodological innovations to this field, some contributions can nevertheless be highlighted: Many studies analyze individual behavior on social media, like estimating ideology and other characteristics (Ceron et al., 2014; Mancosu and Bobba, 2019), using individual data to forecast election results (DiGrazia et al., 2013; Sanders and van den Bosch, 2019), or predicting protests and riots (Alsaedi et al., 2017). I rely heavily on this work in my thesis, but depart from it in terms of user selection: I do not focus on individuals, but on interest groups. This can be relevant in the vast field of computational social science for two reasons. First, it shows that social media data can still be an untapped resource for many different research topics. Second, a key reservation concerning this type of data source - the poor representativeness - is considerably mitigated by focusing on groups where a large part of the population is present on social networking platforms. Both points illustrate the potential for many social science research fields to integrate computational approaches into their agendas.

1.7 Structure of the Thesis

This dissertation contains three distinct research papers, dealing with the interrelationships between trade policy and global value chains in different ways.

The first paper focuses on the effect of GVCs on trade policy preferences. The main argument is based on the assumption, that stronger GVCs lead to an overall increase in support for liberal trade policies. Empirical findings provide evidence for this relationship, but also show that it depends on several country- and industry-level factors. The participation in GVCs has a differential impact on trade preferences - it increases support for free trade in some industries, but leads to more critical positions in others. Significant differences can be found based on a country's level of industrialization, as well as for agricultural industries. By using a novel data set including business group preferences from more than thirty industries in over forty countries worldwide, the paper adds to the state of the art in three ways: First, by its geographical scope, which allows for a comparative perspective absent in most other studies in this field. Second, by its focus on previously neglected - but influential - trade policy actors, business groups. Third, by using a new way of measuring preferences via social media data and classifying large amounts of texts with the help of machine learning techniques.

The second paper extends the analysis to trade policy *outcomes*, and shows how the globalization of production is altering the political economy of trade policy making: Traditionally, exporters seeking market access in foreign countries have been the main actors supporting free trade. With GVC integration, they are joined by new groups: namely import-dependent firms, who use foreign intermediates in their production processes. This broadens the alliance in support of liberal trade policies. Assuming that policymakers are receptive to these preferences, we should see that GVC integration leads to more liberal trade policies. The paper investigates this claim by focusing on powerful trade policy actors, who have both a vested interest in liberal policies, as well as the resources to lobby for their preferences: Multinational corporations (MNCs). Using a finely grained data set on tariff cuts included in trade agreements, and firm-level data covering MNC activities (cross-border mergers and acquisitions, and MNC imports of intermediates) allow for a detailed analysis of the relationship between a key aspect of GVC integration and trade policy outcomes. Findings support the theoretical expectations: stronger MNC linkages lead to faster and more ambitious tariff cuts for intermediate products. The paper advances our knowledge about trade policy-making in a globalized economy, by making use of data on international corporate connections.

The third paper changes the perspective - it shows how trade policy provisions can influence investment decisions, and therefore the establishment and structure of GVCs. Whereas the first two papers try to explain the consequences of (specific aspects of) GVCs, the third one focuses on the their determinants. Preferential trade agreements (PTAs) are international trade policy instruments, mostly used to facilitate trade and investment flows between partner countries - and can therefore, subsequently, affect GVCs. The relationship between PTAs and foreign direct investments (FDI) has been analyzed in numerous studies, but few of them account for the substantial heterogeneity in both PTA design and FDI flows: Trade agreements vary considerably in terms of scope and depth, yet most studies only focus on whether countries have signed an agreement or not and thereby omit potentially important variation. A similar problem arises when FDI flows are aggregated at the country-level: industry- and firm-level differences are neglected, even though we know that they are theoretically and empirically relevant. This paper addresses both issues with two detailed and disaggregated data sources, covering specific PTA provisions (intellectual property rights) as well as firm-level mergers and acquisitions. Findings show that trade policy can influence investment decisions in complex ways, indicating that some provisions do indeed increase investments in specific industries, but others have the opposite effect. This matters for GVCs, since investment decisions influence the shape, strength and governance of global production networks.

Each paper can be read as an independent contribution, although the common theme – trade policy in a globalized world – ties the individual parts together. The following three chapters contain the three papers outlined above. Then, a final discussion of the main findings and some possible avenues for future research conclude the thesis.

Chapter 2

GVCs and Trade Preferences: A Supervised Sentiment Analysis of Interest Groups on Twitter

Abstract:
Global Value Chains (GVCs) are a key feature of today's global economy. Although this globalization of production has far-reaching distributional consequences, we know little about how it affects trade policy preferences. On the one hand, we could assume that more opportunities to engage in international production and trade leads to more support for liberal trade policies. On the other hand, research shows that large and highly productive firms benefit the most from global production processes – leaving smaller, less competitive firms behind and possibly in opposition to free trade. GVC integration could therefore lead to stronger support for, but also to opposition to trade liberalization. In order to advance on this debate, new data on business groups' preferences is used to analyze the impact of GVC integration on industry-level trade preferences.

This paper takes a new approach to measuring preferences: using social media data and supervised sentiment analysis to classify large amounts of texts. Data comes from tweets posted by over a thousand business groups worldwide and shows that GVC integration does indeed impact interest groups' official positions on trade policy: The participation in GVCs has a differential impact on trade preferences - it increases support for free trade in some industries, but also leads to more critical positions in others. Significant differences can be found based on the level of a country's industrialization, as well as for agricultural industries.

These findings contribute to the debate on international trade preference formation and introduce a new way of measuring attitudes of crucial trade policy actors.

Keywords: Global Value Chains, Interest Groups, Trade Preferences, Social Media Data, Machine Learning

2.1 Introduction

For the last three decades, the global economy has changed substantially. Until the 1990s, countries produced and sold most of their products domestically (Eckhardt and Poletti, 2018). Nowadays, production processes often span across countries and even continents, organized in complex Global Value Chains (GVCs). Although GVCs have been a prominent multi-disciplinary research topic (see Kano et al., 2020, for a comprehensive literature review) in the last few years, its inclusion in the political economy literature has been lagging behind (with some notable exceptions mentioned further below) (Yildirim et al., 2018).

We know, for example, surprisingly little about the impact of GVCs on trade preferences. Existing studies either focus on country-level preferences (Orefice and Rocha, 2014) or on specific firms (Blanchard and Matschke, 2015; Kim et al., 2019; Zeng et al., 2020) (with the latter category mostly using data on US- or EU-based firms, Kim et al. (2019) being an interesting exception). Although firms (especially large, multinational companies) and policymakers are undeniably some of the most important trade policy actors, others have been neglected by the literature so far. One of these actors are interest groups (IGs): formal associations, with the goal to influence public policy.

One could assume that the globalization of production leads to an overall positive effect on liberal trade preferences. When focusing on individual firms, this might be the case. However, interest groups have to represent more than just one specific firm - they have to aggregate the preferences of multiple actors. On the one hand, it seems plausible that more actors in favor of trade liberalization shift the aggregated position of IGs towards liberalization. On the other hand, it might be possible that the main benefactors of trade liberalization in a GVC-integrated economy (i.e. big, multinational companies) do not rely on interest groups, but prefer to lobby on their own (Kim and Osgood, 2019; Zeng et al., 2020), which could mean that IGs focus more on their smaller stakeholders with more mixed preferences. The National Board of Trade (2015) additionally argues that the fragmentation of production leads to a fragmentation of interests, which means that IGs have to represent an increasingly polarized set of preferences and could decide to refrain from taking any clear stances on trade policy. These developments could result in less pronounced interest group trade preferences.

In order to address this puzzle, I use indicators measuring GVC-integration, available on the industry-level (OECD, 2020b), and combine them with social media data on trade preferences, covering tweets from over a thousand interest groups worldwide. Working with social media sources means dealing with large amounts of (messy) text data. Hand-coding that many tweets can quickly become very time-consuming, which is why I decided to automate parts of this process, using a supervised sentiment analysis approach. This allows me to train an algorithm to do the majority of the classification work for me. The output is used as a dependent variable (a tweet with the possible trade preference categories positive, neutral, and critical) in multinomial logistic regression models.

Findings suggest that stronger GVC integration leads to an overall higher probability of a positive stance towards free trade among industry-level interest groups. This supports the idea, that the globalization of production strengthens pro-trade alliances, and weakens groups in opposition to more trade liberalization. However, this effect is not robust across all countries and industries: interest groups in less industrialized countries appear to become more critical of free trade when they represent an industry with relatively strong GVC participation. Agricultural industries show the same pattern: Higher GVC integration leads to less positive and slightly more critical statements about free trade.

The political economy field has begun to integrate GVCs in its analyses in recent years, but there are still many aspects of this phenomenon we know very little about. My paper contributes to this research on the effects of GVCs by focusing on trade preferences of key policy actors. Past research shows, for example, that GVC integration can influence countries' compliance with WTO rulings (Yildirim et al., 2018), decrease the possibility of trade disputes (Jensen et al., 2015), and lead to faster tariff reductions (Anderer et al., 2020). But analyzing the effect of GVCs on these outcomes (like trade policy, behavior in international organizations, etc.) must include understanding preference formation as well - if we do not know how preferences are influenced, we miss a crucial part of the whole picture.

In addition to this theoretical contribution, the main advancement of this paper is its empirical strategy: To the best of my knowledge, this is the first attempt to collect and analyze tweets to measure trade preferences. This allows for a broader geographical focus than most other comparable studies have been able to achieve (with a majority of research done exclusively in the US).

2.2 Trade Preferences in a Globalized Economy

In order to develop my arguments about the impact of GVCs on business group trade preferences, I will first discuss determinants of (industrial) trade preferences in general, then introduce the possible effects of GVCs, before focusing on interest groups and my main hypotheses.

2.2.1 Explaining Trade Preferences

Traditionally, the literature on trade preferences has mostly focused on the conflict between exporting and import-competing sectors (Gilligan, 1997a; Hiscox, 2002). Exporters, on the one side, are supposed to support trade liberalization because they have much to gain from foreign market access. Reducing trade barriers reduces exporters' trade costs and increases their chance of entering new markets or offering cheaper products for already established customers. Import-competing industries, on the other side, should oppose trade liberalization because they are threatened by foreign competition. When foreign companies can produce a certain product at a lower price (i.e. comparative advantage industries), domestic (comparative disadvantage) industries favor protectionist policies in order to shield them from this foreign competition. Put simply, exporters should favor trade liberalization, import-competing industries should oppose it.

As long as companies produce their products exclusively in one country and either sell them on the domestic market or export finished goods, the distinction between these two groups – exporting and import-competing industries – makes sense, and allows us to explain different patterns of support for or opposition to trade liberalization. The world economy, however, has become much more complex in the last three decades, with production processes spanning across countries or even continents. Multiple recent contributions (e.g., Anderer et al., 2020; Dür et al., 2020; Eckhardt and Poletti, 2016; Kim, 2017; Kim and Osgood, 2019; National Board of Trade, 2015; Osgood, 2017; Yildirim et al., 2018) therefore argue that we have to adjust these well-established theories to the realities of a globalized world. Before discussing how such an adjustment could look like, the most important characteristics of this *globalized world* should be outlined.

2.2.2 The Role of Global Value Chains

One crucial feature of most of today's advanced and emerging economies is their involvement in Global Value Chains (GVCs). A value chain is defined as "the full range of activities that firms and workers perform to bring a product from its conception to end use and beyond" (Gereffi and Fernandez-Stark, 2016, p. 7). Many everyday objects are 'made in the world', meaning that they are produced in several different countries – interlinked by global value chains. One classic example is the manufacturing process of the iPhone: Apple designs and sells their signature product in the US, but they do not manufacture its parts domestically. There are hundreds of components, which are produced by specialized manufacturers: the camera alone is being built in Australia, Brazil, China, India, Indonesia, Japan, South Korea, and multiple more locations in Europe and Latin America – with most manufacturers having international suppliers of their own (Costello, 2021). Building an iPhone means connecting all these production facilities worldwide, creating a complex system of interdependent buyers and suppliers.

This shift from domestic to international production calls the distinction between the two traditional groups – exporters and import-competing actors – into question. Exporters become increasingly import-dependent: they import intermediate products as part of their international production process. Either they buy intermediates from independent suppliers or they invest in subsidiaries abroad in order to control parts of their international supply chain. In both cases, trade policy becomes even more important for exporters, since their international engagement increases. The second group of actors, import-competing industries, are also affected from GVC integration. On the one hand, they become even more vulnerable to internationally producing competitors. On the other hand, they might also start to outsource parts of their (less competitive) production process and become import-dependent themselves. A third group of actors, becoming more relevant in a GVC-integrated country, are domestic producers. Even if they do not participate in GVCs themselves, they might supply internationally engaged firms with intermediate inputs or buy goods from them for their own production. This means that even firms with solely domestic business relationships can be indirectly linked to global production processes, and can therefore have a stake in the trade policy making process. Put differently, the globalization of production creates new winners and losers of trade liberalization – leading to new cleavages, new conflicts and new alliances in trade politics:

Winners of trade liberalization in a 'GVC world' are countries with highly integrated industries (Yildirim et al., 2018), meaning firms and whole sectors that offshore production, import intermediates and also supply downstream industries in their own country, and then, in turn, export their products (Osgood, 2018). Large and highly productive firms are generally winners of trade liberalization (Baccini et al., 2017) with opportunities to multinationalize production even further and strengthen their international ties. They are among the chief beneficiaries of trade liberalization (Blanchard and Matschke, 2015), and should therefore support liberal policies. In contrast to the traditional view that exporters need trade liberalization mainly in order to have better market access in foreign countries, in a 'GVC world' exporters have even more incentive to support liberal policies. Not only do they benefit from trade liberalization with their (potential) export partners, but also with countries where their suppliers are situated. This means that the group already most supportive of liberal trade policies will have even more reasons to push for liberalization.

Further incentives to support liberal trade policies arise from international investments: a main characteristic of GVCs are foreign direct investments (FDI), which means that multinational companies (partly) own production facilities abroad. Tariffs and other trade barriers make it more costly to operate these subsidiaries, which further increases their support to remove trade barriers between the countries involved – less trade costs between subsidiaries means cheaper production: "increased GVC participation would increase the likelihood of removing trade barriers thanks to FDI and offshoring" (Bown et al., 2020, p. 13). This might also lead to the situation that a company with headquarters in country A might support a trade agreement between countries B and C, because it has subsidiaries in both foreign countries, and less trade costs between them would influence their production.

Not only firms that are directly engaged in GVCs can benefit from trade liberalization: their domestic suppliers are also affected. This means that new actors might join the free trade alliance, because they are indirectly linked to GVCs and will therefore benefit if their domestic suppliers or customers are able to import or export at a better price. Consider an example from the food industry: a large company produces various food products for domestic customers and some foreign markets. They import some inputs for their production, but also rely on the domestic agricultural industry. With liberal trade policies, the food company might be able to increase their exports, which, in turn, also means a higher demand of agricultural inputs. The same logic applies to other domestic industries doing business with the multinational food companies: packaging materials, logistics, special machinery, and so on. Hence, all those industries involved in the supply chain might potentially favor liberalization, not just the specific exporting industry itself. The choice of words here – *might, could, potentially* – illustrates the fact, that we do not know much about these relationships: "The shared fate of firms and downstream industries they supply appears to have been almost totally neglected as a systematic area of study" (Osgood, 2018, p. 3).

Losers of trade liberalization in an interconnected global economy are found in countries with only weak GVC integration. Firms, that only take up a few (if any) tasks in production chains become 'price takers' with considerably less bargaining power than their better integrated suppliers, competitors and buyers (National Board of Trade, 2015). Small and less productive firms and industries without much potential to increase exports are also mostly losing from trade liberalization (Kim and Osgood, 2019), as are industries depending on low-skilled labor, threatened by technological progress like the automation of labor-intensive tasks (Timmer et al., 2014). Smaller firms, especially in comparative disadvantage industries, are often vulnerable to cheap imports. Without any measures protecting these industries, they have to stand against the most productive competitors worldwide. In a 'GVC world', these competitors are able to streamline their production and outsource cost-intensive tasks, which increases their comparative advantage even more and makes it harder for import-competing firms to stand their ground.

GVC participation can also create *winners and losers* within industries and firms: Van Assche and Gangnes (2019, p. 31) argue that GVCs can "drive a wedge between the interests of workers and managers in unskilled-labour-intensive industries, upsetting a traditional coalition that has favoured protectionism against competing imports". GVC integration allows firms to outsource expensive, labor-intensive parts of their production to low-wage countries. Import-competing industries become import-dependent and favor trade liberalization – at least the management of the respective firms do. Workers, on the other hand, would still benefit from protectionist policies, but they lost their allies (the company‘s management) to the pro-trade alliance.

Given these far-reaching distributional consequences, it seems plausible that GVC integration has the potential to shape and influence preferences concerning trade policy. Various studies show a close relationship between GVCs and trade policy outcomes (Bown et al., 2020): Blanchard et al. (2016a) find that governments set lower tariffs and use fewer temporary trade protection measures with countries where GVC linkages are strongest, Ludema et al. (2019) explain how GVC integration reduces a governments' incentives to apply trade protection, Anderer et al. (2020) show that tariffs are cut faster for products in industries with stronger GVC-integration, and Orefice and Rocha (2014) find that higher GVC integration can lead to deeper trade agreements.

Other contributions take a step back and focus not on policy outcomes, but on policy preferences. Zeng et al. (2020), for example, show that US companies with a higher level of GVC participation lobby more for trade liberalization with certain countries. Kim et al. (2019) find that the degree of a firms' involvement in GVCs shape their trade preferences, and Blanchard and Matschke (2015) also find a significant correlation between offshoring and liberal trade preferences.

This is a crucial part of the puzzle: If we want to understand how GVC integration affects trade policy, we first have to know more about the causal mechanism between the two. The preference formation of important trade policy actors (firms, interest groups, trade unions, political parties, governments, international organizations, etc.) are key to our understanding of this relationship between GVCs and policy outcomes. Business groups are among the most active and influential actors in trade politics (Dür, 2010; Gilligan, 1997a; Grossman and Helpman, 2002), yet we know very little about their trade preferences, let alone the impact of GVCs on them.

2.2.3 Interest Groups' Trade Preferences in a Globalized World

Much research about trade preferences focuses on firms. This makes sense, since they are directly affected by trade policy decisions and should therefore also hold distinct preferences concerning this issue area. And although many big firms directly lobby for their preferred outcomes (Kim and Osgood, 2019), they are not the only relevant trade policy actors representing these interests. Business groups aggregate the preferences of single firms, either at a rather narrow product-level (like the Scotch Whisky Association), for specific industries (like the agricultural industry), or in a very broad way (like all manufacturing industries in a country, for example). Investigating these business groups, rather than focusing on single firms, adds an additional layer of complexity to the analysis. However, it seems promising to shift the focus on these relatively neglected, but nevertheless influential actors in the trade policy making process.

Using the theoretical foundations about the distributional consequences of GVC integration outlined above, some expectations about interest group trade policy preferences can be derived. Business groups represent aggregated preferences – which means an additional step has to be added to the argument: GVCs affect firms and whole industries, and alter their trade policy preferences. Business groups have to *aggregate* these – more or less fragmented – preferences and form their own positions. Although it is not possible, in the scope of this paper, to trace this process (i.e. to find out which actors influence business groups' positions in which way), we can observe the outcome: public positions on trade policy issues.

Different patterns of business group trade preferences seem plausible: One possibility is, that we see an overall increase of support concerning liberal trade policies. As described above, GVC integration strengthens the pro-trade alliance. More companies become import-dependent, choose to outsource parts of their production, or become suppliers of internationally engaged firms. Following the arguments outlined above, we have: an increased support for liberal trade policies, a wider geographical focus (due to more diverse business partners), new allies in the pro-trade alliance, and a weaker opposition. The business groups representing these firms and whole industries should therefore also increase their support of trade liberalization. This leads to my first hypothesis:

H1: *The higher the degree of GVC integration in an industry, the stronger the support for free trade among business groups active in the respective industry.*

Measuring GVC participation at the industry level omits a lot of firm-level heterogeneity: a business operating in a highly integrated industry does not necessarily participate in GVCs themselves. As long as (enough) competitors and other firms in the same industry are integrated in global production processes, the aggregated industry-level GVC-measure will be at least moderately high. In the first hypothesis, I propose that even this scenario leads to an *overall* increase of free trade support in a business group representing the respective industry. However, this relationship might be dependent on other factors as well.

It seems plausible, that the interests of the biggest players and all other firms in an industry diverge the most in less industrialized countries, where most domestic competitors do not have access to the same technology, know-how, and international networks as their bigger counterparts, especially multinationals operating subsidiaries in the country. Large (multinational) firms often lobby outside of business groups, so the preferences of these groups might be influenced stronger by smaller firms relying on them for representation. In this case, higher GVC-integration might lead to stronger polarization or even more critical preferences in business groups. Even if all firms in a specific industry were somehow integrated in global production processes, the level of industrialization might still have an effect on the relationship between GVCs and trade preferences. The fact that exporters become more reliant on imports as they enter GVCs, or increase their participation therein, does not *automatically* lead to an increased support for free trade. This proposed causal link is based on the assumption, that import-dependent exporters prefer to keep importing intermediates (or even increase the volume of imports) and therefore need liberal trade policies to do this efficiently. But this might not always be the case. It is possible, for example, that this effect depends on a country's level of industrialization and its ability to 'upgrade' (i.e. improve the position) inside the value chain (Kummritz et al., 2017). Most developing countries often enter GVCs at the end of the chain, providing the (comparatively cheap) labor-intensive assembly of the parts that have been produced abroad. Gross export numbers may be very large in these countries, but the domestic value added portion often accounts for only a few percentage points (Banga, 2014). "Many developing countries worry about this phenomenon and aspire to increase their value added contribution to exports" (Dollar and Khan, 2019, p. 6) - meaning they prefer to produce some of their inputs themselves instead of importing them. Even though this strategy can have a detrimental impact on the competitiveness of the respective industry, the goal of economic upgrading inside the value chain (i.e. contributing more domestic value added to exports) can be of greater importance nevertheless. Examples show that the domestic value added content of exports follows a non-linear trend in many industrializing countries (see Dollar and Khan (2019) for examples): When they first open up their economy, many begin to use imported inputs - which decreases the domestic value added portion of exports. Once the process of industrialization and technology transfer enables industries to produce many of those intermediates competitively inside their borders, the domestic value added content increases again. This can also be the result of - partly protectionist - measures, like China's 'Made in China 2025' industrial policy (Levine, 2020). For many countries, this stage is only temporary, before they start to outsource parts of their production again and domestic value added in exports starts to decrease. The incentive to increase the domestic value added content of exports (and therefore decreasing the foreign value added content) should be highest for industrializing countries, especially for industries with backward linkages - decreasing the dependency on imports and producing high-value-added parts of the GVC domestically, can be part of an upgrading-strategy (Dollar and Khan, 2019). Further trade liberalization hinders this strategy, since domestic industries favor protection against cheaper (and more competitive) imports.

The effect of GVC participation on trade preferences can therefore be dependent on the level of industrialization - for two reasons: Either domestic firms (even if they take part in global production processes) are not able to produce as efficiently as their large multinational competitors in the same industry and will therefore oppose further trade liberalization, or protectionist measures are part of an upgrading strategy with the goal to increase the domestic value added in exports. Both arguments can explain variation between countries with different levels of industrialization:

H2: *The effect of GVC participation on the support for free trade among business groups depends on the level of industrialization in the respective country.*

Variation in the relationship between GVCs and trade preferences might also be found on the industry-level. Among the industries included in this paper, agriculture is a rather special case. Many countries protect their agricultural producers to a large extent (Anderson et al., 2013; Goodhart, 2015) - with reasons ranging from concerns involving food quality (Garmann, 2014) and possible health risks (like the imports of genetically modified organisms) Hillman (2004) to the problem of global food price volatility (Gilbert and Morgan, 2010) and resulting threats to food security. Given the politicization and often heated discussion of agricultural globalization, it seems promising to zero in on the effect of GVC participation on trade preferences in this particular industry. Garmann (2014), for example, shows that globalization even leads to an increase in agricultural protectionism across a wide variety of countries. It is plausible to assume that a similar effect could be observed at the level of interest group trade preferences: GVC participation increases the dependency on global food prices (resulting in vulnerability and less food security), which might lead agricultural groups to lobby for more protection in countries with higher exposure to international competition. The import-dependency of agricultural exporters (i.e. the main argument for a *positive* effect of GVC integration on free trade preferences) might not be enough for the traditionally critical agricultural sector to switch sides and support free trade policies:

H3: *GVC participation does not have a positive effect on the support of free trade policies in agricultural industries.*

2.3 Research Design

Measuring interest group preferences via social media data analysis is – to the best of my knowledge – a new endeavor. There are, however, multiple studies tracking and measuring political preferences of citizens using this type of data (e.g., Ceron et al., 2014; Oliveira et al., 2017). This research serves as a point of reference, since many of the steps necessary to extract tweets and infer preferences from them should be the same for private users and interest groups.

Interest groups cover a wide variety of preferences in most countries and are usually not secretive about their positions. Given that I use industry-level GVC-indicators, preferences should ideally also be aggregated at this level: which is the case for a lot of specific business groups. Much of IG research has focused on influence, lobbying activity and preference attainment of various groups in different institutional settings (De Bièvre and Eckhardt, 2011; Hanegraaff et al., 2015). The translation of interest groups' policy preferences into policy outcomes (e.g. Belloc and Guerrieri, 2008; Grossman and Helpman, 2001) has been a crucial part of this literature.

A prerequisite for these analyses is knowing about attitudes and preferences: if you want to explain how well an actor is able to influence policymakers, you have to have at least an idea about the actor's ideal points in a given policy space. This task has been taken on differently in the literature: some studies focus on lobbying expenditures (Bombardini and Trebbi, 2012) or campaign contributions (Fordham and McKeown, 2003), others conducted interviews with public officials (Bernhagen et al., 2015; Dür et al., 2015) or used various forms of document-coding (Bunea, 2013; Crosson et al., 2019; Ehrlich, 2008) to measure interest group positions on policy issues. Documents of interest for this last approach can come from many sources: press releases, opinion columns (Crosson et al., 2019), congressional testimony (Ehrlich, 2008), official consultation positions (Bunea, 2013), and so on. As Crosson et al. (2019, p. 5) note, social media posts can also be a promising source of information, since they "communicate important information about interest groups' preferences [...], and such positions provide a concrete point of reference upon which to evaluate the organization's views on important issues."

Out of the many social media platforms, Twitter is especially suited as a data source for several reasons: Most tweets are publicly accessible and constrained to a limited number of characters (in contrast to many Facebook posts, for example), which makes them easier to compare. The information is text-based (unlike mostly visual content on Instagram) and therefore much easier to analyze computationally. One of the biggest advantages is the comparatively easy data access: Scraping tweets is facilitated by Twitter's own developer environment. After applying for a developer account, large amounts of data can be accessed via the Twitter-API (application programming interface). Different programming languages have libraries supporting the interaction with this interface, with R's *rtweet* package (Kearney et al., 2020) being one of the most easily accessible ones.

Working with social media data can also be challenging: One of the most widespread concerns is the fact that twitter users are not representative of the population. This is especially problematic for research questions dealing with individual-level relationships - findings are often heavily biased and limited to social media users. Although not completely eliminated, this issue is not a severe problem in the context of this paper: Not all interest groups are active twitter users, but the share is certainly higher than in the individual-level population. An interest group on twitter is more representative for all interest groups than a single user is of the entire population. Other possible problems include the often rather messy format of the data (in contrast to more formal documents), the very limited length of statements (which makes it harder to express more complex opinions), and the sometimes poor reproducibility. Due to the massive amount of new content created every day, collecting social media data at two different times will yield two different data sets. Even if all parameters are the same, it is likely that the two requests do not result in the same output. Older content is deleted, new content is posted, users delete their whole profile, etc.

Despite these limitations, social media data can be a promising source - especially when the data of interest is very clearly defined. Focusing on interest groups, potentially interested in trade, for which GVC-data is available, allows me to sufficiently narrow down my search requests in order to obtain meaningful data without too much noise.

2.3.1 Sample

I started my data collection process with a list of interest group names - which come from multiple different sources: the EU's Transparency register (where groups can indicate trade policy as a field of interest), participation in ministerial meetings at the WTO, the EU Civil Society Dialogues, and/or the ASEAN Civil Society Conference[1]. This collection includes many different types of groups, with headquarters around the world, all potentially interested in trade policy: NGOs operating in very diverse issue areas, professional and business associations, as well as labor unions.

Since my argument only applies to professional and business associations, all other groups were deleted. To improve both country- and industry-coverage, additional groups were added, fol-

[1]This list is based on research carried out in the TRADEPOWER project (Dür et al., 2019).

lowing the industry-classifications used in the TiVA-database[2]. The section Collecting Tweets in the appendix gives a more detailed description of the data collection process. After filtering out only the trade-related tweets (described below and in the appendix), almost ninety thousand tweets from 1,087 groups are left, spanning from 2009 to 2021. The years are not evenly represented in the sample (which is mostly due to restrictions in the data collection process and the fact that twitter's popularity has grown since the beginning of this time frame), with only 13 tweets from 2009, but 24,561 from 2019.

Overall, my sample comprises of 1,341 business groups from 57 different countries (including the EU as a regional entity) and 33 different industries (following the classification in Table A.1). Each group has to meet the following criteria: it has to be a business group or professional association representing a specific industry in a country or EU-wide. For each of these industries, data on GVC participation has to be available. And, in order to measure a group's preferences, it has to have an official and active twitter account (with at least one tweet since the beginning of 2019).

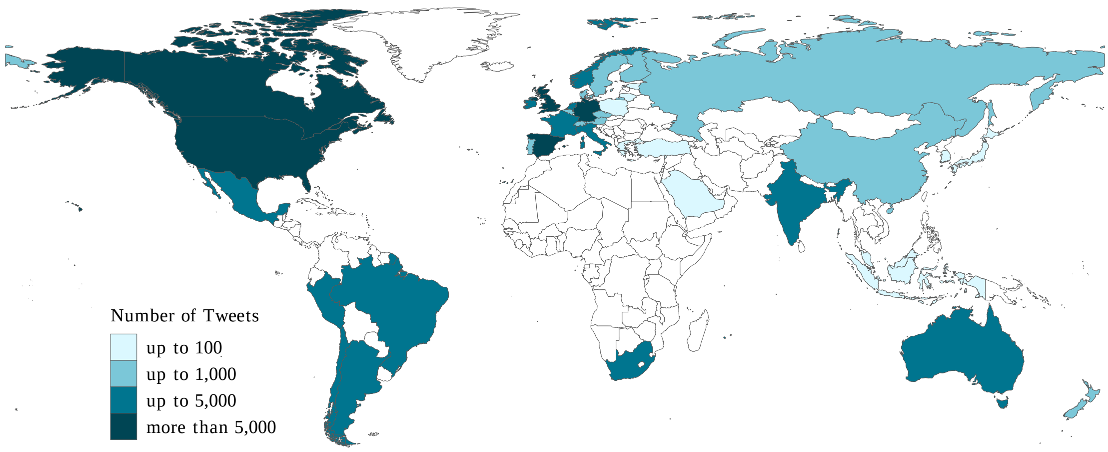
The distribution of the 33 industries (see Table A.1 in the appendix) is relatively unbalanced: For industries like agriculture, forestry and fishing almost 200 groups are included, but there are only a few groups representing service industries (Table A.1 in the appendix). Conclusions about specific industries, or country-comparisons, should therefore be made with caution. Since my main argument is based on the degree of GVC integration of the industry a group is representing, and I do not use aggregate measures for my dependent variable, this uneven distribution of groups should not significantly alter my findings. The only hypothesis dealing with a specific industry (H3), focuses on agriculture - which is the best represented industry in the sample.

42 countries (see Figure 2.1 below and Table B.3 in the appendix) are included[3], which together account for over 80% of the World's GDP. Most groups come from the US and the EU (134 and 133, respectively), whereas I could only find tweets from a handful of groups from countries

[2] A simple google search with "twitter + [industry] + [country]" resulted in several hundred additional groups

[3] The EU 28 as a regional entity is also included here, since many groups are organized at the EU-level and lobby EU-wide. GVC data is also available for the EU 28 as a whole.

Figure 2.1: Geographical coverage of interest groups



like Greece, Peru, or Korea. Most studies explaining trade preferences have a rather narrow geographical focus (a majority of work uses data on the US or European countries). The fact that my data covers all continents (although Africa is still only represented by South Africa), is big advantage in terms of generalization.

2.3.2 Dependent Variable: Interest Groups' Trade Preferences

For my analysis, only tweets directly related to international trade (policy) are relevant (see the section on Collecting Tweets in the appendix for more details). A trade-related tweet can either be coded positive, neutral or critical – depending on the general sentiment of the respective text. Examples of each category are shown below:

Positive: *A "green Deal" for Europe can only work in a world with open markets and multilateral rules – not with new trade barriers and conflicts. Europe needs international co-operation, not confrontation!*[4]

[4] This tweet has been translated. Original text: "Ein "grüner Deal" für Europa kann nur in einer Welt mit

Neutral: *International trade has its own terminology. This guide contains a list of general trade terms as used in international trade agreements concluded by states and as applied in the legal instruments of international organisations #globaltrade*

Critical:[5] *Should an international trade agreement determine how our elected officials may spend our domestic tax dollars? Absolutely not! We need strong Buy Local and Buy American policies.*

Supervised Sentiment Analysis

Hand-coding tens of thousands or even millions of tweets can be an expensive and time-consuming task, which is why the surge of social media use also led to an increase of automated content analysis approaches in the social sciences to deal with this amount of new data (Hopkins and King, 2010). Scholars have used machine learning and social media data to forecast elections (Burnap et al., 2016), measure individual political preferences (Ceron et al., 2014), analyze parliamentary speeches (Rudkowsky et al., 2018) and much more. A widely used approach is called supervised sentiment analysis (see details in the appendix), which is also suited to reach my goal: classifying the sentiment behind each trade-related tweet. Human coders would read a whole tweet and then form their opinion about the sentiment it represents: Which preferences are behind this statement? Does the author support a specific position or not? A classification algorithm has to be trained to do this task – and it will only be as good as the directions and training data it gets. When working with automated text analysis, the acronym *GIGO* often turns up in tutorials and other helpful sources about the topic – it stands for "garbage in, garbage out" (Balatsko, 2019). The best algorithm will not produce good results, if the input data is not appropriately pre-processed. The section Collecting Tweets covers the most important steps of

offenen Märkten und multilateralen Regeln funktionieren – nicht mit neuen Handelsbarrieren und -konflikten. Europa braucht internationale Kooperation, nicht Konfrontation!"

[5] The critical category not only includes tweets that clearly reject trade liberalization, but also positions criticizing the present state of international trade and the design of trade agreements. A tweet acknowledging the role of trade in economic development, but also stating that existing trade agreements disadvantage developing countries systematically, and therefore should include different provisions, would fall into the critical category.

Positive Tweets

Figure 2.2: Wordcloud based on 1,829 tweets, non-English text has been translated

Critical Tweets

Figure 2.3: Wordcloud based on 1,019 tweets, non-English text has been translated

this data pre-processing.

For an algorithm, the difference between a positive, a neutral, and a critical tweet is based on the authors' choice of individual words. What words are used in supportive statements about trade? How do users express their opposition? It 'learns' these differences via a coded training data set, provided by the researcher: 5,000 tweets have been selected randomly and hand-coded into the three categories *critical*, *positive*, and *neutral*. Two word clouds of the most used words (excluding stop words) in the positive and critical[6] group are presented in Figure 2.2 and Figure 2.3.

Positive tweets contain words like *free*, *economy*, *exports*, or *protectionism*, whereas critical tweets are about *rights*, *fair*, *climate* or *standards*, *imports* or *farmers*. Some of the words in each category are rather clear indications for a positive or critical sentiment about trade. The term *protectionism* will mostly be used by supporters of free trade, whereas words like *agreement* can be found in both categories.

After the pre-processing steps described in the appendix (see Classifying Tweets), the coded data is used to train a classification model. Out of the most widely-used algorithms, the random

[6]Note that the analysis includes a neutral category as well. Neutral tweets do not necessarily comprise of certain keywords, like positive or critical statements, but are rather identified by the lack of polarity in their chosen words. Therefore, a wordcloud of neutral tweets is not very informative.

forest classifier yielded the best results (see details and the Table B.2 in the appendix). The output of this whole process is a fully categorized data frame with a sentiment variable for each tweet, based on the words used in the text: positive, neutral, or critical. The distribution of the three classes are roughly the same as in the training data, with 10 percent critical, 47 percent neutral, and 43 percent positive tweets. This unbalanced distribution of categories has an effect on the confidence of regression results presented below. Since examples of critical tweets are far less common, it will be harder to show a significant effect of GVC integration for this category. Nevertheless, the fact that the dataset still covers almost ten thousand critical tweets should mitigate this problem.

2.3.3 Explanatory Variables: GVC Integration

Measuring GVC-integration is not a straightforward task, which is partly due to the complexity of the phenomenon itself. GVCs are more than just intensive trade between partner countries – they connect multiple partners in various countries all over the world. This degree of interconnectedness cannot be captured with national accounts trade data, which "contain no information on how exports are used abroad, and they do not tell us anything about how imported goods are produced" (Johnson, 2018, p. 208). To account for these shortcomings, the concept of value-added trade has been established (e.g., Daudin et al., 2011; Johnson, 2014; Johnson and Noguera, 2012; Koopman et al., 2010). Using value-added trade measures allows to more accurately assess a country's or industry's position and clout in global trade relationships. Chinese domestic value added content of their ICT (information and communication technology) product exports, for example, accounts for only roughly 50 percent of their export value. The other half of the value has been added in one of the many other 'Factory Asia'-countries, or even Europe and North America. If measured in value-added terms, the US trade deficit with China is therefore roughly cut in half, compared to traditional trade measures (Dollar and Khan, 2019).

The OECD hosts the most comprehensive collection of value-added trade measures today in their Trade in Value Added (TiVA) Database. Indicators are provided for 64 economies[7] and

[7] The full list of countries can be accessed here: `https://www.oecd.org/industry/ind/tiva-2018-countries-regions.pdf` (30 November 2020)

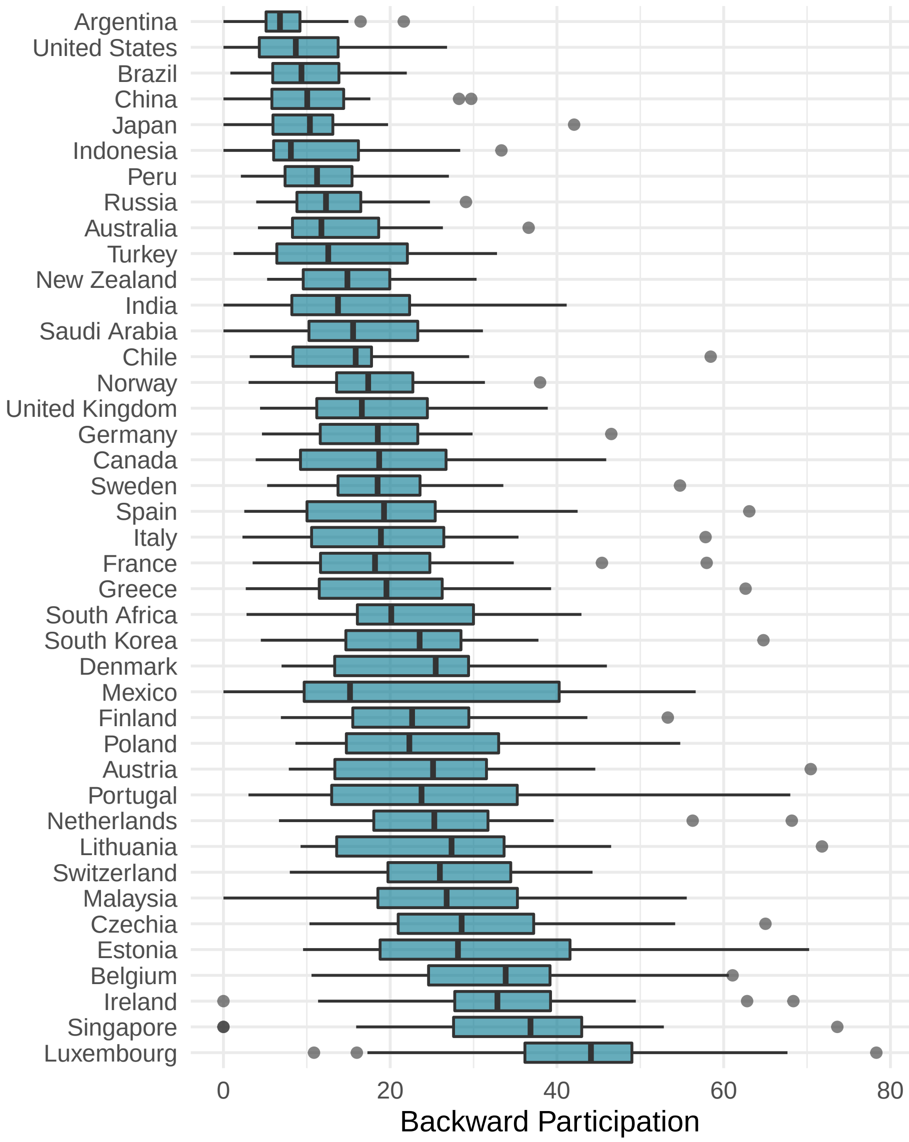
multiple industrial sectors (a list is provided in Table A.1). The newest TiVA edition covers the period between 2005 and 2016 (OECD, 2020b). Since the data measuring the dependent variable (twitter sentiment) ranges from 2009 to 2021, an exact match between the two data sources is not possible without losing a considerable amount of observations. I therefore use the newest available TiVA data. Since GVC integration does not vary quickly over time, but rather between countries and industries, this should not influence results substantively.

The TiVA database (OECD, 2020b) offers many different indicators: *backward participation* indicators capture the “extent to which domestic firms use foreign intermediate value added for exporting”, whereas *forward participation* is based on the “extent to which a given country‘s exports are used by firms in partner countries as inputs into their own exports” (Kowalski et al., 2015, p.14). Both approaches can be used to assess a country‘s or industry‘s position and clout inside global value chains – with backward participation indicators capturing the role of a country or industry in relation to the upstream part of production in more detail, whereas forward participation is focusing on the equivalent relationships concerning downstream activities. Although both operationalizations of GVC participation measure crucial parts of globalized production processes, my arguments focus much more on the backward point of view: support for free trade increases mainly because exporters become import-dependent, which is exactly what backward participation is capturing.

Backward participation in GVCs

One commonly used indicator to measure backward linkages in GVCs is the *foreign value added share of gross exports*. It is defined as “foreign value added embodied in gross exports as a percentage of total gross exports” and can be interpreted as an “intensity measure” (OECD, 2019, p. 23) of GVC participation. Yildirim et al. (2018, p. 67) also use this measure, arguing that it “most directly captures the extent” to which industries ”belonging to a value chain have a stake in both accessing cheaper imports and exporting to foreign markets”. Figure 2.4 shows the distribution of industry-level backward participation values per country. The foreign value

Figure 2.4: GVC participation, distribution per country



added embodied in gross exports ranges from zero percent (e.g. in the mining industry in Singapore) to 78.3 percent (financial and insure activities in Luxembourg). Some countries have a wide range of different GVC backward participation values (see Singapore or Ireland), others much less so (e.g. Argentina or the USA).

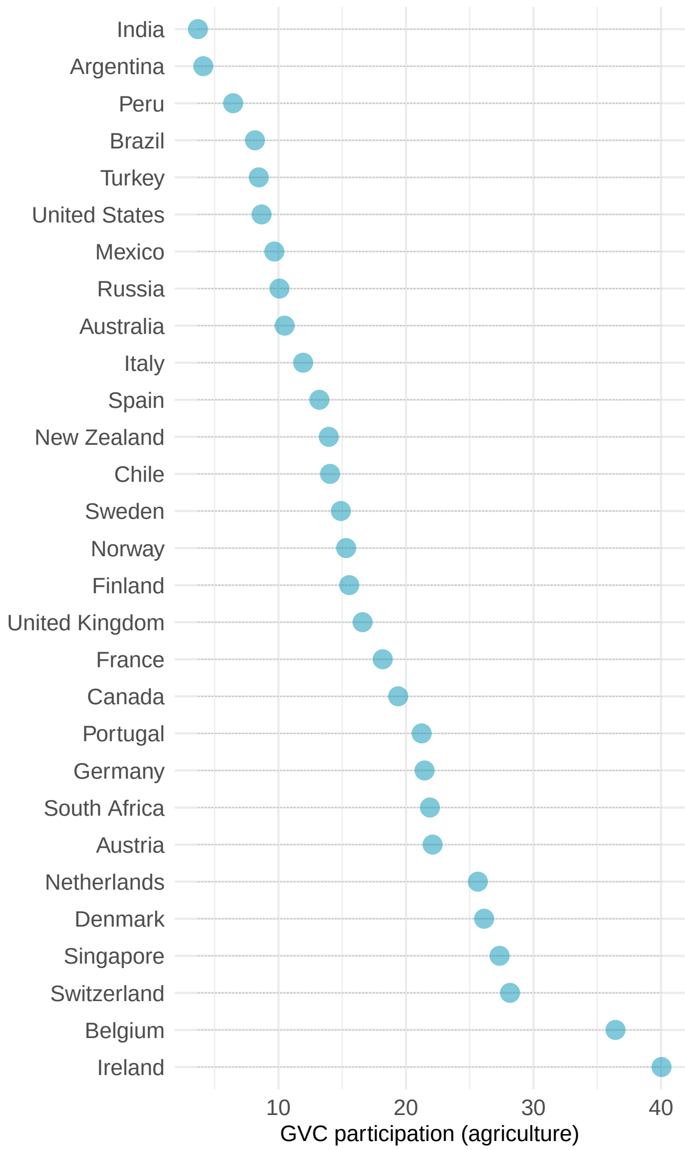
2.3.4 Interaction and Control Variables

H2 and H3 call for two different interaction terms: a country's level of industrialization, and agriculture vs. other industries. For the level of industrialization, I decided to use the proxy of OECD-membership, which is highly correlated with other possible indicators, like GDP per capita or various indices, like the *Competitive Industrial Performance (CIP) index* (Upadhyaya, 2013), for example. Although there are more OECD-countries in my sample (with only 13 percent of tweets coming from non-OECD countries), I still have more than 12 thousand tweets from 153 groups in 11 non-OECD countries. Findings for this group will likely not be as robust, but should suffice to evaluate H2 nevertheless.

The second interaction is simply accounted for by a dummy variable indicating whether a group is representing the agricultural sector or not. Given that backward participation is mostly associated with production steps further along the value chain (where different intermediate inputs have already crossed several borders), it would be possible that a primary sector like agriculture does not show enough variation in the independent variable GVC-integration to estimate meaningful effects in the analysis. Although the highest value of GVC-integration for agricultural industries is only 40.04 (with a maximum value of 78.31 in the full sample, see Table B.4), Figure 2.5 shows that the foreign value added part of exports (i.e. backward GVC integration) in agriculture varies considerably, ranging from 3.7 percent in India to 40 percent in Ireland.

Industry-level *Trade Openness* (The World Bank, 2020) (which is the sum of exports and imports of goods and services measured as a share of GDP) is used to distinguish between the effect of trade openness in general and the degree of GVC integration in particular. *GDP (log)* is included to control for market size and economic power. The Polity IV score (Marshall et al., 2018) captures the level of *democracy*. Following the literature on trade preference formation, all of these control variables are expected to increase the possibility of positive, and decrease the possibility of critical tweets. They are included in the models to distinguish between the effect

Figure 2.5: GVC participation in agriculture, per country



of democracy, trade and market size on preferences from the distinct impact of GVC integration.

2.3.5 Model Specification

The dependent variable – trade preferences expressed by a tweet – has three categories: critical, neutral, and positive. To estimate the effect of GVC integration on this categorical variable, multinomial logistic regression models are used. Country- and year fixed effects are added to account for unobserved heterogeneity. Two interaction terms (*nonOECD* and *agriculture*) capture the relationships proposed in H2 and H3. Standard errors are clustered at the interest group level in all models (Abadie et al., 2017).

Agricultural groups are overrepresented in non-OECD countries (see also Table A.1), which could mean that findings for H2 and H3 are interconnected: traditionally protectionist agricultural groups in non-OECD countries could be responsible for more critical findings. Additional specifications to account for this are provided in Table 2.2 and in the robustness checks section.

2.4 Findings

The findings presented below follow the structure of my theoretical arguments. Regression results (part 1) in Table 2.1 capture H1, dealing with the overall effect of GVC participation on trade preferences. H2 and H3, addressing country- and industry-level variation, are tested in Table 2.2. In order to facilitate the interpretation of the coefficients (log odds), the predicted probabilities are plotted and discussed as well. Several robustness checks and a summary of the most important findings conclude this section.

Table 2.1 shows the results of the first multinomial regression models. Neutral tweets have been selected as the reference category, therefore all coefficients have to be interpreted in relation to this neutral category. A negative coefficient in the column critical, for example, means that the respective independent variable decreases the probability of a critical tweet, compared to a neutral one.

Model 1 in Table 2.1, including the main explanatory variable, control variables, and year fixed effects, shows a positive effect of GVC participation on both critical and positive tweets, which would indicate more of a polarization than a shift to more support. Trade Openness, GDP(log), as well as GDP per capita all show a negative effect, both on critical and positive tweets. Democracy, on the other hand, has a positive effect on both. These rather puzzling effects might result from omitted variables. To account for - at least some part of - this possible heterogeneity, country-level fixed effects are added in Model 2. This changes the coefficients: trade openness increases the probability of positive tweets and decreases it for critical statements, as would be expected following the literature. Importantly, despite controlling for trade openness, GVC Participation has still a significant effect on the sentiment of a tweet: higher participation increases the probability (log odds) of a positive tweet, and decreases it for a negative one. This is in line with my expectations in H1. A lower AIC in Model 2 also indicates that using country fixed effects increases the model fit compared to Model 1.

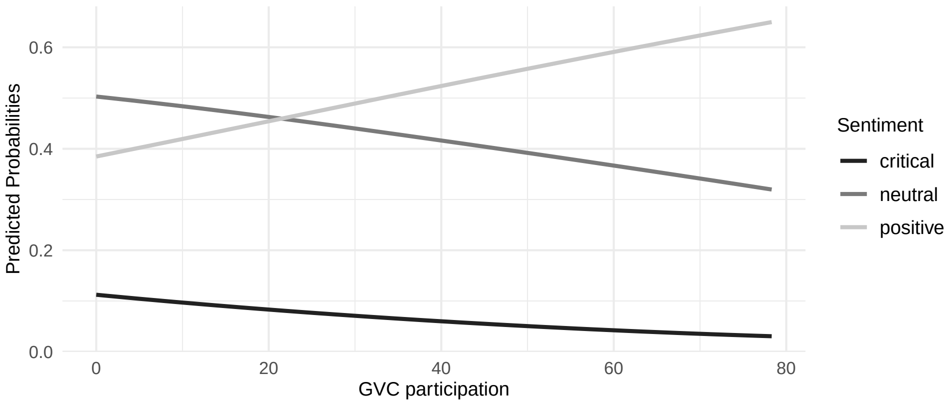
Table 2.1: Regression Results, part 1

	Model 1		Model 2	
	critical	*positive*	*critical*	*positive*
GVC Participation	0.009^{***}	0.003^{***}	-0.011^{***}	0.012^{***}
	(0.0004)	(0.001)	(0.002)	(0.001)
Trade Openness (Ind)	-1.660^{***}	-0.012^{***}	-2.064^{***}	0.237^{***}
	(0.00000)	(0.00001)	(0.083)	(0.039)
GDP (log)	-0.187^{***}	-0.004^{***}		
	(0.001)	(0.001)		
GDP pc	-0.00001^{***}	-0.00000		
	(0.00000)	(0.00000)		
Democracy	0.022^{***}	0.014^{***}		
	(0.0002)	(0.0002)		
AIC	180,950.300	180,950.300	177,869.400	177,869.400
Country FEs	no	no	yes	yes
Year FEs	yes	yes	yes	yes
Observations	95,600	95,600	95,600	95,600

Multinomial Logistic Regressions. Reference category for dependent variable: *neutral*
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, standard errors in parentheses

The interpretation of effect sizes using log odds is not very intuitive - therefore I calculated the predicted probabilities for each outcome level (see Figure 2.6). The plot shows the predicted probabilities for Model 2 in Table 2.1. With rising GVC participation, the probability of a tweet

Figure 2.6: Predicted Probabilities H1



to be positive is increasing substantively from 38 percent at zero participation up to 65 percent at the highest level of the independent variable. The probability of critical tweets only decreases slightly, from - already low - 11 percent if an industry is not taking part in any backward GVCs, down to 3 percent for the most highly integrated industries. This indicates that the effect of GVC participation on trade preferences is mostly driven by the increase in support, rather than the decrease in opposition.

In Table 2.2, interaction terms for H2 and H3 are added: Model 1 captures the differential impact of GVC Participation on OECD and non-OECD countries (H2), Model 2 distinguishes between agriculture and other industries (H3). In non-OECD countries, higher GVC-participation leads to less positive and more critical tweets (interaction-term *GVC:Non-OECD*). To help with the interpretation, predicted probabilities have been plotted again.

Figure 2.7 shows the predicted probabilities for critical and positive tweets, in OECD (solid lines) and non-OECD countries (dashed lines)[8]. In OECD-countries, the predicted probability of tweeting something positive about free trade increases with higher GVC participation (solid line), but it decreases rather strongly in non-OECD countries (dashed line). At a GVC-level of 40 (meaning that 40 percent of the value in exports come from foreign inputs), the predicted probability of a tweet being positive is almost 60 percent in OECD countries and less than 20 percent in non-OECD countries. Higher GVC participation also leads to a slightly lower

[8]Note that the x-axis only ranges from 0 to 42, since there are no industries in non-OECD countries with a GVC-participation higher than 0.42

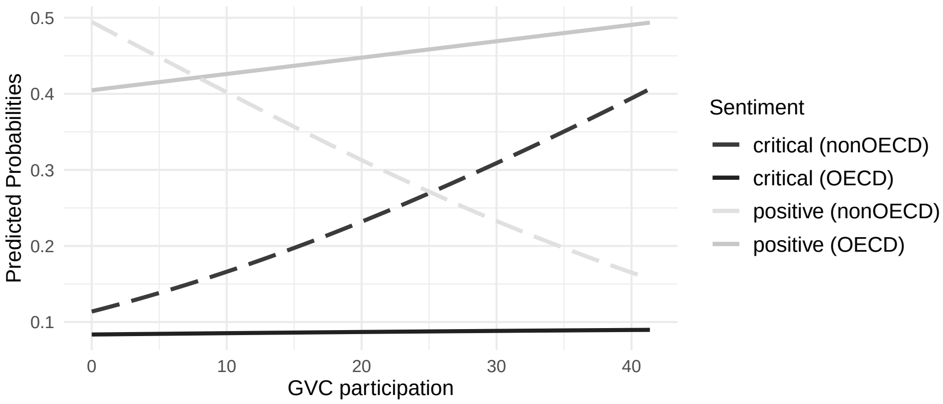
Table 2.2: Regression Results, part 2

	Model 1		Model 2		Model 3	
	critical	*positive*	*critical*	*positive*	*critical*	*positive*
GVC Participation	0.009***	0.008***	−0.013***	0.015***	0.011***	0.008***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Non-OECD	0.425***	0.460***			0.315***	0.445***
	(0.063)	(0.044)			(0.064)	(0.045)
Agriculture			−0.203***	0.510***	0.352***	0.037**
			(0.061)	(0.037)	(0.026)	(0.016)
Trade Openness (Ind)	−1.579***	−0.025**	−1.694***	0.037	−1.306***	−0.022*
	(0.070)	(0.012)	(0.093)	(0.043)	(0.073)	(0.012)
GDP (log)	−0.120***	0.016**			−0.083***	0.018**
	(0.012)	(0.007)			(0.012)	(0.007)
Democracy	0.118***	0.005			0.141***	0.007
	(0.011)	(0.007)			(0.012)	(0.007)
GVC Participation:Non-OECD	0.027***	−0.039***			0.038***	−0.038***
	(0.004)	(0.003)			(0.004)	(0.003)
GVC Participation:Agriculture			0.034***	−0.037***		
			(0.004)	(0.002)		
AIC	180,443.200	180,443.200	177,295.400	177,295.400	180,267.100	180,267.100
Country FEs	no	no	yes	yes	no	no
Year FEs	yes	yes	yes	yes	yes	yes
Observations	95,600	95,600	95,600	95,600	95,600	95,600

Multinomial Logistic Regressions. Reference category for dependent variable: *neutral*

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, standard errors in parentheses

Figure 2.7: Predicted Probabilities H2



probability of voicing opposition to free trade in OECD countries (solid line), but has the opposite effect in non-OECD countries (dashed line). This is in line with H2, which states that the effect of GVC participation depends on the level of industrialization in a country.

Model 2 in Table 2.2 introduces the interaction term *GVC:Agriculture* - which captures the difference between agricultural and other industries. As proposed in H3, agriculture is a special case: food security, health concerns, possible quality issues, and a highly politicized and emotional public discourse often lead to strong protection for the agricultural sector. This could also result in more critical positions towards free trade among agricultural interest groups, especially for those with a higher level of GVC participation. This appears to be the case, with a higher probability of critical tweets and a lower probability of positive tweets with increasing GVC participation. Comparing the predicted probabilities for all three categories of the dependent variable at an average level of GVC-participation (16.5) (see Table 2.3) indicates that agricultural interest groups have an overall lower probability to express positive views towards free trade (40.3 percent vs. 44.1 percent in other industries), and are more likely to take a critical stance (11.9 percent vs. 7.6 percent). These findings support H3: Higher GVC participation does not have a positive effect on the support for free trade - it even leads to a more critical stance.

For both subgroups (non-OECD and agriculture), the range of GVC participation is smaller

Table 2.3: Predicted Probabilities at average GVC-participation

	agriculture	**other industries**
positive	0.403	0.441
	(0.017)	(0.007)
neutral	0.478	0.483
	(0.016)	(0.008)
critical	0.119	0.076
	(0.025)	(0.016)

Pred. probabilities at GVC-participation = 16.5
Standard errors in parentheses

than for the full sample: both non-OECD countries and agricultural industries are generally less strongly integrated in GVCs. This means that H2 and H3 can only be generalized for low and medium levels of GVC participation. Despite these limitations, the results show interesting variation in the effect of GVC integration on trade preferences.

Model 3 in Table 2.2 adds agriculture as a control variable to Model 1. This is supposed to account for the possible interdependence between H2 and H3 - the possibility that effects in non-OECD countries are mainly driven by the (overrepresented) agricultural groups. Controlling for agriculture slightly alters the coefficients, but their direction and significance does not change. Controlling for agriculture does not cancel out the effect of the interaction term GVC Participation:Non-OECD, indicating that H2 is not just a product of stronger agricultural representation in the sample. Additional robustness checks are provided in the next section.

2.4.1 Robustness Checks

Several additional tables and plots in the appendix deal with different subgroups and model specifications, in order to assess the robustness of the findings presented above. The sample contains many EU-wide groups, which have been included in the models as if they were country-level IGs (simply by using the aggregated EU-wide GVC measures provided by the TiVA database). Even if those groups are excluded, the findings presented above are robust (see Table B.7 in the appendix) - EU-wide groups are not the only ones driving the connection between GVC integration and trade preferences.

Another important point concerns the connection between H2 and H3: Since agricultural groups are represented very strongly in non-OECD countries (see also Table A.1), it might be possible that the findings for H2 are (mainly) driven by these generally skeptical groups. However, neither controlling for agriculture (already mentioned above, see Model 3 in Table 2.2) nor estimating the predicted probabilities for non-agricultural IGs in non-OECD countries (see Figure B.1) confirm this hypothesis. H2 is supported across different specifications and subgroups, although the confidence interval grows considerably with higher GVC participation - making predictions less confident with higher values of the independent variable.

The variable *GVC participation* is only available until 2016 - these newest values have been used for all years in the regressions presented above, since GVC measures usually do not change rapidly over time. Nevertheless, a subsample including only tweets posted in 2017 (which means a one year lag) has also been used to estimate the effect of GVC integration on trade preferences (see Table B.5). Model 1 already shows the expected coefficients indicating less critical and more positive tweets with higher GVC integration. Adding country-level fixed effects and control variables does not change the direction or the significance of the findings.

I decided to use the distinction between OECD and non-OECD countries to investigate the impact of the level of industrialization on the relationship between GVC integration and trade preferences. This is by far not the only (and certainly not the most precise) measure of industrialization or economic development available. Table B.8 in the appendix shows how the interaction effect captured in H2 behaves with a different operationalization: namely using GDP per capita. This variable appears to have a polarizing effect (leading to both, more critical and more positive tweets). It is important to note that the variable non-OECD (see Table 2.2) has a positive effect - this makes sense, since non-OECD countries tend to have a lower GDP per capita, so the direction of the coefficient should be vice versa here. The interaction effect is positive in both models in Table B.8, but loses significance when agriculture is introduced as a control (Model 2).

In sum, this alternative measure of industrialization yields more ambiguous results than the binary variable OECD membership. It is obvious that country-level differences play a role in the relationship between GVC participation and trade preferences - alas, the precise nature of these differences cannot be uncovered in the scope of this paper. A larger country sample with more potentially significant control variables would be a good starting point for future research investigating this issue.

One final addition to the analysis addresses an ongoing development: The COVID-19 pandemic has severely disrupted global trade since the beginning of 2020. This external shock is likely to influence trade preferences in numerous ways, going far beyond the scope of this paper. Restricting the sample to 2020-tweets only (see Table B.6 and Figure B.2 in the appendix) shows that in 2020 higher GVC participation lead to more positive, but also to more critical tweets. The predicted probabilities of both categories rise with increasing GVC participation, which suggests a polarization of trade preferences - especially for GVC-integrated industries. This seems plausible, since these are the industries most affected by the disruption of their supply chains. Evaluating this effect more closely goes beyond the scope of this paper, but could be the focus of interesting future research.

2.4.2 Summary

The findings presented above generally support all three hypotheses. GVC participation has an overall positive effect on the support for free trade policies among industry-level business groups (H1), but this relationship is not the same for all countries or industries. IGs in non-OECD countries react differently to GVC participation (H2): a higher foreign value added in exports (= backward participation) leads to *more* critical and *less* positive tweets. This could be the result of MNCs lobbying on their own, leaving only the interests of less competitive firms in the industry to be represented by the respective interest groups. It might also be possible that industries in less industrialized countries strive to increase the domestic value added portion of their exports as part of a development- or upgrading strategy. A similar effect can be observed for agricultural industries (H3): Agricultural interest groups have an overall higher probability of representing a more critical position towards free trade, which increases even more with higher GVC integration.

2.5 Conclusion

Does the participation in global production processes lead to a general increase in support for more liberal trade policies? Do interest groups in GVC integrated industries talk significantly more positively about international trade liberalization? This paper shows one way of engaging with these questions, using social media data to measure interest group preferences, and value-added trade data to account for the complex production processes and relationships in a globalized world.

Findings show an overall increase in positive (and a decrease in critical) tweets with growing GVC participation. A bigger share of foreign value added in an industry's exports leads to more support for free trade policies. Interestingly, this relationship is not constant across all countries or industries. Regression results show, that interest groups in non-OECD countries are more critical towards free trade at any level of GVC integration, with the gap between OECD and non-OECD countries widening with growing integration - OECD countries become slightly less critical, non-OECD countries slightly more. The differences between the two country-groups in holding positive views towards free trade is even more pronounced - especially in industries with higher GVC integration.

Substantive differences can also be observed for specific industries, especially in the primary sector. Interest groups representing the agricultural industry are generally more skeptical towards free trade, with a growing probability of posting a critical comment with increasing GVC participation. This finding is line with research showing that globalization leads to more protectionism in agricultural industries.

The differences between OECD and non-OECD countries, as well as the special case of agriculture, both show that the effect of GVC integration on trade preferences is far from homogeneous and straightforward. Despite an overall positive effect on free trade support, GVC participation can also create more opposition (or at least less clear support). Some possible reasons for this opposite effect have been discussed in this paper, but more research is needed to pin down the specific causal mechanisms resulting in these findings. Focusing on critical groups and explaining the different reasons for holding more skeptical views towards free trade - especially in the context of higher GVC participation - could be one of many interesting avenues for future research.

The economic shock of the COVID-19 pandemic offers another promising area for more studies on the effects of GVCs on trade preferences. A regression model using only tweets from 2020 allows for a very preliminary glimpse into the possible implications: the full country- and industry-sample shows a polarization of trade preferences with increasing GVC participation. The probability of neutral statements declines, whereas positive as well as critical positions become more likely. This could be a temporary reaction to the severe disruptions of global supply chains, or a more long-term shift in trade preferences - only time and future research will answer this question.

The findings in this paper contribute to the growing literature about the effects of GVCs on trade preferences and policy outcomes. They help tracing the causal steps between the fragmentation of production on the one hand and political outcomes on the other. Furthermore, this paper can serve as a reference point for a broad set of social science research questions: Given the rise of social media as a communication tool for all sorts of actors, the massive amount of information generated in this process can be a valuable data source for scholars interested in opinions and preferences. Earlier studies using social media data focused mainly on the volume of data, like the number of posts or the number of followers of specific users (Ceron et al., 2014). While also informative for certain research goals, this sort of data has its limitations. Developments in quantitative text analysis and machine learning enable us to go into much more detail and analyze not only the scope of social media use, but also the content of and sentiment behind each post. For many different disciplines, this sort of analysis can be a – largely – untapped resource of original data. This paper is only one small example of the many different possible applications.

Chapter 3

Trade Policy in a “GVC World”: Multinational Corporations and Trade Liberalization

with Andreas Dür and Lisa Lechner

Abstract:
The globalization of production is changing the political economy of trade policy-making: Traditional supporters of free trade (exporters seeking market access in foreign countries) are joined by new actors (companies needing intermediates from abroad for their production processes) in their lobbying efforts for trade liberalization. Multinational corporations (MNCs) play a crucial role in this new alliance due to their strong involvement in international trade and endowment with resources that can be used to lobby policy-makers. We derive an argument from these premises that leads to the expectation of variation in trade policy outcomes across industries depending on their degree of integration in a global network of multinational corporations. Disaggregated data on the level of tariffs and speed of tariff cuts in preferential trade agreements, international mergers and acquisitions at the firm level, and MNC imports of intermediates by sector allow us to test the argument. The findings support our theoretical expectations. The paper sheds light on the processes and outcomes of trade policy-making in a globalized economy by further developing an existing argument about GVCs and trade policy outcomes as well as expanding on it by adding data on international corporate connections.

Keywords: International Political Economy, Trade Policy, GVCs, Firm-Level Analysis

This paper was published as:
Anderer, C., Dür, A., & Lechner, L. (2020). Trade policy in a “GVC World”: Multinational corporations and trade liberalization. *Business and Politics*, 22(4), 639-666.

3.1 Introduction

Over the last few decades, the emergence and growth of global value chains (GVCs) has transformed international trade. Value chains are defined as “the full range of activities that firms and workers perform to bring a product from its conception to end use and beyond” (Gereffi and Fernandez-Stark, 2016, p. 7). This includes various activities like research and development, design, marketing, production, transportation and distribution, as well as customer services for the end consumer. If a value chain crosses borders, i.e. value is added to a product in more than one country, it is called global. Put simply: “Global value chains (GVCs) can be thought of as factories that cross international borders” (Taglioni and Winkler, 2016, p. 11). In a ‘GVC World’, value chains connect countries on a regional or even on a worldwide scale.

A key aspect of GVCs is the vertical integration of production across borders within the same multinational corporation (MNCs). Vertical integration means that different steps along a value chain are carried out within the same company. This integration takes place via mergers and acquisitions (M&As) or greenfield investments. It allows multinational companies to gain control over a bigger part of their respective GVCs. The vertical integration of production within GVCs inevitably influences trade preferences and, as a result, trade policy decisions. But how does this impact exactly look like?

Traditionally, much of the literature on trade preferences focused on two key trade policy constituencies: exporters that support trade liberalization and import competitors that oppose it (Gilligan, 1997a; Hiscox, 2002). The first set of actors can benefit from liberalization, mainly due to improved foreign market access, while import-competing actors are likely to lose from it because of foreign competition in domestic markets. In this view, a country’s trade policy is a function of the relative importance of these two constituencies: the stronger exporters are relative to import competitors, the more liberal trade policy will be.

Multiple recent studies (e.g., Baccini and Dür, 2018; Baccini et al., 2018; Eckhardt and Poletti, 2016; Kim, 2017; Kim and Osgood, 2019; National Board of Trade, 2015; Osgood, 2017;

Yildirim et al., 2018), however, emphasize one crucial point: trade policy is not just about the old 'exporters vs. import-competing industries'-story anymore. Exporters are increasingly import-dependent (they import intermediate goods to produce their exports) as their participation in GVCs increases. This implies that trade policy preferences are not based on international trade relations alone, but also on international production processes (Baldwin, 2014). The internationalization of production hence is changing the political economy of trade policy-making: "In a world economy increasingly characterized by the emergence of these transnational chains of production, the preferences, patterns of political mobilization, and influence of firms and sectors that rely on income generated from the import of intermediate products for their production process need to be added to the equation" (Yildirim et al., 2018, p. 51). Osgood (2018, p. 1) concurs: "A complete account of industrial preferences over trade policy in the current era must place the globalization of supply chain networks at its center". Yet, "GVCs are largely absent in existing (...) analyses of trade policy" (Blanchard et al., 2016a, p. 1).

We contribute to this new strand of literature conceptually and empirically. The conceptual innovation is that in our argument we specifically concentrate on the role of MNCs and vertical integration in GVCs. The argument that we develop leads to the expectation that trade liberalization should be most ambitious for intermediate goods affected by cross-border M&A deals. Moreover, we anticipate ambitious liberalization for goods with large MNC imports. Our focus on MNCs complements the existing literature's concern with intermediate imports, independent of whether these imports take place within a specific company or at arm's length.

Empirically, just as some earlier studies (e.g., Baccini and Dür, 2018; Baccini et al., 2018), our analysis focuses on preferential trade agreements (PTAs). With the deadlock of multilateral trade negotiations at the WTO level, countries have turned to PTAs as an alternative means to organize international trade relations. As a consequence, since the 1990s the number as well as the scope of PTAs have grown substantively. Although many agreements signed in the last thirty years have been increasingly broad in scope, dealing with a diverse set of provisions, one of the key reasons to sign a PTA still remains trade liberalization through tariff cuts (Baccini et al., 2018). Our original empirical contribution is the combination of a highly disaggregated dataset on tariff cuts between PTA partner countries with data on M&As and on directed dyadic MNC imports at the sectoral level. This allows us to directly test our argument about MNCs, vertical integration, and trade liberalization.

Our paper also makes a contribution to the broader literature on MNCs in the global political economy (Levy and Prakash, 2003; Mikler, 2018). Our findings clearly show that MNCs play a key role in contemporary global trade governance. Their investment decisions shape the structure and nature of global production networks, which in turn affect the trade preferences of MNCs. Because of MNCs' clout and influence, the trade policies chosen by countries reflect these preferences. Going even further, although we do not show this in this paper, these trade policy choices are likely to reinforce MNCs' investment decisions, leading to a further strengthening of GVCs. MNCs thus actively shape the complex interdependencies that characterize the contemporary global political economy.

3.2 MNCs and Trade Policy

Our argument starts with the assumption that trade policy is always made with important economic actors' preferences in mind. Governments want to maximize support and minimize opposition from these actors and therefore design their trade policy accordingly. We assume that MNCs have the means and connections to lobby for their preferred policies – either as individual firms or as part of trade associations, where they often cover decisive shares of all contributions (Kim and Osgood, 2019). In this view, trade policy can be a direct response to lobbying efforts (Chase, 2005; Dür, 2010; Manger, 2015; Milner, 1988). Alternatively, governments may pre-empt lobbying by implementing a trade policy that they know will receive backing from key economic actors. They may do so for fear of losing electoral support, for example when a specific trade policy leads to higher levels of unemployment. In either case, we expect the political clout of actors to be positively related to their economic power (e.g. their economic size). Economically powerful actors will have the necessary resources to lobby government. Moreover, the investment decisions of economically powerful actors are of particular relevance to politicians that want to stay in power (Culpepper, 2015).

But what are the preferences of economic actors with respect to trade policy in the presence of GVCs? The globalization of production leads to a diversification and fragmentation of groups in favor of and in opposition to trade liberalization. The two clear-cut groups of exporters and import-competing industries, facing each other in the process of trade preference formation and lobbying, are disintegrating and new alliances are formed.

One group of economic actors particularly linked to the globalization of production are import-dependent producers. Many companies are increasingly dependent on the import of intermediate goods for their production processes. Reducing the variable costs of these intermediates (e.g. through trade liberalization) has an impact on their productivity and competitiveness (Eckhardt and Poletti, 2016; Jensen et al., 2015; Kim, 2017; National Board of Trade, 2015; Osgood, 2018; Yildirim et al., 2018). The globalization of production thus has not only "super-charged" (Osgood, 2018, p. 27) the support for trade in net-exporting industries, but has also undermined opposition to trade in net-importing and import-competing industries.

A crucial part of GVC-integration is the emergence and growth of multinational corporations (MNCs) – meaning firms with subsidiaries or assets in at least one other than their home country. Multinational production, i.e. production that is carried out by firms outside of their country of origin (Ramondo et al., 2015), is often the most efficient way for companies to organize their business. The history of MNCs goes back a long time, with the British East India Trading Company, established in 1600, being widely considered the very first multinational company. Modern MNCs started to emerge only in the late 19th century, but it was not until after the Second World War that international investments really took off. US firms were the key drivers, later joined by Japanese and European corporations (Cadestin et al., 2018b).

MNCs today are the biggest, most competitive and productive firms inside increasingly fragmented GVCs. These "superstar exporters" (Osgood, 2017) rely heavily on intermediate imports for their production processes and are therefore an integral part of the alliance supporting trade liberalization. Although trade growth has slowed down significantly after the Global Crisis 2008, Lakatos and Ohnsorge (2017) show that this development can mostly be attributed to a sharp decrease in arm's-length trade. Intra-firm trade growth (between firms linked by control or ownership), on the other hand, has been relatively stable in the recent decade. This means that MNC activities like international investments and intra-firm trade are still crucial elements of our global economy, which should influence trade policy in a substantive way.

What kind of trade liberalization is relevant for multinationals? Advantageous trade policy for MNCs can include various dimensions. PTA provisions concerning foreign direct investments, services, intellectual property rights, but also environmental or labor standards can be significant issues for large international companies. Although all these aspects might be relevant and could be included in future research, we decided to focus on the most straightforward means of trade liberalization in this paper, namely tariff cuts.

Tariff liberalization, in the form of tariff cuts, does not apply equally to all goods. Although countries agree to liberalize trade between each other in a PTA, they have a certain amount of leeway concerning the speed and final level of tariff cuts. Hence, we see considerable variation in different tariff schedules included in PTAs (Baccini et al., 2018). Countries are able to set priorities in their trade liberalization in order to support important economic actors. Explaining these different priorities and finding out more about which actors might be influencing countries' decisions are the core objectives of this paper.

Overall, we expect that deeper GVC integration should lead to faster trade liberalization. This is an obvious and almost trivial argument. Yet, the difficulty to retrieve disaggregated MNC-level-data has represented a major challenge in studying and testing the effect of MNCs on trade policy decisions. We access two novel data-sources and examine the question of the relationship between GVCs and trade policy. For one, we use detailed information on M&As for over one million transactions worldwide since the 1970s provided by Thomson Reuters (2020b). To better understand the motives of the firms, we combine the M&As data with information on whether sectors trade intermediate or solely consumer goods. This allows us to distinguish between vertical (M&As for the production of intermediate goods) and horizontal investment (M&As for the production of consumer goods). Second, we rely on a measure of MNC imports of intermediates, which is offered by Cadestin et al. (2018a). By dint of this variable, we measure the degree of vertical integration in a less disaggregated manner than with the M&As data, but more directly.

3.2.1 Mergers and acquisitions

One way of measuring corporate connections is to use international M&As data. M&As are a popular form of foreign direct investment (FDI): almost 50 percent of FDI inflows come in the form of M&As, which amounted to 694 USD billion in 2017 (UNCTAD, 2018).

MNCs' investment choices are typically described as either horizontal or vertical. Horizontal investments are primarily motivated by market-seeking reasons. MNCs want to place production close to customers in order to avoid trade costs (e.g. tariffs) and make use of other locational advantages (Dunning, 1993). Multinationals produce similar products in home and host countries, which means that foreign affiliates are usually not linked to their headquarters by any international production processes. Vertical investments, on the other hand, are mostly based on efficiency-seeking motives. MNCs spread different stages of production across international borders, with foreign affiliates being tightly linked to other production facilities inside the same GVC. In the words of Cadestin et al. (2018b, p. 5), "The production in one country serves as input for production activities in other countries and the location of different stages depend on where the factors of production they use intensively are relatively less costly."

It has to be noted, however, that modern MNCs are far more complex than this dichotomy would suggest. Most multinational companies are engaged in both horizontal and vertical investments (Alfaro and Charlton, 2009; Cadestin et al., 2018b), and most foreign affiliates fulfill market-seeking as well as efficiency-seeking purposes (Herger and McCorriston, 2016; Ray, 2016). To characterize either a multinational company or a foreign affiliate as purely horizontal or vertical, is surely oversimplifying the complex reality of global MNC activity. However, distinguishing dominant investment-motives, rather than assuming that MNCs fit into one of these ideal types, can nevertheless prove valuable for our analysis. The main reason for specific investments should have an impact on MNCs' trade policy preferences.

If a company merges with or acquires another company in a different country, their trade policy preferences towards this partner country are likely to change. The vertical integration of certain steps of a production process should shift the trade policy preferences of the companies involved towards (fast) trade liberalization. Both countries have an interest to facilitate trade along the production chain, which can be achieved by reducing tariffs on intermediate inputs crossing borders. If a specific M&A-deal is predominately driven by market-seeking motives (horizontal investments), the impact on trade preferences is less clear. MNCs investing for market-seeking reasons might even prefer trade barriers, since their subsidiaries put them at a comparative advantage relative to firms exporting to the same market (Kim and Osgood, 2019).

In this vein, we hypothesize that mergers and acquisitions are especially prone to increase the pressure on decision makers to liberalize trade if the deals go beyond purely market-seeking purposes. To incorporate the distinction between horizontal and vertical investment in our analysis, we include an interaction effect, using the type of product as a proxy for investment motives. We assume that investments in industries dealing mainly with finished goods are predominantly driven by market-seeking motives and should therefore not have a substantive impact on MNCs' trade preferences. Hence, our first hypothesis reads as follows:

H1: *Tariff cuts in PTAs are more ambitious in the presence of vertical cross-border investments than in the presence of horizontal cross-border investments.*

3.2.2 MNC Imports of Intermediates

The number of cross-border M&A deals are by far not the only indicator for international corporate connections. M&A deals (especially when the target industry produces intermediate goods) are made to internalize parts of the international production process under the same corporate umbrella. This brings several advantages, compared to other forms of connections between production sites (e.g. arm's-length trade), like more control over the production process, reducing costs, and maximizing profits. In the argument above we implicitly assumed that MNCs invest abroad in order to import intermediates, which they use for further production. We had to make this assumption, since we do not have trade data for the companies involved in these M&A deals, so we are not able to trace their activities at the firm-level. For the second hypothesis, we want to zero in on this specific part of our causal claim: What happens between company headquarters and their foreign affiliates? What effect does intra-firm trade have on trade policy outcomes?

FDI flows (of which M&As are a part) have often been used to study cross-border MNC activities. In many cases, multinational production flows "are a more appropriate empirical object than FDI. This is because the importance of a subsidiary depends on the magnitude of its production activity (...) rather than the way in which it is financed" (Ramondo et al., 2015, p. 530). Using the data described above, under the subsection "Mergers and acquisitions", we were able to capture the first part of a headquarter–subsidiary–connection. This allows us to know who set up a specific relationship, but we do not know anything about the subsequent connection between the MNC and the foreign affiliate. This can result in biased measures of foreign affiliate activity (Beugelsdijk et al., 2010; Blanchard et al., 2016b).

Therefore, the second part of the analysis builds on data capturing the MNC imports of intermediates from foreign affiliates. Along the lines of Ramondo et al. (2015), we expect that high exports of the affiliate company to the headquarter country create pressure for faster tariff liberalization. If a US-owned company with foreign affiliates in Vietnam imports intermediate textile products from these affiliates, we expect the US tariffs towards Vietnam in the US-Vietnam PTA to be cut faster (if the tariff was greater than zero before the PTA). The causal relationship we propose here is similar to our first hypothesis (MNC connections lead to stronger preferences towards the liberalization of specific tariff lines, which triggers lobbying efforts and results in faster tariff cuts), what has changed is the type of MNC connection we focus our analysis on. Therefore, our second hypothesis is the following:

H2: *Tariff cuts in PTAs are more ambitious for industries with stronger cross-border MNC activity than those with weaker cross-border MNC activity.*

3.3 Research Design

3.3.1 Dependent Variable: Tariff Cuts

For our dependent variable, *Tariff Cut*, we rely on data from Baccini et al. (2018). This dataset covers tariff concessions included in 61 preferential trade agreements (PTAs) signed by the seven largest trading entities (i.e. Australia, Canada, China, the EU, Japan, South Korea and the United States) between 1995 and 2014.[1] Tariff lines for the respective partner countries are also included, which results in a total of 50 trading entities covered in the dataset. These countries vary in terms of levels of development, geographical regions and political institutions. Each PTA contains at least two tariff schedules: one for country A towards country B and one vice versa. Plurilateral PTAs often contain even more, which leaves us with a total number of 156 schedules. Each of these tariff schedules includes roughly 5,000 tariff lines at a highly disaggregated level, namely the Harmonized Commodity Description and Coding System (HS) six-digit level.

As far as modern PTAs are concerned, most tariffs between PTA partner countries are cut to zero eventually. This is in line with the WTO obligation that within a PTA, "substantially all trade" should be liberalized. What varies, is the time frame in which the elimination of tariffs takes place. Whether for a tariff line the cut happens sooner or later is decided in negotiations

[1] The fact that this dataset only includes agreements that have been successfully concluded means that we likely underestimate the effect of our key predictors. Pairs of countries with very low levels of vertical integration in GVCs should find it difficult to even sign PTAs. It is then not possible to observe the tariff cuts that would be agreed in these cases.

among the future signatories of the PTA. We especially see considerable variation in the extent of the first-year tariff cut. Many tariffs are cut to zero immediately upon entry into force of a PTA; but other tariff lines are not or just minimally cut in this first year. For economic actors, the extent of the first-year tariff cut should be important, as it makes a difference whether an import-competing company has some time to adjust to a tariff cut.

Hence, following Baccini and Dür (2018), we chose the first-year tariff cut as our measure of the ambition of tariff cuts in PTAs. The variable *TariffCut*, which is calculated as the difference between the tariff rate at time t_0 and the tariff rate at time t_1, divided by the tariff rate at time t_0, can take on values between zero (no tariff cut in the first year) and one (tariffs are cut completely in the first year). A large first-year cut from country A vis-à-vis country B is beneficial for acquirers in country A and their suppliers in country B, since it facilitates trade in intermediates. This helps exporters in country B as well as importers in country A. The dataset we use is directed dyadic, meaning that our dependent variable can take on different values for the dyad country A-country B than for the dyad country B-country A. This also makes sense from a theoretical standpoint: Trade relations between countries are usually asymmetric, which means that tariff cuts in specific industries can have beneficial effects for one partner country, but not for the other. This leads to considerable variation between the different directed dyads.

3.3.2 Explanatory Variables

M&As and Trade in Intermediates

Our first test covers the interaction effect of M&As and intermediate goods trade. Mergers and acquisitions prior to a PTA is based on the Thomson Reuters Eikon Mergers and Acquisitions Database (Thomson Reuters, 2020b). We downloaded data for roughly 14,000 deals between all country-pairs in our tariff dataset. Over 13,000 different target companies in 65 countries have been acquired by (or merged with) around 9,400 companies in 55 countries. After dropping all deals in the service sector (which was necessary given that our dependent variable only captures tariffs on goods), we still have nearly 6,500 deals in our dataset. Table C.1 in the appendix provides a list of all countries in our dataset and the respective number of deals for each one as a target and as an acquirer.

The only industry classification Thomson Reuters provides for all their deals are TRBC codes (Thomson Reuters Business Classification). This classification scheme is similar to, but not fully compatible with other well-known industry classifications. We therefore had to manually match TRBC to NAICS (North American Industry Classification System) and then use the NAICS-HS crosswalk provided in R's *concordance* package (Zhu and Kim, 2016) in order to merge our deals data with the tariff lines described above.

One deal can have an impact on several different HS codes. Consider the following example: if a company in country A, specializing in fertilizers, is investing in country B, we assume that this investment is relevant for tariff lines like "Nitric acid", "Ammonium sulphate" and several other chemicals used in the production of fertilizers. As a result, most deals in our M&A-dataset have been matched with more than one tariff line. Our deals can be connected to over 4,600 different product codes (six-digit HS codes), which allows us to capture the impact of M&A-deals on tariffs at a very disaggregated level.

Our theoretical expectation outlined above is that deals between acquirer companies in country A and targets in country B lead to more lobbying pressure from the acquirer companies for tariff cuts in the concerned sectors in country A. These companies benefit from policies facilitating trade in intermediates with their affiliates in country B – tariff cuts in country A are one very direct way to achieve this goal. We thus calculate a variable that takes the value 1 for the directed dyad "country A-country B" if an HS product has been affected by one or several deals (where country A is the acquirer and country B is the target) prior to a PTA.

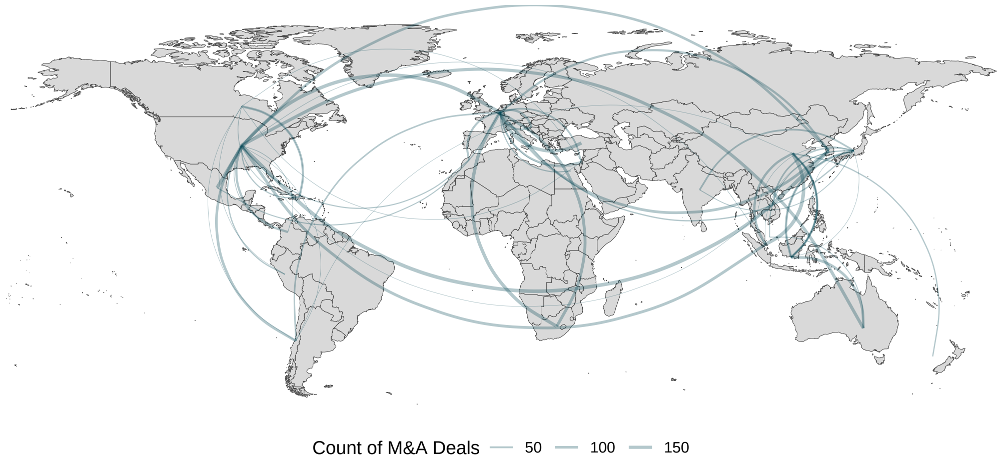
It would have been possible to work with the cumulative sum of deals as value for our variable, but we decided to use a dichotomous variable instead: either there has been at least one deal prior to the PTA (then the variable takes on the value 1) or there has not (then the value equals

0). This makes theoretical sense, since although the second deal in a specific industry might increase the pressure to cut tariffs for the products potentially involved, the additional impact each deal can have is likely smaller than the first one. We do not assume that five deals in a specific industry really have five times the impact on trade policy one deal in the same industry can have. Hence, our explanatory variable tells us if there has been at least one deal between country A (acquirer) and country B (target) with the potential of influencing a specific tariff line in country A towards country B.

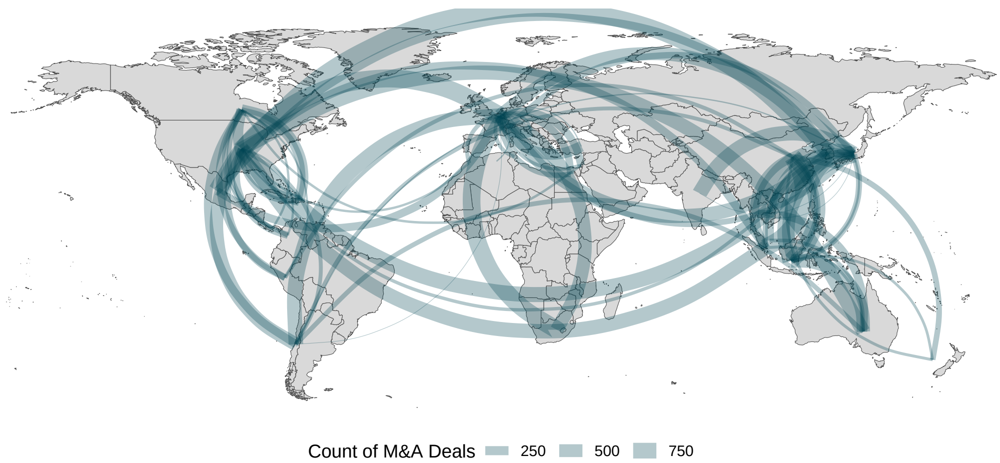
Determining the best time frame for our variable is not a straightforward task. For how long are deals supposed to influence trade policy? Is a deal made in 1995 still relevant for tariff cuts in 2005? To deal with this uncertainty we calculated several different indicators: one capturing all years prior to a PTA (*Mergers & acquisitions*), one restricted to the last ten years before the agreement (*Mergers & acquisitions (10)*), one including the last five years (*Mergers & acquisitions (5)*) and one for the last three years (*Mergers & acquisitions (3)*). We use the 5-year-restricted variable in the baseline model.

We expect the effect of the M&A variables to be conditional on the variable *Intermediates.* As mentioned above, M&As should only influence the ambition of tariff cuts for intermediate products. If a deal is made for market-seeking reasons (horizontal investments, which means that country A simply wants market access in country B), as opposed to a deal to integrate a step in a cross-country production process (vertical integration), we do not expect the deal to have an impact on first-year tariff cuts. We therefore use intermediates as a proxy for vertical integration.

Our operationalization of intermediates is based on Francois and Pindyuk (2012) and Bekkers et al. (2012). Their classification distinguishes between goods that are of "intermediate consumption", of "final consumption", or of "mixed use". If a good is either of intermediate or mixed use, we code it as an intermediate (since we only want to exclude final consumption goods). With this operationalization, intermediates account for 77 percent of the products in the dataset. If we look at tariff levels before a PTA enters into force, we see that intermedi-



(a) Horizontal Investments



(b) Vertical Investments

Figure 3.1: M&As and Trade in Intermediates

ates are at a considerably lower level than finished goods (means of 5.6 and 11.7, respectively), which implies that countries might already have reacted to preferences of industries dependent on imports for their production processes.

Figure 3.1 shows the number of M&A deals in both situations: a) M&A deals in sectors that produce final consumption goods and b) M&A deals in sectors that produce intermediates. Overall, we see that vertical investment is the dominant strategy.

MNC Imports of Intermediates

Several different approaches to measuring multinational production exist. Alfaro and Charlton (2009), for example, use firm-level foreign affiliate sales to distinguish between horizontal and vertical subsidiaries and measure MNC activity. Albeit useful information on the firm-level, limited data coverage in some countries leads to problems at the aggregated industry- or country-level (Ramondo et al., 2015, p. 531). Another important data source, Eurostat's FATS, is employed by numerous scholars (e.g., Alviarez, 2019; Federico, 2016; Fukui and Lakatos, 2012), who assemble bilateral, disaggregated data on multinational production at the sector-level. Alviarez (2019) combines FATS data with OECD data on International Direct Investments, Bureau of Economic Analysis public data, and Bureau van Dijk's Orbis dataset. She aggregates all these sources at the source-location-sector level, which results in a comprehensive database covering 9 manufacturing and 4 non-tradeable sectors, across 32 countries, from 2003-2012. Finally, Miroudot and Rigo (2019) measure foreign affiliate activity using the new OECD analytical AMNE (Activity of Multinational Enterprises) database Cadestin et al. (2018a) to estimate the impact of deep preferential trade agreements on multinational production. This novel database covers more countries than FATS and can distinguish between far more industries. Additionally, the data not only allows us to measure foreign affiliate output, but also intra-firm trade, which is a huge advantage in the context of this paper.

Hence, we follow Miroudot and Rigo (2019) and rely on the OECD's analytical AMNE database (Cadestin et al., 2018a) for our second explanatory variable. The main aim of this new dataset is to combine data on the activities of MNCs with Inter-Country (Inter-Industry) Input-Output (ICIO) tables (see Dietzenbacher et al., 2013 for an introduction into ICIO-analysis) in order to better understand the role of MNCs in the global economy. National Input-Output tables describe sale and purchase relationships inside an economy. Inter-Country Input-Output tables enable us to trace these relationships across borders; and Inter-Country Inter-Industry Input-Output tables additionally differentiate between industries. Combining these ICIO tables with international trade data, we are able to estimate, for example, how much value of Belgian metal products are used in French transport equipment exports (Dietzenbacher et al., 2013, p. 73).

The crucial advantage of AMNE, compared to ICIO tables on their own, is its distinction between three types of firms: foreign affiliates (firms with at least 50 percent foreign ownership), domestic MNCs (domestic firms with foreign affiliates) and domestic firms without any international investments. The analytical AMNE database includes matrices (on a bilateral home country – host country basis) of the output, value added, exports and imports of these companies, for 43 industries, ranging from 2005 to 2016 (De Backer and Miroudot, 2018). Using these matrices, we are able to add an ownership-dimension to international input-output analyses (Cadestin et al., 2018a). AMNE-data therefore enable us to measure the connections between countries and industries on the level of multinational corporations and their foreign affiliates. Not only do we get an idea about the activities of MNCs in their respective host countries, but we are also able to trace their respective outputs. The data tells us, for example, how much intermediates (value in US-Dollars) produced by Japanese-owned foreign affiliates in India are imported into Japan, at the industry level. This allows us to estimate the importance of specific industries for MNCs in their crossborder production chains. The more intermediates are imported from India to Japan, the bigger Japan's incentive will be to reduce tariffs towards India at a faster rate. We call this variable, which captures the imports of intermediates from foreign affiliates in US-Dollars, *MNC imports*.

AMNE data includes industries in agriculture, forestry & fishing, mining & quarrying, several manufacturing industries and numerous service industries. Excluding services leaves us with a total of 17 different industries on the ISIC (International Standard Industrial Classification, Revision 4) 2-digit-level. Although this data is far more aggregated than our tariff data, we still capture MNC activity on a much more fine-grained level than most previous studies, mentioned above. Table C.2 and Table C.3 in the appendix provide an overview of all industries and PTA-country-pairs used in our analysis. Since the variable's distribution is rather skewed (with a couple of very high values), we use the log of *MNC imports* in our estimation. Figure 3.2 shows for which directed dyads we see large values on the *MNC imports* variable. The highest value is for the Japan–Thailand dyad, which reflects the strong GVC ties between the two countries.

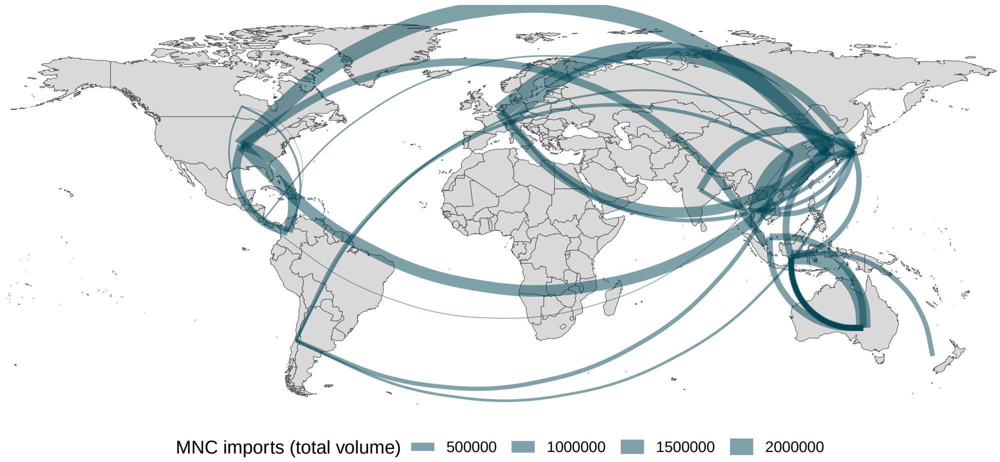


Figure 3.2: MNC Imports of Intermediates

As can be expected, *MNC imports* is positively associated with *Mergers & acquisitions*. The value on *MNC imports* is around four times higher when *Mergers & acquisitions* takes the value of 1 than when it takes the value of 0. However, the two variables are not perfect substitutes. Regressing *MNC imports* on *Mergers & acquisitions* only gives an R^2 of 0.08. The strength of the *Mergers & acquisitions* variable is that the data are highly disaggregated. At the same time, while M&As in sectors producing intermediate goods likely lead to imports of intermediates into the home country of the acquirer, the variable does not directly capture these imports. The *MNC imports* data are less disaggregated, but directly measure the concept that we are interested in.

3.3.3 Control Variables

We include several control variables in our models. The first one is a measure for intra-industry trade (IIT), defined as the extent country A exports and imports the same goods and services to and from country B. Several studies have analyzed the consequences of IIT on the political economy of trade. Some suggest that IIT might lessen the threat of import competition since companies in the same industry can coexist more easily when products are differentiated, which leads to greater net support for trade liberalization (Kim, 2017; Lipson, 1982; Manger, 2012; Milner, 1997). Others argue that IIT may empower narrow protectionist groups (import-competing companies) being able to overcome collective action problems and lobby for protection more effectively (Gilligan, 1997b; Kono, 2009). Baccini et al. (2018) find mixed results, with no clear indication either way. To include intra-industry trade as a control variable, we use the same operationalization as Baccini et al. (2018), who calculate the Grubel Lloyd Index (Grubel and Lloyd, 1971) for imports and exports. The index, labeled *IIT*, ranges from 0 (that means countries only import from or only export to the other country) to 1 (that means two countries simultaneously import and export the same amount of a good). Since some trade data is missing (and it cannot be assumed that this is at random), we also include a dummy variable, assigned a score of 1 in the case of zero trade flows (*IIT missing*).

We account for market size (*GDP*) and level of development (*GDP per capita*) for both countries in a dyad using data from the World Development Indicators database (World Bank, 2014). The level of imports (value over the four years prior to the signature of a PTA) is also included (*Imports*). This variable controls for the effect of import flows on tariff cuts and distinguishes it from our main explanatory variable, M&As. Data comes from CEPII (2014). Building on the literature suggesting that democracies are more open to trade than autocracies (e.g., Mansfield et al., 2000), Barari et al. (2019) show that the regime types of trading partners can have nuanced and complex effects on unilateral and bilateral tariff liberalization. We follow this notion and include the variable *Regime* (data comes from the Polity IV dataset, Marshall et al., 2018) in our model. Moreover, we include a dummy for WTO membership, scoring 1 if both countries are WTO members (*WTO*). Finally, the model captures the tariff rate between countries before signing the respective PTA (*Tariff pre-PTA*).

A summary of univariate statistics for all variables mentioned above is provided in Table 3.1.

3.3.4 Model Specification

The main empirical challenge is that a substantial part of tariffs were set to zero (either unilaterally or within WTO negotiations) even before the implementation of a PTA. To meet this challenge, we estimate a two-stage Heckman selection model with bootstrapped errors (Cameron and Trivedi, 2005; Heckman, 1977; Wooldridge, 1995). The first stage represents a probit model,

Table 3.1: Descriptive Statistics

Variable	Mean	St. Dev.	Min	Max	N
Tariff Cut	0.58	0.45	0.00	1.00	521,929
Mergers & acquisitions (5)	0.03	0.16	0	1	804,538
Intermediates	0.77	0.42	0.00	1.00	785,314
MNC imports	93.62	273.78	0.00	3,775.39	162,729
IIT	0.05	0.17	0	1	804,538
IIT missing	0.79	0.41	0	1	804,538
GDP of A (ln)	26.68	2.42	21.96	30.33	773,009
GDP of B (ln)	27.54	2.18	22.84	31.44	788,562
GDP per capita of A (ln)	9.13	1.45	5.96	11.12	773,009
GDP per capita of B (ln)	9.45	1.32	6.22	10.99	778,474
Imports	0.08	0.48	−1.00	1.00	737,513
Regime	5.50	6.31	−8.00	10.00	762,998
WTO	0.93	0.25	0.00	1.00	788,562
Tariff pre-PTA	7.79	19.14	0.00	3,000	794,284

which explains the pre-PTA zero tariffs. Beyond all predictors in the second stage, we follow the suggestion of Baccini et al. (2018, p. 334) and include a "measure of country competitiveness at the six-digit level as an instrument for the selection equation". This variable contributes to explaining the zero-tariff rate prior to the PTA. The more competitive a country is, the more likely it should be to have a zero tariff on a good. Yet general competitiveness is less likely to matter in the bilateral or plurilateral context of a PTA. Therefore, the specification very likely fulfills the exclusion restriction. In line with Heckman (1977), we derive the Inverse Mills Ratio from the probit estimation. The Inverse Mills Ratio is then included as a covariate in the second stage estimation, where we run an ordinary least squares (OLS) regression with bootstrapped errors and fixed country and year effects on the sub-sample of products that have a tariff higher than zero before the PTA implementation. Whereas the Inverse Mills Ratio accounts for the correlation between error terms of the first and the second stage, the bootstrapped errors allow for an estimation of consistent standard errors (Cameron and Trivedi, 2005, p. 200). We apply this strategy for all models of both our main explanatory variables: *Mergers & acquisitions* as well as *MNC imports*.

3.4 Findings

3.4.1 M&As and Trade in Intermediates

We start with models that include *Mergers & acquisitions* as key predictor. Model 1 in Table 3.2 reports the results of the selection equation. The instrument, which is the competitiveness of countries, is highly significant. This suggests that the variable works well as instrument. Even before the implementation of PTAs, intermediate trade as well as mergers and acquisitions have a positive and significant effect on tariff cuts. Not surprisingly, more democratic countries and WTO members are more likely to cut the tariff to the zero-level.

Models 2 to 5 in Table 3.2 show findings of the second stage, where the dependent variable is the level of tariff cuts at the product level. We alter the fixed effects approaches across the different models, where Model 2 represents the most shallow one without fixed effects and Model 5 is the most comprehensive one with year, country A, and country B fixed effects. H2 is supported across all four models, with the interaction effect of mergers and acquisitions being positive and significant in every column. Yet, the main effect of *Mergers & acquisitions* is negative and significant. This suggests that vertical investment causes tariff cuts, but horizontal FDI triggers the opposite effect (e.g. higher tariffs). This makes sense as companies that engage in horizontal FDI may want to protect their market share in the foreign market.

Figure 3.3 shows the interaction effect in the most restrictive model, namely Model 5. The effect of *Mergers & acquisitions* is negative, but not significant, for sectors that merely trade consumer goods, but positive as soon as intermediate goods are involved. Our findings show that sectors with vertical investment, measured as M&A deals in the past 5 years and trade in intermediates, show on average 3 percent higher tariff cuts than sectors with horizontal investments, measured as M&A deals in the past 5 years, but no trade in intermediates. This effect is even stronger for the less restrictive models.

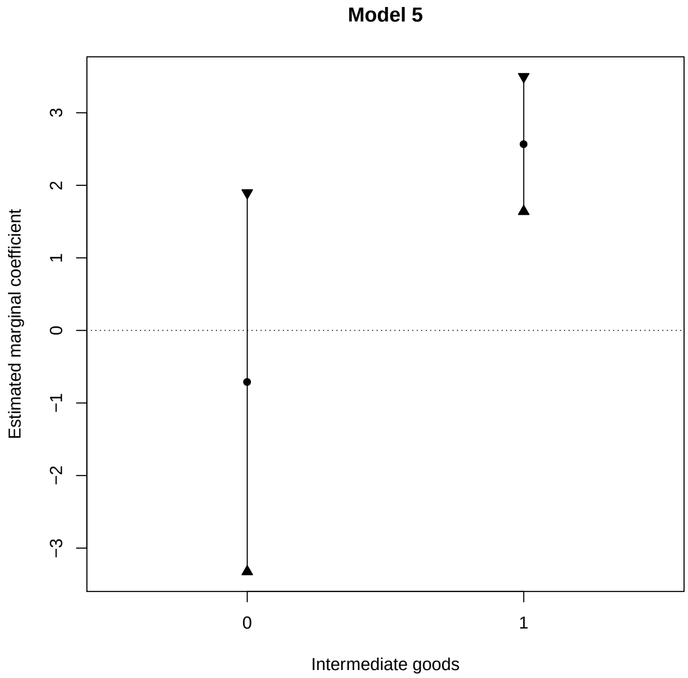
Similar to the selection model, the level of democratization and WTO membership impact tariff

Table 3.2: M&As and Trade in Intermediates

	Dependent variable:				
	Tariff=0 pre-PTA	Tariff Cut post-PTA			
	probit	*felm*			
	(1)	(2)	(3)	(4)	(5)
Mergers & acquisitions (5)	0.489***	−10.182***	−9.338***	−8.365***	−0.714
	(0.028)	(1.116)	(0.900)	(1.266)	(1.332)
Intermediates	0.415***	8.053***	7.895***	7.739***	9.994***
	(0.005)	(0.347)	(0.122)	(0.802)	(0.816)
IIT	−0.606***	−4.727	−4.979	−1.522	−4.799
	(0.151)	(4.195)	(4.782)	(4.313)	(3.999)
IIT missing	−0.384**	0.981	0.172	2.996	−0.208
	(0.151)	(4.194)	(4.782)	(4.249)	(3.930)
GDP per capita of A (ln)	0.064	20.602***	17.596***	18.680***	−17.642***
	(0.045)	(0.088)	(0.073)	(0.847)	(1.728)
GDP per capita of B (ln)	−0.010***	1.858***	1.625***	0.510***	49.731***
	(0.002)	(0.045)	(0.056)	(0.051)	(1.167)
GDP of A (ln)	0.597***	−2.360***	−1.996***	−66.552***	−80.821***
	(0.052)	(0.049)	(0.047)	(1.611)	(2.118)
GDP of B (ln)	−0.001	0.086**	−0.483***	0.317***	−149.572***
	(0.002)	(0.036)	(0.042)	(0.031)	(1.680)
Imports	0.019***	−0.771***	−0.400***	−0.616***	−0.917***
	(0.004)	(0.128)	(0.110)	(0.129)	(0.125)
Regime	0.015***	0.452***	0.620***	−0.034	−0.096*
	(0.002)	(0.014)	(0.011)	(0.053)	(0.052)
WTO	0.040**	2.503***	4.596***	1.220***	
	(0.019)	(0.207)	(0.361)	(0.320)	
Country competitiveness	0.120***				
	(0.004)				
Tariff pre-PTA		−0.131***	−0.140***	−0.128***	−0.139***
		(0.020)	(0.002)	(0.020)	(0.022)
Inverse Mills Ratio		5.118***	4.774***	3.608*	11.083***
		(0.109)	(0.086)	(2.030)	(2.075)
M & A:Intermediates	−0.335***	4.973***	5.632***	4.448***	3.283***
	(0.031)	(1.210)	(0.975)	(1.212)	(1.251)
Constant	−15.941***	−93.448***			
	(0.969)	(4.625)			
Year FE	Yes	No	Yes	Yes	Yes
Country A FE	Yes	No	No	Yes	Yes
Country B FE	Yes	No	No	No	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes
Observations	691,991	464,503	464,503	464,503	464,503
R^2		0.359	0.385	0.450	0.498
Adjusted R^2		0.359	0.385	0.450	0.498
Log Likelihood	−302,341.600				
Akaike Inf. Crit.	604,827.100				
Residual Std. Error		35.524 (df = 464488)	34.804 (df = 464472)	32.920 (df = 464432)	31.447 (df = 464397)

Note: *p<0.1; **p<0.05; ***p<0.01

Figure 3.3: Horizontal versus Vertical Investment (Model 5)



Note: The bars indicate 95% confidence intervals.

cuts positively.[2] Also, a high tariff before a PTA becomes effective decreases the likelihood of ambitious tariff cuts when negotiating a PTA. The significant Inverse Mills Ratio suggests that it was indeed important to estimate a two- rather than a one-stage model.

Besides the baseline models, we ran several robustness checks for which the detailed results are available in the appendix. First, and instead of *Tariff Cuts*, we use a variable called *Time To Zero*, which measures the number of years it takes to lower a tariff to zero. Table C.4 shows that indeed vertical investment is prone to lead to a shorter time-span until zero-tariffs. Next, we modify the time-span used to measure M&A deals. In the baseline model, we coded the variable M&A as 1 if at least one M&A deal was completed within the last 5 years. As a robustness check, we take the last three and ten years as well as all previous years to specify the M&A variable. Table C.6, Table C.7, and Table C.8 show that the results are not sensitive

[2] Note that due to the wide range of fixed effects, the dyadic variable *WTO membership* is not able to explain any further variation and must be omitted from Model 5.

to this empirical choice. Finally, we take a count of M&A deals instead of the M&A dummy variable. Again, the results are in line with the findings from the baseline model (see Table C.9).

3.4.2 MNC Imports of Intermediates

We follow a similar estimation strategy for our second explanatory variable (*MNC imports*). Model 1 in Table 3.3 again reports the selection equation. As before, the coefficient for the instrument, *Country competitiveness*, is highly statistically significant. We also see that *MNC imports* is correlated with zero tariffs prior to the entry into force of a PTA.

Building on the selection model, Models 2 to 5 in Table 3.3 report the coefficients for our second stage estimation. Similar to Table 3.2, we use different fixed effects specifications (year, country A, country B), with the most comprehensive one presented in Model 5. The findings support H2: The coefficient for *MNC imports* is positive in all models and statistically significant in three out of four. Overall we conclude that MNC imports of intermediates indeed increases the size of tariff cuts. In the most comprehensive model, namely model 5, we see that a growth in *MNC imports* by 30 percent leads to a decrease in the tariffs by one percent.

Similar to the findings above, we see that high pre-PTA tariffs decrease the size of tariff cuts. Moreover, greater imports are consistently negatively correlated with the extent of first-year tariff cuts in PTAs. The other control variables do not show consistent effects across models.

Also for the second hypothesis, we change the dependent variable from *Tariff Cuts* to *Time to Zero* to check for the robustness of the results. The results of this test add further confidence to our findings. Indeed, an increase in *MNC imports* leads to a shorter time period until the tariffs hit zero. Again the magnitude of the effect is not large, yet significant across all fixed-effect specifications (see Table C.5).

Table 3.3: MNC Imports of Intermediates

	Dependent variable:				
	Tariff=0 pre-PTA	Tariff Cut post-PTA			
	probit	*felm*			
	(1)	(2)	(3)	(4)	(5)
MNC imports (ln)	0.110***	2.517	3.865***	2.792**	2.697**
	(0.003)	(1.644)	(1.274)	(1.238)	(1.242)
IIT	−0.534	−10.111	−8.206	−2.108	−1.472
	(0.366)	(10.768)	(9.650)	(9.755)	(9.939)
IIT missing	−0.282	−4.946	−5.418	−1.979	−1.279
	(0.366)	(10.615)	(9.253)	(8.605)	(8.859)
GDP per capita of A (ln)	5.039**	20.838***	19.193***	−58.965	
	(2.282)	(2.826)	(2.777)	(252.893)	
GDP per capita of B (ln)	−0.013	−0.932	4.667**	2.282***	
	(0.012)	(0.811)	(1.973)	(0.775)	
GDP of A (ln)	−1.522	2.377	−2.869*	−91.175	
	(1.254)	(2.200)	(1.541)	(123.540)	
GDP of B (ln)	−0.007	1.307	−5.315***	−3.495	
	(0.012)	(2.192)	(1.211)	(2.496)	
Imports	0.014	−2.497**	−2.987**	−3.707***	−3.704***
	(0.009)	(1.186)	(1.230)	(0.934)	(0.908)
Regime	−0.013	−1.160***	−0.423	2.866**	4.125***
	(0.009)	(0.354)	(0.406)	(1.254)	(0.727)
Country competitiveness	0.426***				
	(0.011)				
Tariff pre-PTA		−0.257***	−0.252***	−0.252***	−0.252***
		(0.039)	(0.040)	(0.044)	(0.044)
Inverse Mills Ratio		16.289***	12.800***	2.956	3.163
		(2.637)	(2.860)	(10.923)	(10.994)
Constant	−11.992	−232.984**			
	(13.004)	(106.505)			
Year FE	Yes	No	Yes	Yes	Yes
Country A FE	Yes	No	No	Yes	Yes
Country B FE	Yes	No	No	No	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes
Observations	131,332	85,254	85,254	85,254	85,254
R^2		0.361	0.399	0.434	0.435
Adjusted R^2		0.360	0.398	0.434	0.435
Log Likelihood	−51,157.470				
Akaike Inf. Crit.	102,374.900				
Residual Std. Error		35.172 (df = 85242)	34.112 (df = 85238)	33.097 (df = 85225)	33.064 (df = 85217)

Note: *p<0.1; **p<0.05; ***p<0.01

3.5 Conclusion

GVCs alter the dynamics of trade policy-making by creating a constituency that favors trade liberalization with the aim of lowering the costs of intermediate imports. MNCs are key players within this constituency. They often rely on intermediate imports in their production processes – a cost reduction (e.g. due to tariff cuts) of these imports hence enhances their productivity. They should thus have a preference for ambitious trade liberalization that facilitates cross-border trade in intermediates within the own company. Moreover, these MNCs possess the resources to affect policy-making via lobbying or they simply have sufficient clout to ensure that policy-makers take their interests into account pre-emptively. Our expectation hence has been for MNC involvement in GVCs to lead to more ambitious tariff cuts in PTAs.

So far, a lack of suitable data represented a major challenge to scholars interested in assessing the GVC-trade policy nexus. Our empirical contribution has been to improve on this state-of-the-art by relying on two novel data-sources. More precisely, we have used a) fine-grained data on M&As, which we combined with trade in intermediates to account for vertical versus horizontal investment and b) data on MNC imports of intermediates to capture the extent to which MNCs are involved in GVCs. The combination of a fine-grained but indirect measure of vertical investment (M&As and trade in intermediates) and a more aggregated but also more direct measure of cross-border activity of MNCs (imports of intermediates from foreign affiliates) have allowed us to comprehensively test the effect of MNCs' GVC integration on trade liberalization.

The results from a two-stage regression analysis with tariff concessions at the HS6-level in 61 PTAs as dependent variable offer support for our theoretical expectations. They show that MNCs that invest to obtain intermediates from affiliates abroad indeed push for faster trade liberalization. Whereas vertical investment is prone to lead to tariff cuts, market-seeking (horizontal) investment does not have the same effect. Moreover, we have found that intermediate MNC imports, which are produced by a foreign affiliate, increase the likelihood of ambitious tariff cuts. We conclude that, as expected, GVCs have the potential to speed up the liberalization of trade in certain products, especially if MNCs are involved.

In making the argument and testing it empirically, we also contribute to the broader literature on MNCs in the global political economy. MNCs do not only participate in transnational production networks, but are also able to lead, cultivate and sustain the GVCs they are part of. Their sourcing decisions (either investing abroad and engaging in intra-firm trade or buying at arm's length) fundamentally shape the form and strength of international production networks. This formative role in influencing value chains suggests that MNCs do not operate in a purely economic sphere, but are bound to have distinct preferences concerning international trade policy. Our results also indicate that these preferences get reflected in specific policy decisions, which gives us an idea about MNCs' political power.

In short, although the recent popular backlash against globalization and trade liberalization in many developed countries could have the potential to re-empower protectionist groups, at least in the short term our findings show that powerful actors like MNCs still have a lot at stake when it comes to trade policy. They have the resources to influence policymakers and are very likely to continue their efforts to facilitate trade in intermediates.

Chapter 4

The Impact of PTA Design on Foreign Direct Investment: New Insights from Firm-Level Data

with Christoph Mödlhamer

Abstract:
Preferential trade agreements (PTAs) not only facilitate trade between members states, but can also affect foreign direct investments (FDI). Research shows that especially deep agreements have the potential to increase FDI flows. We challenge this idea of an exclusively positive relationship, by focusing on the impact of specific provisions included in most modern PTAs: intellectual property rights (IPRs). On the one hand, stronger IPRs could lead to more investment, since higher profits and smaller risks of imitation make a country more attractive as a host for FDI. On the other hand, stronger IPRs may make it more efficient for firms to switch to arm's-length trade instead of investing in foreign subsidiaries, as their intellectual assets are protected in a trading partner's market. We expect that the answer to this puzzle can be found at the firm-level: The strength, or even the direction of the effect of specific PTA provisions, such as IPRs, on FDI might depend on firm-level characteristics, such as innovativeness. Changes in IPR protection should have a bigger impact on investment decisions of innovative firms, as IPRs matter more for them since they have more intellectual assets to protect. Until now, most studies in the field work with aggregate FDI data, even though the effect of IPRs on investments should vary between industries and firms. We employ fine-grained firm-level data on cross-border mergers and acquisitions (M&A) to account for this heterogeneity. To assess not only the impact of PTAs in general, but the effect of IPR provisions, we use a novel dataset capturing the strength of IPR protection between PTA member states. Our analysis shows that the relationship between PTAs and FDI is far more complex than generally assumed: Although trade agreements can boost international investments, we find that strong IPRs have a negative effect on M&As, especially for big, innovative firms.

Keywords: International Political Economy, Trade Agreements, International Investment, Intellectual Property Rights, Mergers and Acquisitions

4.1 Introduction

Preferential trade agreements (PTAs) have been shaping international economic activity, such as trade flows and cross-border investments, for decades. Their rapid growth, both in number and depth, has attracted much attention in fields like business studies, economics, international relations, and political economy. The main purpose of PTAs is to facilitate trade between their member countries. They do so by lowering or ultimately removing tariffs, by reducing other trade barriers, and by setting up rules and regulations regarding standards, procurement, or intellectual property rights (IPRs), among others. Apart from the most obvious effect of PTAs, namely influencing trade flows, they can also shape international investments.

Most studies (e.g., Büge, 2014; Büthe and Milner, 2008, 2014; Osnago et al., 2019) find a positive overall effect of PTAs on foreign direct investment (FDI). In a nutshell, the theoretical explanation for this relationship is mostly based on increased credibility and predictability between PTA partners. The legal framework of a PTA reduces the risks involved with international investments, and therefore increases the incentive to establish or expand business activities abroad. Although theoretically plausible and empirically tested, the relationship between PTAs and FDI is far less straightforward than one might initially think. First, PTA design varies considerably – not only in terms of the scope and the topics included, but also concerning the legal obligations and bindingness of the provisions, their so-called depth. Second, the actors responsible for investment decisions, i.e. private firms, differ in many aspects as well (e.g., size, productivity, innovativeness, export-orientation, industry-specific factors, etc.). Neglecting these complexities on both sides of the equation – in PTAs and FDI decisions – omits a lot of interesting and policy-relevant variation.

Exploring these differences and their causal impact further is the main goal of this paper. Our research question is: *What effect does a PTA's design, especially intellectual property rights provisions, have on firms' investment decisions?*

This question is not purely academic: PTAs have far-reaching distributional consequences. We see "concentrated benefits among a relatively small number of very large and productive firms" (Pinto et al., 2017, p. 5). This also applies to IPRs whose main beneficiaries are large, productive multinational corporations in developed economies (Shadlen, 2005b, p. 11; Auriol et al., 2019, p. 65). The concentration of advantages is not only undesirable from a normative point of view, but also problematic economically. Trade and international investment have the potential to boost economic development, but only under certain conditions. If policy-makers want to increase the positive effects of PTAs on economic welfare for a higher number of people, we need to understand how certain provisions, such as IPRs, influence economic actors. The literature still has considerable blind spots in this regard.

We try to add to this by introducing a fine-grained novel dataset on IPR provisions in PTAs, allowing us to account for crucial differences in PTA design. Furthermore, we use firm-level data on one of the most important types of FDI, namely mergers and acquisitions (M&A). In contrast to the widely used country-level FDI flow data, this disaggregated measure makes it possible to include firm-level heterogeneity in our analysis. Additionally, we use data on the number of registered patents per firm to account for different levels of innovativeness – a potentially important, but mostly neglected, firm-level factor possibly influencing investment decisions. This combination of more detailed data sources and a refined theoretical argument aims at advancing our understanding of the complex effects of IPRs in PTAs on international investments. The analyses show an overall positive effect of PTA depth on FDI. Deeper PTAs indeed seem to increase firms' FDI in the form of mergers and acquisitions. However, the relationship is far more complex than generally assumed. We find that the strength of IPR protection has a mostly *negative* effect on investments, which may hint at a switch to arm's-length trade. This effect is even stronger for more innovative firms, indicating that the need to control business operations abroad decreases with stronger IPR protection - especially for firms with much intellectual property to protect. The effects we find are rather small and not always as expected, which shows that much more research is needed to fully understand the causal connections at play. Nevertheless, our findings show that trade policy can have a very differential effect on international investment flows - depending both on the content of policy provisions and specific firm-level characteristics.

The paper is structured as follows: After a literature overview covering research on foreign direct investment, and preferential trade agreement design, including intellectual property rights, we state our theoretical argument and present our two main hypotheses. The next section explains our research design, with a comprehensive description of the data generating process. Then, our findings from multiple model specifications are presented. We conclude with a summary and an outlook for future research.

4.2 PTA Design and International Investments

4.2.1 Foreign Direct Investments (FDI)

A large portion of international trade – especially in the industrialized world – is controlled by multinational companies (MNCs) (Baltagi et al., 2008), with production processes organized in global value chains (GVCs) spanning across multiple countries. If companies decide to move parts of their production to other countries, they can either trade with independent partners (arm's-length trade), or integrate foreign subsidiaries (Osnago et al., 2017). These "make-or-buy decisions" (Osnago et al., 2019, p. 1559) depend on whether the company wants to retain some degree of control over the production process, often "motivated by the need to internalize firm-specific intangible assets" (Blomström and Kokko, 1999, p. 2), such as specific technology or other proprietary parts of the production process. If this is the case, they choose the latter option – foreign direct investment. Sobel (2006, p. 805) defines FDI as "investment in control of productive facilities overseas – usually defined by an investment that amounts to control of 10% or more of a company's equity". The key terms here are *control* and *investment*: Investors seek to control parts of the production process, instead of just trading with intermediate products.

The decision about if, when, and where these investments take place is based on multiple economic, institutional, and firm-level factors. There is no one single theory of FDI determinants, but a "variety of theoretical models attempting to explain FDI and the location decision of multinational firms" (Faeth, 2009, p. 165). One way of conceptualizing MNC's investment incentives is the so-called OLI-framework, which stands for Ownership-Location-Internalization (Dunning and Lundan, 2008). Accordingly, the motives for engaging internationally can be divided into three categories:

Ownership advantages can explain why some firms multinationalize while others do not. Operating in a foreign country always comes with costs (e.g., not speaking the language, not knowing about laws, standards, customs, etc.). For foreign investments to be beneficial, and thus profitable, a company has to have some kind of comparative advantage to balance out this 'liability of foreignness' (Eden and Miller, 2004). Advantages can be based on a specific management style, on productivity, innovativeness, or any other aspect that makes it beneficial to invest abroad despite the additional hurdles of doing business in another country.

Location advantages are related to the question of where firms decide to engage internationally. In order to be beneficial for a firm to do so, operating in a specific country must come with advantages compared to just supplying this country from home or outsource production entirely. These can be divided into two groups: Supply-side factors typically include natural resources, cheap and/or skilled labour, access to specific knowledge, tax regimes, or special tariffs. On the demand side, market size and potential growth are relevant for investors. Location advantages also depend on whether the investment can be characterized as horizontal or vertical. Horizontal, or market-seeking, FDI mainly occurs when a company invests in subsidiaries abroad, to get market access (i.e. targeting consumers in the other country). Simply put, this means that the firm replicates its domestic production facilities in another country (Neary, 2008). Vertical FDI, by contrast, means that only parts of the production process are outsourced to foreign subsidiaries. The main motive for vertical integration are lower production costs in target countries.

Once a firm has determined that expanding production internationally could be beneficial (because of ownership advantages), and has decided which country is best suited (based on location advantages), the question remains: Is it better to integrate a foreign subsidiary through FDI or would an independent partnership with a foreign firm be a more preferable solution?

Internalization advantages are most important for the decision between vertical integration and licensing, or arm's-length trade, with external partners. The protection of proprietary technology and knowledge becomes an issues in countries with weak contract legislation (Cadestin et al., 2018b). Generally speaking, we see that "more uncertainty raises the likelihood that production will be vertically integrated" (Neary, 2008, p. 7), while maintaining control over the processes, instead of working with independent partners.

Although this framework does not constitute a formal theory, much of the empirical work on FDI in economics, business studies, political economy, and other research fields, can be categorized into one or more of these dimensions (Neary, 2008). It is therefore a useful tool to structure theoretical arguments seeking at explaining FDI decisions. From this OLI theory, we can derive (at least) three different types of FDI: market seeking, resource seeking, and efficiency seeking FDI (Wadhwa and Reddy, 2011). The first one, market seeking FDI, is mainly aimed at broadening the (potential) customer base of a company. Resource seeking FDI is mainly done for production purposes, either when natural resources are abundant in the host country, or a cheap (or skilled) labor force, or even a beneficial infrastructure (ports, railways, etc.). Efficiency seeking investments are driven by lower costs of production (which can be linked to resource seeking FDI).

Another approach of conceptualizing research on FDI, is to distinguish between country- and firm-level explanations. The most important firm-level characteristic determining FDI decisions is a company's level of productivity (Antras and Helpman, 2004). Higher productivity allows firms to increase their comparative advantages, which helps them to offset the costs of FDI (Helpman et al., 2004). Country-level factors include regime type (Jensen, 2003; Li and Resnick, 2003), other institutional determinants (such as rule of law, control of corruption, production standards, etc.) (Jadhav and Katti, 2012), membership in international organizations (Dreher et al., 2015), and trade agreements between the headquarter and the target countries (Baltagi et al., 2008; Büthe and Milner, 2014; Kenyon and Margalit, 2014). Democracies with good governance practices generally attract more FDI, as do members of international organizations (Dreher et al., 2015; Jensen, 2003). Trade agreements also, in aggregate, increase FDI flows between partner countries (Baltagi et al., 2008; Büthe and Milner, 2014). The next section describes this relationship in more detail.

4.2.2 FDI and Preferential Trade Agreements

Over the last two and a half decades, we have witnessed a proliferation of PTAs. In general, trade agreements aim at facilitating trade between signatory states by reducing tariffs, dismantling trade barriers, creating rules and regulations, and by the harmonization of standards (Dür and Elsig, 2015; Rodrik, 2018). In doing so, PTAs tend to increase trade flows among their member states (Baier and Bergstrand, 2007, 2009; Kohl, 2014).

Closely related to this strand of the literature is the question of whether and how trade agreements can not only influence trade, but also international investments. Likewise, most studies find a positive overall effect of PTAs on FDI flows. Theoretical arguments for this relationship are mostly based on the fact that trade agreements reduce legal uncertainty: They minimize differences and risks by setting rules, establishing common procedures and authorities, or by allowing for mutual recognition (Osnago et al., 2019). A PTA and its provisions can also be seen as a commitment device for countries to signal credibility of and commitment to (economic, or policy) reforms vis-à-vis potential investors (Kenyon and Margalit, 2014; Mansfield and Pevehouse, 2000; Ridley, 2019). Simply put, PTAs tend to reduce the risks of investing abroad and therefore boost FDI inflows between signatory states (Büthe and Milner, 2014).

While earlier PTA-related studies only focus on the number of signed PTAs per country and its economic implications (e.g., Büthe and Milner, 2008; MacDermott, 2007; Medvedev, 2012), newer research is increasingly interested in the effects of different PTA designs. The contents of trade agreements and the depth of these commitments vary considerably (Dür et al., 2014), so it is plausible to expect that PTA design might have a differential impact on FDI as well: Osnago et al. (2017), for example, demonstrate that deeper trade agreements between countries are related to higher vertical FDI. Büthe and Milner (2014) focus not only on depth, but on specific provisions, and show that investment clauses and dispute settlement mechanisms in PTAs increase FDI inflows. As Lechner (2018) shows, also non-trade issues such as environmental and labour clauses in PTAs matter for investments. PTAs regulating environmental and labour standards reduce FDI by US-firms in polluting, low-skill industries, but lead to increases in clean, high-skilled sectors.

Most recent studies about PTAs emphasize that with growing depth and complexity, the effects of trade agreements become less straightforward. Some provisions boost trade and investment flows, others might only affect one of the two, or none at all. Zeroing in on specific provisions can help to disentangle the often convoluted causal effects of PTAs.

4.2.3 The Role of Intellectual Property Rights for FDI

Not only have PTAs increased in number but also in scope and depth of their provisions, encompassing a wider array of trade-related and non-trade issues with ever more detailed rulings (Dür et al., 2014; Dür and Elsig, 2015; Ridley, 2019; Rodrik, 2018). With ever growing cross-border trade flows in knowledge-intensive/innovative goods and services (Osgood and Feng, 2018; Ridley, 2019), most recent PTAs include regulations regarding intellectual property rights (IPRs) in some form or another (Maskus and Ridley, 2017; Rodrik, 2018; Valdés and McCann, 2014). Moreover, for PTAs these IPRs have proved as a highly contested feature that potentially affects the length (Lechner and Wüthrich, 2018), and the success (Serrano and Burri, 2019) of international trade negotiations, as well as the support of industry groups for a trade agreement (Osgood and Feng, 2018).

In general, IPRs aim at the protection of owners and producers of intellectual property by providing a regulatory framework, which aims at encouraging innovative activities by creating incentives and legal certainty (Blank and Kappos, 2012; Shadlen et al., 2005). As the generation of intellectual property requires expenditures in research and development (R&D), adaptation, and other resource-intensive innovative activities, IPRs as a legal framework seek to reduce uncertainties for those economic actors that partake in innovative activities, generate intellectual property and rely on its economic exploitation (Rapp and Rozek, 1990). As a consequence, IPRs discriminate. On the one hand, they exclude non-owners from utilizing industrially useful innovations, protect original intellectual creations and collectively known marks, and bar free-riding in innovative activities. On the other hand, IPRs protect owners and producers of intellectual assets in exploiting their innovations to recoup innovative activities' costs, which furthermore should serve as an incentive for future innovative activities (Shadlen et al., 2005). There are several different means for the protection of IPRs. Among the most prominent ones are rules and regulations regarding patents, trademarks, and copyrights (Mödlhamer, 2020). In short, patents aim at protecting innovative products and processes by granting monopoly rights to the patent owner (Eaton and Kortum, 1996). Trademarks protect commonly known words and symbols that enable consumers to distinguish a good's origin (Seuba, 2013). Copyrights protect authorship rights especially in music, film, books, arts, software, and other creative works (Jain, 1996).

The effects and consequences of these and other forms of IPR provisions included in PTAs vary. IPRs in PTAs are said to mostly benefit developed countries and within them highly innovative firms, meaning those firms that rely on the generation and exploitation of knowledge-intensive goods, processes, and services (Auriol et al., 2019; Helpman, 1993; Shadlen, 2005b). Linked with this finding, however, it does not seem surprising that it was exactly these innovative firms in developed countries, especially in pharmaceuticals, chemicals, electronics, and entertainment sectors, that began in the 1980s to lobby their governments for the inclusion of IPRs in PTAs (Kapczynski et al., 2017; Maskus, 1997; Ridley, 2019). These firms' and industry interest groups' lobbying efforts proved to be successful as IPRs became a prominent issue on the international trade agenda and governments then started to utilize PTAs to disseminate their regulatory standards in IPRs to trading partners (Auriol et al., 2019; Grossman and Lai, 2004).

For firms, IPRs matter - but not equally so. Firms in sectors such as those mentioned above, that lobbied for IPRs in PTAs base their economic performance on the generation and exploitation of innovative, knowledge-intensive goods, processes and services. Therefore, they are heavily affected by a trading partner's (in)adequate IPRs and this also affects their investment decisions (Lee and Mansfield, 1996; Mansfield, 1994; Osgood and Feng, 2018). Especially for these firms, comprehensive IPRs offer protection from imitation by granting monopoly rights to the usage of innovations and by rendering counterfeiting, piracy, and industrial espionage among others as unlawful, which lowers risks for investing firms. Adequate IPRs protection then increases a partner country's attractiveness for foreign investors.

However, on the one hand, IPRs might be able to foster investments as IPRs, especially for these innovative firms, as new opportunities for international investments arise and their intellectual assets are shielded from violations via piracy, counterfeiting, industrial espionage, and other unauthorized uses. By contrast, IPRs may also lead to a reduction in FDI on the other hand, as adequate IPR protection in a partner country may make retaining full control over production processes of foreign affiliates no longer necessary and in turn for firms it might even become more cost-efficient to switch to arm's-length trade with independent partners, via joint ventures, or licensing and royalty payment agreements instead controlling a foreign affiliate (Branstetter et al., 2011; Jain, 1996). This means that IPRs can and do shape the decision of firms of where and when to invest as well as how to invest, and thus matter for firms' locational decisions for investments as Mansfield (1994) has shown. In sum, the literature argues that PTAs increase FDI, but strong IPRs in PTAs reduce risks for firms and their proprietary knowledge assets, which in turn can be responsible for declining investments and for the switch to arm's-length trade to serve foreign markets of PTA partners (Branstetter et al., 2006; Ridley, 2019).

4.2.4 Firm Innovativeness

Firms do not equally rely on the generation of knowledge and the economic exploitation of these intellectual assets. Firms are thus not equally affected by intellectual property rights provisions included in PTAs when it comes to the decision of where to invest and how to invest. Historical evidence shows that especially firms in sectors such as pharmaceuticals, chemicals, electronics, and entertainment, that intensively generate intellectual property, actively voiced preferences towards the inclusion of IPRs in PTAs and to extend stringent IPRs to PTA trading partners (Helpman, 1993; Kapczynski et al., 2017; Osgood and Feng, 2018). These innovative firms are most affected by inadequate IPRs. Weak IPRs threaten profits generated with their intellectual assets and favour knowledge-theft through piracy, counterfeiting, imitation, and reverse engineering, which decreases their own returns and hurts economic performance (Shadlen, 2005a, 2007).

Therefore, innovativeness can have a positive effect on FDI: The literature shows that the most productive firms have the highest potential to multinationalize their production and engage in foreign investments (Helpman et al., 2004) - partly due to their innovative and efficient production processes and their stock of intellectual assets (Neary, 2008). An overall positive effect of patents on FDI could be a reflection of this. The crucial question is: What happens when we combine innovative firms and strong IPRs protection? Innovative firms might have the resources to invest abroad, but do they still feel the need to retain control over the production process if their intellectual property is sufficiently protected in a partner country anyhow?

4.2.5 Argument

Signing a PTA should alter the utility function of businesses (interested in) investing abroad, since it affects some of the main investment reasons proposed in the literature. As mentioned above, we can distinguish between market, resource, and efficiency seeking FDI. Our argument is mainly based on the second and third type. Although IPRs might matter for market seeking motives as well, we argue that IPR protection should be most important for businesses deciding between operating a foreign subsidiary or dealing with independent partners. This is not the case for market seeking investments, where control over the investment is key to supply the foreign market. Following the OLI-framework described above, PTAs and their respective IPR provisions can influence all three dimensions of advantages outlined above:

Ownership advantages for MNCs can be found in proprietary technology and knowledge assets, patents, designs, and brand names, but also in specific production processes and creative creations. According to Cadestin et al. (2018b, p. 8), these "advantages explain to a large extent" why MNCs are "so concentrated in knowledge-intensive industries". PTAs could change whether a company would benefit from FDI. Stronger IPRs protection, for example, could reduce the risks of foreign production and increase the incentive for firms in innovative industries to engage in FDI.

Trade agreements also have the potential to influence *location advantages*: Besides reduced tariffs, a PTA partner country, with shared dispute settlement procedures, standards, investment provisions, and IPRs protection, can be more attractive to investors than a similar (neighbouring) potential trading partner country that is left out of the agreement. Hence, we expect a positive effect of deep PTAs on location advantages, since certain provisions increase the incentive to invest in partner countries.

While a change in *ownership advantages* should influence whether a firm decides to multinationalize (further), different *location advantages* affect the choice of investment destinations. In both of these dimensions, signing a (deep) PTA should have a positive effect on FDI between partner countries. It is less clear, however, in what way a change in *internalization advantages* would alter investment decisions. Both directions - positive and negative - are theoretically plausible. Stronger IPRs protection could make establishing a new subsidiary more attractive, but they could also reduce the risk of arm's-length transactions, and therefore decrease the benefit of vertical integration. As of now, we simply do not know. In our first hypothesis we expect a positive effect:

H1: *Stronger IPR protection in PTAs leads to more new mergers and acquisitions between PTA members.*

Consider an example: A big MNC in country A has been thinking about outsourcing parts of a production process to a country with lower wage levels, but is concerned about the protection of their proprietary technology and intellectual assets. Talks with production facilities in country

B and country C have been taken up, but no decision has been made. Then, a deep PTA with strong IPRs protection is signed between A and B. This lowers the risk of investing in B, which makes it a more attractive partner than C. In other words: The location advantages for the MNC in country B have been increased by the PTA. Now the company still has to decide whether to invest and integrate vertically, or trade at arm's-length with a partner in country B. The PTA increases the level of IPRs protection between countries A and B, which reduces the risk to work with independent suppliers. This decreased risk has a negative effect on internalization advantages: When intellectual property is sufficiently protected, it might be more efficient to give up control over parts of the production process and agree on some form of independent partnership with a firm in country B, for example through licensing or royalty payment agreements. This decrease of internationalization advantages, caused by strong IPR protection in PTAs, should matter most for innovative firms. If the hypothetical MNC in this example is not concerned about intellectual property, a PTA with strong IPR protection should not affect the MNC's internalization advantages (as much). Our hypotheses reflect this distinction.

Since intellectual property protection is not exclusively granted to PTA partner countries, but becomes domestic legislation, binding for all potential investors (from PTA partners and third countries alike, for example due to most-favoured nation principles for all WTO members), the effects described above should eventually exceed this dyadic setting. In other words, (potential) investors outside of the PTA can, via third party effects, also be affected by stronger IPR provisions. Nevertheless, since partner countries are intensively involved in the (sometimes lengthy) negotiations of PTA provisions, we assume that MNCs situated in the respective countries have a head start on third country investors. We should see a quicker and stronger effect in PTA partner countries. Therefore, we limit our analysis to foreign direct investment flows between PTA partners. Certainly, this is only part of the puzzle, but an important one.

We do not expect that MNCs disinvest or sell their affiliates abroad just because a PTA with stricter IPR protection is signed. Investments are 'sticky', which means they are not easily reversible. What we do propose, is that PTAs can change new investment patterns. Trading with independent and reliable partners can be much more efficient than integrating them into one's own corporation – given a comprehensive legal framework protecting a firm's intellectual property. If this change of internalization advantages is enough to substantively alter investment decisions, is an empirical question - one we try to address in our analysis below.

In sum, we argue that the impact of a PTA's IPR protection on FDI depends on firm-level characteristics. The aggregated effect of strong IPR provisions on FDI inflows may be positive, but it is not the same for all companies. The internalization advantages of innovative firms are lower when IPR protection is higher, which might lead to more arm's-length trade and less FDI. Our first hypothesis captures the effect of IPR protection on FDI for all firms, irrespective of their innovativeness (see H1 above), while our second hypothesis includes the distinction between firms with different levels of innovativeness and therefore allows for the effect of IPR provisions on foreign investments to vary depending on the extent to which firms base their economic rents on intellectual assets:

H2: *Stronger IPR protection in PTAs leads to less new mergers and acquisitions from innovative firms between PTA members.*

Existing studies analyzing the effects of PTAs on FDI between country-pairs have shown that PTAs, especially deep ones, increase FDI flows. However, the effects of specific provisions, especially IPRs, on FDI flows between countries remain inconclusive. We argue that these inconclusive findings may stem from the fact that PTAs in general, and IPRs specifically, have varying effects - not only on countries but more so on firms and their decision on whether, where, and how to invest. Accordingly, a certain level of IPR protection granted via a PTA can alter innovative firms' utility function whereas it becomes more cost-efficient to switch from FDI to arm's-length trade through setting up joint ventures or licensing agreements. In our analysis, we focus on individual firms and their investment decisions, and therefore account for heterogeneous firm characteristics such as productivity, size, and innovativeness. By shifting the focus away from the country-level to the firm-level, our analysis adds to our understanding of the varying effects of PTAs with deep or shallow IPR provisions on firms' investment decisions.

4.3 Research Design

In order to assess previously hypothesized claims, our analysis focuses on M&A activities of a firm k from a home country i conducted in a partner country j over a period starting in 1990 and ending with 2018. Our firm-partner country sample is limited to dyads that have signed PTAs, and for which we have sufficient information (i.e. the agreement text) to derive our PTA design measures. Therefore, we compare firm activities in a dyad that has a PTA without IPRs, with a dyad that has a PTA with (comprehensive) IPRs. In total, our data comprise 112,096 M&A deals done by 57,394 firms in 155 countries that signed a total of 620 trade agreements.[1] We do not limit our sample geographically in order to account for regional, income, and cultural differences. Our comprehensive data set captures a certain headquarter country's firm's activities in its partner country and is structured in directed firm headquarter country-partner country dyads, with individual firm activities in year t. In the remainder, we shortly explain the operationalizations and the data sources of our central variables together with country-, PTA-, and firm-level controls.

4.3.1 Dependent Variable: Mergers and acquisitions (M&A)

Most empirical studies on FDI, especially in political science, use aggregated FDI flow and stock data made available by UNCTAD, the IMF, and the OECD (Kerner, 2014). Depending on the level of analysis, these data sources can provide valuable insights into the determinants or the effects of FDI. However, due to the aggregation level, it is not possible to investigate any firm-level differences. To account for this problem, we use firm-level data on cross-border mergers and acquisitions (M&As) to measure FDI. This data comes from Thomson Reuters's (2020b) Mergers and Acquisitions Database. With over one million data entries, covering worldwide M&As since the 1970s, this source allows us to compare investment strategies of firms between country-pairs as well as across time. The information available for the deals varies (e.g., the volume of the deal or other specifics), but the most important variables for our analysis are provided for each deal: The acquirer (i.e. the firm investing abroad), the headquarter country of the acquirer,

[1] Table D.3 in the appendix reports the countries included among their number of firms, deals, partner countries, and PTAs signed.

its target firm, and the home country of its target firm. Detailed industry classifications are also included for both the acquirer and the target firm. Although this data follows the TRBC (Thomson Reuters Business Classification) framework, which is not widely used, we can rely on (Anderer et al., 2020) for a crosswalk between TRBC and six-digit NAICS (North American Industry Classification) codes. The data set covers acquirer firms in 438 different industries, from Iron Ore Mining to Computer Programming Services.[2]

Since we are not interested in the specific target firm of a deal, we sum up all M&As of an acquirer firm per partner country and year. We end up with the number of deals (*Deals*) by firm k headquartered in country i, done in a certain partner country j (i.e., target country) in year t. It shows, that firms headquartered in the US, the UK, Canada, Germany, France, the Netherlands, Hong Kong, and Japan are among the most active when it comes down to international investment activities.

4.3.2 Explanatory Variable: IPR protection in PTAs

Our measure of PTAs' IPR protection builds on Dür et al.'s (2014) Design of Trade Agreements (DESTA) database which identifies 620 signed PTAs with 515 available full-texts for the period of observation.[3] We then pre-process available PTA texts to ensure machine-readability,[4] manually identify sections devoted to IPRs and tag these sections for text extraction. To proxy a PTAs' IPR comprehensiveness, we rely on a dictionary-based approach.

Our IPR protection measure draws on Abbott et al.'s (2000) framework that distinguishes the degree of legalization of international institutions in three dimensions. First, obligation refers to provisions' bindingness. Second, precision means provisions' elaborateness. Third, delegation

[2]One shortcoming of this data source is its focus on M&As, which means that we lose another relevant form of FDI – namely greenfield investments. This type of FDI is typically designed to hold a high level of control over foreign business operations, which means that greenfield investments are attractive in cases when arm's-length trade is not an option for the investor. Since we are mostly interested in what drives the decision between FDI and independent trade, the exclusion of cases where one of these options was probably not even available, should not be too problematic for our analysis. It is, however, important to keep in mind that our findings only tell us something about M&A-investment decisions, not all forms of FDI.

[3]Table D.4 in the appendix reports the PTAs included, their signature years and whether they cover IPRs.

[4]Preparative measures include conversion to single-column format and to PDF-file type, text translation to English, and the removal of symbols, numbers and stop-words.

[5]This includes 32 dichotomous variables capturing whether central multilateral IPR-related treaties are referenced in a PTA. Table D.1 in the appendix provides a list with the treaties.

Table 4.1: Dictionary of the three Dimensions of Legalization

Obligation	**Precision**	**Delegation**
Commitment	Compulsory licensing	Administrative authority
Compliance	Conferred rights	Agency
Dispute settlement	Copyrights	Assembly
Enforcement	Counterfeiting/infringements	Chairman
Exceptions	Definitions	Commission
Implementation	Geographical indications	Committee
Most-favoured nation	Health/pharmaceutics	Consultation
National treatment	Industrial designs	Council
Penalty	Patents	Court
Remedies	Phyto-/sanitary measures	Delegation
Sanctions	Plant variety	Experts
Transitions	Procedural matters	File
Transparency	Public awareness	Joint body
TRIPS agreement	Television/broadcasting	Monitor
Violations	Topographies	Representative
Cites of other IPR-treaties[5]	Trademarks	Secretariat
	Traditional knowledge	
	Undisclosed information	
	Utility models	
	Word count of IPR section	
	Occurrences of IPR	

captures authority transfers. PTAs vary in these dimensions, ranging from low legalization in non-binding treaties without enforcement and authority transfers, to high legalization in precise, binding, and enforceable treaties with third party authorities (Abbott et al., 2000, p. 19f). We apply this framework to the realm of IPRs and use the dictionary on the text corpus of PTAs' IPR sections to generate our measure of IPR protection in a PTA. For this, we match the inductively identified IPR-related keywords[6] of Table 4.1 to the IPR sections of PTAs which results in 80 dichotomous variables, where a variable is one if a certain keyword appears, and zero otherwise. Additionally, two dichotomous variables capture whether a PTA's IPR section length is above the sample mean and whether a PTA refers to IPRs in its full agreement text more often than the sample mean, for which in both cases these two variables take up a value of one, and zero otherwise.[7] This additional step controls for and privileges PTAs with longer IPR sections and those that frequently refer to IPRs in the treaty text. Our reasoning behind this dictionary approach is that a PTA's IPR section that includes more (less) keywords of Table 4.1,

[6]Keywords are identified by content analyses of the WTO TRIPS agreement, IPR treaties of the World Intellectual Property Organization (WIPO), as well as PTAs of our sample.

[7]An equation outlining these steps is given in Equation (1 in the appendix.

is longer (shorter), and refers to IPRs more (less) frequently, is in sum more (less) protective of IPRs. This leaves us with an additive index classifying a PTA's IPR protection in the variable *IPR Strength (max)* which enables us to differentiate between weaker and stronger IPRs.

Several country-pairs signed multiple PTAs with each other over time, sometimes with varying IPR provisions, and therefore score different values in our IPR-index. To accurately estimate the level of IPR protection between two partner countries that are members to multiple trade agreements, we create the variable *IPR Strength (max)*, which captures the highest IPR-index value of a PTA between a country-pair in year *t-1*. Relying on the maximum is reasonable because in the case where the same country-pair is a member of multiple PTAs over time, first, more recent PTAs are expected to be more influential for current trade flows, second, tend to include more comprehensive IPRs, and third should also matter most for firms' investment decisions, as deeper commitments, also in IPRs, are found to be more influential.

Our semi-computationally generated IPR-index in *IPR Strength (max)* validly proxies IPR protection in PTAs as it is highly correlated with manually coded IPR data in Dür et al. (2014) and Morin and Surbeck (2020) with a Pearson's r between 0.80 and 0.89. This high correlation indeed shows that our index captures the same underlying dimensions. One major caveat with our approach is that an inductively-generated dictionary is never complete, as it cannot account for all possible ways of wording and formulations, nor for individual time and space contexts. Also, this measure cannot make statements about "real-world" state-behaviour and compliance. However, this semi-computational dictionary approach is cost-efficient and easily extendible, while offering flexibility to deal with varying text structures and wording. With its independence of coders' judgements, our approach is reliable and reproducible, yielding a non-biased IPR measure that is on top highly correlated to manually coded data.

4.3.3 Interaction: Innovativeness

Capturing innovativeness is a complex task – innovative firms tend to spend more on research and development (R&D), file more patents, apply for or use other means of IPR protection such as copyrights and trademarks, and are therefore most affected by provisions protecting intellectual property. Analyzing the varying consequences of (in)adequate IPR protection in a PTA with a trading partner by accounting for differences in firms' innovativeness therefore seems plausible and promising.

Patents, a key form of IPR protection, is a widespread measure of innovativeness (Chen and Puttitanun, 2005; Cohen et al., 2000; Ivus et al., 2015; Perelman, 2003). One pitfall of patents as innovativeness proxy is said to be that some patents are more valuable than others, as the number of patents does not say much about their worth and that patenting is more common in certain industries than others (Blank and Kappos, 2012, p. 33). Other frequently used proxies for innovativeness include R&D spending (Branstetter et al., 2006; Osgood and Feng, 2018), tertiary education rate (Zhao, 2006), and skill- and knowledge-intensive exports (Mehlig-Sweet and Eterovic-Maggio, 2015). However, most of these other proxies are either not readily available in temporal and spatial dimensions needed for our analysis, are rather highly aggregated, or – in the case of R&D expenditures – are to a large part conducted by government agencies rendering them impractical for our analysis. Therefore, and because today (multinational) corporations are by far the main applicants for and owners of patents (Perelman, 2003), we rely on registered patents by firms, a highly disaggregated measure of innovativeness, that operates on the output-side of innovative activities.

Since our argument is based on the firm-level, any country- or industry-level data on registered patents – which are widely used in the literature – would not be sufficiently disaggregated to test our expectations. Fortunately, the European Patent Office (EPO) (2020) provides access to firm-level data via their Open Patent Services (OPS) database. OPS data are extracted from the EPO's worldwide full-text databases, which cover information on patents by firms from more than 80 different countries, updated weekly. Although the EPO provides a search function on their website, retrieving data on more than eighty thousand firms for each year would be a tedious and time-consuming task. Therefore, we access the patent data via EPO's API server, utilizing a Python client developed by Song (2020) for interacting with this specific database.

For the 57,394 unique firms in our sample, we are able to collect information on over sixteen million registered patents between 1990 and 2018. Among the countries with the overall most registered patents in our sample's time span are Japan, the US, several European Union countries, and South Korea, which are also said to be the world's most innovative economies (Osgood and Feng, 2018). To measure the innovativeness of a firm, we use the number of patents registered at the EPO. The variable *Patents (CS5)* is the rolling cumulative sum of registered patents in the last five years. This operationalization allows us to capture long-term innovativeness (e.g., firms that continually register patents over a longer period of time) as well as short-term activities (e.g., firms registering a lot of patents over a shorter time span). In robustness checks, we rely on alternative operationalizations of a firm's innovativeness also building on data of firm patents registered at the EPO. The variable *Patents (CS)* is the cumulative sum of registered patents since 1990 and *Patents (new)* represents the number of new patents, both in year *t-1*. Our innovativeness proxy adequately mirrors real-world observations as it highlights firms in economies such as Japan, the US, the Netherlands, Germany, Sweden, Korea, and the UK as the world's most innovative.

4.3.4 Control Variables

As our argument operates on multiple levels, these different levels have to be accounted for when selecting control variables as well. For this, we include control variables capturing effects on the country-, the PTA-, and the firm-level.

Additional country-level control variables that existing scholarship identified as influential for firms' investment decisions include a partner country's gross domestic product (GDP) (The World Bank, 2020) as an indicator for a country's market size and power in *Partner GDP*, GDP per capita (The World Bank, 2020) as a measure for economic development and purchasing power in *Partner GDPpc*, a partner country's regime type proxied with its Polity IV score (Marshall et al., 2018), capturing the effects of (un)democratic governance in the variable *Partner Democracy*, WTO membership (*WTO Members*), and the distance between their capitals (Simplemaps, 2019) in the variable *Distance (km)*.[8] Building on previous findings, we expect

[8]Distance in kilometres is calculated as the Haversine distance between a country-pairs' capital cities.

positive effects for a partner country's market size and economic development (Bergstrand and Egger, 2007), democratic regime (Jensen, 2003; Li et al., 2018), and shared WTO membership (Büthe and Milner, 2008; Dreher et al., 2015) on M&A deals and a negative effect for distance (Bergstrand and Egger, 2007).

On the PTA-level, we account for the effects of other PTA design features identified as influential for international trade, for which we again rely on Dür et al.'s (2014) DESTA database. We control for the overall depth of trade agreements between our acquirer firm-partner country pairs with (*PTA Depth*), which captures the existence of provisions regarding services, investments, procurement, competition, technical barriers to trade, sanitary and phytosanitary standards and dispute settlement mechanisms in a PTA. In order to properly estimate the effect of IPR provisions themselves, we create a dichotomous variable for each of these other important PTA design features that is one if a specific provision is included in a PTA, and zero otherwise. We then aggregate these resulting variables to our depth measure by taking their sum. Again, we follow the same strategy as with our IPR-index: We use the maximum value of depth variable, in order to deal with dyads that signed more than one trade agreement following the same logic as stated above, whereas deeper commitments should outdo shallower ones.

Several firm-level variables have been shown to matter for a firm's investment decisions, as they vary considerably in their industrial sector, size, productivity, capital, and skill intensity (Bernard et al., 2012). We include three different variables to measure firm size and productivity: *Total Revenue*, a firm's earnings before interest and taxes (*EBIT*), and the number of full-time personnel (*Employees (No.)*), each one in year *t-1*. This data come from Thomson Reuters's (2020a) Refinitiv Eikon Database. Unfortunately, data coverage on M&As is more comprehensive than these firm-level control variables. We only have access to firm data for roughly fifteen thousand companies in our sample, with most data being available for *EBIT*. Therefore, we estimate our regression models with and without these firm-level controls separately in order to check whether the loss of a considerable amount of observations due to limited data availability affects our findings.

Table 4.2 reports the descriptive statistics of our response variable, the explanatory variables and the controls. Our dependent variable *Deals* reports the number of M&A deals a firm k headquartered in country i has done in a partner country j in year t and is a count variable. The main independent variable *IPR Strength (max)* ranges from zero, for PTAs with no IPR provisions to 65, for a PTA with most stringent IPRs. PTAs ranking high on our IPR-index comprise the Comprehensive and Progressive Agreement for Transpacific Partnership (CPTPP), the US Mexico Canada Agreement (USMCA), agreements between the European Union on the one hand and Japan or Colombia and Peru on the other, and the US Korea PTA. These PTAs are also identified by the literature as being very deep and comprehensive agreements, also in regards to IPRs, with the most innovative economies as signatory parties (Morin and Surbeck, 2020; Rodrik, 2018). *PTA Depth* accounts for other design features of trade agreements and ranks them on a scale from zero to six, with six meaning very deep agreements.

Table 4.2: Descriptive Statistics

	N	Mean	St. Dev.	Min	Max
Deals	2,366,432	0.05	0.25	0	23
IPR Strength (max)	2,366,432	32.32	21.82	0	65
Patents (CS5)	2,366,432	121.05	2,283.93	0	179,810
PTA Depth	2,366,432	4.74	1.77	0	6
Total Revenue	471,050	394.39	4,589.68	−6,028.50	243,771.40
EBIT	487,031	35.61	674.65	−6,485.57	58,886.67
Employees (No.)	530,048	32,311.69	79,745.91	1.00	2,200,000.00
Partner GDP	2,364,141	1,899.71	3,463.42	0.04	20,529.00
Partner GDPpc	2,364,141	27.81	19.20	0.06	178.85
Partner Democracy	2,363,271	7.82	4.74	−10.00	10.00
WTO Members	2,366,432	0.94	0.23	0	1
Distance (km)	2,366,432	3,224.11	4,111.44	9	19,451

Total Revenue is measured in billions of US-Dollars. The same applies to *EBIT*, which measures earnings before interest and taxes. A negative value in both total revenue and EBIT means that a firm's expenses exceeded its earnings. *Employees (No.)* again is a count variable that proxies firm size via its full-time personnel. *Partner GDP* captures a trading partner's market size and is again scaled in billions of US-Dollars. *Partner GDPpc* is measured in thousands of US-Dollars. In order to account for both variables' distributions, we use the logged values in forthcoming estimations. *Partner Democracy* captures regime type, where -10 refers to most autocratic and 10 to most democratic regime. *WTO Members* is one if both countries in a pair are WTO members and zero otherwise. However, its high mean close to one shows that most countries in our observational period are indeed already members of the WTO. *Distance (km)* is the "as the bird flies"-distance between a country-pair's capitals.[9]

4.3.5 Model Specifications

We rely on negative binomial regressions to account for our over-dispersed dependent variable with count nature (Long, 1997, p. 230). This model has the same mean structure as a Poisson regression, but with extra parameters to model the over-dispersion of our response variable *Deals*, meaning a variable where the conditional variance exceeds its conditional mean (Venables and Ripley, 2002). Depending on the model, we also include fixed effects for year, headquarter, and partner country to control for endogeneity, unobserved variable bias, and temporal trends (Allison and Waterman, 2002). We specify several different models. At the first stage, we only include country-level and PTA-level control variables. Afterwards, we also add control variables operating at the firm-level. The reason for this strategy is that we lose a considerable amount of observations by including various firm-level control variables, such as firm size, due to limited data availability. Therefore, we estimate separate models with these smaller samples.

Moreover, to further assess the robustness of the findings of the baseline models, we specify more restrictive alternative negative binomial regression models, this time with headquarter country-year, partner country-year, and dyad fixed effects. Employing this approach leads to a dropping out of several partner country specific and time-invariant control variables as they are then absorbed by the newly included fixed effects. All of our models are estimated using R's "*alpaca*" package (Stammann and Czarnowske, 2020), which is suitable for estimating negative binomial regressions with a high number of observations while including several fixed effects into the analyses. To get robust estimates of the significance levels, we cluster the standard errors in all of the models on the firm-level in order to account for (intra) group-level correlations

[9] Correlations between our main variables are reported in Table D.5 in the appendix.

and common unobserved factors within individual groups on the most fine-grained level (Abadie et al., 2017; Petersen, 2008).

4.4 Findings

We estimate different models in order to assess our theoretical expectations, with the main models in Table 4.3 focusing on the country-level variables, including our proposed interaction effect, and Table 4.4 adding firm-level controls.[10]

Model 1 in Table 4.3 can be seen as a baseline model to establish whether PTA depth has, as argued in the literature, a positive effect on FDI. This is the case – we estimate a rather restrictive model with most of our control variables, as well as fixed effects for headquarter country, partner country and year. This specification yields a positive and significant coefficient for *PTA Depth*, meaning that deeper agreements indeed increase investments between signatory states. We see that, also in line with the literature, deeper PTAs increase investment activities of firms in the PTA partner countries. This finding holds across all other models and seems quite robust. Additionally, besides a partner country's GDP per capita, our controls behave as expected in Model 1. *Partner GDP (log.)*, *Partner Democracy*, and *WTO Members* all yield a positive and statistically highly significant coefficient, indicating that a larger market, more democratic governance, and common WTO membership increase deals done by firms in a PTA partner country. As expected, *Distance (km)* is negative and highly significant, meaning that fewer deals are done when the distance between a firm's headquarter country and its partner country is larger. The effect size, however, appears to be very small. Economic development as in *Partner GDPpc (log.)* shows a negative significant coefficient, which was not initially expected. However, depending on the purpose of investments, lower economic development might also mean lower wage-levels and thus more prospects for vertical or resource-seeking investments, i.e. cheaper labour. In sum, the findings of the baseline specification appear plausible and are

[10]See Table D.7, Table D.8, and Table D.9 in the appendix for the same full models as reported in the main table with included firm-level controls.

Table 4.3: Negative Binomial Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)
IPR Strength (max)		$-0.001^{\dagger}$	-0.001	0.002^{***}	-0.004^{***}	-0.005^{***}
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Patents (CS5)			0.000^{*}	0.000^{***}	0.000^{***}	0.000^{***}
			(0.000)	(0.000)	(0.000)	(0.000)
PTA Depth	0.014^{***}	0.069^{***}	0.069^{***}	0.033^{***}	0.062^{***}	0.054^{***}
	(0.003)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
IPR Strength (max) x			-0.000^{**}	-0.000^{***}	-0.000^{*}	-0.000^{*}
Patents (CS5)			(0.000)	(0.000)	(0.000)	(0.000)
Partner GDP (log.)	1.321^{***}	0.168^{***}	0.168^{***}	0.068^{***}	1.646^{***}	1.078^{***}
	(0.081)	(0.005)	(0.005)	(0.002)	(0.069)	(0.080)
Partner GDPpc (log.)	-1.071^{***}	0.114^{***}	0.113^{***}	0.032^{***}	-1.283^{***}	-0.839^{***}
	(0.085)	(0.007)	(0.007)	(0.004)	(0.078)	(0.084)
Partner Democracy	0.034^{***}	-0.000	-0.000	-0.007^{***}	0.037^{***}	0.032^{***}
	(0.004)	(0.002)	(0.002)	(0.001)	(0.003)	(0.004)
Distance (km)	-0.000^{***}	-0.000^{***}	-0.000^{***}	0.000	-0.000^{**}	-0.000^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
WTO Members	0.919^{***}	0.932^{***}	0.932^{***}	0.915^{***}	0.890^{***}	0.863^{***}
	(0.039)	(0.032)	(0.032)	(0.030)	(0.039)	(0.040)
HQ FE	Yes	No	No	Yes	Yes	Yes
Partner FE	Yes	No	No	No	Yes	Yes
Year FE	Yes	No	No	No	No	Yes
Deviance	470113.772	484428.326	484434.750	468461.433	469043.920	470174.366
Num. obs.	2361096	2348344	2348344	2361096	2361096	2361096

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.10$; Firm-level clustered standard errors in parentheses

largely in line with our theoretical expectations and previous research.

We continue by adding a PTA's IPR comprehensiveness in *IPR Strength (max)* in Model 2, and firm innovativeness in *Patents (CS5)* as well as our interaction effect in Model 3, before then adding additional fixed effects step by step in the Models 4 to 6. The coefficient for *IPR Strength (max)* is negative and rather insignificant in the less restrictive models (Models 2 and 3), but as soon as we add headquarter country, partner country, and year fixed effects, it turns significant. Following our theoretical argument, we expect that IPR protection has an *overall* positive effect on FDI (H1), but that this effect turns negative for highly innovative firms (H2), meaning that the relationship between IPR protection and mergers and acquisitions is dependent on the firm-level characteristic of innovativeness. After analyzing our data, however, it turns out that our empirical findings point towards another direction. In Table 4.3, the coefficient for

IPR Strength (max) is only positive in Model 4, which we would have expected according to H1. All other model specifications show a negative effect, with the highest significance in our most restrictive models (Models 5 and 6). This suggests a consistent negative effect of IPR protection on investments, even if we control for innovativeness and the combined effect of innovativeness and IPR strength: comprehensive IPRs included in PTAs lead to fewer mergers & acquisitions between partner countries.

The effect of *IPR Strength (max)*, among the coefficients of other explanatory variables, may appear small at first sight. However, as can be seen in Table 4.2, our dependent variable *Deals* is distributed along a rather close range, ranging only between 0 and 23, which is responsible for the effect's size. This also applies to the baseline model and the other models specified and should be kept in mind when interpreting the findings.

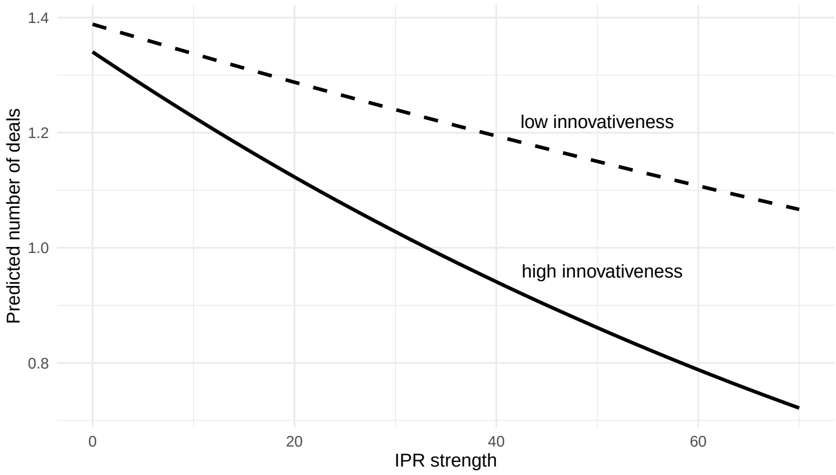
The cumulative number of patents registered in the last five years in *Patents (CS5)*, as a proxy for firm innovativeness, has a positive effect on M&A deals with statistical significance levels ranging from low (Model 3) to high (Models 4, 5, 6). As follows, innovative firms indeed engage more internationally and are more active in regards to M&A deals in their PTA partner countries. In our theoretical section, we mention that a positive effect could indicate that patents can also be seen as a proxy for firm productivity –- which has been shown to affect internationalization strategies. More productive companies can export, trade, and invest more. It is only in combination with IPR strength that this effect should turn negative for innovative economies. This is exactly what the inclusion of the interaction term aims at. Our interaction term, *IPR Strength (max) x Patents (CS5)* is negative and (at times moderately or highly) significant across all specifications displayed in Table 4.3. This is in line with H2, where we argue that stronger IPR protection leads to less investments from innovative firms. A significant and negative coefficient in the interaction term between *IPR Strength (max)* and *Patents (CS5)* indicates that indeed strong IPR provisions included in PTAs decrease M&A deals done by highly innovative firms, meaning those with a high number of registered patents. Again, however, the effect sizes are rather small.

Our second hypothesis captures the idea that firm-level differences account for some variance in the impact of IPR protection on investment deals. We expected our interaction term *IPR Strength (max) x Patents (CS5)* to be negative, which turns out to be the case in all of our model specifications. Given the relatively consistent negative effect of IPR protection on FDI, the coefficients of the interaction term are not surprising. We expected innovativeness to change the direction of the relationship between IPR protection and M&As. Instead, we found that IPR protection alone is already decreasing investment flows, even if we control for the role of innovativeness, as well as the combined effect of IPR protection and patents. Interpreting interaction effects (especially with continuous variables) can be tricky. In order to make it more accessible, Figure 4.1 plots the effect of IPR protection on the predicted number of deals for two different innovativeness-levels[11], based on the specification of Model 5 in Table 4.3. It shows that both types of firms react to stronger IPR protection with fewer investments, but the effect is slightly stronger for more innovative firms. Moving from the smallest IPR strength value to the highest (from zero to 65) decreases the predicted number of investment deals per firm and year by 0.62 for highly innovative firms, and only by 0.32 for less innovative ones. This partly supports our second hypothesis, but since the difference is quite small, it is a lot less definitive than we expected.

The coefficients for our controls behave largely as expected, yet some vary over our specifications. *Partner GDP* (as a proxy for market size) has a consistent positive and significant effect on deals. Therefore, firms prefer to invest in PTA partner countries with larger markets. *Partner GDPpc* (a proxy for economic development, and therefore also, to a degree, for wage levels) and *Partner Democracy* (as an indicator for political regime) vary following the same pattern: Where the level of development has a negative effect, democracy has a positive one, and vice versa. In our most restrictive models (Models 5 and 6) democracy is positively associated with M&A deals (which is consistent with the literature), and *Partner GDPpc* has a negative effect. This could mean that investments are more attractive in countries with lower wage levels,

[11] The cut-off point between low and high innovativeness is the mean of the variable Patents (CS5).

Figure 4.1: Predicted number of deals for different innovativeness-levels



which would especially make sense for vertical investments, where cheap production costs play an important role for investment decisions. *WTO Members* is always positive and significant, as expected. With one insignificant exception (Model 4), *Distance (km)* has a negative effect on deals – which is also consistent with our expectations.

We continue by adding our firm-level control variables in additional models displayed in Table 4.4.[12] Since we lose a lot of observations in these models mainly due to limited data availability for the variables *Total Revenue*, *EBIT* and *Employees (No.)*, we decided to estimate these coefficients separately and not include them in the main models presented above. Firm size, either measured as *Total Revenue*, *EBIT*, or as number of full-time personnel in *Employees (No.)*, always has a positive significant effect on the number of M&A deals. This is also consistent with the literature, where bigger firms are much more inclined to trade and invest internationally.

The variable *PTA Depth* stays positive and significant in all models in Table 4.4, even when we control for firm size in various ways. *IPR Strength (max)* is consistently negative and significant across all specifications, which is largely also in line with our first round of analyses in Table 4.3. Together, these findings mean that our first hypothesis is not supported, also when we include firm-level control variables. When controlling for firm size, IPR strength always

[12]See Table D.7, Table D.8, and Table D.9 in the appendix for the full models, with largely the same findings.

Table 4.4: Negative Binomial Regression Results (including firm-level controls)

	(7)	(8)	(9)
IPR Strength (max)	-0.006^{***}	-0.006^{***}	-0.006^{***}
	(0.001)	(0.001)	(0.001)
Patents (CS5)	$0.000^{\dagger}$	$0.000^{\dagger}$	$0.000^{\dagger}$
	(0.000)	(0.000)	(0.000)
PTA Depth	0.049^{***}	0.069^{***}	0.048^{***}
	(0.008)	(0.010)	(0.008)
IPR Strength (max) x Patents (CS5)	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
EBIT	0.000^{***}		
	(0.000)		
Employees (No.)		0.000^{***}	
		(0.000)	
Total Revenue			0.000^{***}
			(0.000)
Partner GDP (log.)	1.473^{***}	1.628^{***}	1.486^{***}
	(0.160)	(0.174)	(0.165)
Partner GDPpc (log.)	-1.373^{***}	-1.490^{***}	-1.388^{***}
	(0.166)	(0.181)	(0.172)
Partner Democracy	$0.012^{\dagger}$	0.024^{***}	0.010
	(0.006)	(0.006)	(0.006)
Distance (km)	-0.000^{***}	-0.000^{***}	-0.000^{***}
	(0.000)	(0.000)	(0.000)
WTO Members	0.274^{***}	0.552^{***}	0.262^{***}
	(0.073)	(0.073)	(0.077)
HQ FE	Yes	Yes	Yes
Partner FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Deviance	139878.895	116378.473	135895.617
Num. obs.	486017	528975	470081

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.10$; Firm-level clustered standard errors in parentheses

negatively affects M&A deals. *Patents (CS5)* remains positive throughout, however, its statistical significance levels drop to 90 percent once firm-level controls are included. Our interaction effect in *IPR Strength (max) x Patents (CS5)* is also always negative as in previous models, which would support H2, but this time fails to reach common statistical significance levels. The control variables largely behave as expected and are consistent with previous models. Again, a larger GDP in a PTA partner, more democratic governance, and shared membership to the WTO all lead to more investment deals. By contrast, a higher level of GDP per capita and a larger distance between the capital cities of two trading partners decrease deals done by firms.

4.4.1 Robustness Checks

In order to further assess the robustness of our findings, alternative negative binomial regression specifications are necessary.
Since certain industries tend to hold more patents than others (Blank and Kappos, 2012), we add sector-level fixed effects in our first robustness check. The data set covers acquirer firms in 438 different industries (six-digit NAICS classification), which we add in Table D.6 as fixed effects. Findings only marginally differ from our main models: PTA depth has a positive effect on deals, IPR strength a negative (and highly significant) one, and although the combined effect of IPR strength and patents is negative and significant, we also see that including it does not change the main coefficient of IPR strength. This supports the finding that innovativeness does not have a strong impact on the effect of IPR protection on investment activities.

In Table 4.5 we specify alternative models of negative binomial regressions with more restrictive fixed effects. Including these headquarter country-year, partner country-year, and dyadic country-pair fixed effects makes the inclusion of several country- and dyad-specific variables from former models, such as partner country characteristics or the distance between a country-pairs' capitals obsolete. However, for one, relying on headquarter-year, partner-year fixed effects allows to account for market-size effects and (unobserved) barriers to trade each firm in its headquarter country faces with all of its trading partners. Additionally, country-pair fixed effects account for other unobserved dyad-specific and time-invariant factors (Baltagi et al., 2017; Feenstra, 2004; Head and Mayer, 2014; Kohl, 2014). Models 11, 12, and 13 in Table 4.5 are again negative binomial regressions with clustered standard errors at the firm-level and basically the same as Model 6 reported in Table 4.3 and Models 7, 8, and 9 as reported in Table 4.4 respectively, but this time with headquarter-year, partner-year and country-pair fixed effects.

Table 4.5: Robustness Check: Negative Binomial Regressions

	(11)	(12)	(13)	(14)
IPR Strength (max)	-0.000	-0.003^{*}	-0.004^{**}	-0.003^{*}
	(0.001)	(0.001)	(0.002)	(0.001)
Patents (CS5)	0.000^{***}	0.000^{*}	0.000^{*}	0.000^{*}
	(0.000)	(0.000)	(0.000)	(0.000)
PTA Depth	-0.001	0.021	0.039^{*}	0.024
	(0.010)	(0.018)	(0.020)	(0.018)
IPR Strength (max) x Patents (CS5)	$-0.000^{\dagger}$	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
EBIT		0.000^{***}		
		(0.000)		
Employees (No.)			0.000^{***}	
			(0.000)	
Total Revenue				0.000^{***}
				(0.000)
WTO Members	$0.373^{\dagger}$	0.777	0.512	1.467^{*}
	(0.205)	(0.700)	(0.727)	(0.733)
HQ-year FE	Yes	Yes	Yes	Yes
Partner-year FE	Yes	Yes	Yes	Yes
Dyad FE	Yes	Yes	Yes	Yes
Deviance	474313.838	140895.625	117233.818	136926.649
Num. obs.	2278579	465582	487818	451587

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.10$; Firm-level clustered standard errors in parentheses

When including these fixed effects in the Models 11 to 14 in Table 4.5 and excluding partner country-level variables as well as the time-invariant distance variable, we see that, again, *IPR Strength (max)* consistently yields a negative and at most times a statistically significant coefficient. *Patents (CS5)* again is positive and significant. Similarly to the main models, the interaction term in *IPR Strength (max) x Patents (CS5)* is again negative but mostly fails to reach standard levels of statistical significance. The firm-level control variables in *EBIT*, *Employees (No.)*, and *Total Revenue* remain positive and highly statistically significant, all however with very small effect sizes. To our surprise, the formerly discovered robust positive and statistically significant effect of *PTA Depth* becomes rather volatile, is negative and insignificant in Model 11, positive and insignificant in Models 12 and 14 and only upholds statistical significance in Model 13, when including a proxy of firm size in its number of employees. Again, *WTO Members* is positive, however the coefficients statistical significance levels vary.

Further robustness checks utilize alternative variable specifications of the proxy for firms' innovativeness. Instead of the five year cumulative sum of registered patents by an individual firm, we this time rely on only newly registered patents by a firm in year *t-1* in Table D.10 and on the simple cumulative sum in Table D.11. Both tables with the models can be found in the appendix. Largely, the findings uncovered in the main models remain the same. *IPR Strength (max)* consistently yields negative and statistically highly significant coefficients. Both alternative patent measures are positive. *Patents (new)*'s coefficients are statistically highly significant, and the coefficients for *Patents (CS)* fail to reach standard significance levels. Again, *PTA Depth* is consistently positive and statistically highly significant in all models. The interaction terms for *IPR Strength (max) x Patents (new)* are again always negative, with varying statistical significance. When measuring firm innovativeness with newly registered patents, the interaction effect is negative and consistently significant. Newly registered patents seems to be a good proxy capturing the true innovative capacity of firms. All three firm-level controls remain statistically highly significant and positive with very small effect sizes. Also, the coefficients of *Partner GDP (log.)*, *Partner GDPpc (log.)*, *Partner Democracy*, *Distance (km)*, and *WTO Members* all remain substantially unaffected compared to the main models.

4.5 Conclusion

The relationship between trade agreement design and international investment flows has important implications for a large group of different actors worldwide. Despite these far-reaching real-world consequences of trade policy, and some excellent research carried out in various fields, we still do not know exactly how specific provision included in trade agreements influence economic decisions, such as where firms want to invest and how they do so.

In this paper, we have argued that the effect of trade agreements on foreign direct investments is not as straightforward as the literature might suggest. To investigate this claim, we focused on the effect of intellectual property rights provisions on mergers and acquisitions. Initially, we argued that although IPR protection might increase investment flows between partner countries (as is the case with deep PTAs in general), this effect should not be the same for all firms.

Our argument was based on the idea that innovative firms have fewer incentives to invest in another country if their intellectual property is sufficiently protected. We therefore expected an *overall* positive effect of IPR protection on investments (H1), but not for innovative firms (H2). In other words: We argued that the effect of IPR protection on investments is dependent on firm-level innovativeness.

We tested our hypotheses by employing a novel dataset on IPR provisions included in PTAs, highly disaggregated data on firms' foreign direct investments, as well as a firm-level innovativeness indicator. The empirical findings were surprising: Although the depth of a trade agreement significantly increases mergers and acquisitions between partner countries, we found that IPR protection decreases investment flows. We thought that this was only the case for innovative firms, but our findings suggest that this effect is fairly robust across different specifications. Neither introducing an interaction term, controlling for the level of innovativeness (and several other country- and firm-level variables), nor adding various fixed effects to our models changed the effect substantively. This could mean that strong IPR provisions increase the incentive to trade with independent partners in other countries, instead of investing in foreign subsidiaries. One explanation for this relationship is that strong IPR protection mitigates the risk of firms to trade at arm's-length or enter some form of joint venture or licensing agreement – which is usually far more cost-efficient than investing abroad.

These findings add to our understanding of this complex relationship. We assess the impact of IPR provisions on firm-level investment decisions, while controlling for different levels of innovativeness. Our analyses show, that although deeper PTAs do indeed boost investment flows, comprehensive IPR provisions alone have a mostly negative effect. However, certain caveats prevail with our results. We do not know whether the decrease of M&As simultaneously increases arm's-length trade with independent firms in the partner country, or simply leads to a diversion of investments to other countries. To test this hypothesis, we would need investment and trade data at the firm-level for a large country sample. This could be an interesting challenge for future research: Investigating the connection between trade and investment at the firm-level.

With our research, we were only able to capture one part of this bigger puzzle, by showing that IPR protection can decrease investment flows. Whether this means that trade flows simultaneously increase, which then basically offsets the negative effect of comprehensive IPRs, remains an open question.

In sum, our findings suggest that policy-makers can alter the incentives for MNCs' investment decisions by introducing certain provisions in PTAs. Until now, most research simply concluded that deeper PTAs lead to more investment. Our findings indeed show that this is not always the case, and that we need more research in order to better understand the complex effects of different PTA design features on firms' investment decisions.

Chapter 5

Conclusion

This dissertation addresses several questions concerning the complex interrelationships between global value chains and trade policy, while also highlighting the key role of trade preference formation in these causal relationships. In this final section of the thesis I summarize my main findings, discuss their scholarly and societal contributions, and offer some possible avenues for future research.

5.1 Main Findings

The first paper (Chapter 2) investigates the impact of global value chain participation on trade preferences of industry-level business groups. Higher participation leads to an overall increase in support for liberal trade policies. There are, however, limitations to this relationship: neither all countries nor all industries show the same pattern. In non-OECD countries and in agricultural industries, the effect is reversed. Higher GVC participation can lead to a more critical stance towards trade liberalization. These findings show that global value chains and liberal trade policies do not necessarily reinforce and intensify each other automatically. Country- and industry-level variables mediate this relationship in complex ways.

The second paper (Chapter 3) goes one step further in the causal chain, and analyzes how corporate connections between multinational firms can influence trade policy outcomes. By using firm-level information on mergers & acquisitions, as well as a highly disaggregated data set on tariff cuts, the role of private economic actors in trade policy making can be estimated on a very detailed level. Findings show that stronger connections between firms trading intermediate products lead to higher and faster tariff cuts between partner countries in the respective product category.

The third paper (Chapter 4) focuses on the reverse causal relationship by asking in which ways specific trade policy provisions can influence investment decisions - and therefore the establishment and shape of GVCs. The question whether preferential trade agreements (PTAs) have a significant impact on investment flows has been discussed in the literature extensively. Still unclear is the role of various specific trade policy provisions included in modern PTAs. This paper contributes to this open question by zeroing in on intellectual property rights, and shows that they can - in contrast to most other trade agreement provisions - decrease investment flows between partner countries.

5.2 Scholarly and Societal Contributions

This work contributes to a rapidly growing literature on the causes and consequences of GVCs, both theoretically and empirically. Existing research on trade preferences in a GVC-context mostly deals with firms or governments, neglecting some other crucial trade policy actors. With the focus on business groups, this thesis starts to fill this gap and shows some interesting variation - building the foundation for future research in this area. Another theoretical contribution comes from the findings showing that not all trade policy provisions boost investment flows - which goes against most established theories about the impact of trade agreements.

The most important advancements in this thesis are based on novel ways of collecting and measuring the key variables. To the best of my knowledge, this is the first attempt to capture trade preferences of interest groups via social media sources, utilizing machine learning techniques to deal with large amounts of text data. This approach is neither limited to trade policy issues, nor to interest groups. Many different research agendas in the social sciences could benefit from this rich data source - and some already do so. My work can serve as a template or starting point for a wide range of different research fields, looking for a new way of collecting data and measuring opinions, attitudes, networks, communication frames, and many other potentially interesting variables.

Outside of academia, this work can be relevant for several different groups of actors: policymakers, trade unions, private enterprises, NGOs, and parts of the general public. Policymakers can benefit from a clear understanding of the impact of certain PTA provisions on the behavior of multinational corporations, especially when negotiating new PTAs. The distributional consequences of GVCs discussed in this thesis can be relevant as well, for example when it comes to compensations: knowing who wins and who loses from trade liberalization in a ”GVC world” can guide specific policy decisions. This topic can also be interesting for trade unions, representing workers in both groups - winners and losers. Private businesses can learn something about their (potential) allies in lobbying efforts for their preferred trade policy outcomes. The findings in this thesis (and related research) can also help to distinguish between relevant and non-relevant issues in (future) trade agreements: knowing which provisions might impact the costs and benefits of your business decisions can be valuable information. The relevance of this thesis for NGOs depends on their respective focus: environmental groups could be interested in the influence of MNCs on trade policy (especially when this influence is in conflict with environmental concerns) or in the potential of PTAs to change the behavior of big corporations. NGOs focused on international development might also benefit from a clearer understanding of how trade policy influences business decisions - either because attracting foreign investments is part of a development strategy, or because they promote domestic entrepreneurs over foreign ones. In both cases, information about the impact of specific trade policy provisions is vital. Even though international trade policy is traditionally not the most salient topic in the general public, several recent developments have sparked some interest. The politicization of trade agreements (above all TTIP) has lead to broad discussions about international trade and the power of multinational corporations. Although often unfounded, some arguments of anti-globalization activists influenced public opinion and lead to a certain degree of globalization backlash. The serious disruptions of global supply chains during the COVID-19 pandemic also contributed to this development: topics like reshoring and local sourcing are discussed, often in relation to environmentally sustainable production processes. Knowing how GVCs influence trade preferences and policy, as well as how trade policy can shape GVCs, should be relevant for people interested in these broader debates about how we want to organize our global economic interdependencies.

5.3 Future Research

In this thesis I focused on very specific aspects of the interrelationships between GVCs and trade policy. This strategy comes with several advantages, but has also its caveats. On the one hand, I was able to trace particular steps in the causal chain between the main concepts of my research agenda. On the other hand, this approach inevitably leaves out many other potentially important factors. I will discuss some of these shortcomings in this very last section of the thesis, and provide ideas for future research to address them.

Global Value Chains are a complex concept. Operationalizing GVCs will therefore inevitably omit some potentially important dimension of the phenomenon. Although I approached this task from several different angles (using industry-level MNC activities and backward participation indices, as well as firm-level investment data), I was by far not able to cover every aspect of GVCs. Apart from more unconventional ways of measuring global interdependencies (which I will leave to more creative researchers), I can think of two specific ways of improving my approach to operationalizing GVCs. First, both the TiVA and the AMNE database provided by the OECD offer many more indicators than have been used in this dissertation. Depending on the research goal, other variables than I have used could provide valuable insights. Secondly, the firm-level investment data used in two of the three papers only covers parts of FDI flows, namely mergers and acquisitions. Including greenfield investments as well would capture the concept of FDI flows in its entirety, while also allowing for possible variation between different forms of investments. Specific trade agreement provisions might have an effect on mergers and acquisitions, but not on greenfield investments (or vice versa), for example. It might also be the case that one type of FDI flows matters more for trade policy makers and therefore has more influence on policy decisions. These are only some examples of the many more research questions that could be addressed with alternative or additional operationalizations of the GVC concept.

Another way of improving on the research carried out in this thesis could be to expand the scope of actors involved. The GVC-related literature covering firms' interests and influence is growing rapidly. This thesis adds to this development by including interest groups representing these firms. But there are several other actors who might be influenced by different degrees of GVC participation: NGOs, trade unions, consumers groups, political parties, and so on. Given that these groups not only vary in their positions, but also in their ability to mobilize and influence policy makers (De Bièvre and Eckhardt, 2011), broadening the sample and including different types of groups might prove interesting for various research agendas.

As mentioned several times in this thesis, modern trade agreements include many different provisions - some targeted directly at trade flows (e.g. tariffs), some more indirectly (e.g. intellectual property rights), and others concerning non-trade issues. The papers in this dissertation only cover a small part of this large scope of most PTAs currently in effect. One promising avenue for future research could therefore be to take a closer look at some other - previously neglected - provisions, both as an explanatory variable and as a dependent one. Which provisions have the potential to shape GVCs? Do multinational corporations care about non-trade issues? How are their cross-border linkages influencing the design of trade agreements?

International political economy research mostly focuses on industrialized countries. We know much more about the US and other OECD countries than we do about emerging or developing economies. This dissertation is no exception. Even though I tried to cover as many countries as possible, my research is mostly based on the industrialized world. My findings including the few non-OECD countries suggest that GVC participation does not affect all economies equally - it might be the case, that global value chains influence trade preferences and policies differently depending on the level of industrialization. To test this hypothesis, research with a more divers country sample is needed. Limitations arise from data availability issues (many GVC measures cover mostly OECD countries), which could be addressed by finding new ways of capturing GVC integration on the industry- and/or firm-level. Though not an easy task, including developing and emerging economies in this area of research could allow us to refine our theories and test their external validity beyond the industrialized world.

On a more technical level, I see much room for improvement in the selection and classification of trade-related tweets. Researchers could, for example, train an algorithm to detect whether a tweet is trade-related or not. I only used a list of keywords, which produces more noise than a well trained algorithm. Additionally, a more detailed classification (expanding the three categories *critical, neutral, positive*) would allow for a much more nuanced analysis of trade preferences. This would also open up opportunities to address research questions going beyond the simple distinction between preferences for free trade vs. protectionism.

Lastly, the COVID-19 pandemic probably impacts most research questions related to the interrelationship between GVCs and trade policy. The crisis disrupted global trade and sparked discussions about shorter supply chains and self-sufficiency. It is plausible to assume that both the influence of GVCs on trade preferences/policies as well as the creation and shape of GVCs are impacted by the pandemic. One finding in chapter 2 already points in this direction: Whereas in the whole sample, GVC participation lead to more support for liberal trade policy, tweets from 2020 do not match this pattern. Whether this is part of a long-term shift towards more skepticism concerning trade liberalization or only a temporary reaction to the crisis, is one of the many promising questions for future research in this area.

To sum up, the research on the interrelationship between GVCs and trade policy is far from finished. Future research could expand on the way we measure global value chains, focus on different trade policy provisions, include new actors and zero in on the power dynamics between them, expand the country sample, improve the data collection process, and look at all these relationships through a new lens: GVCs in a post-COVID world. This dissertation adds to our understanding of the complex links between global value chains and trade policy. At the same time, it shows that many questions are left unanswered or have not even been asked yet. I wish the best of luck to future researchers addressing these gaps.

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Appendix A

Appendix for Chapter 1

Table A.1: Industry Classifications

OECD TiVA classification	Label	groups (OECD)	groups (non OECD)	groups all
D01T03	Agriculture, forestry and fishing	165	30	195
D05T06	Mining and extraction of energy producing products	57	33	90
D07T08	Mining and quarrying of non-energy producing products	2	0	2
D09	Mining support service activities	0	0	0
D10T12	Food products, beverages and tobacco	95	24	119
D13T15	Textiles, wearing apparel, leather and related products	33	7	40
D16	Wood and products of wood and cork	38	3	41
D17T18	Paper products and printing	24	4	28
D19	Coke and refined petroleum products	5	2	7
D20T21	Chemicals and pharmaceutical products	49	8	57
D22	Rubber and plastic products	21	2	23
D23	Other non-metallic mineral products	4	0	4
D24	Basic metals	4	1	5
D25	Fabricated metal products	33	4	37
D26	Computer, electronic and optical products	39	4	43
D27	Electrical equipment	1	1	2
D28	Machinery and equipment, nec	22	6	28
D29	Motor vehicles, trailers and semi-trailers	20	5	25
D30	Other transport equipment	5	0	5
D31T33	Other manufacturing; repair and installation of machinery	3	0	3
D35T39	Electricity, gas, water supply, sewerage, waste	69	7	76
D41T43	Construction	38	3	41
D45T47	Wholesale and retail trade; repair of motor vehicles	66	3	69
D49T53	Transportation and storage	27	1	28
D55T56	Accommodation and food services	2	0	2
D58T60	Publishing, audiovisual and broadcasting activities	5	1	6
D61	Telecommunications	8	1	9
D62T63	IT and other information services	8	0	8
D64T66	Financial and insurance activities	30	2	32
D68	Real estate activities	0	0	0
D69T82	Other business sector services	9	0	9
D84	Public admin. and defence; compulsory social security	3	0	3
D85	Education	0	0	0
D86T88	Human health and social work	13	0	13
D90T96	Arts, entertainment, recreation and other service activities	21	0	21
D97T98	Private households with employed persons	0	0	0

NOTE: Aggregated industries have been removed

Appendix B

Appendix for Chapter 2

Working with Social Media Data

This section covers some additional information about the dependent variable. Both the data collection process and the machine learning part (supervised sentiment analysis) are explained.

Collecting Tweets

With a list of screen names or IDs as input, Twitter enables registered users to collect the newest 3,200 tweets from each user through their REST-API. Repeating the process increases this number as soon as there are newer tweets available. For the 1,341 active users in the sample, four separate request between February 2020 and January 2021 resulted in more than one million unique tweets. The mean number of tweets per user is over two thousand (with a median of almost three thousand), which shows a relatively high level of activity in the sample. The oldest tweet in the sample was written in 2009, and the newest in 2021, with a majority of tweets having been posted between September 2017 and August 2020. Due to the download restriction (a maximum of 3,200 tweets per user), the data contains a larger time span for less active users.

To extract only those tweets related to international trade policy, several keywords and their equivalents in all languages present in the data have been collected. Determining relevant keywords was an incremental process – the goal was to include as many trade-related tweets as possible, but without too much irrelevant noise (e.g. tweets about online *trading* or about the national retail *trade* in a country). The result are two lists of keywords: one includes a rather broad variety of possible terms (single words, short phrases, names of important trade agreements, etc.), whereas the second one is used to narrow the sample down again and filter out a majority of non-relevant posts.

Keywords to find trade-related tweets include terms like *exports*, *imports*, *trade*, *protectionism*, *isds*, or *tariffs* (and their possible variations, like *exporting*, etc.). Specific trade agreements like *ceta*, *ttip*, *mercosur*, or *nafta* as well as hashtags like *#farmers4ttp* or *#tradematters* are also part of the list. In total, 218 keywords are used to extract potentially trade-related texts. In a next step, the sample is narrowed down again, filtering out irrelevant tweets dealing with *collective bargaining*, *e-commerce*, *online trading*, and other topics falsely included in the trade-category. This list has been established inductively, after several rounds of filtering.

This approach resulted in 95,600 trade-related tweets. Roughly one third is not written in English – dropping these tweets would obviously result in a strong bias. Therefore, all non-english tweets are automatically translated using the Yandex.Translate-API[1] and a corresponding R-package (Chaware, 2016).

Classifying Tweets: Supervised Sentiment Analysis

Data downloaded from the Twitter REST-API comes in a clean format with one tweet per row. Many different additional variables are included (number of followers, device from which the tweet was posted, etc.), but the most important variables for this analysis are status- and user-id (or screen name), date, and text. After deleting all non-necessary data, the next step is to specify the coding units. It would be possible to code each sentence independently (Krippendorff, 2018, p. 372) – sentences as coding units are usually efficient and reliable (Rudkowsky et al., 2018) – but since tweets often consist of fragments and shortened version of full sentences, this does not seem like a feasible strategy. Therefore whole tweets will be the coding units.

[1] Compared to other services, e.g. the Google Translate API, Yandex offered more free requests and had an easy application process. I cross-checked a random sample of translated text and found no substantive difference in the quality of the translation. Given that google translate has been shown to provide unbiased results for quantitative text analysis (De Vries et al., 2018), this comparable service should work adequately as well.

For a supervised sentiment analysis to work well, a clearly coded set, which is used to train the machine learning algorithm, is needed. Since this set does not necessarily have to be a representative sample of the population (Ceron et al., 2014), there are no clear restrictions on selecting tweets to hand-code. Therefore, a random sample of 7,500 individual tweets has been picked and coded into the three categories *positive*, *neutral*, and *critical*. Out of the tweets picked for hand-coding, roughly 95 percent are trade-related in a narrower sense and can be used in a training dataset. The selection of keywords discussed above was crucial in filtering out non-relevant tweets.

The most widely used approach to automated text analysis for measuring opinions, attitudes and preferences are sentiment analysis (SA) techniques. The traditional SA approach makes use of ontological dictionaries (for an example of the use of pre-existing dictionaries, see Kleinnijenhuis et al., 2013). It is also possible to add your own words and/or create unique dictionaries tailored to a specific topic (Aaldering and Vliegenthart, 2016; Haselmayer and Jenny, 2017). Both approaches allow for a totally automated text analysis without any further coding necessary. Text is assigned to a specific opinion category based on the usage of some pre-determined words or expressions. Simply put, you tokenize your text data (i.e., splitting sentences into single words) and compare each word to a list of already categorized words (a dictionary). The more negative words are used, the more negative a text. It is also possible to distinguish words beyond a positive–negative dichotomy and include sentiments like anger, fear, anticipation, and so on. Several extensive freely available databases provide dictionaries in multiple languages, which can be used to analyze data without any additional coding.

A major weakness of this kind of dictionary-based sentiment analyses is the difficulty in dealing with nuanced expressions or ironic statements. Ceron et al. (2014, p. 343) illustrate this point using the example "What a nice rip-off!" – it uses a positive word (nice) to express a negative sentiment. The meaning of this statement is lost in the setting of a dictionary-based SA.

Supervised sentiment analyses are better suited to extract meaning in context-specific settings, going beyond simple cross-checking with a pre-determined dictionary. These approaches follow a two-stage process (Hopkins and King, 2010): First, a subsample of the text data is read and hand-coded: “Human coders are, of course, more effective and careful than ontological dictionaries when it comes to recognizing [...] language specificities and an author’s attitude” (Ceron et al., 2014, p. 343). This subsample then serves as a training dataset for a machine learning (ML) algorithm in the second stage of the supervised SA. For this next part, there are multiple different classification algorithms available, but “apparently there is no consensus on which one to choose for the best performance” (Mozetič et al., 2016, p. 21). Therefore, this part of the analysis will follow a trial-and-error-strategy. Luckily, Mozetič et al. (2016) also show that there are hardly ever any statistically significant differences between the most widely used classification models.

The entire supervised sentiment analysis in this paper is implemented in Python, relying heavily on the widely used *nltk* (Bird et al., 2009) and *scikit-learn* (Pedregosa et al., 2011) libraries, which provide functions for all tasks from text-preprocessing to classification algorithms and, finally, assessing model performance. An extensive collection of online material (tutorials, user guides, examples, etc.) makes these libraries especially user-friendly.

Pre-processing

Text data has to be cleaned and ‘translated’ into numerical features first. There is no one ideal way to pre-process text data, but the process always involves cleaning (e.g., removing punctuation, stopwords, etc.) tokenization (splitting up the text into tokens, which can be words, sentences, etc.), and vectorization (translating text into numbers). Each step can involve different techniques, which in turn influence the quality of the machine learning classification output. My pipeline started with feature selection, i.e. tokenizing tweets into single words. Although so-called n-grams (two or more words) would also be a possibility, restricting the classification to single words only yielded the most accurate results. The next step, cleaning, involved converting all words to lower case, removing standard punctuation and numbers, translating emojis into text (e.g. a Mexican flag is converted to the word "Mexico", a furious, red-faced emoji becomes "angry face", etc.), and removing common stop words. To translate these processed tokens into numbers, various vectorization techniques are available. *Bag of Words* is the simplest form of vectorization, which often yields good results. One shortcoming, though, is the fact that this technique treats every word equally and cannot distinguish between very rare and very common words. *Tf-idf* (term frequency-inverse document frequency), can mitigate this problem, since it takes the importance of a word in consideration, depending on how frequently it occurs in a document (i.e., a tweet) and a corpus (i.e., all tweets). Both approaches have been tested with the twitter-data, but *tf-idf* lead to better results.

Training and Classification

After cleaning and vectorizing the text data, a classification model can be trained. The *scikit-learn* library offers many different algorithms to choose from[2]. As mentioned above, the choice of the best algorithm is often a result of a longer trial-and-error process – after comparing different approaches, a random forest specification yielded the most precise and reliable results.

Evaluating the performance of a classification algorithm usually starts with a confusion matrix (see Table B.1), where the actual (hand-coded) sentiment is compared to the algorithm's predictions. The diagonal values in the matrix should be maximized (where actual and predicted values are the same, values in bold). While a misclassification between the neutral and either the positive or the critical category is not ideal (e.g., 72 tweets that are actually positive, but are labeled as neutral), losing an actual positive tweet to the negative category (and vice versa) is far more problematic for my theoretical argument. To minimize this issue, my goal was to find the algorithm specification with the lowest values in the upper right, and the lower left corner of the confusion matrix.

Various indicators can be derived from this matrix, with precision and recall being the most

[2]See `https://scikit-learn.org/stable/supervised_learning.html` for a complete list

Table B.1: ML Confusion Matrix

	pred. critical	pred. neutral	pred. positive
actual critical	**296**	11	1
actual neutral	5	**742**	53
actual positive	59	72	**1002**

widely used (see Table B.2). A precision score of 0.95 for positive tweets, for example, indicates that 95 percent out of the *predicted* positive tweets are *actual* positive tweets. The rest is neutral or critical. The recall score shows how many of the actual positive/neutral/critical tweets are labeled as such, and the f1-score is a combination of the precision and the recall measure. When optimizing a classification problem, there is always a trade-off between precision and recall – increasing one, typically decreases the other one. A high precision score means that there are fewer false positives, whereas a high recall measure indicates that there are fewer false negatives. Depending on the specific classification problem, either one can be more relevant. It is also possible to focus on the overall accuracy score (which relates to the model as a whole).

Table B.2: ML Classification Report

	precision	recall	f1-score
critical	0.82	0.96	0.89
neutral	0.90	0.93	0.91
positive	0.95	0.88	0.92
accuracy			0.91

The data set is imbalanced (there are far less critical tweets in the sample than positive or neutral ones), which is quite common among classification problems and does make sense theoretically (business groups are expected to have an – overall – more positive attitude towards trade liberalization). Unfortunately, classification algorithms often discriminate against minority classes – which means that many critical tweets would be lost (i.e. misclassified) with a random training set. One way of dealing with an imbalanced data set is to over-sample the minority class, which means including additional negative tweets to the training set. Using this technique significantly improved the classification results. Adding a list of the most distinct keywords for the positive and the critical category further improved the classification. When using over-sampling and additional keywords, the risk of overfitting increases, which means that the algorithm can predict training data very well, but its performance is relatively bad with new data. Cross-validation (splitting up the training set in different groups) and random tests of the output data were used to address this problem.

After training the model, it can be applied to the uncategorized data (i.e. the tweets that have not been hand-coded). This results in the final data used for the regression analysis.

Table B.3: Country Sample, Number of Groups

ISO code	Country Name	Number of Groups
ITA	Italy	25
EU28	EU	132
FRA	France	46
NZL	New Zealand	20
GBR	United Kingdom	106
CAN	Canada	95
BEL	Belgium	8
DEU	Germany	89
FIN	Finland	6
AUT	Austria	15
NLD	Netherlands	14
SWE	Sweden	4
AUS	Australia	52
DNK	Denmark	14
USA	United States	132
SGP	Singapore	7
IRL	Ireland	52
NOR	Norway	15
CHE	Switzerland	10
LUX	Luxembourg	2
IND	India	53
IDN	Indonesia	1
ZAF	South Africa	38
BRA	Brazil	17
MEX	Mexico	17
CHN	China	9
MYS	Malaysia	1
ARG	Argentina	18
POL	Poland	1
CHL	Chile	11
CZE	Czechia	3
EST	Estonia	1
PRT	Portugal	2
ESP	Spain	33
KOR	South Korea	3
JPN	Japan	7
PER	Peru	1
TUR	Turkey	2
RUS	Russia	7
LTU	Lithuania	1
GRC	Greece	1
SAU	Saudi Arabia	1

Table B.4: Descriptive Statistics

Variable	N	Mean	St. Dev.	Min	Max
GVC Participation	95,600	14.971	8.799	0.000	78.310
GDP(log)	95,600	28.728	1.359	24.149	30.654
GDP per capita	95,600	40,940	18,868.93	2010	116,640
Trade Openness (Industry)	95,600	0.229	0.590	0.001	18.672
OECD	95,600	0.873	0.333	0	1
Democracy (Polity IV)	95,600	9.267	1.257	-10	10
Agriculture	95,600	0.291	0.454	0	1
Translated	95,600	0.404	0.491	0	1

Figure B.1: Predicted Probabilities, nonOECD and non-agriculture

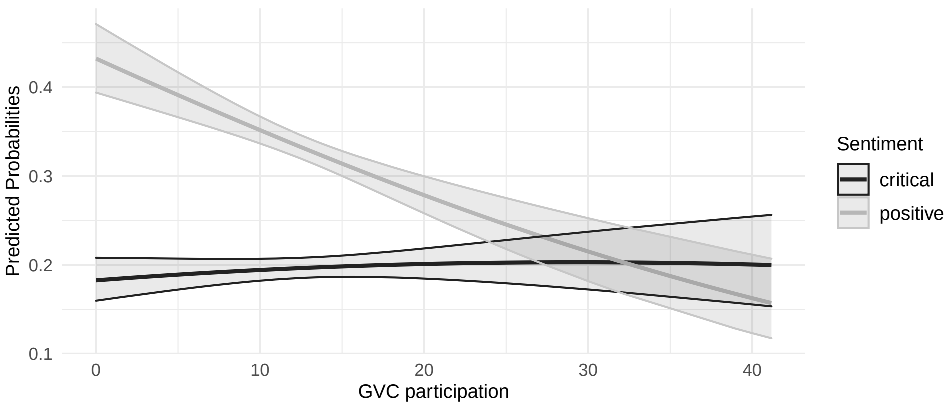

Figure B.2: Predicted Probabilities, year 2020 only

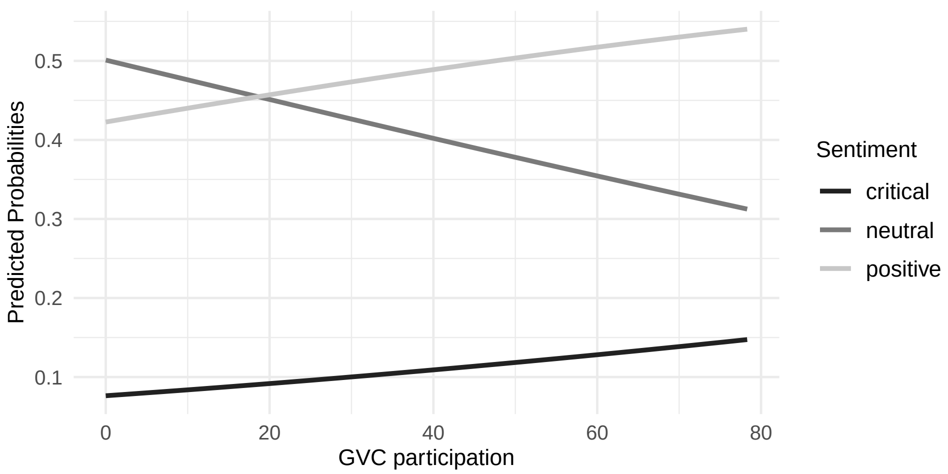

Table B.5: Regression Results, year 2017 only

	Model 1		Model 2	
	critical	*positive*	*critical*	*positive*
GVC Participation	-0.023^{***}	0.012^{***}	-0.041^{***}	0.019^{***}
	(0.001)	(0.002)	(0.007)	(0.004)
Trade Openness (Ind)	-0.867^{***}	-0.043^{***}	-1.336^{***}	0.444^{***}
	(0.00002)	(0.0001)	(0.236)	(0.122)
GDP (log)	-0.207^{***}	-0.002		
	(0.002)	(0.002)		
GDP pc	-0.00001^{***}	0.00000		
	(0.00000)	(0.00000)		
Democracy	0.015^{***}	0.003^{***}		
	(0.001)	(0.001)		
AIC	19,097.930	19,097.930	18,798.330	18,798.330
Country FEs	no	no	yes	yes
Year FEs	yes	yes	yes	yes
Observations	9,917	9,917	9,917	9,917

Multinomial Logistic Regressions. Reference category for dependent variable: *neutral*
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, standard errors in parentheses

Table B.6: Regression Results, year 2020 only

	Model 1		Model 2	
	critical	*positive*	*critical*	*positive*
GVC Participation	0.025***	−0.011***	0.014***	0.009***
	(0.001)	(0.001)	(0.004)	(0.003)
Trade Openness (Ind)	−1.394***	0.056***	−1.922***	0.257***
	(0.00001)	(0.00002)	(0.173)	(0.082)
GDP (log)	−0.165***	−0.026***		
	(0.001)	(0.001)		
GDP pc	−0.00001***	0.00000***		
	(0.00000)	(0.00000)		
Democracy	−0.016***	0.012***		
	(0.0004)	(0.0003)		
AIC	45,023.630	45,023.630	44,073.130	44,073.130
Country FEs	no	no	yes	yes
Year FEs	yes	yes	yes	yes
Observations	23,641	23,641	23,641	23,641

Multinomial Logistic Regressions. Reference category for dependent variable: *neutral*
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, standard errors in parentheses

Table B.7: Regression Results, EU-wide groups excluded

	Model 1		Model 2	
	critical	*positive*	*critical*	*positive*
GVC Participation	0.007***	0.004***	−0.015***	0.013***
	(0.0004)	(0.001)	(0.002)	(0.001)
Trade Openness (Ind)	−1.540***	−0.024***	−2.064***	0.155***
	(0.00001)	(0.00002)	(0.085)	(0.040)
GDP (log)	−0.185***	−0.020***		
	(0.001)	(0.001)		
GDP pc	−0.00001***	0.00000		
	(0.00000)	(0.00000)		
Democracy	0.020***	0.011***		
	(0.0002)	(0.0002)		
AIC	153,749.100	153,749.100	150,680.800	150,680.800
Country FEs	no	no	yes	yes
Year FEs	yes	yes	yes	yes
Observations	80,598	80,598	80,598	80,598

Multinomial Logistic Regressions. Reference category for dependent variable: *neutral*
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, standard errors in parentheses

Table B.8: Regression Results, GDPpc

	Model 1		Model 2	
	critical	*positive*	*critical*	*positive*
GVC Participation	-0.019^{***}	-0.0004^{***}	-0.009^{***}	0.002^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
GDP pc	-0.00002^{***}	-0.00000^{***}	-0.00002^{***}	-0.00000^{***}
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Agriculture			0.268^{***}	0.072^{***}
			(0.000)	(0.000)
Trade Openness (Ind)	-1.669^{***}	-0.033^{***}	-1.480^{***}	-0.018^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
GDP (log)	-0.124^{***}	0.002^{***}	-0.107^{***}	0.021^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Democracy	0.038^{***}	0.015^{***}	0.048^{***}	0.024^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
GVC Participation:GDP pc	0.00000^{***}	0.00000^{***}	0.00000^{***}	0.00000
	(0.00000)	(0.000)	(0.00000)	(0.000)
AIC	180,778.600	180,778.600	180,795.700	180,795.700
Country FEs	no	no	yes	yes
Year FEs	yes	yes	yes	yes
Observations	95,600	95,600	95,600	95,600

Multinomial Logistic Regressions. Reference category for dependent variable: *neutral*
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, standard errors in parentheses

Appendix C

Appendix for Chapter 3

Table C.1: AMNE Industries

Industry Code	Industry Description
A	Agriculture, Forestry and Fishing
B	Mining and Quarrying
C10T12	Food products, beverages and tobacco
C13T15	Textiles, wearing apparel, leather and related products
C16	Wood and wood products
C17T18	Paper and paper products, Printing and reproduction of recorded media
C19	Coke and refined petroleum products
C20T21	Chemicals, chemical products and pharmaceuticals
C23	Other non-metallic mineral products
C24	Basic metals
C25	Fabricated metal products
C26	Computer, electronic and optical products
C27	Electrical equipment
C28	Machinery and equipment n.e.c.
C29	Motor vehicles, trailers and semi-trailers
C30	Other transport equipment
C31T33	Other manufacturing

Notes: Industries from the analytical AMNE Database (Cadestin et al., 2018a), services excluded

Table C.2: Mergers and Acquisitions: Number of Deals per Country

	Country	as target	as acquirer
1	Algeria	36	13
2	Australia	2,643	1,557
3	Austria	25	113
4	Bahrain	5	61
5	Belgium	23	80
6	Brunei	2	5
7	Bulgaria	4	0
8	Cambodia	14	1
9	Canada	232	624
10	Chile	812	67
11	China (Mainland)	762	295
12	Colombia	268	35
13	Costa Rica	64	10
14	Croatia	204	9
15	Cyprus	1	1
16	Czech Republic	6	0
17	Denmark	18	57
18	Dominican Republic	27	0
19	Egypt	112	18
20	El Salvador	18	0
21	Estonia	1	0
22	Finland	13	40
23	France	110	537
24	Germany	185	428
25	Greece	5	39
26	Guatemala	30	3
27	Honduras	18	0
28	Hungary	3	0
29	Iceland	0	6
30	India	228	11
31	Indonesia	312	48
32	Ireland	16	62
33	Israel	288	285
34	Italy	62	158
35	Japan	237	1,302
36	Jordan	31	11
37	Laos	5	0
38	Lebanon	0	18
39	Luxembourg	17	66
40	Malaysia	235	323
41	Malta	0	7
42	Mexico	513	96
43	Morocco	147	16
44	Myanmar	7	0
45	Netherlands	67	327
46	New Zealand	132	32
47	Nicaragua	14	0

Continued on next page

Table C.2: Mergers and Acquisitions: Number of Deals per Country (cont.)

	Country	as target	as acquirer
48	Norway	42	43
49	Pakistan	8	2
50	Panama	72	16
51	Peru	333	18
52	Philippines	153	37
53	Poland	12	0
54	Portugal	8	21
55	Romania	6	0
56	Singapore	818	1,571
57	Slovakia	4	0
58	South Africa	671	349
59	South Korea	749	459
60	Spain	151	411
61	Sweden	15	142
62	Switzerland	117	170
63	Thailand	268	64
64	Tunisia	71	7
65	Turkey	703	101
66	United Kingdom	347	884
67	United States	1,836	3,509
68	Vietnam	245	16

Table C.3: AMNE Country Pairs

Source Country	Receiver Country
ASEAN	Australia
ASEAN	New Zealand
Australia	Indonesia
Australia	Malaysia
Australia	Philippines
Australia	Singapore
Australia	Thailand
Australia	Vietnam
Canada	Colombia
Canada	Iceland
Chile	China
Chile	Japan
China	Chile
China	Costa Rica
Colombia	Canada
Colombia	USA
Costa Rica	China
EU	Korea
India	Japan
Indonesia	Japan
Japan	Chile
Japan	India
Japan	Indonesia
Japan	Switzerland
Japan	Thailand
Korea	EU
Korea	USA
Malaysia	Australia
Switzerland	Japan
Thailand	Japan
USA	Colombia
USA	Korea
USA	Singapore

Table C.4: Robustness Check: Time to Zero instead of Tariff Cut as DV (H1)

	Dependent variable:				
	Tariff=0 pre-PTA	Time to Zero post-PTA			
	probit	*felm*			
	(1)	(2)	(3)	(4)	(5)
Mergers & acquisitions	0.489***	0.218***	0.202***	0.059	−0.042
	(0.028)	(0.032)	(0.023)	(0.036)	(0.037)
Intermediates	0.415***	−0.210***	−0.204***	−0.249***	−0.289***
	(0.005)	(0.009)	(0.003)	(0.022)	(0.022)
IIT	−0.606***	−0.093	−0.054	−0.096	0.065
	(0.151)	(0.121)	(0.120)	(0.123)	(0.113)
IIT missing	−0.384**	−0.253**	−0.200*	−0.239**	−0.098
	(0.151)	(0.121)	(0.120)	(0.122)	(0.111)
GDP per capita of A (ln)	0.064	−0.389***	−0.324***	−0.036*	1.077***
	(0.045)	(0.002)	(0.002)	(0.022)	(0.044)
GDP per capita of B (ln)	−0.010***	−0.050***	−0.052***	−0.016***	−1.016***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.029)
GDP of A (ln)	0.597***	−0.003**	−0.023***	0.454***	0.950***
	(0.052)	(0.001)	(0.001)	(0.042)	(0.052)
GDP of B (ln)	−0.001	−0.010***	−0.011***	−0.002**	2.893***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.040)
Imports	0.019***	0.007**	−0.004	0.020***	0.029***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Regime	0.015***	−0.011***	−0.015***	0.006***	0.015***
	(0.002)	(0.0004)	(0.0003)	(0.001)	(0.001)
WTO	0.040**	0.002	−0.094***	0.059***	
	(0.019)	(0.005)	(0.009)	(0.007)	(0.000)
Country competitiveness	0.120***				
	(0.004)				
Tariff pre-PTA		0.004***	0.004***	0.004***	0.004***
		(0.001)	(0.0001)	(0.001)	(0.001)
Inverse Mills Ratio		−0.092***	−0.075***	−0.193***	−0.328***
		(0.003)	(0.002)	(0.056)	(0.057)
M & A:Intermediates	−0.335***	−0.108***	−0.132***	−0.053	−0.045
	(0.031)	(0.033)	(0.025)	(0.034)	(0.035)
Constant	−15.941***	5.617***			
	(0.969)	(0.131)			
Year FE	Yes	No	Yes	Yes	Yes
Country A FE	Yes	No	No	Yes	Yes
Country B FE	Yes	No	No	No	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes
Observations	691,991	464,503	464,503	464,503	464,503
R^2		0.302	0.326	0.404	0.444
Adjusted R^2		0.302	0.326	0.404	0.444
Log Likelihood	−302,341.600				
Akaike Inf. Crit.	604,827.100				
Residual Std. Error		0.891	0.875	0.823	0.795
		(df = 464488)	(df = 464472)	(df = 464432)	(df = 464397)

Note: *p<0.1; **p<0.05; ***p<0.01

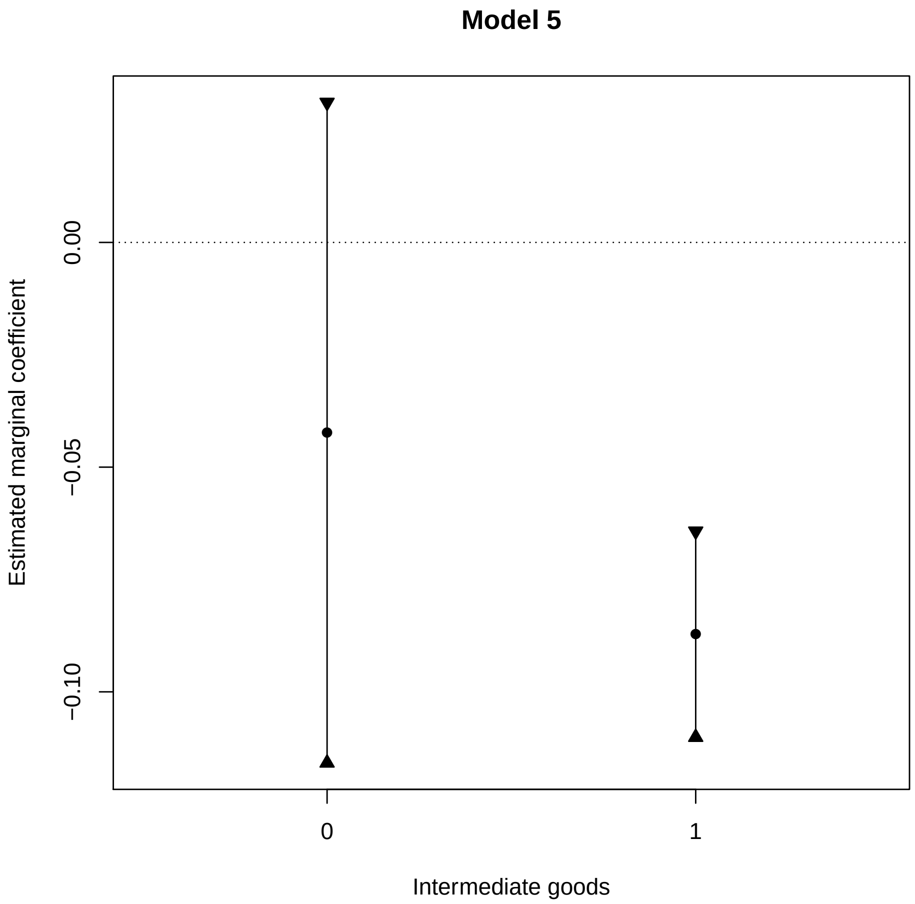

Figure C.1: Robustness Check (Time to Zero instead of Tariff Cut as DV): Horizontal versus Vertical Investment (Model 5)

Table C.5: Robustness Check: Time to Zero instead of Tariff Cut as DV (H2)

	Dependent variable:				
	Tariff=0 pre-PTA	Tariff Cut post-PTA			
	probit	*felm*			
	(1)	(2)	(3)	(4)	(5)
MNC imports (ln)	0.110***	−0.088**	−0.102***	−0.077***	−0.077***
	(0.003)	(0.036)	(0.029)	(0.029)	(0.030)
IIT	−0.534	−0.134	−0.153	−0.290	−0.288
	(0.366)	(0.390)	(0.367)	(0.381)	(0.384)
IIT missing	−0.282	−0.254	−0.255	−0.339	−0.338
	(0.366)	(0.386)	(0.356)	(0.356)	(0.358)
GDP per capita of A (ln)	5.039**	−0.208***	−0.185***	0.639	
	(2.282)	(0.049)	(0.055)	(5.829)	(0.000)
GDP per capita of B (ln)	−0.013	−0.026	−0.065	−0.018	
	(0.012)	(0.021)	(0.057)	(0.023)	(0.000)
GDP of A (ln)	−1.522	−0.088*	−0.044**	−0.125	
	(1.254)	(0.050)	(0.022)	(3.209)	(0.000)
GDP of B (ln)	−0.007	0.054	0.110***	0.119**	
	(0.012)	(0.060)	(0.018)	(0.057)	(0.000)
Imports	0.014	0.052**	0.058**	0.079***	0.079***
	(0.009)	(0.026)	(0.027)	(0.018)	(0.018)
Regime	−0.013	−0.009	−0.016**	−0.052*	−0.052***
	(0.009)	(0.007)	(0.007)	(0.029)	(0.020)
WTO					
		(0.000)	(0.000)	(0.000)	(0.000)
Country competitiveness	0.426***				
	(0.011)				
Tariff pre-PTA		0.008***	0.008***	0.008***	0.008***
		(0.002)	(0.002)	(0.002)	(0.002)
Inverse Mills Ratio		−0.397***	−0.373***	−0.107	−0.107
		(0.048)	(0.077)	(0.275)	(0.276)
Constant	−11.992	4.862*			
	(13.004)	(2.751)			
Year FE	Yes	No	Yes	Yes	Yes
Country A FE	Yes	No	No	Yes	Yes
Country B FE	Yes	No	No	No	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes
Observations	131,332	85,254	85,254	85,254	85,254
R^2		0.218	0.226	0.267	0.267
Adjusted R^2		0.218	0.226	0.267	0.267
Log Likelihood	−51,157.470				
Akaike Inf. Crit.	102,374.900				
Residual Std. Error		0.919 (df = 85242)	0.915 (df = 85238)	0.890 (df = 85225)	0.890 (df = 85217)

Note: *p<0.1; **p<0.05; ***p<0.01

Table C.6: Robustness Check: Count M&A deals within a period of 3 years

	Dependent variable:				
	Tariff=0 pre-PTA	Tariff Cut post-PTA			
	probit	*felm*			
	(1)	(2)	(3)	(4)	(5)
Mergers & acquisitions	0.627***	−16.190***	−15.242***	−16.421***	−7.198***
	(0.035)	(1.442)	(1.128)	(1.813)	(1.812)
Intermediates	0.415***	8.045***	7.889***	7.556***	9.824***
	(0.005)	(0.347)	(0.122)	(0.797)	(0.811)
IIT	−0.603***	−4.733	−4.965	−1.317	−4.541
	(0.151)	(4.194)	(4.782)	(4.311)	(3.995)
IIT missing	−0.383**	0.982	0.192	3.142	−0.028
	(0.151)	(4.194)	(4.781)	(4.248)	(3.927)
GDP per capita of A (ln)	0.074*	20.601***	17.596***	18.723***	−17.396***
	(0.045)	(0.088)	(0.073)	(0.846)	(1.731)
GDP per capita of B (ln)	−0.010***	1.860***	1.628***	0.513***	49.848***
	(0.002)	(0.045)	(0.056)	(0.051)	(1.167)
GDP of A (ln)	0.594***	−2.361***	−1.999***	−66.826***	−81.299***
	(0.052)	(0.048)	(0.047)	(1.604)	(2.111)
GDP of B (ln)	−0.0002	0.085**	−0.486***	0.308***	−149.533***
	(0.002)	(0.036)	(0.042)	(0.031)	(1.685)
Imports	0.019***	−0.755***	−0.390***	−0.612***	−0.923***
	(0.004)	(0.128)	(0.110)	(0.129)	(0.125)
Regime	0.015***	0.453***	0.621***	−0.038	−0.096*
	(0.002)	(0.014)	(0.011)	(0.053)	(0.052)
WTO	0.042**	2.491***	4.585***	1.242***	
	(0.019)	(0.207)	(0.361)	(0.319)	(0.000)
Country competitiveness	0.121***				
	(0.004)				
Tariff pre-PTA		−0.131***	−0.140***	−0.128***	−0.139***
		(0.020)	(0.002)	(0.020)	(0.022)
Inverse Mills Ratio		5.124***	4.775***	3.190	10.626***
		(0.109)	(0.086)	(2.020)	(2.064)
M & A:Intermediates	−0.469***	9.044***	9.882***	11.614***	8.667***
	(0.037)	(1.537)	(1.219)	(1.751)	(1.730)
Constant	−15.966***	−93.413***			
	(0.969)	(4.623)			
Year FE	Yes	No	Yes	Yes	Yes
Country A FE	Yes	No	No	Yes	Yes
Country B FE	Yes	No	No	No	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes
Observations	691,991	464,503	464,503	464,503	464,503
R^2		0.360	0.385	0.450	0.498
Adjusted R^2		0.360	0.385	0.450	0.498
Log Likelihood	−302,353.300				
Akaike Inf. Crit.	604,850.700				
Residual Std. Error		35.519	34.799	32.914	31.444
		(df = 464488)	(df = 464472)	(df = 464432)	(df = 464397)

Note: *p<0.1; **p<0.05; ***p<0.01

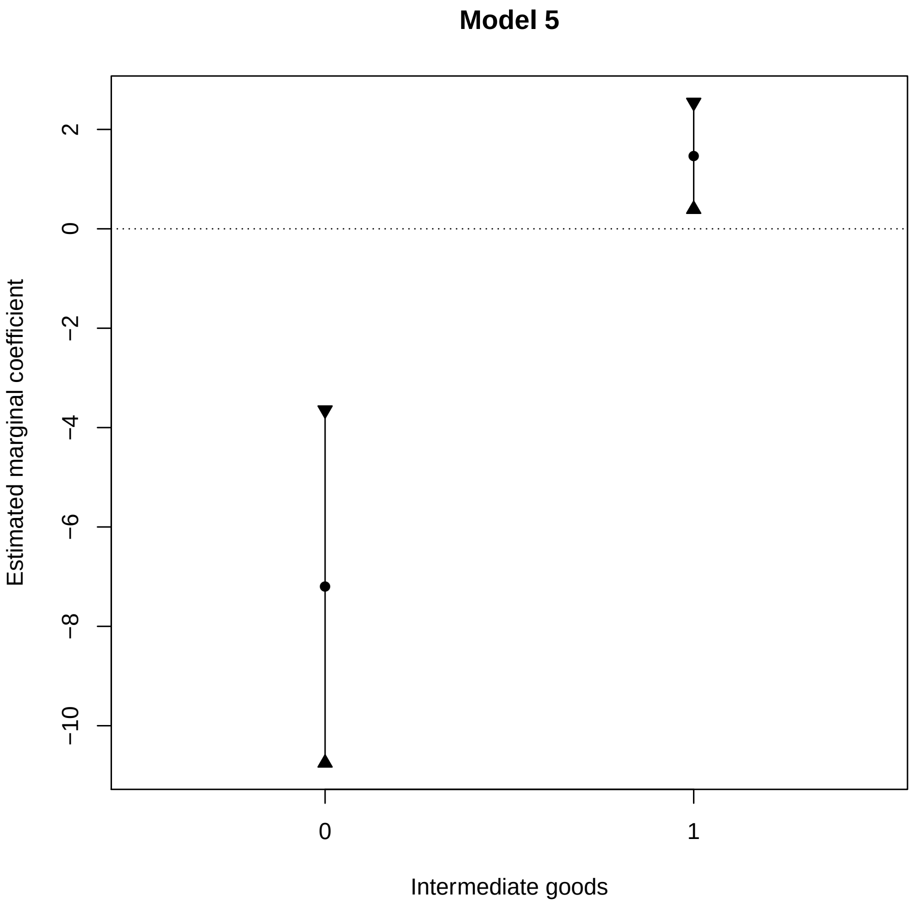

Figure C.2: Robustness Check (M&As of last 3 years): Horizontal versus Vertical Investment (Model 5)

Table C.7: Robustness Check: Count M&A deals within a period of 10 years

	Dependent variable:				
	Tariff=0 pre-PTA	Tariff Cut post-PTA			
	probit	*felm*			
	(1)	(2)	(3)	(4)	(5)
Mergers & acquisitions	0.408***	−9.485***	−8.604***	−8.580***	−2.917**
	(0.025)	(1.018)	(0.748)	(1.152)	(1.225)
Intermediates	0.417***	8.110***	7.935***	7.751***	9.995***
	(0.005)	(0.347)	(0.122)	(0.805)	(0.819)
IIT	−0.603***	−4.683	−4.914	−1.452	−4.716
	(0.151)	(4.196)	(4.782)	(4.308)	(3.996)
IIT missing	−0.382**	0.967	0.200	3.032	−0.141
	(0.151)	(4.196)	(4.781)	(4.245)	(3.928)
GDP per capita of A (ln)	0.065	20.624***	17.618***	18.519***	−17.239***
	(0.045)	(0.088)	(0.073)	(0.848)	(1.728)
GDP per capita of B (ln)	−0.010***	1.861***	1.635***	0.531***	49.861***
	(0.002)	(0.045)	(0.056)	(0.051)	(1.166)
GDP of A (ln)	0.600***	−2.312***	−1.958***	−66.250***	−81.130***
	(0.052)	(0.049)	(0.047)	(1.617)	(2.121)
GDP of B (ln)	−0.001	0.129***	−0.446***	0.374***	−149.537***
	(0.002)	(0.036)	(0.042)	(0.032)	(1.680)
Imports	0.019***	−0.776***	−0.403***	−0.614***	−0.919***
	(0.004)	(0.128)	(0.110)	(0.129)	(0.125)
Regime	0.015***	0.452***	0.620***	−0.037	−0.090*
	(0.002)	(0.014)	(0.011)	(0.053)	(0.052)
WTO	0.040**	2.584***	4.635***	1.332***	
	(0.019)	(0.206)	(0.361)	(0.321)	
Country competitiveness	0.120***				
	(0.004)				
Tariff pre-PTA		−0.131***	−0.141***	−0.128***	−0.139***
		(0.020)	(0.002)	(0.020)	(0.022)
Inverse Mills Ratio		5.114***	4.759***	3.555*	11.086***
		(0.109)	(0.086)	(2.029)	(2.073)
M & A:Intermediates	−0.338***	2.940***	3.589***	3.482***	3.217***
	(0.027)	(1.096)	(0.809)	(1.151)	(1.195)
Constant	−16.024***	−96.158***			
	(0.970)	(4.630)			
Year FE	Yes	No	Yes	Yes	Yes
Country A FE	Yes	No	No	Yes	Yes
Country B FE	Yes	No	No	No	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes
Observations	691,991	464,503	464,503	464,503	464,503
R^2		0.360	0.385	0.450	0.498
Adjusted R^2		0.360	0.385	0.450	0.498
Log Likelihood	−302,414.900				
Akaike Inf. Crit.	604,973.900				
Residual Std. Error		35.514 (df = 464488)	34.797 (df = 464472)	32.913 (df = 464432)	31.446 (df = 464397)

Note: *p<0.1; **p<0.05; ***p<0.01

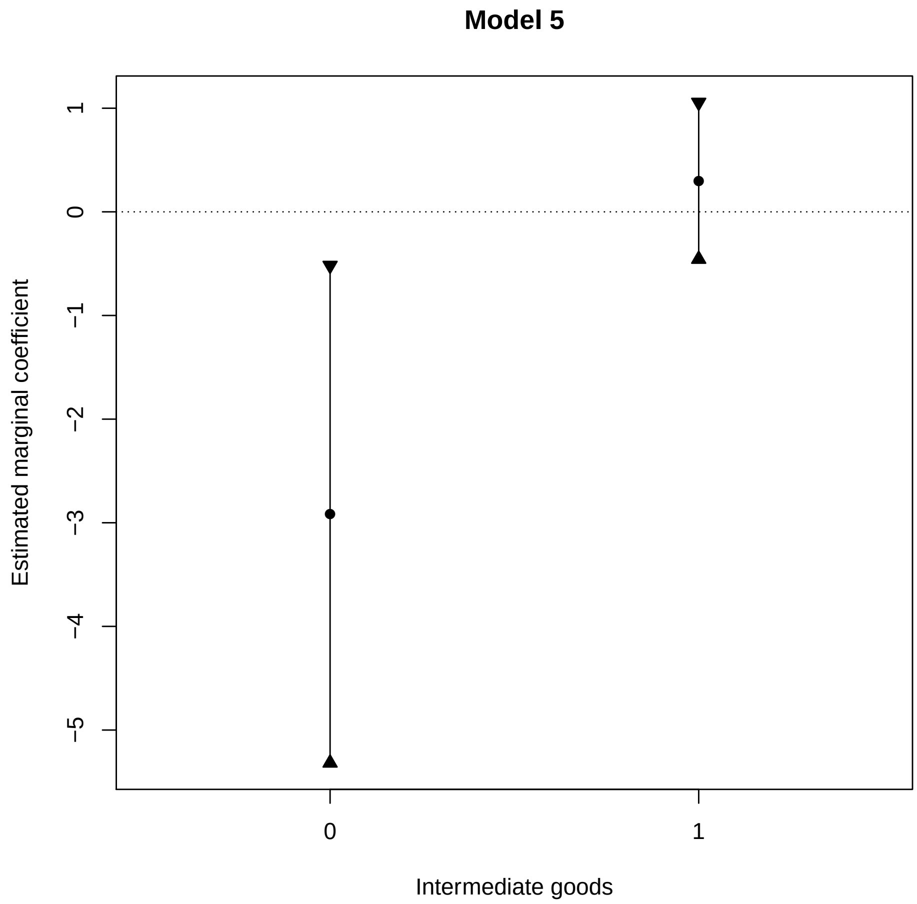

Figure C.3: Robustness Check (M&As of last 10 years): Horizontal versus Vertical Investment (Model 5)

Table C.8: Robustness Check: Using all past M&As as measure

	Dependent variable:				
	Tariff=0 pre-PTA	Tariff Cut post-PTA			
	probit	*felm*			
	(1)	(2)	(3)	(4)	(5)
Mergers & acquisitions	0.393***	−8.674***	−8.122***	−8.210***	−2.881**
	(0.023)	(0.897)	(0.692)	(1.062)	(1.121)
Intermediates	0.417***	8.076***	7.906***	7.682***	9.933***
	(0.005)	(0.347)	(0.123)	(0.808)	(0.821)
IIT	−0.605***	−4.691	−4.908	−1.384	−4.714
	(0.151)	(4.195)	(4.782)	(4.310)	(3.998)
IIT missing	−0.384**	0.982	0.215	3.089	−0.145
	(0.151)	(4.195)	(4.781)	(4.246)	(3.928)
GDP per capita of A (ln)	0.072	20.627***	17.622***	18.480***	−17.336***
	(0.045)	(0.088)	(0.073)	(0.850)	(1.731)
GDP per capita of B (ln)	−0.010***	1.863***	1.632***	0.528***	49.849***
	(0.002)	(0.045)	(0.056)	(0.051)	(1.166)
GDP of A (ln)	0.596***	−2.319***	−1.962***	−66.383***	−81.097***
	(0.052)	(0.049)	(0.047)	(1.615)	(2.121)
GDP of B (ln)	−0.002	0.124***	−0.447***	0.372***	−149.590***
	(0.002)	(0.037)	(0.042)	(0.032)	(1.681)
Imports	0.019***	−0.778***	−0.405***	−0.616***	−0.920***
	(0.004)	(0.128)	(0.110)	(0.129)	(0.125)
Regime	0.016***	0.451***	0.618***	−0.043	−0.094*
	(0.002)	(0.015)	(0.011)	(0.053)	(0.052)
WTO	0.040**	2.577***	4.633***	1.274***	
	(0.019)	(0.206)	(0.361)	(0.321)	
Country competitiveness	0.119***				
	(0.004)				
Tariff pre-PTA		−0.131***	−0.141***	−0.128***	−0.139***
		(0.020)	(0.002)	(0.020)	(0.022)
Inverse Mills Ratio		5.112***	4.761***	3.437*	11.033***
		(0.109)	(0.086)	(2.037)	(2.081)
M & A:Intermediates	−0.305***	3.600***	4.168***	4.076***	4.081***
	(0.025)	(0.966)	(0.748)	(1.043)	(1.075)
Constant	−15.942***	−95.853***			
	(0.970)	(4.628)			
Year FE	Yes	No	Yes	Yes	Yes
Country A FE	Yes	No	No	Yes	Yes
Country B FE	Yes	No	No	No	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes
Observations	691,991	464,503	464,503	464,503	464,503
R^2		0.360	0.385	0.450	0.498
Adjusted R^2		0.360	0.385	0.450	0.498
Log Likelihood	−302,382.100				
Akaike Inf. Crit.	604,908.100				
Residual Std. Error		35.518 (df = 464488)	34.799 (df = 464472)	32.914 (df = 464432)	31.445 (df = 464397)

Note: *p<0.1; **p<0.05; ***p<0.01

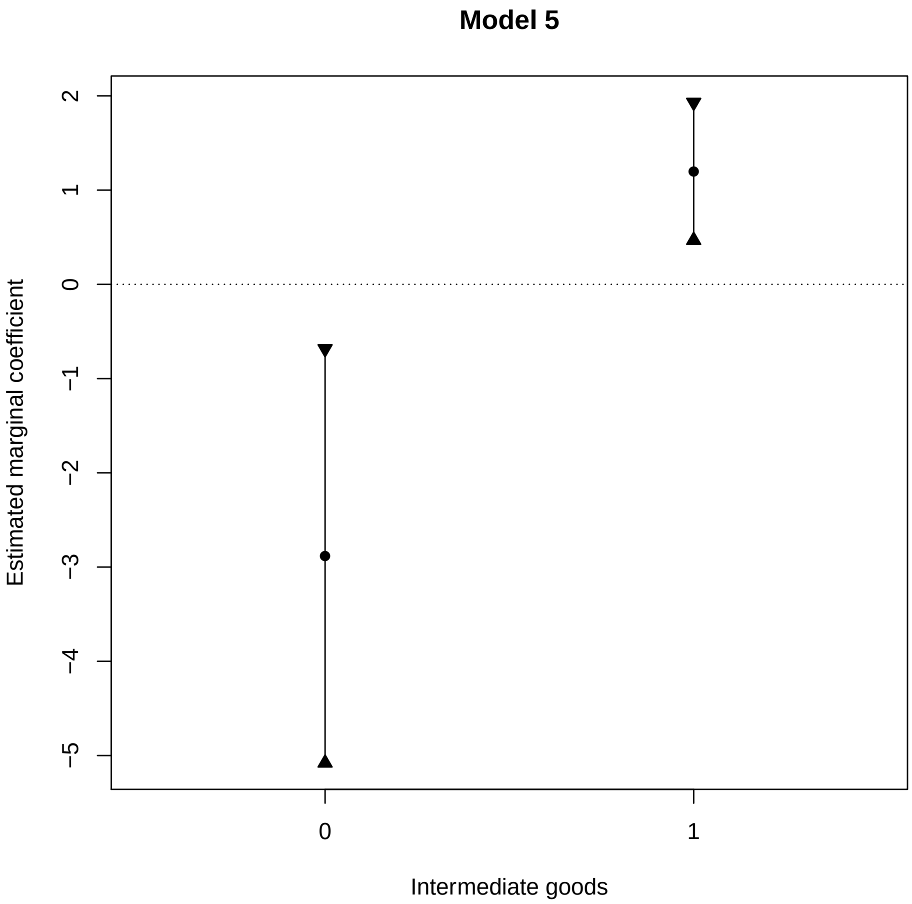

Figure C.4: Robustness Check (M&As of last 3 years): Horizontal versus Vertical Investment (Model 5)

Table C.9: Robustness Check: Count instead of dummy for M&A deals

	Dependent variable:				
	Tariff=0 pre-PTA	Tariff Cut post-PTA			
	probit	*felm*			
	(1)	(2)	(3)	(4)	(5)
Mergers & acquisitions	0.178***	−7.894***	−6.464**	−5.314*	−0.083
	(0.036)	(2.939)	(2.710)	(2.939)	(2.712)
Intermediates	0.409***	8.059***	7.926***	7.573***	9.908***
	(0.005)	(0.350)	(0.121)	(0.794)	(0.807)
IIT	−0.598***	−4.954	−5.172	−1.451	−4.599
	(0.151)	(4.198)	(4.784)	(4.317)	(3.997)
IIT missing	−0.378**	0.856	0.042	3.032	−0.068
	(0.151)	(4.198)	(4.783)	(4.256)	(3.930)
GDP per capita of A (ln)	0.065	20.573***	17.575***	18.190***	−18.477***
	(0.045)	(0.088)	(0.073)	(0.849)	(1.733)
GDP per capita of B (ln)	−0.010***	1.860***	1.628***	0.501***	49.508***
	(0.002)	(0.045)	(0.056)	(0.051)	(1.163)
GDP of A (ln)	0.608***	−2.417***	−2.031***	−66.688***	−80.077***
	(0.052)	(0.048)	(0.047)	(1.623)	(2.127)
GDP of B (ln)	0.001	0.039	−0.513***	0.269***	−149.236***
	(0.002)	(0.036)	(0.042)	(0.031)	(1.680)
Imports	0.019***	−0.758***	−0.392***	−0.616***	−0.927***
	(0.004)	(0.128)	(0.110)	(0.129)	(0.125)
Regime	0.016***	0.455***	0.622***	−0.051	−0.101*
	(0.002)	(0.014)	(0.011)	(0.053)	(0.053)
WTO	0.047**	2.403***	4.552***	0.955***	
	(0.019)	(0.208)	(0.361)	(0.323)	(0.000)
Country competitiveness	0.120***				
	(0.004)				
Tariff pre-PTA		−0.130***	−0.140***	−0.127***	−0.139***
		(0.020)	(0.002)	(0.020)	(0.022)
Inverse Mills Ratio		5.126***	4.788***	3.102	10.766***
		(0.109)	(0.086)	(2.024)	(2.072)
M & A:Intermediates	−0.139***	5.479*	5.540**	5.961**	4.532*
	(0.037)	(2.994)	(2.813)	(2.979)	(2.747)
Constant	−16.265***	−90.313***			
	(0.969)	(4.631)			
Year FE	Yes	No	Yes	Yes	Yes
Country A FE	Yes	No	No	Yes	Yes
Country B FE	Yes	No	No	No	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes
Observations	691,991	464,503	464,503	464,503	464,503
R^2		0.359	0.385	0.450	0.498
Adjusted R^2		0.359	0.385	0.450	0.498
Log Likelihood	−302,541.000				
Akaike Inf. Crit.	605,225.900				
Residual Std. Error		35.537 (df = 464488)	34.814 (df = 464472)	32.929 (df = 464432)	31.448 (df = 464397)

Note: *p<0.1; **p<0.05; ***p<0.01

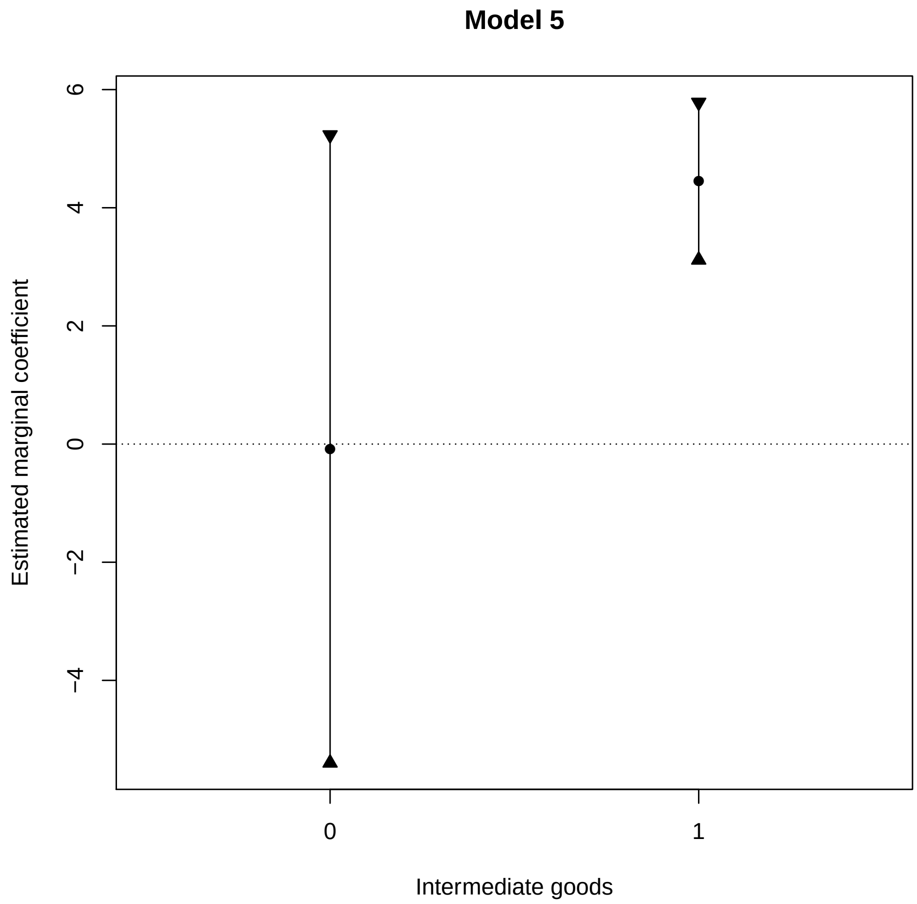

Figure C.5: Robustness Check (M&As count instead of dummy): Horizontal versus Vertical Investment (Model 5)

Appendix D

Appendix for Chapter 4

IPR Strength Operationalization

The strength of intellectual property rights (IPRs) protection provided by the preferential trade agreement (PTA) is measured following the three dimensions of legalization by Abbott et al. (2000). The IPR strength measure is based on the three dimensions obligation, precision, and delegation and results of up to 20 dichotomous variables that are generated by quantitative text analysis. Each of these variables is coded either zero or one, depending on whether a certain keyword is mentioned in the PTA's section on IPRs or in some cases in the whole agreement text or not. Additionally, another dichotomous variable checks whether a PTA's IPR section is longer than the sample's mean, for which this variable is again one and zero otherwise. Another dichotomous variable in precision accounts for total references in the full legal text of a PTA, and this variable is one if a PTA refers to IPRs more frequently than the sample mean and zero otherwise. Then, I calculated the sum (*obligation, precision, delegation*) for obligation, delegation, and precision, and aggregated the three dimensions to one additive index that measures the strength of IPR protection offered by a PTA (*IPR strength (max)*). Equation A.1 below illustrates these steps mathematically.

$$\text{IPR strength} = \sum \begin{cases} +1, & \text{if keyword}_{1,2,3,\ldots,n} \text{ occurs} \\ +1, & \text{if IPR section length} > \text{mean(IPR section length)} \\ +1, & \text{if IPR occurrences} > \text{mean(IPR occurrences)} \\ +0, & \text{otherwise} \end{cases} \tag{A.1}$$

Table D.1: List of IPR treaties

	Name	Year
1	Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS)	1994
2	Anti-Counterfeiting Trade Agreement	2011
3	Beijing Treaty on Audiovisual Performances	2012
4	Berne Convention for the Protection of Literary and Artistic Works	1886/1979
5	Brussels Convention Relating to the Distribution of Programme-Carrying Signals Transmitted by Satellite	1974
6	Budapest Treaty on the International Recognition of the Deposit of Microorganisms for the Purposes of Patent Procedure	1977
7	Buenos Aires Convention on Literary and Artistic Copyright	1910
8	Copyright Law Treaty	1996
9	Doha Declaration on the TRIPS Agreement and Public Health	2001
10	Geneva Convention for the Protection of Producers of Phonograms Against Unauthorized Duplication of Their Phonograms	1971
11	Hague Agreement Concerning the International Deposit of Industrial Designs	1925
12	International Treaty on Plant Genetic Resources for Food and Agriculture (ITPGRFA)	2001
13	International Union for the Protection of New Varieties of Plants Convention (UPOV)	1961
14	Lisbon Agreement for the Protection of Appellations of Origin and their International Registration	1979/2015
15	Locarno Agreement Establishing an International Classification for Industrial Designs	1979
16	Madrid Agreement Concerning the International Registration of Marks	1891/1979
17	Marrakesh Treaty to Facilitate Access to Published Works for Persons Who Are Blind, Visually Impaired or Otherwise Print Disabled	2013
18	Nairobi Treaty on the Protection of the Olympic Symbol	1981
19	Nice Agreement Concerning the International Classification of Goods and Services for the Purposes of the Registration of Marks	1979
20	Paris Convention for the Protection of Industrial Property	1883/1979
21	Patent Cooperation Treaty (PCT)	1970
22	Patent Law Treaty (PLT)	2000
23	Rome Convention for the Protection of Performers, Producers of Phonograms and Broadcasting Organizations	1961
24	Singapore Treaty on the Law of Trademarks	2006
25	Strasbourg Agreement Concerning the International Patent Classification	1979
26	Swakopmund Protocol on the Protection of Traditional Knowledge and Expressions of Folklore (ARIPO)	2010
27	Trademark Law Treaty	1994
28	Vienna Agreement Establishing an International Classification of the Figurative Elements of Marks	1985
29	Washington Treaty on Intellectual Property in Respect of Integrated Circuits	1989
20	WIPO Convention	1967
31	WIPO Copyright Treaty (WCT)	1996
32	WIPO Performances and Phonograms Treaty (WPPT)	1996

Table D.2: Descriptive Statistics

	N	Mean	St. Dev.	Min	Max
Deals	2,366,432	0.05	0.25	0	23
IPR Strength (max)	2,366,432	32.32	21.82	0	65
Patents (new)	2,366,432	28.66	510.34	0	36,544
Patents (CS)	2,366,432	376.79	7,962.34	0	574,423
Patents (CS5)	2,366,432	121.05	2,283.93	0	179,810
PTA Depth	2,366,432	4.74	1.77	0	6
Total Revenue	471,050	394.39	4,589.68	−6,028.50	243,771.40
EBIT	487,031	35.61	674.65	−6,485.57	58,886.67
Employees (No.)	530,048	32,311.69	79,745.91	1.00	2,200,000.00
HQ GDP	2,365,388	2,546.32	4,072.73	0.08	20,529.00
Partner GDP	2,364,141	1,899.71	3,463.42	0.04	20,529.00
HQ GDPpc	2,365,388	34.04	17.80	0.06	178.85
Partner GDPpc	2,364,141	27.81	19.20	0.06	178.85
HQ Democracy	2,363,938	8.19	4.48	−10.00	10.00
Partner Democracy	2,363,271	7.82	4.74	−10.00	10.00
WTO Members	2,366,432	0.94	0.23	0	1
Distance (km)	2,366,432	3,224.11	4,111.44	9	19,451

Table D.3: Countries included, Number of Firms, Partners, Deals, and PTAs

	Country	Firms	Partners	Deals	PTAs
1	Afghanistan	1	1	1	3
2	Albania	2	2	1	12
3	Algeria	6	8	17	19
4	Andorra	10	3	16	5
5	Angola	4	3	9	23
6	Argentina	123	13	198	46
7	Armenia	5	4	6	19
8	Australia	1639	25	2871	21
9	Austria	965	57	2079	96
10	Azerbaijan	7	4	15	12
11	Bahamas	27	23	43	19
12	Bahrain	58	17	155	10
13	Bangladesh	6	5	6	8
14	Barbados	13	11	13	19
15	Belarus	5	2	4	29
16	Belgium	1081	58	2412	79
17	Belize	3	3	5	22
18	Bolivia	6	6	7	19
19	Bosnia & Herzegovina	10	6	12	15
20	Botswana	14	10	25	30
21	Brazil	176	24	303	41
22	Brunei	9	5	9	18
23	Bulgaria	49	23	79	70
24	Cambodia	4	4	3	9
25	Cameroon	3	3	4	18
26	Canada	4849	48	10005	18
27	Chile	211	30	353	48
28	China	1070	20	1380	22
29	Colombia	136	31	259	44
30	Congo - Brazzaville	4	3	5	17
31	Congo - Kinshasa	2	2	2	29
32	Costa Rica	21	11	27	29
33	Cote d'Ivoire	13	12	14	16
34	Croatia	60	23	99	55
35	Cuba	1	1	1	32
36	Cyprus	652	46	981	58
37	Czechia	227	37	357	73
38	Denmark	918	49	2022	79
39	Dominican Republic	6	9	11	14
40	Ecuador	17	7	19	26
41	Egypt	58	39	97	37
42	El Salvador	9	7	12	26
43	Estonia	147	24	211	76
44	Eswatini	8	5	9	36
45	Ethiopia	2	3	3	18
46	Faroe Islands	8	4	8	16
47	Fiji	6	4	6	15
48	Finland	692	49	1779	99
49	France	2956	92	7226	79
50	Gabon	4	3	5	17
51	Gambia	2	2	2	11
52	Georgia	5	6	8	17
53	Germany	3895	74	8062	79
54	Ghana	6	7	7	12
55	Greece	233	48	436	82
56	Guatemala	22	9	27	27
57	Honduras	6	4	12	24
58	Hong Kong SAR China	2152	7	2918	7
59	Hungary	81	33	156	71
60	Iceland	117	32	280	55
61	India	299	39	417	22
62	Indonesia	113	17	160	21
63	Iran	2	2	2	9
64	Iraq	2	1	2	17
65	Ireland	669	51	1590	79
66	Israel	381	39	791	25
67	Italy	1292	67	2307	79
68	Jamaica	10	14	17	19
69	Japan	1804	45	4449	18
70	Jordan	36	21	52	38
71	Kazakhstan	29	7	48	31
72	Kenya	39	17	60	22
73	Kuwait	95	19	162	11
74	Kyrgyzstan	1	1	1	22
75	Laos	2	2	2	15

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Table D.3: Countries included, Number of Firms, Partners, Deals, and PTAs (cont.)

	Country	Firms	Partners	Deals	PTAs
76	Latvia	64	15	86	75
77	Lebanon	39	16	56	18
78	Liberia	6	4	6	13
79	Libya	8	8	15	17
80	Liechtenstein	47	22	71	55
81	Lithuania	92	17	116	75
82	Luxembourg	1001	68	1792	79
83	Macao SAR China	16	2	18	2
84	Malawi	4	4	4	32
85	Malaysia	926	35	1385	25
86	Mali	2	2	2	14
87	Malta	69	30	103	58
88	Marshall Islands	6	3	8	5
89	Mauritania	1	1	1	15
90	Mauritius	86	40	115	30
91	Mexico	318	49	637	50
92	Moldova	5	3	5	25
93	Montenegro	3	2	3	5
94	Morocco	32	27	59	29
95	Mozambique	2	2	2	27
96	Myanmar (Burma)	2	1	3	10
97	Namibia	7	5	8	31
98	Nepal	3	3	3	5
99	Netherlands	2526	89	5502	79
100	New Zealand	368	19	635	17
101	Nicaragua	1	1	2	21
102	Nigeria	38	22	46	11
103	North Macedonia	2	2	1	21
104	Norway	894	49	1916	55
105	Oman	23	8	33	8
106	Pakistan	8	6	8	16
107	Palestinian Territories	4	2	9	6
108	Panama	90	26	113	28
109	Papua New Guinea	11	8	17	15
110	Paraguay	2	2	2	30
111	Peru	86	22	125	43
112	Philippines	69	19	127	17
113	Poland	260	43	417	70
114	Portugal	218	38	407	96
115	Qatar	45	24	91	10
116	Romania	38	19	49	67
117	Russia	273	13	432	32
118	Samoa	1	1	1	10
119	San Marino	2	3	3	5
120	Saudi Arabia	104	17	145	9
121	Senegal	1	1	1	14
122	Serbia	28	11	35	17
123	Seychelles	7	7	7	20
124	Singapore	2526	72	4466	37
125	Slovakia	67	22	98	73
126	Slovenia	74	24	115	76
127	South Africa	423	65	735	30
128	South Korea	591	61	997	23
129	Spain	1211	69	2407	95
130	Sri Lanka	16	6	16	11
131	St. Kitts & Nevis	2	2	2	20
132	St. Lucia	3	11	12	20
133	St. Vincent & Grenadines	1	1	1	20
134	Suriname	1	1	1	17
135	Sweden	1724	67	4572	100
136	Switzerland	1697	61	3912	57
137	Syria	2	2	2	21
138	Taiwan	36	4	39	7
139	Tanzania	7	5	6	29
140	Thailand	173	23	252	20
141	Togo	5	7	9	13
142	Trinidad & Tobago	12	11	24	23
143	Tunisia	18	13	20	31
144	Turkey	155	42	208	41
145	Uganda	7	6	7	22
146	Ukraine	86	27	121	26
147	United Arab Emirates	167	18	258	12
148	United Kingdom	5162	114	11520	100
149	United States	7767	26	12356	23
150	Uruguay	29	6	38	38
151	Venezuela	37	16	52	44

Continued on next page

Table D.3: Countries included, Number of Firms, Partners, Deals, and PTAs (cont.)

	Country	Firms	Partners	Deals	PTAs
152	Vietnam	44	24	51	21
153	Yemen	1	1	1	4
154	Zambia	4	4	4	29
155	Zimbabwe	17	10	20	36

Table D.4: List of Trade Agreements

	Name	Year	IPRs
1	Argentina Brazil	1990	0
2	Guyana Venezuela	1990	0
3	African Economic Community	1991	0
4	Argentina Chile	1991	0
5	Australia Papua New Guinea	1991	0
6	Bolivia Uruguay	1991	0
7	Central American Integration System	1991	0
8	Czech Republic EC	1991	0
9	EC Faroe Islands	1991	0
10	EC Hungary	1991	0
11	EC Poland	1991	1
12	EC San Marino	1991	0
13	Economic Cooperation Organization (ECO) Preferences	1991	0
14	EFTA Turkey	1991	1
15	El Salvador Guatemala	1991	0
16	Estonia Sweden	1991	0
17	India Nepal	1991	0
18	Laos Thailand	1991	0
19	Lithuania Sweden	1991	0
20	MERCOSUR	1991	0
21	Argentina Venezuela	1992	0
22	Armenia Russia	1992	0
23	Association of Southeast Asian Nations (ASEAN) FTA	1992	0
24	Azerbaijan Russia	1992	0
25	Belarus Ukraine	1992	0
26	Caribbean Community (CARICOM) Venezuela	1992	0
27	Central European Free Trade Agreement (CEFTA)	1992	1
28	Czech and Slovak Republic EFTA	1992	1
29	Czech Republic Slovakia	1992	0
30	EC Maastricht	1992	0
31	EFTA Israel	1992	1
32	EFTA Poland	1992	1
33	EFTA Romania	1992	1
34	Estonia Finland	1992	0
35	Estonia Norway	1992	0
36	Estonia Switzerland	1992	1
37	European Economic Area (EEA)	1992	0
38	Faroe Islands Finland	1992	1
39	Faroe Islands Iceland	1992	0
40	Faroe Islands Norway	1992	1
41	Finland Latvia	1992	0
42	Finland Lithuania	1992	0
43	Jordan Lebanon	1992	0
44	Jordan Libya	1992	0
45	Kazakhstan Russia	1992	0
46	Kyrgyzstan Russia	1992	0
47	Latvia Norway	1992	1
48	Latvia Sweden	1992	1
49	Latvia Switzerland	1992	1
50	Lithuania Norway	1992	1
51	Lithuania Switzerland	1992	1
52	Namibia Zimbabwe	1992	0
53	North American Free Trade Agreement (NAFTA)	1992	1
54	Russia Tajikistan	1992	0
55	Southern African Development Community (SADC)	1992	0
56	Armenia Moldova	1993	0
57	Baltic Free Trade Area (BAFTA) industrial	1993	0
58	Bolivia Chile	1993	0
59	Brazil Peru	1993	1
60	Bulgaria EC	1993	1
61	Bulgaria EFTA	1993	1
62	Chile Colombia	1993	0
63	Chile Venezuela	1993	0
64	Colombia Panama	1993	0
65	Common Market for Eastern and Southern Africa (COMESA)	1993	0
66	Czech Republic Slovenia	1993	1
67	EC Estonia	1993	0
68	EC Romania	1993	1
69	EC Slovakia	1993	1
70	EC Slovenia	1993	0
71	Economic Community Of West African States (ECOWAS)	1993	0
72	EFTA Hungary	1993	1
73	Melanesian Spearhead Group (MSG)	1993	0
74	Russia Ukraine	1993	0
75	Slovakia Slovenia	1993	1

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Table D.4: List of Trade Agreements (cont.)

	Name	Year	IPRs
76	South Asian Association for Regional Cooperation, Preferential Trading Arrangement (SAPTA)	1993	0
77	Armenia Kyrgyzstan	1994	0
78	Armenia Ukraine	1994	0
79	Association of Caribbean States	1994	0
80	Bolivia Mexico	1994	1
81	Bolivia Paraguay	1994	1
82	Caribbean Community (CARICOM) Colombia	1994	0
83	Chile Ecuador	1994	0
84	Colombia Mexico Venezuela	1994	1
85	Commonwealth of Independent States (CIS)	1994	0
86	Costa Rica Mexico	1994	1
87	Czech Republic Romania	1994	1
88	EC Latvia	1994	0
89	EC Lithuania	1994	0
90	Economic and Monetary Community of Central Africa (CEMAC)	1994	0
91	Ecuador Paraguay	1994	0
92	Ecuador Uruguay	1994	0
93	Faroe Islands Switzerland	1994	0
94	Georgia Russia	1994	0
95	Group of Three	1994	0
96	Hungary Slovenia	1994	1
97	Israel PLO	1994	0
98	Jordan Morocco	1994	0
99	Kazakhstan Ukraine	1994	0
100	Moldova Romania	1994	1
101	Romania Slovakia	1994	1
102	Turkmenistan Ukraine	1994	0
103	Ukraine Uzbekistan	1994	0
104	West African Economic and Monetary Union	1994	0
105	Armenia Georgia	1995	0
106	Armenia Iran	1995	0
107	Armenia Turkmenistan	1995	0
108	Azerbaijan Ukraine	1995	0
109	Bulgaria Czech Republic	1995	1
110	Bulgaria Slovakia	1995	1
111	Czech Republic Lithuania	1995	1
112	EC Estonia Europe Agreement	1995	1
113	EC Israel Euro-Med Association Agreement	1995	1
114	EC Latvia Europe Agreement	1995	1
115	EC Lithuania Europe Agreement	1995	1
116	EC Tunisia Euro-Med Association Agreement	1995	1
117	EC Turkey	1995	1
118	EFTA Estonia	1995	1
119	EFTA Latvia	1995	1
120	EFTA Lithuania	1995	1
121	EFTA Slovenia	1995	1
122	Estonia Ukraine	1995	1
123	Georgia Ukraine	1995	0
124	Israel Jordan	1995	1
125	Jordan PLO	1995	0
126	Kazakhstan Kyrgyzstan	1995	0
127	Kazakhstan Moldova	1995	0
128	Kyrgyzstan Moldova	1995	0
129	Kyrgyzstan Ukraine	1995	0
130	Azerbaijan Georgia	1996	0
131	Baltic Free Trade Area (BAFTA) agriculture	1996	0
132	Bolivia MERCOSUR	1996	0
133	Bulgaria Slovenia	1996	1
134	Canada Chile	1996	0
135	Canada Israel	1996	1
136	Chile MERCOSUR	1996	1
137	Czech Republic Estonia	1996	1
138	Czech Republic Israel	1996	1
139	Czech Republic Latvia	1996	1
140	EC Faroe Islands	1996	0
141	EC Morocco Euro-Med Association Agreement	1996	1
142	EC Slovenia Europe Agreement	1996	1
143	Egypt Jordan	1996	1
144	Estonia Slovakia	1996	1
145	Estonia Slovenia	1996	1
146	Georgia Turkmenistan	1996	0
147	Israel Slovakia	1996	1
148	Israel Turkey	1996	1
149	Kyrgyzstan Uzbekistan	1996	0
150	Latvia Slovakia	1996	1

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Table D.4: List of Trade Agreements (cont.)

	Name	Year	IPRs
151	Latvia Slovenia	1996	1
152	Lithuania Poland	1996	1
153	Lithuania Slovakia	1996	1
154	Lithuania Slovenia	1996	1
155	Macedonia Slovenia	1996	1
156	Algeria Jordan	1997	0
157	Baltic Free Trade Area (BAFTA) Non Tariff Barriers	1997	0
158	Croatia Macedonia	1997	1
159	Croatia Slovenia	1997	1
160	Czech Republic Turkey	1997	1
161	EC Amsterdam	1997	0
162	EC Jordan Euro-Med Association Agreement	1997	1
163	EFTA Morocco	1997	1
164	Estonia Faroe Islands	1997	1
165	Estonia Turkey	1997	1
166	Georgia Kazakhstan	1997	0
167	Greater Arab Free Trade Agreement	1997	0
168	Guinea Morocco	1997	0
169	Hungary Israel	1997	1
170	Hungary Turkey	1997	1
171	Israel Poland	1997	1
172	Kazakhstan Uzbekistan	1997	0
173	Latvia Poland	1997	1
174	Lithuania Turkey	1997	1
175	Mexico Nicaragua	1997	1
176	Romania Turkey	1997	1
177	Slovakia Turkey	1997	1
178	Bulgaria Turkey	1998	1
179	Caribbean Community (CARICOM) Dominican Republic	1998	1
180	Central America Dominican Republic	1998	1
181	Chile Mexico	1998	1
182	Chile Peru	1998	0
183	Egypt Jordan	1998	1
184	Egypt PLO	1998	0
185	Estonia Hungary	1998	1
186	Faroe Islands Poland	1998	1
187	Hungary Lithuania	1998	1
188	India Sri Lanka	1998	0
189	Israel Slovenia	1998	1
190	Jordan Morocco	1998	1
191	Jordan Tunisia	1998	1
192	Latvia Turkey	1998	1
193	Slovenia Turkey	1998	1
194	Andean Countries Brazil	1999	0
195	Argentina Cuba	1999	0
196	Armenia Kazakhstan	1999	0
197	Belarus Russia (Union State)	1999	0
198	Brazil Cuba	1999	0
199	Bulgaria Macedonia	1999	1
200	Central America Chile	1999	1
201	Chile Cuba	1999	1
202	Cuba Guatemala	1999	0
203	Cuba Uruguay	1999	0
204	Cuba Venezuela	1999	1
205	East African Community (EAC)	1999	0
206	EC South Africa	1999	1
207	EC Switzerland Bilaterals I	1999	1
208	Eurasian Economic Community (EAEC)	1999	0
209	Hungary Latvia	1999	1
210	Macedonia Turkey	1999	1
211	Morocco Tunisia	1999	0
212	Poland Turkey	1999	1
213	Andean Countries Argentina	2000	0
214	Bolivia Cuba	2000	1
215	Bosnia and Herzegovina Croatia	2000	1
216	Caribbean Community (CARICOM) Cuba	2000	1
217	Colombia Cuba	2000	1
218	Cotonou Agreement	2000	1
219	Cuba Ecuador	2000	1
220	Cuba Paraguay	2000	1
221	Cuba Peru	2000	1
222	EC Mexico	2000	1
223	EFTA Macedonia	2000	1
224	EFTA Mexico	2000	1
225	Guatemala Mexico	2000	0
226	Israel Mexico	2000	1

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Table D.4: List of Trade Agreements (cont.)

	Name	Year	IPRs
227	Jordan UAE	2000	1
228	Jordan US	2000	1
229	Mexico Northern Triangle	2000	1
230	New Zealand Singapore	2000	1
231	Russia Serbia and Montenegro	2000	1
232	US Vietnam	2000	1
233	Bahrain Jordan	2001	0
234	Bosnia and Herzegovina Slovenia	2001	1
235	Brazil Guyana	2001	0
236	Bulgaria Estonia	2001	1
237	Bulgaria Israel	2001	1
238	Bulgaria Lithuania	2001	1
239	Canada Costa Rica	2001	0
240	Caribbean Community (CARICOM) revised	2001	1
241	Croatia EC	2001	1
242	Croatia EFTA	2001	1
243	EC Egypt Euro-Med Association Agreement	2001	0
244	EC Macedonia SAA	2001	1
245	EC Nice	2001	0
246	EFTA Jordan	2001	1
247	Gulf Cooperation Council (GCC)	2001	1
248	Israel Romania	2001	1
249	Jordan Kuwait	2001	0
250	Jordan Syria	2001	0
251	Macedonia Ukraine	2001	1
252	Pacific Island Countries Trade Agreement (PICTA)	2001	0
253	Tajikistan Ukraine	2001	0
254	Albania Croatia	2002	1
255	Albania Macedonia	2002	1
256	Algeria EC Euro-Med Association Agreement	2002	1
257	Armenia Estonia	2002	0
258	Bosnia and Herzegovina Macedonia	2002	1
259	Bosnia and Herzegovina Moldova	2002	1
260	Bosnia and Herzegovina Serbia Montenegro	2002	1
261	Bosnia and Herzegovina Turkey	2002	1
262	Brazil Mexico	2002	0
263	Bulgaria Latvia	2002	1
264	Central America Panama	2002	1
265	Chile EC	2002	1
266	Croatia Lithuania	2002	1
267	Croatia Macedonia (amended)	2002	1
268	Croatia Turkey	2002	1
269	EC Lebanon Euro-Med Association Agreement	2002	1
270	EFTA Singapore	2002	1
271	GUAM/GUUAM Organization for Democracy and Economic Development	2002	0
272	Japan Singapore	2002	1
273	Jordan Lebanon	2002	0
274	MERCOSUR Mexico Auto Agreement	2002	0
275	Pakistan Sri Lanka	2002	0
276	Southern Africa Customs Union (SACU)	2002	0
277	Afghanistan India	2003	0
278	Albania Bosnia and Herzegovina	2003	1
279	Albania Bulgaria	2003	1
280	Albania Kosovo	2003	1
281	Albania Moldova	2003	1
282	Albania Romania	2003	1
283	Albania Serbia	2003	1
284	Argentina Uruguay	2003	0
285	Australia Singapore	2003	1
286	Bosnia and Herzegovina Bulgaria	2003	1
287	Bosnia and Herzegovina Romania	2003	1
288	Bulgaria Serbia	2003	1
289	Chile EFTA	2003	1
290	Chile Korea	2003	1
291	Chile US	2003	1
292	China Hong Kong	2003	0
293	China Macao	2003	0
294	Common Economic Zone	2003	0
295	Economic Cooperation Organization Trade Agreement (ECOTA)	2003	1
296	Jordan Sudan	2003	0
297	Laos US	2003	1
298	Macedonia Romania	2003	1
299	Moldova Serbia	2003	1
300	Moldova Ukraine	2003	1
301	Panama Taiwan	2003	1
302	Romania Serbia	2003	1

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Table D.4: List of Trade Agreements (cont.)

	Name	Year	IPRs
303	Singapore US	2003	1
304	Agadir Agreement	2004	1
305	Andean Countries MERCOSUR	2004	1
306	Association of Southeast Asian Nations China	2004	0
307	Australia Thailand	2004	1
308	Australia US	2004	1
309	Bahrain US	2004	1
310	Bulgaria Moldova	2004	1
311	Caribbean Community (CARICOM) Costa Rica	2004	0
312	Central American Free Trade Agreement (CAFTA)	2004	1
313	Central American Free Trade Agreement (CAFTA) Dominican Republic	2004	1
314	Croatia Moldova	2004	1
315	Croatia Serbia Montenegro	2004	1
316	EFTA Lebanon	2004	1
317	EFTA Tunisia	2004	1
318	India MERCOSUR	2004	0
319	Iran Pakistan	2004	0
320	Japan Mexico	2004	1
321	Jordan Singapore	2004	1
322	Macedonia Moldova	2004	1
323	MERCOSUR Southern African Customs Union (SACU)	2004	0
324	Mexico Uruguay	2004	1
325	Morocco Turkey	2004	1
326	Morocco US	2004	1
327	South Asian Free Trade Area (SAFTA)	2004	0
328	Syria Turkey	2004	1
329	Tunisia Turkey	2004	1
330	Asia Pacific Trade Agreement (Bangkok Agreement amended)	2005	0
331	Brazil Suriname	2005	0
332	Chile China	2005	1
333	EFTA Korea	2005	1
334	Egypt Turkey	2005	1
335	Faroe Islands Iceland	2005	0
336	Guatemala Taiwan	2005	1
337	India Singapore	2005	1
338	Japan Malaysia	2005	1
339	Korea Singapore	2005	1
340	Malawi Mozambique	2005	0
341	MERCOSUR Peru	2005	1
342	New Zealand Thailand	2005	1
343	Peru Thailand	2005	0
344	Trans Pacific Strategic EPA	2005	1
345	Albania EC SAA	2006	1
346	Albania Turkey	2006	1
347	Association of Southeast Asian Nations Korea	2006	0
348	Belize Guatemala	2006	0
349	Bhutan India	2006	0
350	Chile Colombia	2006	0
351	Chile India	2006	0
352	Chile Panama	2006	1
353	Chile Peru	2006	1
354	China Pakistan	2006	0
355	Colombia US	2006	1
356	Cuba MERCOSUR	2006	0
357	D8 PTA	2006	0
358	EFTA Southern African Customs Union (SACU)	2006	1
359	Iran Syria	2006	0
360	Japan Philippines	2006	1
361	Malawi Zimbabwe	2006	0
362	Nicaragua Taiwan	2006	1
363	Oman US	2006	1
364	Panama Singapore	2006	0
365	Peru US	2006	1
366	Brunei Japan	2007	1
367	Chile Japan	2007	1
368	Colombia Northern Triangle	2007	0
369	EC Lisbon	2007	1
370	EC Montenegro SAA	2007	1
371	EFTA Egypt	2007	1
372	El Salvador Honduras Taiwan	2007	0
373	Georgia Turkey	2007	1
374	Indonesia Japan	2007	1
375	Israel MERCOSUR	2007	0
376	Japan Thailand	2007	1
377	Korea US	2007	1
378	Malaysia Pakistan	2007	1

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Table D.4: List of Trade Agreements (cont.)

	Name	Year	IPRs
379	Mauritius Pakistan	2007	0
380	Panama US	2007	1
381	Algeria Tunisia	2008	1
382	Association of Southeast Asian Nations Japan	2008	1
383	Australia Chile	2008	1
384	Bosnia and Herzegovina EC SAA	2008	1
385	Canada Colombia	2008	0
386	Canada EFTA	2008	0
387	Canada Peru	2008	0
388	CARIFORUM EC EPA	2008	1
389	Chile Ecuador	2008	0
390	China New Zealand	2008	1
391	China Singapore	2008	0
392	Colombia EFTA	2008	1
393	Cote d'Ivoire EC EPA	2008	0
394	EC Serbia SAA	2008	1
395	Economic and Monetary Community of Central Africa (CEMAC) revised	2008	0
396	Gulf Cooperation Council (GCC) Singapore	2008	0
397	Japan Vietnam	2008	1
398	MERCOSUR Southern African Customs Union (SACU)	2008	1
399	Montenegro Turkey	2008	1
400	Paraguay Venezuela	2008	0
401	Peru Singapore	2008	1
402	Uruguay Venezuela	2008	0
403	Albania EFTA	2009	1
404	Association of Southeast Asian Nations Australia New Zealand FTA (AANZFTA)	2009	1
405	Association of Southeast Asian Nations Goods	2009	0
406	Association of Southeast Asian Nations India	2009	0
407	Belarus Serbia	2009	1
408	Canada Jordan	2009	0
409	Canada Panama	2009	0
410	Chile Turkey	2009	1
411	China Peru	2009	1
412	EC Pacific States EPA Fiji Papua New Guinea	2009	0
413	EFTA GCC	2009	1
414	EFTA Serbia	2009	1
415	India Korea	2009	1
416	India Nepal	2009	0
417	Japan Switzerland	2009	1
418	Jordan Turkey	2009	1
419	Malaysia New Zealand	2009	1
420	Serbia Turkey	2009	1
421	Chile Malaysia	2010	0
422	China Costa Rica	2010	1
423	Costa Rica Singapore	2010	1
424	EC Korea	2010	1
425	EFTA Peru	2010	1
426	EFTA Ukraine	2010	1
427	Egypt MERCOSUR	2010	0
428	Hong Kong New Zealand	2010	1
429	Central America Mexico	2011	1
430	Chile Vietnam	2011	0
431	Commonwealth of Independent States (CIS)	2011	0
432	Costa Rica Peru	2011	1
433	Cuba El Salvador	2011	0
434	EFTA Hong Kong	2011	1
435	EFTA Montenegro	2011	1
436	Guatemala Peru	2011	1
437	India Japan	2011	1
438	India Malaysia	2011	0
439	Japan Peru	2011	1
440	Korea Peru	2011	1
441	Mauritius Turkey	2011	1
442	Mexico Peru	2011	0
443	Montenegro Ukraine	2011	0
444	Panama Peru	2011	1
445	Australia Malaysia	2012	1
446	Brazil Venezuela	2012	0
447	Central America EC	2012	1
448	Chile Hong Kong	2012	1
449	Colombia EC Peru	2012	1
450	Indonesia Pakistan	2012	0
451	Korea Turkey	2012	1
452	Pacific Alliance	2012	0
453	Peru Venezuela	2012	0

Continued on next page

Table D.4: List of Trade Agreements (cont.)

	Name	Year	IPRs
454	Bosnia and Herzegovina EFTA	2013	1
455	Canada Honduras	2013	0
456	Central America EFTA	2013	1
457	Chile Thailand	2013	0
458	China Iceland	2013	1
459	China Switzerland	2013	1
460	Colombia Costa Rica	2013	1
461	Colombia Israel	2013	0
462	Colombia Korea	2013	1
463	Colombia Panama	2013	1
464	New Zealand Taiwan	2013	1
465	Panama Trinidad and Tobago	2013	0
466	Singapore Taiwan	2013	1
467	Australia Japan	2014	1
468	Australia Korea	2014	1
469	Canada Korea	2014	1
470	EC Georgia	2014	1
471	EC Moldova	2014	1
472	EC Ukraine	2014	1
473	Eurasian Economic Union (EAEU)	2014	1
474	Malaysia Turkey	2014	1
475	Mexico Panama	2014	1
476	Moldova Turkey	2014	1
477	Australia China	2015	1
478	China Korea	2015	1
479	Common Market for Eastern and Southern Africa (COMESA) East African Community (EAC) Southern African Development Community (SADC)	2015	0
480	EC Kazakhstan	2015	1
481	EC Kosovo SAA	2015	1
482	Eurasian Economic Union (EAEU) Vietnam	2015	1
483	Honduras Peru	2015	1
484	Japan Mongolia	2015	1
485	Korea New Zealand	2015	1
486	Korea Vietnam	2015	1
487	Singapore Turkey	2015	1
488	Canada EC (CETA)	2016	1
489	Chile Uruguay	2016	1
490	EC South African Development Community (SADC) EPA	2016	1
491	EFTA Georgia	2016	1
492	EFTA Philippines	2016	1
493	Transpacific Partnership (TPP)	2016	1
494	Argentina Chile	2017	0
495	Armenia EC	2017	1
496	Canada Ukraine	2017	1
497	Chile Indonesia	2017	1
498	China Georgia	2017	1
499	Ecuador El Salvador	2017	0
500	Hong Kong Macao	2017	1
501	Pacific Agreement on Closer Economic Relations (PACER) Plus	2017	0
502	Paraguay Taiwan	2017	1
503	Australia Peru	2018	1
504	Central America Korea	2018	1
505	Comprehensive and Progressive Agreement for Transpacific Partnership (CPTPP)	2018	1
506	Continental Free Trade Agreement	2018	0
507	EC Japan	2018	1
508	EC Singapore	2018	1
509	Ecuador EFTA	2018	1
510	EFTA Indonesia	2018	1
511	EFTA Turkey	2018	1
512	Eurasian Economic Union (EAEU) Iran	2018	0
513	Georgia Hong Kong	2018	1
514	Singapore Sri Lanka	2018	1
515	US Mexico Canada Agreement (USMCA)	2018	1

Table D.5: Correlation Matrix

	M&A Deals	IPR Strength (max)	Patents (CS5)	PTA Depth	Partner GDP	Partner GDPpc	Partner Democracy	WTO Members	Distance (km)	Total Revenue	Employees (No.)	EBIT
M&A Deals	1.00											
IPR Strength (max)	0.00	1.00										
Patents (CS5)	0.00	0.07	1.00									
PTA Depth	0.02	0.73	0.04	1.00								
Partner GDP	0.04	0.11	0.01	0.08	1.00							
Partner GDPpc	0.02	0.26	0.00	0.20	0.27	1.00						
Partner Democracy	0.01	0.29	0.01	0.23	0.04	0.36	1.00					
WTO Members	0.01	0.10	0.01	0.08	0.07	0.19	0.28	1.00				
Distance (km)	-0.02	0.01	0.09	-0.23	0.20	-0.03	-0.02	0.05	1.00			
Total Revenue	0.01	0.00	0.09	-0.03	0.02	-0.01	-0.02	0.00	0.07	1.00		
Employees (No.)	0.00	0.01	0.12	0.01	-0.08	-0.07	0.02	-0.03	0.01	0.05	1.00	
EBIT	0.01	0.00	0.02	-0.02	0.01	-0.01	-0.01	0.00	0.04	0.88	0.03	1.00

Table D.6: Negative Binomial Regression Results (including sector FEs)

	(1)	(2)	(3)
IPR Strength (max)		-0.005^{***}	-0.005^{***}
		(0.000)	(0.000)
Patents (CS5)			0.000^{***}
			(0.000)
PTA Depth	0.013^{***}	0.053^{***}	0.053^{***}
	(0.003)	(0.004)	(0.004)
IPR Strength (max) x Patents (CS5)			-0.000^{*}
			(0.000)
Partner GDP (log.)	1.313^{***}	1.070^{***}	1.070^{***}
	(0.081)	(0.080)	(0.080)
Partner GDPpc (log.)	-1.061^{***}	-0.829^{***}	-0.829^{***}
	(0.085)	(0.083)	(0.083)
Partner Democracy	0.035^{***}	0.032^{***}	0.032^{***}
	(0.004)	(0.004)	(0.004)
Distance (km)	-0.000^{***}	-0.000^{***}	-0.000^{***}
	(0.000)	(0.000)	(0.000)
WTO Members	0.920^{***}	0.864^{***}	0.865^{***}
	(0.039)	(0.040)	(0.040)
HQ FE	Yes	Yes	Yes
Partner FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Deviance	470277.572	470309.961	470368.022
Num. obs.	2359707	2359707	2359707

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Firm-level clustered standard errors in parentheses

Table D.7: Negative Binomial Regressions (including firm-level controls: EBIT)

	(A1)	(A2)	(A3)	(A4)	(A5)	(A6)
IPR Strength (max)		-0.009^{***}	-0.009^{***}	-0.007^{***}	-0.008^{***}	-0.006^{***}
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Patents (CS5)			0.000	0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)
PTA Depth	-0.000	0.083^{***}	0.083^{***}	0.066^{***}	0.064^{***}	0.049^{***}
	(0.006)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)
IPR Strength (max) x			-0.000	-0.000	-0.000	-0.000
Patents (CS5)			(0.000)	(0.000)	(0.000)	(0.000)
EBIT	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Partner GDP (log.)	1.787^{***}	0.176^{***}	0.176^{***}	0.105^{***}	1.283^{***}	1.469^{***}
	(0.163)	(0.008)	(0.008)	(0.005)	(0.133)	(0.160)
Partner GDPpc (log.)	-1.681^{***}	-0.021^{*}	-0.021^{*}	-0.007	-1.271^{***}	-1.369^{***}
	(0.169)	(0.010)	(0.010)	(0.007)	(0.152)	(0.166)
Partner Democracy	0.014^{*}	0.006^{**}	0.006^{**}	0.005^{**}	0.013^{*}	0.012^{*}
	(0.006)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)
Distance (km)	-0.000^{***}	-0.000^{***}	-0.000^{***}	-0.000^{***}	-0.000^{***}	-0.000^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
WTO Members	0.316^{***}	0.012	0.011	0.044	0.219^{**}	0.275^{***}
	(0.073)	(0.053)	(0.053)	(0.046)	(0.074)	(0.073)
HQ FE	Yes	No	No	Yes	Yes	Yes
Partner FE	Yes	No	No	No	Yes	Yes
Year FE	Yes	No	No	No	No	Yes
Deviance	139878.209	144289.796	144292.425	139405.242	139502.927	139869.729
Num. obs.	486017	460563	460563	486067	486017	486017

Notes: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, †$p < 0.10$; Firm-level clustered standard errors in parentheses

Table D.8: Negative Binomial Regressions (including firm-level controls: Employees)

	(A7)	(A8)	(A9)	(A10)	(A11)	(A12)
IPR Strength (max)		-0.002^{*}	-0.002^{*}	-0.000	-0.005^{***}	-0.006^{***}
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Patents (CS5)			0.000	0.000^{*}	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)
PTA Depth	0.021^{**}	0.080^{***}	0.079^{***}	0.058^{***}	0.077^{***}	0.069^{***}
	(0.007)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)
IPR Strength (max) x			-0.000	$-0.000^{\dagger}$	-0.000	-0.000
Patents (CS5)			(0.000)	(0.000)	(0.000)	(0.000)
Employees (No.)	0.000^{***}	-0.000^{*}	-0.000^{*}	0.000^{***}	0.000^{***}	0.000^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Partner GDP (log.)	1.934^{***}	0.207^{***}	0.207^{***}	0.123^{***}	2.292^{***}	1.626^{***}
	(0.178)	(0.009)	(0.009)	(0.006)	(0.144)	(0.174)
Partner GDPpc (log.)	-1.785^{***}	0.085^{***}	0.085^{***}	0.049^{***}	-1.932^{***}	-1.488^{***}
	(0.184)	(0.011)	(0.011)	(0.008)	(0.164)	(0.181)
Partner Democracy	0.027^{***}	-0.006^{*}	-0.006^{*}	-0.005^{*}	0.034^{***}	0.024^{***}
	(0.006)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)
Distance (km)	-0.000^{***}	-0.000^{***}	-0.000^{***}	-0.000^{***}	-0.000^{***}	-0.000^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
WTO Members	0.599^{***}	0.563^{***}	0.562^{***}	0.604^{***}	0.554^{***}	0.552^{***}
	(0.073)	(0.055)	(0.056)	(0.052)	(0.074)	(0.073)
HQ FE	Yes	No	No	Yes	Yes	Yes
Partner FE	Yes	No	No	No	Yes	Yes
Year FE	Yes	No	No	No	No	Yes
Deviance	116328.296	120513.506	120540.385	115951.715	115987.904	116360.871
Num. obs.	528975	527397	527397	528975	528975	528975

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.10$; Firm-level clustered standard errors in parentheses

Table D.9: Negative Binomial Regressions (including firm-level controls: Total Revenue)

	(A13)	(A14)	(A15)	(A16)	(A17)	(A18)
IPR Strength (max)		-0.009^{***}	-0.009^{***}	-0.006^{***}	-0.007^{***}	-0.006^{***}
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Patents (CS5)			0.000	0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)
PTA Depth	0.001	0.082^{***}	0.082^{***}	0.063^{***}	0.062^{***}	0.048^{***}
	(0.006)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)
IPR Strength (max) x			-0.000	-0.000	-0.000	-0.000
Patents (CS5)			(0.000)	(0.000)	(0.000)	(0.000)
Total Revenue	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Partner GDP (log.)	1.780^{***}	0.178^{***}	0.178^{***}	0.103^{***}	1.352^{***}	1.482^{***}
	(0.167)	(0.009)	(0.009)	(0.005)	(0.139)	(0.165)
Partner GDPpc (log.)	-1.676^{***}	-0.010	-0.010	-0.000	-1.342^{***}	-1.384^{***}
	(0.174)	(0.010)	(0.010)	(0.007)	(0.158)	(0.172)
Partner Democracy	0.013^{*}	0.004	$0.004^{\dagger}$	0.003^{*}	$0.010^{\dagger}$	0.010
	(0.006)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)
Distance (km)	-0.000^{***}	-0.000^{***}	-0.000^{***}	-0.000^{***}	-0.000^{***}	-0.000^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
WTO Members	0.297^{***}	-0.008	-0.009	0.039	0.205^{**}	0.263^{***}
	(0.077)	(0.057)	(0.057)	(0.050)	(0.079)	(0.077)
HQ FE	Yes	No	No	Yes	Yes	Yes
Partner FE	Yes	No	No	No	Yes	Yes
Year FE	Yes	No	No	No	No	Yes
Deviance	135897.219	140344.777	140347.671	135442.407	135538.124	135886.770
Num. obs.	470081	447548	447548	470134	470081	470081

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.10$; Firm-level clustered standard errors in parentheses

Table D.10: Negative Binomial Regressions (Patents (new))

	(1)	(2)	(3)	(4)
IPR Strength (max)	-0.005^{***}	-0.006^{***}	-0.006^{***}	-0.006^{***}
	(0.000)	(0.001)	(0.001)	(0.001)
Patents (new)	0.000^{***}	0.000^{**}	0.000^{***}	0.000^{**}
	(0.000)	(0.000)	(0.000)	(0.000)
PTA Depth	0.054^{***}	0.049^{***}	0.069^{***}	0.048^{***}
	(0.004)	(0.008)	(0.010)	(0.008)
IPR Strength (max) x Patents (new)	-0.000^{***}	$-0.000^{\dagger}$	-0.000^{*}	-0.000^{*}
	(0.000)	(0.000)	(0.000)	(0.000)
EBIT		0.000^{***}		
		(0.000)		
Employees (No.)			0.000^{***}	
			(0.000)	
Total Revenue				0.000^{***}
				(0.000)
Partner GDP (log.)	1.079^{***}	1.475^{***}	1.632^{***}	1.488^{***}
	(0.080)	(0.160)	(0.174)	(0.165)
Partner GDPpc (log.)	-0.840^{***}	-1.375^{***}	-1.494^{***}	-1.390^{***}
	(0.084)	(0.166)	(0.181)	(0.172)
Partner Democracy	0.032^{***}	$0.012^{\dagger}$	0.024^{***}	0.010
	(0.004)	(0.006)	(0.006)	(0.006)
Distance (km)	-0.000^{***}	-0.000^{***}	-0.000^{***}	-0.000^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
WTO Members	0.862^{***}	0.274^{***}	0.550^{***}	0.262^{***}
	(0.040)	(0.073)	(0.073)	(0.077)
HQ-year FE	Yes	Yes	Yes	Yes
Partner-year FE	Yes	Yes	Yes	Yes
Dyad FE	Yes	Yes	Yes	Yes
Deviance	470154.992	139877.782	116378.513	135894.127
Num. obs.	2361096	486017	528975	470081

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.10$; Firm-level clustered standard errors in parentheses

Table D.11: Negative Binomial Regressions (Patents (CS))

	(1)	(2)	(3)	(4)
IPR Strength (max)	-0.005^{***}	-0.006^{***}	-0.006^{***}	-0.006^{***}
	(0.000)	(0.001)	(0.001)	(0.001)
Patents (CS)	$0.000^{\dagger}$	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
PTA Depth	0.054^{***}	0.049^{***}	0.069^{***}	0.048^{***}
	(0.004)	(0.008)	(0.010)	(0.008)
IPR Strength (max) x Patents (CS)	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
EBIT		0.000^{***}		
		(0.000)		
Employees (No.)			0.000^{***}	
			(0.000)	
Total Revenue				0.000^{***}
				(0.000)
Partner GDP (log.)	1.077^{***}	1.469^{***}	1.626^{***}	1.482^{***}
	(0.080)	(0.160)	(0.174)	(0.165)
Partner GDPpc (log.)	-0.837^{***}	-1.369^{***}	-1.488^{***}	-1.384^{***}
	(0.084)	(0.166)	(0.181)	(0.172)
Partner Democracy	0.032^{***}	0.012^{*}	0.024^{***}	0.010
	(0.004)	(0.006)	(0.006)	(0.006)
Distance (km)	-0.000^{***}	-0.000^{***}	-0.000^{***}	-0.000^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
WTO Members	0.864^{***}	0.275^{***}	0.552^{***}	0.263^{***}
	(0.040)	(0.073)	(0.073)	(0.077)
HQ-year FE	Yes	Yes	Yes	Yes
Partner-year FE	Yes	Yes	Yes	Yes
Dyad FE	Yes	Yes	Yes	Yes
Deviance	470144.554	139869.729	116360.871	135886.770
Num. obs.	2361096	486017	528975	470081

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.10$; Firm-level clustered standard errors in parentheses