Exploiting Modern Trade Data: Sanctions, Trade Agreements, and Product Classifications

DISSERTATION
of the University of St.Gallen,
School of Management,
Economics, Law, Social Sciences,
International Affairs and Computer Science,
to obtain the title of
Doctor of Philosophy in Economics and Finance

submitted by

Piotr Lukaszuk

from
Poland

Approved on the application of

Prof. Simon Evenett, PhD

and

Prof. Marcelo Olarreaga, PhD

Dissertation no. 5127

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The University of St.Gallen, School of Management, Economics, Law, Social Sciences, International Affairs and Computer Science, hereby consents to the printing of the present dissertation, without hereby expressing any opinion on the views herein expressed.

St.Gallen, May 28, 2021

The President:

Prof. Dr. Bernhard Ehrenzeller

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St.Gallen, May 28, 2021 Piotr Lukaszuk

Abstract

This dissertation exploits fine-grained trade data to study how the evasion of trade sanctions may be detected, which factors determine the utilization of free trade agreements, and how to improve the quality of intertemporal product-level trade data.

Chapter 1 investigates whether sanctions imposed in the wake of the Ukraine crisis by the Western countries and Russia have been evaded by analyzing monthly product-level trade patterns. Consolidating different methods from the literature related to the detection of illicit trade, the analysis shows that in particular goods facing sanctions imposed by the Russian government have most likely been evaded. While the detected amounts do not question the general effectiveness of the sanctions, they are non-negligible: roughly 482 million US dollars (USD), or 8.56% of the total estimated trade loss of 5.633 billion USD from the Russian sanctions, may have been smuggled either directly or through its neighboring countries. As more than half of the estimated evasion involves trade flows through Belarus and Kazakhstan, the findings highlight the importance of trade policy coordination with third countries, especially if these are part of the same customs union.

Chapter 2 looks at the factors determining whether firms utilize free trade agreements (FTAs). In order to benefit from lower tariff rates, companies must apply for preferential customs treatment and comply with rules of origin requirements. This is costly and explains why preference utilization rates (PUR) are typically far below 100 percent. Analyzing Switzerland's wide network of FTAs using a novel dataset on all transactions spanning four years of Swiss imports, Chapter 2 identifies new insights on what determines FTA utilization. The findings call into question the notion of a fixed preference margin threshold for FTAs to be utilized. Furthermore, using a revealed preference criterion, it identifies a fixed cost component of the utilization, which firms avoid especially for urgent shipments. The chapter also shows limited evidence of learning effects among firms and provides well-identified estimates of the restrictive effects of rules of origin. Moreover, the study documents that the mix of products that FTA partners trade has substantial predictive power for the overall utilization rate.

Chapter 3 tackles the common problem of product (HS) code reclassifications in trade data which affect up to 44% of goods trade. Existing methods either pool changed codes together or simplify the links between different vintages. The former approach bulks up to a quarter of world trade into one synthetic code, while the latter creates artificial jumps in the number of non-traded products. The chapter provides an alternative method whereby codes are converted based on their relative importance in trade values. The proposed method largely addresses the aforementioned issues and is robust to year and sample choices. Further, its merits are shown in simple applications concerning supply and demand trends in trade.

Zusammenfassung

Diese Dissertation untersucht anhand detaillierter Handelsdaten, wie die Handelssanktionen umgangen werden, welche Faktoren die Nutzung von Freihandelsabkommen bestimmen und wie die Qualität von Handelsdaten auf Produktebene verbessert werden kann.

Kapitel 1 untersucht, ob die im Zuge der Ukraine-Krise von den westlichen Ländern und Russland verhängten Sanktionen umgangen wurden, indem monatliche Handelsströme auf Produktebene analysiert werden. Durch die Zusammenführung verschiedener Methoden aus der Literatur zur Aufdeckung von illegalem Handel zeigt die Analyse, dass insbesondere Güter, die von der russischen Regierung mit Sanktionen belegt wurden, höchstwahrscheinlich umgangen wurden. Die aufgedeckten Beträge stellen zwar nicht die generelle Wirksamkeit der Sanktionen in Frage, sind aber nicht unerheblich: Etwa 482 Millionen US-Dollar (USD), oder 8,56% des geschätzten Gesamthandelsverlustes von 5,633 Milliarden USD durch die russischen Sanktionen, könnten entweder direkt oder über die Nachbarländer eingeschleust worden sein. Da die Mehrheit der geschätzten Umgehungen Weissrussland und Kasachstan betreffen, unterstreichen die Ergebnisse die Bedeutung der handelspolitischen Koordinierung mit Drittländern, insbesondere innerhalb einer Zollunion.

Kapitel 2 befasst sich mit den Faktoren, welche die Nutzung von Freihandelsabkommen (FHAs) durch Firmen beeinflussen. Um von niedrigeren Zollsätzen zu profitieren, müssen Unternehmen eine präferenzielle Zollbehandlung beantragen und die Anforderungen der Ursprungsregeln erfüllen. Dies ist kostspielig und erklärt, warum die Präferenznutzungsraten (PUR) typischerweise weit unter 100 Prozent liegen. Durch die Analyse des breiten FHA-Netzwerks der Schweiz und unter Verwendung eines neuerstellten Datensatzes über alle Transaktionen von Schweizer Importen über vier Jahre hinweg, liefert Kapitel 2 neue Erkenntnisse darüber, was die Nutzung von FHAs bestimmt. Die Ergebnisse stellen die Vorstellung eines festen Präferenzgrenzwertes für die FHA-Nutzung in Frage. Das Kapitel zeigt auch begrenzte Evidenz für Lerneffekte bei Unternehmen und liefert klar identifizierte Schätzungen für die restriktiven Effekte von Ursprungsregeln. Darüber hinaus dokumentiert die

Studie, dass der Produktmix, mit dem die FHA-Partner handeln, eine erhebliche Vorhersagekraft für die Gesamtnutzungsrate hat.

Kapitel 3 befasst sich mit dem häufigen Problem der Neuklassifizierung von Produktcodes (HS) in Handelsdaten, die bis zu 44% des Warenhandels betreffen. Bestehende Methoden fassen entweder geänderte Codes zusammen oder vereinfachen die Verbindungen zwischen verschiedenen Jahrgängen. Der erste Ansatz bündelt bis zu einem Viertel des Welthandels in einem synthetischen Code, während der zweite künstliche Sprünge in der Anzahl nicht gehandelter Produkte erzeugt. In diesem Kapitel wird eine alternative Methode vorgestellt, bei der Produktcodes anhand iherer relativen Grösse zugeteilt und umgewandelt werden. Die vorgeschlagene Methode löst die oben genannten Probleme weitgehend und ist robust gegenüber der Wahl der Jahre und der Stichprobe. Darüber hinaus werden ihre Vorzüge in einfachen Anwendungen bezüglich Angebots- und Nachfragetrends im Handel gezeigt.

Contents

Chapter 1

You can smuggle but you can't hide: Sanction evasion during the Ukraine crisis

1.1 Introduction

The past decade in trade policy has seen a return to its politicization. Whether one focuses on the rise of protectionism since the financial crisis of 2008, the active tariff policy introduced by the Trump administration, or more recently China's trade restrictions on Australia for pushing for an independent investigation over the Covid-19 outbreak, trade measures have increasingly become an instrument of foreign and industrial policies rather than a multilateral effort to facilitate trade on a level playing field.

This trend involves — besides targeting of trade with particular countries — often forensic interventions aimed at particular sectors, goods, firms, or even individuals. In the case of United States, for instance, trading partners retaliated to tariffs introduced by the Trump administration by (successfully) targeting goods produced in counties with Republican politicians participating in contested 2018 Congress midterm elections (Blanchard, Bown and Chor, 2019).

Traditionally, such trade policy measures were restricted to political sanctions, which overtly followed foreign policy objectives and included targeted trade measures (Hufbauer et al., 2008). In particular, so-called smart sanctions have aimed at individual firms, products, or persons (Cortright and Lopez, 2002). Apart from more focused targeting, modern sanctions go beyond outright trade bans and instead have expanded to, e.g., licensing requirements or tariffs; some facing imports, whilst others exports.

This rise in active, targeted trade policy obfuscates the already complex international trading system and offers trade actors ample opportunities (and incentives) to evade the new barriers. For instance, when the United States introduced punitive tariffs on China in 2018, the U.S. Customs and Border Protection saw a nearly 50% rise in customs rulings related to the misclassification of goods, as firms tried to exploit the fact that early tariff rounds spared products similar to theirs.[1] Similarly, when Russia introduced counter-sanctions on Western agricultural products in the wake of the Ukraine crisis, Russian newspapers reported on Belarusian seafood and tropical fruits appearing in local supermarkets — clearly cases of mislabeled country of origin certificates to evade the import sanctions imposed on products from the European Union (Yeliseyeu, 2017).

The incentives to evade trade barriers are particularly high for political sanctions, as they aim (inter alia in the form of goods sanctions) to economically impact the target economy and key decision makers by minimizing trade flows (Eaton and Engers, 1992; Kaempfer and Lowenberg, 1988) — unlike import tariffs, which are mainly intended to extract rent and to support the implementing jurisdiction's industry. Therefore, a large string of the sanction literature addresses their effectiveness in the context of their (lack of) enforce-

[1] See the U.S. CBP's Customs Ruling Online System (CROSS) and, e.g., ruling NY N300833 where beard kits from China had to be reclassified and additional China-specific duties of 10% incurred.

ability (Caruso, 2003; McLean and Whang, 2010; van Bergeijk and Biersteker, 2015). While factors such as missing support from the target's main trading partners (Dizaji and van Bergeijk, 2013; Noland, 2009) or scope of the sanctions (Caruso, 2003; Hufbauer, Oegg et al., 2003) play prominent roles, these factors are directly linked to the question whether the imposed barriers are evaded: If large trading partners provide economic assistance (Bonetti, 1998) or enable trade routes such that the sanctioned products arrive in the target country anyway (Early, 2009), sanctions imposed on any goods are unlikely to achieve their desired effect.

While these sanction evasion concepts are theoretically well-established and have been empirically analyzed for comprehensive sanctions typical for the 20th century, this area of research remains largely unexplored in relation to modern targeted sanctions. Instead of sanctions facing goods, recent research on sanction evasion has focused on the enforceability of person- and firm-related sanctions (Ahn and Ludema, 2020; Haidar, 2017) as well restrictions related to financial flows (Besedeš, Goldbach and Nitsch, 2017).

I contribute to this literature by analysing the prevalence of sanction evasion in the context of modern targeted goods sanctions. More precisely, I identify five different channels of sanction evasion and empirically analyze four of them, thus consolidating the various concepts of smuggling and evasion recorded in the literature.

Based on the example of sanctions implemented by Western economies and Russia in 2014 in relation to the Ukraine crisis, I find evidence for direct smuggling that may have occurred for agricultural products banned by Russia. Furthermore, certain neighboring countries — particularly those within the same customs union as Russia — significantly increased their trade with Western sanctioning jurisdictions, indicating potential reexports or indirect smuggling for Kazakhstan and Georgia. Meanwhile, evidence related to Belarus may be hindered by suppressed or undocumented trade flows, as indicated by the significant increase of the country's net imports with respect to Russian sanctioned agricultural goods. The analysis does not find any evidence for misclassification of goods. Overall, I estimate sanction evasion of up to 482 million USD. This represents 8.56% of the estimated decline resulting from the Russian sanctions.

The paper also contributes directly to the literature on the impact of modern sanctions studied concretely in the context of the Ukraine crisis. For instance, Crozet and Hinz (2020) focus on the direct impact the sanctions had on trade between the Western economies and Russia, whereas I look indirectly at whether the impact would have been worse if the sanctions were not evaded.

More broadly, the study offers a contribution to the literature on the effectiveness of modern trade policy. Given how multifaceted trade policy has become by targeting particular product-origin combinations, I provide direct evidence to what degree countries are able to enforce the complex network of trade policy instruments. The studied example is particularly interesting, as targeted sanctions involve also the enforcement of trade policy by third countries not directly involved in the trade measures. The findings thus illustrate a further channel through which trade policy may have a political impact on the multilateral stage.

The remainder of the paper is structured as follows. The next Section 1.2 summarizes the sanctions introduced in the context of the Ukraine crisis and provides anecdotal evidence on how they may have been evaded. Section 1.3 then details the methodology of the empirical analysis and discusses the various evasion channels, while Section 1.4 describes the data applied in the analysis. Results are presented in Section 1.5. Section 1.6 concludes the paper.

1.2 Sanctions during the Ukraine crisis

The following section first provides an overview of the sanctions introduced during the Ukraine crisis and then contextualizes them in terms of their overall and sector-specific importance. It also illustrates indications of sanction evasion using the anecdotal case of apple trade involving Belarus.

History of the sanctions. Following the military invasion of Ukraine by Russia in February 2014, Canada, the European Union (EU), and the

United States responded by introducing sanctions against certain Russian and Ukrainian officials[2] on 17 March 2014. The measures included asset freezes, a prohibition for local operators to provide financing, as well as travel bans. In the following weeks, similar sanctions were introduced by Australia, Albania, Iceland, Japan, and Montenegro. In addition, diplomatic measures were imposed: Russia's voting rights in the Council of Europe were suspended, regular bilateral talks with the country were halted, and Russia was no longer invited to G-8 meetings.

In the coming months, the Western economies expanded the list of individuals and firms that were covered by sanctions. On 26 June 2014, the European Union additionally introduced an import ban on all goods and an export ban on certain goods and technologies from Crimea and Sevastopol. European businesses were also prohibited from offering any tourism services in the two listed areas.

The largest round of sanctions — which is of primary focus in this paper — was introduced at the end of July as a reaction to the downing of the Malaysia Airlines MH17 airplane on 17 July 2014. On 29 July 2014, the European Union introduced a vast set of "economic sanctions" spanning the areas of finance, energy, defense, and dual-use goods[3].

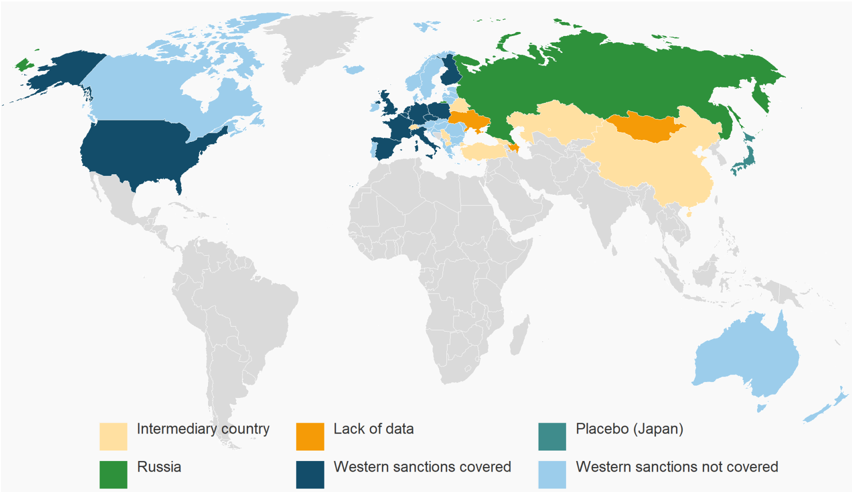
In terms of goods sanctions, this round included an embargo on weapons trade, an export ban for dual-use goods used for military purposes, as well as an export licensing regime for energy-related equipment and technology. The license would be denied in cases where the goods were exported inter alia for deep water oil exploration and production. With respect to financial restrictions, EU capital markets were limited for Russian state-owned financial institutions to financial instruments lasting maximum 90 days[4]. The European Investment Bank (EIB) and the European Bank for Reconstruction and

[2] These targeted sanctions against individuals and entities were later expanded over time and e.g. in the case of the EU involve 177 people and 48 entities as of January 2021.

[3] Dual-use goods are products and technology which may be used for both civil and military purposes.

[4] This was later restricted to a maximum of 30 days through sanctions imposed on 11 September 2014. The September sanctions also introduced a complete ban on transactions with the five major Russian state-owned banks.

Figure 1.1: World map of countries included in the study.



Note: This figure illustrates the different country groups involved in the sanctions imposed in relation to the Ukraine crisis. Blue-colored jurisdictions imposed sanctions on Russia, with the 11 dark blue ones covered in this study. The identified intermediary countries (cf. Section 1.3) are denoted in beige, while Japan serves as a placebo. Azerbaijan, Mongolia, and Ukraine were not included due to a lack of data.

Development (EBRD) were no longer allowed to provide lending to Russia. These economic sanctions came into force on 1 August 2014 and need to be renewed every six months. As of January 2021, they remain in force.

Canada and the United States introduced similar, even if less extensive, sanctions on the defense, energy and finance industries in July and September 2014, respectively. In August, Ukraine and Japan introduced more individual- and firm-related sanctions, while Norway adopted the same regulations as EU's July sanctions. On 28 August 2014, Switzerland passed measures to prevent the circumvention of the EU sanctions (in the form of export licensing regimes) through the Swiss territory.[5]

In summary, Western sanctions on traded goods may be divided largely into

[5]The report by Evenett et al. (2017) found that these measures indeed prevented the circumvention of goods sanctioned by the EU. However, the report also found some indications of potential circumvention in relation to the Russian sanctions.

three categories: (i) a full trade ban (on weapons); (ii) a partial ban (on dual-use goods if used for military purposes); and (iii) an export licensing regime (for goods used in the oil sector). Out of the dozen studied (cf. Figure 1.1) countries, only the European Union members imposed all three categories of sanctions. The United States, on the other hand, covered the first and third category. In total, 39 countries[6] imposed sanctions against Russia in relation to the Ukraine crisis. This paper focuses on the twelve largest ones based on 2013 trade statistics, which are either Japan, the United States, or EU member states: Belgium, Czechia, Finland, France, Germany, Italy, Netherlands, Poland, Spain, and the United Kingdom. While Japan is used as a placebo (having imposed only non-goods sanctions), the other jurisdictions implemented goods sanctions in August 2014, which is applied as the starting point for the sanction analysis.

Russia retaliated to the Western sanctions by introducing on 7 August 2014 an import ban on a large share of agricultural products from the European Union, the United States, Australia, Canada, and Norway. The list of sanctioned countries was expanded a year later — on 13 August 2015, to be precise — to Albania, Montenegro, Iceland, and Liechtenstein. The update would also cover Ukraine starting from 1 January 2016 if it joined the EU Association Agreement (which it did). Furthermore, Russia imposed sanctions on Turkey on 1 December 2015 following the shooting down of a Russian jet by the Turkish military. The Turkish sanctions, similarly to the ones on Ukraine, came into force on 1 January 2016. Unlike for other targets of Russian measures, the Turkish sanctions were (partially) lifted on 11 October 2016 and on 2 June 2017.

Apart from the clearly announced sanctions, Russia also banned certain meat types from the European Union, Moldova, and Ukraine on health grounds in September and October 2014 (Blanchard and Wu, 2019). However, these measures were not (officially) politically motivated and are hence not covered in this study as sanctions. Instead, they are accounted for in the policy covariates

[6]The full set of countries which imposed sanctions on Russia following the Ukraine crisis include the European Union, Japan, the United States, as well as Albania, Australia, Canada, Georgia, Moldova, Montenegro, New Zealand, Norway, and Ukraine.

(cf. Section 1.4).

An overview of the HS product codes covered by the sanctions on traded goods has been listed in Table A.2. The list excludes sanctions imposed by and on jurisdictions that are not covered in this paper (e.g., Canada, Norway, or Australia).

Contextualization of the sanctions. As this study abstracts from the analysis of weapons trade due to their special nature[7], there are three types of goods sanctions covered in this paper. First, Russia imposed sanctions in the form of a “traditional” import ban on large sections of agricultural produce. Based on 2013 import figures, these concern 9.43 billion U.S. dollars (USD) of Russian imports (39.8% of total agricultural imports). According to Table A.2 in Appendix A, the sanctions target primarily imports from Poland, the United States, Germany, Netherlands, and Spain. However, in terms of their relative share of trade with Russia, Poland, Spain, and Netherlands are most affected.

Meanwhile, the Western sanctions have a more complex structure. While the export licenses were imposed on ca. 30 to 50 products worth 2.4 billion USD (cf. Table A.2), the dual-use goods cover over 6000 different detailed tariff lines classified at the 10-digit CN level (spanning 756 different 6-digit HS codes; or ca. 15% of all product codes) worth up to 63.6 billion USD. Importantly, the information registered in the available trade data does not distinguish between cases where a given dual-use good was exported for civil purposes or whether a good was halted from shipping due to being classified for military purposes. As this data is not publicly available, the analysis of goods facing Western sanctions needs to be interpreted as potentially harmed by the sanctions. Russian sanctions are therefore considered to be more stringent in terms of both their intensity — as they cover a complete ban with no exceptions — and their scope — all products within a product category are covered. One may thus expect a larger impact on trade with regard to the Russian than the Western goods sanctions:

[7] Trade in weapons is often underreported or hidden in official figures and this paper is based on a detailed analysis of trade flows.

Hypothesis 1. *Trade declines between Western sanctioning countries and Russia are more pronounced for goods facing Russian than Western sanctions.*

Should Hypothesis 1 hold, this implies I am more likely to observe sanction evasion for goods facing Russian sanctions assuming that evasion is positively correlated with the amount of trade lost due to the sanction imposition.

In terms of trade covered, roughly a quarter of Russian imports (23.8%) are directly impacted by Western or Russian sanctions, with the majority of that trade relating to dual-use goods. Also, one should take into account that imports from the sanctioning countries represent over half of Russia's total imports (cf. Table A.1). Most of the other important trading partners are analyzed as intermediary countries (cf. Section 1.3). As a result, the study includes trade covering ca. 80% of Russia's imports (in 2013 terms) and all of its 20 most important trading partners with the exception of the Republic of Korea and Ukraine.

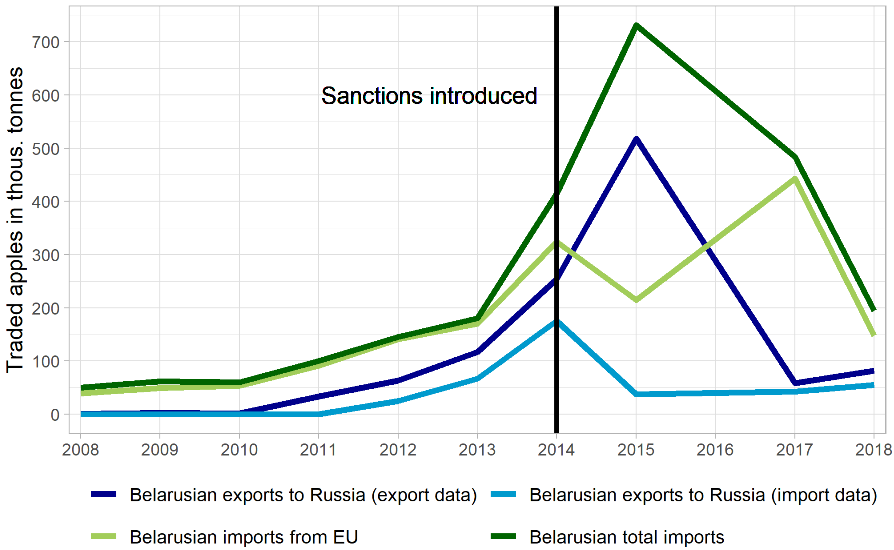
With respect to the timing, all goods sanctions were imposed within a week of their announcement. Hence, it is unlikely to observe anticipation effects often seen in the sanctions literature (Kaempfer and Lowenberg, 2007); however, this hypothesis is tested in the empirical analysis:

Hypothesis 2. *There are no anticipation effects on the imposed goods sanctions by Russia nor on those by the Western countries.*

Lastly, one should take into account that trade flows may have been impacted also by sanctions not directly related to goods trade. For instance, Crozet and Hinz (2020) find that over 80% of the trade decline can be attributed to products not directly impacted by the goods sanctions. Their analysis further shows that these declines are positively correlated with those sectors that rely heavily on trade finance. Hence, when estimating the impacts of goods sanctions on trade flows, the paper at hand controls for sector-specific effects caused inter alia by the financial sanctions (cf. Section 1.3).

Example of sanction evasion evidence. When Russia imposed its import ban on agricultural products, Belarus and Kazakhstan, which share a customs union with Russia, refrained from similar measures. Instead, shortly after their imposition by their large neighbor, news articles emerged quoting cases of EU products being smuggled through Belarus into the Russian market (Yeliseyeu, 2017).

Figure 1.2: Belarusian trade in apples during the Ukraine crisis.



Note: This figure illustrates annual quantity flows related to the trade in fresh apples (HS code 080810) as reported by Belarus and Russia to UN Comtrade.

While this paper analyzes the case for sanction evasion more systematically, the example of Belarusian apple trade provides an interesting anecdote of how such smuggling can be identified through irregular patterns in trade data. As Figure 1.2 illustrates, while in 2014 — the year sanctions were introduced — Belarus' apple exports to Russia doubled, they quickly returned to pre-sanction levels and remained very stable, according to Russian import data. Meanwhile, Belarusian export data of the same trade flow saw a five-fold increase, with similar surges for Belarus' total imports. A potential explanation of such a pattern could be the (illegal) practice of redirecting EU exports through an intermediary country such as Belarus — which is a member of the same customs union as Russia (the Eurasian Economic Union) — allowing for an easier illegal reexport into Russia.

Furthermore, Figure 1.2 indicates that Belarus started sourcing apples from non-EU countries in the years 2014–16, despite nearly all imports previously originating from the EU[8]. Yeliseyeu (2017) documents how this pattern may be explained by forged certificates of origin, with Belarus officially importing apples from such unlikely countries as Ecuador or Sierra Leone. As these practices repeatedly caught the attention of Russia[9], Belarus appeared to suppress its export (and to a lesser degree import) data after 2015, leading to net imports suddenly reaching 425 thousand tonnes in 2017, nearly seven times their pre-sanction amounts.

As this example of sanction evasion shows, indications for such activities can be derived directly from international trade flows. Second, there seem to be numerous methods through which sanction may be evaded. This paper looks to analyze these points in greater detail and investigate whether sanction evasion occurred on a broader scale beyond the anecdotal evidence presented above. Thus, a systematic approach to detecting evidence of sanction evasion is presented in the following section.

1.3 Methodology

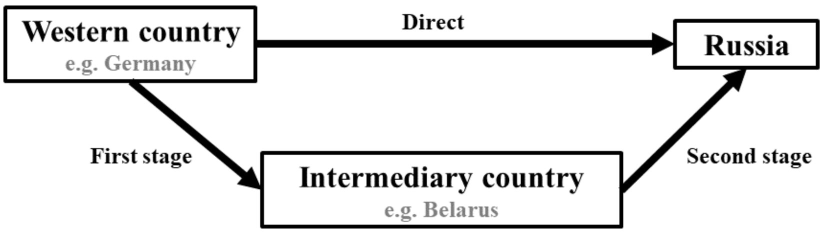
The sanction evasion analysis is based on trade flows between three country groups: the two parties which imposed sanctions on each other — Russia and

[8] Polish export data alone show larger apple exports to its Eastern neighbor in 2015 than the figure indicated by the Belarusian data on total imports from the EU.

[9] Within weeks after the imposition of agricultural sanctions, Russian newspapers reported the appearance of Belarusian oysters and shrimps in Russian supermarkets, which lead Russia to send veterinary officials to Minsk to monitor the situation (Reuters, 2014). In November 2014, Russia also banned imports from 23 Belarusian companies accused of smuggling EU produce (Secrieru, 2015, p.58). Despite these efforts, anecdotal examples of banned products sold in Russian stores continued in the following years. During a joint press conference of the Russian and Belarusian prime ministers on 29 September 2015, Dmitry Medvedev jokingly referred to hopes of replacing the European goods with "good supplies of citrus fruits, papaya, and some other exotic fruits that are grown well on Belarusian territory". (Russian Government, 2015)

the Western countries — as well those countries that have potentially offered a stage to circumvent those sanctions and which are referred to as intermediary countries:

Figure 1.3: Flow chart of the analyzed trade flows.



The Western country group introducing sanctions against Russia has been restricted to the 12 most important trading partners with Russia prior to the sanction imposition (cf. Section 1.2). This set of dozen countries includes Japan as a de facto placebo check (as Russia's largest trading partner outside the three country groups). While it did join the remaining G-7 member states in imposing (minor) financial sanctions, it refrained from restricting its goods exports to Russia and was hence not targeted by Russia's agricultural counter-sanctions.

Meanwhile, intermediary countries have been chosen either (i) based on a joint border — adjacent countries are well known to trade more which is, e.g., manifested by a standard border variable in gravity equations — or (ii) based on their role as a trading hub — large ports are often reported as frequent smuggling grounds and have been investigated in the academic literature (Fisman and Wei, 2004). The first category includes Belarus, China, Georgia, Kazakhstan, North Macedonia, Serbia, Switzerland, and Turkey.[10] As trading

[10] Azerbaijan, Mongolia, and Ukraine were not included due to lack of monthly data availability. Furthermore, one should point out that Georgia also imposed sanctions on Russia; however, these were not goods-specific. Furthermore, Russia introduced sanctions against Turkey on 1 January 2016.

hub countries, the study includes Hong Kong and Singapore.[11] All country groups have been illustrated in Figure 1.1.

Since the Western economies introduced sanctions on its exports and Russia on its imports, the analysis concerns only trade flowing — directly or indirectly — towards Russia (as indicated by the direction of the arrows in Figure 1.3). In terms of terminology, I refer to trade flows from the Western economies to Russia as direct flows. Exports from the Western countries to the intermediary countries are referred to as the first stage, while those from the intermediary countries to Russia as the second stage.

1.3.1 Channels of sanction evasion

As described in the examples in Sections 1.1 and 1.2, there are numerous channels through which sanctions may be evaded. This paper differentiates between five such channels for potential sanction evasion (cf. Table 1.1), which are investigated using direct, first, and second stage trade flows. As import and export data for the same trade flow differ according to the reporting jurisdiction, differences between the two variables are also exploited to investigate some channels.

Each sanction evasion channel is analyzed in an event study-type setting, exploiting the variation across products in terms of which trade flows were (directly) impacted by the sanctions. The treatment variables ($sanctions^c$) thus take on unity whenever a given product was targeted and the sanctions are in force. In general, the Difference-in-Difference regression equation looks as following:

$$Trade_{ijpst} = \sum_c \beta_c sanctions^c_{ijpst} + \gamma X_{ijpst} + \phi_{ijst} + \kappa_p + \epsilon_{ijpst} \qquad (1.1)$$
$$\text{for } c = \text{ Russia, West}$$

where the subscript i denotes the exporter, j denotes the importer, p denotes the product (classified in one of 5,206 6-digit HS code products), s denotes the sector (classified into 21 HS sections[12]), and t denotes time.

[11] United Arab Emirates was also considered but no monthly trade data was available.
[12] The sectors are relatively broadly defined, as some Russian sanctions covered (nearly)

The dependent variable is based on monthly product-level trade flows between a given country pair ij. Some regressions use other variables such as import-to-export-data ratios or net imports as the dependent variable (cf. sanction evasion channels below) but they refer to the same $ijpst$ dimensions.

Most specifications contain two treatment coefficients with one *sanctions* variable each for Western and Russian sanctions; however, in some cases the Western sanctions are split into two categories (partial ban and export licensing), as they varied according to the instrument applied on different products.[13]

The coefficient ϕ_{ijst} captures sector- and time-specific fixed effects for each country pair in the given regression. This set of fixed effects is meant to capture any sector-specific trends in trade flows between a pair of countries; in particular, in relation to the effect the financial sanctions imposed on Russia might have had on trade across sectors. It also implies that the treatment variables explain the variation in trade flows between sanctioned and non-sanctioned products within a given sector. In addition, product-specific fixed effects are captured by the coefficient κ_p.

Meanwhile, the set of controls X_{ijpst} is focused on other policy instruments which may have affected specific products in the studied time frame. Based on information concerning tariffs, sanitary and phytosanitary measures (SPS), technical barriers (TBT) as well as other non-tariff barriers, two policy covariates are included to capture further unilateral trade policies[14]:

- *Protectionist trade barrier* takes on unity if the given trade flow is facing protectionist at-the-border interventions introduced by the exporting country (e.g., export quotas) or the importing jurisdiction (e.g., a TBT). These interventions may, for example, include tariff increases, new licensing requirements, or import bans.

entire 2-digit HS code groups (07 — Vegetables; and largely 08 — Fruits and Nuts). However, robustness checks are conducted with more detailed sector classification.

[13]Note that in trade flows concerning the United States, the Western sanctions cover only the oil sector, as the U.S. — unlike the European Union — did not sanction exports of dual-use goods.

[14]The covariates abstract from free trade agreements as none of the country pairs introduced new bilateral agreements in the given time frame.

- *Liberalizing trade intervention* takes on unity if the given trade flow benefits from an at-the-border trade liberalization; e.g., a tariff reduction or the reversal of a previously implemented non-tariff barrier.

While Equation 1.1 focuses on the identification of the effect sanctions may have on trade flows in general, the event study setup allows the analysis of the strength of any potential effect over time. For that reason, a second regression equation is used where the sanction variables (dummy variables for sanctioned products) are interacted with time dummies[15]:

$$Trade_{ijpst} = \sum_{c} \beta_c sanctions^c_{ijpst} \xi_t + \gamma X_{ijpst} + \phi_{ijst} + \epsilon_{ijpst} \quad \text{for } c = \text{ Russia, West} \tag{1.2}$$

The estimated coefficients from the interaction terms are then plotted as a time series to infer the sanctions' effects over time. One would expect the coefficient to be indistinguishable from zero prior to the sanction implementation (in August 2014) and potentially statistically significant after the treatment.

The regressions are estimated linearly at first. However, as most of the observations contain zero trade values and trade figures are known to be not normally distributed, all regressions are also run using a standard-practice Pseudo-Poisson Maximum Likelihood estimation. This method has been proven to correct for both of the above-mentioned issues (Silva and Tenreyro, 2006) and is used as the baseline specification. Given the large amount of fixed effects, the regressions are conducted using the *ppmlhdfe* package in Stata by Correia, Guimarães and Zylkin (2020).

The estimation is repeated for particular country pairs and sectors in order to investigate in detail for which countries or industries the given sanction evasion channel might have played a role.

Direct smuggling. The first investigated channel relates directly to trade flows between the sanctioning countries, i.e., Western economies and Russia. These flows are — by the very nature of trade statistics — reported by both the exporting and importing nation. While one would expect both figures

[15] The first period (January 2012) is used as a reference point.

Table 1.1: Channels of sanction evasion.

Stage	**Direct**		**1st stage**		**2nd stage**	
Type	**Imp. data**	**Exp. data**	**Imp. data**	**Exp. data**	**Imp. data**	**Exp. data**
Data reporter	Russia	Western	Interm.	Western	Russia	Interm.
Direct smuggling	$\downarrow/\rightarrow^{*}$	$\rightarrow/\downarrow^{*}$	$\rightarrow$	$\rightarrow$	$\rightarrow$	$\rightarrow$
Visible reexports	$\downarrow$	$\downarrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$
Indirect smuggl.	$\downarrow$	$\downarrow$	$(\uparrow)$	$\uparrow/\rightarrow^{\diamond}$	$\rightarrow/\uparrow^{\diamond}$	$(\uparrow)$
Misclassification	$\downarrow^{\dagger}$	$\downarrow^{\dagger}$	$\rightarrow$	$\rightarrow$	$\rightarrow$	$\rightarrow$
Black market	$\downarrow$	$\downarrow$	$\rightarrow$	$\rightarrow$	$\rightarrow$	$\rightarrow$

Note: This table indicates expected changes (or there lack of) in trade flows of sanctioned products in relation to potential channels of sanction evasion. The $\rightarrow$ represents no expected changes, $\uparrow$ a trade increase, and $\downarrow$ a trade decline. The combinations containing an asterisk $*$ should see a decline in the export data for goods facing export sanctions (i.e. by Western countries) and no change for other products; and vice versa for goods facing import sanctions (i.e. by Russia) in the case of import data. Similarly, flows marked with an $\diamond$ should face an increase in trade for Western sanctioned goods in the second stage but no change in the first stage; and vice versa for goods facing Russian sanctions. The $\dagger$-sign relates to an expected increase in trade for similar products (based on neighboring HS codes). Lastly, brackets () are used in cases where the intermediary country may suppress trade statistics or, as in the case of the black market channel, shipments cross borders unreported in any trade figures.

to be identical, it is well-documented in the trade literature that export and import data often differ (Markhonko, 2014). These differences, also referred to as bilateral asymmetry, arise from varying accounting methods, where only importers include the related freight and insurance costs of shipments. Other known reasons relate to unclear sources of an import or the usual time delay between the point of departure and arrival of a good. (Berger and Nitsch, 2012)

While the above-mentioned arguments may explain general discrepancies between export and import data, Bhagwati found as early as 1964 that the level of discrepancy varies starkly across products and may often be associated with illicit trade. This variation in discrepancy is caused by flows being under- or overreported to evade import tariffs or other forms of trade controls, i.e., while there generally is a bilateral asymmetry in trade data, this asymmetry tends to increase when goods are smuggled across borders. More recent examples by

Rozanski and Yeats (1994), Fisman and Wei (2004), and Berger and Nitsch (2012) provide further evidence that this phenomenon persists in modern trade data.[16]

Should such underreporting be present in the case at hand, export data from the Western economies would see declines with respect to goods sanctioned by the West but there would be a less pronounced decline in trade related to goods sanctioned by Russia. On the other hand, Russian import data would show the opposite effect with the sanctioned agricultural goods collapsing, whereas the dual-use goods and oil-sector-related products would continue to be imported.

This hypothesis of no trade decline for the sanctioned goods in the target country's statistics rests on the notion that none of the firms concerned would enforce the ban and all would engage in the act of direct smuggling. As this notion is rather unlikely, the paper at hand shall instead use as the dependent variable in Equation 1.1 the logarithm of the ratio of import to export data ratio for a given trade flow (henceforth: *tradegap*). This follows the method of Fisman and Wei (2004), with the difference being that here a unity is added to each value[17] for trade data provided by the exporter and the importer:

$$tradegap_{ijpst} = log(1 + trade^{importer}_{ijpst}) - log(1 + trade^{exporter}_{ijpst})$$

$$tradegap_{ijpst} = \sum_{c} \beta_c sanctions^{c}_{ijpst} + \gamma X_{ijpst} + \phi_{ijst} + \kappa_p + \epsilon_{ijpst} \quad \text{for } c = \text{ Russia, West} \tag{1.3}$$

As long as there are no accounting reasons for the bilateral asymmetry to significantly increase for sanctioned goods compared to non-sanctioned products, changes to the *tradegap* can be attributed to an increase in smuggling

[16] A further method for detecting smuggling in trade was proposed by Demir and Javorcik (2020) through identifying deviations in the reported trade amounts from Benford's law. As such an analysis would require transaction-level data (which are not available), this paper focuses on identifying smuggling based on bilateral asymmetry instead.

[17] The reason for this deviation from Fisman and Wei (2004) is that, consistent with the implementation of any trade bans, one may expect no trade at all for some products and would in those cases still very much be interested in absolute and relative changes between the export and import data.

behavior, given the mechanism described above. In this setting, one would expect the Western sanction coefficient to be positive and the Russian sanction coefficient negative when regressing on the *tradegap* in Equation 1.3:[18]

Hypothesis 3. *For goods sanctioned by Russia, importer-based trade figures decline relatively stronger than exporter-based data, and vice versa for goods sanctioned by Western economies.*

Visible reexports. The second channel of potential sanction evasion focuses on trade flow patterns related to intermediary countries (cf. Figure 1.3): Sanctioned products are exported to one of the intermediary countries and then reexported to Russia. In order to evade the Russian sanctions, the products ought to be relabeled with respect to their country of origin. In the case of the Western sanctions, they would have to be exported out of the Western economy as destined for an intermediary country and then rerouted to Russia. While such reexports are illegal under the sanctioning countries' legislation, evaded trade flows may have occurred undetected.[19]

The study of this channel follows largely the methodology of Evenett et al. (2017) and would see increases in trade flows at both stages, i.e., one would expect visible reexports only if a sanction coefficient is positive in regressions based on Equation 1.1 for the first and the second stages:

Hypothesis 4. *Following the sanction imposition, trade in sanctioned goods increases in the first and second stages relative to non-sanctioned goods.*

A similar method has been also applied by Rotunno, Vézina and Wang (2013) who find that Chinese apparel exports were shipped through African countries after the United States imposed quotas on certain Chinese textiles.

[18] Due to the large amount of fixed effects, the regressions are conducted using the *reg2hdfe* package in Stata by Guimaraes and Portugal (2010).

[19] In the case of Switzerland for instance, a 2017 report for the Swiss parliament (Parlamentarische Verwaltungskontrolle, 2017) found no evidence of non-compliance in aggregate statistics; however, sanctions-related measures were insufficiently enforced. For example, only very few on-site inspections of sanctions compliance were carried out, and all of them were announced to the firm in advance. Furthermore, the Swiss Customs reported that export restrictions — such as the ones enforced here by the Western economies — are particularly difficult to monitor due to time constraints and insufficient information about downstream activities.

The researchers' definition of "quota-hopping export platform" may thus be compared with the intermediary countries in this paper. However, they find such visible reexports mostly for American imports facing no rules of origin when shipped from Africa; the observed trans-shipments were therefore legal — unlike potential visible reexports in this study.

Indirect smuggling. The third mechanism combines the previously described direct smuggling and visible reexports channels, as it relates to goods being smuggled indirectly through an intermediary country — in the case of Russian sanctioned products, the goods would be smuggled into Russia, whereas for Western sanctioned products they would be smuggled out of the Western country. Hence, regressions for both the first and second stage are needed, as indicated in Figure 1.3. For products sanctioned by Russia, the Western economies would (visibly) export more Russian sanctioned goods to intermediary countries relative to non-sanctioned goods as relates to the first stage. In the second stage, the *tradegap* between import and export data would change in the same direction as analyzed in the direct channel for direct smuggling (cf. Equation 1.3). Meanwhile for goods sanctioned by the Western countries, one would anticipate an increase of the *tradegap* in the first stage and a trade increase in the second stage:

Hypothesis 5. *Goods facing Russian sanctions are exported to intermediary countries and then smuggled into Russia; whereas Western sanctioned goods are smuggled into the intermediary countries and in a second stage shipped to Russia.*

Using the example of Figure 1.2 described in Section 1.2, there are indications for indirect smuggling in the apple example particularly for the years 2015 and 2016 when Belarusian exports to Russia significantly increased compared to pre-sanction levels — only according to Belarusian and not Russian data. This discrepancy would lead to a strong decrease of the *tradegap* for apples in the regressions related to the second stage trade flows.

Any findings related to the channel of indirect smuggling (as well as visible reexports) rest on the smuggling entities registering their trade flows in the intermediary country. For example, should indirect smuggling of Russian sanctioned goods have occurred, the trade gap in the second stage flows will only be visible if the exports from the intermediary country were reported (and imports into Russia not). At the same time, even if the exports from the intermediary country were registered, the country might have decided to suppress these figures for political motives; e.g., to avoid angering the sanctioning jurisdictions which may be crucial trading partners (cf. see example of Russia's reaction to Belarusian anecdotal evidence in Section 1.2). My analysis does not distinguish between the two mechanisms but indications of indirect smuggling — even without export numbers rising — may be found in the data.

In Figure 1.2, this hypothesis would arise particularly for the year 2017 when Belarus officially imported nearly half a million tonne of apples while exporting less than a sixth of that amount. This led to net imports being seven times higher than the figures registered before any sanctions were imposed. Whether this was a widespread phenomenon is analyzed by regressing on net imports of the intermediary countries. Should the hypothesis be supported, one would expect positive coefficients for the sanction variables in these regressions:

Hypothesis 6. *Intermediary countries suppressed trade data with the sanctioning economy for sanctioned goods.*

For these regressions, the function differs slightly, as the subscript i refers to the intermediary country:

$$Netimports_{ipst} = \sum_c \beta_c sanctions^c_{ipst}\xi_t + \gamma X_{ipst} + \phi_{ist} + \kappa_p + \epsilon_{ipst} \quad (1.4)$$
$$\text{for } c = \text{ Russia, West}$$

Lastly, one may argue that the increase in net imports can instead be explained by supply chain processing: Firms in intermediary countries imported the sanctioned products, processed them and exported them, for instance, legally to Russia. Since the Russian sanctions were far more focused on raw materials and intermediate products, this mechanism can be tested particularly for the sanctioned agricultural goods:[20]

Hypothesis 7. *Intermediary countries increased imports of sanctioned products in order to process them and (legally) reexport the processed goods.*

To test this hypothesis, all goods are classified into intermediary and final goods using the Broad Economic Classifaction (BEC). Should the increase of net imports be related to supply chain processing, that effect would be more pronounced for intermediary goods. This hypothesis can therefore be tested by interacting the sanction coefficient in Equation 1.4 with an intermediate goods dummy. Evidence for supply chain processing would require a positive coefficient of the interaction.

Misclassification. A further channel often explored in the context of illicit trade is the case of misclassifying products to avoid trade barriers. As indicated in the example related to the US-Chinese trade war in Section 1.1, misclassifications increased for products facing higher tariffs. Similar findings were recorded by Fisman and Wei (2004), where imports of resembling products increased following the imposition of higher Chinese tariffs.

This paper follows the methodology of the two researchers and assumes goods classified in the same four-digit HS category to be similar. Hence, misclassifications are analyzed by looking at the trade patterns of products which were not sanctioned but were located in the same four-digit HS code as at least one sanctioned good:

Hypothesis 8. *Trade in products adjacent to the sanctioned ones increases.*

In this case, the analysis is restricted to Western sanctions as nearly all Russian sanctions were relatively broad (covering each time a 4-digit HS code group). Applying the same methodology for similar products on the 2-digit HS code level to accommodate for the Russian sanction structure would be

[20] An alternative analysis would be to investigate the exports of intermediary countries for downstream products processed from the sanctioned products. However, as available Input-Output-Tables are relatively coarse, it is not possible to distinguish downstream products made from sanctioned versus non-sanctioned products.

overly coarse.

Black market. Unlike the previous channels, the notion behind the fifth type is that any sanction evasion is undetectable, as the sanctioned goods are shipped via the black market instead. Unlike the case of direct smuggling, they do not appear in exports from the Western economies. Furthermore, should goods be smuggled undetected through the black market, this would reduce the total potential amount of sanction evasion estimated in this analysis. The identified amounts may thus be seen as likely lower bounds on the aggregate extent of sanction evasion.

1.3.2 Methodology-related issues

Trade diversion. Overall, two of the five sanction evasion channels (indirect smuggling and visible reexports) involve explicitly trade with intermediary countries. However, the observed trade patterns may not necessarily be related to illegal activities and instead to trade diversion (e.g., Haidar, 2017). Rather than trade being routed through intermediary countries, market forces may lead to Western suppliers diverting their goods from the barred Russian market to the markets of the intermediary countries (Bown and Crowley, 2007). At the same time, firms from intermediary countries may exploit the new Russian market conditions and increase their exports to Russia where they no longer face competition from Western firms (for the sanctioned goods).

Such a scenario, unlike the studied sanction evasion channels, would fully comply with the legal frameworks of all affected countries. However, the following discussion shall provide evidence why potential trade diversion may be of limited concern.

First of all, while trade diversion does not weaken the direct enforceability of sanctions, it weakens their effectiveness: The more firms are able to divert their sales, the less of an economic impact will the sanctions have on the target economy. Therefore, should any of the sanction evasion channels through intermediary countries be substantiated, this would provide at the very least evidence for a reduced effectiveness of the sanctions — even if not necessarily due to sanction evasion. In addition, shifting economic ties away from the sanctioning jurisdictions (to intermediary countries) weakens the ability of the sanctioning country to introduce sanctions in the future, as the target economy reduces its dependence on the sanctioning market.

Furthermore, entering a new market is associated with a Melitz (2003)-like fixed costs, resulting in exporters entering markets only gradually (Ruhl and Willis, 2017). It is accordingly questionable that such vast amounts of goods can be shifted to a new market in such a short space of time (Yang et al., 2009). If the observed trade shifts would indeed be linked to trade diversion, one would expect them to occur gradually in a space of several years, as this is investigated in estimations based on Equation 1.2.

This paper also takes into account that the sanctions may have increased trade with intermediary countries (and thereby led to trade diversion) in the context of global supply chains, as described in the section on indirect smuggling. For instance, it would be within the legal bounds of the sanctions, e.g., for a Belarusian company to import milk from the European Union, produce dairy products from that milk, and export them to Russia — even though shipping both product categories from the European Union into Russia was banned under the agricultural countersanctions. Such supply chain adjustments are, however, likely to occur only over time and not immediately after the sanction imposition — but they are indirectly investigated in the context of net import surges.

The role of the sanction evasion versus trade diversion mechanisms is also studied in regressions on particular subsamples of countries or sectors: For sanction evasion to hold, the effects need to align for the first and second stages for particular countries and sectors, when only those subsets are regressed. Should there be a lack of alignment, this would point to trade diversion.

Identification concerns. A key concern related to the identification strategy is that the sanctioned products were not chosen at random but instead have been strategically selected by the implementing jurisdictions. This could become particularly concerning should trade in sanctioned products follow a different trend and thus conflict the parallel trends assumption needed for the Difference-in-Difference setting.

One method of investigating whether this concern is substantiated relies on checking the pre-treatment trends (e.g., Freyaldenhoven, Hansen and Shapiro, 2019). Should there be no significant differences in trade flows for sanctioned and not sanctioned products prior to their implementation in August 2014, this would provide evidence that the parallel trends assumption indeed holds. For this purpose, the coefficients on the treatment and time dummies interaction prior to treatment are checked based on Equation 1.2.

Furthermore, roughly at the same time as the imposition of the goods sanctions, the Russian economy faced a recession following a rapid fall in the oil price (cf. Figure B.1) (Dreger et al., 2016). Hence, a rich fixed effects setting has been chosen which should capture sector-specific time trends. For endogeneity to be a concern, e.g., the oil price collapse would have to differently impact sanctioned (e.g pork) than non-sanctioned products (e.g. sheep meat) within the same sector — which is unlikely.

1.4 Data

The main data have been obtained from the International Trade Center's Trade Map, as it contains the most comprehensive compilation of monthly trade statistics. These data are supplemented with trade figures for Belarus, Hong Kong, and North Macedonia from the UN Comtrade monthly trade database. Neither of the two data sources provide sufficient data for Azerbaijan, Mongolia, and Ukraine (as indicated in Figure 1.1). Furthermore, data for Hong Kong for October 2013 and for Netherlands in December 2016 are missing. Otherwise, the obtained dataset consists of a balanced panel for direct, first, and second stage trade flows covering in total 142 country pairs (cf. Figure 1.3) for 60 continuous months from January 2012 until December 2016. The study's timeframe is capped for the period 2012 until 2016, as Russian monthly trade statistics are available only starting from 2012 and several jurisdictions report only scarcely from 2017 onward.

Coincidentally, the selected period matches the five year cycle of the HS product classification system, allowing to forgo the reclassification of HS codes for consistency. Furthermore, data from the ITC Trade Map is aggregated to the 6-digit HS code level, despite more granular data being available. This is done due to the fact that lower level HS structures are not coordinated between countries, which would impede in particular the comparison of importer and exporter data (cf. Equation 1.3). Residual product codes such as 999999 covering 4.1% of total trade have been excluded as they cannot be assigned to any standard HS code and usually relate to confidential transactions.[21]

In the context of indirect smuggling (Equation 1.4), annual trade data from UN Comtrade was used, as this required total import and export data for each intermediary country. Such monthly trade statistics are unavailable for Belarus, Hong Kong, and North Macedonia. Therefore, this part of the analysis is conducted using annual data instead. The sanction variables receive values of 1 where products were affected for the years 2015 and 2016, and a value of $\frac{5}{12}$ for 2014, since the sanctions came into force in August of that year.

With regard to the main monthly trade dataset, the summary statistics show that mean trade flows are between 110 and 150 thousand USD. Furthermore, trade figures provided by exporter are on average smaller in first stage flows — which is in line with usual trade data — however, this is reversed for exports to Russia, as indicated in the on average negative trade gap for direct and second stage flows.

Information on the relevant sanctions has been obtained from the legal documents of the implementing jurisdictions. As indicated in Table 1.2, 14–15% of observations have been affected by Western sanctions, with the vast majority (ca. 13–14%) focused on dual-use goods. Products facing Russian countersanctions account for ca. 7% of the trade flows.

[21] Russian imports in these confidential trade categories increased significantly in the months May–July 2014, especially from the United States. However, the numbers quickly declined thereafter and there is no statistically significant change to confidential trade following the imposition of goods sanctions.

Table 1.2: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Direct flows					
$trade^{importer}$	139,006	1,702,253	0	541,484,000	3,725,280
$trade^{exporter}$	149,029	1,904,472	0	502,990,941	3,725,280
$tradegap$	-0.365	4.043	-19.859	18.722	3,725,280
sanctions Russia	0.074	0.261	0	1	3,725,280
sanctions West	0.136	0.343	0	1	3,725,280
protectionist policy	0.08	0.271	0	1	3,725,280
liberalising policy	0.01	0.098	0	1	3,725,280
First stage flows					
$trade^{importer}$	130,270	6,027,175	0	11,210,574,000	36,644,424
$trade^{exporter}$	114,104	4,805,734	0	7,430,435,483	36,654,620
$tradegap$	0.029	3.149	-22.425	22.514	36,593,444
sanctions Russia	0.065	0.246	0	1	36,705,600
sanctions West	0.138	0.345	0	1	36,705,600
protectionist policy	0.016	0.127	0	1	36,705,600
liberalising policy	0.01	0.098	0	1	36,705,600
Second stage flows					
$trade^{importer}$	110,749	2,228,885	0	1,022,441,000	3,058,800
$trade^{exporter}$	113,872	1,798,663	0	398,394,000	3,053,702
$tradegap$	-0.058	2.787	-19.296	20.042	3,053,702
sanctions Russia	0.065	0.246	0	1	3,058,800
sanctions West	0.151	0.358	0	1	3,058,800
protectionist policy	0.069	0.253	0	1	3,058,800
liberalising policy	0.005	0.072	0	1	3,058,800

Note: This table summarizes the statistics related to the main dataset in this paper. The statistics are presented separately for the three stages of analysis: direct, first stage, and second stage.

Meanwhile, the policy covariates were largely constructed based on information from the Global Trade Alert (GTA). It summarizes economic policy interventions which were taken unilaterally by governments since November 2008 and affect foreign commercial interests (Evenett, 2019). The database contains detailed information on the affected products at the 6-digit HS code level, the affected jurisdictions, the type of intervention, as well as the inception and removal dates of each policy intervention. The protectionist and liberalizing trade barrier covariates are constructed as dummy variables which take on unity when at least one at-the-border trade policy was in force for a given product-country pair-month combination. These at-the-border policies include import tariffs, licensing regimes, contingent trade-protective measures, and quotas.

The GTA information is supplemented by SPS and TBT notifications obtained from the WTO notification databases. As the affected HS codes are not reported for roughly half of the notifications, relevant policy measures are identified using available International Classification of Standards (ICS) codes and string matching from the notification descriptions. Table 1.2 indicates that between 1.6 and 8% of the observations face a protectionist trade barrier depending on whether one looks at direct, first stage, or second stage trade flows. However, it is noticeable that exports to Russia face on average more protectionist policies. Liberalizing policies affect only 0.5 to 1% of the observations.

1.5 Results

The following section first assesses how much trade has been lost due to the sanctions, before turning to the posited hypotheses with respect to the various sanction evasion channels in the second subsection. For those channels where evasion is detected, it will be quantified and benchmarked against the aggregate amount of (lost) trade.

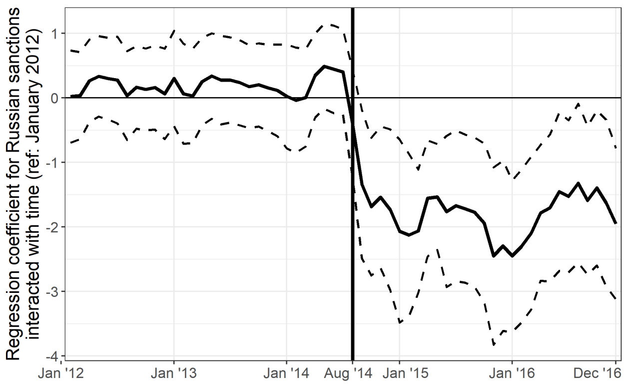
1.5.1 Impact of the sanctions

Prior to analyzing the sanction evasion channels, the effectiveness of the sanctions ought to be assessed first — if there was no trade reduction caused by the measures, no efforts would be necessary to study their evasion.

The first analysis is based on the Difference-in-Difference setting specified in Equation 1.1. As indicated in Table 1.3, the Russian sanctions have significantly reduced imports from the Western economies. The effect is stable to different choices of covariates, even if it is less pronounced when using export data instead of import data (columns 5–7 and 2–4, respectively)[22]. Figure 1.4

[22] As a robustness check, the regressions were also run with a more conservative definition of sectors at the 2-digit HS code level (Table B.2). The results are very similar, with only the Russian sanction coefficient being ca. a third lower. This is expected, as most Russian sanctions target entire 2-digit HS codes (cf. Table A.1).

Figure 1.4: Russian sanction coefficient in direct trade flows over time.



Note: This figure illustrates the effect of Russian sanctions on direct trade flows over time. The coefficient is based on Equation 1.2 and the standard errors are clustered at the sector-country pair-time level. The dotted lines represent the 95-percent confidence interval for each month's estimated coefficient. January 2012 serves as the reference time point.

shows that this trade reduction caused by the Russian sanctions remains persistent over the studied two and half years following their imposition.

According to the figure, there was also no statistically significant effect of the sanctions prior to their announcement, which may address the selection issues raised in Section 1.3. There is a slight positive increase in the months prior to August 2014 (relative to the referenced January 2012); however, the rise is not statistically significant based on the 95% confidence interval. This result supports Hypothesis 2 that there are no anticipation effects of the sanctions, as they were rapidly implemented.

The negative impact of the Russian sanctions holds separately for all eleven studied Western economies facing sanctions (cf. Table B.3 in Appendix B). The strongest declines occurred for Belgium, Poland, and Spain. Meanwhile, the placebo regressions conducted for Japan and depicted in Table B.1 show no significant changes to trade patterns for goods sanctioned by Russia compared to other goods within those sectors[23]. In terms of sectors, the animal and

[23] The export data-based regressions show a small positive coefficient; however, it is statistically significant only at the 10% level.

Table 1.3: Regression results for direct trade flows.

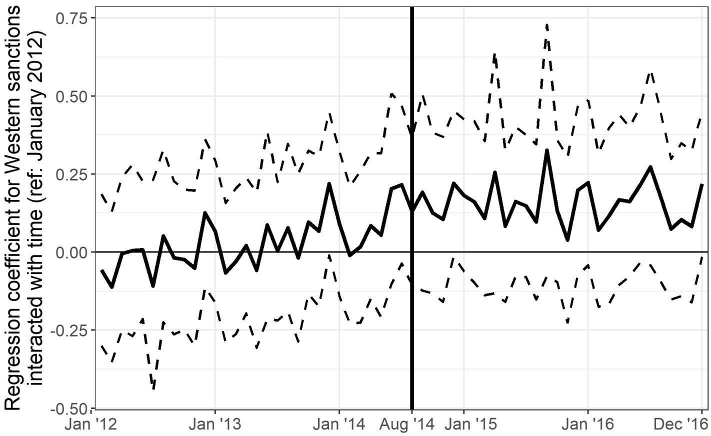
	(1) Import data	(2) Import data	(3) Import data	(4) Import data	(5) Export data	(6) Export data	(7) Export data
Regression	linear	PPML	PPML	PPML	PPML	PPML	PPML
sanctions Russia	-0.430*** (0.071)	-1.852*** (0.113)	-1.852*** (0.113)	-1.852*** (0.113)	-1.513*** (0.096)	-1.513*** (0.096)	-1.513*** (0.096)
sanctions West	-0.049*** (0.013)	0.086*** (0.023)	0.071*** (0.025)		0.112*** (0.035)	0.136*** (0.040)	
sanctions West dual-use				0.073*** (0.026)			0.132*** (0.040)
sanctions West oil technology				0.073 (0.064)			0.033 (0.100)
misclass. West			-0.040 (0.028)			0.065** (0.027)	
misclass. West dual-use				-0.018 (0.030)			0.058** (0.027)
misclass. West oil technology				-0.100* (0.057)			0.045 (0.058)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.526	0.734	0.734	0.734	0.735	0.735	0.735
N	1,020,551	3,132,029	3,132,029	3,132,029	3,274,785	3,274,785	3,274,785

Note: The regressions are based on Equation 1.1. Standard errors clustered at the sector-country pair-time level in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For the PPML regressions a Pseudo R^2 is displayed. The dependent variable in the linear regression is logarithmised, i.e., it only includes positive trade flows.

vegetable industries were more severely impacted in relative terms than food processing (cf. Table B.4).

Hypothesis 1 is also supported by the empirical results, as the negative impact is significantly higher for Russian than Western sanctions. In fact, the effect of the Western measures is even positive, though significantly smaller in absolute terms than the counterpart's negative effect. Based on columns 4 and 7 in Table 1.3, this positive effect is driven by the sanctions facing dual-use goods. Given that the list of dual-use items has been constructed in 2005 (with only minor annual amendments since), it is hard to argue that the positive coefficient may be explained by endogeneity concerns. Rather, these results point to a potentially ineffective use of the Western sanctions. Another explanation coud be that, as explained in Section 1.2, the dual-use measures affected only parts of the studied 6-digit HS codes and were banned solely for military purposes. The available trade data thus do not allow for a conclusive statement on the impact of the Western sanctions related to dual-use goods.

Figure 1.5: Western sanction coefficient in direct trade flows over time.



Note: This figure illustrates the effect of Western sanctions on direct trade flows over time. The coefficient is based on Equation 1.2 and the standard errors are clustered at the sector-country pair-time level. The dotted lines represent the 95-percent confidence interval for each month's estimated coefficient. January 2012 serves as the reference time point.

A similar conclusion can be drawn based on the Western sanction coefficient for individual month-year combinations. As shown in Figure 1.5, there is a rise in the coefficient around the time the sanctions were introduced — notably already prior to their imposition. However, all of the time-specific coefficients are indistinguishable from zero based on a the 95% confidence interval.

In terms of country variation, the significant increase was observable for seven of the eleven countries[24] (cf. Table B.3). Furthermore, the increase is concentrated in the construction, textile, and machinery industries (Table B.4), as only six of the thirteen sectors concerned saw significant increases.

[24]Interestingly, there is an even stronger increase in sanctioned dual-use products from Japan (cf. Table B.1) than for any of the countries that imposed dual-use goods sanctions.

Two sectors (chemicals and wood) even recorded significant negative impacts of the Western sanctions.

Overall, these results suggest that Russian sanctions were more effective (in terms of trade flows aggregated to 6-digit HS codes) and I am more likely to observe evasion for the agricultural sanctioned products. The following evasion analysis therefore puts a strong emphasis on the Russian as opposed to the Western sanctions. Also, the size of any detected evasion is benchmarked against the estimated loss directly from the goods sanctions. Keeping everything else constant, the decline resulting from the goods sanctions alone reduced imports of agricultural produce into Russia from the (studied) eleven sanctioned countries by 5.633 billion USD between August 2014 and December 2016 according to the regression specification 3 in Table 1.3. This amount is equivalent to 59.73% of total agricultural imports in 2013 affected by the sanctions[25]. While this loss over nearly two and half years may appear surprisingly low given that roughly half of all agricultural imports were banned, one should take into consideration that these goods faced also numerous other sanctions such as new restrictions on trade finance. Furthermore, this finding is in line with Crozet and Hinz (2020) who show that the majority of the goods trade decline was caused by non-goods sanctions.

1.5.2 Testing the sanction evasion channels

Direct smuggling. Evidence of direct smuggling is detected by comparing exporter- and importer-reported trade flows of the sanctioned products. In line with Hypothesis 3, the estimated decline for goods facing Russian sanctions is more pronounced in data reported by Russia than in the equivalent export data of the Western sanctioned economies (cf. Table 1.3). This difference is further explored in *tradegap* regressions based on Equation 1.3. As the estimated coefficients for Russian sanctioned goods in Table 1.4 is statistically significant at any of the usual levels, the estimation further strengthens the claim that

[25] According to export data-based estimates in specification 6 in Table 1.3, the decline was lower at 4.227 billion USD and equal to 44.82% of the 2013 agricultural imports affected by the sanctions. This difference is further discussed in the context of direct smuggling in the following subsection.

Table 1.4: Regression results for direct smuggling.

	(1) *Tradegap*	(2) *Tradegap*	(3) *Tradegap*	(4) *Tradegap*
sanctions Russia	-0.165*** (0.039)	-0.161*** (0.039)	-0.161*** (0.039)	-0.157*** (0.039)
sanctions West	0.009 (0.018)	0.030 (0.019)		-0.010 (0.011)
sanctions West dual-use			0.010 (0.019)	
sanctions West oil technology			0.503*** (0.073)	
Sample	Full	Full	Full	Int. margin
Covariates	No	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes
R^2	0.154	0.155	0.155	0.271
N	3,414,840	3,414,840	3,414,840	336,144

Note: The regressions are based on Equation 1.3. Standard errors clustered at the sector-country pair-time level in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

direct smuggling occurred for products sanctioned by Russia following the imposition of the sanctions. The obtained coefficient remains also stable when the regression is repeated only for those observations which saw positive trade of at least 50 thousand USD both in export and import data[26].

Based on the relevant coefficient from the third specification in the table, a back-of-the-envelope calculation is conducted to estimate the approximate value of goods that may have been directly smuggled into Russia[27]. If the sanctions had not been imposed, the *tradegap* between the import and export data of the sanctioned products would have been ca. 16 percentage points

[26] The threshold of 50 thousand USD to define the extensive margin is based on the widely used definition from Evenett and Venables (2002).

[27] This estimation is based on the assumption that no other factors other than smuggling may have impacted the bilateral asymmetry of import and export data for the sanctioned products relative to other products in the given sector.

higher[28]. In other words, the sanctions led to import data being underreported for the sanctioned products. The counterfactual amount of trade using import data without the effect of the sanctions would have been ca. 187 million USD higher, providing a rough estimate of the amount smuggled directly in trade between the eleven Western economies and Russia. This equals 3.31% of the total estimated decline in direct trade flows of sanctioned agricultural goods.

Interestingly, specification 3 in Table 1.4 provides evidence of direct smuggling also for oil-sector products facing Western sanctions: In line with Hypothesis 3, the coefficient for Western sanctioned products is positive. The *tradegap* increased by ca. 50% for those goods, despite no trade decline being estimated in the direct channel (cf. regressions 4 and 7 in Table 1.3). No such effects were detected for dual-use goods.

Repeating the *tradegap* regression for Japan as a placebo test (cf. specification 5 in Table B.1), the bilateral asymmetry between import and export data did not significantly change for the Western sanctioned relative to non-sanctioned goods. While there is a small increase for the Russian sanctions coefficient, the estimate is statistically significant only at the 10% level. These findings largely support the notion that no direct smuggling occurred for Japan, as it did not impose goods sanctions and it did not face the Russian countermeasures.

Visible reexports. Following Evenett et al. (2017) and Rotunno, Vézina and Wang (2013), a further method to investigate sanction evasion is based on analyzing trade flows through intermediary countries (cf. Figure 1.3). Should reexports of sanctioned goods have taken place, there would be a significant increase of trade in sanctioned relative to non-sanctioned goods at both stages of the evasion.

As indicated in Tables 1.5 and 1.6, there is no evidence that such visible reexports occurred for goods sanctioned by Russia in the context of all the

[28] Before the sanctions were imposed, the average observation for a good sanctioned by Russia was 105,670 USD according to import data and 93,020 USD based on export data. After August 2014, the *tradegap* turned negative as the average flow was 8,053 USD and 9,192 USD, respectively.

Table 1.5: Regression results for first stage trade flows.

	(1) Import data	(2) Import data	(3) Import data	(4) Export data	(5) Export data
Regression	linear	PPML	PPML	PPML	PPML
sanctions Russia	0.060** (0.024)	0.046 (0.111)	0.046 (0.111)	-0.161 (0.117)	-0.161 (0.117)
sanctions West	-0.096*** (0.008)	-0.351*** (0.026)		0.216*** (0.053)	
sanctions West dual-use			-0.342*** (0.027)		0.232*** (0.055)
sanctions West oil technology			-0.338*** (0.042)		-0.116** (0.050)
Covariates	Yes	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes
R^2	0.484	0.809	0.809	0.788	0.788
N	6,822,405	32,850,185	32,850,185	31,731,981	31,731,981

Note: The regressions are based on Equation 1.1. Standard errors clustered at the sector-country pair-time level in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For the PPML regressions a Pseudo R^2 is displayed.

studied intermediary countries combined. Similarly, there is no evidence of reexports for any individual sector (cf. Tables B.7 and B.10). However, three intermediary countries did significantly import more products sanctioned by Russia from the Western economies (cf. Table B.6): Belarus, Kazakhstan, and Georgia[29]. All three countries border Russia and the former two are part of the Eurasian Economic Union — a customs union led by Russia — making transportation without strict border controls more likely.

While a significant increase in trade for sanctioned goods in the first stage is a necessary condition for visible reexports, this evasion channel requires a

[29] Note that a significant effect for each of three economies is detected only when regressions are based on import (and not export) data. Also, the regression relating to Turkey indicates a slight increase for Russian sanctioned goods as well; however, that effect is significant only at the 10% level.

similar increase at the second stage as well. Here, however, such a surge is documented only for one of the three jurisdictions, namely Kazakhstan. The regressions therefore provide only very limited evidence for Hypothesis 4.

Table 1.6: Regression results for second stage trade flows.

	(1) Import data	(2) Import data	(3) Import data	(4) Export data	(5) Export data
Regression	linear	PPML	PPML	PPML	PPML
sanctions Russia	0.166**	0.107	0.107	0.141	0.141
	(0.065)	(0.110)	(0.110)	(0.111)	(0.111)
sanctions West	0.077***	0.138**		0.182***	
	(0.020)	(0.060)		(0.039)	
sanctions West dual-use			0.141**		0.166***
			(0.061)		(0.040)
sanctions West oil technology			0.041		0.537***
			(0.071)		(0.139)
Covariates	Yes	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes
R^2	0.520	0.794	0.794	0.801	0.801
N	519,551	2,681,985	2,681,985	2,639,659	2,639,659

Note: The regressions are based on Equation 1.1. Standard errors clustered at the sector-country pair-time level in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For the PPML regressions a Pseudo R^2 is displayed.

Performing a counterfactual exercise without the effect of the sanctions for Kazakh trade, exports of the sanctioned agricultural products from the eleven studied Western countries to the Central Asian economy would have been 163.4 million USD lower. In the second stage, Kazakh exports to Russia for those goods would have been 92.4 million USD less. Taking the lower of the two figures as an approximation of the detected visible reexports, this amount represents 1.64% of the estimated decline in Russian sanctioned goods.[30]

[30] As suggested in Section 1.3, the visible reexports could have occurred due to trade diversion rather than reexports. Therefore, a sector-level regression for Kazakhstan is conducted

Meanwhile, the Western sanctions coefficients indicate statistically significant changes for Western sanctioned goods compared to non-sanctioned goods in both stages. In the first stage, all flows of Western sanctioned goods seem to fall except for dual-use goods when using export data. The second stage sees increases across the board — with the exception of goods related to the oil industry when using (Russian) import data. Similarly to the regressions on the impact of sanctions (cf. previous subsection), the results related to Western sanctions produce unexpected results. They do not only reject Hypothesis 4 but provide statistically significant results in the opposite direction. In order to test in further detail what drives these results, more fine-grained trade data on the Western sanctioned products would be required.

Lastly, regressions in Table B.9 showed a significant surge of Russian sanctioned goods in the second stage from Serbia. However, the strong effect is observed only for the second stage, as the coefficient in the first stage (see column 7 in Table B.6) is both small and statistically insignificant. This result may point towards trade diversion rather than sanction evasion regarding agricultural goods originating from Serbia.

Indirect smuggling. In the context of visible reexports, Belarus and Georgia saw increases in Russian sanctioned products in the first stage but there were no significant surges in trade flows related to the second stage. As suggested by Hypothesis 5 on indirect smuggling, sanction evasion could have also occurred by routing Russian sanctioned goods to intermediary countries and then smuggling them indirectly from these neighboring or trade hub countries. For such a channel to be present, one would expect a decrease in the *tradegap* for the Russian sanction coefficient in the second stage regressions, since the smuggled products would appear only in export and not import data between the intermediary countries and Russia.

As indicated in Table B.9 in Appendix B, the Russian sanction coefficient is significantly negative only for Georgia (while being positive for Belarus). Across all countries, the coefficient is positive at the 5% significance level and turns negative when the sample is reduced to flows on the intensive margin

for both stages. The estimates are particularly large and significant for HS section I and are aligned for both stages, providing support for the reexport hypothesis.

(cf. columns 1-4 in Table B.9). There is thus limited evidence for indirect smuggling to have occurred in relation to the Russian sanctions. For Georgia, the estimated smuggled amount is equal to 38.95 million USD for the years 2014–2016. While this amount may seem negligible, it corresponds to 57% of Georgia's 2013 imports from the eleven Western economies for the (Russian) sanctioned products and 3.36% of Georgian total 2013 imports from those countries.

Looking at potential indirect smuggling of Western sanctioned goods, we see an increase in the *tradegap* in the first stage only for oil-technology goods and a slight decrease in the coefficient for dual-use goods (Table B.5). However, for indirect smuggling of the Western sanctioned oil goods to occur as described in Hypothesis 5, there would have to be a significant increase in trade in the second stage flows. As the results show a surge only using export and not import data, I conclude that there is insufficient evidence to support the case for large-scale indirect smuggling of goods related to the Western sanctions. There is also no indication for such sanction evasion using country-specific regressions (cf. Tables B.6 and B.9).

Given the limited evidence for indirect smuggling, one may have to take into account the possibility of data suppression or unreported trade, as suggested by Hypothesis 6 in Section 1.3. Therefore, potential effects of sanctions on net imports are analyzed as described in Equation 1.4. On aggregate, there is no significant effect of the sanctions on net imports of the intermediary countries.[31] However, when the regressions are repeated on a country level (cf. upper part of Table B.11), a strong and statistically significant (Russian) sanction coefficient stands out for Belarus. In fact, based on the estimated coefficient, counterfactual net imports of goods sanctioned by Russia ceteris paribus would have been less than half as large. This corresponds to roughly 771 million USD, or 32% of Belarus' net import value in 2013 (in the sanctioned products). Notably, this figure relates to total net imports and not only the eleven studied Western economies. Since the first stage regressions (cf. Table B.6) represent a trade increase in sanctioned goods worth 163.7

[31] Also, Figure 1.2 indicated that data suppression became a problem only in 2017. Hence, the regressions were also run for specific years but no significant effects were found.

million USD (42.75% of 2013 trade in the sanctioned products), this amount provides a more comparable estimate of indirect smuggling through Belarus.

As described in Section 1.3, the effect of net imports is also analyzed in an interaction term with an intermediate goods dummy (cf. Hypothesis 7). Would the rise in net imports be due to supply chain adjustments rather than indirect smuggling, we would expect the interaction term of the sanction coefficient and the intermediate good dummy to be positive. However, the coefficient in the context of Belarus is not statistically significant (cf. lower part of Table B.11).

Lastly, in the context of Figure 1.2, it was discussed that some amount of sanction evasion may have occurred by forging the certificates of origin to disguise the products' EU origin before being shipped to Russia (Yeliseyeu, 2017). This was investigated using annual world product-level import and export data for the years 2012 until 2016. Indications of such forging were identified through unlikely origin-product combinations of intermediary countries' imports. These unlikely combinations were defined as those that were not recorded in a given year in the imports of any other destinations (i.e., not intermediary countries) as well as not in the exports of those origin countries. Several hundred such combinations were found but there was no significant uptick in such anomalies after August 2014. Sanctioned products were also not more likely to experience such unusual flows, also when the statistics were checked for individual intermediary countries. I hence conclude that there is no evidence of large-scale forging of certificates of origin in the context of the evasion of sanctioned goods.

Misclassification. The last investigated sanction evasion channel relates to one of the most frequently used statistics to detect the evasion of trade policies: Firms try to avoid a given policy by misspecifying their product as a similar good not facing the trade barrier. In this example, given that Russian sanctions were defined relatively coarsely, this analysis is restricted to the goods facing Western sanctions. For those products, I find a statistically significant increase only in relation to dual-use goods, which on average did not face a decline in the first place (cf. specifications 4 and 7 in Table 1.3). I therefore reject Hypothesis 8.

Overall, I find only limited amounts of sanction evasion in relation to the Ukraine crisis, given that the total amount of lost trade between 2014 and 2016 due to the Russian sanctions is estimated at 5.633 billion USD. For Western sanctioned dual-use goods, I even estimate a trade increase for direct flows between the Western economies and Russia. However, the evasion that was detected is observed for numerous channels: Apart from evidence of ca. 187 million USD of trade being directly smuggled, there are indications of sanction evasion through intermediary countries. Interestingly, the countries concerned all border Russia and two of them share a customs union with Russia. Sanctioned products worth 92 million USD may have been visibly reexported through Kazakhstan, while 39 million USD worth of agricultural produce may have been indirectly smuggled through Georgia. Lastly, a surge in Belarusian net imports of sanctioned products may indicate an indirect smuggling of products worth 164 million USD. The combined total of 482 million USD represents 8.56% of the total estimated decline in direct trade flows resulting from the Russian sanctions on agriculture. While the exact estimates should be treated as back-of-the-envelope calculations, they amount to a non-negligible share of total trade – especially considering the exclusion of undocumented trade between the Western economies and Russia (cf. black market channel in Table 1.1).

Furthermore, one should note that the analysis above was conducted to investigate large-scale sanction evasion across numerous channels for two dozen countries. The results abstract from firm- or product-specific cases of evasion evidence as presented anecdotally in Figure 1.2. A further analysis of spotting individual cases of sanction evasion would require transaction-level data ideally from all countries concerned. This, however, would require a level of cooperation between jurisdictions that imposed sanctions on each other.

1.6 Conclusion

This paper investigated to what degree modern trade policy measures are evaded, given their increased targeted and political nature. Building on various methods related to detecting illicit trade in international goods flows, I apply them in the context of sanctions introduced in the wake of the Ukraine crisis. Constrained by the very fine-grained and complex structure of the Western sanctions, I estimate a decline in trade of sanctioned goods only for those affected by the Russian measures.

The results point towards relatively small, yet non-negligible amounts of sanction evasion. Of the estimated 5.633 billion USD trade loss caused by the Russian sanctions on agricultural goods, I find indications of evasion for 482 million USD. Over a third of that evasion relates to direct smuggling between the Western economies and Russia, as highlighted by the change in the *tradegap* between import and export data. A similar amount of evasion is estimated for indirect smuggling related to Belarus, which significantly increased its net imports of goods sanctioned by Russia. As these increases were not particularly focused on intermediate goods, I do not find evidence that the larger imports were used for scaled up supply chain processing. Further evasion is detected in connection with visible reexports for Kazakhstan and indirect smuggling through Georgia.

As more than half of the estimated evasion involves trade flows through Belarus and Kazakhstan — members of the Russia-led Eurasian Economic Union, the findings highlight the importance of trade policy coordination with third countries, especially if these are part of the same customs union. Furthermore, the analysis showcases how, provided a mutual and rapid exchange of trade data, countries may benefit from a joint effort of detecting illicit trade. Lastly, while my analysis offers numerous indications of how sanctions may be smuggled, more fine-grained data is necessary to provide further robustness to these results (particularly to estimate the impact of the Western sanctions). Such resources would allow to apply also other indicators of illicit trade, for example, deviations from Benford's law (cf. Demir and Javorcik (2020)).

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Appendix A: Sanctions introduced in relation to the Ukraine crisis

Table A.1: Russia's main trading partners based on 2013 import data.

Exporter	Trade Value (in m USD)	Country category	Share	Cumul. share	Rus. sanct.	West. sanct.
World	314,945	-	100.00%	-	9,431	65,982
China	53,173	Intermediary	16.88%	16.88%	980	18,752
Germany	37,905	Sanctions	12.04%	28.92%	814	9,529
USA	16,718	Sanctions	5.31%	34.23%	846	501
Ukraine	15,791	Sanctions	5.01%	39.24%	-	-
Italy	14,554	Sanctions	4.62%	43.86%	299	4,098
Belarus	13,959	Intermediary	4.43%	48.29%	2,501	3,536
Japan	13,560	Non-goods san.	4.31%	52.60%	7	2,686
France	13,021	Sanctions	4.13%	56.73%	445	2,893
South Korea	10,305	-	3.27%	60.01%	-	-
Poland	8,321	Sanctions	2.64%	62.65%	1,145	2,014
UK	8,106	Sanctions	2.57%	65.22%	66	1,624
Turkey	7,273	Intermediary	2.31%	67.53%	1,527	1,081
Netherlands	5,837	Sanctions	1.85%	69.38%	797	1,051
Kazakhstan	5,665	Intermediary	1.80%	71.18%	31	1,033
Finland	5,396	Sanctions	1.71%	72.90%	367	1,693
Czechia	5,318	Sanctions	1.69%	74.59%	19	1,738
Spain	4,915	Sanctions	1.56%	76.15%	796	647

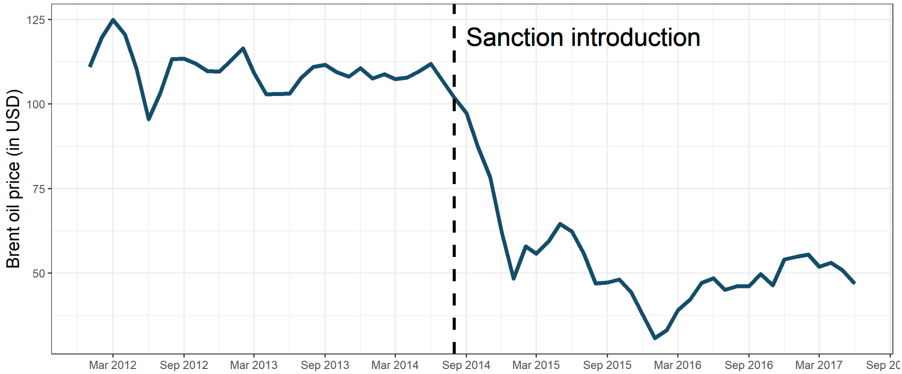
Note: The amounts in the last two columns relate to trade affected by Russian / Western sanctions in 2013 million USD; whereas the totals in the first row of the last two columns relate to the direct trade flows (cf. Figure 1.3). The aggregate trade statistics are based on annual data, whereas the last two columns on monthly figures.

Table A.2: List of HS codes hit by sanctions during the Ukraine crisis.

Implementer	**EU**			**USA**	**Russia**	
Type	**Export licensing**	**Dual-use goods ban**	**Arms embargo**	**Export licensing**	**Import ban**	**Import ban**
Target	Russia	Russia	Russia	Russia	i.a. EU, USA	Turkey
Products	73041100	Too long; 6197 tariff lines	93	7304110000	0201	020714
	73041910			7304191020	0202	020727
	73041930			7304191050	0203	060312
	73041990			7304191080	0207	070200
	73042200			7304195020	0210	070310
	73042300			7304195050	0301	070410
	73042910			7304195080	0302	070700
	73042930			7304220000	0303	080510
	73042990			7304233000	0304	080520
	73051100			7304236000	0305	080610
	73051200			7304241000	0306	080810
	73051900			7304246000	0307	080830
	73052000			7304291055	0308	080910
	730611			7304293155	0401	080930
	730619			7304295000	0402	080940
	73062100			7304296100	0403	081010
	73062900			7305111000	0404	250100
	82071300			7305115000	0405	
	82071910			7305121000	0406	
	841350			7305125000	0701	
	841360			7305191000	07020000	
	84138200			7305195000	0703	
	84139200			7305203000	0704	
	84304900			7305207000	0705	
	87052000			7306110000	0706	
	89052000			7306191000	070700	
	89059010			7306195000	0708	
	84313900			7311000000	0709	
	84314300			7613000000	0710	
	843149			8207130000	0711	
				8207191030	0712	
				8207192030	0713	
				8207195030	0714	
				8413500010	0801	
				8413600050	0802	
				8413820000	0803	
				8413920000	0804	
				8421398020	0805	
				8421398030	0806	
				8421398040	0807	
				8430494000	0808	
				8430498010	0809	
				8430498020	0810	
				8431390050	0811	
				8431434000	0813	
				8431438010	160100	
				8431438090	1901901100	
				8479899850	1901909100	
				8705200000	2106909200	
				8708998175	2106909804	
				8905200000	2106909805	
				8905901000	2106909809	

Appendix B: Additional charts and tables

Figure B.1: The Brent oil price during the Ukraine crisis.



Note: This figure illustrates the Brent oil price over the period 2012 until 2017. Source: IMF Primary Commodity Data.

Table B.1: Placebo regression results for direct trade flows (Japan).

	(1) Import data	(2) Import data	(3) Export data	(4) Export data	(5) Data gap
Regresion	PPML	PPML	PPML	PPML	Linear
sanctions Russia	-0.026	-0.026	0.360*	0.360*	0.060*
	(0.199)	(0.199)	(0.215)	(0.215)	(0.032)
sanctions West	0.287***		0.350***		-0.038
	(0.049)		(0.062)		(0.039)
sanctions West dual-use		0.284***		0.349***	
		(0.048)		(0.063)	
sanctions West oil technology		-0.013		0.102	
		(0.157)		(0.113)	
Covariates	Yes	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes
R^2	0.943	0.943	0.952	0.952	0.386
N	167,907	167,907	138,979	138,979	310,440

Note: The regressions are based on Equations 1.1 (specifications 1–4) and 1.3 (specification 5). Standard errors clustered at the sector-country pair-time level in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For the PPML regressions a Pseudo R^2 is displayed.

Table B.2: Regression results for direct trade flows using 2-digit HS codes as sectors.

	(1) Import data	(2) Import data	(3) Import data	(4) Export data	(5) Export data	(6) Export data
Regression	PPML	PPML	PPML	PPML	PPML	PPML
sanctions Russia	-1.169***	-1.169***	-1.169***	-1.110***	-1.110***	-1.110***
	(0.090)	(0.090)	(0.090)	(0.089)	(0.089)	(0.089)
sanctions West	0.070***	0.049**		0.075***	0.097***	
	(0.022)	(0.024)		(0.021)	(0.023)	
sanctions West dual-use			0.053**			0.094***
			(0.025)			(0.021)
sanctions West oil technology			0.050			0.006
			(0.065)			(0.099)
misclass. West		-0.050*			0.049**	
		(0.027)			(0.021)	
misclass. West dual-use			-0.022			0.053**
			(0.028)			(0.020)
misclass. West oil technology			-0.143**			-0.022
			(0.058)			(0.058)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.766	0.766	0.766	0.773	0.773	0.773
N	2,937,381	2,937,381	2,937,381	3,129,430	3,129,430	3,129,430

Note: The regressions are based on Equation 1.1 with sectors specified as 2-digit HS codes instead of the usual HS sections. Standard errors clustered at the sector-country pair-time level in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For the PPML regressions a Pseudo R^2 is displayed.

Data source: UN Comtrade Database.

Table B.3: Regression for direct channel by country.

	(1) Belgium	(2) Czechia	(3) Finland	(4) France	(5) Germany	(6) Italy	(7) Netherl.	(8) Poland	(9) Spain	(10) UK	(11) USA
Import data regressions											
sanctions Russia	-3.278***	-1.269***	-1.073***	-1.288***	-0.964***	-2.535***	-2.022***	-3.130***	-4.034***	-0.417**	-1.351***
	(0.328)	(0.174)	(0.194)	(0.170)	(0.103)	(0.295)	(0.198)	(0.356)	(0.554)	(0.184)	(0.221)
sanctions West	-0.007	0.246***	0.006	-0.069	0.144***	0.152***	0.074	0.127***	0.391***	0.142**	0.176*
	(0.127)	(0.049)	(0.070)	(0.054)	(0.035)	(0.050)	(0.107)	(0.030)	(0.090)	(0.065)	(0.100)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.853	0.885	0.867	0.879	0.907	0.862	0.851	0.891	0.840	0.891	0.862
N	159,398	157,638	141,536	212,880	248,160	229,020	180,178	193,140	188,220	192,540	218,340
Export data regressions											
sanctions Russia	-2.722***	-1.789***	-1.287***	-1.129***	-0.728***	-1.875***	-0.842***	-2.363***	-4.956***	-0.957***	-1.358***
	(0.248)	(0.223)	(0.288)	(0.189)	(0.099)	(0.185)	(0.170)	(0.278)	(0.494)	(0.177)	(0.258)
sanctions West	0.067	0.213***	-0.019	0.216***	0.032	0.225***	-0.120**	0.161**	0.256***	0.620***	0.034
	(0.042)	(0.056)	(0.044)	(0.078)	(0.037)	(0.041)	(0.049)	(0.066)	(0.063)	(0.151)	(0.124)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.890	0.889	0.880	0.855	0.920	0.867	0.869	0.872	0.828	0.885	0.813
N	210,780	195,780	233,820	215,340	268,800	235,440	230,880	250,740	212,280	207,180	206,589

Note: Standard errors clustered at the sector-country pair-time level in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4: Regression for direct channel by section.

HS section	(1) I Animals	(2) II Vegetables	(3) IV Foodstuffs	(4) V Minerals	(5) VI Chemicals	(6) VII Plastic	(7) X Wood	(8) XI Textiles
sanctions Russia	-3.284*** (0.298)	-3.766*** (0.247)	-0.250*** (0.087)					
sanctions West				-0.142 (0.119)	-0.168*** (0.052)	0.097*** (0.030)	-0.261* (0.156)	0.064 (0.104)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.768	0.586	0.619	0.817	0.803	0.659	0.676	0.625
N	169,448	186,480	141,840	87,840	513,360	151,200	99,360	541,440

HS section	(9) XII Footwear	(10) XIII Construction	(11) XIV Stones	(12) XV Metals	(13) XVI Machinery	(14) XVII Vehicles	(15) XVIII Instruments	(16) XX Misc.
sanctions West	-0.075 (0.216)	0.209*** (0.064)	-0.363 (0.225)	0.018 (0.063)	0.125*** (0.032)	0.336** (0.170)	0.167*** (0.048)	0.482*** (0.126)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.877	0.579	0.739	0.642	0.586	0.794	0.772	0.732
N	33,182	101,520	27,778	385,200	548,640	79,200	149,760	84,960

Note: Standard errors clustered at the sector-country pair-time level in parentheses. Sign. levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.5: Regression results for indirect smuggling (1st stage).

	(1) *Tradegap*	(2) *Tradegap*	(3) *Tradegap*	(4) *Tradegap*
sanctions Russia	0.035*** (0.012)	0.036*** (0.012)	0.036*** (0.012)	0.028 (0.020)
sanctions West	-0.043*** (0.005)	-0.025*** (0.005)		-0.032*** (0.004)
sanctions West dual-use			-0.030*** (0.005)	
sanctions West oil technology			0.088*** (0.019)	
Sample	Full	Full	Full	Int. margin
Covariates	No	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes
R^2	0.061	0.061	0.061	0.145
N	34,039,746	34,039,746	34,039,746	1,623,139

Note: The regressions are based on Equation 1.3. Standard errors clustered at the sector-country pair-time level in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.6: Regression for first stage by country.

	(1) Belarus	(2) China	(3) HongKong	(4) Georgia	(5) Kazakhstan	(6) N. Maced.	(7) Serbia	(8) Singapore	(9) Switzerl.	(10) Turkey
Import data regressions										
sanction	0.374**	-0.013	0.169	0.227***	0.343***	0.042	0.097	0.112	0.107	0.134*
.Russia	(0.152)	(0.066)	(0.109)	(0.082)	(0.107)	(0.070)	(0.077)	(0.132)	(0.079)	(0.075)
sanctions	0.084**	-0.347***	-0.433***	0.138*	0.109	0.464***	-0.188***	-0.488***	-0.059*	-0.137***
West	(0.042)	(0.045)	(0.078)	(0.083)	(0.071)	(0.056)	(0.033)	(0.044)	(0.030)	(0.045)
Pseudo R^2	0.641	0.855	0.867	0.599	0.666	0.818	0.728	0.855	0.912	0.749
N	2,780,219	3,146,450	2,713,688	2,323,626	2,682,163	2,734,684	2,942,417	3,096,816	3,356,818	3,064,299
Export data regressions										
sanctions	0.119	-0.385***	0.068	-0.215	0.042	-0.087	0.056	0.030	0.010	0.139
Russia	(0.192)	(0.094)	(0.112)	(0.152)	(0.132)	(0.082)	(0.070)	(0.129)	(0.078)	(0.100)
sanctions	0.172***	0.129***	0.382**	0.196*	0.081	0.181	0.094*	-0.094*	0.638***	0.052
West	(0.034)	(0.044)	(0.175)	(0.115)	(0.083)	(0.120)	(0.053)	(0.057)	(0.156)	(0.039)
Pseudo R^2	0.669	0.839	0.841	0.674	0.639	0.814	0.674	0.804	0.858	0.738
N	2,762,576	3,189,484	3,131,177	2,465,533	2,750,984	2,421,637	2,951,959	3,072,571	3,230,173	3,145,246
Tradegap regressions										
sanctions	0.015	0.009	-0.026	0.019	0.027	0.007	0.078***	0.096**	0.089	0.039
Russia	(0.019)	(0.028)	(0.019)	(0.014)	(0.022)	(0.008)	(0.025)	(0.042)	(0.079)	(0.024)
sanctions	-0.039**	-0.052***	0.022	0.007	-0.007	-0.049***	-0.084***	-0.019	0.013	-0.029*
West	(0.015)	(0.017)	(0.014)	(0.010)	(0.014)	(0.013)	(0.016)	(0.014)	(0.013)	(0.017)
R^2	0.143	0.099	0.090	0.067	0.106	0.125	0.103	0.081	0.130	0.098
N	3,409,666	3,409,666	3,352,752	3,409,666	3,409,666	3,409,666	3,409,666	3,409,666	3,409,666	3,409,666

Note: Standard errors clustered at the sector-country-time level in parentheses. Significance levels: $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.
The import and export data regressions are based on Equation 1.1, whereas the tradegap regressions on Equation 1.3.
All regressions contain policy covariates and sector-country-time as well as product fixed effects.

Table B.7: Regression for first stage by section.

HS section	(1) I Animals	(2) II Vegetables	(3) IV Foodstuffs	(4) V Minerals	(5) VI Chemicals	(6) VII Plastic	(7) X Wood	(8) XI Textiles
sanctions Russia	-0.073 (0.051)	0.266 (0.246)	0.046 (0.056)					
sanctions West				0.038 (0.117)	-0.332*** (0.045)	0.074*** (0.023)	0.427*** (0.084)	0.096 (0.059)
Pseudo R^2	0.720	0.871	0.679	0.788	0.779	0.766	0.744	0.678
N	1,624,912	1,827,189	1,377,180	914,836	5,132,052	1,387,536	924,960	5,190,716

HS section	(9) XII Footwear	(10) XIII Construction	(11) XIV Stones	(12) XV Metals	(13) XVI Machinery	(14) XVII Vehicles	(15) XVIII Instruments	(16) XX Misc.
sanctions West	0.103 (0.117)	0.011 (0.045)	0.161 (0.187)	0.079*** (0.030)	-0.412*** (0.030)	-0.810*** (0.099)	-0.208*** (0.045)	-0.010 (0.035)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.860	0.637	0.902	0.691	0.739	0.818	0.810	0.771
N	279,697	927,970	253,817	3,700,208	5,080,119	837,081	1,383,527	771,366

Note: Standard errors clustered at the sector-country pair-time level in parentheses. Sign. levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The regressions are based on Equation 1.1 and use importer-reported trade data. They all contain policy covariates.

Table B.8: Regression results for indirect smuggling (Second stage).

	(1) *Tradegap*	(2) *Tradegap*	(3) *Tradegap*	(4) *Tradegap*
sanctions Russia	0.105**	0.106**	0.106**	-0.108***
	(0.051)	(0.051)	(0.051)	(0.034)
sanctions West	-0.010	-0.009		0.044***
	(0.015)	(0.015)		(0.013)
sanctions West dual-use			-0.009	
			(0.016)	
sanctions West oil technology			0.001	
			(0.055)	
Sample	Full	Full	Full	Int. margin
Covariates	No	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes
R^2	0.067	0.067	0.067	0.380
N	3,099,226	3,099,226	3,099,226	190,185

Note: The regressions are based on Equation 1.3. Standard errors clustered at the sector-country pair-time level in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.9: Regression for second stage by country.

	(1) Belarus	(2) China	(3) HongKong	(4) Georgia	(5) Kazakhstan	(6) N. Maced.	(7) Serbia	(8) Singapore	(9) Switzerl.	(10) Turkey
Import data regressions										
sanctions Russia	-0.161**	-0.005	-3.570***	-0.705	1.157***	1.417***	1.171***	-0.602	-0.044	-0.250
	(0.078)	(0.076)	(1.207)	(0.505)	(0.212)	(0.355)	(0.347)	(0.780)	(0.104)	(0.352)
sanctions West	0.051	0.134*	-0.010	-1.188***	-0.035	-0.534	0.374***	-0.348*	0.206**	0.122
	(0.043)	(0.077)	(0.238)	(0.453)	(0.115)	(0.588)	(0.075)	(0.209)	(0.100)	(0.075)
Pseudo R^2	0.861	0.909	0.671	0.931	0.864	0.783	0.861	0.780	0.847	0.852
N	240,420	252,780	93,217	24,733	158,803	20,918	77,630	60,726	146,825	176,713
Export data regressions										
sanctions Russia	-0.231**	0.200***	-0.089	-0.210	0.584***	-0.308	1.073***	0.830*	-0.359***	-0.032
	(0.094)	(0.064)	(0.574)	(0.595)	(0.192)	(0.701)	(0.300)	(0.427)	(0.106)	(0.251)
sanctions West	0.001	0.204***	0.310***	-1.984***	0.063	-0.326	0.406***	0.394	-0.104	0.128**
	(0.045)	(0.039)	(0.086)	(0.455)	(0.115)	(0.530)	(0.064)	(0.260)	(0.066)	(0.059)
Pseudo R^2	0.935	0.906	0.923	0.934	0.914	0.803	0.856	0.721	0.893	0.868
N	247,140	243,720	74,263	24,250	165,960	12,177	86,335	74,109	147,485	198,118
Tradegap regressions										
sanctions Russia	0.684**	-0.138**	-0.014	-0.061***	0.344***	0.330***	0.066**	0.040**	-0.026	-0.170***
	(0.295)	(0.055)	(0.022)	(0.023)	(0.075)	(0.065)	(0.031)	(0.018)	(0.025)	(0.040)
sanctions West	-0.135***	0.106**	-0.099***	-0.010	0.087**	-0.011	-0.002	-0.228***	0.088**	0.108***
	(0.029)	(0.043)	(0.034)	(0.011)	(0.039)	(0.008)	(0.020)	(0.033)	(0.036)	(0.039)
R^2	0.335	0.317	0.380	0.224	0.202	0.527	0.236	0.323	0.356	0.248
N	310,440	310,440	305,266	310,440	310,440	310,440	310,440	310,440	310,440	310,440

Note: Standard errors clustered at the sector-country-time level in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
The import and export data regressions are based on Equation 1.1, whereas the tradegap regressions on Equation 1.3.
All regressions contain policy covariates and sector-country-time as well as product fixed effects.

Table B.10: Regression for second stage by section.

HS section	(1) I Animals	(2) II Vegetables	(3) IV Foodstuffs	(4) V Minerals	(5) VI Chemicals	(6) VII Plastic	(7) X Wood	(8) XI Textiles
sanctions Russia	-0.056 (0.083)	0.155 (0.165)	-0.184 (0.139)					
sanctions West				-0.119 (0.356)	-0.087 (0.125)	0.076 (0.072)	-0.425*** (0.129)	0.310*** (0.082)
Pseudo R^2	0.853	0.691	0.574	0.751	0.663	0.758	0.714	0.797
N	97,610	150,855	113,878	59,309	408,945	107,952	69,387	465,842

HS section	(9) XII Footwear	(10) XIII Construction	(11) XIV Stones	(12) XV Metals	(13) XVI Machinery	(14) XVII Vehicles	(15) XVIII Instruments	(16) XX Misc.
sanctions West	-0.347** (0.167)	0.473*** (0.062)	0.519** (0.235)	0.186*** (0.068)	0.216** (0.102)	0.005 (0.107)	-0.308*** (0.116)	0.219*** (0.049)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.922	0.787	0.715	0.694	0.822	0.735	0.663	0.914
N	22,889	74,166	17,094	319,992	457,800	61,258	109,917	62,946

Note: Standard errors clustered at the sector-country pair-time level in parentheses.
The regressions are based on Equation 1.1 and use importer-reported trade data. Sign. levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
They all contain policy covariates and sector-country-time as well as product fixed effects.

Table B.11: Regression for net imports by intermediary country.

	(1) Belarus	(2) China	(3) H.Kong	(4) Georgia	(5) Kazakhstan	(6) N. Maced.	(7) Serbia	(8) Singapore	(9) Switzerl.	(10) Turkey
Baseline regressions										
sanctions Russia	0.750***	0.044	0.163	-0.005	-0.402**	0.096	0.006	-0.043	0.053	0.089
	(0.248)	(0.104)	(0.100)	(0.210)	(0.165)	(0.158)	(0.081)	(0.036)	(0.082)	(0.066)
sanctions West	-0.017	0.049	-0.013	0.146**	0.017	-0.047	-0.095*	-0.104**	0.033	0.127***
	(0.058)	(0.041)	(0.087)	(0.061)	(0.039)	(0.043)	(0.050)	(0.047)	(0.032)	(0.032)
FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.921	0.957	0.913	0.904	0.914	0.915	0.914	0.912	0.956	0.948
N	19,201	8,307	15,330	20,252	22,439	19,378	18,781	17,150	19,604	15,736
Regressions containing interaction of Russian sanction and intermediate good dummy										
sanctions Russia	0.772***	0.086	0.138	-0.010	-0.411**	0.102	0.034	-0.042	0.056	0.088
	(0.243)	(0.111)	(0.103)	(0.218)	(0.164)	(0.162)	(0.087)	(0.035)	(0.080)	(0.075)
intermediate good	6.763	0.165	-0.034	11.008	-0.507	3.721	2.248	-0.259	-0.529	0.789
	(5809)	(173)	(261)	(2503)	(1341)	(2974)	(5983)	(1341)	(675)	(1201)
interaction: sanction x intermediate good	-0.772	-0.503**	0.636***	0.113	0.202	-0.102	-0.539**	-0.072	-0.106	0.014
	(0.520)	(0.249)	(0.220)	(0.281)	(0.315)	(0.181)	(0.263)	(0.077)	(0.310)	(0.301)
sanctions West	-0.017	0.049	-0.013	0.146**	0.017	-0.047	-0.095*	-0.104**	0.033	0.127***
	(0.058)	(0.041)	(0.087)	(0.061)	(0.039)	(0.043)	(0.050)	(0.047)	(0.032)	(0.032)
FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.921	0.957	0.913	0.904	0.914	0.915	0.914	0.912	0.956	0.948
N	19,201	8,307	15,330	20,252	22,439	19,378	18,781	17,150	19,604	15,736

Note: All regressions include sector-year fixed effects. Standard errors clustered at the sector-year level in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The regressions are based on Equation 1.4.

Chapter 2

Estimating the Hidden Costs of Free Trade Agreements

Joint with Stefan Legge

2.1 Introduction

Over the recent decades, the trade policy debate has seen a consensus emerge that free trade agreements have become the center of shaping international trade patterns. Due to the multilateral failings of the WTO Doha round, substantial trade liberalization largely occurs through the vast network of over 400 trade agreements currently in place or being negotiated. In fact, the majority of international trade now takes place between countries that have an active trade agreement.[32] Each of them promises to enlarge trade flows between its

[32] We document this in Figure C.1 in the Appendix using data from UN Comtrade and the WTO RTA-IS and DESTA databases on trade agreements.

signatories by cutting tariffs and removing various non-tariff barriers. Yet, one key element which is largely overlooked in the debate on the effects of these trade agreements is their utilization. Many studies assume that once a free trade agreement (FTA) is put into place, it will be automatically used by all firms of the signatory countries. If at all, the only two limitations usually mentioned at the conclusion of such agreements are the exemptions of certain sectors – mainly agriculture – as well as rules of origin requirements, intended to prevent transshipments from third countries misusing preferential tariff rates.

What this debate largely misses is the degree to which these rules of origin and other factors impede the utilization of FTA provisions. In the case of Switzerland, for instance, over a quarter of imports that would be eligible for preferential tariffs under an FTA regime do not utilize them. This in turn leads each year to unrealized tariff savings of over 400 million Swiss francs (CHF) – nearly a fifth of what could be potentially saved. Similar utilization and savings statistics are seen for FTAs implemented by the European Union and the United States.

In this paper, we take a closer look at the factors influencing whether an FTA is used, by looking at the large variation in preference utilization rates (henceforth PUR). These rates reveal what percentage of imports utilize preferential duties offered by the free trade agreements[33]. There are several reasons why the PUR would fall below 100%. For instance, the tariff preference margin offered by the FTA might be too small, firms may not yet be aware of the agreement, or simply applying for the preferential duties may be too costly. This paper attempts to filter out which of these factors explain the in some cases low PURs.

Our analysis is based on highly detailed Swiss import data, a country with one of the largest networks of free trade agreements spanning 31 deals with more than 40 countries. We use not only HS 8-digit product data but the full

[33] These PURs are adjusted for the cases where the preference margin (the difference between the non-preferential import duty – or the most-favored-nation (MFN) duty – and the preferential import duty agreed in the trade agreement) is zero. In these cases, free trade agreements do not offer any further reductions in import duties.

set of transaction-level import data for the years 2016 to 2019. These data provided by the Swiss Federal Customs Administration cover about 45 million unique observations. Such a high-dimensional dataset allows us to explore the various factors driving the FTA utilization.

We broadly classify these factors into benefits and costs. The former are the potential tariff savings which show a strong positive correlation with FTA utilization. However, the data reject the idea that there is some threshold value for the preference margin (i.e., the difference between MFN and FTA duties) for FTAs to be utilized. Among the costs, we document that restrictive rules of origin lead to substantially lower FTA utilization rates. This is particularly the case among highly complex goods. Furthermore, we find evidence for fixed costs of FTA utilization: Firms that used FTAs in the past are more likely to use them for future shipments. Finally, the results provide some support for the notion that administrative burdens play a role and that large firms do not utilize FTAs to a greater extent.

Our research contributes to three strands of literature. First, we generally contribute to the growing body of literature on the pros and cons of free trade agreements. Second, our work adds to research on the determinants of FTA preference utilization. Lastly, given that our dataset allows to exploit firm-specific transactions over four years, we contribute to the growing literature on firm dynamics in trade as well (Alessandria, Arkolakis and Ruhl, 2020).

In the trade literature, there is a general discussion of the benefits and disadvantages of trade liberalization through (bilateral or multilateral) trade agreements. A summary of this discussion is provided by Rodrik (2018). While trade agreements can reduce barriers and might pave a road toward further liberalization (Limão, 2006), an alternative perspective holds that FTAs are the result of rent-seeking, self-interested behavior on the part of politically well-connected firms. FTAs create a complex network ('spaghetti bowl') of trading relations, which discriminate between countries, firms, and consumers. There is an ongoing debate about who influences how FTAs are written up (Blanga-Gubbay, Conconi and Parenti, 2020; Rodrik, 2018). Furthermore, the necessity of rules of origin requirements can substantially mitigate (or even reverse) the trade-creating effects (Chase, 2008; Conconi et al., 2018).

In line with this discussion, research on the economic effects of trade agreements has been mixed. Baier, Yotov and Zylkin (2019) find that the impact of FTAs varies substantially. Moreover, bilateral trade agreements are found to create trade diversion (Dai, Yotov and Zylkin, 2014). Often reductions in import duties are the main content of trade agreements. Goldberg et al. (2010) show that lower input tariffs account on average for 31 percent of the new products introduced by domestic firm. Furthermore, tariffs affect the rate at which firms upgrade product quality (Amiti and Khandelwal, 2013), alter sourcing behavior (Ornelas, Turner and Bickwit, 2018), and increase productivity (Ornelas, Turner and Bickwit, 2018; Topalova and Khandelwal, 2011).

The second strand of literature to which we contribute examines what determines firms' decision to utilize free trade agreements. Existing research on the determinants of preference utilization has established some important factors. The first one is based on the idea that a larger incentive to utilize an agreement leads to a higher preference utilization rate (PUR). Prior research documents that larger preferential margins (i.e., the difference between the MFN tariff and the FTA preferential tariff set out in an agreement) significantly affect utilization rates (Bureau, Chakir and Gallezot, 2007; Hayakawa et al., 2013; Hayakawa, Kim and Lee, 2014; Keck and Lendle, 2012; Nilsson, 2016). Many researchers document estimates of a threshold value for FTAs to be utilized. Estimates of this cutoff vary across studies but are typically between 2 and 6 percentage points (Bureau, Chakir and Gallezot, 2007; Cadot and Ing, 2014; Manchin, 2006). Studying the Cotonou agreement (a treaty between the European Union and developing countries), for example, Francois, Hoekman and Manchin (2006) argue that the preferential tariff must be 4.0 to 4.5 percentage points lower than the most favored nation tariff for traders to request preferences. Hayakawa (2011) uses a larger sample and finds a threshold of just 3.2 percentage points.

The second crucial determinant of FTA utilization discussed in the literature are costs. Here, a distinction must be made between fixed and variable costs. Both Keck and Lendle (2012) as well as Nilsson and Dotter (2012) argue that the utilization of tariff preferences is associated with fixed rather than variable costs. Based on transaction-level data for Iceland, Albert and Nilsson (2016) estimate the fixed costs of utilizing preferential tariff rates. Using a kink regression model, they find that the utilization rate picks up at duty savings of roughly EUR 20 and levels off at EUR 260. Due to such costs, PUR can be high despite low preferential margins if the trade volume is sufficiently large (Hayakawa, 2015*b*). Also, they use transaction-level data but it does not include information about the firms, therefore not allowing a linkage between individual entries.

Bearing the costs of complying with FTA provisions, some argue, is easier for larger firms, thus raising their utilization rate compared to smaller companies.[34] Demidova and Krishna (2008) find that more productive firms utilize tariff preferences to a larger extent than less productive firms. They argue that this is because less productive firms cannot afford to pay the administrative costs related to preferences. Whether larger firms are generally more likely to utilize FTAs is subject to debate in the literature. Using survey data, Takahashi and Urata (2010) find evidence for this while Wignaraja (2014) does not find a correlation between firm size and utilization rates. Related to the debate about the nature of the costs of FTA utilization, prior research provides some evidence of ‘ effects’ with the idea that once a firm has mastered the administration of rules of origin and other procedures, it is more likely to use tariff preferences in subsequent imports. Hayakawa (2015*a*) as well as Wignaraja (2014) provide evidence for this learning mechanism.

A third determinant of FTA utilization examined in the literature is the restrictive nature of rules of origin (or short RoO). These RoO are necessary to ensure that only trade between countries signing an FTA benefits from lower duties. They define under which conditions a good is said to originate from a member country of the FTA so that it can be eligible for the preferential tariff. While being a necessary part of FTAs, RoOs distort exporters’ sourcing decisions and burden them with red tape (Felbermayr, Teti and Yalcin, 2019).

[34]Using a transaction-level dataset of Colombia’s imports in 2000 and 2001, Cadot et al. (2014) find that the cost of complying with rules of origin is higher for larger firms because those tend to source internationally their intermediates.

Already in the 1990s, economists examined the impact of rules of origin on international trade (Krishna and Krueger, 1995). Generally, trade economists expect that the costlier the compliance with an FTA, the lower its utilization. In this context, the restrictiveness of rules of origin plays a crucial role as documented by Takahashi and Urata (2010) as well as Hayakawa, Kim and Lee (2014). Furthermore, Kim and Cho (2010) study Korean FTAs and document that more restrictive ROO have a negative impact on the utilization rates. In another study, Augier, Gasiorek and Lai Tong (2005) provide empirical evidence from the EU suggesting that rules of origin do significantly restrict trade. Comparing Jordanian exports to the EU and the US, Brunelin, De Melo and Portugal-Perez (2019) document that origin requirements suppress market access. In this regard, differences in PUR across sectors are important (Hayakawa et al., 2013). Furthermore, firm size and experience with utilization have been found to shape utilization (Hayakawa, 2015*a*; Wignaraja, 2014).

We contribute in multiple ways to this research, largely thanks to the detailed Swiss data. First, the country has one of the most developed networks of free trade agreements; hence, FTAs are of particular importance for the country[35]. As shown by Halpern, Koren and Szeidl (2015), productivity gains from tariff cuts are larger when an economy has many importers and many foreign firms. Second, we are able to utilize a much larger transaction-level trade dataset than previous studies. For instance, Kasteng, Kokko and Tingvall (2020) only employ data for Swedish imports from South Korea during November 2016. However, in order to examine the impact of RoO on FTA utilization, we must have multiple FTAs with different RoOs for the same product. Our data also allow a more precise identification of the RoO effects, as previous studies rely largely on aggregated average restrictiveness of entire FTAs. The time dimension enables us also to investigate firm dynamics at a much more granular level than previously possible. Finally, our paper adds to the literature on which firms benefit most from international trade. Bernard et al.

[35] The Swiss example is particularly interesting in the context of preference utilization as it is often argued that a vast network of trade agreements leads to preference erosion (Francois, Hoekman and Manchin, 2006). However, as this study emphasizes, these preferences are not automatically used and face different hurdles.

(2018) show that much of international trade is dominated by a few 'global firms'. In our study, we examine whether it is also a small number of large firms that dominate FTA utilization.

The remainder of the paper is structured as follows. In Chapter 2.2, we explain the fundamentals of FTA utilization, discuss the costs and benefits associated with it, and set out hypotheses about the determinants of FTA utilization. Chapter 2.3 then provides an overview of the dataset used for our empirical analysis. Subsequently, in Chapter 2.4 we document and examine the variation in the utilization rates to test the hypotheses about the determinants driving the decision to utilize FTAs. Based on the findings, Chapter 2.5 discusses some policy implications before we conclude in Chapter 2.6.

2.2 The Utilization of FTAs

The most crucial part of free trade agreements (FTAs) are preferential tariff rates. However, the mere existence of an FTA between two countries does not imply that all bilateral trade is duty-free or that preferential tariffs are applied automatically. In what follows, we briefly describe the fundamentals of FTA utilization before discussing its associated costs and benefits.

Most countries already have a general most-favored nation (MFN) tariff of zero for many goods, and among the remaining products not all have lower tariffs set out in the FTA.[36] Then, even if a positive preference margin exists ($\text{tariff}_{\text{MFN}} - \text{tariff}_{\text{FTA}} > 0$), restrictions apply: Most importantly, each shipment must comply with rules of origin (RoO) which aim to prevent FTAs being misused by third countries. For example, for a t-shirt imported from China to be eligible for preferential treatment at the Swiss border, the FTA's rules of origin require either a change to the HS chapter[37] or that the value of non-

[36] According to the WTO Tariff Download Facility database, countries have MFN tariffs of zero on average for 27% of products. In addition, for some products, negotiators of the FTA do not set out preferential tariffs and sometimes, lower duties are only introduced over a period of several years.

[37] The internationally applied Harmonized System (HS) classifies traded products into over five thousand codes as so-called 6-digit sub-headings. These are aggregated into 4-digit headings, which in turn belong to 96 different 2-digit HS chapters. Countries may specify

originating materials (VNM) allowed in relation to the ex-works price of the product does not exceed 60 percent. Such regulations imply that firms must actively decide whether or not to utilize FTAs. Put differently, the utilization of FTAs is associated with benefits and costs. The latter are related to production adjustments, shipping adjustments, and administration/bureaucratic costs.

Consider a firm f that seeks to import good i from origin country o with shipment s in year t. At the Swiss border, there are two different tariffs for product i: the regular most-favored nation (MFN) duty τ_i^{MFN} and a lower tariff τ_i^{FTA} specified in the FTA that Switzerland has signed with country o. Abstracting from the discussion of FTA salience, firm f is aware that it can potentially save customs duties. However, utilization of the FTA might require adjustments to the production of i, changes in the shipment s, and create some bureaucratic costs for documentation. We summarize the costs of utilization as $C_{t,o,i,f,s}$ where the subindices show that there is variation across five dimensions: time, country of origin (i.e., FTA), product, firm, and shipment. If firm f decides to utilize the FTA, it must hold that duty savings exceed total costs of utilization. Formally,

$$v_{t,o,i,f,s} * (\tau_i^{MFN} - \tau_i^{FTA}) > C_{t,o,i,f,s} \tag{2.1}$$

with $v_{t,o,i,f,s}$ denoting the value of the shipment.[38] Preference utilization rates of Swiss FTAs differ across five dimensions: t, o, i, f, and s. This is shown in the empirical evidence provided later in this paper. To infer the costs of preference utilization, we use the utilization status of each shipment and exploit the variation in utilization. But before we empirically estimate these costs, we first provide a theoretical discussion of the costs and benefits of FTA utilization.

more detailed product codes as long as they are aligned with the 6-digit sub-headings.

[38]Note that for the purpose of illustration we assume Switzerland to impose ad-valorem duties. The logic would be identical when using q_s for the weight of shipment s and weight-based tariffs.

2.2.1 Costs of FTA Utilization

Firms do not automatically benefit from preferential tariffs if they import goods from FTA partners. Instead, they must actively apply for preferential customs treatment. In the first place, this requires that firms are aware of available FTA benefits. While salience of FTA regimes in general is typically high, some firms might not be aware of all FTAs and their respective options for tariff savings (e.g., Table 4 in Wignaraja (2014)). With Switzerland having a network of dozens of trade agreements, firms that frequently source from different nations must invest resources to inform themselves about all relevant FTAs.

A firm that is aware of potential FTA benefits must comply with the rule of origin (RoO) to be granted preferential tariff rates. This can be costly for three reasons. First, some sourcing adjustments might be necessary in order to fulfill requirements. For example, the percentage of the value of non-originating materials allowed in relation to the ex-work's price of the product must be kept below the allowed maximum. Second, the utilization of FTAs requires filling out paperwork for each transaction. Finally, some adjustments to logistical processes might be necessary. This includes not only measures to avoid time delays related to compliance risks but also changes to packaging.[39]

In this context, it is important to distinguish between fixed and variable costs of FTA utilization. Some costs occur only once; for example, information costs about regulations or adjustment costs related to finding suppliers that fulfill the associated RoO. Other costs are recurring and variable, such as the increased expenses due to different sourcing and logistics. Among the variable costs, some are fixed per shipment while others increase with the value of the shipment. We discuss these differences later in the paper.

[39] Containers from China are often shipped with the European market in general as destination. However, when such containers are opened after arrival in the EU (e.g., Rotterdam) and products are repackaged for the Swiss market, benefits of the FTA between Switzerland and China can no longer be utilized.

2.2.2 Benefits of FTA Utilization

The primary benefits of FTA utilization for firms is the potential of tariff savings. In the present paper, we focus on this benefit and neglect other benefits such as cumulation possibilities.[40] The Swiss Federal Customs Administration defines the latter as a deviation from the principle that goods must be produced entirely in the country of origin, or have undergone sufficient processing there, in order to qualify as originating goods. Essentially, cumulation makes it possible for goods from a free trade partner to be treated equal to those originating in the country of origin. Concerning the potential for tariff savings, we must take into account that roughly half of Swiss imports from FTA partner countries is already subject to zero regular tariffs. Accordingly, we focus our empirical analysis on products with a positive preference margin.

2.2.3 Hypotheses

If firm f decides to utilize the FTA in year t for shipment s of product i from country o, it must hold that duty savings exceed the total costs of utilization:

$$U_{t,o,i,f,s} = \begin{cases} 1 & \text{Benefits} > \text{Costs} \\ 0 & \text{Benefits} < \text{Costs} \end{cases} \tag{2.2}$$

Following equation (2.2), utilization of FTAs varies across 5 dimensions: t, o, i, f, s. We can interpret forgone tariff savings as the costs of preference utilization: If FTAs are utilized, the associated benefits must outweigh the costs. Using the variation in FTA utilization, we can gain an understanding of the importance of the determinants of preference utilization. Knowing potential tariff savings (i.e., benefits of utilization) and assuming firms to rationally decide whether to utilize an available preference margin, we can estimate the costs of FTA utilization. For this, we apply the revealed preference criterion: Estimated costs of FTA utilization must be less than preference margins when utilization occurs. Based on this framework, we can set out hypotheses about the determinants of preference utilization. These will be tested in Chapter 2.4.

[40] This topic is discussed, for example, by Hayakawa (2014).

Hypothesis 1. *Larger potential tariff savings increase preference utilization.*

For any given costs of FTA utilization, we expect based on equation (2.2) that firms will make larger use of preferential tariffs *ceteris paribus* if the associated benefits increase. Notice that potential tariff savings can be split into two parts: preference margin and the value of a shipment. We argue that the product of the two parts is what determines FTA utilization but explore the relationship between utilization rates and both parts separately as well.

Hypothesis 2. *Larger firms utilize FTAs more than smaller ones.*

To the extent that there are bureaucratic costs associated with the utilization of free trade agreements, larger companies arguably have more resources to cover those expenses. Since firm size —proxied by the number of employees— is also an indicator of firms' productivity, it is difficult to carve out the exact mechanism at work. But nevertheless, we expect larger firms to utilize FTAs to a greater extent.

Hypothesis 3. *High administrative costs reduce preference utilization.*

Any facilitation of the FTA utilization process for a selected group of firms should lead to a higher FTA utilization. In Switzerland, some firms benefit from being granted the status of 'authorized importer'. They benefit from privileged conditions such as higher flexibility (e.g., regarding timing and location of declaration) and quicker customs processes.[41] In order to receive this status, however, firms must go through a certification process which can be thought of as a fixed cost. Moreover, authorized importers must still provide all documentation if requested by the customs administration.

Hypothesis 4. *FTA preference utilization is lower for urgent shipments.*

[41] Details on the process are provided by the Swiss Federal Customs Administration here: https://bit.ly/2Laq5O9, and in the detailed documentation here: https://bit.ly/3b56slw.

Many firms can choose from several modes of transportation when shipping goods internationally. For example, when firms want to import goods from China, ocean container ships are typically the most cost-efficient option. However, for urgent export from China to Switzerland, air freight is likely the preferred alternative. It outperforms ocean shipping in terms of speed and flexibility but is often a much costlier option. When flying goods to Switzerland, they can reach their final recipient in just a few days. In contrast, sea freight is much slower than that and will arrive only after three weeks or more. Firms that choose to utilize the more expensive air transport option do not want to slow down customs processes with the application and approval process for FTAs. Hence, we expect a lower utilization among urgent shipments.

Hypothesis 5. *There is path dependency in FTA utilization.*

Firms that utilized preferential tariffs in the past should be more likely to use them for future shipments. This is due to learning effects but also expected if there are substantial one-time *fixed* costs of FTA utilization.

Hypothesis 6. *More restrictive rules of origin reduce preference utilization rates.*

To the extent that we can rank the restrictiveness of rules of origin, we expect that *ceteris paribus* the preference utilization rate is lower when requirements are more severe. For instance, a change in HS chapter is more demanding than a change in heading or sub-heading. Moreover, the larger the share of the necessary regional value content, the lower the expected FTA utilization rate.

Hypothesis 7. *Rules of origin reduce preference utilization more for complex products.*

When products are composed of a large number of intermediates, the utilization of FTAs becomes increasingly cumbersome. This is for two reasons:

First, sourcing multiple inputs such that rules of origin are not violated becomes more costly. Second, the documentation becomes more tedious. Both of this is only problematic if rules of origin require respective sourcing and documentation. Hence, we expect restrictive rules of origin to have a particularly negative impact on preference utilization rates in the case of highly complex products.

2.3 Data

For our empirical analysis we utilize trade data from Switzerland. To provide some background information on Switzerland's trading relationships, in this chapter we first illustrate the country's network of free trade agreements. Afterwards we describe in detail the structure and content of our dataset. Finally, we provide some descriptive statistics.

2.3.1 Switzerland's Network of Trade Agreements

Switzerland has spent the last decades building a network of more than 30 free trade agreements (FTAs) with over 40 partner countries. In Legge and Lukaszuk (2018), we provide an overview of Switzerland's trading relationships. Figure C.2 in the appendix illustrates the country's trade treaty status with all partner countries. Additional information on Switzerland's imports by customs treatment as well as its key foreign trade relationships are provided in Tables C.1 and C.2 in the appendix. The two main countries that currently have no preferential agreement with Switzerland and also no negotiations are the United States as well as Australia[42].

Overall, more than 80 percent of Swiss trade is covered by free trade agreements, with roughly three quarters of this being with members of the European Union. The key non-EU FTA partners are China, the United Arab Emirates, and Japan which are responsible for 5.5, 5.4 and 1.6 percent of total Swiss imports, respectively.

[42] A number of relevant countries such as Thailand or India benefit from tariff preferences through Switzerland's General System of Preferences (GSP).

2.3.2 Description of the Dataset

For our empirical analysis, we use a novel dataset on Swiss imports from FTA partner countries in the four years 2016 to 2019. In the following, we describe the parts and sources of all data.

2.3.2.1 Transaction-Level Trade Data

The most crucial part of these data is information on Swiss transaction-level imports obtained from the Swiss Federal Customs Administration. This includes the import value, weight, customs treatment, and duties paid. We can use the complete data for the years 2016–2019. For the years 2014–15, the same data is available but without firm information. Using data for the year 2019, we illustrate in Table 2.1 how we select relevant transaction-level data.

One key step in the data preparation process is the dropping of transactions which do not benefit from a positive preference margin (cf. step 8 in Table 2.1). Also, the observations are restricted to transactions with potential tariff duties above 5 Swiss Francs (step 12), as Switzerland does not collect duties below this threshold due to high revenue collection costs. Other steps narrowing the dataset include the removal of products facing quotas (as quota utilization information is not available) and those facing multiple tariff levels (e.g., depending on the harvest season for some agricultural products). Lastly, outliers are identified based on transactions with higher values than the corresponding product-level information from the aggregated and cleaned dataset provided by the Swiss Federal Customs Administration, and accordingly removed. The final dataset consists of over 45.5 million transactions, with 12.1 million of them occurring in 2019.

For every transaction, we know the ID and description of the importing and consignee firm (the two overlap for ca. 80% of the transactions). Furthermore, we have descriptions of the exporting firm and traded product as well as a code for the transportation mode. The latter includes, for instance, a dummy variable for air transport which we use as proxy for urgency. Our data include firm-specific information such as firm size (by employee bracket), the 5-digit sector (NOGA code), as well as a dummy variable for whether a firm is an authorized importer (i.e., a firm with experience in complying with origin requirements and passed an application process). All these additional variables are obtained from the Swiss Federal Statistical Office.

Table 2.1: Preparation of the Transaction-Level Dataset

Steps	**Obs. (in mn)**	**Trade (in bn CHF)**	**No. of products**
0. Raw data	65.8	289.1	8'261
1. Keep latest version of transactions	65.5	285.8	8'259
2. Remove non-commercial transactions	58.4	277.2	8'256
3. Restrict to FTA & GSP countries	55.5	244.6	8'229
4. Restrict to MFN & preferential flows	55.0	231.1	7'811
5. Remove duplicate rows	53.8	224.6	7'811
6. Remove products with quotas	53.0	222.0	7'494
7. Restrict to FTA countries	45.3	192.0	7'481
8. Restrict to positive preference margin	33.6	84.3	4'991
9. Remove gold & other special goods	33.5	80.3	4'953
10. Remove products with multiple tariffs	33.1	75.6	4'826
11. Drop products with 0 value	33.0	75.6	4'826
12. Transactions with duties > 5 CHF	12.1	70.9	4'671
13. Remove outliers (based on aggregated data)	12.1	70.3	4'670

Note: The table illustrates how we select transaction-level data for the empirical analysis. Each row indicates a change with the reduction in observations, import volume, and number of products shown in columns 2–4. Data is taken from the year 2019. The last column refers to the number of products defined as 8-digit HS product codes.
The raw data relates to the original figures received from the Swiss Federal Customs Administration. In the first step, older versions of the same transactions are removed and non-commercial transactions dispersed. This is followed by eliminating countries that do not receive any preferences from Switzerland. In the next step, flows are restricted to those within an MFN or preferential regime (for other regimes see Group B in Table C.4). After checking for duplicates and taking out products facing quotas, we further restrict the data to FTA countries and trade flows benefiting from a positive preference margin. Next, gold and other special commodities (defined in Switzerland under so-called "Total 2") as well as goods facing potentially different tariff lines that cannot be distinguished in the dataset are removed. There are also a number of transactions with zero value that are dropped. Importantly, the data are restricted to those transactions facing import duties of at least 5 Swiss Francs – otherwise the importer does not need to pay them under Swiss customs law. In a last step, transactions which have a higher value than the corresponding aggregated product-level import data are removed, as they are deemed to be outliers.

2.3.2.2 Aggregate Trade Data

We complement these transaction-level import data with official product-level import statistics. While in theory these data should mirror the aggregated transaction-level data, there are some differences.

The main reason for discrepancies is that the obtained transaction-level

dataset was corrected for outliers before being aggregated to product-level statistics. However, only uncorrected transaction data were made available. Second, there is no clear correspondence of importing regime classifications (such as MFN, GSP, or FTA) between the two datasets. Furthermore, the transaction-level data abstract from trade in electricity.
Despite these inconsistencies, the prepared transaction data correspond to roughly 97% of the official import statistics. As described above, the detailed data are then restricted to transactions which potentially have to pay duties and do not fall below the 5 Swiss Francs (CHF) threshold – a detail which cannot be accounted for in aggregated official statistics.

The official import figures include yearly import data at the tariff line level (more than ten thousand products). We know the country of origin, import value, weight, customs treatment, and duties paid for the years 2000 to 2019. The underlying data have been obtained from Swiss-Impex, the database of the Swiss Federal Customs Administration. It contains information at the 8-digit HS code level on all Swiss imports, including the tariff regime under which each good has entered Switzerland. This piece of information is crucial for the determination whether the importer has utilized (if applicable) the available preferential tariff rates. In addition, for the sake of comparing Swiss import data with that of other countries we use similar data provided by the United States International Trade Commission (henceforth: USITC) and by Eurostat. This allows us to look at the overall preference utilization rate (PUR) for the trade partners of the United States and the European Union.

2.3.2.3 Complementary Data

All Swiss trade data are augmented with information on tariff rates. These include both the most-favored nation (MFN) as well as the preferential FTA tariff rates at the 8-digit HS-level. While Swiss duties are typically expressed in Swiss Francs per 100kg of import weight (instead of ad valorem rates), we estimate percent charges using average import values per 100kg. For the US and EU, we also utilize information from the WTO Tariff Download Facility.

Notably, we focus on tariff rates and neglect non-tariff measures.[43]

We enrich the dataset further with information on rules of origin (RoO). These define under which conditions a preferential tariff rate set out in an FTA can be granted. Drawing on the annexes of the original FTA documents provided by the Swiss State Secretariat for Economic Affairs, we standardized the RoO at the 6-digit HS product-level for Swiss imports from the European Union, EFTA partner countries, Japan, China, Turkey, Korea, and Gulf Cooperation Council (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, United Arab Emirates). These countries account for 97.5% of Swiss imports from FTA partners. The standardization is largely based on the method of the International Trade Center's Rules of Origin Facilitator. We provide a full list and description of the different RoO in Table C.5 in the appendix.

Finally, we add information on the product complexity. For this, we draw on the data from Hidalgo and Hausmann (2009) provided by the Harvard Atlas initiative and match information at the 6-digit HS level. Products with a high product complexity index (PCI) value (i.e., the most complex products that only a few countries can produce) include electronics and chemicals while products with a low PCI value (i.e., the least complex products that nearly all countries can produce) include raw materials and simple agricultural products.

2.3.3 Descriptive Statistics

We provide descriptive statistics for the key variables in Table 2.2. In total, over the time period 2016–2019 our dataset covers about 45 million observations with each being a combination of year, country of origin, 8-digit product codes, firm, and shipment.

[43]Niu et al. (2018) find that trade protectionism has been rising over the last two decades, despite the perception of falling protection due to tariff cuts over this same period. This evidence is also supported by the Global Trade Alert database (Evenett, 2019).

Table 2.2: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Part I. Aggregate Data					
Year	2017.52	1.12	2016	2019	527'668
Imports (total)	1268256.81	28849864.3	1	7517498467	527'668
Imports (MFN)	209929.03	3540301.46	0	828803939	527'668
Imports (FTA)	488475.27	8439049.1	0	2004672509	527'668
Imports (MFN zero)	470780.94	21336560.79	0	5322575378	527'668
Imports (other preference)	52674.88	12792322.3	0	6898779354	527'668
Imports (refinements)	5903.47	265165.29	0	46654435	527'668
Imports (other)	40426.07	3129204.32	0	1196084514	527'668
Tariff duties paid	7673.92	159543.51	0	30884167	527'668
MFN Tariff Rate (in CHF/100kg)	111.73	231.92	0.06	3999	368'613
FTA Tariff Rate (in CHF/100kg)	2.12	16.39	0	618.7	235'221
PUR	38.8	42.52	0	100	424'204
Part II. Transaction-Level Data					
Year	2017.56	1.12	2016	2019	45'502'318
Import Value	5832.56	94939.81	1	156617981	45'502'318
Import Weight	1639.99	32965.4	0.2	51489910	45'502'318
Duties Paid	38.87	242.53	0	203630.95	45'502'318
Preference Utilized	0.48	0.5	0	1	45'502'318
FTA Tariff Rate (in CHF/100kg)	1.44	9.80	0	815	45'502'318
MFN Tariff Rate (in CHF/100kg)	175.01	231.84	0.06	3863	45'502'318
FTA Duty	9.07	155.43	0	28242	45'502'318
MFN Duty	221.8	1093.92	5.05	1100250	45'502'318
Firm Size (employees bracket)	5.69	4.17	0	12	38'725'622
Authorized Importer	0.1	0.3	0	1	38'725'622
Mode of Transportation	3.03	0.36	2	9	45'498'283
RoO: ALW	0.1	0.3	0	1	43'689'237
RoO: CC	0.12	0.33	0	1	43'689'237
RoO: CTH	0.41	0.49	0	1	43'689'237
RoO: CTSH	0	0.03	0	1	43'689'237
RoO: ECT	0.09	0.29	0	1	43'689'237
RoO: NC	0.05	0.21	0	1	43'689'237
RoO: RVC	0.61	0.49	0	1	43'689'237
RVC Percentage	59.02	5.16	30	80	26'436'706
RoO: SP	0.21	0.41	0	1	43'689'237
RoO: WO	0.02	0.15	0	1	43'689'237
Product Complexity Index	-0.49	1.07	-3.47	2.99	45'307'803

Note: The table provides descriptive statistics for the main variables in our dataset for the years 2016–2019. The upper part shows aggregate trade data at the 8-digit HS level, while the lower part is based on transaction-level data. Trade values are expressed in Swiss Francs, trade volumes in kg.

As the descriptive statistics at the transaction-level indicate, preferential tariffs were utilized in roughly half of all cases. Furthermore, we observe that there is substantial variation in shipment values, ranging up to 156 million Swiss Francs. The firm size is grouped into twelve categories and the mode of transportation into eight. Finally, the product complexity index ranges from -3.47 to 2.99 for the most complex goods.

2.4 Empirical Analysis

In this section, we first discuss the methodology and illustrate the variation in FTA preference utilization. Then we analyze the determinants of preference utilization by exploring the hypotheses set out earlier.

2.4.1 Methodology

All Swiss imports can be grouped by customs treatment. The first option is that regular non-zero tariffs are applied according to the most-favored nation (MFN) principle. Second, the MFN tariff can be zero and thus no charge is levied. A third option is that preferential tariffs according to the FTA are applied. Finally, non-FTA related preferential tariffs are applied — for instance according to the Generalized System of Preferences (GSP) for developing countries, or products imported for refinement or research purposes. We provide an overview of the trade shares by trading partner and customs treatment in Tables C.1 and C.4 in the appendix. Slightly over half of Swiss imports profit from MFN-free duty rates. Roughly half of the remaining trade – 24% of total imports – applies preferences stemming from the FTAs. Their importance varies starkly across countries: in 2019, over 60% of total imports from Czechia was processed through the FTA regime, while only 0.4% in the case of the United Arab Emirates.

Throughout our empirical analysis, one crucial variable is the preference utilization rate (PUR). This indicates the value-weighted share of Swiss imports that could have benefited from preferential FTA tariffs and actually did so. It is defined as follows:

$$\text{PUR} = \frac{\text{Imports utilizing FTA}}{\text{Imports that could benefit from FTA}}$$

$$= \frac{\text{Imports utilizing FTA}}{\text{Total imports} - \text{MFN-free imports} - \text{Other free imports}}$$

Note that the denominator is also equal to FTA imports plus MFN imports.

A final methodological aspect we have to describe is the treatment of rules of origin (RoO). In order to distinguish the costliness of RoOs, we follow the approach by Estevadeordal (2000). This defines a categorical variable 'RoO Restrictiveness' according to the following rule:

$$\begin{aligned} \text{RoO Restrictiveness} &= 1 \ \text{ if } \ NC = 1 \\ &= 2 \ \text{ if } \ CTSH = 1 \ \text{ and } \ RVC = 0 \\ &= 3 \ \text{ if } \ CTSH = 1 \ \text{ and } \ RVC = 1 \\ &= 4 \ \text{ if } \ CTH = 1 \ \text{ and } \ RVC = 0 \\ &= 5 \ \text{ if } \ CTH = 1 \ \text{ and } \ RVC = 1 \\ &= 6 \ \text{ if } \ CC = 1 \ \text{ and } \ SP = 0 \\ &= 7 \ \text{ if } \ CC = 1 \ \text{ and } \ SP = 1 \end{aligned}$$

We provide a description of the different RoO in Table C.5 in the appendix. For each product at the 6-digit HS level of the most important FTAs we created a corresponding RoO Restrictiveness score.[44] The results of the standardization are summarized in Table C.6 in the appendix: roughly half of the RoO for the EFTA, EU, and Turkish FTAs and two thirds of the Chinese FTA could be standardized. The empirical analysis therefore ought to compare only those products whose rules of origin could be standardized for multiple FTAs. Restricting the sample to those 1'775 (out of 5'387) 6-digit HS products which were in fact standardized for all seven FTAs, we see that on average the

[44] We apply the method across all goods without distinction of final and intermediate goods, as discussed by Carrère and De Melo (2006).

EU, EFTA, Turkish and Chinese agreements were nearly as restrictive with an average score of 4.1. The Japanese and Korean FTAs had similar scores of 4.5 and 4.6, respectively, whereas the GCC FTA may be considered most restrictive with a score of 5.0 on average.

Methodologically, we first use descriptive statistics to examine whether the (raw) data support the hypotheses set out in Chapter 2.2. Such statistics can, however, be misleading. It could be, for example, that large firms do not show on average a higher FTA utilization than smaller firms. Such an observation might indicate that firm size is no significant determinant of FTA utilization. However, it could also be a distorted observation because larger firms in our dataset import a larger share of products for which there is a generally lower FTA utilization (e.g., textiles). To address such confounding factors, we run regression models with a large set of fixed effects. Expressed in general terms, we estimate the following model:

$$U_{t,o,i,f,s} = \alpha_0 + \mathbf{X}_{t,o,i,f,s}\,\beta + \gamma_{t,o,i} + \varepsilon_{t,o,i,f,s} \tag{2.3}$$

where $U_{t,o,i,f,s}$ is a dummy variable that takes the value 1 if shipment s of product i by firm f from country o in year t utilized the respective FTA. We use a different set of explanatory variables summarized by $\mathbf{X}_{t,o,i,f,s}$ and can vary across the five dimensions. To reduce the effect of confounding factors, we include a set of fixed effects indicated by $\gamma_{t,o,i}$. Note that the latter varies across models. Finally, the standard errors $\varepsilon_{t,o,i,f,s}$ are clustered at the HS8–Country–Year level.

While the dependent variable is a dummy, we chose a linear model instead of Probit or Logit due to computational reasons and the inclusion of fixed effects (Honoré and Weidner, 2020). Based on subsample-regressions, however, we conclude that results are very similar irrespective of whether we use a linear or non-linear model.

2.4.2 Variation in FTA Utilization

In what follows, we discuss the variation in FTA utilization across the five dimensions year, country of origin, product, firm, and shipment. This provides us with a first understanding of what determines FTA utilization.

2.4.2.1 Variation across Years and Country of Origin

The overall preference utilization rate (PUR) differs substantially across Switzerland's trading partners. For imports from Germany, its largest trading partner, the data show a PUR of about 75% for the years 2016 to 2019. In contrast, the overall PUR is significantly higher among products that come from Italy, France, or Austria. Much lower aggregate PURs are observed among imports from China or Great Britain. Panel (a) of Figure 2.1 provides an illustration of aggregate PURs for Switzerland's top-10 FTA partner countries. Overall, we see that the PUR for Switzerland's trading partners varies from nearly 0% for the United Arab Emirates to over 90% for Norway, with most European Union member states having a PUR of 60 to 80%.

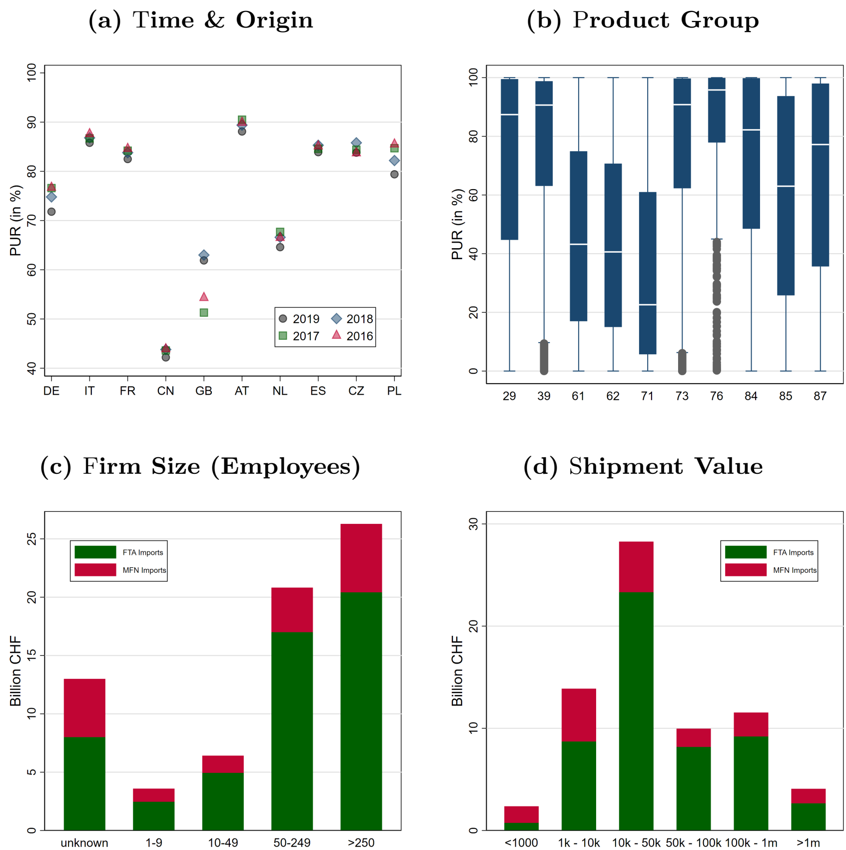
One notable observation concerning Figure 2.1 is that — with the exception of trade with Great Britain which is volatile in general — the PUR per country is very stable over time. This allows us to focus much of the descriptive analysis on data from the year 2019.

To put these overall PUR levels for Swiss imports into perspective, we can compare them with the European Union. Nilsson and Preillon (2018) find that for EU exports in 2016 the overall PUR was 77.4% with significant variations across country-pairs and products. In Table C.3 in the appendix we illustrate some key numbers.

2.4.2.2 Variation across Products

Imports from countries that have relatively recently signed a free trade agreement with Switzerland such as China (in 2014), Japan (2009), or Canada (2009) have relatively low utilization rates compared to imports from EU countries — which have bilateral agreements with Switzerland dating back

Figure 2.1: Variation in Preference Utilization Rates



Note: The figures plot the distribution of the preference utilization rate (PUR) along five dimensions. In plot (a), we illustrate the aggregate PUR for Switzerland's top-10 FTA partners (by trade volume) for the years 2016–2019. Plot (b) shows a boxplot of the PUR for the top-10 product groups (2-digit HS) in 2019. Plots (c) and (d) illustrate the distribution of the PUR by firm size and shipment value in 2019.

to 1973. On the one hand, this could be explained with a lack of salience regarding these agreements. On the other hand, these countries are likely to export different products and are geographically located further away than its

European peers.[45] Which factor is actually responsible for this low utilization will be explored in the following chapter.

The variation in the PURs can be seen not only across countries of origin but also across products, as shown in Panel (b) of Figure 2.1. For Switzerland's ten most important HS chapters in terms of trade value, we show the distribution of PURs across 8-digit HS tariff lines. The boxplots indicate, for example, that FTA utilization is generally low for textiles (HS chapters 61 and 64).

Another way of illustrating the variation in FTA utilization across products is provided by Figure C.3 which portrays the cumulative distribution of PURs of products classified at the 8-digit HS code level for four trading partners: Austria, China, Germany, and the United Kingdom. There are two interesting observations concerning this cumulative distribution. First, the PURs of products vary from 0 up to 100 percent, with a relatively sizeable distribution between the two extremes. This suggests that the product composition of a trade relationship could play an important role in determining the overall PUR of a free trade agreement. This implications will be further explored in Chapter 2.5. Second, the variation across products differs significantly across trading partners. For example, China's PUR distribution seems relatively uniform. Meanwhile, forty percent of products that the United Kingdom's exports to Switzerland do not utilize the preferential duty rates at all. At the other extreme, more than 80 percent of Austrian exports to Switzerland have a PUR of above 80%.

2.4.2.3 Variation across Firm Size and Shipment Value

We conclude the descriptive analysis by examining how the FTA utilization varies with firm size and shipment value. Panels (c) and (d) of Figure 2.1 show the imports in 2019 that utilized or did not utilize available tariff preferences. We observe that larger firms trade a lot more than those with less than 50

[45] Other non-observable factors driving the higher utilization for EU may be linked to the European regulatory framework. Switzerland – as part of EFTA – has harmonized many non-tariff regulations with the EU, reducing uncertainty and facilitating the utilization of the bilateral agreements.

employees. However, there is little descriptive evidence in Panel (c) that larger firms utilize FTAs more also in relative terms. One potential explanation could be that small firms outsource their transportation to large logistics providers that are just as efficient at utilizing FTAs as large firms. While our data does contain both carrier and consignee information to explore this hypothesis, in over 80% of the cases the two entities are identical (with unexpectedly little variation along the firm size dimension). Another reason could be that large firms trade different, more complex products. We return to this discussion later in the paper. Finally, Panel (d) of Figure 2.1 shows that most shipments are worth between 10'000 and 50'000 CHF. Notably, the FTA utilization is very low among shipments worth less than one thousand CHF.

2.4.3 The Determinants of Utilization

In Chapter 2.2 we stated that firms utilize FTAs if benefits exceed costs. Based on this general framework, we set out seven hypotheses about the determinants of FTA utilization. These can be tested using the available dataset.

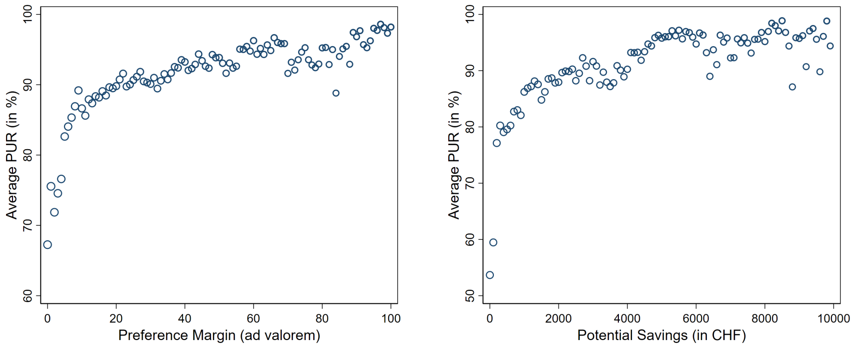
2.4.3.1 Preference Margins

A key variable often cited in the literature in the context of preference utilization is the preference margin: the difference between regular MFN duties and preferential tariffs. In particular, we are interested in whether there is a threshold of, for instance, 3% for firms to utilize FTAs. Such a cutoff is often cited among trade economists and builds upon studies such as Francois, Hoekman and Manchin (2006) who find a threshold for non-LDC ACP countries in their preferential trade with the European Union to be between 4.0 and 4.5 percent. Similarly, Amiti and Romalis (2006) documented a relationship between preference margins and preference utilization. We examine this relationship using our dataset and obtain the results shown in Panel (a) of Figure 2.2.

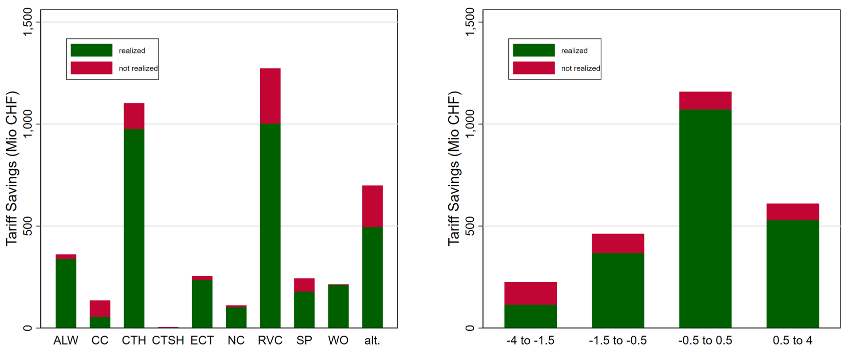
As the results illustrate, utilization rates are large even if preference margins are near zero. This contradicts the notion that FTAs are only utilized

Figure 2.2: Correlates with Preference Utilization Rates

(a) Preference Margin **(b) Potential Savings**



(c) Rules-of-Origin **(d) Product Complexity**



Note: The figures plot the distribution of the preference utilization rate (PUR) against four variables. In plot (a), we illustrate the aggregate PUR by preference margin (= MFN tariff - FTA tariff). Plot (b) shows the same using potential savings (= duties under MFN - duties under FTA). Plots (c) and (d) illustrate the aggregate PUR by rules-of-origin (RoO) type and product complexity. We chose five selected types of RoO: wholly obtained, change in sector, change in product category, change in product subcategory, as well as minimum local value added.

if the preference margin exceeds some threshold level of, for instance, 3 percentage points. The gradient in Panel (a) of Figure 2.2 is large for preference margins below 10 percentage points but remains positive when extending the range to 100 percentage points. Figure C.4 in the appendix focuses on the range of zero to twenty percentage points and shows a steep increase for margins below ten percentage points.

2.4.3.2 Savings Potential

The first factor we suspect to drive preference utilization is the potential savings (sometimes labeled 'incentive channel'). To explore this, we multiply for each transaction in our dataset the preference margin by the trade volume. This yields the potential savings for the transaction. Following hypothesis 1 described in Chapter 2.2, we expect a clear positive relationship between potential savings and FTA utilization.

Panel (b) of Figure 2.2 clearly supports this idea: FTA utilization is much larger among shipments with high potential tariff savings. The correlation is also highly significant in a regression model with control variables and high-dimensional fixed effects, as shown in Table 2.3.

The point estimates suggest that a twenty percent larger savings potential increases the FTA utilization rate by about 0.4 percentage points ($\log(1.2) \times 0.05 = 0.003959$). To put this into context, we can note that the probability of FTA utilization was about 29% among imports with a savings potential of about 1'000 Swiss Francs.[46]

Finding support for hypothesis 1 is also essential for the following regression analyses: as we are able to control for the benefits of FTA utilization, the estimated coefficients for various cost components can be identified as such based on the revealed preference criterion.

2.4.3.3 Firm Size, Administrative Costs, and Shipment Urgency

Figure 2.1 and Table 2.3 also shed light on hypotheses 2, 3, and 4 we set out in Chapter 2.2. While panel (c) of Figure 2.1 supports the notion specified

[46] For robustness, we also run regressions for each quantile of potential savings. Interestingly, despite the concavity seen in Panel (b) of Figure 2.2, the estimated coefficient for potential savings remains very stable across all four quantiles.

Table 2.3: Regression Models for Savings Potential

	FTA Utilization				
	(1)	(2)	(3)	(4)	(5)
log Savings Potential	0.067***	0.060***	0.066***	0.041***	0.040***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm size: small		0.013***			
(Ref.: Micro firms)		(0.002)			
Firm size: medium		0.021***			
		(0.003)			
Firm size: large		0.021***			
		(0.003)			
Authorized Importer			0.050***		
			(0.004)		
Air Transport					-0.093***
					(0.003)
HS8–Country–Year FE	√	√	√	√	√
Firm FE	-	-	-	√	√
Observations	45,478,941	30,068,527	45,478,941	38,725,622	38,725,622
R-squared	0.487	0.454	0.487	0.627	0.643

Note: The table shows the result of five separate regressions using preference utilization as the dependent variable. In the second regression, each firm size dummy ought to be compared against the effect of micro firms. Standard errors clustered at the HS8–Country–Year level are shown in parentheses. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

in hypothesis 2 that larger firms utilize FTAs more, the statistic seems to be driven more by the larger amount of trade associated with bigger firms, rather than a higher efficiency in the utilization. Once we control for potential savings, medium-size (50 to 249 employees) and large firms (over 250 employees) both have *ceteris paribus* a PUR that is only 2.1 percentage points higher than micro firms with up to 9 workers. Meanwhile, small firms with 10 to 49 employees utilize FTAs 1.3 percentage points more frequently than micro firms when controlling for the same product category and potential savings level. Overall, we therefore conclude that large (and medium) firms utilize FTAs only slightly more than micro and small firms. However, this conclusion relates only to the efficiency in using FTA preferences. In absolute terms, larger firms ship more goods per transaction and therefore profit more from FTAs.

Hypothesis 3 – stating that high administrative costs reduce preference utilization – is addressed in column (3) of Table 2.3. The estimation indicates that authorized importers (i.e., firms benefiting from facilitated customs procedures) have a 5 percentage points higher FTA utilization rate. As these authorizations are not distributed randomly but are awarded after applicant firms show sufficient experience in import procedures, regression (3) suffers from endogeneity concerns. Therefore, the positive coefficient may only be interpreted as a correlation; that is, it shows that firms with authorisation do indeed utilize FTAs more. It's unclear whether they became more efficient due to the authorization or were so already before.[47]

Finally, the regressions also support our fourth hypothesis that FTA utilization is lower for urgent shipments when proxied by air transport. Column (5) of Table 2.3 shows that the utilization rate drops by 9.3 percentage points when a given firm imports by plane the same product from the same country of origin in the same year given a certain savings potential. However, as Figure C.5 in the appendix illustrates the share of Swiss imports that arrive by air transport is small compared to shipments by train and road. The limited common support may thus dampen the external validity of this finding.

2.4.3.4 Path Dependency in FTA Utilization

Our fifth hypothesis defined in Chapter 2.2 stated that there is path dependency in FTA utilization. If the utilization of FTAs is driven by fixed costs[48], firms that have benefited from preferential tariffs for a certain transaction size in the past should have a higher FTA utilization rate than other firms in similar (or larger) follow-up transactions. We test this hypothesis and consider several subsamples of our dataset, in order to investigate the different dimensions of these fixed costs.

Table 2.4 shows in the first row the share of transactions that utilize preferential tariffs. In the full dataset containing firm information, this amounts to 58 percent. If we restrict the sample to follow-up transactions with equal

[47] If there was information available on when each firm-specific authorisation comes into force, one would be able to check if these firms possessed a higher utilization rate already prior to the authorisation.

[48] One can imagine interpreting the notion of a fixed cost related to using FTAs in a Melitz (2003)-like model with a third type of fixed costs τ, which are paid only by more productive firms. Unfortunately, in order to connect such a model with our data, we would require firm-level information on the exporting rather than importing firm.

or larger size, firms that used any or this FTA in the past utilize preferential tariffs, respectively, in 64.3 or 75.7 percent of the cases. These figures indicate that the fixed cost component seems to be FTA-specific.

In further steps, we restrict the subsample to transactions of the same product, the same product with similar unit price or product description, as well as from the same exporter. As is shown in Table 2.4, in the most restrictive subsample we observe that firms utilize FTAs in about 85.6 percent of follow-up transactions. These results, on the one hand, show that the fixed cost component may be based on the product level – even if the share increase is not as substantial as for applying a given FTA before – and, on the other hand, they provide evidence that there is a non-negligible amount of residual variation. Otherwise, once a given firm utilizes FTA preferences for a given product (with an identical description) from the same exporter, we would have expected the share of follow-up transactions using FTAs to be closer to 100 percent.

One potential explanation for this remaining gap to a full utilization is the fact that our dataset contains also a number of firms with very small, potentially irregular transactions. The final four columns in Table 2.4 therefore restrict the sample for above-median or large transactions as well as for transactions with above-median or large savings potential. One should note that the median transaction is merely 1000 CHF and median savings are 27 CHF. In all four subsamples, the general importance of FTA- and product-specific fixed cost components is confirmed. Furthermore, the share of transactions using FTAs converges to the expected share of nearly 100 percent utilization.

The fact that in each column of Table 2.4 we find a positive gradient supports hypothesis 5 about path dependency in FTA utilization. This could be the result of significant fixed costs as described above. An alternative explanation is that firms must learn how to utilize FTAs. To test for such learning effects, we exploit the firm dynamics dimension of our data and consider firms that appear in our dataset for the first time in 2019 (this is about 21,304 or 12% of the total sample). These firms, which we hereafter refer to as '2019–firms', are restricted to those that record at least five transactions (over 72%

Table 2.4: FTA Utilization in Selected Subsamples

	Share using FTA (in %)				
	Full sample	**Above median transaction**	**Large transaction**	**Above median savings**	**Large savings**
Raw data (as comparison)	58.0	71.7	83.7	70.1	90.2
Follow-up transactions with equal/larger size of a firm which used this FTA . . .					
...or any other FTA before	64.3	80.9	90.8	85.2	94.8
...before	75.7	85.4	87.6	88.2	95.4
. . . **for this product**. . .					
...before	81.1	87.4	93.3	90.8	97.5
...with similar unit price before	87.1	92.0	94.4	93.7	98.1
...with this product description	84.5	90.3	96.1	93.0	98.6
...with this exporter	84.0	90.3	95.6	93.0	98.2
...with this product desc. & this exporter	85.6	91.5	96.8	93.7	98.8

Note: The table shows the share of shipments that utilized available preferential tariffs in the top row. Subsequent rows indicate the share in subsets of the data. Data is taken from the years 2016–2019. The median transaction size is 1000 CHF and large transactions are considered to be those with at least 50000 CHF. THe median savings amount is rounded to 27 CHF and large savings are defined as at least 500 CHF.

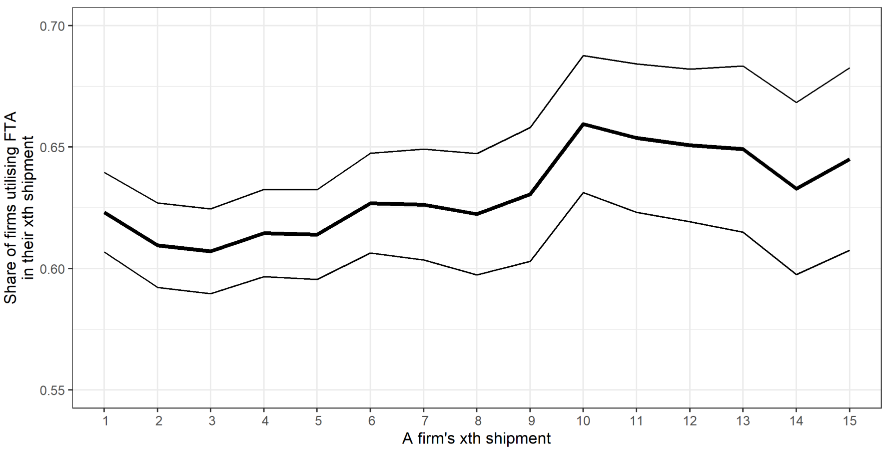
of 2019–firms have only one transaction).[49] This ensures that we can examine some form of (short-term) time dynamics. What remains are 1'887 firms for which we sort the shipments by clearance date.

Figure 2.3 plots the share of shipments that used an FTA. In addition, a 95% confidence interval is shown. The results indicate that learning effects do not appear to play a significant role. While there is some increase in the share of firms utilizing FTAs in their later shipments, this increase is both small in quantity and insignificant when considering the 95% confidence intervals.[50] We may therefore conclude that while fixed costs elements play a substantial role, these are more likely to be associated with recurring fixed costs per transaction

[49] Additionally, we remove those 2019–firms that have more than 100 transactions in 2019. For these, it is usually the case that a large company only received a new UID. This step removes about two dozen companies and 46% of trade.

[50] As a robustness check, we repeat the exercise also for firms that have started importing in 2018 or 2019, in order to obtain a larger sample. The results remain very similar. Furthermore, we find no statistically significant learning effects when redefining the learning to a particular FTA (instead of any FTA).

Figure 2.3: FTA Learning Effects



Note: The figure shows the share of shipments utilizing FTA preferences for 1'887 firms that started importing only in 2019 (i.e., firms which did not import in the years 2016–18) and had at least five (but less than 100) transactions. The x-axis is defined as the first, second, etc. shipment of a given firm. The thin lines indicate that 95% confidence interval of each point estimate.

rather than one-time fixed costs related to understanding FTAs in general.

2.4.3.5 Rules of Origin Restrictiveness

As a further determinant of utilization rates, we analyze the restrictiveness of rules of origin (RoO). Following Estevadeordal (2000) as well as Carrère and De Melo (2006), we expect FTA utilization rates to differ across the types of RoO that are specified in Switzerland's free trade agreements. Hypothesis 6 defined in Chapter 2.2 stated that preference utilization is lower the more restrictive rules of origin are specified.

Panel (c) of Figure 2.2 shows for the different types of RoO the value of Swiss imports in 2019. We distinguish those imports that utilized FTAs and those that did not.[51] The bars illustrate several aspects. First, most

[51]Note that Figure C.5 in the appendix provides the respective import values while Panel (c) of Figure 2.2 shows potential tariff savings.

tariff savings (realized and not realized) fall into the RoO categories CTH and RVC. There is very little trade in the CC and CTSH groups. Hence, a simple comparison of CC, CTH, and CTSH is of limited value. Second, the plot indicates that almost all imports under WO (wholly obtained), a very restrictive RoO, realized the potential tariff savings.

With the descriptive evidence not painting a clear picture, we refer to the regression results shown in Table 2.5. Here, we cannot have product-country-year fixed effects (FE) because this would not leave any variation for the test of whether restrictive RoO reduce FTA utilization. Therefore, the regressions include year FE, HS 4-digit FE, and firm FE.

Table 2.5: Regression Models for Rules-of-Origin

	FTA Utilization					
	(1)	(2)	(3)	(4)	(5)	(6)
log Savings Potential	0.041***	0.050***	0.046***	0.051***	0.053***	0.044***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
Air Transport	-0.128***	-0.159***	-0.108***	-0.186***	-0.140***	-0.121***
	(0.015)	(0.014)	(0.020)	(0.013)	(0.014)	(0.016)
RoO Restrictiveness	-0.086***					
	(0.018)					
RVC added to CTH		-0.400***	-0.370***	-0.443***		-0.403***
		(0.035)	(0.046)	(0.022)		(0.035)
RVC percentage					-0.007	
					(0.016)	
CC instead of CTH						-0.388***
						(0.044)
Sample	full	full	low complexity	high products	CTH & RVC	full
Year FE	√	√	√	√	√	√
HS-4 FE	√	√	√	√	√	√
Firm FE	√	√	√	√	√	√
Observations	21,753,226	15,446,151	7,232,400	8,117,361	9,366,384	19,818,971
R-squared	0.619	0.535	0.638	0.452	0.556	0.633

Note: The table shows the result of six separate regressions using preference utilization as the dependent variable. Standard errors clustered at the HS4–product level are shown in parentheses. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Column (1) of Table 2.5 uses the RoO restrictive index based on Estevadeordal (2000) and finds support for the hypothesis that more restrictive rules — defined as increasing the index by one unit — lead to an FTA utilization rate that is about 8.3 percentage points lower. Given that Panel (c) of Figure 2.2 shows that CTH and RVC are the predominant rules among Swiss imports, we replace the restrictiveness index in column (2) by a dummy variable that is zero if only CTH applies and takes the value one if CTH and RVC apply. This represents an increase of the RoO restrictiveness index from 4 to 5. With the latter arguably being more restrictive, the estimated coefficient again supports the notion that restrictive rules reduce FTA utilization. In fact, exacerbating the RoO leads *ceteris paribus* to a very large reduction of utilization by 44 percentage points.

A similar test of CC against CTH, i.e. a jump in the index from 4 to 6, shown in column (6) also supports the notion that more restrictive RoO substantially reduce the utilization of FTAs. Nonetheless, the increase from 4 to 6 appears to have a similar, if not smaller negative impact on the PUR than the increase from 4 to 5. This finding therefore does not align with the RoO ranking presented in Estevadeordal's (2000) index. It would be further interesting to analyze whether this index inconsistency extends to all values of the index. However, Switzerland's mix of RoO across its most important FTAs does not offer sufficient common support for such an analysis.

Finally, among imports that fall into the RoO category CTH and RVC, we do not find evidence that a higher RVC percentage leads to lower FTA utilization (see column 5). While the coefficient is negative, it remains statistically insignificant also in less conservative regression setups, e.g., without firm fixed effects.

2.4.3.6 Sourcing Complexity

Lastly, we explore the relation between the PUR and the complexity of a product. For this, we apply the Product Complexity Index from the Atlas of Economic Complexity, specified at the 6-digit HS code level.[52] The complexity of a product is particularly problematic for FTA utilization if there are restrictive rules-of-origin requirements, as the index is defined not only in

[52]Detailed information on this measure can be found in the "The Atlas of Economic Complexity" at the Center for International Development, Harvard University, http://www.atlas.cid.harvard.edu

terms of how many inputs are needed but also how scarce the country sample is which produces those inputs.

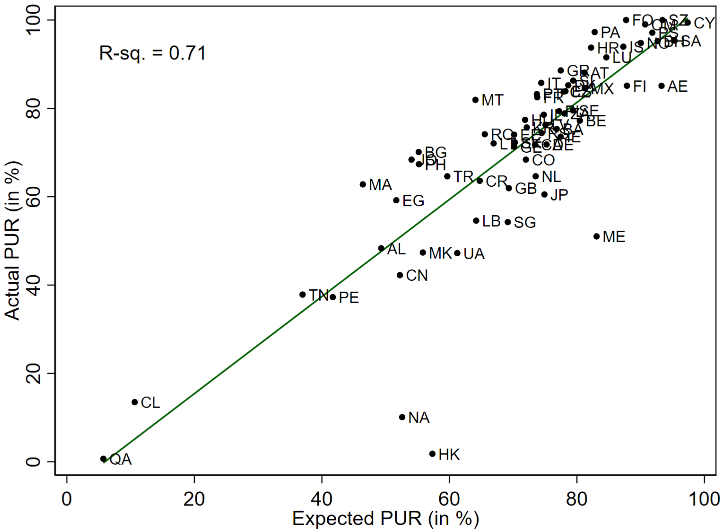
Regression results shown in columns (3) and (4) of Table 2.5 compare the effect of restrictive RoO on FTA utilization in two subsamples: products with low- and those with high-complexity. These goods are defined by whether they are situated below or above the median complexity score. As expected and described by hypothesis 7, restrictive rules of origin have a stronger negative impact on FTA utilization in the sample of highly complex goods. While this difference is statistically significant (by roughly two standard errors), restrictive RoO on both complex and non-complex goods have a significant negative impact of roughly forty percentage points on the FTA utilization.

2.5 Policy Implications

All seven hypotheses we set out in Chapter 2.2 largely found support in the data; with the exception of hypothesis 2 as large firms seem to utilize FTAs just as much as medium-size firms and only slightly more than small and very small ones. While rejecting our hypothesis 2, this finding may be of particular interest to policy makers: A large part of the discussions on the benefits and costs of free trade agreements centers on their advantages being skewed towards large companies (Rodrik, 2018), as small firms rather suffer from increased competition than benefiting from the new agreements. Thanks to the transaction-level and firm-specific dimension of our dataset, we can show for the first time that — controlling for such factors as the size of transaction, the imported product, and country of origin — firm size does not play a significant role in the utilization of FTAs.

Another key insight gained from our analysis is the fact that utilization rates seem to be shaped to a large extent by recurring fixed costs (with each transactions), whereas one-time fixed costs do not seem to play a significant role. For policy makers this finding implies that benefits of FTAs – at least in terms of tariff savings – materialize quickly after their signing and do not seem to increase over time. This is also in line with our findings that PURs of

Figure 2.4: Product Mix and Preference Utilization Rates



Note: The figure shows the correlation between the actual preference utilization rate (PUR) and the predicted PUR, which is calculated based on product mix of imports from a country as well as the the average PUR of each 8-digit HS product.

newly signed FTAs quickly rise and stabilise within the first two years.

With regard to costs, a key determinant of preference utilization is the cost associated with application and compliance with rules of origin requirements. Such costs differ substantially across products – even if to a lesser degree also within a given product. As a result, we suspect that countries which export primarily goods to Switzerland for which costs of utilization are high should have a lower aggregate preference utilization rate. Testing this hypothesis, we calculate the average PUR for each 8-digit product using Swiss import statistics from 2017. Then we combine each origin country's exports to Switzerland with the average PURs to obtain a predicted overall PUR.

In Figure 2.4 we plot for all countries the predicted against the actual preference utilization rate. The strong positive correlation indicates that the product mix has high predictive power for overall PURs. Given that Switzerland's trade agreements differ (slightly) from each other, we perform the same exercise as shown in Figure 2.4 using only countries from the European Union. These trade with Switzerland on the basis of the same FTA. The results indicate a similarly good prediction of the aggregate PUR using solely the product mix.

For policymakers these findings suggest that the utilization rate of new FTAs can be easily predicted with a limited amount of uncertainty. Furthermore, the determinants of FTA utilization —tariff savings, administrative burden, restrictiveness of rules of origin— are subject to political decisions. If the intention of negotiators is to achieve a maximum of trade liberalization through signing free trade agreements, our results provide new and valuable insights. FTAs are not disproportionately used by large firms. Thus the benefits of trade liberalization are potentially widespread. If restrictive RoO are necessary — a point that Felbermayr, Teti and Yalcin (2019) debate — facilitating administrative customs processes can lead to higher FTA utilization.

Our findings also show utilization of the trade agreements can in fact be significantly increased through less restrictive rules of origin. The rich set of agreements signed by Switzerland and the variation in the associated RoO allow us to empirically support the notion that more restrictive rules on the same type of product reduce the effectiveness of FTA preferences. Policy makers should therefore strongly reconsider whether certain rules could be softened, e.g., by removing the RVC component or downgrading CC requirements to leaner CTH provisions.

2.6 Conclusion

Since the failure of the Doha Round within the World Trade Organization, the total number of bilateral and multilateral trade agreements has surged. One downside of this type of liberalization is that in order to benefit from preferential tariff rates, firms must actively apply for preferential tariffs and also comply with rules of origin requirements. This process is costly and thus preference utilization rates (PUR) are far below 100 percent. In this paper, we document the large variation in PUR both across products and countries of origin. Analyzing determinants of utilization rates, we highlight key determinants of preferential tariff utilization. Our findings call into question the notion of a fixed preference margin threshold for FTAs to be utilized. The application for the preferences seems to be associated with a certain amount of bureaucratic costs, which firms prefer to avoid particularly for urgent shipments. Furthermore, our analysis shows limited evidence of learning effects among firms. However, the FTA- and product-specific fixed cost component of each transaction using preferences plays an important role. With respect to such fixed costs, we use Switzerland's RoO variation in its FTAs to provide well-identified estimates of the restrictive effects of certain RoO. During this analysis, we discover only limited support for the RoO ranking in the commonly used Estevadeordal (2000) restrictiveness index. Moreover, the paper documents that the mix of products two countries trade has substantial predictive power for the overall utilization rate.

Our findings thus contribute to the literature on the benefits of free trade agreements. Moreover, they are informative to policymakers intended on advancing trade liberalization (Saggi, Stoyanov and Yildiz, 2018; Saggi, Wong and Yildiz, 2019). To the extent that the product mix two countries trade remains largely stable post-FTA, policymakers can use preference utilization rates from established trade agreements to estimate the PUR of additional agreements.

Future research could explore sourcing decisions in greater detail if transaction data of multiple countries could be connected. This would allow to directly trace back which firms are impacted by rules of origin. Such data would also enable the exploration of other non-tariff components of modern trade agreements such as cumulation regimes. Another field which may be studied using similar data are the firm dynamics following the imposition of free trade agreements. Unfortunately, the dataset assembled for the present study does not allow to examine such events, as Switzerland did not sign any new significant free trade agreement since transaction-level information became available in 2016. Furthermore, most of the recent Swiss FTAs (e.g., China in 2014 or the Philippines in 2018) are with countries that switched from one preference regime (GSP) to another (FTA). Firms were thus exposed to a change rather than an introduction of rules of origin. Finally, information on lobbying efforts of firms for trade agreements connected to transaction-level trade data would enable insightful research. One possible question is whether large firms that already have high market shares lobby for FTAs and then benefit the most after their implementation. This line of research would contribute, among others, to recent work by Rodrik (2018) as well as Maggi and Ossa (2020).

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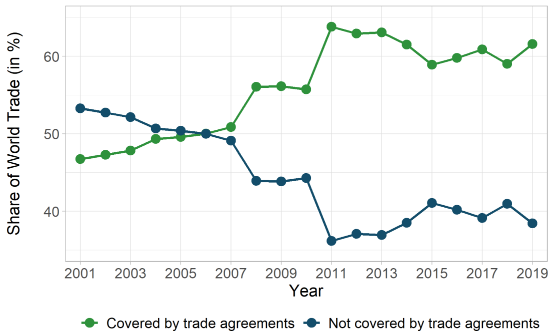
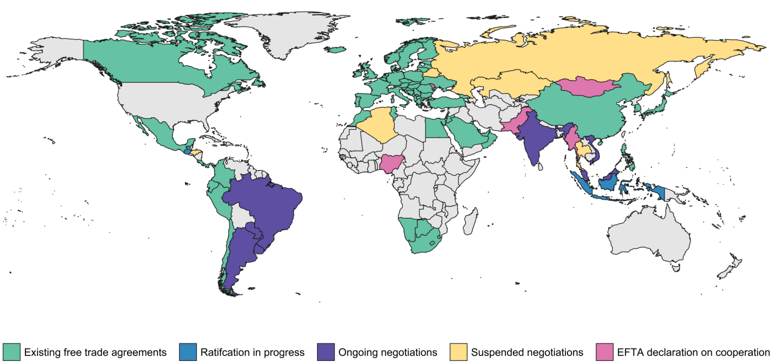
Appendix C: Additional Tables and Information

Figure C.1: Global Trade Shares within and across Trade Agreements



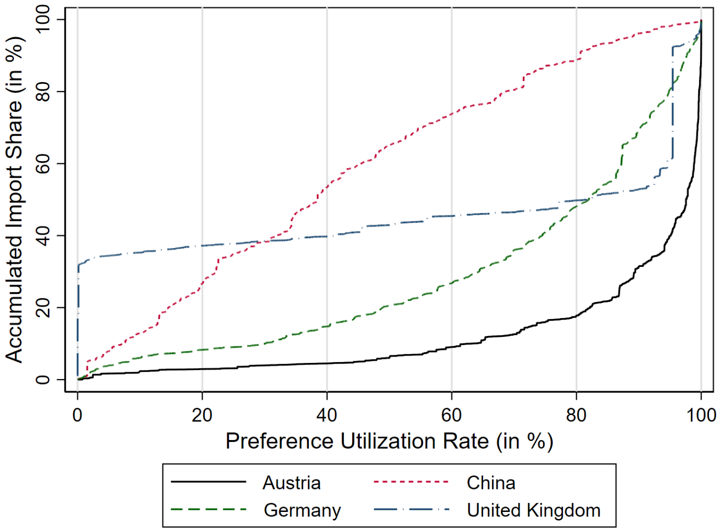
Note: The figure shows the share of global trade between countries within / without a trade agreement. Trade data originates from the UN Comtrade database. Meanwhile, the list of active trade agreements has been assembled based on the DESTA and WTO's RTA-IS datasets.

Figure C.2: Switzerland's Trading Relationships



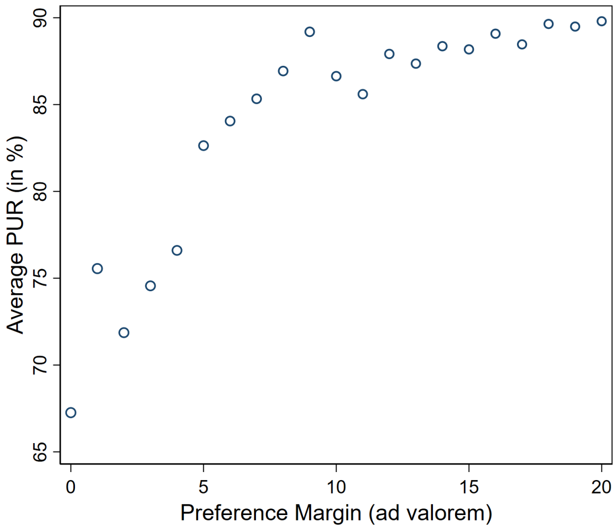
Note: The figure shows for all countries in the world the trading relationship status with Switzerland. Countries are grouped into EU (blue), bilateral or EFTA free trade agreement (yellow), as well as in FTA negotiations (orange). Countries trading at most-favored-nation WTO terms are not colored. Source: State Secretariat for Economic Affairs (Seco).

Figure C.3: Distribution of PUR for Selected Sources of Origin



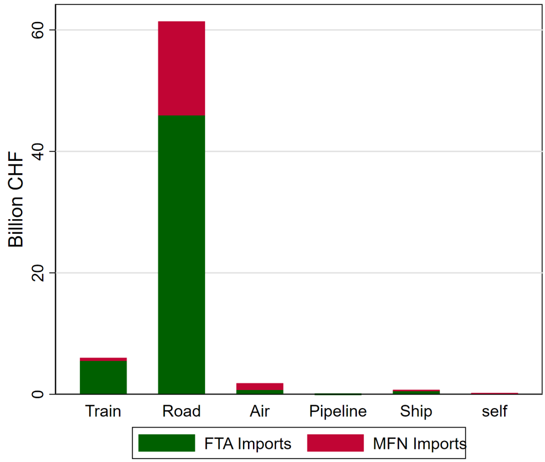
Note: The figure shows the cumulative distribution of PURs by 8-digit HS product for four Swiss trading partners.

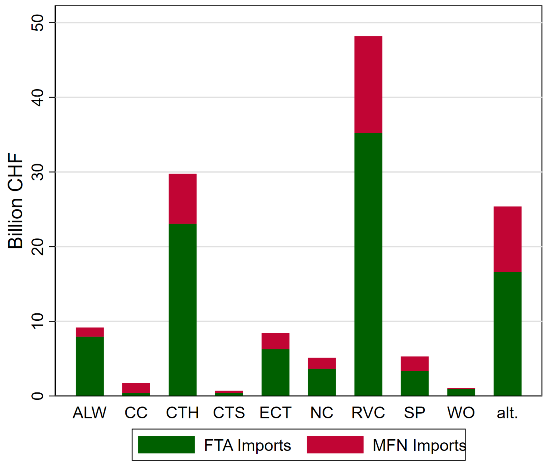
Figure C.4: Preference Margin and Preference Utilization Rates



Note: The figure plots the aggregate PUR by preference margin (= MFN tariff - FTA tariff), focusing on margins up to 20 percentage points.

Figure C.5: FTA and MFN Imports by Transportation Method and RoO





Note: The figure shows FTA and MFN imports in 2019 by transportation method as well as by rules-of-origin (RoO).

Table C.1: Switzerland's Imports From Its Top-30 Trading Partners in 2019

Trading Partner	Total Trade (bn CHF)	Relation-ship	% MFN Imports	% MFN-free Imports	% FTA Imports	% GSP Imports
Total Imports	276.1	—	15.7	51.1	23.8	0.7
Germany	57.2	EU-28	16.6	40.3	39.7	0
Italy	22.2	EU-28	10.6	40.1	45.5	0
France	18.9	EU-28	11	41.7	34	0
USA	18.9	—	24.9	57.1	0	0
United Kingdom	16.4	EU-28	14.7	57.7	20.5	0
China	15.1	FTA	32.4	41.3	23.1	0
United Arab Emirates	14.9	FTA	4.9	46	0.4	0
Austria	8.5	EU-28	7.8	45.9	43.4	0
Ireland	7.5	EU-28	1.4	94.5	2.1	0
Spain	6.4	EU-28	11.3	52.1	27.7	0
Thailand	5.6	—	9.9	83.9	0	5.5
Belgium	5.5	EU-28	21.5	52.5	21	0
Netherlands	5.5	EU-28	18.2	47.5	25	0
Japan	4.5	FTA	21.3	55.8	14.9	0
Hong Kong	3.8	FTA	33.3	46.7	0.2	0
Vietnam	2.9	—	25.1	22.2	0	4.9
South Africa	2.8	FTA	14.2	79.5	2.9	0
Czech Republic	2.8	EU-28	12.6	24.9	60.6	0
Uzbekistan	2.6	—	0	99.2	0	0.8
Singapore	2.6	FTA	6.4	83.3	0.5	0
Ghana	2.5	—	0.2	99.3	0	0.4
Poland	2.5	EU-28	15.5	29.7	53	0
Peru	2.3	FTA	5	93.8	1.1	0
India	2.2	—	40.1	27.9	0	26.3
Burkina Faso	1.7	—	0	100	0	0
Argentina	1.7	—	7.5	91.2	0	0.7
Turkey	1.7	FTA	27	22.1	46.3	0
Sweden	1.6	EU-28	12.5	43.6	40.9	0
Hungary	1.4	EU-28	20.1	22.4	56.1	0
Brazil	1.4	—	4.5	81.6	0	7.7

Note: The table shows Switzerland's top-30 trading partners by import value for the year 2019. For each partner, we indicate whether an FTA exists and the shares of imports in 2019 that were subject to regular MFN duties, zero MFN duties, or preferential treatment according to the free trade agreement or the Generalized System of Preferences. Following the departure of the United Kingdom from the Europen Union, Switzerland has signed a transition agreement with the United Kingdom to continue benefiting from preferential trade. As our analysis focuses on the years 2016–19, the United Kingdom will be counted as part of EU-28. Note that trade statistics shown here cover all imports, including gold.

Table C.2: Switzerland's Network of Free Trade Agreements

Partner	Total Imports (bn CHF)	Share of Total Imports	FTA	FTA since
Germany	57.2	20.7	EU-28	1.1.1973
Italy	22.2	8	EU-28	1.1.1973
France	18.9	6.8	EU-28	1.1.1973
United Kingdom	16.4	5.9	EU-28	1.1.1973
China	15.1	5.5	FTA	1.7.2014
United Arab Emirates	14.9	5.4	FTA	1.7.2014
Austria	8.5	3.1	EU-28	1.1.1973
Ireland	7.5	2.7	EU-28	1.1.1973
Spain	6.4	2.3	EU-28	1.1.1973
Netherlands	5.5	2	EU-28	1.1.1973
Belgium	5.5	2	EU-28	1.1.1973
Japan	4.5	1.6	FTA	1.9.2009
Hong Kong	3.8	1.4	FTA	1.10.2012
Czech Republic	2.8	1	EU-28	1.1.1973
South Africa	2.8	1	FTA	1.5.2008
Singapore	2.6	0.9	FTA	1.1.2003
Poland	2.5	0.9	EU-28	1.1.1973
Peru	2.3	0.8	FTA	1.7.2011
Turkey	1.7	0.6	FTA	1.4.1992
Sweden	1.6	0.6	EU-28	1.1.1973

Note: The table shows Switzerland's top-20 FTA trading partners, sorted by total import volume. Shares of total imports are expressed in % and trade statistics are from the year 2019.

Table C.3: EU's Imports by Tariff Regime

Tariff Regime	EU-28	Germany	France	Italy	UK	Austria	Spain
				Import Value (billion Euro)			
MFN	8.00	4.70	0.47	0.55	0.28	0.19	0.62
MFN duty-free	51.58	16.93	6.06	5.23	9.03	2.50	1.50
FTA duty-free	43.30	18.91	9.80	3.82	1.93	3.05	1.41
Other	2.21	2.12	0.02	0.01	0.01	0.01	0.00
Total	105.09	42.66	16.34	9.62	11.25	5.75	3.54
PUR (excl Other)	84.40%	80.10%	95.40%	87.30%	87.50%	94.20%	69.50%

Note: The table groups imports in the European Union (as well as selected EU member countries) by tariff treatment.

Table C.4: Customs Treatments applied by Swiss Customs

Code	FCA Description	Group	PUR Group	Imports Value	Duties paid
110	Under tariff	MFN Imports		43’273.4	1’047.3
140	Customs relief	Special Imports	B	10’573.3	54.6
180	Returned goods	Special Imports	B	0.0	0.0
185	Goods of Swiss origin	Special Imports	B	970.8	1.7
210	EFTA	FTA Imports	A	0.2	0.0
212	EFTA, associated	FTA Imports	A	45.8	2.3
215	Bilateral agreements	FTA Imports	A	16.6	1.2
220	EU	FTA Imports	A	1’312.8	114.6
230	Developing countries	Special Imports	B	272.5	20.7
240	Customs relief	Special Imports	B	14.5	3.2
265	Processing traffic under contr.	Special Imports	B	5.7	0.6
270	Commercial processing traffic	Special Imports	B	2.3	0.3
305	Under tariff	MFN free Imports	B	141’071.3	0.0
310	EFTA	FTA Imports	A	153.9	0.0
311	EFTA, associated	FTA Imports	A	2’386.4	0.0
312	Bilateral agreements	FTA Imports	A	4’132.2	0.0
320	EU	FTA Imports	A	57’423.1	0.0
330	Developing countries	Free Imports	B	1’550.5	0.0
340	War material (art. 8 m CA)	Free Imports	B	245.9	0.0
350	UNESCO (art. 8 g, h CA)	Free Imports	B	335.1	0.0
355	Customs relief	Free Imports	B	3’266.5	0.0
370	Processing traffic under contr.	Free Imports	B	733.2	0.0
375	Commercial processing traffic	Free Imports	B	196.8	0.0
380	Returned goods	Free Imports	B	6’416.6	0.0
385	Goods of Swiss origin	Free Imports	B	1’451.3	0.0
390	Change of ownership	Free Imports	B	207.5	0.0

Note: The table shows all customs treatment categories applied by the Swiss Federal Customs Administration (FCA). The Preference Utilization Rate (PUR) is defined as: PUR = A / (Total – B). Import values and duties paid are from 2019 and expressed in million CHF.

Table C.5: Definitions of Rules of Origin according to the WTO

ALW	The originating status is allowed to be conferred from non-originating inputs of specific HS codes.
CC	The originating status is conferred to a good that is classified in a different HS chapter than the non-originating inputs.
CTH	The originating status is conferred to a good that is classified in a different HS heading than the non-originating inputs
CTSH	The originating status is conferred to a good that is classified in a different HS subheading than the non-originating inputs.
ECT	The originating status cannot be conferred to a good if the non-originating inputs are from HS codes listed under exception.
NC	The non-originating inputs are not required to be classified in a different HS code than the final good to confer originating status.
RVC	A good obtains originating status if a defined regional value content percentage has been reached.
SP	A good originates in the country where a defined technical requirement, i.e. a specified processing or working, has taken place.
WO	Good is entirely (i.e. wholly) obtained or manufactured in one country without using any non-originating materials.
alternative	There are multiple RoO to choose from.

Note: The table define the different RoO categories used to standardize the vast network of Switzerlands' FTAs. The categories are largely based on the standardization of the International Trade Centre's Rules of Origin Facilitator portal.

Table C.6: Statistics of standardized Rules of Origin by FTA

FTA	Year	Min.	Median	Mean	Max.	NA
EFTA	1960	1	5	4.254	5	2'794
EU	1973	1	5	4.254	5	2'794
Turkey	1992	1	5	4.287	5	2'752
South Korea	2006	1	5	4.650	7	923
Japan	2009	2	5	5.014	6	6
China	2014	2	5	4.758	6	1'683
GCC	2014	4	5	4.966	6	743

Note: The table shows the key statistics for the rules of origin which have been standardized for Switzerland's seven most important FTAs covering 97.5% of imports. The table refers to the 5'387 HS codes based on the 2017 vintage.
Over half of the rules related to the EFTA, EU, and Turkish FTAs and a third of rules from the Chinese FTA could not be standardized – making a comparison of aggregate RoO restrictiveness across FTAs difficult. When restricting the sample to 1'775 HS codes, for which RoO of all seven FTAs could be standardized, the average RoO score is 4.1 for the EFTA, EU, Turkish and Chinese FTAs. The Korean FTA has a mean score of 4.5, while the Japanese and GCC FTAs on average have an index of 4.6 and 5.0, respectively.

Chapter 3

Disappearing Products and Jumbo Clusters: Addressing the HS Vintage Conversion Problem

Joint with David Torun

3.1 Introduction

Empirical international trade research has long expanded from the aggregate analysis of trade flows to more granular data at the sector, product, firm, and even transaction level. Given that international trade figures by default include flows between two different jurisdictions, these granular data require an internationally harmonized classification of the shipped products. Since 1988, the World Customs Organization (WCO) has developed the Harmonized Commodity Description and Coding System (HS) in order to globally standardize the classification of products into over 5,000 6-digit HS codes.[53] Before, goods were largely classified under the so-called SITC system.

Although the harmonization in 1988 created a standard allowing for cross-country comparisons of trade figures going beyond trade flows to, e.g., tariff lines, it was unable to avoid necessary product code adjustments over time. Hence, on average every five years the WCO updates its list of HS product codes and publishes a new vintage.[54] The amendments have been necessary, inter alia, due to technological progress (creating new products and making some void), shifting trade patterns (increasing or declining relevance of specific products), adaptation to reflect trade practice (unclear product classifications or bundling of product parts by firms), as well as amendments related to social and environmental fields (e.g., to improve the tracking of endangered plants and animals).

While these adjustments are meant to facilitate trade, they often result in products being split up ("1:n"), merged ("m:1"), or generally reassigned ("m:n"). This in turn complicates a comparison of trade flows both across time and across countries. The former comparison is difficult because it is unclear how to convert trade flows from one HS classification to another whenever a link is 1:n or m:n, while the fact that some jurisdictions adopt the new HS code version ("vintage") with a delay hinders cross-sectional analyses.[55] Below we revisit commonly used conversion methods and develop an alternative to tackle several issues that arise when applying these existing techniques.

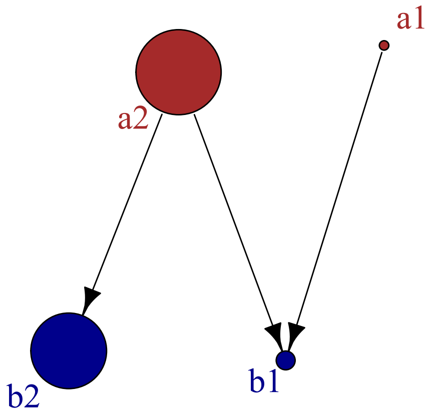
Given that some HS code adjustments are interlinked, they may not be viewed as individual changes but rather as a connected network or *group* of adjusted HS codes. Put differently, whenever two codes of an "initial" vintage are assigned to the same code of a "target" vintage, they are (indirectly) linked, and will thus belong to the same group. Figure 3.1 visualizes an exemplary

[53]Each country may determine and adjust its HS codes at a more granular level. For instance, the United States classifies its products at the 10-digit level in its so-called HTS classification. However, the HS codes remain globally harmonized at the 6-digit level.

[54]More precisely, revised HS vintages were introduced in 1992, 1996, 2002, 2007, 2012, and 2017. We will refer to a vintage introduced in a specific year as, e.g., HS 2007.

[55]For instance, according to article 4(2) of the HS Convention of the WCO, developing countries – representing three-quarters of WCO's 183 members – may adopt the newest vintage with a delay of up to five years.

Figure 3.1: Network Visualization of an Exemplary HS Code Group



Note: This figure illustrates an exemplary HS code group in the form of a network diagram. In this example, code $a1$ was reassigned to code $b1$ (therefore receiving a conversion weight equal to one), while code $a2$ was reassigned to codes $b1$ and $b2$, which means that we do not know a priori how much trade should be allocated to which new code. Larger circles depict larger product trade shares. We refer to such networks of linked products as product groups.

group of HS codes in the form of a network chart, where bigger circles depict larger trade shares within this group. In this example, the "initial" codes $a1$ and $a2$ are reassigned to "target" codes $b1$ and $b2$. Therefore, we want to know how we can convert trade flows reported in the a-vintage into the b-vintage. Since product $a1$ has only a link to product $b1$, all trade flows reported in product category $a1$ will be added to product $b1$ when converting to this new HS vintage. By contrast, because code $a2$ has a link with both $b1$ and $b2$, it is a priori unclear which part of trade flows classified in the initial vintage should be allocated to $b1$ or to $b2$. We will refer to the share of $a2$ flows being allocated to $b1$ as the *conversion weight* from $a2$ to $b1$, given that overall trade in $b1$ will be a weighted sum of trade in the linked initial products (here, $a1$ and $a2$). The conversion weight from $a1$ to $b1$ is equal to 1, and, accordingly, equal to 0 for $a1$ to $b2$, while the conversion weights from $a2$ to $b1$ and $b2$ are

Table 3.1: Distribution of Product Links between HS 2017 and Other Vintages

Relationship with HS 2017	HS 2012	HS 2002	HS 1992	Conversion Weight
1:1	4744	3966	3332	1
m:1	578	948	1332	1
1:n	36	262	360	?
m:n	60	316	538	?

Note: This table depicts how many product links between HS 2017 codes and other vintages are of a specific type. As illustrated by the question marks, whenever a link is "1:n" (i.e., the code has to be split into multiple codes of the other reporting standard) or "m:n" (i.e., m HS 2017 codes are interlinked with n codes of the other HS vintage), the correct conversion is unknown.
Data source: UN Comtrade Database.

unknown.

While in each amendment most HS codes remain unchanged, the non-1:1 adjustments accumulate when the conversion is performed over multiple vintages. As indicated in Table 3.1, the majority of HS codes remain the same and have a 1:1 assignment when converting the HS 2017 codes into HS 2012. However, the further one extends the conversion back to earlier vintages, the larger the share of conversions with undefined weights becomes. When trying to convert HS 2017 codes into HS 1992 codes, the share of products with unknown conversion weights increases to about 16%.[56] More generally, out of 6,539 HS codes applied between 1992 and 2017, 48% have faced a non-1:1 adjustment at least in one of the classification updates. In terms of 2018 trade, these codes accounted for 43.7% of total trade.

Widely-used methods address the HS code conversion issue by either forcing a one-to-one mapping between product codes across vintages (UNSD, 2017), and thus ignoring remaining product links, or by pooling adjusted codes into synthetic codes (Pierce and Schott, 2012). The former method leads to intertemporal inconsistencies in HS vintage amendment years. For instance,

[56] Note that one may instead want to convert HS 1992 to HS 2017 codes. In that case, those HS codes summarized in Table 3.1 as "m:1" will have unknown conversion weights.

when converting HS 2007 codes into the HS 2002 vintage, the number of non-traded products increases from 0 in the year 2006 to 299 in the year 2007, which represents 42% of codes where the assignment is not pre-determined. Meanwhile, the Pierce and Schott (2012) method increases the share of the largest product code in overall trade of the year 2018 from about 7% to 26%, when converting the HS 2017 codes into HS 1992 codes. Not only do we then receive, by construction, more aggregated data, the distribution also appears to become more skewed due to the fact that unchanged codes are never lumped into these synthetic clusters. Researchers may circumvent these issues either by using only data at coarser levels, as in gravity regressions at the country level (cf. Head and Mayer (2014) for an overview), or by focusing solely on products with a 1:1 mapping (e.g., Boehm, Levchenko and Pandalai-Nayar, 2020). While the former approach eliminates potentially interesting variation, the latter one substantially reduces the sample size for longer time horizons.[57]

In light of the available methods, this paper aims to contribute to the existing literature by proposing an alternative conversion technique between different vintages of HS product codes. The key feature of trade data we exploit is their persistence over time. Specifically, we provide an algorithm that through the choice of appropriate conversion weights minimizes the squared deviations between pre- and post-classification change country pair data. Our minimization imposes a set of constraints which respects the product links. The algorithm solves the aforementioned issues of existing methods, and the calculated weights are robust to altering the set of years and country pair observations.

In a simple descriptive application, we illustrate how our method may facilitate answering simple questions like: how many different varieties did the United States import every year over the past three decades? We show that using data converted to HS 1992 by Comtrade suggests that the number of prod-

[57]In the paper we exclusively present results based on converting backwards (i.e., from newer vintages to older ones), because Comtrade provides only backward conversions. However, our algorithm can also be applied to forward conversion. For illustrative purposes, we focus on the example of converting HS 2007 to HS 2002, since that change lies in the middle of our sample and happened before the Great Trade Collapse. Results for other conversions look very similar.

ucts with positive U.S. imports has declined by about 10% from 1992 to 2018. By contrast, data converted into HS 1992 using our weights shows that this number has been fairly stable over that time span. Pierce and Schott's (2012) method has a level effect in that there are a quarter less product categories available in the sample, but the trend looks very similar to that suggested by our conversion. Such differences matter, e.g., when we want to investigate the evolution of product varieties à la Broda and Weinstein (2006), where a variety is defined as an exporter-product combination. For instance, when looking at the impact of the Great Trade Collapse, data converted using our technique or the Pierce and Schott (2012) method suggest that the number of varieties imported by the U.S. had recovered its pre-crisis level by 2011. The Comtrade converted data, however, hints at a more sluggish regeneration, as there the number of imported varieties reaches its pre-crisis level only by 2015.

The following section summarizes existing methods. Section 3.3 then describes conceptually the proposed method. Section 3.4 investigates the impact of our method on trade data, while Section 3.5 contextualizes it in the context of trade supply and demand analyses. Section 3.6 explores the heterogeneity and robustness of the conversion weights. Section 3.7 concludes.

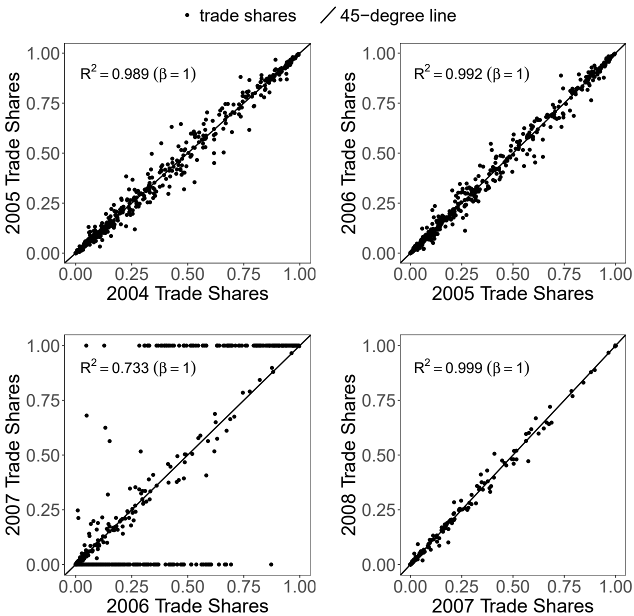
3.2 Related Literature

Thus far there have been two main approaches to address the HS code conversion issue: the method applied by the UN Statistics Department which generates the Comtrade trade database ("Comtrade method"), and an algorithm developed by Pierce and Schott (2012).

According to the Comtrade method, "the data conversions [...] assign one single code (subheading) of an earlier HS edition to each HS 2017 subheading" (UNSD, 2017, p.1). This method thus always assigns a weight of 1 to a single target HS code, and ignores the remaining target HS codes. In terms of the conversion problem depicted in Figure 3.1, this would, e.g., imply that the link between $a2$ and $b1$ is ignored with all $a2$ trade now converted to $b2$, thus imposing conversion weights of 0 and 1, respectively.

In general, the Comtrade approach therefore tends to assign (too) much weight to one single code, and thus results in some codes not receiving any trade at all. Furthermore, using this method may lead to significant jumps at the extensive margin in HS code amendment years (Cebeci, 2012, p.5).

Figure 3.2: Product Trade Shares within HS Product Groups over Time (Comtrade Method)



Note: This figure plots for each product its trade share within its specific group across several years. We include only groups which contain at least one 1:n or m:n assignment from HS 2007 to HS 2002. The figure uses Comtrade data provided in HS 2002, i.e., 2007 and 2008 trade data have been converted into HS 2002, while previous years were originally reported in HS 2002. The data are restricted to 70 importers reporting in the latest available HS code version in a given year. Product groups are explained in the main text. The provided R-squared assumes a fit along the 45-degree line.
Data source: UN Comtrade Database.

In terms of data continuity, the Comtrade assignment also leads to jumps at the intensive margin of trade. As depicted in Figure 3.2, when we look at trade data provided in HS 2002, the relative trade shares within conversion-dependent groups jump in a conversion year (here, in 2007), as the Comtrade method simplifies product links. By contrast, these product hierarchies (i.e., the product trade shares within groups) are highly persistent over time, as Figure 3.2 shows. Accordingly, there is no a priori reason to expect (large) jumps in product shares within their groups which are not due to a misspecified conversion. The share of zeros jumps from 0% in 2006 to 42.4% in 2007. Note that this figure includes only groups (or, networks) with at least one 1:n or m:n assignment from HS 2007 to HS 2002.

Alternatively to this method, Pierce and Schott (2012, p.58) developed an algorithm which avoids the data continuity issues by pooling the adjusted HS codes together and "assigning a common synthetic code to all HS codes in a growing family tree." A family tree is an HS product group in our notation. While this method has been widely used (e.g., Felbermayr, Teti and Yalcin (2019), Wagner and Zahler (2015), Piveteau and Smagghue (2019), Fort, Pierce and Schott (2018)), pooling linked codes together becomes an issue when analyzing trade data reported in multiple HS code vintages.

Table 3.2: Largest Trade Shares by Actual/Synthetic HS Code in 2018 Trade Data

Category	Covered vintages	Largest code	2nd largest	3rd largest	4th largest	5th largest
Actual	HS 2017	6.66%	2.17%	1.92%	1.61%	1.59%
Synthetic (P&S method)	HS 2012–HS 2017	13.43%	6.66%	4.17%	2.17%	1.92%
Synthetic (P&S method)	HS 2002–HS 2017	16.00%	6.66%	4.17%	3.43%	2.35%
Synthetic (P&S method)	HS 1992–HS 2017	25.74%	6.66%	4.17%	3.43%	1.92%
Comtrade converted	HS 2012	6.66%	2.17%	1.92%	1.61%	1.61%
Comtrade converted	HS 2002	6.66%	4.17%	2.46%	2.25%	1.92%
Comtrade converted	HS 1992	6.66%	4.19%	3.44%	2.46%	1.91%

Note: This table depicts trade shares in overall trade of the largest products in the year 2018. The first row displays the trade share of the largest HS 2017 products. The following three rows depict the trade shares of the largest products after applying Pierce and Schott's (2012) method to standardize the vintages from 2017 to those of 2012, 2002, and 1992, respectively. The bottom three rows summarize the shares of the top five products after the Comtrade conversion of 2018 trade data into HS 2012, HS 2002, and HS 1992.
Data source: UN Comtrade Database.

In fact, the longer the time series, the more HS codes are piled together. For instance, when converting 2018 data back to HS 1992 using their method, one synthetic cluster of HS codes ends up covering over a quarter of overall trade (cf. Table 3.2).[58] Apart from creating synthetic codes not applied in

[58]This largest synthetic group covers 607 different HS 2017 codes and includes sectors

practice, pooling that much trade across sectors may have significant consequences for what kind of variation is (not) picked up by product fixed effects. Moreover, Table 3.2 clearly illustrates that this method tends to artificially skew the distribution, especially when we consider that 1:1 links are never piled together.[59]

At the same time, one should point out that the Pierce and Schott (2012) method was initially developed to address monthly adjustments of individual 10-digit HTS codes (the U.S. version of the detailed HS codes), and was extended to the HS code conversion. For the initial purpose, their method seems adequate provided a small number of irregular code amendments. However, as indicated in the paper (p. 56), most of the HTS code adjustments are clustered around the general HS code vintage updates.

Similar methods to that of Pierce and Schott (2012) have been proposed by Cebeci (2012) and Diodato (2018). The former also pools product codes together but applies the method directly to HS codes and accounts for the fact that some developing countries may implement the HS code adjustment at a later stage.

On the other hand, Diodato (2018) analyzes product linkages across vintage versions using a network-adjusted structure of codes. Following Pierce and Schott's (2012) terminology, each network can be interpreted as a "family of related products." Displaying the linkages as networks allows for a better visualization of the clusters and isolating individual linkages responsible for creating large clusters ("bridging nodes"). His method removes such nodes – using a community discovery algorithm, or manually inspecting the networks and removing such nodes – to deconstruct the larger networks.

Although Diodato (2018)'s method helps in alleviating the issue faced by bundling many products (cf. Table 3.2), it still pools numerous codes into syn-

ranging from chemicals (ca. 27% of the codes) through paper products (10%) to machinery and electrical equipment (40%). The second largest HS code group which accounts for almost exactly a fifteenth of 2018 trade is crude oil and the corresponding HS code 270900 remains unchanged from 1992 to 2017, as can be seen by the unchanged share of 6.66% in each row of Table 3.2.

[59] The bottom three rows in Table 3.2 also illustrate that the Comtrade conversion method leads to bigger product groups but to a much lesser extent.

thetic groups. Furthermore, by removing bridging nodes, the method ignores by construction certain dependencies between product codes across vintages which may be of importance for particular products. Also, the amount of removed bridging nodes may be selected on an individual basis, thus not allowing for a systematic construction of product code correspondences.

Below, we develop a simple conversion algorithm to alleviate the issues encountered when applying the above-mentioned approaches.

3.3 Methodology

This section briefly introduces the data we use, before explaining our conversion algorithm.

Data. The data used in this paper have been extracted from UN Comtrade and include all import data reported by UN members between 1988 and 2018. This data source is standard to the international trade literature. The import figures are corrected for re-import numbers, as the raw import data includes re-imports. The analysis focuses on those countries that in each year applied the latest available HS vintage, and are thus considered "compliers."[60] An exemplary phasing in of the HS 2007 vintage is shown in Figure E.1. The bilateral country pairs include complying importers and all of the partners with which they had at least one non-zero trade flow in a given year.

Furthermore, the analysis includes import data that have been converted by Comtrade to a given HS vintage (e.g., the 2007 and 2008 numbers converted by Comtrade into HS 2002 used in Figure 3.2).

Persistence. The key feature of trade data we want to exploit is the persistence of trade flows over time. The data show that, e.g., if a specific product was relatively important for a country pair in one year, it is very likely to be

[60] For instance, Vietnam reported its 2017 trade figures using the HS 2012 version and would thus not be included when estimating conversion weights between HS 2012 and HS 2017. However, it did change to the latest available version in 2012, so it would be included when converting HS 2012 to HS 2007.

Table 3.3: Persistence of Bilateral Product-Level Trade Flows

Year	2005	2006	2007	2008	2009
All HS codes	0.874	0.867	*skipped*	0.854	0.862
	(0.009)	(0.008)	*due to*	(0.009)	(0.009)
Adjusted HS codes	0.876	0.889	*vintage*	0.880	0.836
	(0.020)	(0.018)	*change*	(0.024)	(0.045)

Note: This table depicts first-order autoregressive coefficients for bilateral trade flows at the product level for the years 2005, 2006, 2008 and 2009 (2007 was left out due to the HS vintage change). The bilateral product-level flows are scaled by overall trade in the product's group in a given year. The data include 70 countries which reported in the latest available HS code version in the years 2005–2009. The first row depicts the coefficients for all trade flows, whereas the second is restricted to HS codes facing a change in 2007 (i.e., which have a non-1:1 assignment between HS 2002 and HS 2007). We regress the bilateral product-level flows on their respective first lags without a constant. Robust standard errors are reported in parentheses.
Data source: UN Comtrade Database.

important for that country pair in surrounding years. Similarly, if a country is a large importer of a specific product in one year, it is likely to also have relatively high imports of that product in other years. Accordingly, when we look at product hierarchies within groups over time (for a given HS vintage), they appear to be fairly stable (cf. Figure 3.2). Product-level trade flows at the bilateral (i.e., country pair) level also reveal a relatively high persistence over time. Table 3.3 shows this by regressing the share of bilateral product-level flows in their groups on their first lags (cf. also Figure E.2). Therefore, we use information on bilateral flows reported in one HS vintage to predict how trade flows should be allocated within a target vintage in cases where the allocation is not a priori clear (i.e., neither 1:1 nor m:1). The reasoning behind our method is that we do not expect (substantial) changes in product hierarchies within groups due to a change in classification standards. Moreover, using disaggregated rather than aggregate product-level trade flows is appealing for two reasons. Not only does this add information on how trade flows are distributed across country pairs, it also avoids encountering regressions where we have less observations than unknowns.

Algorithm. The algorithm can be split into three components. As a first step, we identify groups of HS codes that are linked together, and keep those groups which contain ex ante unspecified conversion weights.[61] Note that one group would be pooled to one synthetic cluster when applying Pierce and Schott's (2012) method.

Second, in order to maximize the number of observations, we use trade flows at the country-pair level. Specifically, we prepare the trade data in form of an $(I \times J) \times K$-matrix separately for each group and year, where an entry is equal to $X_{ij,k}$, i.e., the exports from country $i \in I$ to country $j \in J$ of product $k \in K$ in a specific group and year. For notational simplicity we suppress time and group subscripts. We restrict the sample to importers which actually switched reporting standards in the years we focus on. Moreover, in order to consider product hierarchies within groups, we scale each pair's product-level imports by the total imports within a group. Note that this also allows us to control for group-specific trends. This procedure yields our scaled flows, $x_{ij,k}$, defined as

$$x_{ij,k} \equiv \frac{X_{ij,k}}{\sum_{\hat{i},\hat{j}} \sum_{\hat{k}} X_{\hat{i}\hat{j},\hat{k}}},$$

which will be the inputs in our regressions. Recall that the scaling is computed separately for each group and year. It is worth noting that this could be further adjusted to calculate, e.g., region- or country-group-specific conversion weights, as addressed in Section 3.6.

The third component of the algorithm tries to fit the trade flows which are reported in the "target" reporting standard by using flows reported in the "initial" reporting standard and a constrained least-squares procedure. Note that these flows will, by construction, not belong to the same year. Hence, we (implicitly) assume that product-level bilateral flows relative to overall group flows are fully persistent over time. That is why most figures report a fit along the 45-degree line. In Section 3.6 we relax this assumption.

[61] Accordingly, groups that are left out will contain only conversion weights which are a priori known to be equal to zero or one.

As an example, consider "initial" HS codes $k \in K$ used in year t_0, and "target" HS codes $s \in S$ used in year t_1.[62] We need three types of constraints in our optimization. First, the conversion weights for an initial product k need to sum up to one across target products s, otherwise overall trade might artificially increase or decrease across vintages. Second, the weights should be non-negative, else we would subtract product flows, which might improve the fit but would make no intuitive sense.[63] Third, some weights are known to be equal to zero or one from the correlation tables provided by the WCO.[64] Our constrained minimization problem is outlined in Equation (3.1).

$$
\begin{aligned}
\min_{\{\beta_{k,s}\}} \quad & \textstyle\sum_s \sum_{i,j} \left(x_{ij,s}^{t_1} - \sum_k x_{ij,k}^{t_0} \beta_{k,s} \right)^2 \\
\text{s.t.} \quad & \beta_{k,s} \geq 0 \ \forall k, s \\
& \textstyle\sum_s \beta_{k,s} = 1 \ \forall k,
\end{aligned}
\tag{3.1}
$$

where $\beta_{k,s}$ is the conversion weight from initial product k to target product s. Note that various $\beta_{k,s}$ are a priori known to be equal to zero or one. This problem can then be estimated separately for each group to reduce the size of the coefficient matrix, given that conversion weights across groups are, by construction, always equal to zero. This is the specification we use for our main results, and variations can be found in Section 3.6.

In order to apply our conversion weights to trade data, one has to multiply the trade flow reported in the initial HS vintage by the respective weight, and then sum up across initial codes.[65] Or, put differently, one computes the fitted value, $\hat{x}_{ij,s}^{t_0} = \sum_k x_{ij,k}^{t_0} \hat{\beta}_{k,s}$. Furthermore, in order to convert one vintage to another which is not adjacent, we multiply the weights across conversions. For instance, if we want to convert HS 2017 codes $k \in K$ to an HS 2007 code l, which are linked through HS 2012 codes $s \in S$, we compute $\hat{x}_{ij,l}^{t_0} =$

[62] Note that we can also estimate conversion weights going, e.g., from 2017 to 2016 data, in which case $t_0 > t_1$.

[63] These two constraints together restrict conversion weights to be smaller than or equal to one.

[64] The correlation tables were downloaded from the UN Comtrade webpage.

[65] Also, we recommend rounding the weights to, e.g., the sixth digit after the comma, in order to set weights which are numerically indistinguishable from zero to 0.

$\sum_s \sum_k x_{ij,k}^{t_0} \hat{\beta}_{k,s} \hat{\beta}_{s,l}$. The weights $\hat{\beta}_{k,l}$ ($= \sum_s \hat{\beta}_{k,s} \hat{\beta}_{s,l}$) have the same properties as those constructed based on adjacent vintages $\hat{\beta}_{k,s}$ and $\hat{\beta}_{s,l}$.

3.4 Results

In Section 3.1, or in Figure 3.2, we illustrate how product shares within groups jump in 2007 when applying Comtrade's conversion method, despite product hierarchies being strikingly stable over time. When applying our estimated conversion weights, we receive a substantially smoother transition from 2006 to 2007, as depicted by Figure 3.3. The share of zeros in the graph drops heavily from 42.4% to only 5.6%. We thus manage to reduce the share of HS 2002 products (in total 5,224) with no trade from 6 to below 1%. Moreover, although we tend to slightly decrease the variation between the years 2007 and 2008, it is important to note that it was already very low in the original vintage. Results for other vintages look very similar. Hence, our method alleviates the aforementioned issues introduced by the Comtrade method. Pierce and Schott's (2012) method would reduce the number of product categories in the graph by roughly three-quarters from 706 to 183, given that we identify 183 groups in our conversion.

We can verify how these estimated conversion weights perform with other year constellations. Specifically, in Figure 3.4, we convert 2011 data into HS 2002 using the conversion weights from above, and compare the resulting product hierarchies within groups with those in the year 2002. This is the widest year range we can take when comparing HS 2007 with HS 2002. We also re-include the comparison of 2006 shares and converted 2007 shares (left panel). The product shares closely follow the 45-degree line in both panels, with (intuitively) somewhat more variation in the wider year range. In order to compare the product shares in different years but with unconverted data, we can confront the two "initial" as well as the two "target" years. Figure E.3 in Appendix E illustrates that the similarity should be expected (and desirable) given the persistence of product hierarchies measured in the reported HS vintages. Overall, this suggests that, if our method is deemed appropriate to convert 2007 data into HS 2002, it also allows for a conversion of later years into that HS vintage.

Importantly, we obtain similar outcomes when comparing absolute (i.e., not scaled by group totals) values. In Figure E.4 we re-produce Figure 3.3 using the log of product-level trade flows. There are only a few products for which we get somewhat large deviations. However, these products tend to be relatively small. This in turn implies that exploiting product group hierarchies in our estimation routine seems to yield conversion weights which are suitable for the analysis of absolute trade flows.

In Section 3.3 we explain how to standardize HS vintages which are non-adjacent by multiplying the conversion weights for the intermediate vintages. In Figure E.5 we plot the log of product-level trade flows for products which have at least one non-1:1 assignment over our sample period. The figure shows that this procedure does not create significant inconsistencies when converting all the way back to HS 1992, even in recent years, although we do eliminate a little less than 1% of the HS 1992 products (5,020 in total) over the years. In comparison, the Comtrade conversion drops almost 10% of the HS 1992 products by 2017. Importantly, note that our technique does not artificially fix the importance of a product over longer time spans. The multiplication of the weights, which are recalculated whenever there is an amendment, implies that long-run trends should be captured by our method, as long as the HS vintage adjustments reflect such trends.

Additionally, as illustrated in Table 3.4, our method seems not to skew the distribution, as opposed to Pierce and Schott's (2012) method (cf. Table 3.2). Accordingly, at least in terms of relative size, the converted product categories remain interpretable as such. The trade shares obtained using our conversion method perform slightly better than the Comtrade method also in this dimension (cf. bottom three rows in Table 3.2).

Table 3.4: Largest Trade Shares by Actual/Converted HS Code in 2018 Trade Data (Our Conversion Weights)

Category	Covered Vintages	Largest Code	2nd largest	3rd largest	4th largest	5th largest
Actual	HS 2017	6.66%	2.17%	1.92%	1.61%	1.59%
Converted	HS 2012	6.66%	2.17%	1.92%	1.73%	1.61%
Converted	HS 2002	6.66%	2.58%	2.25%	1.92%	1.73%
Converted	HS 1992	6.66%	3.43%	2.09%	1.92%	1.73%

Note: This table depicts trade shares in overall trade of the largest products in the year 2018. The first row displays the trade share of the five largest HS 2017 products. The remaining rows depict the trade shares of the five largest products after applying the algorithm described in this paper and converting 2018 data from HS 2017 to HS 2012, HS 2002, and HS 1992, respectively.
Data source: UN Comtrade Database.

3.5 Application

Having shown in the previous section that the proposed method addresses the trade data issues caused by prevalent methods, this section analyses the impact our method has on several trade applications. We provide illustrative examples related to both the demand and supply side.

Import demand trends. One key dimension of assessing welfare gains from trade continues to be the gains from product variety in trade. As shown in Broda and Weinstein (2006), product varieties have significantly increased over the past decades, substantially contributing to the increased role of trade in the global economy (Hsieh et al., 2020). In order to track product varieties correctly, one ought to have a continued standardised classification of products throughout the sample, requiring thus to correct for the HS code adjustments every five years.[66]

Taking U.S. imports as an example, we illustrate in Figure 3.5 that using

[66] In fact, the aggregate price index by Broda and Weinstein (2006) accounts for the possibility of codes being merged and split depending on whether their importance in trade decreases or increases. They do not account, however, for trade being reclassified due to other reasons (cf. Appendix D).

our method we obtain a stable flow of 6-digit HS products being imported each year into the United States. Applying instead the Comtrade method to convert all codes back to the HS 1992 vintage leads to artificial reductions of imported products in 2002 and especially in 2007 – years in which the United States updated its applied HS vintage. Therefore, over time the number of imported products appears to be shrinking, despite there being no obvious reason for that to be the case.

This is turn leads to different interpretations when looking at recent trends of U.S. imported product varieties after the Great Trade Collapse (cf. Figure E.6 in Appendix E). Following Broda and Weinstein (2006), we define a variety as a product imported from a specific origin country. While data based on our method imply a relatively swift return to pre-crisis levels, data based on the Comtrade method would suggest that the number of imported product varieties did not recover until 2015.

Meanwhile, applying the Pierce and Schott (2012) method leads to nearly a quarter less of products (and thus product varieties). In terms of recovery patterns, the trends captured by the Pierce and Schott (2012) data resemble those suggested by our method, as both versions show a strong post-crisis upturn. This pattern is also in line with aggregate U.S. imports (depicted as bars in Figure E.6), which had recovered to pre-crisis values by 2011.

Supply-side analysis. While the example above is meant to illustrate the benefits of our conversion method to study import demand trends, similar statements may be made on the supply side. For instance, Figure 3.6 investigates entry and exit rates of product-exporter combinations for 71 countries which reported data between 1996 and 2017. For these countries, we find an unwarranted jump nearly doubling the exit rate in the year 2007 when applying the Comtrade method, in line with findings of Cebeci (2012). Similar artificial jumps – while less pronounced – occur in each of the other years facing an HS code amendment. Otherwise, all three methods seem very much aligned with respect to the exit rate statistics.[67,68]

With regard to the entry rate, all three methods seem more aligned; with the notable exception of using our method in 2007. The jump may indicate that our method generates "too many" positive product flows in that year. However, this increase – as well those in 1996 and 2002 – are not as pronounced as the ones noticeable for the Comtrade method regarding exit rates.

3.6 Heterogeneity and Robustness of Weights

This section presents variations of our main specification outlined in Section 3.3.

Product-specific trends. One potential concern is that we do not account for product-specific trends in the data. In order to tackle the issue of product categories potentially becoming more or less relevant over time, we can estimate product-specific autoregressive coefficients which are then used to augment our minimization problem. Specifically, using all years in which the "initial" HS vintage was the latest available (i.e., the years where this specific classification standard was officially in place), let us estimate the following regression

$$x_k^t = \rho_k x_k^{t-1} + \varepsilon_k^t,$$

where x_k^t is the (aggregate) trade flow of product k in year t, ρ_k is the product-specific autoregressive coefficient, and ε_k^t is an error term. We can then assign more weight to flows in t_0 where we measured a higher persistence over time.

[67] Note that not all 71 countries each time adjusted the HS vintage in the same year, leading to the fact that the HS-conversion-related jumps may be lagged for some countries. Reducing the pool to the 35 complying countries – i.e., those which each year applied the latest available HS vintage – further sharpens the jumps seen in the vintage adjustment years. However, the overall picture does not change.

[68] The Pierce-Schott method results in very similar entry and exit rates as the two other methods (despite having a quarter fewer products) largely due to the share of unchanged HS codes. Restricting the products in Figure E.6 to those HS codes that change at least once results in the entry and exit rates of the Pierce-Schott method being roughly three percentage points lower than those based on the other approaches.

The objective function for both $t_0 < t_1$ or $t_0 > t_1$ is illustrated in Equation (3.2).

$$\sum_s \sum_{i,j} \left(x_{ij,s}^{t_1} - \sum_k (x_{ij,k}^{t_0} \hat{\rho}_k^{t_1 - t_0}) \gamma_{k,s} \right)^2, \tag{3.2}$$

where $\gamma_{k,s}$ is the new conversion weight.[69]

When applying the adjusted objective function, our results remain largely the same (cf. Figure E.7). Overall, we see very few weights receiving substantially different values. The majority of conversion weights remain the same, as the correlation coefficient for not a priori determined weights is 0.97.

Multiple years. A further limitation might be the use of only one initial and one target year. We therefore re-estimate the conversion weights by using average product-level bilateral flows over the "initial" and "target" periods, each scaled by their respective total group flows. This averaging may be particularly important for products ordered irregularly such as airplanes or trains, as well as for goods subject to multi-annual seasonal patterns, especially in agriculture. Nonetheless, when applying the algorithm on conversion weights for the vintages HS 2007 to HS 2002, we obtain very similar results between

[69] In order for trade shares to still sum up to one in year t_0, we rescale the flows by total trade within groups after multiplying them with the product-specific autoregressive coefficients. Also, note that this reasoning can be extended to higher-order autoregressive processes. For instance, let $\underline{t}_0$ and $\bar{t}_0$ be the earliest and latest year, respectively, in which the "initial" reporting standard was mostly applied. Further, let T_0 be the set containing these two years as well as those in between. We can then estimate

$$x_{ij,k}^{\bar{t}_0} = \sum_{z=\underline{t}_0}^{\bar{t}_0 - 1} \rho_{k,(\bar{t}_0 - z)} x_{ij,k}^z + \nu_{ij,k}^{\bar{t}_0},$$

where $\rho_{k,l}$ is the coefficient on the l^{th} lag, and $\nu_{ij,k}^{\bar{t}_0}$ is an error term. Correspondingly, if, e.g., $t_1 - \bar{t}_0 = 1$, the adjusted objective function looks as follows

$$\sum_s \sum_{i,j} \left(x_{ij,s}^{t_1} - \sum_k \left(\sum_{z \in T_0 \setminus \{\underline{t}_0\}} x_{ij,k}^z \hat{\rho}_{k,(t_1 - z)} \right) \tilde{\gamma}_{k,s} \right)^2.$$

averaged and single-year trade data. As Figure E.8 shows for averaged (2007–2009 and 2004–2006) and single-year (2007 and 2006) data, most weights are close to the 45-degree line, with a correlation coefficient of 0.96.

Sampling. To further verify the robustness of our weights, we re-estimate them using subsamples of our data. More precisely, we randomly divide the data into 20 equi-sized bins and look at the distribution of weights after running the regressions twenty times, where each regression leaves out one block (or, five percent of the observations). The conversion weights appear to be fairly stable. For instance, when we convert HS 2007 to HS 2002, the difference between the maximum and minimum estimated coefficient for a given initial and target product pair rarely surpasses 0.1, as illustrated in Figure E.9.[70] Moreover, in order to see whether large fluctuations happen for products which are relatively important, in Figure E.10 we plot this difference against the multiplication of the relative size of the initial and target products in their groups. The northeastern area of the graph depicts relatively important links which feature rather unstable conversion weights. As can be seen in Figure E.10, that area is almost empty. Results for other vintages look very similar.

Overall, this exercise suggests that our weights are generally not driven by only a few country pairs, and that if they are, it mostly concerns relatively unimportant products. Also, note that taking the difference between the maximum and minimum coefficients is the most conservative test we may choose.

Aggregation level. As discussed in Section 3.3, bilateral product-level flows tend to be persistent over time, although not perfectly so. Product-level imports, on the other hand, tend to fluctuate less over time for a given country, probably because a country's demand structure changes more sluggishly than bilateral transactions at the product level. Hence, one may argue that using importer-level rather than country pair-level data – i.e., aggregating our input

[70] This figure excludes pre-specified weights (i.e., conversions known to be equal to zero or one), as these would, by definition, always yield a difference of zero. Also, keeping in mind that about 85% of the groups in the conversion from HS 2007 to HS 2002 have less than five weights which are not pre-specified, a difference of less than ten percentage points can be considered small.

variables $x_{ij,k}$ across exporters $i \in I$ – better suits our optimization routine, despite reducing the number of observations substantially. In a similar vein as in the subsection above, we thus look at how conversion weights estimated using importer-level data compare with our baseline results. In Figure E.11 we do this for the conversion from 2007 to 2006 data (or, from HS 2007 to HS 2002).[71] Most absolute differences between the coefficients are again below 0.1. Furthermore, in order to assess whether large fluctuations appear for products which are relatively important, in Figure E.12 we scale the coefficients by the relative size of the initial and target products in their groups, and plot them against each other. The outcome reveals that if there are large differences, we find them only for relatively small products. Results for other vintages look very similar.

Given that, although the results are similar, the importer-level data tends to estimate more coefficients (very) close to zero, which is likely due to the lower number of observations, we stick to the country pair-level data for our baseline results.

Regions. Our calculations thus far were focused on global trade patterns. As countries differ in their product mixes, the estimated conversion weights may vary across jurisdictions. In Figure E.13 we compare how the conversion weights calculated using the entire sample perform relative to country-group-specific weights. Panel E.13a compares the 2007 trade shares converted into HS 2002 using country-group-specific weights with the 2006 shares for both OECD and non-OECD countries. In panel E.13b we convert the 2007 figures using our "global" conversion weights (i.e., those we used in Figure 3.3). Intuitively, the country-group-specific conversion provides a better fit for both country groups, although the global weights also work fairly well. It should be expected that the estimates from the entire sample better suit the OECD countries, since most large pairs belong to that country group.

[71] As above, this figure excludes pre-specified weights (i.e., conversions known to be equal to zero or one), as these would, by definition, always yield a difference of zero.

3.7 Conclusion

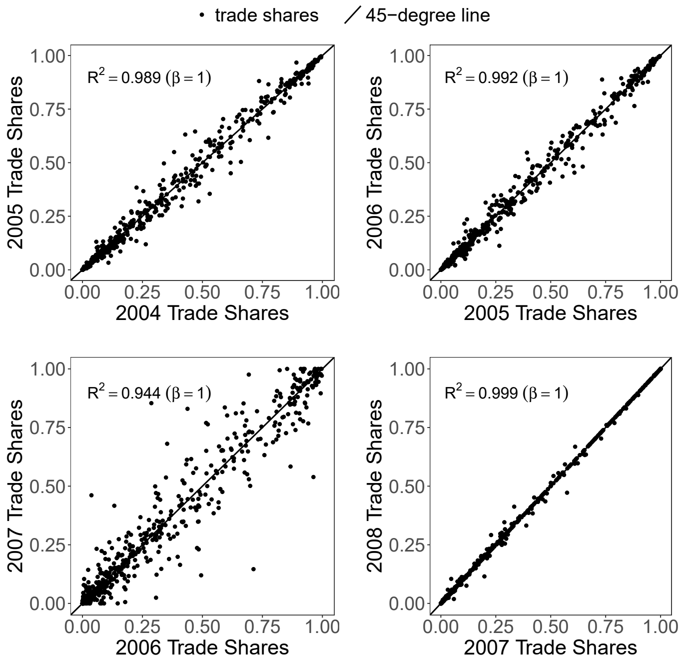
Product-level trade data often suffer from intertemporal inconsistencies due to classification changes. Existing methods either oversimplify product links across HS vintages (UNSD, 2017) or bulk the changed HS codes together (Pierce and Schott, 2012). This paper presents an approach to overcome the issues related to those methods by estimating conversion weights between linked HS codes.

The calculated conversion weights avoid the intertemporal inconsistencies encountered with the Comtrade approach (UNSD, 2017), and also do not significantly change the distribution of trade among HS codes (unlike the Pierce and Schott (2012) method). Robustness checks indicate that the weights are not significantly affected by the set of year and country pair observations we include. Similarly, the weights remain relatively stable when using importer-specific rather than country-pair-specific data in the optimization.

The weights may be readily applied to existing trade data and combined for multiple vintage changes (e.g., multiplying HS 2007 to HS 2002 and HS 2002 to HS 1996 weights when converting HS 2007 to HS 1996). If required, the algorithm can be applied to particular regions or country groups (e.g., OECD vs. non-OECD countries), which may improve the accuracy of the conversion.

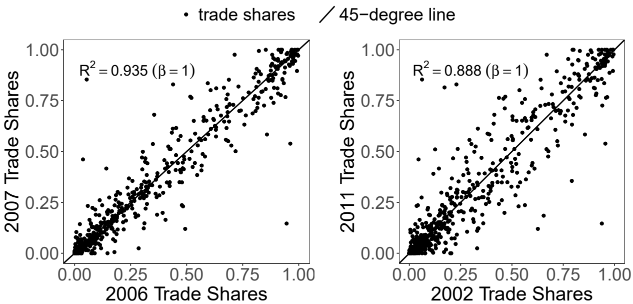
Applying the proposed conversion method also allows for a more sensitive analysis of trade patterns. When looking at imported product varieties as in Broda and Weinstein (2006), our method largely smooths observed trends and is line with general trade developments. The same holds for the analysis of exporter entry and exit rates, which relates to a growing literature investigating firm-level exporter dynamics (cf. Alessandria, Arkolakis and Ruhl (2020) for an overview), in the sense that we should be able to compare the trends in micro and macro data.

Figure 3.3: Product Trade Shares within HS Product Groups over Time (Our Conversion Weights)



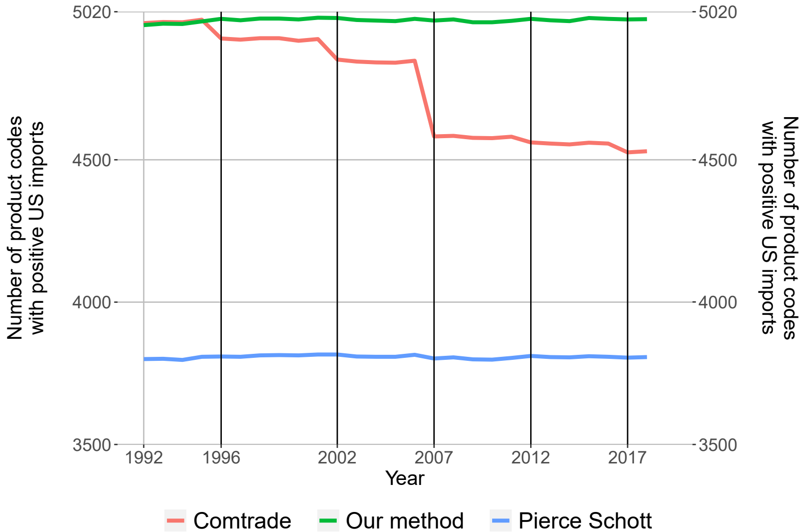
Note: This figure plots for each product its trade share within its specific group across several years. We include only groups which contain at least one 1:n or m:n assignment from HS 2007 to HS 2002, and trade data for 72 countries which used the latest available HS code classification in each year between 2004 and 2008. The figure uses Comtrade data provided in the latest available HS vintage, and transforms 2007 and 2008 data using our weights back into HS 2002. Product groups and the algorithm to obtain our conversion weights are explained in the main text. The provided R-squared assumes a fit along the 45-degree line.
Data source: UN Comtrade Database.

Figure 3.4: Product Trade Shares within HS Product Groups (Our Conversion Weights)



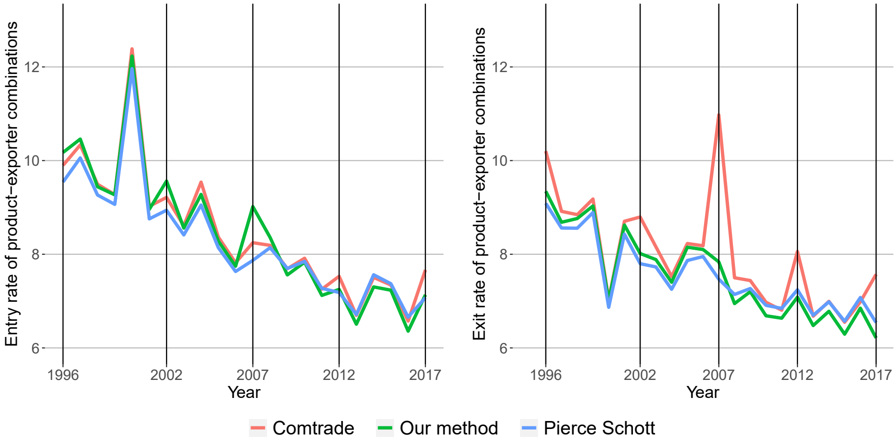
Note: This figure plots for each product its trade share within its specific group across several years. We include only groups which contain at least one 1:n or m:n assignment from HS 2007 to HS 2002, and trade data for 63 countries which used the latest available HS code classification in each of the years used in the plot. The figure uses Comtrade data provided in the latest available HS vintage, and transforms 2007 and 2011 data using our weights back into HS 2002. Product groups and the algorithm to obtain our conversion weights are explained in the main text. The conversion weights are calculated using 2006 and 2007 trade data. The provided R-squared assumes a fit along the 45-degree line.
Data source: UN Comtrade Database.

Figure 3.5: Number of Products Imported by U.S. according to Different Conversion Methods



Note: This figure plots for each year the number of 6-digit HS products (in the case of Pierce Schott: synthetic codes) imported by the United States. The three lines depict the different numbers of products based on the Comtrade, the Pierce and Schott (2012), and our conversion method; with the first and the last method used to convert all codes back to the HS 1992 vintage (containing 5,020 codes).
Data source: UN Comtrade Database.

Figure 3.6: Entry and Exit Rates (in Percent) for Product-Exporter Combinations using the Different Conversion Methods



Note: This figure plots for each year the entry and exit rates (in percent) for product-exporter combinations. Products are defined as 6-digit HS codes (in the case of Pierce Schott: synthetic codes) and observations are restricted to those 71 countries which reported trade data for the years 1995 through 2017. The three lines depict the different rates based on the Comtrade, the Pierce and Schott (2012), and our conversion method; with the first and the last method used to convert all codes back to the HS 1992 vintage. The large 2000 increase in the entry rate seen in all three versions relates to a large wave of trade liberalisation, in particular to China.
Data source: UN Comtrade Database.

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Appendix D: The Harmonized System Codification

The classification of products into Harmonized System (HS) codes is administered by the World Customs Organisation through the HS Convention signed in 1983. Each of the 150+ signatory countries is obliged to align its tariff schedules with the HS code classification. As the HS code system at its most disaggregated level reaches 6 digits, individual countries can expand their tariff schedule to a more detailed classification – at the 8-, 10-, or even 12-digit level – as long as those codes adhere at the 6-digit level to the internationally agreed standard (art.3(3) of the HS Convention).

Amendments to HS codes are proposed by the Harmonized System Committee, consisting of representatives from each contracting country. This Committee shall "propose amendments [to the current HS classification system] as may be considered desirable, having regard, in particular, to the needs of users and to changes in technology or in patterns of international trade" (art.7(1)a of the HS Convention). The proposed changes are then recommended to all contracting parties of the HS Convention and – provided no objections are received within 6 months – enter into force on the 1st of January of the following year (art.16 of the HS Convention).

Changes to the HS code classification may also be due to other reasons than those explicitly listed in the HS Convention. According to the Compilers Manual of the International Merchandise Trade Statistics (2004), some of the HS code changes in 2002 reflected "user needs but many of which were made at the request of other international organizations seeking to be able to identify trade in sensitive goods, including other hazardous materials" (p.32).

The latest HS code vintage to be adopted (HS 2022) will inter alia provide new classifications to address environmental issues (better tracking of e-waste), health concerns (separate codes for fentanyl), public security (clearer classification of components for explosives), or to facilitate international medical research (by reclassifying placebo drugs without having to differentiate by their ingredients). However, the 2022 amendments will also take into account technological progress through separate HS codes for smartphones, drones, and a reclassification of the glass fibre products.

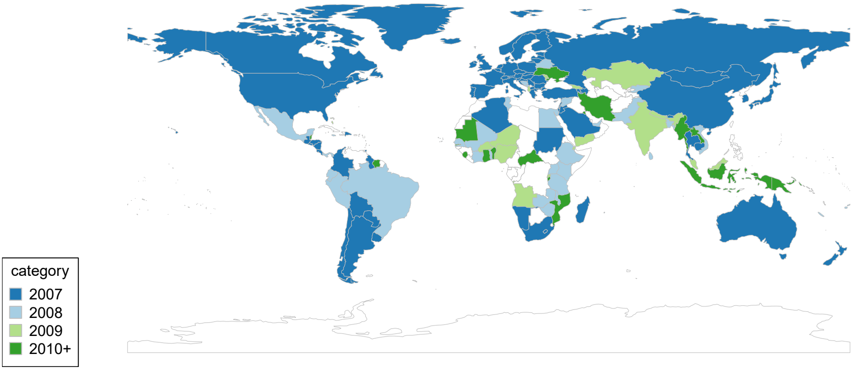
The algorithm in this paper is based on the correlation tables provided by the World Customs Organisation (and published by UN Comtrade[72]). Despite these tables being "examined by the Harmonized System Committee, they are not to be regarded as constituting classification decisions taken by that Committee; they constitute a guide published by the Secretariat and whose sole purpose is to facilitate implementation of the 2017 edition of the Harmonized System" (WCO, 2015).

Furthermore, the correlation tables are drawn up in a way that is "as comprehensive as possible" (WCO, 2015) – meaning that it is not required for a majority of country members of the HS Committee to agree on every link between a given old and new code. The final correspondence tables published by the Secretariat may therefore result in being too broad, i.e., creating too many links. This characteristic further supports our approach of letting trade data "speak for itself" in terms of which HS codes have a quantitatively significant correspondence, instead of selecting an HS code relation which may not be of much substance.

[72] The tables can be obtained here: https://unstats.un.org/unsd/trade/classifications/correspondence-tables.asp.

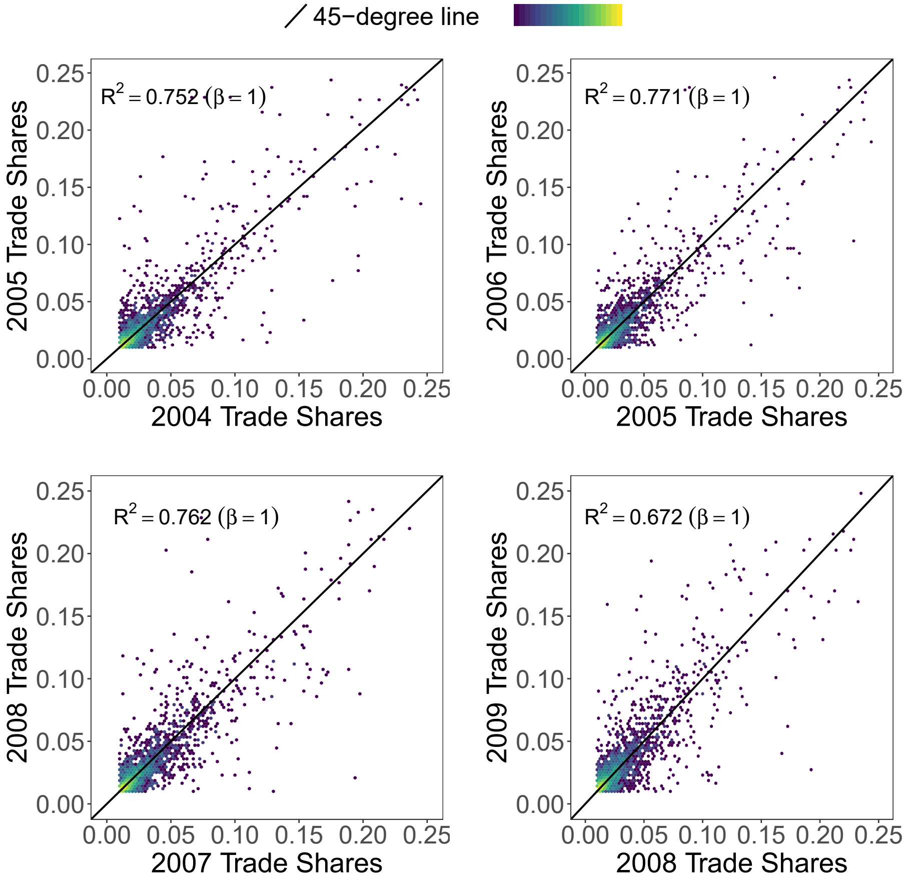
Appendix E: Additional Figures

Figure E.1: Year of HS 2007 Vintage Adoption by Countries Worldwide



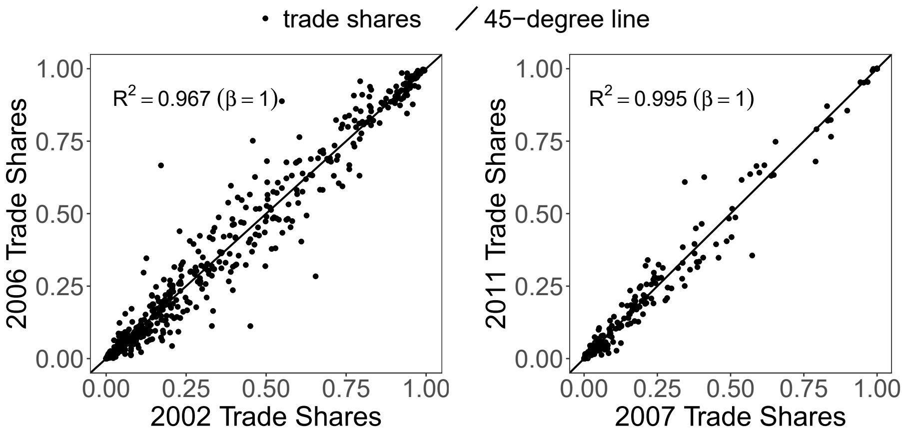
Note: This figure plots for each country the year in which it first adopted the HS 2007 code vintage. Note that some countries never adopted the HS 2007 classification (marked by white filling).
Data source: UN Comtrade Database.

Figure E.2: Bilateral Product-Level Trade Shares within HS Product Groups over Time



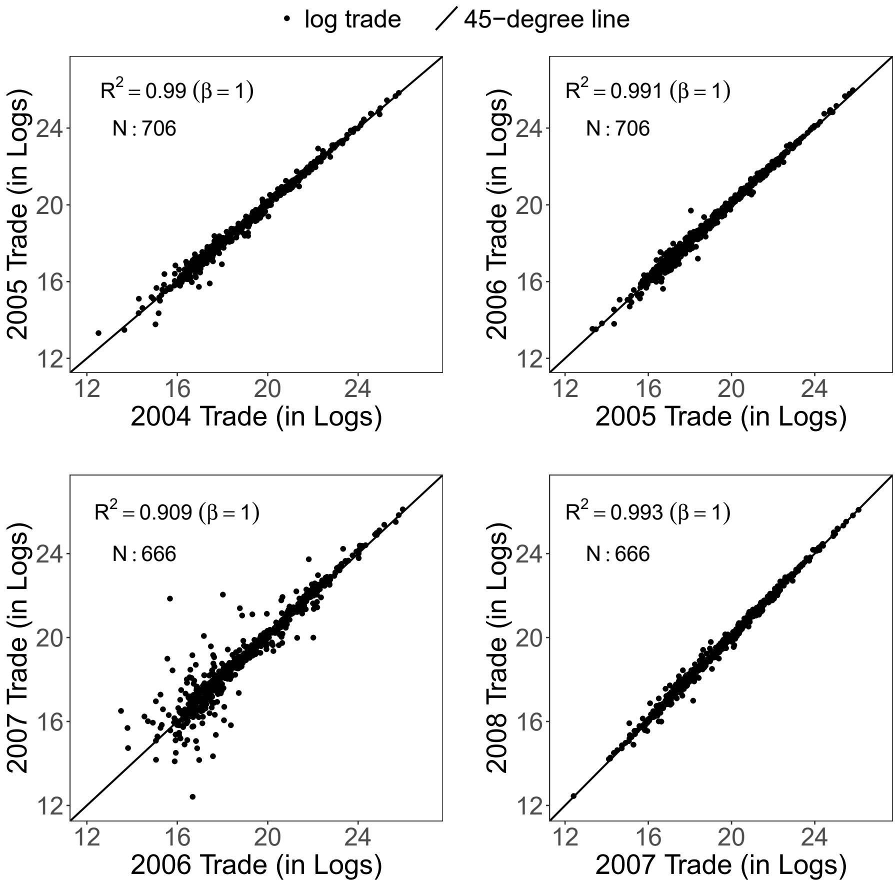
Note: This figure plots for each bilateral product-level flow its trade share within its specific group across several years. We include only groups which contain at least one 1:n or m:n assignment from HS 2007 to HS 2002. The figure uses Comtrade data provided in the original HS code version and is restricted to 70 importers reporting in the latest available HS code version in a given year. Due to the volume of observations, the data is plotted in 100 bins (per axis), and a lighter color is applied to areas with more observations. Product groups are explained in the main text. The provided R-squared assumes a fit along the 45-degree line. For illustrative purposes, the axes are capped at 0.25, and observations are excluded for which the trade share was below 0.01 in both years.
Data source: UN Comtrade Database.

Figure E.3: Product Trade Shares within HS Product Groups (HS Codes as Reported)



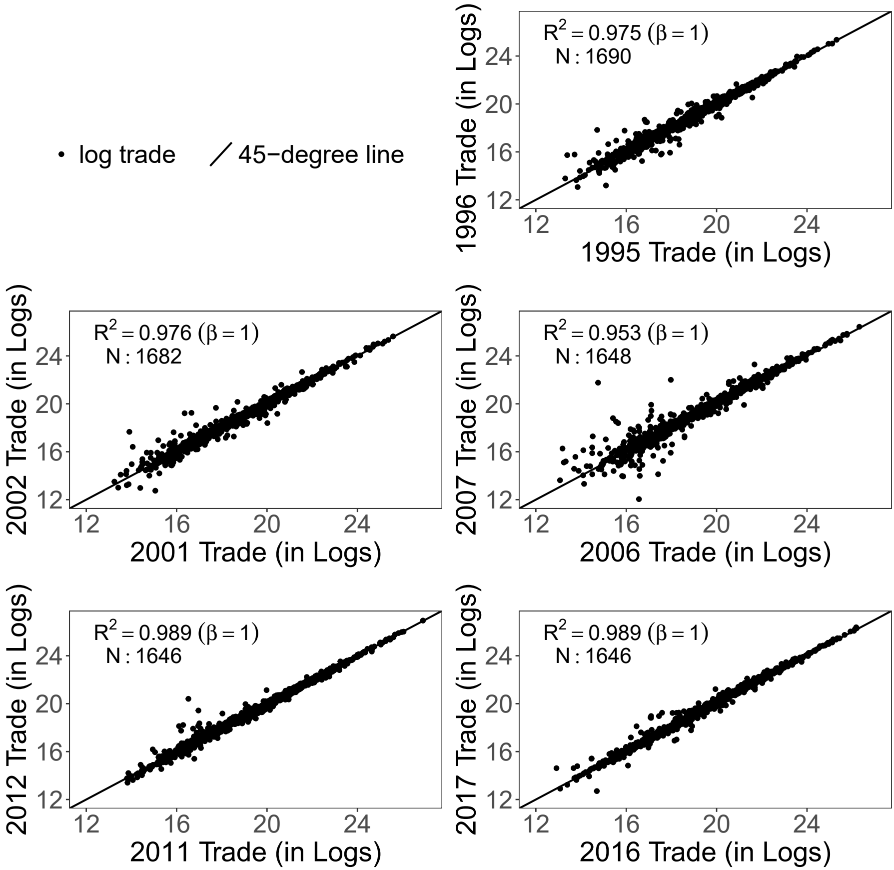
Note: This figure plots for each product its trade share within its specific group across several years. We include only groups which contain at least one 1:n or m:n assignment from HS 2007 to HS 2002, and trade data for 70 countries which used the latest available HS code classification in each of the years used in the plot. The figure uses Comtrade data provided in the latest available HS vintage. Product groups are explained in the main text. The provided R-squared assumes a fit along the 45-degree line.
Data source: UN Comtrade Database.

Figure E.4: Log of Product-Level Trade over Time (Our Conversion Weights)



Note: This figure plots for each product its log of overall trade across several years. We include only products in groups which contain at least one 1:n or m:n assignment from HS 2007 to HS 2002, and trade data for 70 countries which used the latest available HS code classification in each year between 2004 and 2008. The figure uses Comtrade data provided in the latest available HS vintage, and transforms 2007 and 2008 data using our weights back into HS 2002. Product groups and the algorithm to obtain our conversion weights are explained in the main text. The provided R-squared assumes a fit along the 45-degree line.
Data source: UN Comtrade Database.

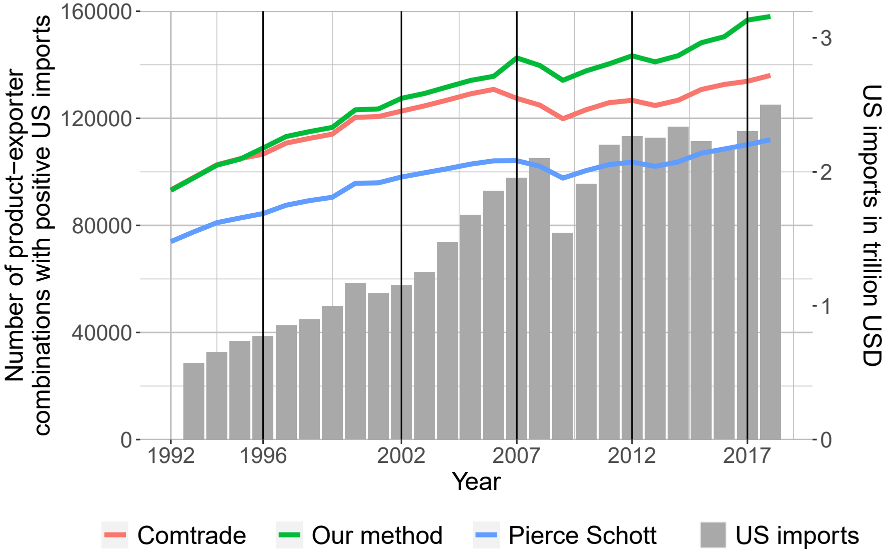
Figure E.5: Log of Product-Level Trade over Time (Our Conversion Weights – HS 1992)



Note: This figure plots for each product its log of overall trade across several years. We include only products which had at least one non-1:1 assignment over the period 1995–2017, and trade data for 38 countries which used the latest available HS code classification in each year between 1995 and 2017. The figure uses Comtrade data provided in the latest available HS vintage, and transforms all years after 1995 using our weights back into HS 1992. Product groups and the algorithm to obtain our conversion weights are explained in the main text. The provided R-squared assumes a fit along the 45-degree line.

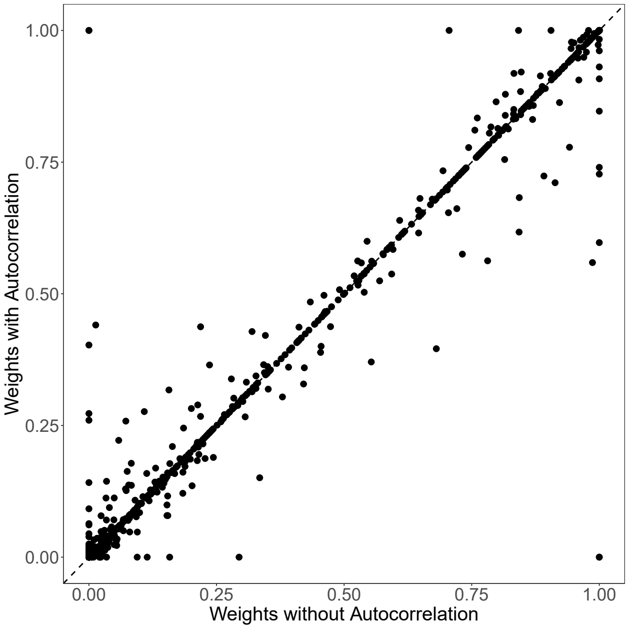
Data source: UN Comtrade Database.

Figure E.6: Number of Varieties Imported by the U.S. according to Different Conversion Methods



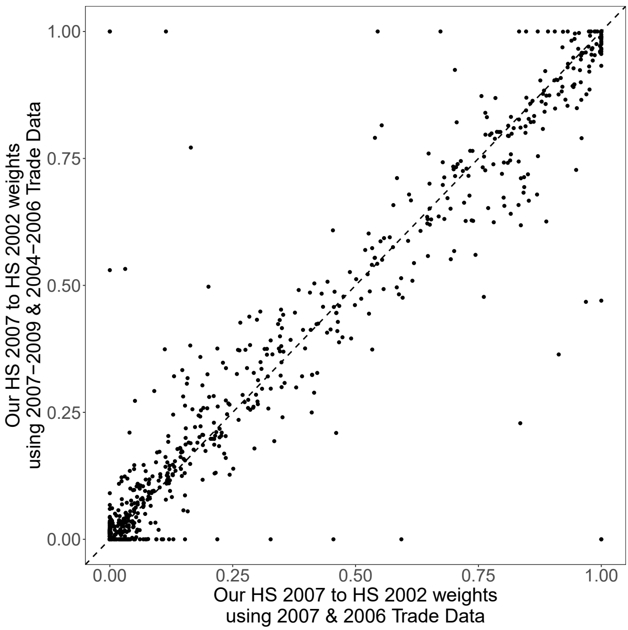
Note: This figure plots for each year the number of varieties imported by the United States. A variety is defined as an exporter-product combination (in the case of Pierce Schott: synthetic product codes). The three lines depict the different number of products based on the Comtrade, the Pierce and Schott (2012), and our conversion method; with the first and the last method used to convert all codes back to the HS 1992 vintage. The bars show total U.S. imports in trillion current USD.
Data source: UN Comtrade Database.

Figure E.7: Conversion Weights for HS 2007 to HS 2002 with and without Autocorrelation Adjustment



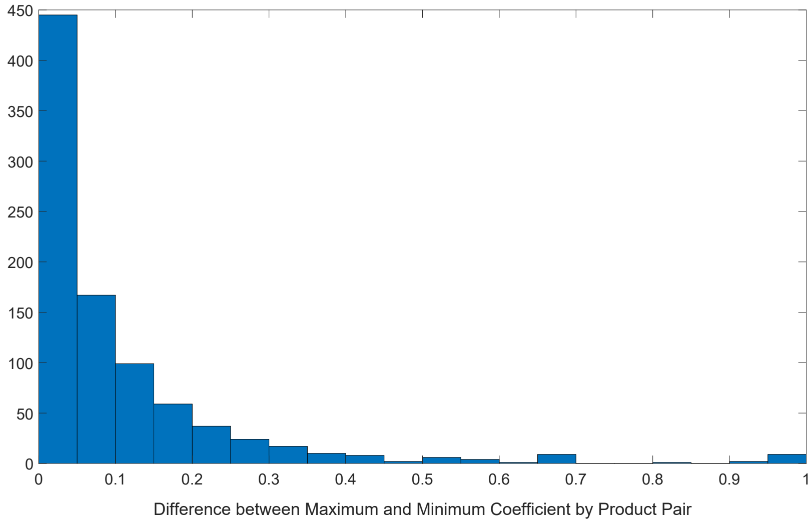
Note: This figure plots every not a priori determined weight for converting HS 2007 to HS 2002, once estimated while adjusting for product-specific trends (cf. Equation (3.2)) and once without trend adjustments (cf. Equation (3.1)).
Data source: UN Comtrade Database.

Figure E.8: Conversion Weights for HS 2007 to HS 2002 using Averaged vs. Single-Year Trade Data



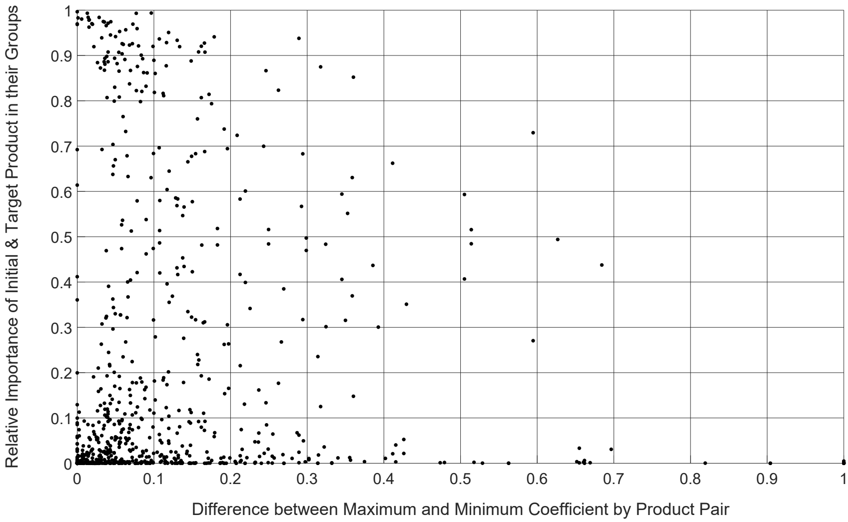
Note: This figure plots every not a priori determined weight converting HS 2007 to HS 2002 when using trade data for only 2006 and 2007 against using averaged trade for the years 2004–2006 and 2007–2009.
Data source: UN Comtrade Database.

Figure E.9: Sampling: Maximum Fluctuations of Conversion Weights



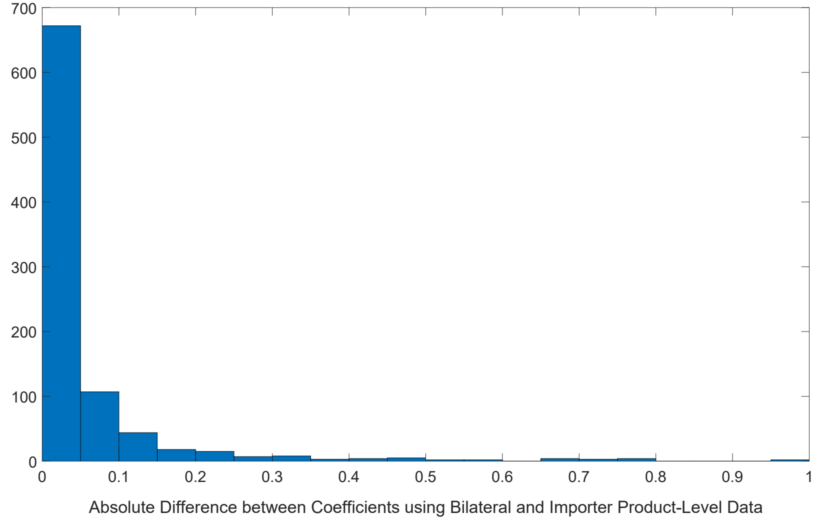
Note: This figure plots the distribution of maximum differences in estimated conversion weights across bins (cf. Section 3.6). The initial year is 2007 and the target year is 2006 (i.e., converting HS 2007 to HS 2002). The data are randomly split into 20 blocks, and twenty regressions are computed, each leaving out one block. The difference we plot is the difference between the largest and smallest coefficient we get for each product pair. This figure excludes pre-specified weights (i.e., conversions known to be equal to zero or one), as these would, by definition, always yield a difference of zero.
Data source: UN Comtrade Database.

Figure E.10: Sampling: Maximum Fluctuations of Weights and Relative Importance of Products



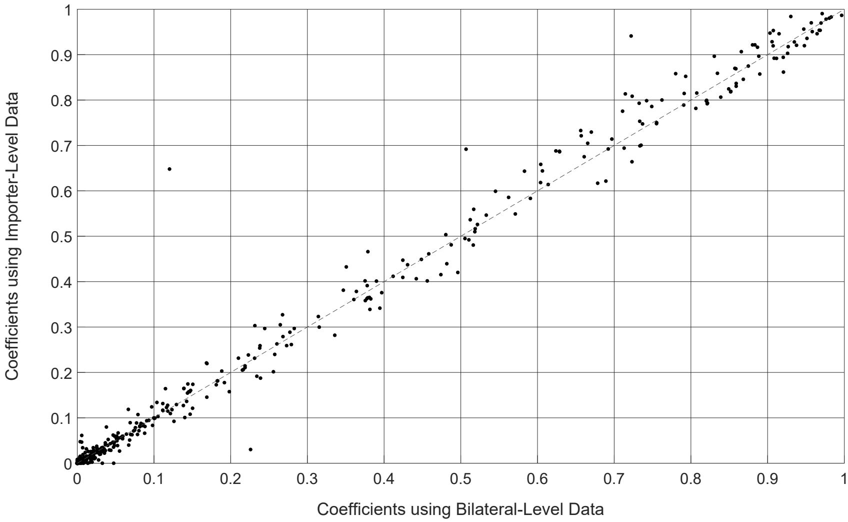
Note: This figure plots the maximum difference in estimated conversion weights across bins against the relative importance of initial and target products in their groups (cf. Section 3.6). The initial year is 2007 and the target year is 2006 (i.e., converting HS 2007 to HS 2002). The data are randomly split into 20 blocks, and twenty regressions are computed, each leaving out one block. The difference we plot is the difference between the largest and smallest coefficient we get for each product pair. The relative importance is measured as the multiplication of the initial and target product trade shares within their groups. This figure excludes pre-specified weights (i.e., conversions known to be equal to zero or one), as these would, by definition, always yield a difference of zero.
Data source: UN Comtrade Database.

Figure E.11: Aggregation: Absolute Differences in Coefficients Estimated Using Bilateral vs. Importer Product-Level Data



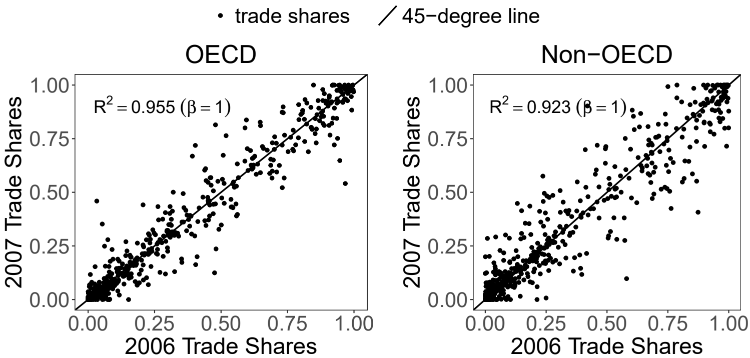
Note: This figure plots the distribution of absolute differences between conversion weights estimated using bilateral and importer product-level data, respectively (cf. Section 3.6). The initial year is 2007 and the target year is 2006 (i.e., converting HS 2007 to HS 2002). This figure excludes pre-specified weights (i.e., conversions known to be equal to zero or one), as these would, by definition, always yield a difference of zero.
Data source: UN Comtrade Database.

Figure E.12: Aggregation: Coefficients Estimated Using Bilateral vs. Importer Product-Level Data Scaled by Relative Importance of Products

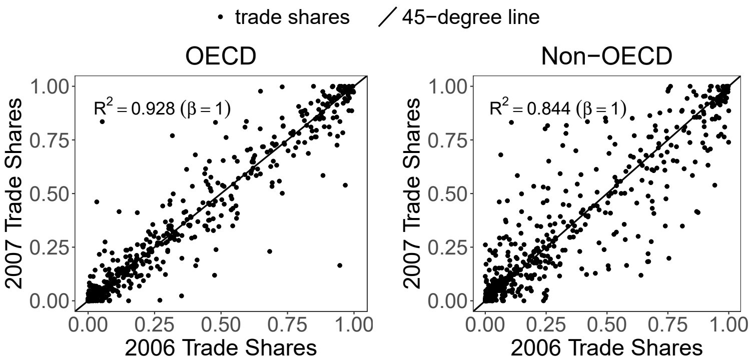


Note: This figure plots the conversion weights estimated using bilateral and importer product-level data, respectively, scaled by the relative importance of initial and target products in their groups (cf. Section 3.6). The initial year is 2007 and the target year is 2006 (i.e., converting HS 2007 to HS 2002). The relative importance is measured as the multiplication of the initial and target product trade shares within their groups. The dashed line depicts the 45-degree line. This figure excludes pre-specified weights (i.e., conversions known to be equal to zero or one), as these would, by definition, always yield a difference of zero.
Data source: UN Comtrade Database.

Figure E.13: Product Trade Shares within HS Product Groups over Time (Our Conversion Weights – Country-Group-Specific vs. Global Weights)



(a) Country-Group-Specific Conversion Weights



(b) Global Conversion Weights

Note: This figure plots for each product its trade share within its specific group across several years. We include only product groups which contain at least one 1:n or m:n assignment from HS 2007 to HS 2002, and trade data for 36 OECD (left-hand side) and 41 non-OECD (right-hand side) countries which used the latest available HS code classification in 2006 and 2007. The figure uses Comtrade data provided in the latest available HS vintage, and transforms 2007 data using our weights back into HS 2002. In panel E.13a we use OECD- and non-OECD-specific conversion weights, respectively, while panel E.13b uses the weights we calculated with the entire sample. Product groups and the algorithm to obtain our conversion weights are explained in the main text. The provided R-squared assumes a fit along the 45-degree line.
Data source: UN Comtrade Database.

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Curriculum Vitae

PIOTR LUKASZUK

Born May 26, 1993 in Warsaw (Poland)

EDUCATION

Ph.D. in Economics and Finance, University of St.Gallen, 2021 (expected)
M.A. in Economics, University of St.Gallen, 2016
B.A. in Economics, University of St.Gallen, 2013
Abitur, German International School Jakarta, 2010

VISITS

Visiting Researcher, Institute of Intern. Trade, University of Adelaide, 01/2019
Visiting Student, Università Bocconi, 01/2013–06/2013

EXPERIENCE

Director, St.Gallen Endowment for Prosperity Through Trade, 01/2021–
Research Assistant, SIAW-HSG, University of St.Gallen, 07/2014–12/2020
Internship, Swiss News Agency, 03/2014–04/2014
Internship, Bureau of World Econ., National Bank of Poland, 08/2013–09/2013

TEACHING ASSISTANCE

Macroeconomics I (Undergraduate), University of St.Gallen, 02/2020–07/2020
Macroeconomics II (Undergraduate), University of St.Gallen, 09/2017–12/2020
Microeconomics I (Undergraduate), University of St.Gallen, 09/2017–12/2018
Quantitative Methods (Undergraduate), University of St.Gallen, 02/2020–12/2020

PRESENTATIONS

2020: University of St.Gallen, IHEID Virtual PhD Workshop
2019: University of St.Gallen, University of Zurich, UNCTAD NTM Week
2018: ERWIT (poster), University of St.Gallen

POLICY-RELATED PROJECTS

Investigation of the Underutilization of Free Trade Agreements
with Stefan Legge, *SECO*, 09/2020–12/2020

Analysis of the Utilization of the Swiss Network of Free Trade Agreements
with Stefan Legge, *SECO*, 07/2019–11/2019

Analysis of Potential Evasion of Crimea-related Sanctions through Switzerland
with Simon Evenett, Reto Föllmi, Roland Hodler, & Philline Widmer,
The Parliamentary Control of the Administration (PVK), 11/2016–04/2017

CERTIFICATES

2018: Study Center Gerzensee, Adv. Course in Quantitative Models in Trade
2014: University of St.Gallen, Certificate in Business Journalism