IRREGULAR TRADE POLICY: REVERSALS, UNCERTAINTY AND DIVERSION

by
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DISSERTATION ABSTRACT

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Recent economic, political, and geostrategic developments are upending the global trade framework, weakening global multilateralism and international coordination. The stability and predictability that characterized a slow-moving and consensus-based global system of rules is ceding ground to increasingly more common deviations and irregularities. This invites new questions about the properties of international trade policy. Using a variety of econometric tools and data collection and construction tools, this dissertation empirically investigates three such irregularities that are becoming more prevalent or likely. I find that the economic costs and implications of such irregularities are rather contained in scope and limited in size. This suggests that a transition out of the existing international trade model and into a new framework might be conducted at reduced cost to the continuity and stability of overall economic activity.

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Chapter I

Introduction

Every year, about 60% of the world's output is traded internationally. In this context, trade policy, understood as the rules and regulations that govern the transit of goods, services, and financial flows across borders, is an important tool of government action worldwide.

For close to a century, trade policy has been a matter of multilateral and multinational coordination. The international rule-based trade system began as a transatlantic post-war arrangement, wherein the United States traded the opening of its market for the dismantling of British colonial trade preferences (Zeiler (1998)). It has since morphed into a complex set of rules and regulations that facilitate trade through a decidedly liberal lens. The General Agreements on Tariffs and Trade (GATT), signed in 1947 between the US and Western European nations, is now a 164-nation strong World Trade Organization (WTO), complete with its own enforcement and dispute resolution mechanisms.

Today, as multilateralism weakens, trade policy–making is undergoing deep transformations. In recent years, North Atlantic countries have begun tearing apart the same system they themselves once designed, and spent decades courting poorer economies into. By the end of 2019, the United States had violated several WTO rules by reintroducing discriminatory trade barriers, and brought the WTO dispute resolution system to a complete halt by objecting to the renewal of its members. Earlier this year, the United Kingdom all but withdrew from the European Union's common market, the largest trading bloc in the world. Accelerating this process of policy divergence is the Covid-19 pandemic. The preference for national flexibility in trade policy–making has permeated the entirety of the political spectrum. Whether rule-making bodies such as the WTO, let alone the rules themselves, can withstand this pressure, is an open question. It is clear, however, that trade policy–making is far less predictable than once thought, and that political affinity for unilateral trade policy flexibility is gaining traction.

In the context of this increasingly dynamic, decentralized global system, trade policy displays new properties. My dissertation focuses on three such properties of trade policy: policy reversals, policy uncertainty, and the divergence of international policies.

Reversals: Evaluating The Symmetry of Trade Policy Shocks

As national economies begin to exercise increased flexibility in trade policy–making, policy reversals are increasingly common. Periods of trade liberalization (lower trade tariffs, fewer regulatory barriers) alternate with protectionist tides (increasing trade tariffs, new barriers). In this context, I ask : how do gains from liberalization compare to losses from protectionism? The question of *'directional symmetry'* in policy reversals has been studied in monetary policy as early as 1992 (Cover (1992)). This paper pioneers the analysis of trade policy symmetry.

One of the challenges of empirical research is identifying the appropriate data necessary to evaluate theoretical predictions. The value of this paper comprises in its successful identification of observable cases of reversals, and its employment of both available and constructed data variables to evaluate the question of symmetry in trade policy. The paper's findings suggest that the effects of protectionist versus liberalizing trade policy reversals are not symmetrical, with liberalizing policies showing more lasting and larger effects on trade volumes. This is a positive finding for policymakers worried about the economic and social costs of increased trade policy flexibility.

Uncertainty: Measurement and Financial Impacts

Economic policy uncertainty has received significant attention in the economic literature. It is associated with greater stock market volatility and reduced investment and employment in policy-sensitive sectors like defense, healthcare, finance and infrastructure construction (Baker et al. (2016a)). Attempts to isolate and evaluate the impact of trade policy uncertainty (TPU) specifically, from other economic policy components, have suffered from the absence of a methodology to measure perceptions of TPU (Feng et al. (2017) Handley and Limão (2015a) Julio and Yook (2016)). I address this by developing a methodology for empirically gauging the public's perception of trade policy uncertainty, and employ the construct index to study the impact of TPU on stock market performance.

The index extracts data signals from two sources. To approximate public attention, I sample trade related tweets and observe the amplification they receive (retweets, likes, quotes etc.). To anchor the measure in real policy developments, I incorporate data from the US Federal Register on anticipated policy actions. The index appears very informative. An initial peak is observed following the 2016 elections, and a significant departure from historical averages begins in late 2017, concurrent with the initial stages of the US-China tariff war. The index begins to trend downwards after an initial agreement is signed between the two trading rivals in late 2019. The proposed measure performs well against two contemporaneously developed indices in Caldara et al. (2020a) and Baker et al. (2019a) and is highly informative.

Using the index, I find that stock market volatility responds negatively to trade policy uncertainty in the 2015–2020 study period. This is in direct negation of the positive relationship between broader economic policy uncertainty and volatility documented in the literature, suggesting that public response to trade policy uncertainty is distinct from other policy-related risks. The chapter suggests that TPU deserves increased and singular attention, and provides a critical tool to carry out further research in this area.

China's Aid and Trade Diplomacy: A Zero-Sum Game?

Though trade tensions have been exacerbated by populist rhetoric, they do not resolve with its retreat. Intellectual property, public subsidies to production, frictions from national security concerns (Berger et al. (2019)), regulatory divergence, and currency manipulation are all sources of trade policy tensions unlikely to relent. The international rule-based trade system has successfully accommodated the competing Transatlantic interests it was founded to serve for close to a century. It now appears unsuited for the increasingly hegemonic Transpacific trade relationship.

One area of competition between large international trade participants concerns market shares in poor and emerging markets. Of specific interest is China's economic diplomacy which mobilizes state resources to the benefit of business internationalization. Viewed as a form of new-mercantilism wherein the government advances private sector interests, it is widely decried in the West as a threat to existing trade relations (Mawdsley (2008)).

In my third and last chapter, I evaluate the extent to which China's aid and trade diplomacy displaces existing trade links. To do this, I look at a combination of policy tools: official financing (including official development aid, and other official flows), trade agreements, and the Belt and Road Initiative, which one can think of as an investment agreement. I focus on the effects of these policies in Africa, a region that has been particularly targeted by China's activism.

In this chapter, I am guided by three questions: Do these policy treatments increase countries' exports to China? If such an increase is observed, is it happening at the cost of pre-existing export flows? And how are different export industries affected differently?

This is a data intensive project. I mobilize different methods adapted to the variety of data structures at hand: gravity methods, long-difference estimation equations, and synthetic controls. My research will contribute to understanding whether trade diplomacy is setting us on a path to polarization, and whether indeed these policy interventions are a zero-sum game.

Chapter II

Evaluating The Symmetry of Trade Policy: Evidence From Liberalization Reversals

2.1 Introduction

Trade policy reversals, understood as back and forth changes in trade openness, are characteristic of the competing tides of protectionism and liberalization. This tension was recently put on full display in the context of the most intensive trade relation: China-US trade. Bound by the rules of indiscriminate treatment under the WTO agreement since 2001, the two countries have restored significant trade barriers in the form of tariffs and ad-hoc restrictions over the past few years. Some have been since removed, and others are being evaluated for removal by the new administration. This back and forth invites a policy conversation about the cost of these policy reversals and their symmetry.

Policy reversals are not specific to US-China trade or circumscribed to a context of weakening global trade regulation. Within the multilateral trade system, countries exercise much of their trade policy flexibility through bilateral trade agreements. The 164 member governments of the World Trade Organization benefit from non-discriminatory treatment from peers – shielding their trading firms from targeted tariff and regulatory shocks. In return, they accept to treat all partners equally, losing the ability to adjust their policy at the margins towards different trading partners. Trade policy flexibility is significantly limited by this arrangement but not entirely lost. Indeed, the WTO agreement allows countries to grant more favorable treatment to targeted partners via preferential systems, free trade agreements, and customs unions, all indiscriminately referred to in this paper as trade agreements. As a result, for all the growth in WTO membership, the number of country pairs operating under trade agreements has grown much faster (see figure 2.1). This stresses the degree to which trade agreements have become an essential tool to extract and exercise trade policy flexibility within an otherwise restrictive environment within the global trade system. Countries exercise trade policy flexibility through trade agreements by entering into them. They also exercise that flexibility by reviewing and revising them, suspending or leaving them, and even at times, reentering them after periods of retraction. Policy flexibility entails policy reversal, and from policy reversals arise the question of policy symmetry.

In this paper, I ask: is trade policy symmetric? Since the inception of the General Agreement on Tariffs and Trade (GATT) in 1947, the dominating trend in global trade has been towards increased liberalization. While international trade liberalization is unlikely to become undone, protectionist discourse and policies create more frequent exceptions to the norm. Fluctuating political discourse promotes policy reversals. And new crises, such as the Covid pandemic, bring traditional policy choices into focus, promising possible departures from the trend. This has been evidenced by the tide of trade barrier reintroduction over the past years, from the US-China tariffs to the recent export restrictions put in place by several countries to control price inflation in the context of global trade tensions. Even as they reintroduce protectionist barriers, these policies are temporary by design and invite future reversals. This paper aims to study one of the core properties of the policy reversals - their symmetry.

Policy symmetry has been the topic of a large literature within monetary economics. This extensive literature looking into the asymmetry of monetary policy shocks distinguishes three dimensions: asymmetry related to the direction of the shock, the size of the shocks, and asymmetry associated with the phase of the business cycle (Stockwell (2020)). This paper focuses exclusively on directional asymmetry. It answers the question of symmetry by leveraging liberalization agreement reversals as policy shocks and comparatively studying the response of trade volumes to positive and negative policy shocks. In this context, perfect trade policy symmetry would require that the response of trade flows to a positive shock is equal in absolute value but has the opposite sign from the response to a negative shock.

In my analysis, the identifying trade policy shocks are liberalization and protectionist policy actions. I exploit the variation from trade agreements that have experienced subsequent withdrawal. Thus, I am able to capture two policy shocks of equal size that affect the same country pair, i.e., the entry into and exit from the agreement. Testing the symmetry hypothesis is achieved by jointly estimating and subsequently comparing country pairs' trade volume response to the liberalization and protectionist policies, respectively.

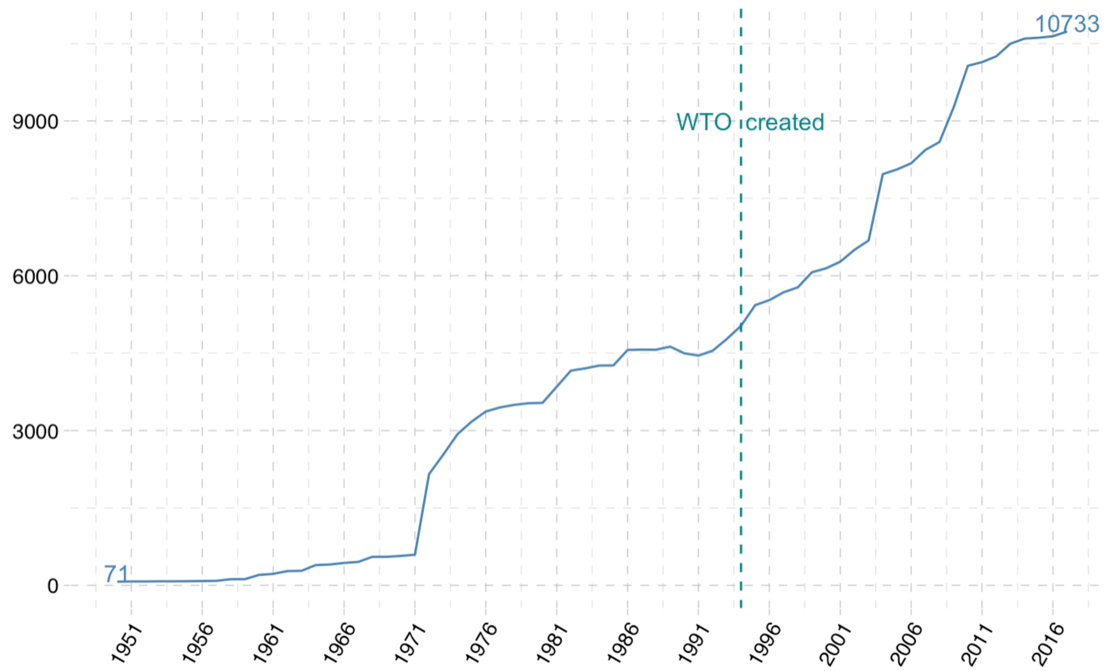
The treatment group is constructed from an exhaustive dataset collected for agreements from 1950 to 2016 for all existing countries. Within this dataset, I identify and isolate all instances of trade liberalization reversals and document several of their key characteristics. The control group is a larger set of country pairs that do not experience any policy reversals during the study period. Using a panel data generalization of the gravity equation, I measure trade volume response to entry and exit for treated units against the control group. The point estimates of the treatment parameters and the associated confidence intervals allow me to compare the trade responses across policy directions.

The paper presents results from three main estimations: a pooled regression, an analysis of deep trade policy shocks proxied by free trade agreements, and a focus on the symmetry properties of less comprehensive preferential trade agreements. In all three cases, point estimates display signs of asymmetry: protectionist policies do not erase the gains achieved from prior, equal-sized liberalization. However, at the 95% confidence level, the symmetry of trade policy cannot be rejected.

The paper closest to this work is a recent study by USITC affiliates Daigle and LaRocca (2019) which surveys country exits from agreement and describes some common patterns and subsequently focuses on 6 case studies to illustrate geographic and situational diversity of reversal decisions. This paper goes further by quantifying the impacts of exits using econometric methods and firmly placing the analysis in the context of policy symmetry. While the study of symmetry in the context of trade policy and trade agreements is a new question, this exercise borrows from and builds on two trade literatures. Identifying the impact of trade agreements, specifically, free trade agreements (FTAs), has been a ubiquitous research agenda for many years. This has allowed for a constant improvement of the econometric techniques required for accurate impact measurement. Earlier research reached contradictory and "fragile" results (Ghosh and Yamarik (2004)). Baier and Bergstrand (2007) seminal paper developed a framework that adequately handles the issue of trade agreement endogeneity using panel methods. The specification is anchored in theory and derived from the trade gravity equation. This workhorse model is the starting point for my estimation equation. My approach will also reflect a recurrent concern in recent contributions to this literature, namely the heterogeneity in trade response to policy shocks. Geographic, regulatory and economic characteristics have been found to drive this heterogeneity (Eicher and Henn (2011), Kohl (2014), Kohl et al. (2016)).

The study of symmetry conducted in this paper sheds light on the trade costs of policy reversals and volatility. It also contributes to reemerging literature about protectionism and liberalization reversals. Recent swings in trade policy have supplied multiple protectionist case studies that have been measured and analyzed. Auer et al. (2018) estimate

Figure 2.1: Country-pairs sharing a trade agreement, frequency 1950-2016



NSF-Kellogg's Database on Economic Integration and WTO RTA database

that revoking NAFTA would have reduced US welfare by 0.2%. Fajgelbaum et al. (2019) find that US retaliatory tariffs introduced in 2018 generated a loss to US consumers and firms of 0.27% of GDP. Oberhofer and Pfaffermayr (2018) expect UK exports to the common market to shrink by 45.7% following an exit from the common market. Adverse shocks to non-tariff measures have also received increased attention (Miromanova (2019), Haidar (2019)).

The rest of the paper is organized as follows. Section 2 presents the data, sample construction, and the stylized facts surrounding policy reversals. Section 3 lays out the empirical strategy and identification framework. The section then describes a set of theoretical underpinnings and candidate hypotheses and predictions to clarify what is meant by symmetry and parse out the possible cases. I subsequently present baseline results. Section 4 slices the sample along heterogeneity dimensions to reveal context-specific results. Section 5 concludes.

2.2 Data

2.2.1 Agreements data

Data on trade agreements is derived primarily from the NSF-Kellogg Institute Data Base on Economic Integration Agreements (EIA). This dataset distinguishes six types of trade agreements based on the depth of economic integration going from less to most integrated. These are asymmetric preferential agreements, bi-directional preferential agreements, free trade agreements, customs unions, common markets, and economic unions. The latest release of the EIA covers all country pairs from 1953 to 2014.

To ensure that the study is as current as possible, I supplement the EIA data with two additional years of observations using the World Trade Organization's (WTO) database on regional trade agreements. This extends the time-series dimension of the data until 2016 and allows me to expand the treatment group.

Symmetry is evaluated by comparing the response of trade volumes to a liberalization agreement and to a withdrawal from the said agreement - which can be equivalently understood as a protectionist policy shock to the extent that it involves the introduction of new trade barriers. The comparison is performed *within those country pairs* that have experienced a reversal. A trade policy reversal is defined as an initial liberalization that is later followed by a withdrawal. The initial analysis will lump all withdrawals into the same treatment - regardless of whether the withdrawal is towards the default state of no agreement or a less integrated arrangement. The limited number of treated pairs dictates this generalization. Identifying exit and agreement downgrading (respectively entry and upgrading) as separate protectionist (respectively liberalization) policies results in a loss of explanatory power. Therefore the initial analysis will adopt a more general definition of policy shocks. Subsequent heterogeneity analysis will allow for differentiation, with the caveat that statistical power will be reduced.

Table 2.1. lists all country pairs that I consider to be treated. There are 159 observed reversals, and 33 of these have to be removed from the treatment sample due to unavailable data on the response variable, trade volumes. The 72 treated countries span a broad geography, including African, European, American, and Asian countries. There is also a diversity of income levels, trade openness, and trade volume levels. Figure 2.2 captures the diversity of the treated sample by focusing on the varying levels of wealth and trade openness. Panel A represents the distribution of GDP per capita for treated countries and reveals that the treated sample spans the whole income distribution spectrum. It also shows that poorer countries concentrate. Panel B plots the distribution of treated countries' trade-to-GDP ratios, a measure of their trade openness. Again, the distribution is

wide, ranging from one of the world's most closed countries, Eritrea, to one of the most open to trade, Hong Kong.

Table 2.1: Sample of treated units

Pair	Year	Pre-Exit	Post-Exit	Agr. length	Ex. length	Reentry
BDI-LSO	1998	2	0	20	17	None
BDI-MOZ	1998	2	0	20	17	None
BDI-NAM	2005	2	0	13	10	None
BDI-TZA	2001	2	0	7	6	2008
BEN-MRT	2000	2	0	18	19	None
BFA-MRT	2000	2	0	18	19	None
BGR-BIH	2007	3	1	11	2	None
BGR-MDA	2007	3	0	7	3	2014
BIH-ROU	2007	3	1	11	3	None
BIH-SVN	2004	3	1	14	2	None
BOL-VEN	2012	4	3	6	17	None
BWA-SYC	2004	2	0	4	23	2008
CHL-POL	1999	1	0	5	10	2004
CHN-ITA	1990	1	0	28	9	None
CHN-MMR	2011	3	2	7	5	None
CHN-POL	2004	1	0	14	14	None
CIV-MRT	2000	2	0	18	19	None
COL-HTI	2004	2	0	14	2	None
COL-VEN	2012	4	3	6	17	None
COM-LSO	1998	2	0	20	17	None
COM-MOZ	1998	2	0	20	17	None
COM-NAM	2005	2	0	13	10	None
COM-TZA	2001	2	0	17	6	None
CPV-MRT	2000	2	0	18	19	None
ECU-VEN	2012	4	3	6	17	None
EGY-NAM	2005	2	0	13	6	None
ERI-TZA	2001	2	0	17	6	None
EST-CAN	2004	1	0	13	12	None
EST-UKR	2004	3	0	10	7	2014
ETH-LSO	1998	2	0	20	17	None

Table 2.1: Sample of treated units, continued

Pair	Year	Pre-Exit	Post-Exit	Agr. length	Ex. length	Reentry
ETH-MOZ	1998	2	0	20	17	None
ETH-NAM	2005	2	0	13	10	None
ETH-TZA	2001	2	0	17	6	None
GHA-MRT	2000	2	0	18	19	None
GIN-MRT	2000	2	0	18	19	None
GMB-MRT	2000	2	0	18	19	None
HKG-ITA	1998	1	0	20	17	None
HKG-POL	1990	1	0	28	9	None
HUN-BGR	1991	2	0	8	10	1999
HUN-CUB	1991	2	0	27	10	None
HUN-ITA	1990	1	0	2	1	1992
HUN-MNG	1991	2	0	27	10	None
HUN-POL	1991	2	0	1	10	1992
HUN-ROU	1991	2	0	6	10	1997
HUN-RUS	1991	2	0	13	10	2004
HUN-VNM	1991	2	0	27	10	None
KEN-LSO	1998	2	0	20	17	None
KEN-MOZ	1998	2	0	20	17	None
KEN-NAM	2005	2	0	13	10	None
KNA-POL	1999	1	0	5	10	2004
LKA-BGR	2007	1	0	11	8	None
LKA-HUN	2004	1	0	14	23	None
LKA-ITA	1990	1	0	28	9	None
LKA-POL	2004	1	0	14	23	None
MDA-ROU	2007	3	1	11	12	None
MDG-LSO	1998	2	0	3	17	2001
MDG-MOZ	1998	2	0	3	17	2001
MDG-SYC	2004	2	0	4	23	2008
MLI-MRT	2000	2	0	18	19	None
MOZ-ZAF	1997	2	0	4	3	2001
MRT-GNB	2000	2	0	18	19	None
MRT-LBR	2000	2	0	18	19	None
MRT-NER	2000	2	0	18	19	None
MRT-NGA	2000	2	0	18	19	None
MRT-SEN	2000	2	0	18	19	None

Table 2.1: Sample of treated units, continued

Pair	Year	Pre-Exit	Post-Exit	Agr. length	Ex. length	Reentry
MRT-SLE	2000	2	0	18	19	None
MRT-TGO	2000	2	0	18	19	None
MUS-LSO	1998	2	0	3	17	2001
MUS-MOZ	1998	2	0	3	17	2001
MUS-POL	1999	1	0	5	18	2004
MUS-SYC	2004	2	0	4	23	2008
MWI-SYC	2004	2	0	4	23	2008
NAM-DJI	2005	2	0	13	10	None
NAM-ERI	2005	2	0	13	10	None
NAM-RWA	2005	2	0	13	10	None
NAM-SDN	2005	2	0	13	10	None
NAM-SOM	2005	2	0	13	10	None
NAM-SYC	2004	2	0	4	9	2008
NAM-UGA	2005	2	0	13	10	None
PER-VEN	2012	4	3	6	17	None
PHL-BGR	2007	1	0	11	8	None
PHL-HUN	2004	1	0	14	23	None
PHL-ITA	1990	1	0	28	9	None
PHL-POL	2004	1	0	14	23	None
POL-BGR	1991	2	0	8	10	1999
POL-CUB	1991	2	0	27	10	None
POL-ITA	1990	1	0	2	1	1992
POL-MNG	1991	2	0	27	10	None
POL-ROU	1991	2	0	6	10	1997
POL-RUS	1991	2	0	13	10	2004
POL-VNM	1991	2	0	27	10	None
ROU-BGR	1991	2	0	8	10	1999
ROU-CAN	2007	1	0	11	26	None
ROU-CUB	1991	2	0	27	10	None
ROU-ITA	1990	1	0	3	9	1993

Table 2.1: Sample of treated units, continued

Pair	Year	Pre-Exit	Post-Exit	Agr. length	Ex. length	Reentry
ROU-MNG	1991	2	0	27	10	None
ROU-RUS	1991	2	0	27	10	None
ROU-VNM	1991	2	0	27	10	None
RWA-LSO	1998	2	0	20	17	None
RWA-MOZ	1998	2	0	20	17	None
RWA-TZA	2001	2	0	17	6	None
SDN-LSO	1998	2	0	20	3	None
SDN-MOZ	1998	2	0	20	17	None
SDN-TZA	2001	2	0	17	6	None
SVN-CAN	2004	1	0	13	12	None
SWZ-SYC	2004	2	0	4	23	2008
SYC-AGO	2004	2	0	4	23	2008
SYC-COD	2004	2	0	4	9	2008
SYC-POL	1999	1	0	5	18	2004
SYC-TZA	2004	2	0	4	9	2008
SYC-ZAF	2004	2	0	4	3	2008
SYC-ZMB	2004	2	0	4	9	2008
SYC-ZWE	2004	2	0	4	9	2008
SYR-POL	1999	1	0	5	18	2004
TUR-POL	1990	1	0	10	9	2000
TUR-SYR	2012	3	0	6	5	None
TZA-DJI	2001	2	0	17	6	None
TZA-LSO	1998	2	0	3	3	2001
TZA-MOZ	1998	2	0	3	3	2001
TZA-SOM	2001	2	0	17	6	None
UGA-LSO	1998	2	0	20	3	None
UGA-MOZ	1998	2	0	20	17	None
VEN-HTI	2004	2	0	14	2	None
VEN-POL	1990	1	0	14	9	2004

Table 2.1: Sample of treated units, continued

Pair	Year	Pre-Exit	Post-Exit	Agr. length	Ex. length	Reentry
ZMB-LSO	1998	2	0	3	3	2001
ZMB-MOZ	1998	2	0	3	17	2001

Regimes : 0. No agreement, 1. APA, 2. SPA, 3. FTA, 4. FTA + CU
Sources: NSF-Kellogg Institute & WTO, adjusted by author

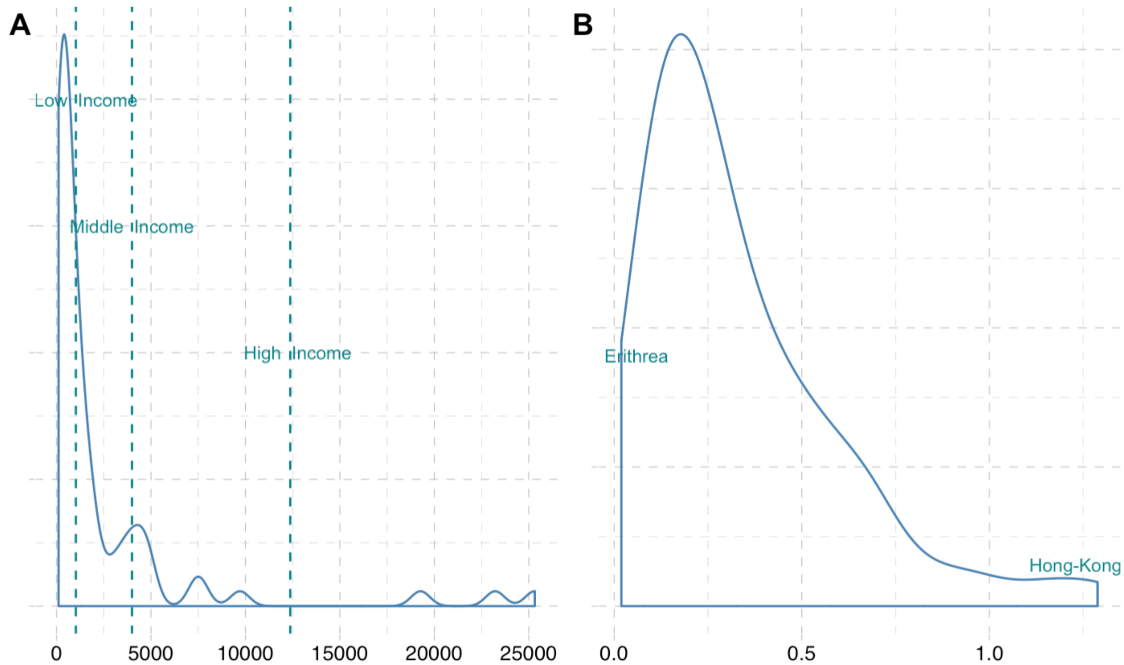
There are different margins of treatment heterogeneity in the constructed data, and these margins are coded in my dataset for later analysis. The first source of heterogeneity is the variation in the length of the agreement's enforcement period. Another source of heterogeneity is that a few country pairs experience more than one reversal. For example, over the period of study, Romania and Bulgaria experienced an alternation of three shocks: they started the period within an agreement, suspended it in 1991, and later entered into a new agreement in 1999. A third and final source of treatment heterogeneity is the size of the reversal. The trade barrier restoration implied by an exit from an FTA to an MFN regime is larger than a downgrading from an FTA to a bilateral preferential agreement. Coding these dimensions in the data allows me to account for them in subsequent heterogeneity analysis.

2.2.2 Trade data

I use import volumes as the response variable to agreement reversals. The empirical literature favors import over export flows as they are generally believed to be more precisely measured by reporting countries. Import volumes are extracted from the UN's Commission on Trade's database (COMTRADE). Analysis with exports yields very similar results.

I choose to focus the analysis on the 31 years from 1986 to 2016. Starting the sample in 1986, instead of an earlier date, serves two purposes. First, it minimizes the multiplicity of time breaks that would exist if the data started earlier. The empirical strategy described in the next section assumes that unobserved bilateral characteristics are constant over time, and this assumption becomes increasingly questionable as the time window expands and the possibility for structural breaks increases. Second, as observed in the data, withdrawals were very rare before the 1990s. For these two reasons, extending the time horizon before 1986 is more likely to generate noise than to support identification in the subsequent analysis.

Figure 2.2: Distributions for GDP per capita, and trade to GDP ratios for treated countries



CEPII Gravity Data, 2000

COMTRADE collects data in a way that has potential implications for empirical analysis. On the one hand, it receives data from member countries, making it a reporting-based database. On the other hand, it applies a filter to reported data and drops 0- and negligible trade flows. This approach creates some data ambiguity: missing values can indicate either truly missing reports or a zero-trade flow. Leaving this ambiguity unaddressed can generate bias through measurement errors. To resolve this ambiguity, I proceed as follows. A country that reports a total of 0 imports with all partner countries in year t is considered to have failed to report, and all of its import flows for the year t are treated as missing. Conversely, if a country reports a strictly positive total value of imports, its unreported flows with other countries are treated as zeroes. This approach assumes that a country that reports any flow in year t will report all flows in that year. This is a strong but necessary assumption to extract additional information from a dataset that would be lost with indiscriminate treatment. Table 2.2 shows the structure of the data and the result of this filtering algorithm.

In addition to the 72 countries that experience policy reversals at some point in time, I include 11 additional countries. These are chosen randomly among a list of countries that have not experienced any policy reversals over the time of the study. Therefore, the complete data consists of a panel of 83 countries, or 6806 pairs, over 31 years.

Table 2.2: Summary trade data

	1990	1995	2000	2005	2010	2015
Reporting countries	40	58	76	74	73	60
Missing flows	4262	4184	2930	2566	2261	2878
Treated as na	2388	1581	526	540	514	1040
Treated as zero	1874	2603	2404	2026	1747	1838

Sources: NSF-Kellogg Institute & WTO, adjusted by author

2.2.3 Stylized facts

Next, I present some stylized facts observed in the constructed dataset. Within this sample, the disappointing track record of multilateral trade liberalization is reflected (and perhaps reinforced) by the proliferation of bilateral and regional agreements, as captured in table 2.3. From 1996 when the Uruguay round of tariff reductions (the latest negotiation round to date) had been finalized, until 2016, the number of enforced agreements amongst our sample of 83 countries went up by a staggering 70%. By 2016, about 18% of the pairs in the sample operated under a negotiated preferential trade regime. Over the same period, the number of FTAs increased 17-fold. This trend points to the importance of bilateral arrangements in regulating global trade and shapes the geography of trade flows, making the unraveling of these arrangements essential to track and evaluate.

Table 2.3: Summary agreement data

	1986	1996	2006	2016
Number of countries	83	83	83	83
Number of possible pairs	6889	6889	6889	6889
Number of agreements	576	700	974	1194
Of which				
PTAs	566	644	740	818
FTAs	2	16	170	297
CUs	7	40	65	80

Sources: NSF-Kellogg Institute & WTO, adjusted by author

In my sample, 72 countries were involved in an exit from an existing agreement between 1986 and 2016. Exits add up to 126 cases, summarized in table 2.4. 93% of exits are not immediately replaced by an interim agreement and are complete reversals to the default trade regime. The default trade regime is WTO's *Most Favored Nations* (MFN) for most of the country pairs. African countries are over-represented in the sample due to (a) significant volatility in trade policy choices as countries have historically chosen to leave regional trading blocs either to join an alternative region or to, later on, return to the original one (b) their status as beneficiaries of asymmetric preferential trade agreements that come with expiration criteria. The average length of an exit in our sample is 13 years, after which some exits are reversed, and renegotiated agreements are introduced. We refer to these reintroductions as "reentries."

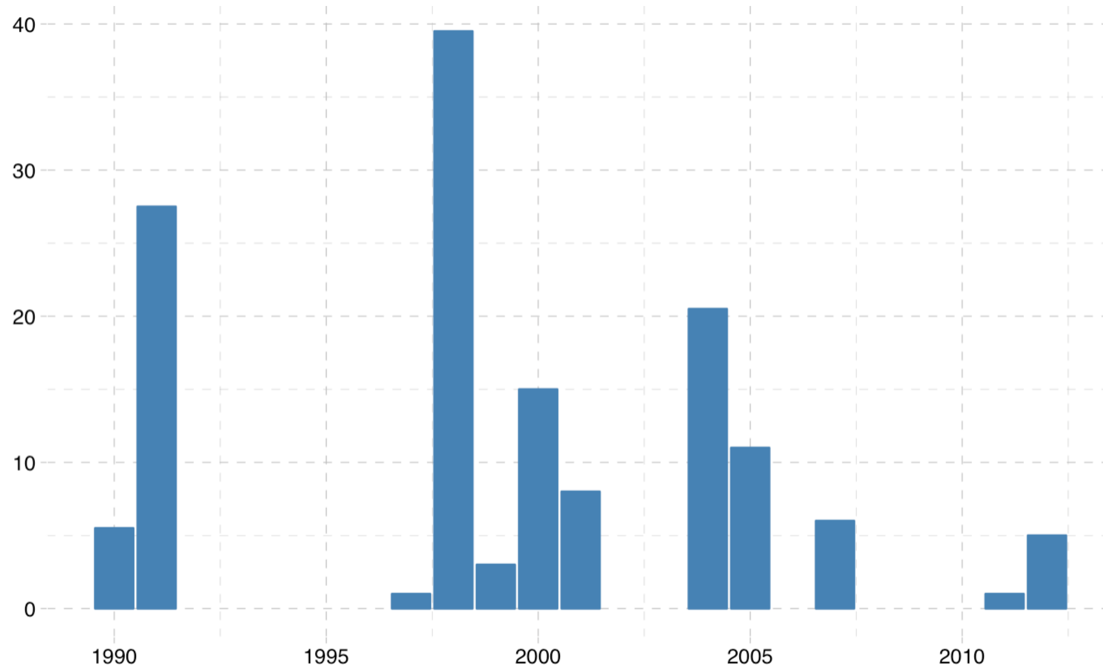
Table 2.4: Trade liberalization reversals

Number of exits	126
Of which	
from FTA	12
to nothing	117
African Pairs	68
EU accession	17
Reversed	42
Average length of exit (years)	13
Maximum	28
Minimum	1

Sources: NSF-Kellogg Institute & WTO, adjusted by author

It is worth noting that the trade liberalization reversals span the whole time dimension of the panel (figure 2.3). Peaks are registered around globally or regionally relevant dates. The 1990-1991 peak reflects a string of preferential trade agreements amongst the Socialist Bloc countries that unraveled upon the collapse of the Soviet Union. The peak around 1998 demonstrates a series of realignments between different African trade blocs. The third peak in 2004 is the consequence of the EU's most significant enlargement to date when 10 Eastern European countries joined the common market and consequently relinquished some of their existing agreement with third parties. Each of these three different episodes is controlled separately in the rest of this study.

Figure 2.3: Exits by year



Source: NSF-Kellogg Institute & WTO, adjusted by author

2.3 Methodology and Results

2.3.1 Main specification

I follow the framework in Baier and Bergstrand (2007) for estimating the trade effect of FTAs using the gravity equation. It starts with the gravity equation proposed by Anderson (1979) and refined for panel estimation by Baier and Bergstrand (2007) :

$$X_{ij} = \frac{A_i \omega_i^{-\theta} \tau_{ij}^{-\theta}}{\sum_l A_l \omega_l^{-\theta} \tau_{lj}^{-\theta}} E_j \tag{II.1}$$

Exports from country i to country j are given as a function of several variables. E_j is total expenditure by country j on all goods. A_i is a measure of the quality of goods in country i, ω_i is the wage in i; and τ_{ij} is the iceberg trade cost between i and j. Origin characteristics are weighted against characteristics from competing import sources, which are captured by the aggregator in the denominator. θ is the constant trade elasticity.

Trade frictions $\tau_{ij,t}$ are assumed to have an observable and an unobservable component such that:

$$\tau_{ij,t} = \text{Trade regime}_{ij,t} + \psi_{ij} + \nu_{ij,t} \tag{II.2}$$

Where ν_{ij_t} is a measure of time-varying costs and frictions not related directly to the trading regime, and ψ_{ij} summarizes pair-specific time-invariant characteristics. An identifying assumptions is that the unobserved time-varying frictions are uncorrelated with the trade regime.

For the purpose of this study, the trade regime has two components: a base component that captures whether the pair is operating under a trade agreement, and an additional component that describes whether the ongoing trade regime is a result of a policy reversal (i.e. agreement exit, or reentry into an agreement). To the extent that these components do not have to contribute equal shares to trade frictions, we can rewrite equation (2.2) as :

$$\tau_{ij,t} = \alpha_1 \text{Agr}_{ij,t} + \alpha_2 \text{Exit}_{ij,t} + \alpha_3 \text{Agr}_{ij,t} \times \text{Reentered}_{ij,t} + \nu_{ij_t} \tag{II.3}$$

Where $Agr_{ij,t}$ is an indicator variable that takes value 1 when the pair ij shares a trade agreement in year t and 0 otherwise (preferential trade agreements, free trade agreements, or more integrated trading regimes).

Similarly, $Exit_{ij,t}$ assumes a value of 1 if the pair ij in year t is trading outside of an agreement they previously shared. Note that because the sample includes ij pairs that never share or exit an agreement, $Exit_{ij} \neq (1 - agreement_{ij})$.

Finally, $Reentry_{ij,t}$ takes value if in year t the pair ij 1 is trading under an agreement that was previously exited and then restored.

By combining (1) and (3), allowing for time variation, rewriting in exponential form and replacing the endogeneous and non-observable variables with country-time, and pair fixed effects, we obtain the following specification:

$$\begin{aligned} X_{ij,t} = exp(&\eta_{i,t} + \psi_{j,t} + \gamma_{ij} + \beta_1 \text{Agr}_{ij,t} + \beta_2 \text{Exit}_{ij,t} \\ &+ \beta_3 \text{Agr}_{ij,t} \times \text{Reentered}_{ij,t}) + \varepsilon_{ij,t} \end{aligned} \tag{II.4}$$

Under this specification, the identifying assumption is that once we account for time-varying import market characteristics (such as country size, market competition, and total spending), time-varying exporter characteristics (product quality and price), and time-invariant pair characteristics (distance, and other proximity measures), the only remaining source of variation among trade volume predictors is the bilateral cost of trade $\tau_{ij,t}$. Additionally, my derivation assumes that the bilateral costs of trade are predicted by the trade regime.

Finally, the specification is augmented with an additional term. The impact of exited agreements prior to exit can be different from unexited agreements. To address this, I incorporate a dummy that takes value 1 while an agreement that is subsequently dismantled is enforced. I denote this variable as $Agr \times Pre - Exit$. Note that this specification controls for individual and pairwise characteristics based on which selection into agreements, exits and reentries happens.

$$\begin{aligned} X_{ij,t} = exp(&\eta_{i,t} + \psi_{j,t} + \gamma_{ij} + \beta_1 \text{Agr}_{ij,t} + \beta_2 \text{Agr}_{ij,t} \times \text{Pre-Exit}_{ij,t} \\ &+ \beta_3 \text{Exit}_{ij,t} + \beta_4 \text{Agr}_{ij,t} \times \text{Reentered}_{ij,t}) + \varepsilon_{ij,t} \end{aligned} \tag{II.5}$$

Given the specification above, the control group is implicitly defined as country pairs for which all treatment dummies are 0. That is, country pairs that do not share an agreement, that have not exited an agreement, and that have not reentered an agreement. It follows that parameter β_1 measures the effect of trade agreements on trade flows. $\beta_1 + \beta_2$ is the trade effect of exited agreements prior-to the exit. β_3 measures the effect of exits from an agreement. A positive estimate for β_3 would indicate that countries who exit agreements continue to trade more intensively than the control group, even if they no longer share a liberalizing agreement. A negative estimate for β_3 would suggest that country pairs that reverse a liberalization policy experience reductions in their trade flows and trade less than countries that never liberalized at all. The parameter β_4 measures the marginal effect of reentry, such that $\beta_1 + \beta_4$ is the total effect of reentered agreements. A positive estimate of β_4 would therefore indicate that reentry not only reestablishes original trade gains, but contributes new ones. Conversely, a negative β_4 would mean that re-liberalization is not sufficient to reestablish the original gains, which would point to sustained and permanent damages from the protectionist reversal.

To account for phase-in and phase-out periods of trade agreements, I also incorporate lagged terms of each variable.

The final estimating equation is :

$$
\begin{aligned}
X_{ij,t} = exp(&\eta_{i,t} + \psi_{j,t} + \gamma_{ij} + \beta_1 \text{Agr}_{ij,t} + \beta_2 \text{Agr}_{ij,t} \times \text{Pre-Exit}_{ij,t} \\
&+ \beta_3 \text{Exit}_{ij,t} + \beta_4 \text{Agr}_{ij,t} \times \text{Reentered}_{ij,t} + \gamma_1 \text{Agr}_{ij,t-l} \\
&+ \gamma_2 \text{Agr}_{ij,t-l} \times \text{Pre-Exit}_{ij,t-l} + \gamma_3 \text{Exit}_{ij,t-l} \\
&+ \gamma_4 \text{Agr}_{ij,t-l} \times \text{Reentered}_{ij,t}) + \varepsilon_{ij,t}
\end{aligned} \tag{II.6}
$$

2.3.2 Hypotheses

Table 2.5 summarizes the possible cases of symmetry using notation from equation (2.6), in the limiting case where $l = 0$.

Table 2.5: Symmetry cases

	Coefficients		
Scenario	$\beta_1 + \beta_2$	β_3	β_4
"Positive" Asymmetry	$+$	$-$	$> \beta_2$
Perfect Symmetry	$+$	0	$\approx \beta_2$
"Negative" Asymmetry (liberalization shocks dominate)	$+$	$+$	$< \beta_2$

$\beta_1 + \beta_2$ is expected to assumed to take on positive values

Under this specification, if shocks to trade regimes are *symmetric*, we would expect the gains materialized over the period of the agreement ($\beta_1 + \beta_2 > 0$) to disappear following an exit ($\beta_3 = 0$), whereas, assuming identical scope across initial and renegotiated agreements, reentry should restore trade to volumes close to those observed under the original agreement ($\beta_1 + \beta_4 = \beta_1 + \beta_2$).

There are two possible cases of asymmetry. In the first one, liberalization policies dominate protectionist ones. Under this scenario gains from liberalization are persistent, meaning that exit does not completely reverse the gains, and that after dismantling the agreements, pair's trading volumes remain above baseline. Additionally, under this scenario, reentry would not only restore the full gains but further build on them. I refer to this case as "positive" asymmetry. A scenario where exits generate losses beyond a return to baseline, and where reentry does not suffice to restore gains is also a case of asymmetry, with protectionist policies dominating liberalization. I refer to this scenario as "negative" asymmetry.

This terminology choice is not normative. Rather, it describes the net effect of the sequence of liberalization and protectionist policies. In the first case, the net trade effect of the removal and subsequent restoration of barriers to trade is positive. In the second case, the restoration of barriers to trade causes more damage than the erasure of the liberalization gains, which results in a net negative impact on trade volumes.

What factors would drive each of these theoretical scenarios?

Half of the treated pairs are members of the WTO at the time of exit. This implies that following exit, tariffs are restored to their *most favored nation* levels, thus eroding the targeted comparative advantage that was extended to the partner country. Some non-tariff barriers can also be restored, as the end of a trade regime can facilitate regulatory divergence among the pair of countries. All else being equal, exiting an agreement should return flows to their no-agreement baseline, leading to symmetry in the impact on the trade volume of entry and exit from agreements.

This channel ignores the possible persistence of trade gains. The direct impact of trade agreements might be tariff reductions, which are reversed upon exit. But much of the progress achieved under an agreement might not be immediately reversed. Improved knowledge of the partner's market, new relations between suppliers and importers, and value chain connections between the pair are likely to outlast the immediate return to pre-agreement tariffs. If the contribution of these factors to trade creation is large enough, we should expect to see some persistence that would support "positive" asymmetry, ie. a case where an exit keeps trade flows above baseline."Positive"asymmetry is a hypothesis that matches our knowledge of gains from trade and liberalization. Indeed, the literature demonstrates that liberalization causes significant reallocations and changes to market structures, which are likely to resist to a protectionist policy of similar magnitude. Industry-wide and within firm productivity gains (Pavcnik (2002)) as well as changing competitive pressures and exit dynamics (Melitz (2003)), durably alter the production base. Sticky investment decisions generated by liberalization, such as FDI and vertical integration, might not be entirely reversed by protectionism. Additionally, trade agreements introduce significant regulatory overhauls (Rodrik (2018)). The undoing of the regulatory convergence created by a protectionist policy might not result in straightforward divergence if the transition costs for firms have already been incurred and market access benefits already achieved.

Conversely, a less intuitive hypothesis is that trade liberalization policies might be *negatively asymmetric*. Targeted trade liberalization increases flows by giving the targeted partner a competitive edge. From the gravity equation (2.1) we know that the import volume of country i from country j is increasing in quality and decreasing in price and trade costs. The diversion potential of trade agreements is well documented in the literature (Dai et al. (2014)). An upgrade of the trade regime will therefore increase trade at the expense of partners who produce at better quality and equal cost. This distortion might be entirely reversed when the price-competition advantage is removed. Could this effect be as large as to depress trade volumes below baseline? Trade agreements also confer other benefits on partners, including credibility, signaling and insurance (Fernández and Portes (1998)). It is possible that the perceived uncertainty caused by the policy reversals hinder credibility and reliability and lead market participants to divest from the affected trade relationship.

A similar logic applies to reentries into exited agreements. In the symmetric case, the coefficient on the reentry dummy should be equal in magnitude and significance to the coefficient on the original agreements. However, if repeated changes in trade regimes increase the perception of uncertainty by economic agents, the elasticity of their decisions to liberalize might be lower, leading to "negative" asymmetry. If, on the other hand, reentry builds on the remaining network and supply chain gains from the previous agreement, the differential impact of reentry might exceed that of the original agreement, translating into "positive" asymmetry.

2.3.3 Results

I estimate specification (5) using OLS and Poisson Pseudo-Maximum Likelihood (PPML). OLS forces us to log linearize the estimating equation, with the obvious shortfall of information loss due to 0 flows being discarded. PPML, originally proposed by Silva and Tenreyro (2006) and Santos Silva and Tenreyro (2011) and since adopted in gravity equation estimations, allows us to estimate the exponential version of the estimating equation. PPML does not require that the dependent variable be Poisson-distributed, but only that the model be correctly specified. It is well behaved in a wide range of situations and is resilient to the presence of many zeros in the dataset. For these reasons, PPML is my preferred estimation throughout this paper.

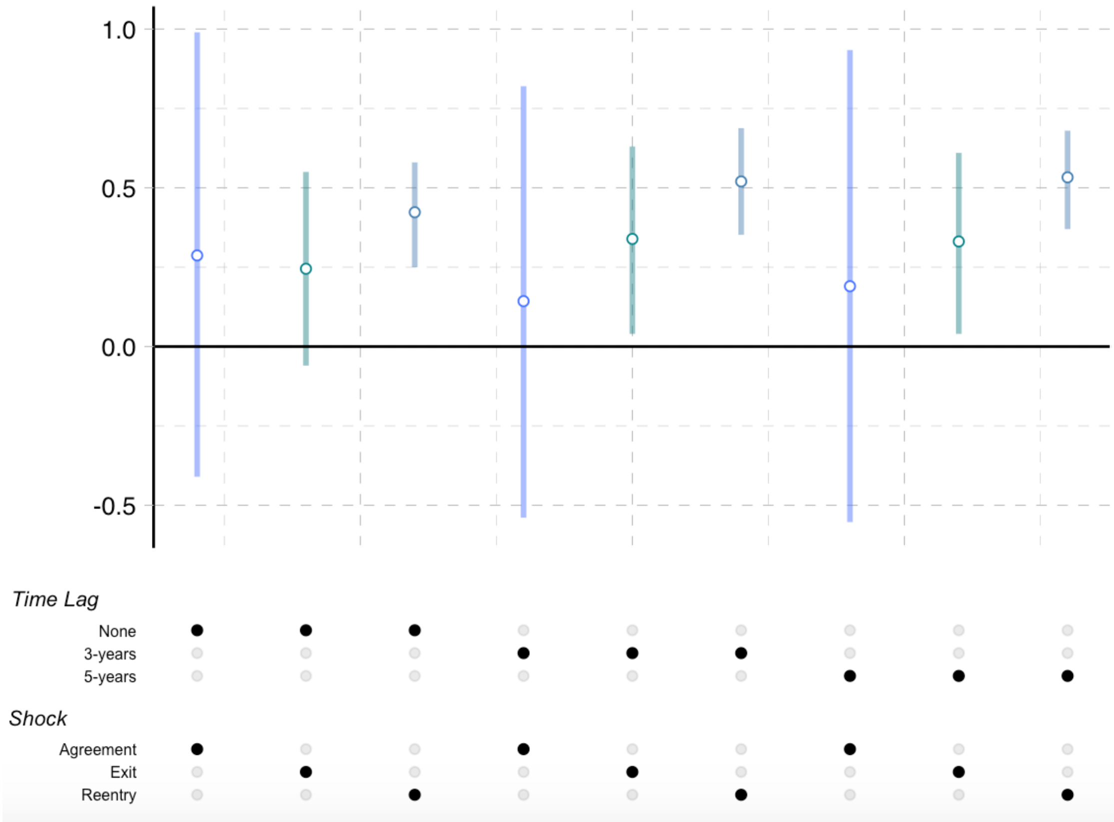
Tables 2.6-2.7 present the results of the estimation, and figure 2.4 visualizes the results when the equation is estimated using PPML. The blue lines represent the 95% confidence interval around the point estimate of the trade flow's response to the initial liberalization policy ($\beta_1+\beta_2$). The green light gives the same confidence interval for the response to the exit (β_3). And the turquoise line shows the cumulative response to reentry ($\beta_1+\beta_4$). The model is multi-way clustered along importer, exporter, and year to account for standard error correlation between groups. This method of clustering controls for correlation in the error term within 6 clusters i, j, t, ij, it, jt. This is the most conservative approach to clustering and will support me in making the most conservative inference (Larch et al. 2017). Results are given at three different lags : 0, 3 and 5.

Table 2.6: Pooled Estimation of Exit Symmetry

	OLS			PPML		
	(1)	(2)	(3)	(4)	(5)	(6)
	log(flow)	log(flow)	log(flow)	flow	flow	flow
$(Agreement)_t$	0.209**	0.143*	0.184*	0.218***	0.154**	0.189**
	(0.0716)	(0.0697)	(0.0714)	(0.0646)	(0.0580)	(0.0627)
$(Agreement \times Pre-Exit)_t$		0.0815	0.0389	0.0695	-0.126	0.0329
		(0.289)	(0.265)	(0.366)	(0.361)	(0.333)
$Exit$	0.114	0.116	0.0553	0.246	-0.426	-0.00342
	(0.148)	(0.307)	(0.292)	(0.156)	(0.297)	(0.178)
$(Agreement \times Reentred)_t$	0.402	0.0738	0.0293	0.205***	-0.445	-0.0881
	(0.336)	(0.423)	(0.438)	(0.0564)	(0.301)	(0.173)
$Agreement_{t-3}$		0.120			0.128***	
		(0.0797)			(0.0379)	
$(Agreement \times Pre-Exit)_{t-3}$		-0.0543			-0.0134	
		(0.172)			(0.332)	
$Exit_{t-3}$		0.0765			0.765*	
		(0.203)			(0.325)	
$(Agreement \times Reentered)_{t-3}$		0.521			0.682*	
		(0.269)			(0.298)	
$Agreement_{t-5}$			0.0909			0.0996*
			(0.0811)			(0.0503)
$(Agreement \times Pre-Exit)_{t-5}$			0.00914			-0.132
			(0.128)			(0.265)
$Exit_{t-5}$			0.216			0.335
			(0.190)			(0.215)
$(Agreement \times Reentered)_{t-5}$			0.692**			0.333*
			(0.244)			(0.158)
Constant	15.67***	15.65***	15.65***			
	(0.0223)	(0.0275)	(0.0290)			
Observations	80121	80121	80121	103600	103600	103600

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Reference group is country pairs not currently or previously bound by a trade agreement. All regressions include exporter-time, importer-time, and pair fixed effects. Fixed-effects results not reported. Standard errors (in parentheses) are multi-way clustered at importer, exporter, and year

Figure 2.4: PPML Estimation of Gravity Equation: Exit Effects



Estimates and confidence intervals of shock responses from equation (5)

Table 2.7: Joint significance test of cumulative effects

	OLS		PPML	
	Lag = 3	Lag = 5	Lag = 3	Lag = 5
***Agreements* Impact Pre-exit**				
Joint significance Test P-value	0.143	0.092	0.681	0.616
***Exit* Impact**				
Joint significance Test P-value	0.556	0.419	0.022	0.024
***Reentry* Impact**				
Joint significance Test P-value	0.109	0.071	0.000	0.000

P-values for chi-square joint-significance tests

In figure 2.4, we see some weak signs of **"positive" directional asymmetry**. Initial liberalization policies appear to have a positive but statistically insignificant impact on trade flows. A pair that exits an agreement maintains a trade volume that is statistically greater than the baseline. A subsequent liberalization policy has a larger positive impact than the initial one, on average. This can be interpreted as country-pairs retaining some of the gains from liberalization, beyond the enforcement period of the agreement.

The robust takeaway from figure 2.4 is, however, that trade policy symmetry is a hypothesis that cannot be rejected at the 95% confidence level. Indeed, at that level, the repeated policy shocks have statistically indistinguishable impacts on trade flows, regardless of their direction.

2.4 Robustness & Heterogeneity analysis

The results presented in figure 2.4 can hide significant heterogeneity along many dimensions. The exit variable does not discriminate between downgrades and complete exits, it does not distinguish between different magnitudes of trade liberalization reversals: an exit from an FTA signifies a larger reversal than the expiration of an asymmetric trade agreement. The depth of the exited agreement therefore matters, as well as its length. Longer agreements, upon dismantlement, could have longer lasting effects - and therefore, lead to less detrimental exits. These and other margins of heterogeneity are explored in this section.

2.4.1 Strict Exogeneity

To confirm that there are no anticipatory effects or phase out effects that pollute the causal estimates in previous regressions, I run one more regression using the fixed-effects specification. Baier and Bergstrand (2007) suggests that it is easy to test for the "strict exogeneity" of agreements. To do this, I add a lead variable of treatment (entry/exit/reentry) into the equation. Strict exogeneity would require that the coefficients associated with the lead regressors indexed $ij, t+1$ are small and statistically insignificant. Results in table 2.8 yield results that support the hypothesis of exogeneity of treatment to trade flows. Conditional on treatment, lead variables in all three columns are statistically indistinguishable from 0. The anticipation effects of exited agreements are similar to those of surviving agreements, both directionally and statistically. The signs suggest that, if anything, firms temporarily delay imports -rather than increase them- ahead of a new agreement, as found in Baier and Bergstrand (2007). They also temporarily - though not significantly - increase imports ahead of an exit.

2.4.2 Agreement Depth

Do deep trade policies have different symmetry properties than the less comprehensive ones?

To evaluate this proposition I estimate equation (2.6), for two groups separately : pairs who experience reversals relating to comprehensive agreements such as FTAs or custom unions, and pairs who experience smaller reversals to preferential trade agreements only. Preferential trade agreements are usually unilateral discriminatory trade preferences. Most PTAs are extended under North-South development programs, such as the Generalized System of Preferences (GPS), the US's African Growth and Opportunity Act. PTAs can be reciprocal. In this case, they are distinguishable from FTAs in that they do not aim to eliminate trade barriers - but merely lower them. Figures 2.5 and 2.6 visualise the results of these estimations.

Deep trade policy decisions show stronger signs of "positive" asymmetry. The liberalization shocks have a large and significant impact on trade flows, and these gains persist, and continue to grow beyond the negative exit effect. Reentries appear to be somewhat symmetric to initial liberalization policy. PTAs present weak evidence of "positive" directional asymmetry. In both cases, however, and similarly to the baseline analysis, the

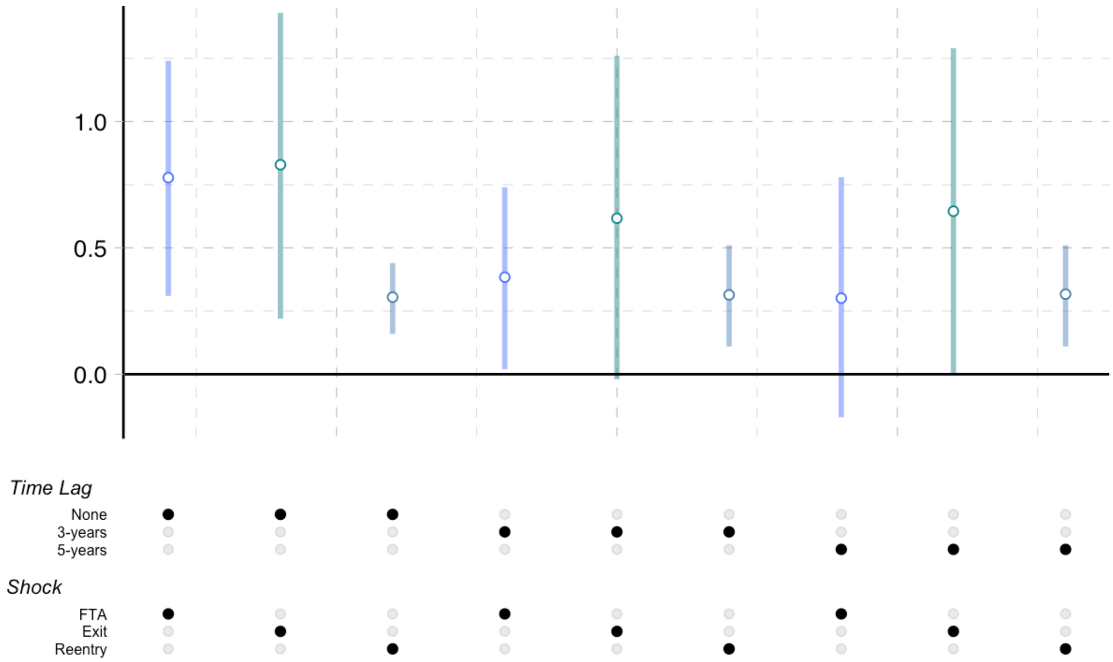
Table 2.8: Panel Gravity Equation with Lead Treatment Variables

	(1) log(flow)	(2) log(flow)	(3) log(flow)
$(Agreement)_t$	0.249**	0.214*	0.211*
	(0.0849)	(0.0839)	(0.0845)
$(Agreement)_{t+1}$	-0.0164	0.000680	-0.00420
	(0.0783)	(0.0833)	(0.0800)
$(AgreementxPre-Exit)_t$	0.0173	-0.117	-0.0270
	(0.207)	(0.244)	(0.314)
$(AgreementxPre-Exit)_{t+1}$	-0.239	-0.211	0.0318
	(0.219)	(0.230)	(0.290)
$(Exit)_t$		-0.260	-0.158
		(0.148)	(0.397)
$(Exit)_{t+1}$		0.0808	0.336
		(0.140)	(0.429)
$(AgreementxReentered)_t$			0.167
			(0.545)
$(AgreementxReentered)_{t+1}$			0.294
			(0.479)
Constant	15.67***	15.68***	15.66***
	(0.0207)	(0.0224)	(0.0273)
Observations	80121	80121	80121

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 2.5: PPML Estimation of Gravity Equation: FTA Exit Effects



Trade flow response to deep liberalization shocks, proxied by FTAs

hypothesis of trade policy symmetry cannot be rejected at the 95% confidence level.

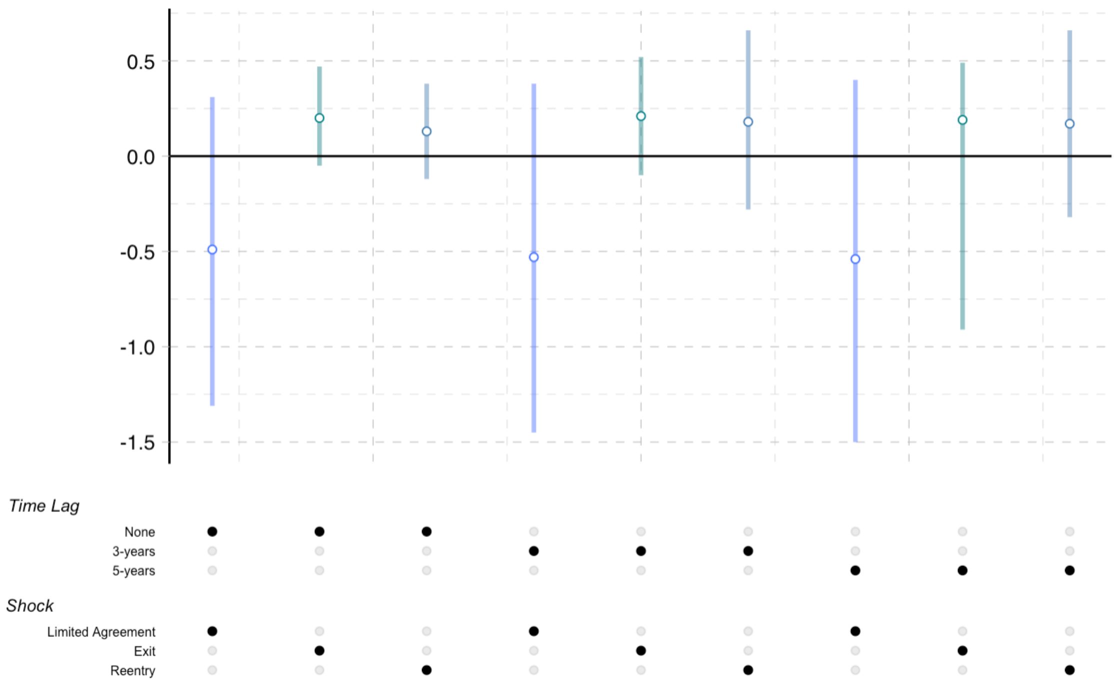
2.4.3 Geographic and political contexts

To account for geographic disparities, I perform three exercises.

The Common European Market offers an appealing case study. Upon joining the common market, a new member must align its trade policy with the bloc. This creates a series of agreement exits that fall within the purview of this study. There are 16 such cases comprising the 2004 and 2007 Common Market expansion to Central and Eastern European Countries (PECO). For instance, upon entering the European Union in 2004, Estonia left a free-trade agreement with Ukraine that had been enforced since 1998.

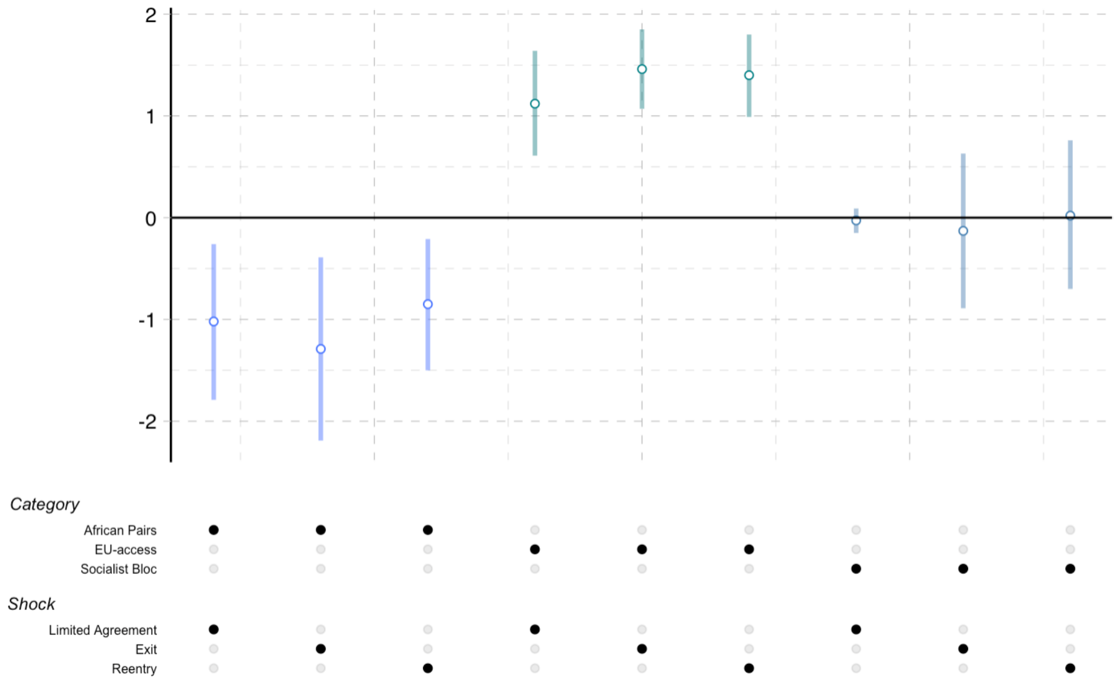
I also slice the data sample to focus on African trade. African trade is documented to be less responsive to liberalization policy shocks. The African continent is divided into 6 different trading blocs with different levels of trade liberalization and barrier removal. Some of these areas, mainly the South African Development Community (SADC) and the Economic Community of West African States (ECOWAS) have experienced a set of member exits and suspensions, mostly, due to political reasons. The regional economic

Figure 2.6: PPML Estimation of Gravity Equation: PTA Exit Effects



Trade flow response to weak liberalization shocks, proxied by PTAs. See appendix Table A.2

Figure 2.7: PPML Estimation of Gravity Equation: Exit Effects by Geography



Trade flow response to liberalization shocks in different contexts.

areas (REC) model of trade policies in Africa has failed to deliver growth in flows. In 2013, formal intra-Africa trade made up about 10% of total annual trade of each REC (Geda and Seid (2015)). Numerous studies confirm the disappointing performance of intra-regional trade within RECs (Geda and Kibret, 2008, Longo and Sekkat (2004) Yeats, 1999). This is generally attributed to export supply constraints that hamper trade development : weak infrastructure, productivity and trade facilitation. The applicability of the gravity model to African trade is therefore itself a point of contention (Foroutan and Pritchett (n.d.)).

Finally, I look at the trade policy reversals that surrounded the collapse of the Soviet Union. Several socialist countries were bound by preferential trade agreements, many of which were dismantled in a large wave of exits in or around 1991.

The results for all three contexts are presented in figure 2.7. The behavior of African trade flows in response to liberalization shocks is unusual but not surprising in light of the above mentioned literature. The statistical insignificance of policy liberalization shocks between members of the Socialist Bloc is also commensurate with the particular structure of their economies. Once again, there are signs of “positive” asymmetry among European countries and their partners. Still, the hypothesis of perfect trade policy symmetry cannot be ruled out.

2.5 Conclusion

This paper evaluates the cost of reversals in trade policy. It investigates whether the trade response to liberalization and protectionist policies is symmetric. Evaluating the symmetry of trade policy is important in the context of economic retrenchment and resurgent protectionism after what had seemed like an irreversible march towards increased liberalization. Using an exhaustive sample of agreement exits between 1986-2016, I find weak evidence of "positive" asymmetry in the impact of liberalization: leaving an agreement with no immediate replacement - and reintroducing trade barriers - does not appear to obliterate all liberalization gains, and trade between the treated pairs can remain significantly above baseline. Furthermore, after a period of exit, a reentry can also be positively asymmetrical and exceed the gains from the initial liberalization shock.

The weak evidence of "positive" asymmetry does not preclude the hypothesis of perfect policy symmetry. At the 95% confidence level, the size of the response of trade flows to liberalization policies is statistically indistinguishable from their response to protectionist policies. This paper looked at different geographical and economic contexts and analyzed the role of agreement depth in determining symmetry outcomes. In all considered cases, the hypothesis of perfect policy symmetry was not rejected.

The issue of policy symmetry deserves increased attention. While widely hailed amongst economists, trade policy liberalization has become a polarizing theme in political discourse. In this context, policy reversals are likely to materialize frequently. I see three possible extensions to this research agenda. This paper reveals significant heterogeneity in treatment effects. Baier et al. (2018) developed an approach for estimating the trade impact of FTAs heterogeneously and obtaining individual estimates by agreement, pair, and direction. Applying this framework to evaluating exit impacts would elicit more specific - if less precise - estimates. A second empirical extension is to narrow the focus on tariff policies. A large part of the liberalization reversals that we observed in recent years centered around tariff increases. Estimating tariff elasticities of trade on the way up and down can shed further light on tariff policy symmetry specifically. Finally, to enrich the theoretical framework that lacks the question at hand, the findings elicited in this paper can be integrated into a gravity model of a trade by adjusting the trade cost parameters to reflect the persistence and dynamics suggested by this study and move away from the symmetric elasticity generally imposed on trade costs.

Chapter III

Perception of Trade Policy Uncertainty and Stock Market Volatility : New Measures

3.1 Introduction

Does trade policy uncertainty increase volatility in financial markets? Affirmative answers to this question pervaded stock market news coverage in 2018-2019 [1]. In the context of rising trade and geostrategic tensions, the financial news sources widely accredited trade policy for increasing market volatility, pointing out both policy actions and the perceived uncertainty surrounding them as potential causality channels. In this paper, I investigate this hypothesis by quantifying the contribution of trade policy uncertainty (TPU) to excess financial volatility. I examine this relationship using a novel measure of TPU that addresses concerns with prevalent news-based measures, and employ these existing measures for robustness checks.

That trade policy could contribute to stock market volatility is a reasonable hypothesis. Rational asset-pricing theory conceives of stock prices as the discounted value of the stream of future dividends. Therefore, changes to the expectations of future returns or the discount parameters will translate into larger variations that add to excess volatility.

[1] Example headlines include: ”Lagarde Expects More Market Volatility With Trade Trouble” (Bloomberg, 10/13/2018), ”Volatility Erupts Everywhere as Trade War Becomes a Currency War” (Bloomberg, 8/6/2019), ”Dow Plunges 760 points in worst day of 2019 as trade war intensifies” (CNBC, 8/4/2019), ”Markets close lower, hit by earnings and trade war uncertainty” (Los Angeles Times, 5/22/2019), ”How the trade war became the stock market’s biggest driver” (MarketWatch, 9/9/2019), ”US-China trade tensions lead to volatile markets” (Marketplace, 6/19/2018)

In this context, news, including trade policy news, can drive volatility. A news-based equity volatility tracker proposed by Baker et al. (2019b) shows that the share of trade-policy-related articles has increased from just over 2% in 1985 to 26% in 2015. Less clear is the impact of the uncertainty that the public perceives when internalizing trade policy trajectories. This paper bridges this gap in the literature by providing a timely analysis of the impact of TPU on stock market volatility from 2015 to 2021.

Improving our understanding of TPU and its impacts is imperative. The predictability of U.S. trade policy has weakened over the past few years. This reduced predictability came from the Trump administration's willingness to deviate from the World Trade Organization's (WTO) multilateral rules to pursue its own policy goals on trade relations with China and other partners. This widening trade policy space continues under the Biden administration, which has endorsed an active industrial policy. In this context, the weakening commitment to the multilateral trade system coupled with the WTO's inability to enforce its own rules, as its dispute resolution mechanisms grind to a halt, opens the economy to new and repeated TPU shocks. Measuring the size of these shocks, and their impact on sectors of the economy has therefore become a new focus of the trade literature (Caldara et al. (2020b), Liu et al. (n.d.), Steinberg (2019), Feng et al. (2017), Handley and Limao (2017), Handley and Limão (2015b)). This paper gives the most extensive account to date on the impact of TPU on stock price volatility, distinguishing short- and long-run dynamics as well as industry heterogeneity.

The market volatility / economic policy uncertainty nexus carries renewed importance in this context. To the extent that policy uncertainty is a byproduct of a unilateral trade policy agenda and that uncertainty in policymaking is undesirable for investors, a trade-off between the unilateral pursuit of trade policy goals and the stability of financial markets might arise. The bull market has dominated U.S. equities since the end of the Great Recession. It has come to be perceived as an indicator of the state of the economy, therefore, creating incentives for policymakers to protect the bull market against transitory volatility and reversals. Attention to market volatility also has economic motivations, given its role in asset-pricing and investment behaviors. Volatility shocks change the compensations that shareholders require for bearing systematic risk (Guo (2002)), which in turn impacts the cost of equity capital. Through its implications for investors and publicly traded firms, volatility can spill over to the real economy. Campbell et al. (2001) shows that stock market volatility leads volatility in other economic indicators and has significant predictive power for real GDP growth. Further, and precisely because it leads volatility in other economic series, volatility can be an early sign of financially induced recessions (Chauvet et al. (2015)).

This paper employs time-series methods to measure the impact of TPU shocks on volatility and looks both at in-sample causality and out-sample forecasting gains. In addition to overall market volatility, I look at the volatility of specific portfolios with varying degrees of exposure to international trade. I also allow for heterogeneity in the outcome variable by distinguishing transitory and persistent components of volatility.

Two contributions stand out. First, the methodological approach delivers a new measure of TPU perceptions, which combines social network data and institutional signals. It displays desired properties of consistency with known shocks and improves upon existing news-based measures. It can be replicated and used for future research. Second, the analysis delivers a new result that negates the causal effect of TPU on market volatility. I find that TPU shocks do not create excess volatility, meaning that investors do not respond systematically to trade policy uncertainty shocks. This result contrasts with the finding in the literature that uses news-based measures to identify the volatility impact of broad economic policy uncertainty (e.g. Brogaard and Detzel (2015), Phan et al. (2018), Liu and Zhang (2015)). I argue that this discrepancy emphasizes the unique character of trade as a component of policy uncertainty and reflects methodological differences in proxying for uncertainty.

The rest of the paper is structured as follows—section 1 reviews both the literature on trade policy uncertainty and stock market volatility. Section 2 describes data construction methods and a new approach to measuring public perceptions of trade policy uncertainty. Section 3 elicits causal relationships between market volatility and TPU using in and out-of-sample analyses and discusses the results.

3.2 Background

3.2.1 Literature on Trade Policy Uncertainty

Economists distinguish notions of risk from volatility (Knight (1921)). An agent facing risks can assign probabilities to different outcomes and optimize based on the resulting expectations. Uncertainty results in a failure of the probabilistic approach: the probabilities are unknown, or the outcome space itself is not known (Bloom (2014)).

In the context of policy, uncertainty is often used to refer to a mix of risk and uncertainty proper. Economic policy uncertainty is an umbrella term covering uncertainty in all policy fields: fiscal, monetary, regulatory, and otherwise. The contribution of policy to agents' perception of economic uncertainty is a corollary of the increasing role of governments in the economy. To the extent that they engage in decision-making that relies on expectational optimization, economic agents bear the costs of economic policy uncertainty. Increased uncertainty means that assigned probabilities are more likely to be erroneous or incomplete, leading to optimization mistakes and economic and welfare losses. Using firm-level data, Baker et al. (2016b) find that economic policy uncertainty is associated with greater stock price volatility and reduced investment and employment in policy-sensitive sectors like defense, healthcare, finance, and infrastructure construction.

Earlier research of trade policy uncertainty was theoretical. Handley and Limão (2015b) theoretically model export market entry in the context of policy uncertainty. The policy variable is the tariff level imposed by the foreign market, the policy space is comprised of three different scenarios, and the switching probabilities follow an exogenous stochastic process. Firms optimize entry decisions using beliefs about switching probabilities. Unsurprisingly, the model predicts that entry is a decreasing function of switching probabilities when tariffs are below their maximum level. The model is tested empirically using Portuguese-Spanish trade in the wake of the countries' accession to the European Community. The evidence suggests that when uncertainty subsides following a trade agreement, industries with higher potential profit loss in the worst-case scenario see the most entries.

The early empirical studies of the impacts of TPU use policy events as a proxy for time-variation in uncertainty. One such event is the US-China trade relation prior to the latter's WTO accession. Starting in 1980, the United States extended MFN treatment to China. This decision was conditional on yearly Congressional renewal, which created a recurrent uncertainty shock every time the regime came up for a vote. Alessandria et al. (2019) use these moments of increased uncertainty to examine trade response to uncertainty shocks. The results suggest that trade increases in anticipation of uncertain future increases in tariffs. These recurrent positive TPU shocks resolved in 2000 when China received permanent MFN status as a WTO member. The resolution of the uncertainty was associated with simultaneous entries and exits into export markets, favoring more competitive firms (Feng et al. (2017)), and delivered higher growth to the industries that had higher initial potential losses from uncertainty (Handley and Limao (2017)).

Brexit has also served as an experiment to study the impact of TPU. Steinberg (2019) builds a three-country heterogeneous firm model using an input-output production structure, and where uncertainty about trade costs impacts the firm's export entry decision. Uncertainty is captured through a stochastic process for trade costs. The model is calibrated to match a pre-Brexit I-O Table. The predicted post-Brexit equilibrium indeed delivers a significant welfare loss; however, uncertainty's contribution to the loss is marginal and accounts for less than a quarter of a percent of the overall welfare cost. In sum, uncertainty in trade policymaking appears to impact the real economy negatively, mainly through its impact on firms that participate in international trade.

Recently, the literature focused on developing empirical measures of TPU to study its impact. This approach promises several advantages. The use of proxies in theoretical and empirical studies focuses heavily on tariff-related uncertainty, consequently downplaying other components of trade policy such as non-trade barriers. A direct empirical measure can be more comprehensive in scope if it does not target a single aspect of TPU. Further, directly measuring TPU is the first step towards studying its short and long-term time-series dynamics and making more general statements about its impacts that are not constricted to specific case studies. Finally, tractable time-variant indices can capture the public perception of uncertainty and the ensuing implications of this perception for agents' behaviors and market outcomes, which is the intent of this paper.

Two attempts at building such empirical measures of TPU stand out. Following their previously referenced 2016 seminal paper on economic policy uncertainty (EPU) measurements, Baker, Bloom, and Davis have developed corollary break-downs of EPU components as part of their Economic Policy Uncertainty project. Their approach to identifying the trade component of EPU relies on frequency counts of uncertainty-related news articles. They select articles from a panel of 10 leading newspapers based on the occurrence of uncertainty terms. Caldara et al. (2020b) introduces a similar news-based index, with a variation in the selection of key terms, and also adds two new indices: a firm-specific index using word counts from earnings call transcripts and a tariff-volatility measure of TPU. The authors favor the news-based measure as an index of aggregate trade policy uncertainty. Accordingly, variations of the news-based measures of TPU are the most common empirical indices currently available to and employed by researchers. Olasehinde-Williams (n.d.) uses the trade component of Baker et al. (2016b)'s EPU to evaluate the ability of U.S. trade policy uncertainty to predict global output volatility. Ongan and Gocer (2020) also uses the news-based index to analyze the role of uncertainty in US-China trade balances.

Though they align well with general events of U.S. trade policy history, the news-based measures currently used in the literature present some shortcomings. Perhaps the most important is the conflation of realized volatility and future uncertainty. Realized volatility relates to the size of realized policy shocks, such as a change in tariff. On the other hand, future uncertainty is about the size of future shocks as expected by agents. The ability to distinguish the two forms of shocks is important to the extent that recent literature reveals that responses of macroeconomic variables - and possibly financial variables - to the two classes of shocks can be very different. **?** shows that while financial outcomes are sensitive to volatility shocks, they do not respond to uncertainty. In their assessment of their own measures, Caldara et al. (2020b) point out that their tariff volatility measure requires changes in tariff rates to signal changes in tariff uncertainty – making it unresponsive to negotiations and proposals. They also indicate that the news-based measure picks up high tariff volatility episodes as uncertainty shocks. Additionally, a high coincidence between the index and the timeline of known policy actions can be a source of concern. A news-based measure that mostly picks up policy breaks is more likely to measure policy volatility, which, while a contributing factor to uncertainty, is only a functional input and not a sufficient statistic. Finally, newspaper coverage might not exactly coincide with market participants' perceptions.

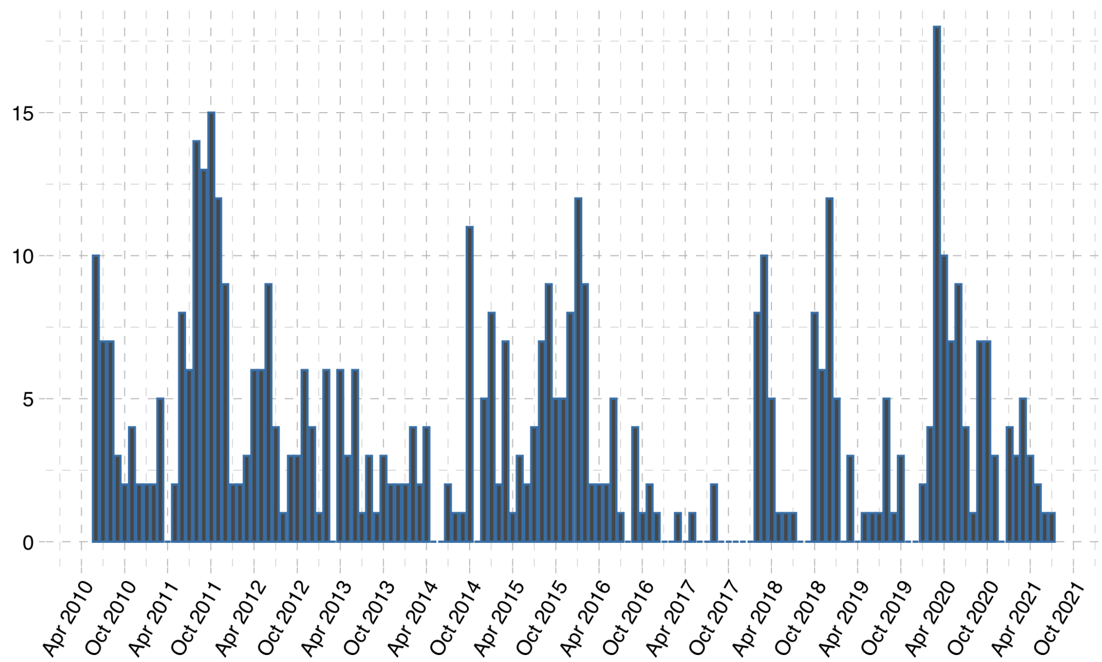
In this paper, I develop a novel trade policy uncertainty index that aims to precisely replicate public perceptions of uncertainty and anticipation surrounding trade policy rather than the actual policy breaks and ex-post responses. To do this, I employ two different types of datasets: a social-media-based dataset consisting of tweets and twitter-based interactions over policy uncertainty content and institutional data comprising the USTR's published notices and calls for comments. Section II discusses data strategy, including the methodology for constructing the proposed TPU index.

3.2.2 Market Volatility: Stylized Facts

The subject of stock market volatility continues to receive ample attention in economics. Schwert (1989)'s seminal paper revealed a 'volatility puzzle.' The author observes that macroeconomic fundamentals and other economic variables cannot explain the time variation in stock volatility between 1857 and 1987. Attempts at resolving this puzzle have sought to identify causalities by introducing new variables or applying new methods (Christiansen et al. (2012), Choudhry et al. (2016), Asgharian et al. (2013), Chiu et al. (2018)). Another equally prolific strand of the literature is methodological in nature and aims to improve volatility forecasting by introducing new models (see Poon and Granger (2003) for review). A precise forecasting model and a comprehensive list of determinants continue to be elusive.

This broad attention to market volatility from economists has several justifications. When market participants are risk-averse, volatility plays a role in asset-pricing and investment behaviors. Volatility shocks change the compensations that shareholders require for bearing systematic risk (Guo (2002)), which in turn impacts the cost of equity capital. Through its implications for investors and publicly traded firms, volatility can spill over to the real economy. Campbell et al. (2001) shows that stock market volatility leads volatility in other economic indicators and has significant predictive power for real GDP growth. Further, and precisely because it leads volatility in other economic series, volatility can be an early sign of financially induced recessions (Chauvet et al. (2015)).

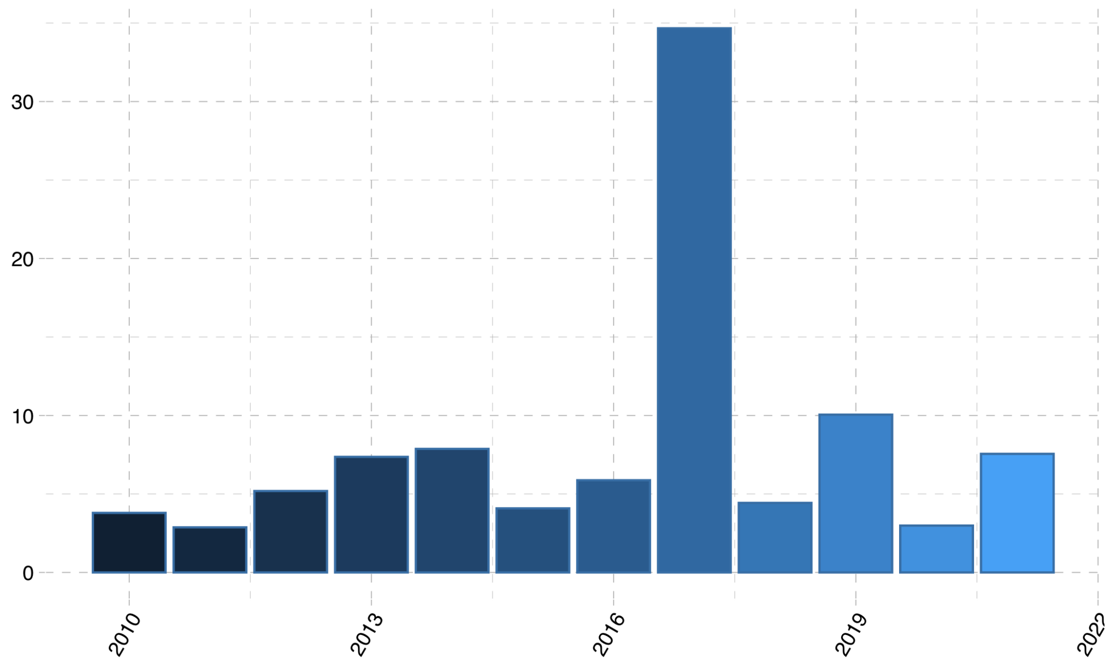
Figure 3.1: Number of High Return Sessions Per Month



High return session defined as trading days with a +/- 1% S&P500 close.

Figures 1-2 show recent trends in market volatility. Figure 3.1 displays the number of high session days, defined as days with returns larger than $\pm 1\%$, per month. 2020 stands out as a high volatility year, with March consisting almost exclusively of high return sessions. Before the pandemic, 2018 saw a significant increase in volatility after a two-year retreat. Compared to 2016 and 2017, the number of high return sessions was significantly up. Figure 3.2 also shows that 2018 was marked by rapid successions of high return days. The financial press interpreted the rise in volatility as a consequence of the anti-globalist pivot of U.S. trade policy and the implied uncertainty surrounding the U.S. and world economic trends. However, this hypothesis has not been analyzed by the academic literature, a gap that this paper tries to fill. The following section describes the construction of market volatility and trade policy uncertainty measures, later used in analyzing the causal claim.

Figure 3.2: Average Number of Days Between Two High Return Sessions



High return session defined as trading days with a +/- 1% S&P500 close.

3.3 Data and measurements

3.3.1 Modelling financial volatility

I am interested in evaluating the impact of TPU on the persistent and transitory components of stock market volatility. In constructing the outcome variables, I follow the cyclical volatility model proposed by Harris et al. (2011) and outlined in Chiu et al. (2018) paper on investor sentiment and financial market volatility. In this model, the natural logarithm of the asset price at time s follows a continuous-time diffusion given by :

$$dp(s) = \sigma^2(s)dW(s) \tag{III.1}$$

Where $dW(s)$ is the increment of a Wiener process and $\sigma^2(s)$ is the instantaneous variance, which is strictly stationary and independent of $dW(s)$.

Conditional on the sample path of $\sigma^2(s)$, the logarithmic return is normally distributed with variance :

$$\sigma_t^2 = \int_{t_1}^{t} \sigma^2(s)ds \tag{III.2}$$

This framework assumes that the integrated standard deviation follows a two-factor dynamic structure of the form :

$$\begin{aligned} \sigma_t &= q_t + c_t, \\ c_t &= \alpha c_{t-1} + u_t \end{aligned}$$

where q_t is a long-run component, and c_t is a transitory component of volatility. Several papers in the finance literature corroborate this two factor approach to modelling volatility (Lee and Engle (1999), Alizadeh et al. (2002), Brandt and Jones (2006)).

For empirical implementation, I follow Chiu et al. (2018). I proxy daily standard deviation using daily returns defined as the logarithmic difference of close and open prices:

$$r_t = p_{close,t} - p_{open,t} \tag{III.3}$$

I then apply the Hodrick and Prescott one-sided low-pass filter to the daily standard deviation to estimate the daily transitory component of volatility. To avoid look-ahead bias, the filter is applied to a rolling window of 134 days. The filter's tuning parameter is set to $\lambda = 5,760,000$ which is the recommended value for data of daily frequency (Ravn and Uhlig (2002)). The resulting daily persistent component, and daily standard deviation are aggregated to a monthly measure as :

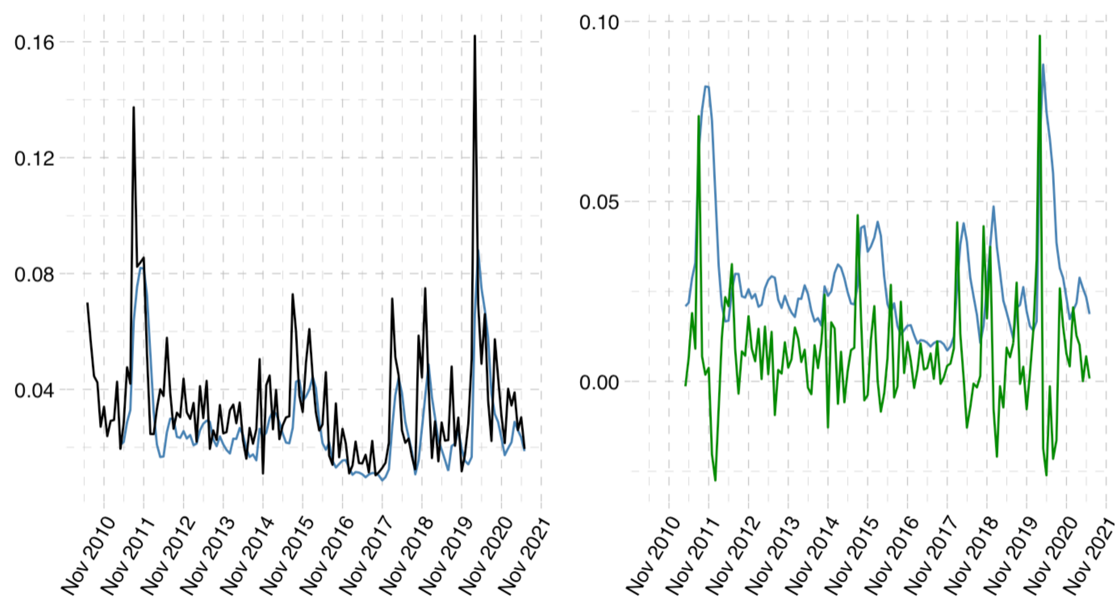
$$\begin{aligned} q_t &= \left(\sum_{i=1}^{N_t} q_{t_i}^2 \right)^{1/2} \\ \sigma_t &= \left(\sum_{i=1}^{N_t} r_{t_i}^2 \right)^{1/2} \end{aligned}$$

Finally, I calculate the transitory component of monthly volatility using the two factor definition of volatility:

$$c_t = \sigma_t - q_t \tag{III.4}$$

For the baseline estimation, I compute persistent and transitory volatility for the S&P500 index over the study period. The resulting volatility series for the S&P500 index are

Figure 3.3: Volatility Measures for the S&P500 Index



Left panel : Total monthly volatility (black) and persistent volatility (blue). Right panel : persistent (blue) and transitory (green) components of monthly volatility.

presented in figure 3.3.

3.3.2 A perception based measure of TPU: Twitter Component

I propose a composite measure of TPU that tracks perceptions and policy developments by combining two indicators. The first indicator measures the public's attention to trade policy and trade policy uncertainty, using Twitter data. A Twitter application programming interface (API) allows me to achieve better precision and explore richer data than news-based proxies. First, due to the limited character count, tweets are more concise statements than articles. Keyword searches can therefore lead to fewer misclassification of tweets as TPU-focused than of news articles. In other words, the joint appearance of uncertainty-related and trade-related keywords in a non-TPU related news article is more likely than in a non-TPU related tweet. Second, by using Twitter data, I can look beyond press coverage and further into the responsiveness of the wider public to trade policy news. Indeed, newspaper reporting on trade policy does inform public perception, but the relationship is mediated by the size, attention, and interaction of the readership. Newspaper-based indicators cannot capture these dimensions. Social media, due to their

Figure 3.4: Word Cloud: Word Frequency in Selected TPU Tweets

Based on a panel of 1543 trade policy uncertainty related tweets

network structure, allow us to measure reactions to TPU-content, specifically the size of the audience and the share of recipients who deem the message worth spreading or responding to.

How to convert tweets into data? In generating the Twitter-based TPU measure, I begin by constructing a panel of 12 news sources[2] and 15 economist commentators[3] with a significant presence on the social network platform. For the news sources, I pick the most circulated national newspapers and referential sources in the finance and economics spheres, such as Bloomberg and CNBC. I selected economists with large follower bases who are more likely to represent and influence general perceptions. I also seek to build a panel that is gender and background-balanced so as not to pick up the bias of a specific subset of economists. I survey the timelines of each of the accounts in the panel for trade

[2]The panel's 12 news sources are: Bloomberg, CNN, The Financial Times, The Washington Post, CNBC, Newsweek, The Boston Globe, The Wall Street Journal, The New York Times, The Los Angeles Times, USA Today, The Economist (US)

[3]The economist in the panel are: Dean Baker, Sandy Black, Leah Boustan, Beatrice Cherrier, Steeve Hanke, Seema Jayachandran, Paul Krugman, Dina Pomeranz, Dani Rodrik, Nouriel Roubini, Claudia Sahm, Betsey Stevenson, Joseph Stiglitz, Mark Thoma, Justin Wolfers

policy uncertainty content over the period extending from January 2015 to June 2021. For tweet selection, I use a similar approach to Caldara et al. (2020b) and Baker et al. (2014). To be selected into the panel, the tweet needs to contain one word each from a set of trade policy terms and a set of uncertainty words. The keywords are listed in Table 3.1.

Table 3.1: Tweet Selection keywords

Trade Policy	Uncertainty
Trade polic*	Uncertain*
Trade agreement*	Risk*
Trade deal*	Potential
Tariff*	Unclear
Import*	Likely
Export*	
Trade deficit*	
Dumping	

The asterisks indicate potential additional letters - mostly to account for plurals. Import and Export must appear in conjunction with additional policy words (polic*, tax*, quota*, fee*, limit*, restriction*, duty*, deal*, agreement*).

Using a Twitter API, I extract all trade-uncertainty-related tweets generated by the panel members throughout January 2015 to June 2021. The proposed index is a perception-based indicator that reflects the public's attention to TPU and how much they interact with trade uncertainty-related content. Let:

$i = 1...N$ indexes the tweets,
$j = 1, ..., K$ indexes users active in month t
$t = 1...T$, with $T = 65$ index the time.

I define the *amplification weighted-frequency* measure as :

$$AWF_t = \sum_{j=1}^{K} \frac{\sum_{i=1}^{N} Interactions_{ijt}}{followers_{jt}} \tag{III.5}$$

Interactions are defined as the sum of retweets, likes, replies, and quotes. The historical follower data is not available via Twitter API and was recovered using the Internet

Archive's Wayback Machine. The followers' data is missing in 9 tweet-month observations, and the associated tweets are dropped. This generates a slight loss of information. For this, and all other indices presented here, the series are standardized to unit-standard deviation and then normalized to have a mean of 100.

Notice that this index is a weighted sum of published TPU tweets, where the associated weights are the number of received interactions (normalized by follower base). Each one of these interactions in itself amplifies the original message: retweets expand the readership base, likes indicate the number of people who align themselves with the message, and replies measure the number of readers who engage with the content favorably or unfavorably. Together, they indicate the contemporary relevance of the tweet and determine the size of the audience it will reach, thus propagating the uncertainty message. For normalization purposes and to give a notion of scale, the total number of reactions is divided by the total number of followers at the end of the given month.

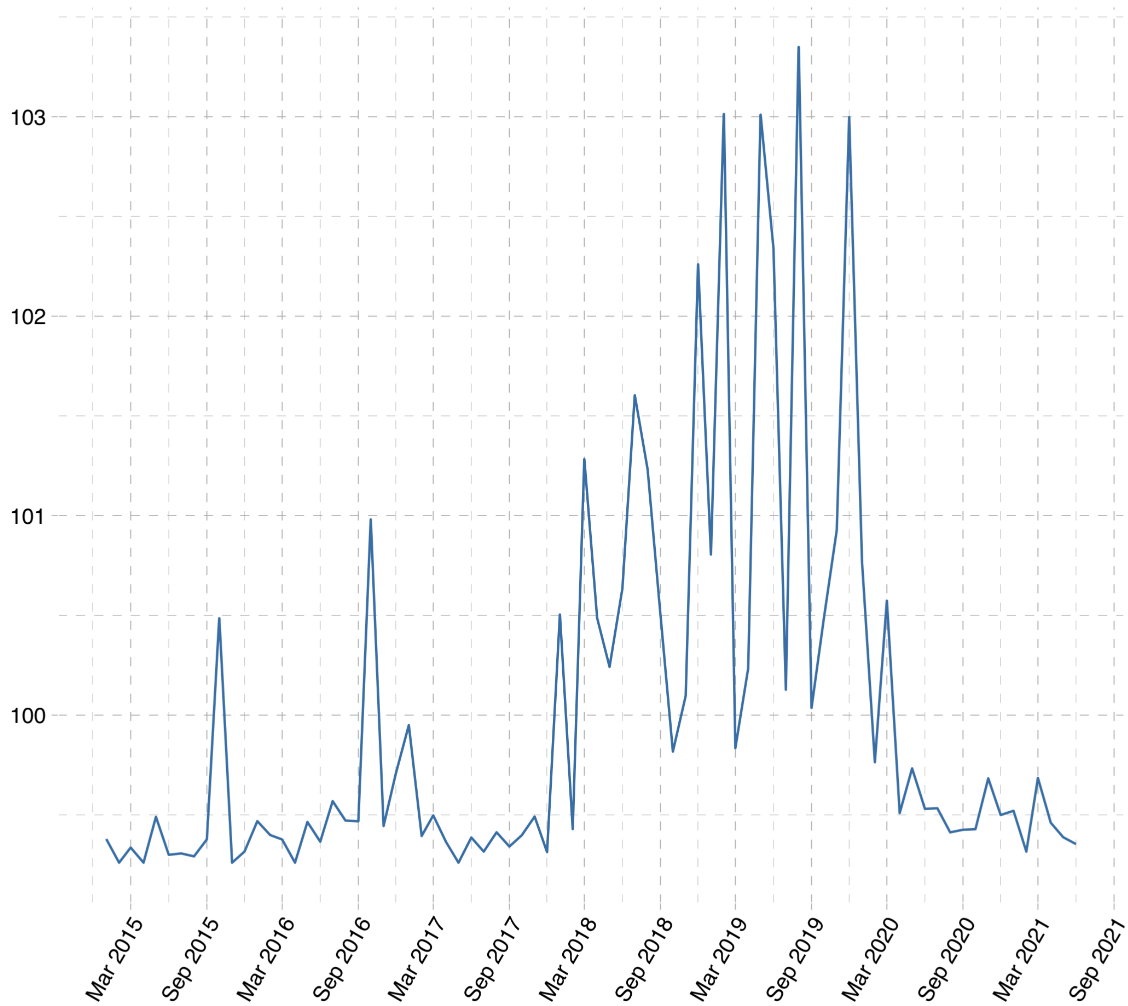
One property of this indicator is that it will not count tweets that do not draw any reactions. This is a desirable property because such tweets are likely not indicative of increased uncertainty perception by the public. Conversely, a tweet that elicits large numbers of interactions receives a higher weight. In short, the indicator answers the following question: among the persons who were exposed to the TPU-related tweet, how many deemed the topic relevant and/or worthy of amplification?

3.3.3 A perception based measure of TPU: Institutional Component

The second indicator uses institutional signals of trade policy uncertainty. Within the architecture of the U.S. government, the United States Trade Representative (USTR) enjoys a wide purview overrules and policies that regulate U.S. trade. The USTR is responsible for negotiating, implementing, and reviewing the U.S. trade agreement, resolving disputes, and shaping global trade policy in the different multilateral venues such as the WTO. Under the Administrative Procedure Act (APA), the USTR's decisions are subject to public notice and call for comment procedures. Potential policy changes and actions are signaled at a very early stage, as they become entertained by the administration. At this stage, rules and policies are yet unformed and very much in progress: their scope, implementation, and viability are uncertain. This process provides a rare opportunity for capturing uncertainty about policymaking ex-ante instead of picking up the informed response to fully formed policy changes ex-post.

I have reviewed and extracted data on all USTR public notices and calls for comments from 2013 to 2021. I classified all releases by theme and by partner. In the federal register, notices are associated with a release date and, if applicable, an expiration date.

Figure 3.5: Twitter-Based Indicator of Trade Policy Uncertainty



Designed using Twitter application programming interface.

For each notice, I research a *resolution date*, that is, the date at which the issue raised by the notice is resolved. For instance, the resolution date of a notice announcing a WTO dispute is the release date of the WTO panel report. In contrast, the resolution date for a notice announcing an out-of-cycle country review under the Generalized System of Preferences (GSP) is the publication of the review decision. Between its publication and its resolution, each notice corresponds to a potential disruption in the way trade and trade policy are conducted - generating additional uncertainty. A notice is considered *open* at time t if and only if t is between the publication and resolution times. Under this assumption, the count of *open* notices at any given time becomes a good indicator of the trade policy uncertainty that market participants experience at any given time. This indicator is simply defined as :

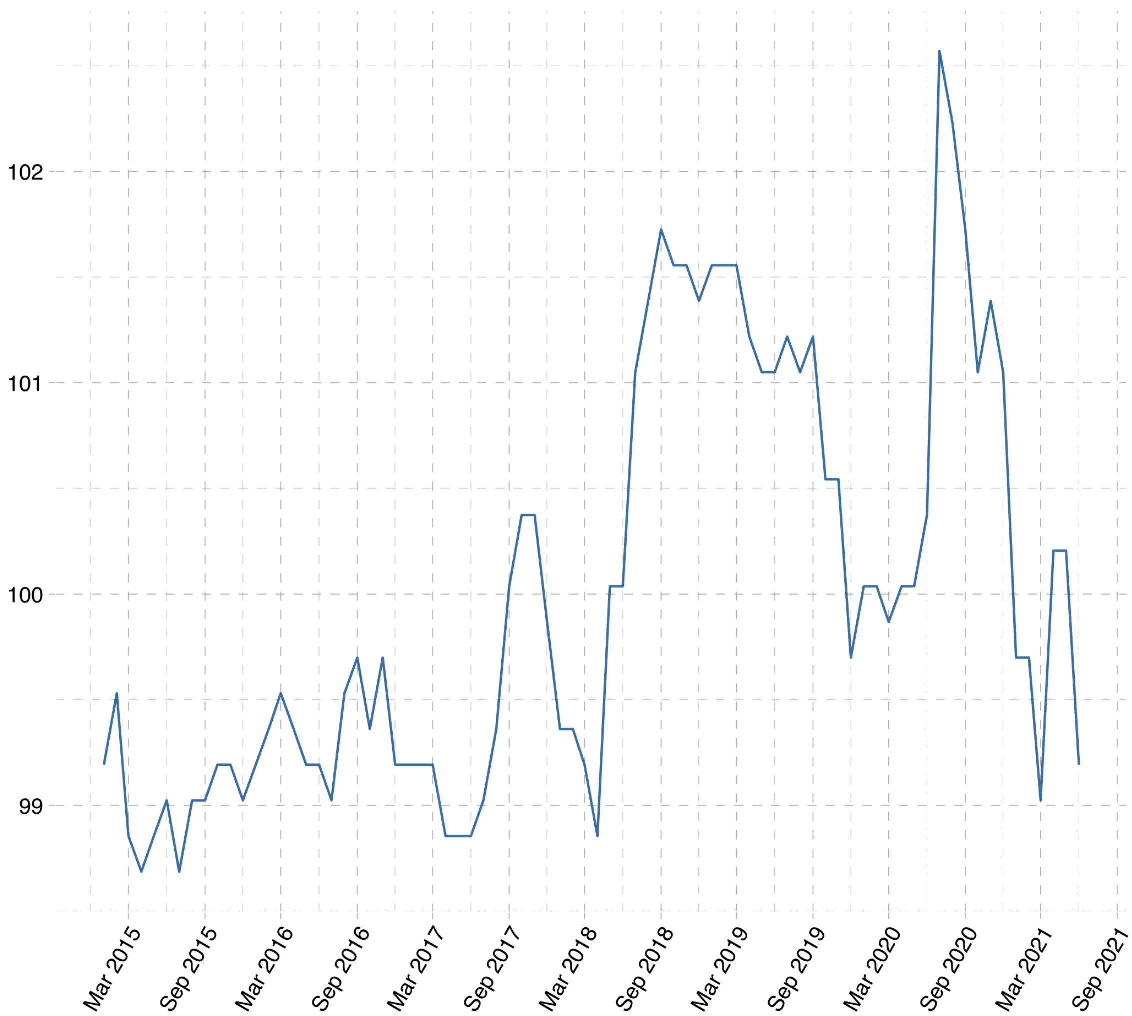
$$ORC_t = \text{the number of open calls and notices at time } t \tag{III.6}$$

where ORC stands for *open review count*. This indicator addresses a common issue with existing indices and proxies of trade policy uncertainty. Previous studies of policy uncertainty exploited policy changes, specifically tariff policy, as proxies for uncertainty, due to the volatility they can generate in the time window following their enactment. Such a proxy can be misleading. After a policy is enacted, agents only face the risks of implementation. The state of the world, as relates to that policy component, is well known to agents who can now update their optimization frameworks with knowledge of the surrounding environment. This makes policy breaks an inadequate proxy to measure policy uncertainty. My proposed indicator measures genuine uncertainty around trade policy: at the time where a policy is added to the count in ORC_t, there is uncertainty about whether the policy will, in fact, change, and even more uncertainty about how it will change if it does. As a result, the release of a new policy-related call for comments increases the level of uncertainty that agents face by bringing into question their optimization environment without providing complete probabilities on the possibility, direction, and size of the change.

Arguably, this measure can be further refined. While every additional call for comment increases perceived uncertainty, not all calls for comments contribute in equal proportions to agents' perceptions depending on the scope of the announcement. For instance, calls for comments could be weighted by the impacted trade volumes to account for these disparities. I do without this refinement to reduce the number of inputs and facilitate the replication of the index.

The two individual indicators capture different components of public perceptions of TPU. They also each contain noisy signals that are not related to TPU. I employ a dynamic

Figure 3.6: Institutional Signals Indicator of Trade Policy Uncertainty



Designed using USTR notices and calls for comments.

factor model to extract TPU information from both series while reducing the amount of noise they contain. One can decompose each of the time-series into two orthogonal unobserved processes: the common component, driven by a shock that captures policy uncertainty, and the idiosyncratic component, which is driven by shocks that are series-specific or local. This approach reinforces the consistency of the final index in that it elicits the underlying process that is common to both the institutional signals of TPU and media coverage and discussions of the same while minimizing noisy signals. It also improves upon existing methods in the literature that are limited to a single source and type of uncertainty, and therefore more prone to imprecision.

Let f_t be the single hidden factor (or common component). Each one of the indicators is a function of the hidden factor such that :

$$I_{it} = \lambda_{i,0} f_t + \lambda_{i,1} f_{t-1} + ... + \lambda_{i,p} f_{t-p} + e_{i,t} \tag{III.7}$$

where $I_{it} = [AFW_t, ORC_t]'$ and,

$$f_t = \psi_1 f_{t-1} + ... + \psi_r f_{t-r} + \eta_t \tag{III.8}$$

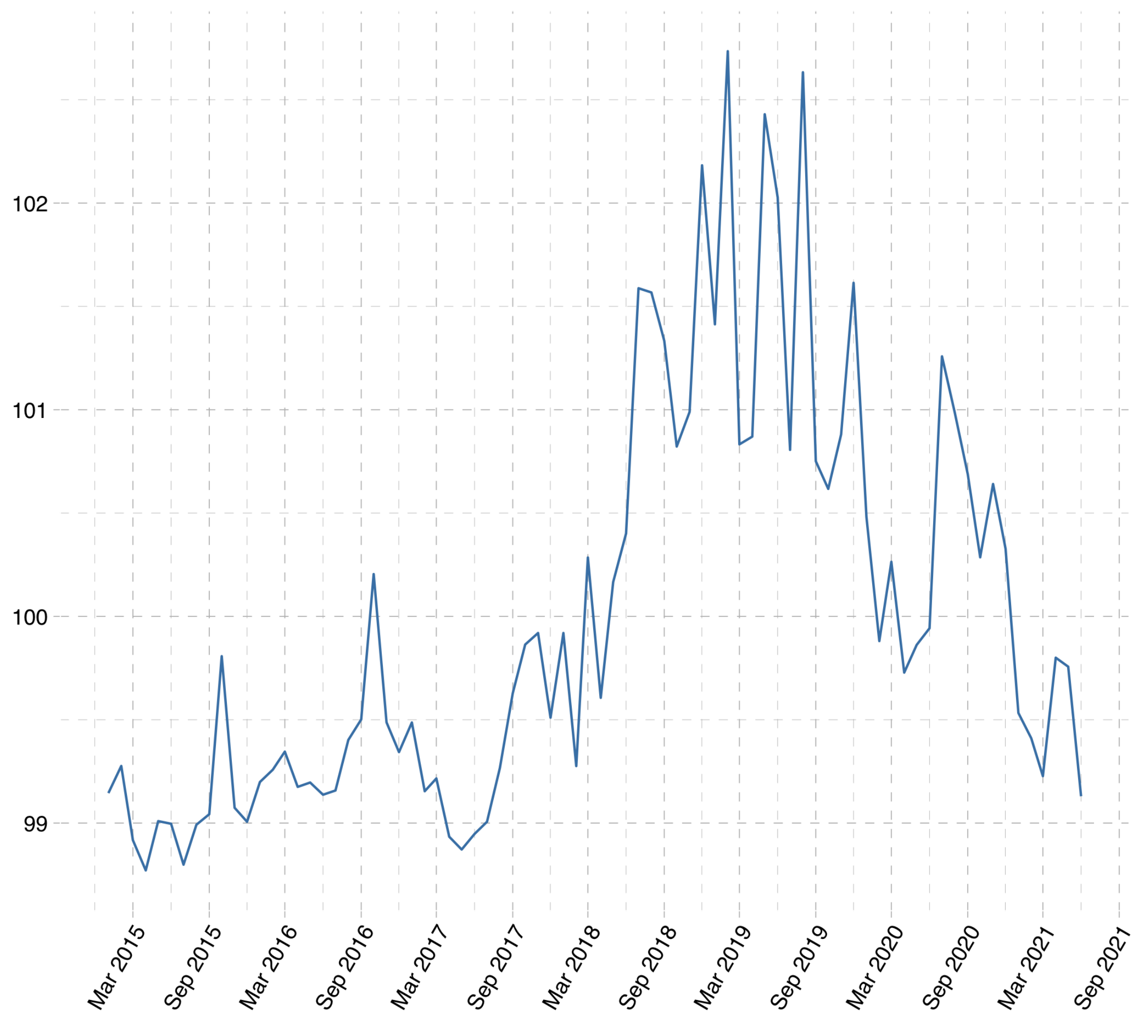
where, p is the lag order of the measurement equation, $e_{i,t}$ is an idiosyncratic component and r is the lag order of the common factor's autoregressive process. The static version of the model can be written as :

$$\begin{cases} I_t = \Lambda F_t + e_t \\ F_t = \Phi(L) F_{t-1} + G\eta_t \end{cases} \tag{III.9}$$

The dynamic factor model is estimated via Principal Component Analysis (PCA). Being a non-parametric technique, PCA does not require additional model specifications and thus provides potential robustness against misspecification. This property allows me to remain agnostic about underlying relationships in the model.

The final TPU perception index is presented in figure 3.6.

Figure 3.7: Proposed TPU Perception Index



The index is constructed as the common factor of the Twitter and Policy signal indicators.

3.3.4 Discussion of proposed index

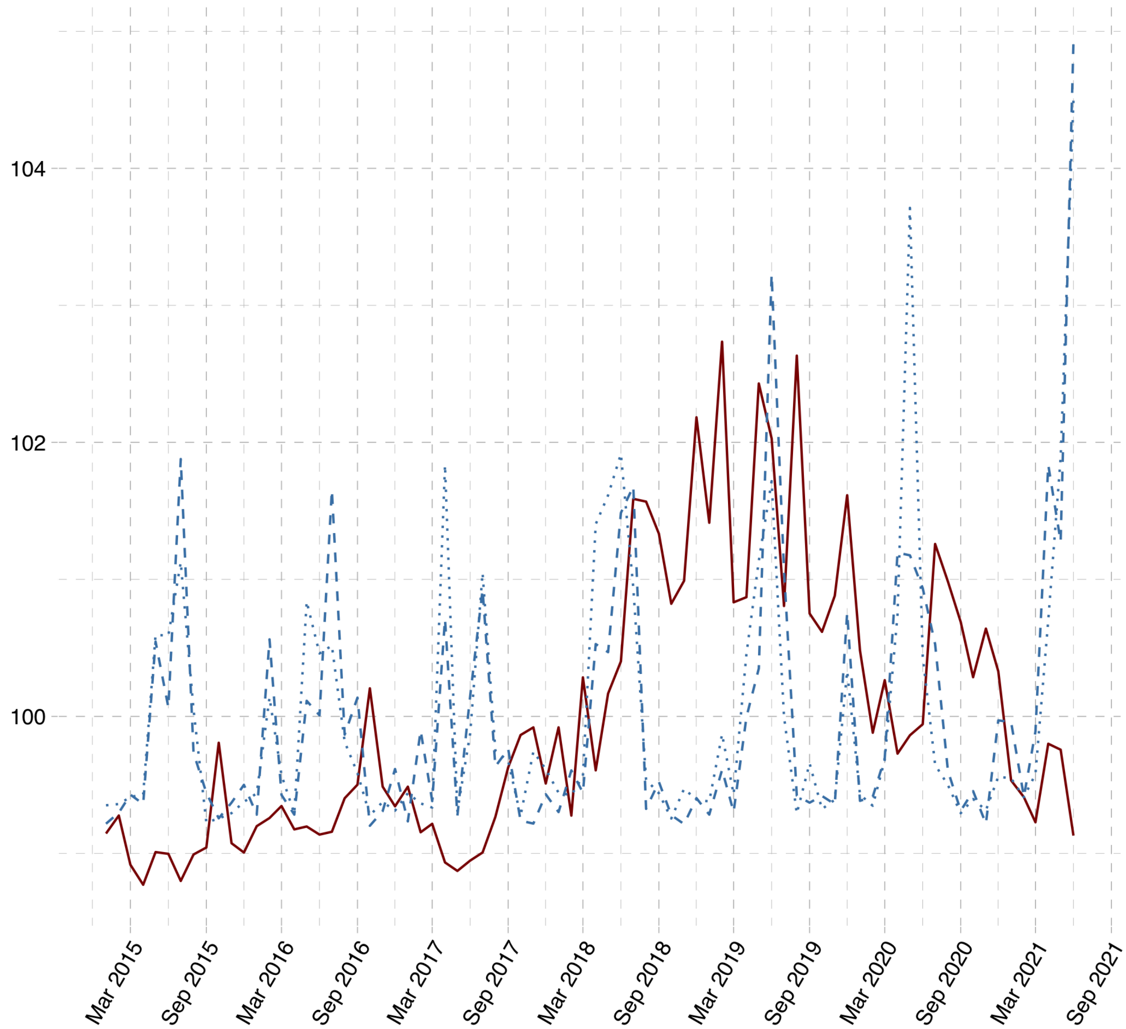
The Twitter amplification-weighted frequency measure aligns well with event-based priors on TPU. The series, presented in figure 3.3, is below average throughout 2015 and for most of 2016. The first peak appears in the lead-up to the 2016 election. The index remains consistently above the period's average from March 2018, which coincides with the early tariff decisions of the new U.S. administration. The February 2019 peak was caused by highly-amplified tweets about the likely impact of tariffs on future inflation and growth, a possible US-China trade deal, and renewed tensions in the US-EU trade relations, including threats of tariffs on European car-makers. The August 2019 peak picks up wide attention to Fed statements about TPU and trade policy in general, including statements by Federal Reserve Chairman Jerome Powell and branch presidents about monetary policy adjustments in the face of mounting trade tensions. The peak also incorporates tweets about a possible change in the first tranche of tariffs imposed on Chinese goods, the finalization of the second tranche, and threats of retaliation from China. This month is also marked by a general interest in economist commentaries on trade policy uncertainty as a risk factor for the economy. This is reflected in the unusually high interactions received by these tweets. A main advantage of this proposed index is precisely its ability to go beyond the news cycle, and monitor the intensity and breadth of TPU-related conversations amongst the public as they happen.

Similar to the first indicator, institutional signals of uncertainty increase after March 2018 and post-above-average measures for the remainder of the study period (figure 3.6). The shape of the series also presents a clear break following the political transition of 2017. Unlike its twitter-based counterpart, this indicator is more persistent, which appears consistent with its institutional nature. It is not surprising that public attention should be more volatile than the underlying policy signals of uncertainty.

Figure 3.8 plots the proposed index against two existing TPU indicators in the literature, both proposed by Baker and co-authors. The dashed line represents their newspaper-based TPU component of EPU index Baker et al. (2016b), whereas the dotted line is the trade-component of their equity market volatility tracker Baker et al. (2019b). The two indices are similar in construction, but the latter is normalized to match the period average of the CBOE volatility index, the VIX.

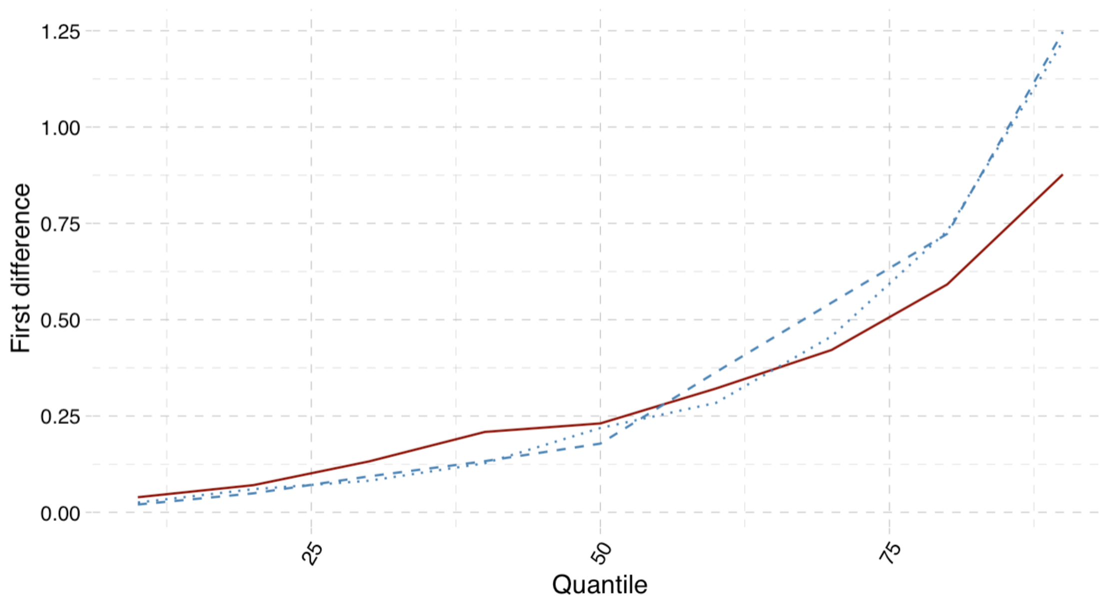
My proposed index has a comparable shape to existing measures. However, it presents desirable properties that separate it from them. First, it is noticeably smooth. Figure 3.9 depicts the quantile distribution of first-order differences. Large and sudden jumps and troughs are fewer in the proposed index. This property results from the index's inclusion of fundamental policymaking developments by including the USTR data and

Figure 3.8: Proposed Index and Existing TPU measures



proposed TPU perception index (solid line) against Baker et al. 2016 TPU component of EPU (dashed line) and Baker et al. 2019 TPU component of a news-based Equity Market Volatility Tracker (dotted line).

Figure 3.9: Proposed Index and Existing Measures : Quantile Distributions



Quantile distribution of first difference series of compared indices : proposed TPU perception index (solid line) against Baker et al. 2016 TPU component of EPU (dashed line) and Baker et al. 2019 TPU component of a news-based Equity Market Volatility Tracker (dotted line).

its comparatively small dependence on the fast-moving news cycle. Indeed, while we expect to see some variability in the index, vast movements are not commensurate with public perception of uncertainty, which should be highly serially correlated. We can see an expression of the index smoothness towards the end of the study period. Policy actions have significantly subsided in the second half of 2019 and going into 2020. The landing of the perception index is phased and progressive in this period but much faster in the alternative measures. News outlets might be quicker to turn the pages of the news cycle than the informed public perceptions, and institutional process develop. The higher persistence of the index is a desirable property for a measure of perceptions.

The USTR policy signals instill a forward-looking property into the index, which is a desirable property. This is visible in the behavior of the indices in March 2018, a period when the U.S. took several highly mediatized policy actions. The decision to slap tariffs on aluminum imports was announced on March 1st. The unfair trade practices review of China was released on March 22nd, laying the ground for the ensuing tariff increases. Both of these developments were, however, already folded into the perception index. The steel and aluminum tariffs enter the index as early as March 2016, when the USTR issued a call for comments on the global steel and aluminum markets, teasing a possible policy action. The out-of-cycle review of China's trade practices under section 301 was announced in August 2017 and enter our index then. Neither the decision to enforce tariffs nor the release of the report is clear positive shocks to uncertainty. In fact, both of these developments resolve some uncertainty about the trajectory of U.S. trade policy. They are primarily realized shocks to policy rather than a change in the size or direction of expectations about the future. The forward-looking property of the index is also demonstrated by the earlier and slower build-up towards the high uncertainty period. In contrast, the alternative indices rapidly climb on the first reports of policy actions.

The indices carry different information. The comparatively high peaks recorded by the alternative indices in December 2018 are much smaller in my proposed index. It is unclear what these peaks are associated with. In that month, the major U.S. trade policy development was a tariff truce agreed to by the United States and China following a G-20 summit, arguably a negative shock to uncertainty. The large February 2019 peak in the proposed index is conversely absent from the other series. Instead, the proposed index picks up the U.S. last-minute decision to delay to an unspecified date a 15-percentage-points tariff increase on $200 billion of imported Chinese goods. It is also heavily boosted by the public attention to a January U.S. government threat against European auto imports.

In an additional verification, I compare the proposed TPU index to an indicator measuring the number of policy actions that the USTR has taken over the study period.

This indicator is a simple count of the number of trade policy actions, standardized and normalized to a mean of 100. Figure 3.10 reveals that the proposed uncertainty index contains different information than one would get from observing trade policy changes. The correlation coefficient between the two series is low, at 0.164.

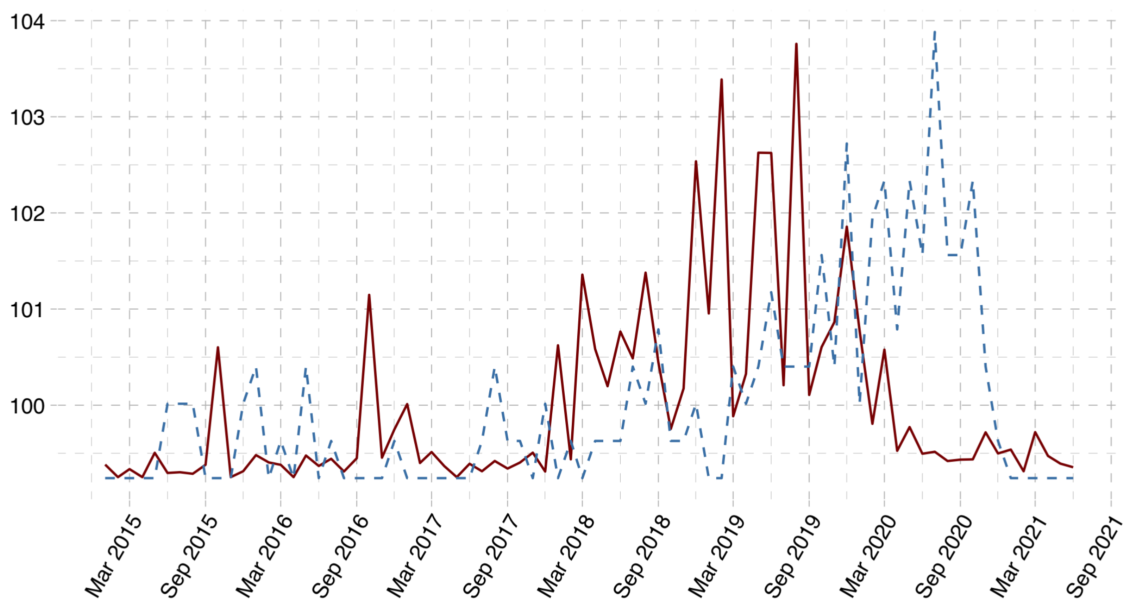


Figure 3.10: Proposed Uncertainty Index and Trade Policy Volatility
Note: Proposed TPU perception index (solid line) against a constructed measure of US trade policy actions (dashed line).

In sum, the proposed index meets the design goals. It captures variations in TPU, as shown by its similarity with alternative indices. It is forward-looking and does not track moments of policy changes. It also does not align with policy actions. Finally, it successfully integrates institutional and social media signals on trade policy uncertainty and displays the stickiness that characterizes public perceptions.

3.4 TPU and Stock Market Volatility

Analyzing the impact of TPU on stock market volatility serves two purposes. First, it attempts to assess the economic and financial cost of the recent high uncertainty episode. The policy goals telescoped by the U.S. administration from 2017 to 2020 were narrowly defined in terms of trade balance improvement with specific trading partners. This has translated into deviations from past policy trends, revisions of existing agreements, and suspension of WTO resolution mechanisms, all of which have significantly increased the level of uncertainty as perceived by market participants, and as relayed by the media coverage.

Nevertheless, due to the short track record of the policy shift, the literature has focused less on counting the cost and more on simulating potential impacts[4], understanding the tariff and retaliation policy designs (Fetzer and Schwarz (n.d.)), or cataloging previous episodes of trade conflicts (Mattoo and Staiger (2020)). Using the constructed TPU perception index, we can begin to investigate one of the consequences of this policy change: increased uncertainty. In this context, financial markets offer an excellent early case study: they respond quickly to policy changes, they inform about investors' attitudes towards policymaking, and their dynamics can have relevance for the real economy. Stock market volatility, according to Schwert (1989), reflects uncertainty about future cash flows and discount rates, and thus informs on future economic activity. It also increases the cost-of-capital, which can reduce future investment (Guo (2002)). Campbell et al. (2001) shows that stock market volatility is a significant predictor of GDP growth. Therefore, through its impact on volatility, we can make informed hypotheses on TPU's impact on aggregate economic performance. Furthermore, understanding the stock market impact of uncertainty can support investors in designing adequate responses to adjust their positions when they anticipate an uncertainty shock.

This section describes the approach for in-sample and out-of-sample analyses and discusses the results of this exercise.

3.4.1 Model and Estimation

The relationship between the TPU and market volatility series is explored using a structural vector autoregression (Sims (1980)). This is a common approach in the investigation of sentiment shocks and their market outcomes. I begin with the following VAR equation:

$$Y_t = A_0 + \sum_{k=1}^{p} A_k Y_{t-k} + u_t \tag{III.10}$$

And,

$$Y_t = [g_t, \pi_t, r_t, tpu_t, vol_t]' \tag{III.11}$$

The inclusion of macroeconomic variables allows one to control for business-cycle-

[4] Bouët and Laborde (2018), Caceres et al. (2019) and Jeanne (2019) for theoretical modeling of trade wars consequences

related shocks. The macroeconomic variables are from the St Louis Fed database, FRED. g_t is output growth, proxied by the log difference of the monthly industrial production index, π_t is monthly PCE inflation, and r_t is the effective federal funds rate to capture shocks to monetary policy. tpu_t is the TPU perception index. The model is separately estimated for different specifications of vol_t: total, persistent and transitory volatility. The main estimation centers on the volatility response of the S&P 500 index, and I look at heterogeneity responses of a selection of individual stocks in a following subsection. The chosen lag for the VAR equation is $k = 1$, as suggested by the AIC criterion.

The structural shocks are derived using the Cholesky decomposition. The ordering of the endogenous variables captures the restriction imposed on the system. The key restriction is that TPU shocks do not propagate contemporaneously to the macroeconomic variables. This restriction rests on the notion that the changes in investor and market participant behavior that lead to variation in macroeconomic variables lag changes in perception and sentiment, as measured by the index (Baker and Wurgler (2006)).

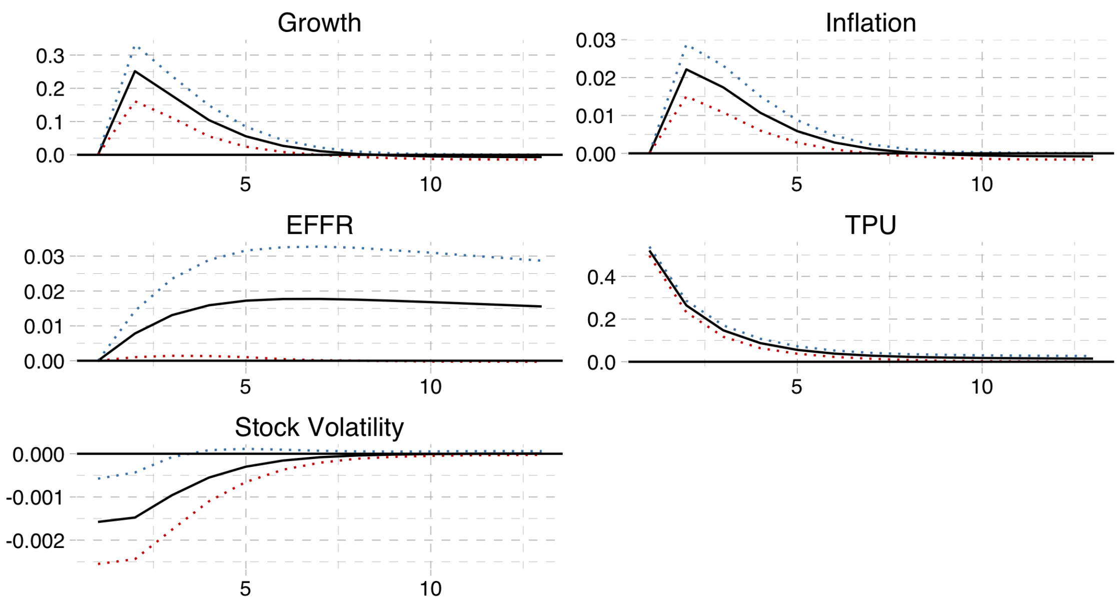
3.4.2 Baseline Results

Figure 3.11 presents the resulting impulse response functions of macroeconomic fundamentals and S&P500 volatility following a positive shock to TPU as computed by the Cholesky decomposition. A positive shock to TPU leads to a positive response of industrial production and inflation. The response appears short-lived. Monetary policy responds with lower rates initially, but the response is not significant at the 95% confidence level.

Figure 3.12 shows that the volatility components respond uniformly to TPU shocks: both persistent and transitory volatilities decline slightly at the 95% confidence level. Transitory volatility is quicker to absorb the shock, whereas persistent volatility is slower to adjust back from an initial dip. As a result, total index volatility responds with a quick dip and a somewhat slow recovery. The persistent and transitory volatility responses are larger at the peak than total volatility response. This reflects a negative correlation between the persistent and transitory component. The Spearman correlation coefficient between the two series over the study period is -0.18.

The negative and consistent response of stock market volatility suggests that TPU has a chilling effect on market transactions overall, generating perhaps a wait-and-see attitude that stabilizes stock prices. Bootstrapped confidence intervals show that we cannot, however, rule out the null hypothesis that TPU shocks do not propagate to stock market volatility. The volatility forecast-error variance decomposition in the context of the specified SVAR, as reported in table 3.2, further reflects the weak contribution of TPU shocks to volatility variations.

Figure 3.11: Responses to a Trade Policy Shock



Impulse response function of the SVAR system variables (industrial production growth, inflation, interest rate, TPU and total monthly volatility of the S&P500 index) to a one standard deviation shock to Trade policy uncertainty.

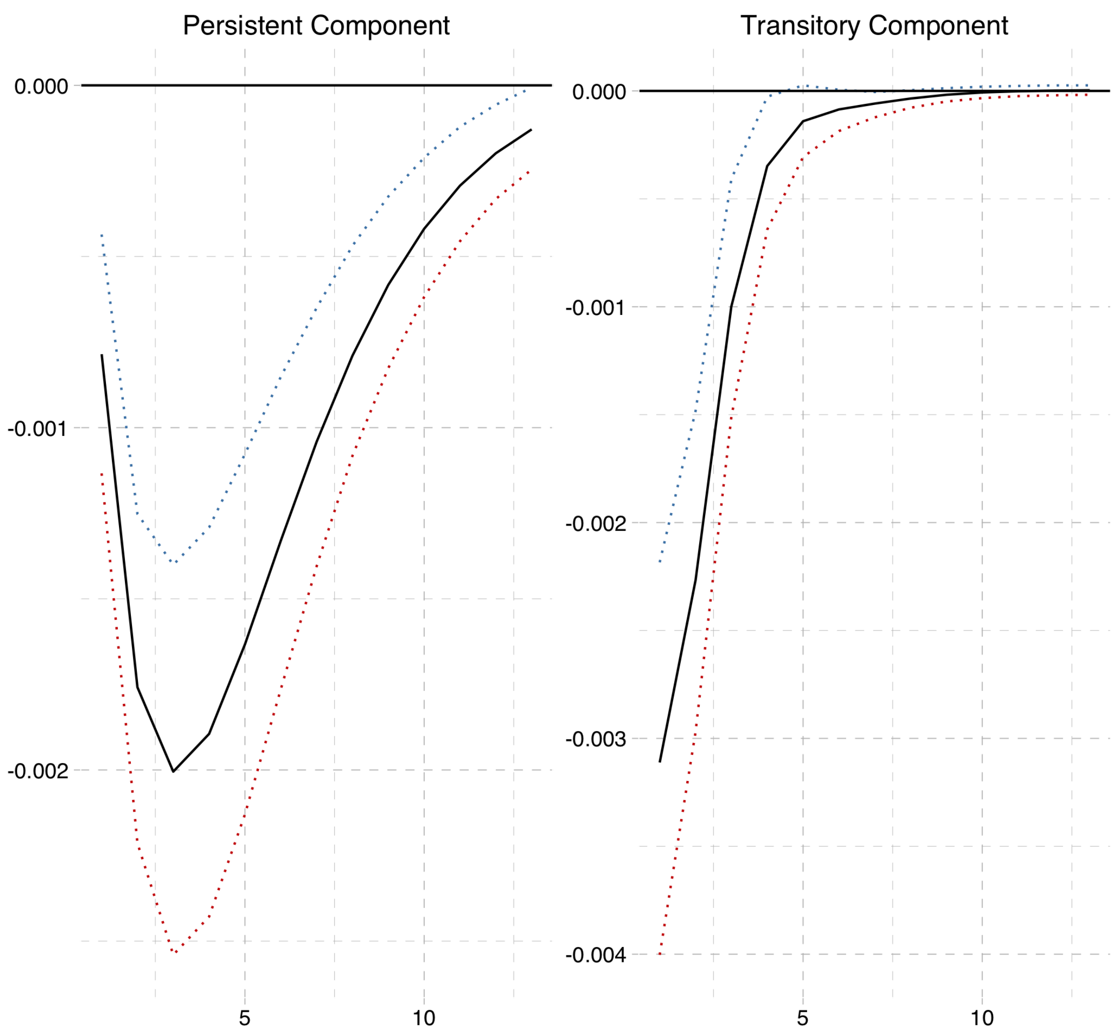
Table 3.2: Forecast Error Variance Decomposition of S&P500 Monthly Realized Volatility

Horizon	Economic Growth Shock	Inflation Shock	Monetary Shock	TPU Shock	Other Shocks
1	0.0013	0.0656	0.2191	0.01024	0.70362
5	0.0020	0.0636	0.2165	0.01320	0.70455
10	0.0020	0.0636	0.2165	0.01323	0.70449
15	0.0020	0.0636	0.2165	0.01323	0.70447
19	0.0020	0.0636	0.2166	0.01323	0.70446

3.4.3 Out-of-Sample Analysis

Investors and market participants use historical trends and correlations to predict future market dynamics better. The in-sample performance of TPU in explaining volatility is weak. Can the inclusion of trade policy uncertainty in forecast models of volatility improve their accuracy?

Figure 3.12: Responses of Volatility Components to a Trade Policy Shock



Impulse response function estimated using the structural VAR model separately using transitory and persistent volatility components as fifth endogenous variables.

In keeping with the literature, I estimate an AR(6) benchmark forecasting model of volatility. The benchmark forecasts are denoted $V_{t+m,B}$. I then use this benchmark to evaluate the performance of a TPU-augmented forecast model given by:

$$Vol_{t+m,\text{A}} = \alpha_m + \sum_{p=1}^{6} \beta_{p,m} Vol_{t+m-p} + \delta_m TPU_{t+m-1} + \varepsilon_{t+m} \tag{III.12}$$

Forecasts are generated using a one-step-ahead recursive approach with an expanding window, starting with an in-sample of 35 observations. At each step, from $t = 35$ onwards, the model's parameters are estimated via OLS using historical data available up to time t. The forecast is generated using the observed lag values of the predictive variables. This process generates monthly volatility forecasts from July 2018 through June 2021.

Following Wang et al. (2018), Rapach et al. (2009) and Campbell and Thompson (2007), I evaluate model performance using out-of-sample R^2 given by:

$$\Delta R^2_{OOS} = 1 - \frac{MSPE_B}{MSPE_A} \tag{III.13}$$

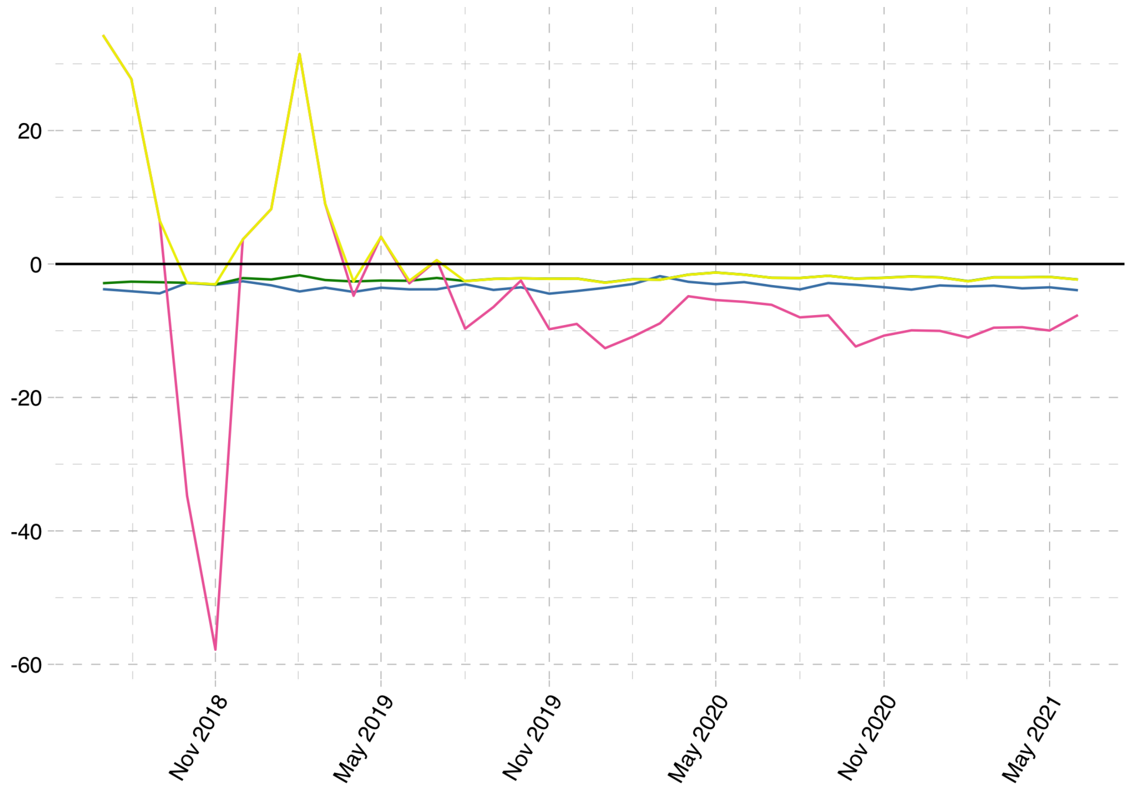
where ΔR^2_{OOS} measures the percent reduction in mean squared predictive error (MSPE) gained by transition from the benchmark to the augmented model. A positive value therefore means that the augmented model improves upon the accuracy of the benchmark model. Following Wang et al. (2018), I compute the ΔR^2_{OOS} for two versions of the augmented model: with and without restrictions. The unrestricted model follows the method laid out above. The restricted model is such that:

$$\hat{Vol}_{t+m,\text{A,R}} = \begin{cases} \hat{\alpha}_m + \sum_{p=1}^{6} \hat{\beta}_{p,m} Vol_{t+m-p} + \hat{\delta}_m TPU_{t-1}, & \text{if } \delta_m > 0 \\ \hat{\alpha}_m + \sum_{p=1}^{6} \hat{\beta}_{p,m} Vol_{t+m-p}, & \text{if } \delta_m < 0 \end{cases} \tag{III.14}$$

The investor using the restricted model minimizes overfitting by excluding TPU from the forecast when the associated coefficient is not consistent with their prior that TPU must correlate positively with volatility.

Figure 3.13 reports the forecast performance results. The out-of-sample R-squared on the unrestricted and restricted models are -49.19 and -16.20, respectively. The inclusion of TPU into volatility forecast models does not improve upon the benchmark autoregressive model, further reinforcing the results from the in-sample analysis.

Figure 3.13: Log Volatility: True value and Alternative Forecasts



TPU-augmented forecast (pink) $\Delta R^2_{OOS} = -49.19$ and restricted TPU-augmented forecast (yellow) $\Delta R^2_{OOS} = -16.20$ against the benchmark volatility forecast (green) and the true volatility value (blue).

3.4.4 Portfolio Evaluation

Lastly, I identify the utility gain from the internalization of TPU dynamics in portfolio allocation decisions. This exercise follows Wang et al. (2018) which builds on prior literature (Neely et al. (2014), Rapach et al. (2009)).

Assume that a risk-averse investor has access to two assets: risk-free bonds and stock equity. The utility function of the investor displays mean-variance preferences. It has two components: the expected portfolio return, which enters positively, and a portfolio volatility component that enters negatively with a weight that increases with the degree of risk-aversion. The utility function can be written as:

$$U(r_t) = E_t(w_t r_t + r_{f,t}) - \frac{1}{2}\gamma var_t(w_t r_t + r_{f,t}) \qquad \text{(III.15)}$$

Where $r_{f,t}$ is the risk-free rate on bonds, r_t is the excess return on stocks, and w_t is the weight of stock equity in the portfolio. γ measures risk aversion. The optimal level for the choice variable w_t is a function of expected stock returns, volatility, and risk aversion.

$$w_t^* = \frac{1}{\gamma}\left(\frac{\hat{r}_{t+1}}{\hat{\sigma}^2_{t+1}}\right) \tag{III.16}$$

Where $\hat{r}_{t+1}$ is a simple historical-average forecast of stock returns. The volatility forecast is formed in three alternative ways using the benchmark forecast, the TPU-augmented model, and the TPU-augmented restricted model $\hat{\sigma}^2 = \{\hat{Vol}_{\mathrm{B}}, \hat{Vol}_{\mathrm{A}}, \hat{Vol}_{\mathrm{A,R}}\}$. This yields three possible portfolios indexed by p.

Once the weight is chosen, the portfolio return is given by:

$$R_{t+1} = w_t \times r_{t+1} + r_{f,t+1} \tag{III.17}$$

The performances of the three different portfolios can be compared by using the certainty equivalence return (CER):

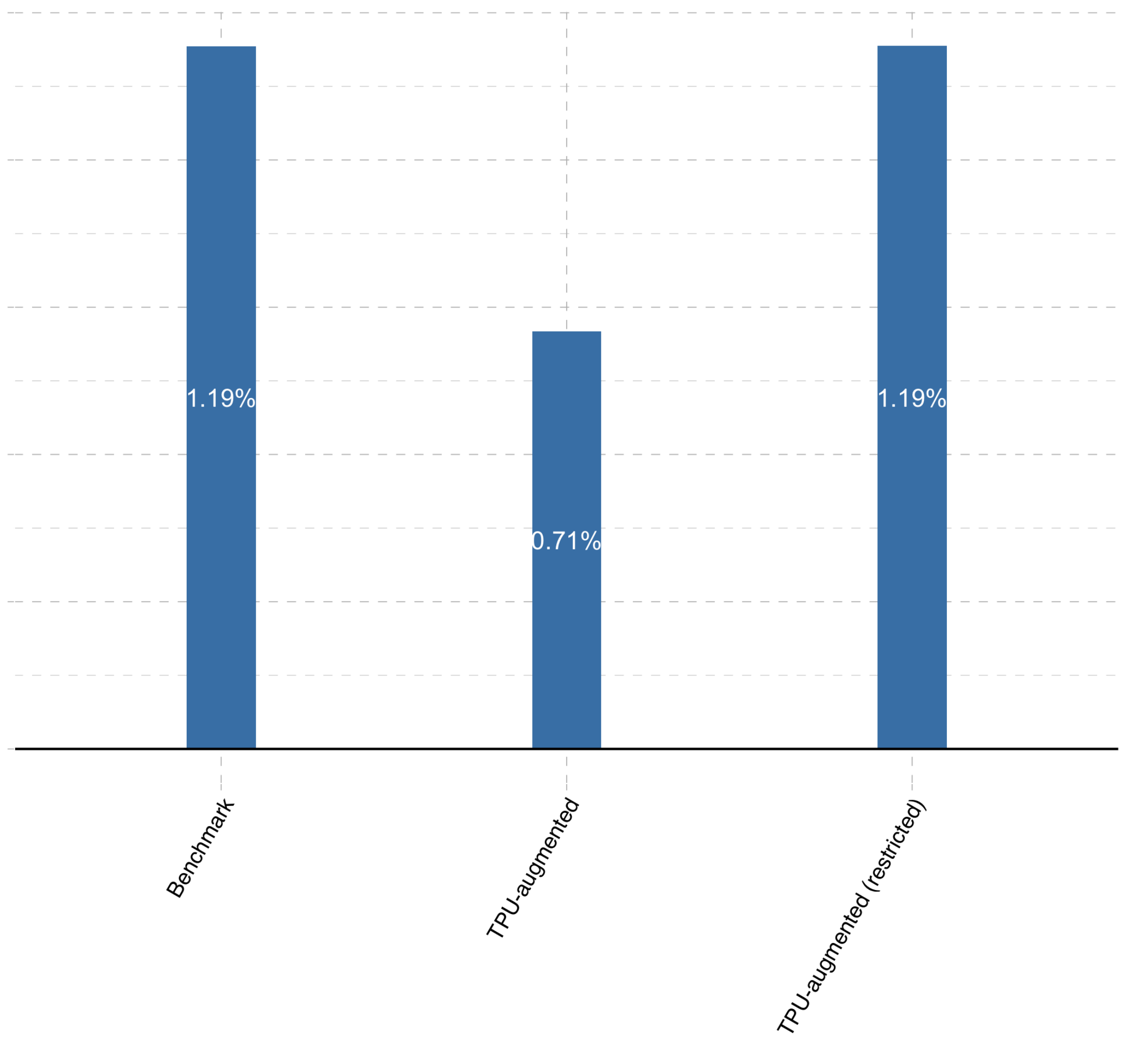
$$CER_p = \hat{\mu}_p + \frac{\gamma}{2}\hat{\sigma}^2_p \tag{III.18}$$

Where $\hat{\mu}_p$ is the mean and $\hat{\sigma}$ is the variance of the chosen portfolio over the entire period. The CERs of the three alternative portfolios are shown in figure 3.14. Models that internalize TPU fail to improve the asset allocation and the associated returns.

3.4.5 Heterogeneity Analysis

The limited relevance of trade policy uncertainty shocks to market volatility broadly measured through the S&P 500 might hide differences across sectors. To investigate this possibility, I conduct a heterogeneity analysis using six sectoral exchange-traded funds (ETFs) of the S&P-500. The chosen sectors have varying degrees of exposure to trade policy and to international market conditions. On the one hand, the technology (XLK) and industrials (XLE) sub-indices cover companies with high trade exposure due to both a large share of revenues from non-US sales and global value chain linkages. On the other hand, the utilities (XLU) and healthcare (XLV) ETFs represent more insulated industries whose revenues are overwhelmingly domestically derived and are thus less exposed to direct trade policy shocks. I also include two additional indices: energy (XLE)

Figure 3.14: Certainty Equivalence Return of Alternative Portfolios

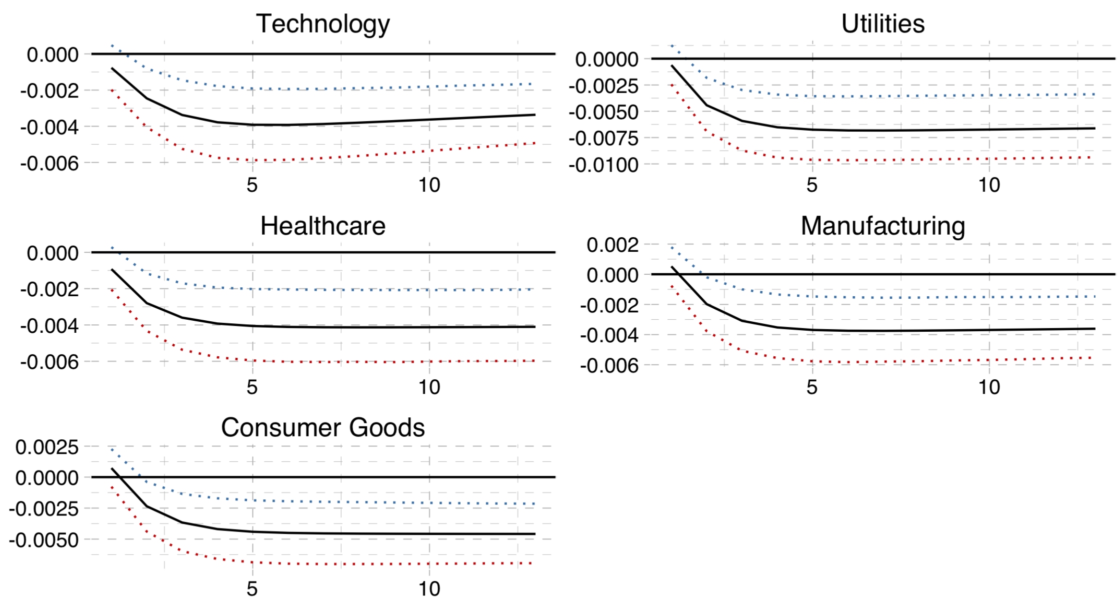


Portfolios constructed using three different forecasting methods for the derivation of the optimal equity weight: a benchmark forecast, a TPU augmented model and a restricted TPU augmented model.

and consumer staples (XLP), intermediate sectors with majority domestic revenues and moderate sensitivity to supply chain perturbations.

Figure 3.15 shows impulse-response functions for the total realized volatility to a shock of TPU, across sectors. Consumer goods and manufacturing sectors appear to respond with a slight uptick in volatility, but the increase is short-lived and quickly reversed. The response of the different sectors displays similar magnitudes and trends and aligns with the response of the aggregate S&P500 index. There is no evidence of sectoral heterogeneity. This result emphasizes that rather than propagating the uncertainty shocks in specific sectors, the stock market tends to respond with decreased volatility across the board. It emphasizes that investors do not collectively and systematically change their positions or substitute across sectors following a TPU shock.

Figure 3.15: Impulse Response Function of Volatility to TPU Shocks: By Sector



IRFs estimated using the specified SVAR in (10) using different measures of volatility for specific sector-ETFs.

Another level of possible heterogeneity is across individual stocks. Of particular interest are stocks of firms with significant trade exposure. These firms might indeed respond more strongly and differently than general market trends. To test this hypothesis, I choose 7 US companies with some of the highest earning-exposures to China. Figure 15 shows the total volatility response of these high China-exposure stocks to a TPU shock. Here we observe both size and directional heterogeneity. Tesla's strong volatility response could be driven by the company's reliance on China both for production capacity and sales revenue. Still, revenue exposure does not appear to be a crucial discriminating factor in determining the size of the response. QCOM and MU, generate more than half their earnings through sales to China but their stocks appear less volatile in response to TPU shocks than IPGP and TSLA both of which are less reliant on exports to China. Rather than eliciting a systemic volatility response of the whole market or along specific segments, trade policy uncertainty appears to affect individual stocks idiosyncratically without significantly destabilizing financial markets.

Table 3.3: List of High Exposure Stocks

Ticker Symbol	China as Share of Revenues
QCOM	66%
MU	57%
TXN	44%
IPGP	43%
AMD	39%
VECO	35.8%
TSLA	21%

Financial data from Yahoo! Finance and CNBC

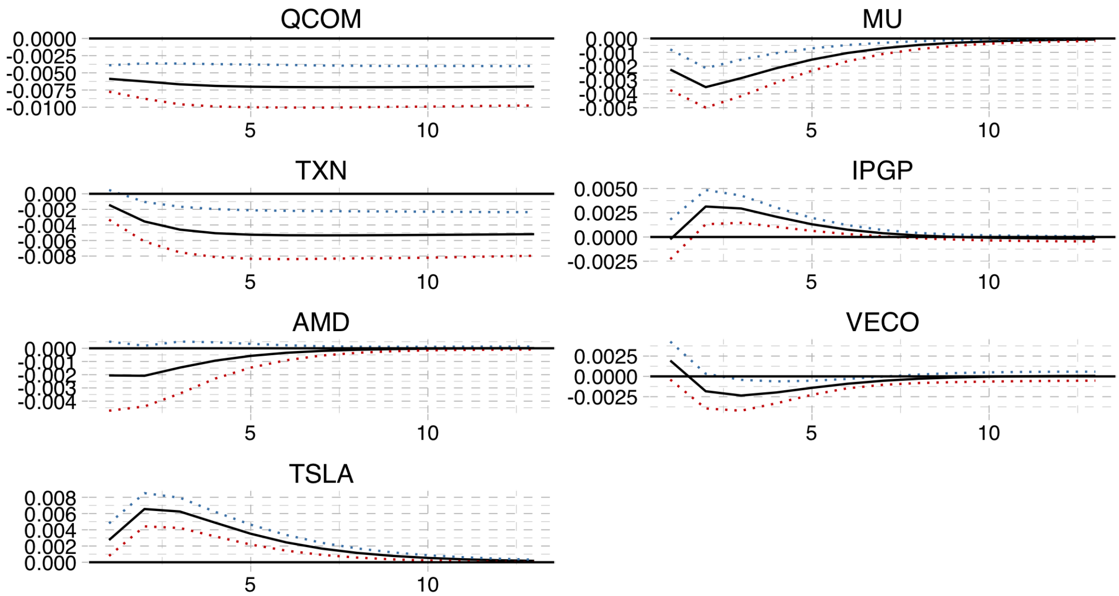
3.4.6 Robustness

To insure that the results of the analysis are not driven by properties of the constructed index, I run the same SVAR using Baker et al. (2016b) trade policy component of economic policy uncertainty as a measure of TPU. The impulse response functions are presented in figure 3.17. These results corroborate my own analysis. The impact of TPU on market volatility continues to be insignificant initially, and then slightly negative.

3.4.7 Discussion

The above analysis demonstrates that trade policy uncertainty does not systematically increase volatility on stock markets and that where a causal relation is significant, it is usually negative. Trade policy uncertainty also has no predictive power for volatility, and internalizing it in investment decisions does not improve portfolio performance. Trade policy uncertainty does not contribute to market instability. Furthermore, the heterogeneity analysis emphasizes that the absence of a financial volatility response to TPU cannot be explained away by the moderate degree of exposure to international trade of U.S. markets.

Figure 3.16: Impulse Response Function of Volatility to TPU Shocks: Individual Stocks

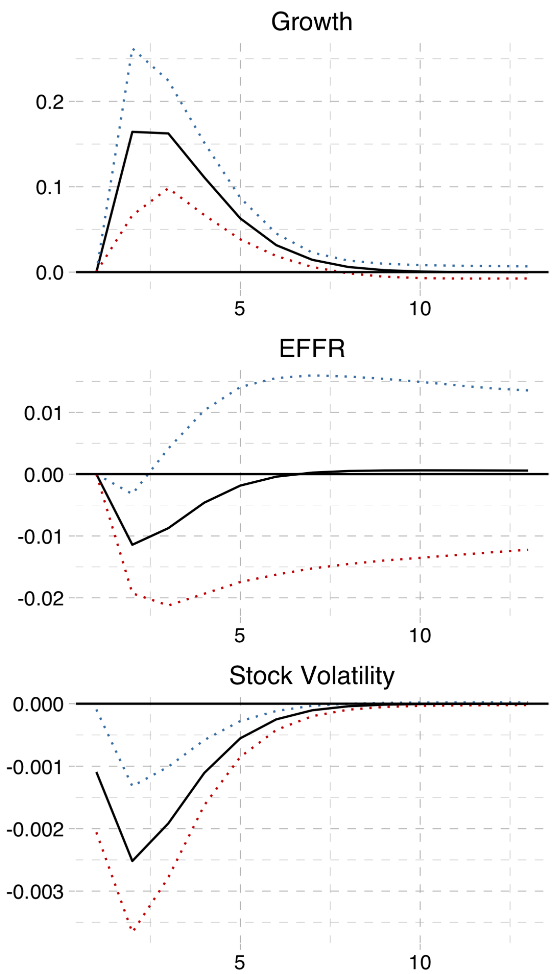


IRFs estimated using the specified SVAR in (10) using different measures of volatility for specific companies.

The findings of this paper stand in contrast with the existing literature on the volatility-effect of economic policy uncertainty (EPU). Using Baker et al. (2016b) EPU index, Liu and Zhang (2015) show that a one standard deviation increase in EPU leads to a 0.03% increase in volatility and that EPU has a strong out-of-sample predictive power. Running a structural VAR using my main specification in (10) but replacing TPU by Baker et al. (2016b) EPU index yields similar results (figure 3.18). Asgharian et al. (2013) find that a macroeconomic uncertainty index based on forecast dispersion significantly increases long-run stock market volatility. This increased volatility causes a flight-to-quality behavior as evidenced by a reduced cross-correlation of stock and bond markets at times of high macroeconomic uncertainty. Amengual and Xiu (2018) find that downward volatility jumps are associated with a resolution of monetary policy uncertainty, mostly through statements from the FOMC and Fed chairman speeches.

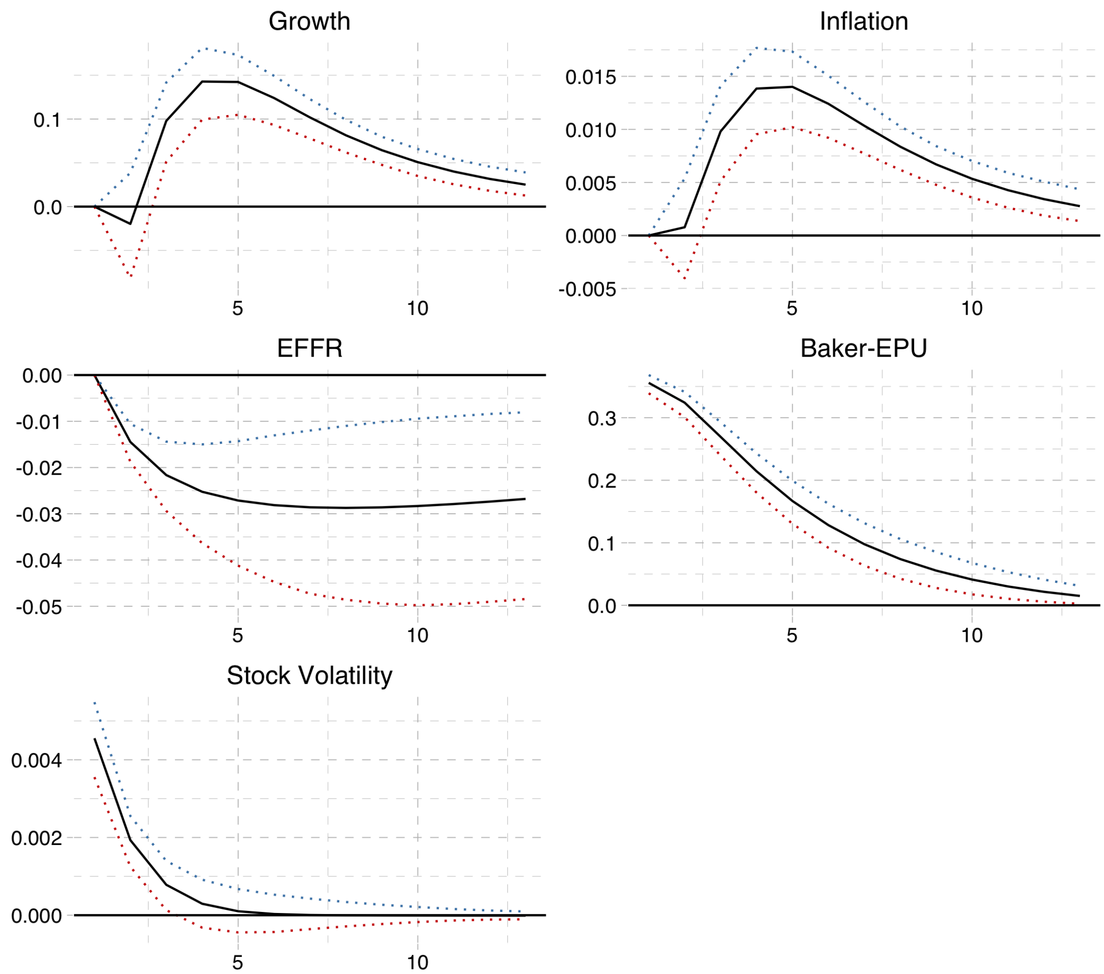
What drives the difference in volatility response to EPU and TPU? Trade policy uncertainty is a new form of uncertainty. For most of recent economic history, trade policy has been stabilized by the commitment of the U.S. government to the WTO's multilateral framework that dictates the rules of global engagement. The transparency and anti-discriminatory intent of the rules-based trading system and the alignment of consecutive administrations with global trade liberalization enhanced the predictability and stabil-

Figure 3.17: Impulse Response Function to a TPU Shock, using Baker et al's Trade Component of EPU



IRFs estimated using the specified SVAR in (10), and using total S&P500 volatility as stock volatility measure.

Figure 3.18: Impulse Response Function to an EPU Shock



IRFs estimated using the specified SVAR in (10), and using total S&P500 volatility as stock volatility measure.

ity of the policy framework. The precipitated rise in trade policy uncertainty in recent years is unusual. It combines institutional changes, global tensions, a volatile domestic policy agenda, rendering it harder to navigate for the public. Faced with an unfamiliar shock, investors might fail to develop a hedging strategy or reallocate assets - and choose to hold positions in a wait-and-see attitude. In other words, investors choose to ignore uncertainty when they do not know how to interpret it correctly.

This interpretation finds support in the theoretical literature on uncertainty and volatility. According to Ederington and Lee (1993), unanticipated news are resolved by the market through increased volatility. Indeed, **?** show that economic variables respond to current economic volatility, defined as the size of shocks that have just occurred. However, uncertainty shocks, defined as changes to agents' expectations of large future shocks, do not affect economic variables. The authors show that investors paid premia that average to zero to hedge shocks to uncertainty. Dew-Becker et al. (2021) supports this distinction between realized shocks and perceived uncertainty. The former carries negative risk premia, whereas the latter does not. According to the authors, forward-looking uncertainty shocks do not drive investor's marginal utility - an argument that the asset allocation exercise in this paper supports. The previously cited studies that relate uncertainty shocks to increased volatility rely on uncertainty proxies that might not narrowly capture pure uncertainty. News indices are indeed much more likely to capture realized shocks to policy rather than forward-looking uncertainty perceptions. It follows that attempts at studying TPU using news-based indices are likely to lead to mistaken conclusions precisely because they are backward-looking and reflective of the size of realized shocks rather than expectations of future shocks. Hedging behavior appears very limited when trade policy uncertainty shocks are measured using forward-looking perception indices. The stock market response is limited in scope and small in size across sectors.

Conclusion

The secular stability of trade policy brought about by the post-war multilateral trade system has been disrupted by new geopolitical rivalries, populist discourses, and the supply-chain challenges posed by a global pandemic. Protectionist policies are challenging the sense of inevitability that cloaked multilateral liberalism. As a result, market participants have to contend with a new and increasingly relevant source of uncertainty: trade policy uncertainty (TPU).

I propose a new measure of trade policy uncertainty to support empirical research into its drivers and economic consequences. The index aims at capturing market participants' perceptions of TPU. It combines information from two distinct indicators measuring public attitudes towards TPU on Twitter and institutional signals of trade policy changes. The index reveals a large and sustained increase in TPU between March 2018 and early 2020.

Using the constructed index, I study the effects of TPU on macroeconomic variables and stock market volatility. Whereas the literature shows a positive relationship between economic policy uncertainty and returns volatility, I find that trade policy uncertainty, in particular, does not increase overall market volatility. Heterogeneity analysis reveals that increased uncertainty does not impact sectors differently. Investors do not appear to flee to under-exposed sectors. The negative relation between TPU and excess returns stresses the particularity of the uncertainty episode under study.

This paper advances the research on trade policy uncertainty in two significant regards. On the one hand, it puts forth a new tractable, reproducible measure of TPU perception that can support further empirical research of this increasingly relevant source of uncertainty. On the other hand, it shows that the market's response to TPU is markedly different from its response to uncertainty stemming from other economic policy components. The results of this paper invite questions about the significance of impacts of short-term trade uncertainty episodes on the real economy. Its methodological contribution provides a tool that can help address such questions.

Chapter IV

China's Aid and Trade Diplomacy: A Zero-Sum Game?

4.1 Introduction

In 125 BC, Zhang Qian returned to the Han Imperial capital of Chang'an from a 13-year long trip, bearing news of lands "rich in unusual products whose people cultivated the land and made their living in much the same way as the Chinese" (Sima (1993)). Zhang Qian was China's first government-mandated diplomat. Through successive missions to western China and Central Asia, his travel diplomacy facilitated the establishment of the Han empire's silk road, for long the world's largest trade network. Today, China's *capitalism with Chinese characteristics* continues to rely on diplomacy in the conduct of international business. Active Chinese diplomacy continues to support business expansion into new markets.

The ongoing attempt to recreate a 21st-century silk road, embodied in the Popular Republic of China (PRC)'s Belt and Road Initiative, is only the latest example of this practice. Since the 2000s, China has also increased its contributions to development aid and official lending and multiplied its trade agreements with partners across the globe.

China's African strategy is a good example. From 2000-to 2017, China initiated over 5800 development aid projects on the continent. It extended over USD 153.4 billion in loans to African countries and canceled at least 1.9 billion in outstanding debt. Today China is the largest bilateral lender in the continent. Since 2005, over 30 African countries have received zero-tariff treatment on exports. The Belt and Road Initiative, China's effort to place itself at the center of a modern trade network, now covers over 40 African economies.

As official aid, loans, and agreements multiplied, so did the volumes of Sino-African economic flows. Between 2003 and 2019, Chinese foreign direct investment in Nigeria, Egypt, South Africa, and Algeria, the continent's top four economies, grew by 67, 75, 136, and 310, respectively. Over the same period, Chinese imports from these markets grew between 7 and 12 folds. Chinese exports to all African countries increased by a staggering 1,016%. Imports increased by 964%. For comparison, U.S. exports to the region grew by 146% over the same period, whereas imports increased by 94%.

The use of state resources to benefit business internationalization and the securing of supply chains by China has been the focus of several studies. They emphasize the role of government policies in shaping global supply chains in key sectors such as mining (Humphreys (2013)), energy (Lind and Press (2018)), and agriculture (Belesky and Lawrence (2019)). In all of these sectors, a solid state-business relationship allows political-diplomatic action and firm operations to move in lockstep to achieve power and profit's combined political and economic goals. In the West, some have decried Chinese mercantilist tendencies for their illiberal nature (Mawdsley (2008)). In Africa, others point to the neocolonial nature of China's interventions (Asongu et al. (2018)). These critics perceive the PRC's aid and trade diplomacy as a zero-sum game: for China's western rivals, it carries the threat of displacement and in the targeted economies of dependence.

This paper evaluates this premise. From the perspective of China's African partners, it asks: does Chinese commercial diplomacy have export diversion effects? In other words, does China's commercial diplomacy rearrange the export network of targeted economies to the exclusive benefit of China, or does it increase their export capabilities across the board?

Whereas the literature on the growth and trade effects of China's aid and trade diplomacy has made significant progress in recent years, it has so far overlooked the question of diversion. This paper aims to fill this gap. It identifies associations between China's aid and trade interventions and recipient countries' exports to third-party countries. In the process, it also contributes a more disaggregated analysis of the trade creation effects. I look at four tools of Chinese commercial diplomacy: trade agreements, development aid, government loans, and the Belt and Road Initiative, arguably the crown jewel of Chinese commercial diplomacy. The choice of these tools is dictated by data availability, though several other instruments could also be essential to study. For each of these policy instruments, I measure the trade diversion effects from the angle of the target country. The analysis covers the period between 2000 and 2017.

The results suggest that China's aid and trade interventions do not systematically displace existing export flows and have net positive effects. China's official development assistance finance and preferential tariff treatments are associated with an increase in African countries' manufacturing exports. The Belt and Road Initiative, though a recent phenomenon on the continent, does not present any signs of export diversion.

The rest of the paper is structured as follows: Section 2 discusses the literature on aid and trade diplomacy and trade diversion in more length. Section 3 introduces the data, section 4 presents the methodology, and section 5 discusses the results. Section 6 concludes.

4.2 Literature Review

This paper evaluates the export creation and export diversion effects of China's aid and trade diplomacy in Africa. To do so, it considers two main types of treatments.

On the one hand, official finance (OF) comprises foreign aid and other forms of concessional and non-concessional state financing. In a 2006 policy paper titled "China's African Policy," the country pledged more efforts to increase trade and investment and provide economic assistance (Copper (2015)). The paper emphasized that "in light of its own financial capability and economic situation, China will do its best to provide and gradually increase assistance to African nations with no political strings attached." The PRC's OF takes different forms, spanning technical assistance and training programs, concessional and non-concessional lending, debt relief, grants, and scholarships.

On the other hand, the second class of treatments relates to trade and investment agreements. China is linked to over 30 African countries by preferential trade agreements and has concluded over 40 memoranda of agreements under its flagship infrastructure investment project: the Belt and Road Initiative.

The growth effect of China's OF has been recently studied in Dreher et al. (2017). Using the same treatment data as this paper but with a broader geographic focus, the authors identify a positive effect of Chinese official financing on growth. They estimate that one additional Chinese official development assistance (ODA) project produces 0.7 percentage points increase in economic growth two years after the pledge.

Two recent papers have studied the trade creation effects of China's official finance interventions in Africa. Liu and Tang (2018) investigate the impact of the US and China's foreign aid to countries on the continent on trade flows between donor and recipient countries. They find that China's development aid increases African exports to China, whereas the same is not true of the US. Savin et al. (2020) corroborate this result. These papers echo findings from previous research with broader geographic scope. For instance, **?** shows that bilateral aid is not only positively correlated with donor exports but also positively associated with recipient exports to donors and that recipient exports of strategic materials display a stronger association with bilateral aid. These findings challenge the prior theoretical work that emphasized the negative impact of aid on recipient countries' exports due to exchange rate appreciation.

Due to China's timid participation in trade deal-making, few studies look at the country's trade agreements' effects. Two studies have looked at the trade effects of China's preferential tariff policies in Africa. Sun and Omoruyi (2021) find that zero-tariff treatment in favor of African partners significantly promoted export diversification from the manufacturing industry. An older policy paper by Berhelemy (2011) analyzes the response of African countries' China imports in the early phase of the zero-tariff policy and finds that they increase alongside imports from other partners.

To the exception of Berhelemy (2011) who tangentially brings up the question of import diversion, the existing literature has overlooked the trade diversion effects of China's OF and trade agreements.

Yet, an old finding in the trade literature is that asymmetric trade policy can cause trade diversion. First suggested by Viner (2014) in his research on customs unions, trade diversion can often be a corollary to trade creation. The original theoretical framework that motivates trade diversion reduces to a Cournot competition framework. Country A allocates import decisions between countries B and C. If country A enters into a zero-tariff trade agreement with country B, country B's marginal cost of production for exports to country A decreases. As a result, exports from B to A increase, all else equal. Additionally, B receives a competitive advantage over C due to the asymmetric tariff treatment. Thus, on the international trade network, part of the increased trade on the A $\longrightarrow$ B edge is diverted away from the C $\longrightarrow$ A edge.

The empirical evidence on trade diversion varies on a case-by-case basis. In a highly aggregated study, Dai et al. (2014) looks at the trade diversion effects of free trade agreements using manufacturing export data from 1990 to 2002 for a total of 41 trading partners. The results confirm that FTAs divert trade away from non-member countries. Furthermore, Trade diversion is stronger for internal trade than external trade and imports than exports. These aggregated results appear to hide discrepant dynamics at less aggregated scales. In an econometric analysis of trade diversion under NAFTA, Fukao et al. (2003) find evidence of US import diversion in specific industries. Out of 60 HS 2-digit manufacturing lines, only 15, mainly textile and apparel products, experience significant import diversion due to the entry into force of the regional liberalization agreement. Contrastingly, a study on the trade diversion effects of the ASEAN-China free-trade agreement finds no evidence of trade diversion (Yang and Martinez-Zarzoso (2014)). Instead, it identifies pure trade creation effects in exports and imports, both for countries within and outside the trading bloc. This heterogeneity reveals the need for further empirical localized studies of trade diversion dynamics, such as this one.

Trade diversion is not specific to trade agreements. Potentially any asymmetrical policy intervention can also divert existing flows. Such is the case of anti-dumping (AD) and countervailing (CV) measure actions. Prusa (2019) studies the trade impacts of 428 anti-dumping petitions filed between 1980 and 1988. The results show that in the year following the filing of the petition, imports from non-named countries increase by 22%. This growth in imports from non-named countries exceeds the reduction that affects the named country during the investigation or after duties are levied. Bown and Crowley (2007) document the causal nature of this dynamic, using the low-intensity US trade war with Japan in the 1990s. The authors show that Japanese exports are 'deflected' to third countries in response to remedial measures. The average anti-dumping duty on Japanese exports leads to a 5–7% increase in Japanese exports of the same product to the average third-country market. However, here too, sectoral heterogeneity is substantial. While manufacturing flows appear to be reallocated in response to "trade remedies," agricultural flows do not (Carter and Gunning-Trant (2010)), likely resulting from their less liberalized nature. Besides AD and CV actions, voluntary export restrictions (VER) have also been documented to reallocate trade flows (Hamilton (1985)).

Like AD and CV actions, or bilateral liberalization policies, China's OF actions and trade agreements, and investment deals under the BRI, are an asymmetric trade policy instrument targeting specific countries, with possible diversion effects. In fact, this distortionary effect is often assumed to be true. In an analysis of China's energy mercantilism, Lind and Press (2018) argues that market considerations heavily inform China's use of political and diplomatic clout. Political resources are deployed to gain control or influence over key suppliers, diversify products, suppliers, and transport routes, create inventories, and provide security to protect vulnerable assets. This mercantilist logic extends to other non-energy markets where the Chinese government seeks a stronger presence. The use of these instruments and the ensuing reinforcement of China's economic presence in target countries has been portrayed in Western media as exclusive and antagonistic to the interests of such third-party partners like the European Union and the United States (Mawdsley (2008)). The depiction of economic diplomacy interventions as a zero-sum game implicitly presumes a distortionary diverting effect. The goal of this paper is to evaluate these effects econometrically.

Whereas it has not provided a quantitative evaluation of the role of economic diplomacy in restructuring trade networks, the previously described literature offers helpful pointers to guide our work. A first takeaway is that it is essential to adopt a disaggregated approach to allow for sectoral heterogeneity. Furthermore, different policy instruments must be studied separately, even if seemingly similar (Moons and Bergeijk (2017)). Lastly, the literature provides some candidate econometric models for this study. The gravity model of trade, as adapted by Baier and Bergstrand (2007), can be readily used to estimate both creation and diversion effects as in Dai et al. (2014) and Yang and Martinez-Zarzoso (2014). However, data structure and variation will impede the implementation of a standard gravity model à la Baier and Bergstrand (2007). In such cases, I will use alternative specifications such as diff-in-diff (Nitsch (2007)) or cross-sectional approaches (Rose (2007)). The estimation equations chosen for this paper are discussed further in the methodology section.

4.3 Data & Stylized Facts

I analyze the trade creation and diversion effects of two broad classes of treatments: official financing, trade agreements, and an investment agreement: the BRI. This section describes the data on these different tools and provides some stylized facts on their structure.

4.3.1 Trade and Investment agreements

Trade agreements are the quintessential trade diplomacy instrument. Governments entering into these arrangements seek to foster trade between their countries, possibly to the detriment of third-party countries. Data on trade agreements is derived primarily from the NSF-Kellogg Institute Database on Economic Integration Agreements (EIA). The latest release of the EIA covers all country pairs from 1953 to 2014. To ensure that the study is as current as possible, I supplement the EIA data with three additional years of observations using the World Trade Organization's (WTO) database on regional trade agreements. Thus, the panel's time dimension runs through 2017. Due to inaccuracies in the EIA's China trade regimes [1], I make corrections to the dataset using Sun and Omoruyi (2021)'s China's customs data. Table 4.1 presents the profiles and counts of trade agreements binding China with third-party countries.

China's free-trade strategy has until recently been cautious. The country is part of a limited number of free-trade agreements, the largest of which are ASEAN-China and the Asia-Pacific Trade Agreement. Indeed, China's most significant FTAs center around its immediate geographic environment. China signed its first African trade agreement with Mauritius in 2019, and it entered into force in January 2021 and is thus outside of the time scope of this study. The China-Mauritius trade agreement remains the last one of its kind in Africa to date.

Table 4.1: China's Trade Agreement Diplomacy

	All Countries				African Countries			
Year	No Agreement	Asymmetric	Preferential	FTA	No Agreement	Asymmetric	Preferential	FTA
2000	192	0	0	0	51	0	0	
2001	187	0	5	0	51	0	0	
2002	187	0	5	0	51	0	0	
2003	187	0	5	0	51	0	0	
2004	186	0	5	1	51	0	0	
2005	162	24	5	1	27	24	0	
2006	153	24	4	11	27	24	0	
2007	149	26	4	13	25	26	0	
2008	146	28	4	14	23	28	0	
2009	145	28	4	15	23	28	0	
2010	141	29	5	17	22	29	0	
2011	135	35	6	16	21	30	0	
2012	136	34	6	16	22	29	0	
2013	137	33	6	16	23	28	0	
2014	137	33	6	16	23	28	0	
2015	137	33	5	17	23	28	0	
2016	137	33	5	17	23	28	0	
2017	135	35	5	17	21	30	0	

China has more heavily relied on asymmetric preferences to facilitate trade. Under the Forum on China-Africa Cooperation (FOCAC), China extended zero-tariff treatment to thirty least-developed countries (LDCs) in Africa in 2005. The roll-out has been progressive. As of July 1st, 2010, 30 countries [2] in Africa benefited from zero tariffs on 95% of

[1]The EIA database considers a trade cooperation agreement between Egypt and China as a preferential system - even though it lacks tariff measures. Additionally, it only incorporates zero-tariff treatments under the Forum on China-Africa Cooperation (FOCAC) from 2011 - once registered with the WTO.

[2]Ethiopia, Angola, Benin, Burundi, Equatorial Guinea, Togo, Eritrea, Cape Verde, Democratic Republic of the Congo (DRC), Djibouti, Guinea, Guinea-Bissau, Comoros, Lesotho, Liberia, Rwanda, Madagascar, Mali, Mauritania, Mozambique, Niger, Sierra Leone, Senegal, Sudan, Somalia, Tanzania, Uganda, Zambia, Chad, and the Central African Republic. Note that the analysis excludes Sudan and South Sudan due to the 2012 partition.

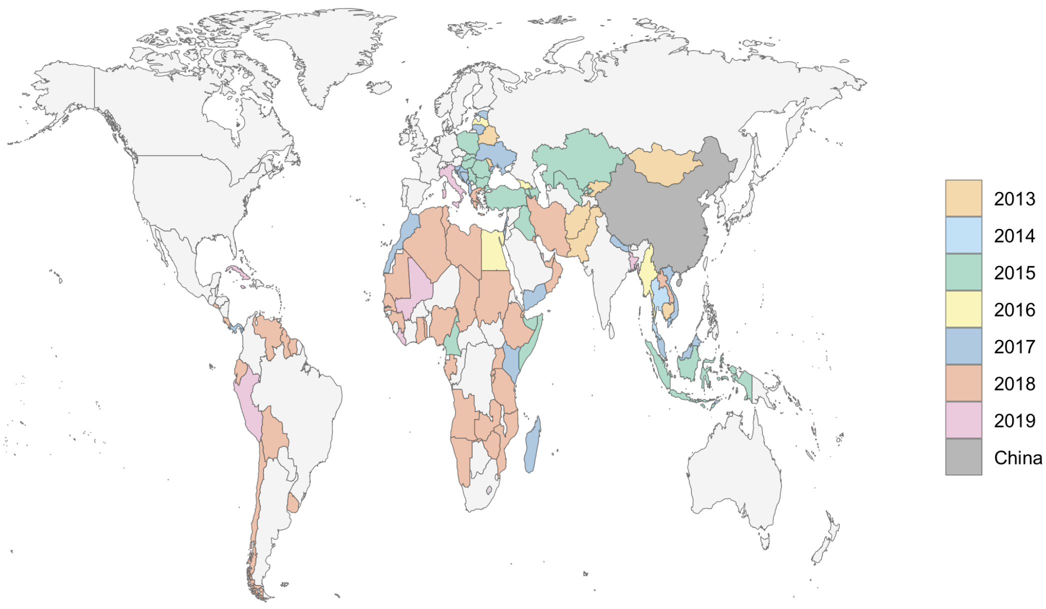


Figure 4.1: Belt and Road Initiative Members, and Entry Years

products under China's Duty-free treatment for LDCs.

In addition to trade agreements, I also look at investment agreements signed under the Belt and Road Initiative (BRI), a cornerstone instrument of China's trade diplomacy. The BRI envisions the emergence of a China-centric trade network in the process. "The Silk Road Economic Belt focuses on bringing together China, Central Asia, Russia, and Europe (the Baltic); linking China with the Persian Gulf and the Mediterranean Sea through Central Asia and West Asia; and connecting China with Southeast Asia, South Asia, and the Indian Ocean. The 21st-Century Maritime Silk Road is designed to go from China's coast to Europe through the South China Sea and the Indian Ocean in one route, and from China's coast through the South China Sea to the South Pacific in the other".

By 2019, 38 African countries had signed MoUs under the Belt and Road Initiative, including the continent's largest economies of Nigeria, Egypt, South Africa, and African LDCs (see figure 1). As a result of the peripheral location of most African countries relative to the Belt and Road, the level of scheduled and disbursed investments varies significantly from one country to the other. In the absence of cross-continental projects like Eurasia's China-Mongolia-Russia or Bangladesh-China-India-Myanmar Economic Corridor, the roll-out of the BRI in Africa is at the bilateral level.

Total BRI engagements in Sub-Saharan Africa towered at over 25 billion USD in 2019, second only to investment commitments in East Asia (Green Finance and Development Center). These engagements are unevenly distributed across countries, with some seeing significant investments (Nigeria, Egypt, Ethiopia), while others have yet to identify a joint project. Data on investment engagements and project construction under the BRI is not centrally collected, and ad-hoc sources can be discrepant, with some reports failing to disentangle investments within the BRI framework from other general flows. Therefore, I use MoU signing as the treatment proxy. Therefore, the results cannot be interpreted on the intensive margin but only on the extensive margin. Additionally, over half of the African members joined in 2018, which means that the data will not reveal long-term dynamics and will only provide treatment response to a one-year horizon.

4.3.2 Financial Aid Data

Despite contributing billions of dollars in aid annually and being the world's top bilateral creditor (Horn et al. (2021)), China does not participate in existing global reporting systems, such as the OECD's Creditor Reporting System (CRS) and the International Aid Transparency Initiative (IATI). As a result, there is a significant gap in the availability of internationally comparable statistics on Chinese official financing.

This paper uses William & Mary's AidData research lab **Global Chinese Official Finance Dataset, Version 2.0** (Custer and Zhang (2021)). The dataset records the known universe of projects supported by official financial and in-kind commitments (or pledges) from China from 2000 to 2017. It does so by synthesizing and standardizing vast amounts of unstructured, open-source, project-level information published by governments, intergovernmental organizations, companies, non-governmental organizations, journalists, and research institutions. The database includes official development assistance (ODA) and other official flows (OOF)s. The distinction follows the OECD rules. Under these rules, ODAs must be concessional (i.e., grants and soft loans) and administered to promote the economic development and welfare of developing countries as the main objective. OOFs are official sector transactions that do not meet the concessionality criterion.

The dataset reveals that China has spent $843 billion on financial aid between 2000 and 2017. This sum is roughly equivalent to the amount spent by the US, the world's largest donor of foreign aid. This volume breaks into 13,427 Chinese development 'projects' officially pledged, committed, in implementation, or completed between 2000 and 2021. The dataset identifies different official finance flow types: grants, free-standing technical assistance, scholarships and training, loans, debt relief, and export credit.

For analysis, the data is restricted geographically to African recipients and economically to projects that have at least been officially committed to. Once this filtering is applied, the data consists of 5,152 projects. Table 4.2 provides summary statistics on allocations, and figure 2 shows the disaggregated composition. It is worth noting that virtually all African countries are receiving some form of development aid from China by the end of the period. Correspondingly, the number of new development projects increased five-fold from 79 in 2000 to 502 in 2017.

Table 4.2: China's Development Assistance Flows To Africa (all categories)

	Development Assistance	
Commitment Year	Number of Recipients	Number of Projects
2000	36	79
2001	37	105
2002	42	126
2003	41	140
2004	41	145
2005	45	199
2006	45	270
2007	47	333
2008	47	276
2009	49	327
2010	47	289
2011	48	385
2012	47	349
2013	47	343
2014	49	350
2015	49	415
2016	50	481
2017	51	502

Table 4.3 provides a yearly breakdown of new loan and debt relief flows. In terms of volumes, China issued countries in Africa over 153 billion USD in new official loans. Over the same period, 49 African countries received at least one loan, with the yearly number of recipients oscillating between 12 and 27. Over the same period, China restructured *at least* 2 billion USD in existing debt to benefit a total of 40 countries. These figures highlight the scope of China's aid and trade activism in Africa, and explain the media attention and suspicion that it fuels in the West (Mawdsley (2008)).

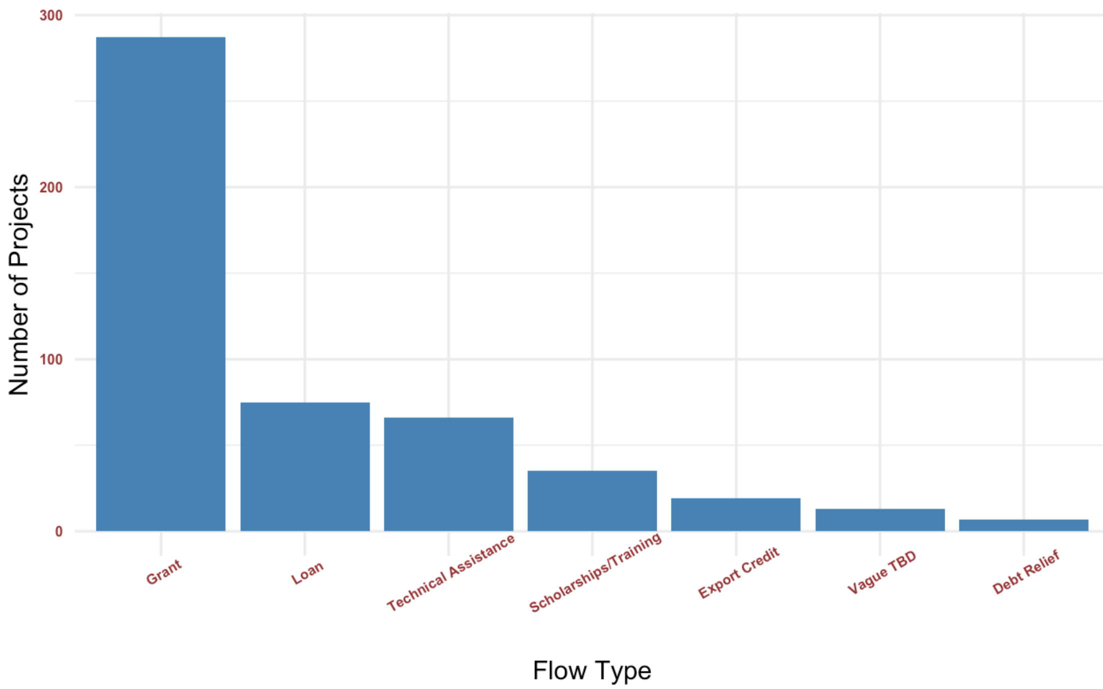


Figure 4.2: Composition of China's Development Assistance to Africa (2017)

Table 4.3: Official Chinese Loans To African Countries (Excluding Trade Finance)

	New Loans		Debt Cancellation	
Year	Num. Recipients	Total Volume (Million USD)	Num. Beneficiaries	Total Volume (Million USD)
2000	12	99.49	1	*Not Available*
2001	13	152.64	24	798.11
2002	13	231.12	6	124.42
2003	10	922.99	4	2.44
2004	12	642.32	3	*Not Available*
2005	16	803.91	3	51.0
2006	22	2,329.25	5	60.77
2007	23	1,760.84	28	619.02
2008	22	5,282.04	1	*Not Available*
2009	23	4,162.77	2	2.54
2010	25	5,809.31	5	10.34
2011	26	5,608.60	7	98.98
2012	27	10,600.94	3	44.65
2013	27	11,015.16	0	0
2014	21	9835.87	0	0
2015	24	5,250.71	0	0
2016	23	2,5347.16	7	57.19
2017	23	1,3199.05	6	83.07

4.4 Methodology

4.4.1 Official Financing (OF) Treatments

To evaluate the trade creation and diversion effects of official financing, I estimate a gravity equation augmented with an official finance treatment variable. The use of gravity equation to estimate the trade impact of financial flows has so far been the standard approach in the literature (Pettersson and Johansson (2013), Savin et al. (2020), Liu and Tang (2018)). The log linear version of the model has the following form:

$$\begin{aligned} log(X_{ijt}) = & \alpha_0 + \alpha_1 log(gdp_{it}) + \alpha_2 log(gdp_{jt}) + \alpha_3 log(pop_{it}) + \alpha_4 log(pop_{jt}) \\ & + \alpha_6 \text{RTA}_{ijt} + \beta_1 \text{treatment}_{it} + \beta_2 (\text{treatment}_{it} \times \text{NotChina}_j) + \eta_t \\ & + \eta_{ij} + \varepsilon_{ijt} \end{aligned} \tag{IV.1}$$

Where $X_{ij,t}$ is the value of exports from country i to country j in year t. Gross domestic products (gdp) and populations (pop) are explicitly included as predictors, whereas time-invariant bilateral gravity variables are absorbed in γ_{ij}, which also captures multilateral resistance. Time fixed effects absorb variations over the time dimension. The treatment variable will take value 1 if country i has received official financing from China in year t and 0 otherwise. Because I seek to check for differential response to treatment of exports to China and exports to third party countries, I interact the treatment variable with a dummy variable $NotChina$ that takes value 1 when the importer is not China, and 0 otherwise.

In this specification, β_1 measures the increase in export flows to China for countries that receive financial aid. $\beta_1 + \beta_2$ measures the response of export flows of recipient countries to third-party trading partners. Thus, values of the parameters such that $\beta_2 + \beta_1 < 0$ would point at an export diversion effect of China's OF.

Equation (4.1) can suffer from simultaneity bias if a feedback exists between export flows and OF allocations, and from reverse causality. To address this concern, I specify the following preferred model:

$$\begin{aligned} log(X_{ijt}) = & \alpha_0 + \alpha_1 log(gdp_{it}) + \alpha_2 log(gdp_{jt}) + \alpha_3 log(pop_{it}) + \alpha_4 log(pop_{jt}) \\ & + \alpha_6 \text{RTA}_{ijt} + \beta_3 \text{treatment}_{i,t_{1-3}} + \gamma_3 (\text{treatment}_{i,t1-3} \times \text{NotChina}_j) \\ & + \eta_t + \eta_{ij} + \varepsilon_{ijt} \end{aligned} \tag{IV.2}$$

I estimate this specification using two different definitions of treatment. Following Savin et al. (2020), I define treatment as a binary variable that takes value 1 if exporter i has been a recipient of China's official financing (OF) between years -1 and -3, and 0 otherwise. I will refer to this as the extensive margin of treatment. In a second estimation, I define treatment as the number of OF flows received; i.e. the intensive margin of treatment. In this latter case, the specification is augmented with additional dummy variables on recipient status. This allows me to evaluate the impact of treatment intensity conditional on treatment.

Equations (4.1) and (4.2) are estimated for aggregate exports, as well as for three broad sectors: manufacturing, raw materials, and agriculture. The differential response to economic diplomacy treatments across industries is established in the literature (Moons and Bergeijk (2017)). Additionally, in subsequent estimations, the treatments are disaggregated into categories and types, following the literature on aid and growth which finds significant differences in growth effects across flow types (Pettersson and Johansson (2013)).

4.4.2 Trade Agreements

The export creation and diversion effects of China's preferential treatments for African countries are estimated separately, via two equations:

$$log(X_{ij,t}) = \alpha_0 + \beta_1 \times ATA_{ij,t} + \beta_2 \times ATA^C + \eta_{ij,t} + \eta_{it} + \eta_{jt} + \varepsilon_{ij,t} \tag{IV.3}$$

$$log(X_{i,t}^{RoW}) = \alpha_0 + \gamma_1 ATA_{i,t}^C + \delta_1 pop_{i,t} + \delta_2 gdp_{i,t} + \delta_3 wto_{i,t} + \eta_i + \eta_t + \varepsilon_{i,t} \tag{IV.4}$$

Equation (4.3) follows the literature on the effects of trade agreements initially proposed in (Baier and Bergstrand (2007)) seminal paper. Export flows are a function of a series of interacted fixed effects and of the trade regime captured in the dummy ATA which stands for *asymmetric trade agreement* and takes value 1 if the flow from $i \to j$ benefits from preferential treatment, and 0 otherwise. For estimation, the data is restricted to country pairs that have no trade agreements, or that share an asymmetric preferential agreement. Dropping deeper agreements (PTAs, FTAs, etc.) allows me to compare the performance of China's asymmetric treatments against a control groups of pairs that do not have any agreement. In this context, γ_1 measures the average performance of asymmetric preferential treatments extended by importer countries to African exporters. γ_2 captures the additional effect of preferential treatments by China. A positive γ_2 would mean that China's preferential treatment is better at supporting African exports to China than are other systems of preferences.

Equation (4.5) estimates the diversion effects of China's zero-tariff policies. The outcome variable is total export flows to the rest of the world (RoW). Because China's preferential tariff program is tied to LDC status, which is defined based on income per capita, $GDP_{i,t}$ and $POP_{i,t}$ are added into the equation to control for selection into treatment. Furthermore, the regression controls for the World Trade Organization membership status. Individual and time fixed effects control for other sources of variation.

My approach to the estimation of the trade diversion effect deviates from the existing literature. In a study of the trade-diversion effects of free trade agreements Dai et al. (2014) use a gravity specification similar to equation (4.4), augmented with two dummies that take value 1 when the exporter or importer have trade agreements with other countries, respectively. Their specification captures the export and import diversion effects of the agreements - which they find to be significant. Adapting this approach to the isolated case of Chinese agreements is not possible due to limited variations that do not allow for the inclusion of a full set of fixed effects.

4.4.3 Investment Agreements

To be able to exploit variations in trade dynamics, analysis of the impact of BRI membership is confined to countries that have joined in 2015: South Africa, Cameroon. While Somalia also joined in 2015, its trade flows are generally unstable and hard to predict given the country's perpetual instability, and very small economic size, which makes it a bad candidate for a comparative estimation approach. Most other members joined the initiative in 2018 - which is outside the time span of this study.

Given the short treatment period and low number of treated units, which limit the applicability of a panel data, I rely on a synthetic controls approach. In this method, the export flows of each treated country post-treatment are compared to those of a synthetic counterfactual that is specific to each treated unit. The synthetic counterfactual is a weighted sum of comparable, non-treated, African economies. The weights are constructed to match the pre-treatment trends as closely as possible. This addresses concerns of selection into treatment, and relaxes the parallel trend assumptions (Abadie et al. (2010)).

To build the synthetic controls, I use the Generalized Synthetic Control Method developed by Xu (2017). This method allows me to mach units on pre-treatment observables while also including unobserved time-varying heterogeneities using interactive fixed effects. The matching is performed over the outcome only (export flows), to avoid bias. Using a relatively long pre-treatment period (2000-2014) additionally allows me to get a better pre-treatment fit.

4.5 Results

4.5.1 Official Financing Results

Table 4.4: Trade Creation and Diversion Effects of Official Finance (OF)

	Dependent variable:			
	All exports	Manufacturing	Agriculture	Raw materials
Control: Importer's GDP	0.589***	0.813***	0.705***	0.533***
	(0.0345)	(0.0401)	(0.0455)	(0.0505)
Control: Importer's Population	0.940***	0.796***	0.391**	0.599***
	(0.0921)	(0.114)	(0.122)	(0.142)
Control: Exporter's GDP	0.391***	0.212***	0.319***	0.485***
	(0.0324)	(0.0379)	(0.0436)	(0.0470)
Control: Exporter's Population	-0.955***	-1.069***	-1.708***	-1.552***
	(0.134)	(0.167)	(0.209)	(0.219)
Control: RTA (yes/no)	0.328***	0.158**	0.437***	0.337***
	(0.0448)	(0.0512)	(0.0542)	(0.0641)
Treatment: OF received (yes/no)	0.954***	0.976***	0.981**	1.291***
	(0.271)	(0.293)	(0.334)	(0.312)
Treatment: OF received × Not China	-0.997***	-0.991***	-0.948**	-1.178***
	(0.272)	(0.295)	(0.336)	(0.314)
Constant	-4.424**	-4.795**	6.317**	3.188
	(1.440)	(1.775)	(2.170)	(2.366)
Observations	88329	71037	49506	52805
Fixed-Effects	T, EX×IM	T, EX×IM	T, EX×IM	T, EX×IM
Joint significant P-value	0.13	0.64	0.35	0.0051

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.4 presents results from the estimation of equation (4.1). The evidence suggests that receiving official financing from China is significantly associated with higher exports to China, and this effect is particularly large for raw materials. However, this increased trade does not appear to happen at the expense of existing flows with third-party partners, as reflected by the diversion coefficient's lower magnitude and the combined effects' statistical insignificance.

Equation (4.1) imposes contemporaneity on the treatment and exports' response and is likely prone to simultaneity and reverse causality biases. Using lagged treatment, equation (4.2) addresses this concern. The results from the estimation are reported in table 4.5. Official Finance does not appear to associate significantly with exports to China or third-party countries in this setup.

Table 4.5: Trade Creation and Diversion Effects of Official Finance (OF) - Lagged Treatment (Extensive)

	Dependent variable:			
	All Exports	Manufacturing	Agriculture	Raw Materials
Control: Importer's GDP	0.653***	0.869***	0.807***	0.541***
	(0.0421)	(0.0496)	(0.0557)	(0.0619)
Control: Importer's Population	0.441***	0.449**	0.174	0.571**
	(0.121)	(0.154)	(0.163)	(0.193)
Control: Exporter's GDP	0.316***	0.0838	0.299***	0.419***
	(0.0394)	(0.0476)	(0.0529)	(0.0585)
Control: Exporter's Population	-0.443**	-0.338	-0.966***	-1.462***
	(0.156)	(0.202)	(0.260)	(0.264)
Control: RTA	0.260***	0.0381	0.353***	0.0896
	(0.0576)	(0.0664)	(0.0677)	(0.0820)
Treatment: OF Received (dummy)	0.688	1.120	1.727*	-0.275
	(0.560)	(0.633)	(0.799)	(0.786)
Treatment: OF Received (dummy) x Not China	-0.871	-1.467*	-1.825*	0.123
	(0.564)	(0.638)	(0.803)	(0.793)
Constant	-4.165*	-6.767**	0.148	4.127
	(1.767)	(2.232)	(2.732)	(2.989)
Observations	71702	56616	38684	41282
Fixed-Effects	T, EX×IM	T, EX×IM	T, EX×IM	T, EX×IM
Joint significant P-value	0.0062	0.0001	0.255	0.17

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Using specification (2) but adjusting treatment variables to the number of OF flows received, I can look at the intensive margin of treatment effects. Results in Table 4.6 suggest that the intensive treatment margin is more relevant to export response than the extensive margin. Countries targeted with a higher number of assistance projects can experience more significant changes in their export flow structures. Thus, an additional project is associated with a 2% increase in exports to China that concerns all sectors. More importantly, there is no evidence of trade diversion on the intensive margin. Indeed, overall exports and manufacturing and raw material exports experience a significant but marginal increase of less than a percentage point. The results in table 4.6 are robust to conditioning whether a country receives financing from China.

Table 4.6: Trade Creation and Diversion Effects of Official Finance (OF) - Lagged Treatment (Intensive)

	Dependent variable:			
	All Exports	Manufacturing	Agriculture	Raw Materials
Control: Importer GDP	0.634***	0.766***	0.728***	0.481***
	(0.0439)	(0.0489)	(0.0557)	(0.0616)
Control: Importer GDP	0.412**	0.623***	0.209	0.477**
	(0.130)	(0.148)	(0.158)	(0.185)
Control: Exporter GDP	0.268***	0.0244	0.280***	0.441***
	(0.0406)	(0.0474)	(0.0526)	(0.0583)
Control: Importer GDP	-0.597***	-0.682***	-1.152***	-1.755***
	(0.162)	(0.201)	(0.261)	(0.264)
RTA (yes/no)	0.200***	0.0776	0.389***	0.143
	(0.0585)	(0.0649)	(0.0679)	(0.0806)
Treatment: Cumulative OF	0.0229**	0.0512***	0.0381***	0.0415***
	(0.00733)	(0.00866)	(0.0113)	(0.00941)
Treatment: Cumulative OF x Not China	-0.0200**	-0.0439***	-0.0366**	-0.0360***
	(0.00735)	(0.00866)	(0.0113)	(0.00942)
Constant	-1.363	-2.918	3.041	8.085**
	(1.881)	(2.213)	(2.746)	(2.963)
Observations	66452	60008	41402	44293
Fixed-Effects	T,	T,	T,	T,
	EX×IM	EX×IM	EX×IM	EX×IM
Joint significant P-value	0.0069	0.0000	0.3031	0.0006

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Disaggregating OF into flow categories, model 2 yields the results presented in tables 7 and 8. The data consists of 3 broad categories: Official Development Aid (ODA) flows, which have a significant concessional component, and Other Official Financing (OOF) that do not. In addition, the dataset contains some financing flows that are ambiguous or not yet clearly determined. Being a recipient of ODA flows appear to have little bearing on export volumes. However, conditional on being a recipient, the intensity of ODA treatments, measured by the number of projects received over three years, does associate with higher exports to China. One additional ODA project increases total exports to China by an average of 3% and reduces exports to other countries by an average of 0.7% (significant at 1% confidence level). This effect is driven mainly by the manufacturing sector. Contrastingly, receiving other official finance flows is associated with a net increase in exports, but the impact does not fluctuate by treatment intensity.

Table 4.7: Effects of Official Finance (OF) By Category - Lagged Treatment (Extensive)

	Dependent variable:			
	All Exports	Manufacturing	Agriculture	Raw Materials
Control: Importer GDP	0.635***	0.882***	0.768***	0.556***
	(0.0437)	(0.0526)	(0.0578)	(0.0656)
Control: Importer Population	0.401**	0.504**	0.225	0.560**
	(0.129)	(0.172)	(0.174)	(0.215)
Control: Exporter GDP	0.284***	0.0500	0.240***	0.435***
	(0.0400)	(0.0489)	(0.0531)	(0.0597)
[1em] Control: Exporter Population	-0.482**	-0.292	-0.896***	-1.667***
	(0.160)	(0.212)	(0.271)	(0.277)
RTA (dummy)	0.202***	-0.0180	0.294***	0.0477
	(0.0586)	(0.0698)	(0.0686)	(0.0857)
Treatment: Other Official Finance (dummy)	0.328*	0.439*	0.311	0.519**
	(0.162)	(0.177)	(0.212)	(0.190)
Treatment: OOF x Not China	-0.276	-0.366*	-0.215	-0.409*
	(0.163)	(0.178)	(0.213)	(0.192)
Treatment: Official Development Aid (dummy)	0.392	0.576	0.951	-0.581
	(0.508)	(0.562)	(0.639)	(0.672)
Treatment: ODA (dummy) x Not China	-0.546	-0.842	-0.996	0.509
	(0.511)	(0.566)	(0.642)	(0.676)
Treatment: Ambiguous (dummy)	0.279	0.556**	0.461*	0.398
	(0.184)	(0.198)	(0.218)	(0.209)
Treatment: Ambiguous (dummy) x Not China	-0.140	-0.473*	-0.372	-0.316
	(0.185)	(0.199)	(0.219)	(0.210)
Constant	-2.476	-7.406**	0.856	5.775
	(1.849)	(2.400)	(2.876)	(3.210)
Observations	66753	51250	34902	37254
Fixed-Effects	T, EX×IM	T, EX×IM	T, EX×IM	T, EX×IM
Joint significant P-value : OOF	0.0081	0.0014	0.0001	0.0002
Joint significant P-value : ODA	0.0060	0.0001	0.4821	0.3769
Joint significant P-value : AMB	0.0000	0.0005	0.0005	0.0049

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.8: Effects of Official Finance (OF) By Category - Lagged Treatment (Intensive)

	Dependent variable:			
	All Exports	Manufacturing	Agriculture	Raw Materials
Control: Importer's GDP	0.622***	0.855***	0.755***	0.539***
	(0.0440)	(0.0531)	(0.0583)	(0.0662)
Control: Importer's Population	0.409**	0.550**	0.241	0.618**
	(0.130)	(0.173)	(0.175)	(0.216)
Control: Exporter's GDP	0.247***	0.00775	0.296***	0.387***
	(0.0407)	(0.0504)	(0.0546)	(0.0613)
Control: Exporter's Population	-0.810***	-1.056***	-0.835**	-1.923***
	(0.170)	(0.228)	(0.288)	(0.297)
Control: RTA (dummy)	0.200***	-0.0315	0.277***	0.0257
	(0.0586)	(0.0700)	(0.0685)	(0.0857)
Conditioning var: OOF (dummy)	0.185	0.259	0.185	0.396
	(0.175)	(0.191)	(0.238)	(0.207)
Conditioning var: OOF (dummy) x Not China	-0.119	-0.165	-0.0618	-0.262
	(0.176)	(0.192)	(0.239)	(0.209)
Treatment: Cumulative OOF	0.00472	0.0355	0.0513	0.0101
	(0.0153)	(0.0189)	(0.0350)	(0.0200)
Treatment: Cumulative OOF x Not China	0.00719	-0.0275	-0.0666	0.00528
	(0.0154)	(0.0190)	(0.0351)	(0.0203)
Conditioning var: ODA (dummy)	0.0704	0.314	0.961	-0.767
	(0.528)	(0.584)	(0.663)	(0.687)
Conditioning var: ODA (dummy) x Not China	-0.135	-0.541	-0.970	0.803
	(0.531)	(0.588)	(0.666)	(0.692)
Treatment: Cumulative ODA	0.0276*	0.0298*	-0.000428	0.0197
	(0.0122)	(0.0139)	(0.0175)	(0.0150)
Treatment: Cumulative ODA x Not China	-0.0344**	-0.0295*	-0.00351	-0.0322*
	(0.0123)	(0.0140)	(0.0176)	(0.0151)
Conditioning var: Cumulative AMB	0.235	0.311	0.430	0.311
	(0.206)	(0.222)	(0.363)	(0.233)
Conditioning var: Cumulative AMB x Not China	-0.166	-0.332	-0.306	-0.324
	(0.207)	(0.224)	(0.364)	(0.235)
Treatment: Cumulative AMB	-0.0258	0.0732	-0.0442	0.00842
	(0.0477)	(0.0503)	(0.185)	(0.0536)
Treatment: Cumulative AMB x Not China	0.0659	-0.00936	0.0324	0.0485
	(0.0479)	(0.0507)	(0.185)	(0.0542)
Constant	1.247	0.347	-0.509	8.760**
	(1.938)	(2.537)	(3.006)	(3.357)
Observations	66452	50965	34664	36911

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Disaggregating by type, loans stand out as the most effective tool in impacting export volumes to China but do not divert existing flows. Borrowing from China is associated with a 77% increase in exports to China and a 3% increase in exports to third-party partners. On the intensive margin, one additional loan increases manufacturing exports to China by 13%. Other types of financing, including export credit, debt relief, and technical assistance, do not significantly correlate with variations in exports to China or third-party partners.

4.5.2 Trade and BRI Agreements Results

The esults in table 4.11 show that the export-creation effects of China's preferential treatment program for African LDCs are, on average, larger than other iterations of the Generalized System of Preferences, specifically in the manufacturing and raw materials sectors. Receiving zero-tariff treatment increases manufacturing exports to China 4-fold, whereas receiving preferential treatment from non-China importers has no significant effect on recipients' manufacturing exports. This might be a reflection of the different designs of these preferential frameworks. Indeed, the US's AGOA applies tariff reduction selectively on products, and specifically excludes import-sensitive products in the manufacturing and agriculture sector (Frazer and Biesebroeck (2010)). The discrepancy can also be due to differential utilization rate of agreements, given that preferences can be significantly underutilized by exporting countries. For instance, Brenton (2006) the EU's GSP system is particularly underutilized.

In conjunction with table 4.12, the results above show that China's African trade agreements are net trade creators. Indeed, there is no significant evidence of export diversion, in aggregate and across industries. Controlling for a country's gross domestic product, population, and WTO membership status, benefiting from preferential treatment by China does not significantly lower exports to the rest of the world. This is true for aggregate exports (column 1) and of industry-level flows (columns 2-4).

The net export creation effects of China's zero-tariff policies echo findings from prior literature. Sun and Omoruyi (2021) demonstrate that these policies significantly support export diversification, especially in the manufacturing sector. An earlier working paper by Engel (2014) also finds that Chinese LDC preferences favorably impact exports at both the intensive and extensive margins.

Lastly, I turn to the trade creation and diversion effects of BRI agreements. The estimation method uses synthetic controls, and obtains treatment effects by comparing the performance of a treated country's export flows to those of a synthetic counterfactual constructed from observed data. The results are presented in figure 4. Three countries

Table 4.9: Effects of Official Finance (OF) By Flow Type - Lagged Treatment (Extensive)

	Dependent variable:			
	All Exports	Manufacturing	Agriculture	Raw Materials
Control: Importer's GDP	0.634***	0.888***	0.762***	0.565***
	(0.0438)	(0.0528)	(0.0579)	(0.0657)
Control: Importer's Population	0.396**	0.474**	0.256	0.550*
	(0.130)	(0.173)	(0.175)	(0.215)
Control: Exporter's GDP	0.253***	0.0330	0.216***	0.381***
	(0.0412)	(0.0503)	(0.0540)	(0.0615)
Control: Importer's Population	-0.601***	-0.432*	-1.231***	-1.797***
	(0.162)	(0.214)	(0.276)	(0.280)
Control: RTA (dummy)	0.202***	-0.0205	0.278***	0.0389
	(0.0586)	(0.0700)	(0.0685)	(0.0855)
Treatment: Export Credit (dummy)	0.0676	0.180	0.497*	0.225
	(0.187)	(0.203)	(0.227)	(0.213)
Treatment: Ex. Credit (dummy) x Not China	0.0181	-0.0836	-0.425	-0.144
	(0.187)	(0.204)	(0.228)	(0.215)
Treatment: Debt Relief (dummy)	-0.170	-0.0579	-0.0371	-0.328
	(0.163)	(0.177)	(0.212)	(0.189)
Treatment: Debt Relief (dummy) x Not China	0.212	0.0181	-0.0192	0.335
	(0.164)	(0.178)	(0.213)	(0.190)
Treatment: Technical Assistance (dummy)	0.176	-0.0259	0.154	-0.0843
	(0.260)	(0.272)	(0.293)	(0.283)
Treatment: Tech. Ass. (dummy) x Not China	-0.119	0.000887	-0.0976	0.175
	(0.261)	(0.273)	(0.294)	(0.285)
Treatment: Loan (dummy)	0.579***	0.824***	0.577**	0.449*
	(0.168)	(0.184)	(0.218)	(0.196)
Treatment: Loan (dummy) x Not China	-0.552**	-0.802***	-0.480*	-0.402*
	(0.169)	(0.185)	(0.219)	(0.197)
Treatment: Other OF (dummy)	0.220	0.484	0.441	-0.0715
	(0.360)	(0.390)	(0.517)	(0.436)
Treatment: Other OF (dummy) x Not China	-0.270	-0.551	-0.451	0.0185
	(0.362)	(0.393)	(0.519)	(0.439)
Constant	-0.942	-5.770*	4.214	7.784*
	(1.894)	(2.463)	(2.964)	(3.279)
Observations	66522	51039	34720	36986
Fixed-Effects	T, EX×IM	T, EX×IM	T, EX×IM	T, EX×IM
Joint significant P-value : Ex. Credit	0.0001	0.0001	0.0100	0.0095
Joint significant P-value : Debt Relief	0.383	0.0891	0.0290	0.8138
Joint significant P-value : Tech. Ass.	0.0377	0.42	0.0716	0.0157
Joint significant P-value : Loan	0.1632	0.3221	0.0001	0.0998
Joint significant P-value : Other	0.2351	0.1627	0.8441	0.3623

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.10: Effects of Official Finance (OF) By Flow Type - Lagged Treatment (Intensive)

	Dependent variable:			
	All Exports	Manufacturing	Agriculture	Raw Materials
	Conditioning and control variables omitted from table			
Cumulative Export Credit (count)	0.0124	0.0247	0.0408	0.0140
	(0.0205)	(0.0207)	(0.0437)	(0.0221)
Cumulative Export Credit (count) x Not China	-0.00383	-0.0257	-0.0569	-0.00861
	(0.0207)	(0.0209)	(0.0439)	(0.0224)
Cumulative Debt Relief (count)	0.0235	-0.404	-0.123	0.111
	(0.247)	(0.253)	(0.258)	(0.279)
Cumulative Debt Relief (count) x Not China	-0.0701	0.440	0.0807	-0.172
	(0.248)	(0.255)	(0.260)	(0.281)
Cumulative Technical Assistance (count)	0.0928	0.105	-0.105	0.0411
	(0.0558)	(0.0614)	(0.0804)	(0.0667)
Cumulative Tech. Ass. (count) x Not China	-0.109	-0.116	0.108	-0.0693
	(0.0561)	(0.0619)	(0.0809)	(0.0673)
Cumulative Lending (count)	0.00676	0.118***	0.0606	0.0269
	(0.0191)	(0.0316)	(0.0487)	(0.0330)
Cumulative Lending (count) x Not China	0.00662	-0.0891**	-0.0681	-0.0154
	(0.0192)	(0.0318)	(0.0489)	(0.0333)
Cumulative Other (count)	0.0104	0.00491	-0.0111	0.0247
	(0.0151)	(0.0175)	(0.0208)	(0.0186)
Cumulative Other (count) x Not China	-0.0150	-0.00269	0.00463	-0.0301
	(0.0152)	(0.0176)	(0.0209)	(0.0188)
Constant	0.171	-1.787	3.140	6.978*
	(1.949)	(2.535)	(3.040)	(3.361)
Observations	66452	50965	34664	36911

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.11: Trade Creation Effects of Preferential Tariff Treatment

	Dependent variable:			
	All Exports	Manufacturing	Agriculture	Raw Materials
Preferential Treatment (Dummy)	0.0714	-0.0912	0.249	-0.0210
	(0.392)	(0.437)	(0.259)	(0.367)
Preferential Treatment x China	1.051	1.622*	0.313	1.206*
	(0.521)	(0.605)	(0.524)	(0.554)
Constant	11.61***	10.29***	11.48***	11.93***
	(0.0615)	(0.0762)	(0.0550)	(0.0762)
Observations	31743	24333	14963	16183
Fixed-Effects	EX×T, IM×T, EX×IM	EX×T, IM×T, EX×IM	EX×T, IM×T, EX×IM	EX×T, IM×T, EX×IM
Joint significant P-value	0.203	0.0113	0.2421	0.0188

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.12: Trade Diversion Effects of Preferential Tariff Treatment

	Dependent variable:			
	All Exports	Manufacturing	Agriculture	Raw Materials
Exporter's Population	0.169	0.178	-0.506	0.717
	(0.415)	(0.669)	(0.797)	(0.717)
Exporter's GDP	0.539***	0.157	-0.354*	0.498**
	(0.102)	(0.151)	(0.180)	(0.161)
Exporter's WTO	0.156	-0.637	1.237**	1.975***
	(0.214)	(0.340)	(0.404)	(0.365)
PTA with China (dummy)	-0.148	-0.0451	0.203	0.0153
	(0.0815)	(0.120)	(0.143)	(0.128)
Constant	8.735*	12.58*	25.09***	1.663
	(3.535)	(5.648)	(6.725)	(6.049)
Observations	896	847	841	847

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

are retained for analysis: South Africa (ZAF), Cameroon (CMR) and Somalia (SOM). These are the earliest African members in the BRI, with entry years spanning 2014-2015. For each of the three countries three outcomes are analyzed: flows to China, flows to the United States, and flows to the European Union. This yields 9 estimated treatment effects. The point estimates of the treatment effect are represented by the white circles. The segments represent the 95% confidence interval around the point estimate.

As shown on the figure, the treatment effects on trade with China, the US, and Europe, are all indistinguishable from zero. It is clear that we cannot reject the hypothesis that BRI does not divert existing trade flows with China's Western rivals. These results might however be sensitive to the recent nature of the initiative in Africa and the peripheral status of member countries in the region in the overall vision and financial commitments of the BRI. Indeed Sebastian Ibold's BRI data collection project Ibold (2022) only identifies one project that tangentially targets Cameroon consisting in the Chad-Cameroon railway, and no committed projects for South Africa or Somalia.

4.5.3 Discussion

The trade creation results are broadly in line with prior findings in the literature: receiving more Official Financing from China is associated with increases in recipients' exports to China (table 4.6). This relationship is primarily due to the role played by official development assistance (ODA). The fact that ODA flows are more beneficial to recipients' exports is supported by results from Savin et al. (2020) who show that African exports to China associate positively with ODA flows, with manufacturing industries leading the response. The finding that manufactured African exports are most sensitive to ODA is also in line with Savin et al. (2020) results. Pettersson and Johansson (2013) on the other hand, points to a particularly strong link between ODA and recipient's exports of strategic material. This does not seem to materialize in the context of China's aid to Africa, as the manufacturing sector repeatedly appears as the most responsive across specifications.

This paper sheds light on which type of official finance (OF) flows drives the association between official finance and trade. It shows that lending is the primary mechanism through which official finance impacts recipients' exports. This result is particularly relevant in a context where China has become the first bilateral lender to Africa.

Furthermore, the results above demonstrate that how we define treatment matters to our study of the response of African exports to China's official finance. The impact of ODA depends on its intensity, and being a recipient of official flows does not elicit significant responses from export flows. However, receiving *more* official finance, particularly more ODA, leads to a positive response of the recipient's exports. Conversely, increasing OOF

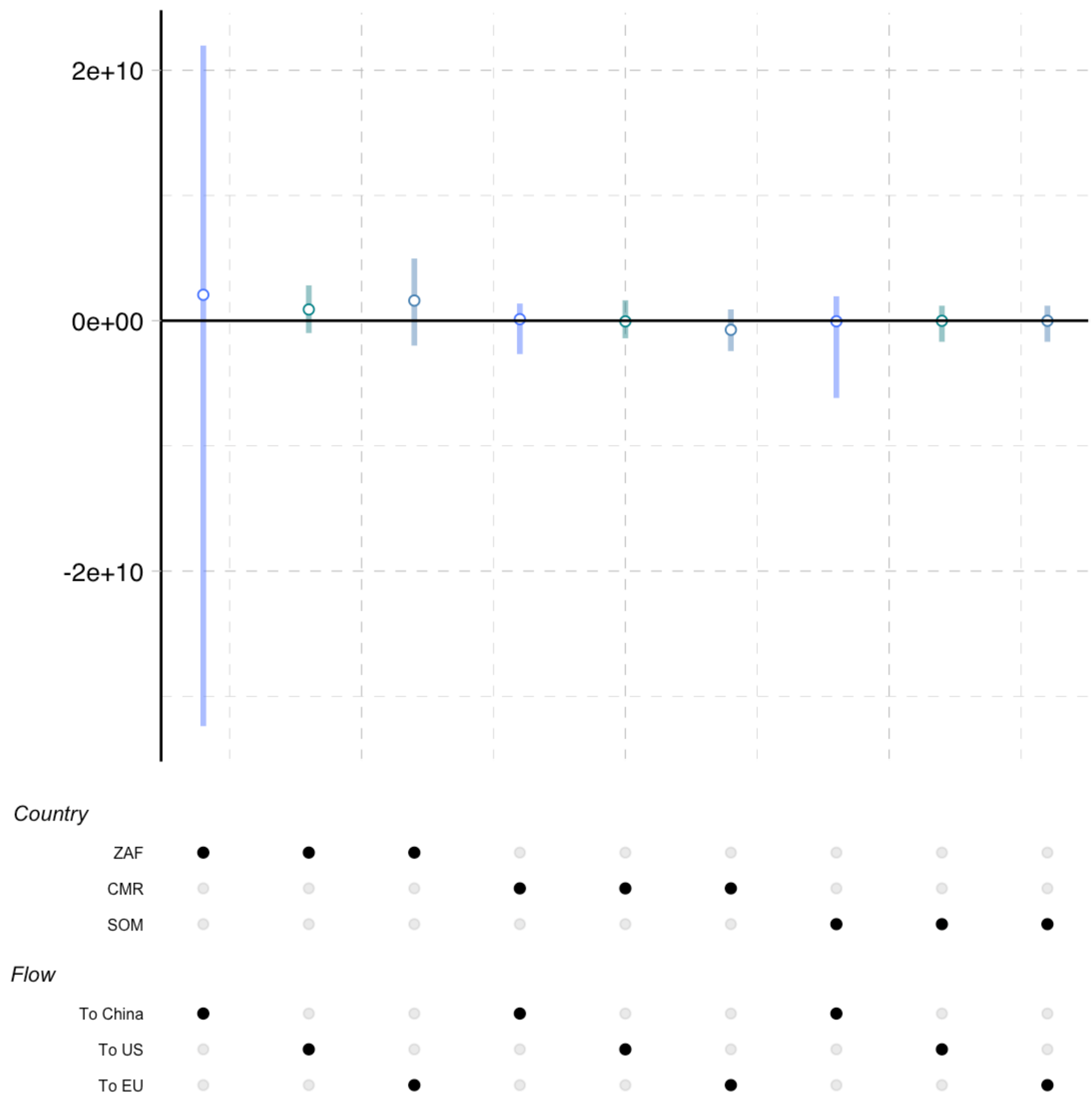


Figure 4.3: Belt and Road Initiative Members, and Entry Years

flows - generally more commercially oriented - does not significantly increase trade.

On trade diversion, the hypothesis that China's OF in Africa displaces existing trade flows is not supported in the aggregate analysis (Table 6). In fact, in most cases, OF treatments coincide with a net increase in exports: to China and third-party countries. However, a closer look at disaggregated treatment reveals that ODA financing diverts raw materials exports to third-party countries. Indeed, one additional ODA flow decreases raw material exports to non-China partners by a statistically significant 2%. Due to the predominance of commodity exports in Africa, this translates into a total export diversion of 0.6%. While not large, this figure brings into focus the aid/commodity nexus in China's Africa strategy. Previous empirical work on trade creation effects saw no "there there," but trade diversion effects indicate that there might yet be a "there there."

Like much of the empirical research on China's aid and trade diplomacy, results of this paper dispel export-diversion and concentration criticism about China's approach to Africa. China's official finance, trade agreements, and investment memoranda with African countries do not appear to increase her market share in Africa at the expense of other partners. There is also no evidence of these intervention reinforcing a "dutch disease". Exports of raw materials experience increases smaller than the manufacturing sector, and where there is diversion it remains very low. These results are similar to findings in the recent literature on China's aid and trade diplomacy. Dreher et al. (2017) test the claim that significant financial support from China impairs the effectiveness of grants and loans from Western donors and lenders, and find no support for this claim. Bon and Cheng (2021) show that China's increasing involvement in debt restructuring, rather than being obscure, is similar in its approach to the Paris Club. Bräutigam and Gallagher (2014) analyze China's resource-secured or commodity-backed loans, and find that contrary to many of the claims in the popular press, Chinese finance is not out of line with interest rates found in global capital markets, and does not bring windfall commodity profits to China. Dreher and Fuchs (2015) argue, after an analysis of China's aid allocation, that its patterns are comparable to Western donors' and that it appears to be independent of recipients' natural resource endowment - and conclude that denoting Chinese aid as "rogue aid" seems unjustified. Many elements that underlie the suspicion towards the "Beijing Model" do not appear to find support in empirical economic analysis.

Instead, the evidence in this paper lends support to the argument that China's African trade involvement is mutually beneficial. The net export creation effect in manufacturing shows that China's involvement can support export diversification, not only through preferential treatment, as showed in Sun and Omoruyi (2021), but alsoalso contribute to addressing supply-side issues through ODA and ODA-adjacent financing, leading to an improvement in production capacities and competitiveness of recipient economies - which rather than a zero-sum game could be a win-win strategy.

4.6 Conclusion

Today, China is Africa's largest trading partner, investor, and creditor, making it an essential player in its economy. Her engagement is promoted through active aid and trade diplomacy. The absence of rigorous empirical evidence on the economic impacts of these interventions has allowed the policy debate around it to become polarized and suspicious. This paper aims to fill this gap and inform this debate by evaluating the export creation and diversion effects of China's aid and trade diplomacy in Africa.

The results show that China's economic diplomacy activism in Africa does not significantly divert exports away from existing links. In addition, it does not appear that it pushes African economies towards more specialization in natural resource exports. Instead, manufacturing industries appear to benefit from ODA flows and trade agreements, both of which generate significant net trade creation effects. Early evidence on the Belt and Road Initiative shows no sign of trade diversion. These results do not preclude the existence of potential negative economic externalities of Chinese engagement and do not presume that their welfare or distributional impacts are positive on balance.

This paper also offers methodological insights into future research on trade diplomacy effects. It suggests that the margin of treatment needs to be carefully defined, and it also shows that heterogeneity analysis must be applied systematically to explore different sub-types of treatment and to distinguish the response of different sector-level outcomes.

The paper's findings invite further empirical research into the mechanisms that account for the patterns that have been identified. A more granular approach at the geography and industry level could generate new data that isolates the causality channels. Is this a supply-side effect that improves the production capabilities of target countries? Additionally, as the implementation of the BRI advances, richer data will become available to study its trade and economic effects in Africa. Finally, as our macroeconomic understanding of the impacts of China's engagement in Africa improves, another question becomes more accessible and more urgent to address. Research into China's Africa strategy will have to turn to its welfare and distributional consequences, the actual litmus test of policy interventions.

Chapter V

Conclusion

The World Trade Organization enumerates five foundational principles of the multilateral trade system: non-discrimination, predictability and transparency, competitiveness, benefits for less developed countries, and environmental protections. Events in the past few years have brought the interplay of trade policy-making frameworks and an evolving political and geopolitical context into sharp focus. Economically populist discourse, with protectionist undertones, has pervaded trade policy-making, shifting priorities, reviving old paradigms such as industrial policy, and directly threatening the stability of the trade policy order epitomized by the World Trade Organization.

Without arguing the importance of these principles, or the WTO's ability to deliver on the associated promises, we can economically and quantitatively anticipate the potential losses from a weakening of the rule-based system by studying instances where these five principles are relaxed. Such is the goal of this volume. The findings minimize the economic and financial cost of recent developments in trade-policy making. The trade policy irregularities that came under study in this work do not generate the prohibitive losses needed to advocate for the preservation of the trade system as it exists, at all costs. Reversals in trade policy do not appear to have any spillover or externality effects beyond their first-order impact. Fluctuations in trade policy uncertainty do not generate the large movements in financial flows that other forms of uncertainty can cause. And maligned "mercantilist" policies appear to be trade increasing and supportive of export diversification.

This analysis is by no means definitive, and much remains to be evaluated when it comes to the potential costs of the emergence of a decentralized atomic trade system. I have here focused on macroeconomic implications. Further research needs to be conducted into the individual and social welfare. But even as we, as economists, contemplate the gains from what exists, and the costs of transitions, we must too imagine alternative designs able to generate benefits that can exceed the identified costs.

Bibliography

Abadie, Alberto, Alexis Diamond, and Jens Hainmueller, "Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program," *Journal of the American Statistical Association*, 2010, *105* (490), 493–505.

Alessandria, George A., Shafaat Y. Khan, and Armen Khederlarian, "Taking Stock of Trade Policy Uncertainty: Evidence From China's Pre-WTO Accession," 2019.

Alizadeh, Sassan, Michael W Brandt, and Francis X Diebold, "Range-Based Estimation of Stochastic Volatility Models," *The Journal of finance (New York)*, 2002, *57* (3), 1047–1091.

Amengual, Dante and Dacheng Xiu, "Resolution of policy uncertainty and sudden declines in volatility," *Journal of Econometrics*, 2018, *203* (2), 297–315.

Anderson, James E., "A Theoretical Foundation for the Gravity Equation," *The American Economic Review*, 1979, *69* (1), 106–116.

Asgharian, Hossein, Ai Jun Hou, and Farrukh Javed, "The Importance of the Macroeconomic Variables in Forecasting Stock Return Variance: A GARCH-MIDAS Approach," *Journal of Forecasting*, 2013, *32* (7), 600–612.

Asongu, Simplice A, Jacinta C Nwachukwu, and Gilbert A A Aminkeng, "Lessons from a Survey of China's Economic Diplomacy," *Journal of world trade*, 2018, *52* (5), 789–814.

Auer, Raphael, Barthélémy Bonadio, and Andrei A Levchenko, "The Economics and Politics of Revoking NAFTA," Working Paper 25379, National Bureau of Economic Research December 2018.

Baier, Scott L. and Jeffrey H. Bergstrand, "Do free trade agreements actually increase members' international trade?," *Journal of international Economics*, 2007, *71* (1), 72–95.

Baier, Scott L, Jeffrey H Bergstrand, and Matthew W Clance, "Heterogeneous effects of economic integration agreements," *JOURNAL OF DEVELOPMENT ECONOMICS*, nov 2018, *135*, 587–608.

Baker, Malcolm and Jeffrey Wurgler, "Investor Sentiment and the Cross-Section of Stock Returns," *The Journal of Finance*, 2006, *61* (4), 1645–1680.

Baker, Scott R, Nicholas Bloom, and Steven J Davis, "Measuring economic policy uncertainty.(Report)," *Quarterly Journal of Economics*, 2016, *131* (4), 1593.

_ , _ , and _ , "Measuring economic policy uncertainty.(Report)," *Quarterly Journal of Economics*, 2016, *131* (4), 1593.

_ , _ , Brandice Canes-Wrone, Steven J Davis, and Jonathan Rodden, "Why has US policy uncertainty risen since 1960?(Author abstract)," *American Economic Review*, 2014, *104* (5), 56–60.

_ , _ , Steven J Davis, and Kyle Kost, "Policy News and Stock Market Volatility," *SSRN Electronic Journal*, 2019.

_ , _ , _ , and _ , "Policy News and Stock Market Volatility," *SSRN Electronic Journal*, 2019.

Belesky, Paul and Geoffrey Lawrence, "Chinese state capitalism and neomercantilism in the contemporary food regime: contradictions, continuity and change," *The Journal of Peasant Studies*, 2019, *46* (6), 1119–1141.

Berger, David, Ian Dew-Becker, and Stefano Giglio, "Uncertainty Shocks as Second-Moment News Shocks," *The Review of Economic Studies*, 04 2019, *87* (1), 40–76.

Berhelemy, Jean-Claude, "China's Engagement and Aid Effectiveness in Africa," *African Development Bank*, 2011, (129).

Bloom, Nicholas, "Fluctuations in Uncertainty," *The Journal of Economic Perspectives*, 2014, *28* (2), 153–175.

Bon, Gatien and Gong Cheng, "Understanding China's role in recent debt relief operations: A case study analysis," *International economics (Paris)*, 2021, *166*, 23–41.

Bouët, Antoine and David Laborde, "US trade wars in the twenty-first century with emerging countries: Make America and its partners lose again," *World economy*, 2018, *41* (9), 2276–2319.

Bown, Chad P and Meredith A Crowley, "Trade deflection and trade depression," *Journal of international economics*, 2007, *72* (1), 176–201.

Brandt, Michael W and Christopher S Jones, "Volatility Forecasting With Range-Based EGARCH Models," *Journal of business & economic statistics*, 2006, *24* (4), 470–486.

Brian, Samantha DeCarlo Daigle and Gregory LaRocca, "When Trade Agreements End: A Survey of Cases 1949–2019.," *International Commerce and Economics*, 2019.

Brogaard, Jonathan and Andrew Detzel, "The asset-pricing implications of government economic policy uncertainty," *Management Science*, 2015, *61* (1), 3.

Bräutigam, Deborah and Kevin P Gallagher, "Bartering Globalization: China's Commodity-backed Finance in Africa and Latin America," *Global policy*, 2014, *5* (3), 346–352.

Caceres, Carlos, Diego A Cerdeiro, and Rui C Mano, "Trade Wars and Trade Deals: Estimated Effects using a Multi-Sector Model," *IMF working paper*, 2019.

Caldara, Dario, Matteo Iacoviello, Patrick Molligo, Andrea Prestipino, and Andrea Raffo, "The economic effects of trade policy uncertainty," *Journal of Monetary Economics*, 2020, *109*, 38–59.

_ , _ , _ , _ , and _ , "The economic effects of trade policy uncertainty," *Journal of Monetary Economics*, 2020, *109*, 38–59.

Campbell, John Y. and Samuel B. Thompson, "Predicting Excess Stock Returns Out of Sample: Can Anything Beat the Historical Average?," *The Review of Financial Studies*, 11 2007, *21* (4), 1509–1531.

Campbell, John Y, Martin Lettau, Burton G Malkiel, and Yexiao Xu, "Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk," *The Journal of finance (New York)*, 2001, *56* (1), 1–43.

Carter, Colin A and Caroline Gunning-Trant, "U.S. trade remedy law and agriculture: trade diversion and investigation effects: U.S. trade remedy law and agriculture," *The Canadian journal of economics*, 2010, *43* (1), 97–126.

Chauvet, Marcelle, Zeynep Senyuz, and Emre Yoldas, "What does financial volatility tell us about macroeconomic fluctuations?," *Journal of Economic Dynamics and Control*, 2015, *52*, 340–360.

Chiu, Ching-Wai, Richard D F Harris, Evarist Stoja, and Michael Chin, "Financial market Volatility, macroeconomic fundamentals and investor Sentiment," *Journal of Banking & Finance*, 2018, *92*, 130–145.

Choudhry, Taufiq, Fotios I. Papadimitriou, and Sarosh Shabi, "Stock market volatility and business cycle: Evidence from linear and nonlinear causality tests," *Journal of Banking & Finance*, May 2016, *66*, 89–101.

Christiansen, Charlotte, Maik Schmeling, and Andreas Schrimpf, "A comprehensive look at financial volatility prediction by economic variables," *Journal of Applied Econometrics*, 2012, *27* (6).

Copper, John F., *China's Foreign Aid and Investment Diplomacy, Volume III: Strategy Beyond Asia and Challenges to the United States and the International Order*, New York: Palgrave Macmillan, 2015.

Cover, James Peery, "Asymmetric Effects of Positive and Negative Money-Supply Shocks," *The Quarterly journal of economics*, 1992, *107* (4), 1261–1282.

Dai, Mian, Yoto V Yotov, and Thomas Zylkin, "On the trade-diversion effects of free trade agreements," *Economics letters*, 2014, *122* (2), 321–325.

Dew-Becker, Ian, Stefano Giglio, and Bryan Kelly, "Hedging macroeconomic and financial uncertainty and volatility," *Journal of Financial Economics*, 2021.

Dreher, Axel and Andreas Fuchs, "Rogue aid? An empirical analysis of China's aid allocation," *The Canadian journal of economics*, 2015, *48* (3), 988–1023.

_ , _ , Bradley Parks, Austin M. Strange, and Michael J. Tierney, "Aid, China, and Growth: Evidence from a New Global Development Finance Dataset," *SSRN Electronic Journal*, 2017.

Ederington, Louis H. and Jae HA Lee, "How Markets Process Information: News Releases and Volatility," *The Journal of Finance*, 1993, *48* (4), 1161–1191.

Eicher, Theo S and Christian Henn, "In search of WTO trade effects: Preferential trade agreements promote trade strongly, but unevenly," *JOURNAL OF INTERNATIONAL ECONOMICS*, mar 2011, *83* (2), 137–153.

Fajgelbaum, Pablo D, Pinelopi K Goldberg, Patrick J Kennedy, and Amit K Khandelwal, "The Return to Protectionism*," *The Quarterly Journal of Economics*, 11 2019, *135* (1), 1–55.

Feng, Ling, Zhiyuan Li, and Deborah L Swenson, "Trade policy uncertainty and exports: Evidence from China's WTO accession," *Journal of International Economics*, 2017, *106*, 20.

Fernández, Raquel and Jonathan Portes, "Returns to Regionalism: An Analysis of Nontraditional Gains from Regional Trade Agreements," *The World Bank economic review*, 1998, *12* (2), 197–220.

Fetzer, Thiemo and Carlo Schwarz, "Tariffs and Politics: Evidence from Trump's Trade Wars," *SSRN Electronic Journal.*

Foroutan, Faezeh and Lant Pritchett, "Intra-Sub-Saharan African Trade: is it too Little?," *Journal of African Economies*, *2* (1), 74–105.

Frazer, Garth and Johannes Van Biesebroeck, "Trade Growth Under The African Growth and Opportunity Act," *The Review of Economics and Statistics*, 2010, *92* (1), 128–144.

Fukao, Kyoji, Toshihiro Okubo, and Robert M Stern, "An econometric analysis of trade diversion under NAFTA," *The North American Journal of Economics and Finance*, 2003, *14* (1), 3–24.

Geda, Alemayehu and Edris Hussein Seid, "The potential for internal trade and regional integration in Africa," *Journal of African Trade*, 2015, *2* (1-2), 19–50.

Ghosh, Sucharita and Steven Yamarik, "Does trade creation measure up? A reexamination of the effects of regional trading arrangements," *Economics letters*, 2004, *82* (2), 213–219.

Guo, Hui, "Stock Market Returns, Volatility, and Future Output," *Review*, 2002, *84* (5).

Haidar, J. I., "Sanctions and export deflection: Evidence from Iran," *Economic Policy*, 2019, *90* (32), 319–355.

Hamilton, Carl, "Voluntary Export Restraints and Trade Diversion," *Journal of common market studies*, 1985, *23* (4), 345–355.

Handley, Kyle and Nu Limao, "Policy Uncertainty, Trade, and Welfare: Theory and Evidence for China and the United States.(Author abstract)," *American Economic Review*, 2017, *107* (9), 2731–2783.

— **and Nuno Limão**, "Trade and Investment under Policy Uncertainty: Theory and Firm Evidence," *American Economic Journal: Economic Policy*, 2015, *7* (4), 189–222.

— **and** — , "Trade and Investment under Policy Uncertainty: Theory and Firm Evidence," *American Economic Journal: Economic Policy*, 2015, *7* (4), 189–222.

Harris, Richard D F, Evarist Stoja, and Fatih Yilmaz, "A cyclical model of exchange rate volatility," *Journal of banking & finance*, 2011, *35* (11), 3055–3064.

Hoppe, Mombert Brenton Paul;, "The African Growth and Opportunity Act, Exports, and Development in Sub-Saharan Africa," 2006, (No. 3996).

Horn, Sebastian, Carmen M. Reinhart, and Christoph Trebesch, "China's overseas lending," *Journal of International Economics*, 2021, *133*, 103539.

Humphreys, David, "New mercantilism: A perspective on how politics is shaping world metal supply," *Resources Policy*, 2013, *38* (3), 341–349.

Ibold, Christian, "BRI Projects," 2022.

Jeanne, O., "Currency Wars, Trade Wars and Global Demand," in "in" 2019.

Jouanjean, Marie-Agnes Engel Jakob;, "More than a gesture? Examining the export impact of Chinese and Indian duty-free quotafree trade preferences for Least Developed Countries," 2014.

Julio, Brandon and Youngsuk Yook, "Policy uncertainty, irreversibility, and cross-border flows of capital," *Journal of International Economics*, 2016, *103* (C), 13.

Knight, Frank, *Risk, Uncertainty and Profit*, Houghton Mifflin, 1921.

Kohl, Tristan, "Do we really know that trade agreements increase trade?," *Review of World Economics / Weltwirtschaftliches Archiv*, 2014, *150* (3), 443–469.

— **, Steven Brakman, and Harry Garretsen**, "Do Trade Agreements Stimulate International Trade Differently? Evidence from 296 Trade Agreements," *The World Economy*, 2016, *39* (1), 97–131.

Lee, Gary GJ and Robert Engle, "A permanent and transitory component model of stock return volatility," in R. Engle and H. White, eds., *Cointegration, Causality, and Forecasting: A Festschrift in Honor of Clive W.J. Granger*, New York: Oxford University Press, 1999, pp. 475–497.

Lind, Jennifer and Daryl G Press, "Markets or Mercantilism? How China Secures Its Energy Supplies," *International Security*, 2018, *42* (4), 170–204.

Liu, Ailan and Bo Tang, "US and China aid to Africa: Impact on the donor-recipient trade relations," *China Economic Review*, 2018, *48*, 46–65.

Liu, Li and Tao Zhang, "Economic policy uncertainty and stock market volatility," *Finance Research Letters*, 2015, *15*, 99–105.

Liu, Qing, Fei Pei, Huaqing Wu, and Xianfeng Zhang, "Trade Policy Uncertainty, Firm Heterogeneity and Export Mode," *Emerging Markets Finance and Trade.*

Longo, Robert and Khalid Sekkat, "Economic Obstacles to Expanding Intra-African Trade," *World Development*, 2004, *32* (8), 1309–1321.

Mattoo, Aaditya and Robert W Staiger, "Trade Wars: What do they mean? Why are they happening now? What are the costs?," *Economic policy*, 2020.

Mawdsley, Emma, "Fu Manchu versus Dr Livingstone in the Dark Continent? Representing China, Africa and the West in British broadsheet newspapers," *Political Geography*, 2008, *27* (5), 509–529.

Melitz, Marc J, "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica*, 2003, *71* (6), 1695–1725.

Miromanova, Anna, "Quantifying the Trade Reducing Effect of Embargoes: Firm Level Evidence from Russia," *Working Paper*, 2019.

Moons, Selwyn J V and Peter A G Bergeijk, "Does Economic Diplomacy Work? A Meta-analysis of Its Impact on Trade and Investment," *World economy*, 2017, *40* (2), 336–368.

Neely, Christopher J., David E. Rapach, Jun Tu, and Guofu Zhou, "Forecasting the Equity Risk Premium: The Role of Technical Indicators," *Management Science*, 2014, *60* (7), 1772–1791.

Nitsch, Volker, "State Visits and International Trade," *World economy*, 2007, *30* (12), 1797–1816.

Oberhofer, Harald and Michael Pfaffermayr, "Estimating the Trade and Welfare Effects of Brexit: A Panel Data Structural Gravity Model," January 2018, (6828).

Olasehinde-Williams, Godwin, “Is US trade policy uncertainty powerful enough to predict global output volatility?,” *Journal of International Trade & Economic Development.*

Ongan, Serdar and Ismet Gocer, “Does trade policy related uncertainty affect international trade? Evidence from the US-China commodity trade,” *China Economic Journal*, 2020.

Pavcnik, Nina, “Trade Liberalization, Exit, and Productivity Improvements: Evidence from Chilean Plants,” *The Review of Economic Studies*, 2002, *69* (1), 245–276.

Pettersson, Jan and Lars Johansson, “Aid, Aid for Trade, and bilateral trade: An empirical study,” *Journal of International Trade and Economic Development*, 2013, *22* (6), 866–894.

Phan, Dinh Hoang Bach, Susan Sunila Sharma, and Vuong Thao Tran, “Can economic policy uncertainty predict stock returns? Global evidence.(Report),” *Journal of International Financial Markets, Institutions & Money*, 2018, *55*, 134.

Poon, Ser-Huang and Clive W.J. Granger, “Forecasting Volatility in Financial Markets: A Review,” *Journal of Economic Literature*, June 2003, *41* (2), 478–539.

Prusa, Thomas J, “The Trade Effects of U.S. Antidumping Actions,” in “The Effects of U.S. Trade Protection and Promotion Policies,” Chicago: University of Chicago Press, 2019, pp. 191–214.

Rapach, David E., Jack K. Strauss, and Guofu Zhou, “Out-of-Sample Equity Premium Prediction: Combination Forecasts and Links to the Real Economy,” *The Review of Financial Studies*, 08 2009, *23* (2), 821–862.

Ravn, Morten O and Harald Uhlig, “On Adjusting the Hodrick-Prescott Filter for the Frequency of Observations,” *The review of economics and statistics*, 2002, *84* (2), 371–376.

Rodrik, Dani, “What Do Trade Agreements Really Do?,” *Journal of Economic Perspectives*, May 2018, *32* (2), 73–90.

Rose, Andrew K, “The Foreign Service and Foreign Trade: Embassies as Export Promotion,” *World economy*, 2007, *30* (1), 22–38.

S., Dreher A.-Elston T.B. Fuchs A. Ghose S. Lin J. Malik A. Parks B.C. Russell B. Solomon K. Strange A. Tierney M.J. Walsh K. Zaleski L. Custer and S. Zhang, "Tracking Chinese Development Finance: An Application of AidData's TUFF 2.0 Methodology," 2021.

Santos Silva, J M C and Silvana Tenreyro, "Further simulation evidence on the performance of the Poisson pseudo-maximum likelihood estimator," *Economics Letters*, 2011, *112* (2), 220–222.

Savin, Ivan, Marta Marson, and Marina Sutormina, "How different aid flows affect different trade flows: Evidence from Africa and its largest donors," *Structural Change and Economic Dynamics*, 2020, *55*, 119–136.

Schwert, G William, "Why Does Stock Market Volatility Change Over Time?," *The Journal of finance (New York)*, 1989, *44* (5), 1115–1153.

Silva, J M C Santos and Silvana Tenreyro, "The Log of Gravity," *The Review of Economics and Statistics*, 2006, *88* (4), 641–658.

Sima, Qian, "Records of the grand historian. Qin dynasty," 1993.

Sims, Christopher A., "Macroeconomics and Reality," *Econometrica*, 1980, *48* (1), 1–48.

Steinberg, Jb, "Brexit and the macroeconomic impact of trade policy uncertainty," *Journal Of International Economics*, 2019, *117*, 175–195.

Stockwell, Thomas, "Accommodative Monetary Policy Shocks Do Not Stimulate Output," Technical Report September 2020.

Sun, Zhina and Ehizuelen Michael Mitchell Omoruyi, "Effect of China's Zero-Tariff Treatment under Forum on China-Africa Cooperation (FOCAC) on Export Diversification in Beneficiary Countries in Africa," *Journal of African Trade*, 2021, *8*, 23–32.

Viner, Jacob, *The customs union issue*, New York: Oxford University Press, 2014.

Wang, Yudong, Yu Wei, Chongfeng Wu, and Libo Yin, "Oil and the short-term predictability of stock return volatility," *Journal of Empirical Finance*, 2018, *47*, 90–104.

Xu, Yiqing, "Generalized Synthetic Control Method: Causal Inference with Interactive Fixed Effects Models," *Political Analysis*, 2017, *25* (1), 57–76.

Yang, Shanping and Inmaculada Martinez-Zarzoso, "A panel data analysis of trade creation and trade diversion effects: The case of ASEAN–China Free Trade Area," *China Economic Review*, 2014, *29*, 138–151.

Zeiler, THOMAS W, "Managing Protectionism: American Trade Policy in the Early Cold War," *Diplomatic history*, 1998, *22* (3), 337–360.