Master Thesis

Synthetic Trade Costs: Measuring the Economic Impact of the Chinese Import Stop on US Soybeans

July 2020

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Abstract

The aim of this paper is to assess the economic impact the temporary Chinese import stop on US soybeans in 2018 has had on the US-China soybean trade flow – a major bilateral trade flow. The trade shock's effect on the US-China soybean trade flow is analysed by comparing the actual US-CHN soybean trade flow with a counterfactual 'no shock' situation. This work applies a combination of the Gravity Model of Trade and the Synthetic Control Method in a general equilibrium framework. Referring to an increase of estimated bilateral trade costs in 2018, the results show that the bilateral US-China soybean trade would have been 33% higher than the actual trade flow in 2018 was. Moreover, the results show significant trade diversion effects in 2018 – including increased purchases of US soybeans by EU member states – which decreased in 2019 just as the estimated bilateral trade costs. The robustness checks prove the validity of the results and the applicability of the methodological approach. Therefore, the approach represents a suitable tool to econometrically estimate the general equilibrium effect of economic or policy interventions, whereas the evaluation tool can be applied to a broad range of topics.

Acknowledgements

I would like to extend my gratitude to my supervisors for their excellent feedback and Julian Hinz from the Kiel Institute for the World Economy for his outstanding support and the successful cooperation.

Special thanks go to my family and friends for their support throughout the writing process.

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List of Abbreviations

CES	…	Constant Elasticity of Substitution
CHN	…	China
e.g.	…	for example
etc.	…	et cetera
EU	…	European Union
FAO	…	Food and Agriculture Organization
GE	…	General Equilibrium
IMR	…	Inward Multilateral Resistance
MR	…	Multilateral Resistance
MSPE	…	Means squared predictor error
OMR	…	Outward Multilateral Resistance
PE	…	Partial Equilibrium
PIIE	…	Peterson Institute for International Economics
PPML	…	Poisson Pseudo-Maximum-Likelihood
SCM	…	Synthetic Control Method
UN	…	United Nations
US	…	United States
USDA	…	United States Department of Agriculture
USITC	…	United States International Trade Commission
USTR	…	United States Trade Representative

1. Introduction

Following months of escalating import tariffs, an economically damaging trade conflict and seemingly never-ending negotiations, the United States (US) and China (CHN) signed an initial trade deal in January 2020. However, the bulk of record level tariffs both administrations have placed over the last two years remains, just as does the threat of new import tariffs. In February 2020, the average US-tariff on imports from China was at 19,3 percent (%), more than six times higher as prior to the bilateral trade shock in 2018. The average Chinese import tariff on US goods and services also remained elevated at an average of 20,3%. These tariffs affected various sectors on both sides, including the agricultural sector. A series of 25% Chinese retaliatory import tariffs worth $34 billion in US exports to China provoked the collapse of the largest US agricultural export to China by the end of 2018 – the export of soybeans (NYT, 2020; PIIE, 2020a; USTR, 2019).

The US-CHN soybean trade flow has still not recovered from the bilateral trade shock and resulted in significant economic losses on both sides. Hence, the aim of this paper is to assess the economic impact a temporary Chinese import stop on US soybeans in 2018 has had on the US-CHN soybean trade flow. To do so, this work conducts a comparative case study. It analyses the shock's economic impact on the US-CHN soybean trade flow, by comparing the actual US-CHN soybean trade flow in the past decade – given the trade shock in 2018 – with a counterfactual 'no shock' situation. This work applies a new methodological approach developed by Hinz, Scholz, Sirries and Wanner (2020) by combining the Gravity Model of Trade and the Synthetic Control Method (SCM) in three steps. This approach ensures a comprehensive estimation of the general equilibrium (GE) effect of this bilateral trade shock on the respective trade flow. As a first step, the bilateral trade costs between the US and China are estimated since they serve as the initial economic indicator to estimate the difference of a pre- and a post-shock situation. In order to derive the trade costs for a counterfactual situation, the SCM as developed by Abadie and Gardeazabal (2003) is applied to generate synthetic trade costs. These synthetic costs are comprised of the trade flows between country pairs unexposed to the bilateral shock and are compared to the exposed country pair – US and China – which allows the observation of change in bilateral trade costs. To derive the actual difference in terms of bilateral trade flow and hence, the counterfactual 'no shock' trade flow, the synthetic trade costs are plugged back into the seminal structural gravity equation by Anderson and van Wincoop (2003).

The economic impact of the imposed bilateral tariffs by the US and China in terms of change in trade flow, production, and prices, have been forecasted and measured throughout the literature in recent years. The focus has mainly been set on the overall economy, but also on specific sectors – including the agricultural sector and soybeans as a product. Zheng, Wood, Wang, and Jones (2018) predict the US value of soybean exports to China to decrease by approximately 34%, US domestic soybean prices by 3,9% and US-production by 1,6%. Taheripour and Tyner (2018) forecast a decrease in the value of US soybean exports to China by 40,3%. Sabala and Devadoss (2019) find that the US and China incur welfare losses through higher producer and consumer prices as a result of the tariffs. In addition, Adjemian, Smith, and He (2019), estimate that the US soybean prices will decrease by 9,9% compared to the average price in the US in 2017 (USDA, 2020).

A great majority of the literature applies partial equilibrium (PE) models to measure the impact of the tariffs on the US-CHN soybean trade. These models exclude bilateral trade flows and barriers amongst other trading partners of both countries. Yet, as outlined in this work, multilateral trade flows and barriers in return have an impact on the US-CHN soybean trade flow and need to be included in the estimates to ensure comprehensive and valid results (Anderson & van Wincoop, 2003; Head & Mayer, 2013). Given the commonly applied PE models, this work sets itself apart from the existing literature by: 1) estimating the GE effect of the bilateral trade shock and 2) applying a recently developed combination of the Gravity Model of Trade and the SCM. The applied Gravity Model of trade includes the effect of the often-neglected multilateral trade flows and barriers. As the model resembles a structural model with solid theoretical foundations, it is particularly appropriate for counterfactual analysis, such as quantifying the effects of trade policies like import tariffs. In addition, this paper applied the methodological advantages of the SCM to identify the shock and to generate the unobservable synthetic counterfactual scenario. The combination of both methods enables a comprehensive 'best of both worlds-approach' to estimate the GE effect of the bilateral trade shock on the US-CHN soybean trade flow.

As outlined, the two main countries acting in the conflict are the US and China, which at the same time are the world's two largest economies by Gross Domestic Product (GDP). When including the European Union (EU) in this sequence not as a country but as an additional entity, it ranks second, behind the US and before China (IMF, 2019). Besides a similar economic size, the EU's total trade in goods is highest with the US, closely followed by China (EU Parliament, 2019). Given these economic power structures, the bilaterally imposed trade restrictions and the large amount of EU-imports of US soybeans, it is reasonable to analyse the economic impact the bilateral trade shock has had on the US-EU trade flow.[1] Hence, the economic impact of the bilateral trade shock on the US-EU soybean trade flows is estimated by means of a counterfactual analysis.

[1] When mentioning the US-EU trade flow I refer to trade flows from the US to EU member states.

By applying a combination of the structural gravity equation and the SCM within the mentioned three-step approach, this work aims to estimate the GE effect of the Chinese import stop on US soybeans in 2018 on the US-CHN soybean trade flow. Hence, this raises the following research question: *What is the general equilibrium effect of the Chinese import stop on US soybeans in 2018 on the US-CHN soybean trade flow?*

The results of this work clearly show the significant economic impact the bilateral trade shock has had on the US-CHN soybean trade flow in 2018. Based on the estimated counterfactual US-CHN trade flow, the bilateral soybean trade between the US and China would have been 33% higher than the actual trade flow in 2018. This can be attributed to the estimated trade costs, which approximately tripled in 2018 or vice versa would have been three times lower without the occurrence of the Chinese import stop on US soybeans. Furthermore, the estimated results show, that the trade flow of US soybeans to EU member states, would have clearly been lower without the trade shock. For example, both Spain and the Netherlands would have imported 35% and 22% less US soybeans in a counterfactual 'no shock' situation. The impact of the trade shock is clearly mitigated with regards to the decreased trade costs and trade diversion effects in 2019.

The following chapter briefly presents the background on the US-CHN soybean trade and the implied sequence of bilaterally imposed import tariffs which resulted in the Chinese import stop on US soybeans. This case-introduction is conducted before presenting the literature on trade shocks, the economic impact of trade shocks as well as the measurement or estimation of this impact, since the imposed tariffs resulted in the trade shock and not conversely. Furthermore, the literature on the economic impact of a trade shock is outlined exemplarily by an analysis of the recent research on the US-CHN trade conflict. The estimation of the economic impact of a trade shock for its part is presented by focusing on the impact of the bilateral trade shock on the US-CHN soybean trade flow itself. This enables a more practical and case-related understanding of the applied measurements and allows a direct derivation of the research question from the shortcomings in previous literature. Thereafter, the theoretical framework on trade costs in international trade and the gravity model of trade is presented, before introducing the research design of this work. Within this chapter the applied structural gravity equation and SCM are outlined in detail, before the methodological combination of both methods is explained. To conclude, the results are presented and discussed, and the research question is answered.

2. The Case of the US-CHN Soybean Trade

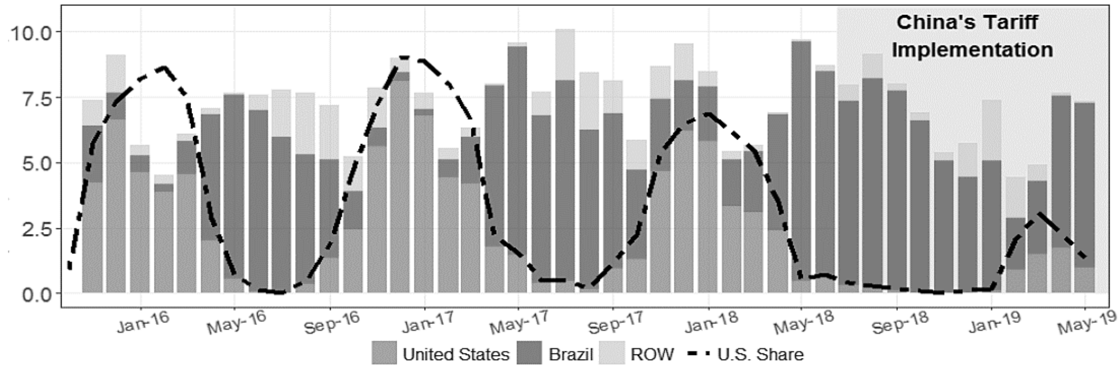
Soybeans are the largest segment of global agricultural trade. Lee, Tran, Hansen, and Ash (2016) observed that the volume of trade in soybeans (including the processed product) surpassed that of wheat and other grains and has become the most traded agricultural commodity. They state that soybeans account for over 10% of agricultural trade value. The US and Brazil together accounted for approximately 80% of global soy supply in past years, whereas Brazil but also Argentina emerged as top US competitors in export of soybeans in the last decade (Gale, Valdes, & Ash, 2019). Fuelled by its growing soybean demand, the world's largest soybean importer, China, has turned into a key agri-business player in the global, and especially South American, political economy. Chinese firms have increased their influence in the governance of the soybean nexus in South America, where soybeans are a significant export product for several countries (Giraudo, 2020).

Given the hemispheric temperature differences, the main soybean producers, US and Brazil, alternate the months in which they predominantly export soybeans throughout the year. The US supplies most soybeans from October to March, while Brazil supplies the remaining months. Soy is the US' largest agricultural export product and averaged $20.9 billion (US dollars) per year (approximately 16% of US agricultural exports) from 2014 to 2018. As mentioned, China accounts for the most global soybean imports, equal to approximately 65% in 2016/2017. China's soybean import volume surpassed the EU's in 2002 and was six times the EU's volume in 2017. It purchased more than half of all US soybean exports up to 2018. US total exports of agricultural products to China totalled $9.3 billion in 2018, whereas soybeans as a single product accounted for $3.1 billion. Yet, compared to the US soybean exports to China in 2017, which valued $12.2 billion (57% of US soybean exports), a significant decrease of exports is visible. This equals a drop of 75% or $9.1 billion in 2018, as a result of the bilateral trade shock (Gale et al., 2019; USITC, 2019; USTR, 2019).

2.1 The Chinese Import Stop on US Soybeans

Starting July 6, 2018, Beijing imposed 25% retaliatory import tariffs worth $34 billion in US exports to China, after the US had imposed import tariffs on Chinese exports of the same value. American agricultural products – especially soybeans – were most affected by the tariffs with a combined import value of $21 billion in 2017 (Politico, 2018; USTR, 2018). The Chinese imports of US soybeans dropped to a small fraction in the following month compared to previous years, as China accounted for only two percent of all US soybean exports in August 2018. By November 2018, China's US soybean imports plunged to zero (see Figure 1), marking it the first time since the start of the trade conflict between the world's two largest economies, that China had imported no US soybeans (Reuters, 2018a).

Figure 1: China's monthly soybean imports by country (imports in million metric tons)



ROW = Rest of the World
Source: USITC (2019) based on Global Trade Atlas

In December 2018, the US and China agreed on a temporary "tariff-truce", which included the US refraining from increasing and threatening to impose new tariffs, while China agreed on lowering US auto-tariffs as well as importing more US-products, especially US soybeans.[2] However, due to ongoing trade talks and surging trade tensions, including new bilateral tariffs in mid-2019, the bilateral soybean trade did not fully recover in 2019. Less than 20% of US soybeans were exported to China in 2019.

The "Phase One Deal", that the US struck with China in October 2019 signed in January 2020, occurred as a glimpse of hope as it included the commitment by Beijing to import an additional $200 billion worth of American goods and services in the upcoming two years. The deal obligates China to increase its US agricultural purchases – predominantly including soybeans – to $40-50 billion by 2021, up from the 2017 baseline of roughly $24 billion. However, this goal seems difficult to achieve, given the incomplete nature of the trade deal and the fear that China's need for US soybeans will decrease due to the impact of the African swine fever outbreak on China's supply of pigs, a major soybean consumer as feed (PIIE, 2019; 2020b).

2.2 The Impact of the EU

As mentioned in the introduction, this work additionally examines the effect of the bilateral trade shock on the US-EU soybean trade flow. Since the EU imported 39% of its soybeans

[2] The Chinese purchase of US soybeans in December 2020 remained "peanuts in the big pot" (Reuters, 2018b).

from the US in the first half of the marketing year 2017/2018, the development of its bilateral soybean trade with the US is outlined below (EU Commission, 2019).

As indicated in a report by the EU Commission, the EU's Market Access Database lists both, China and the US, in the top five countries with the highest number of barriers hindering EU export and investment opportunities (EU Commission, 2018a). The implemented Chinese import tariffs on US soybeans occurred as a barrier, yet, affected China and the US initially on a bilateral level. Despite the similar economic size, a long historical trade relationship, similar structures and values, the US and the EU follow different approaches with regard to trade barriers. The practice of implementing barriers to trade is far more common in the US – and in China – than in the EU. This is quite clear, when comparing the variable 'Tariff rate, applied, simple mean, all products (%)' from the World Bank's 'World Development Indicators' over the last twenty years. Besides China accounting for a multiple of the EU's tariff rates, the US also constantly records tariff rates above those of the EU, which is reinforced by the imposed tariffs of the current US-administration (The World Bank, 2020). In contrast, the EU's actions in the economic field are much more connected to issues such as free trade or non-tariff barriers – despite there being critical voices on this image (Fioramonti & Poletti, 2008; Larsen, 2014).

The Chinese import stop on US soybeans functioned as an economic and perhaps also as a political incentive for EU member states to buy more US soybeans. Referring to a joint statement of the EU Commission and the US-administration, the EU's purchase of US soybeans after the Chinese import stop increased by 112% between July and December 2018 – which makes it even more interesting to analyse the counterfactual US-EU trade flow (EU Commission 2018b; 2019). The change in EU-imports of US soybeans after the bilateral trade shock outlines how much multilateral trade barriers can determine trade flows between two countries. In terms of the EU's total imports of soybeans, the US share rose to 74,5% in the first 27 weeks in the marketing year 2018/2019 (EU Commission, 2019).

In August 2019, EU Commission President Juncker stated: "The European Union can import more soybeans from the US, and this is happening as we speak" (EU Commission, 2018c). However, the EU's demand of soybeans cannot replace China's demand as the top US soybean importer. Even if the US would cover the EU's entire soybean demand, it could only offset about 35% of the demand lost from China (DW, 2018). Hence, political purposes of the EU are not precluded as this purchase contributed to the prevention of US-tariffs on the EU automotive industry (DW, 2018). Besides these possible political incentives, the assumed economic impact on the US-EU trade flow underlines the necessity of estimating the economic impact within a GE framework, since the derived GE effects capture multilateral trade barriers and coherent reallocations of products.

3. Literature Review

In this chapter trade shocks are defined, and the economic impact of a trade shock is analysed. Furthermore, the models applied in previous research to forecast and measure the economic impact of trade shocks are presented. Given the focus on the bilateral US-CHN trade shock, the economic impact of a trade shock is exemplified by analysing recent literature on the impact of this shock. Possible procedures on measuring the economic impact of a trade shock are demonstrated, focusing on past measurements of the Chinese import stop on US soybeans. This practical approach provides an understanding of trade shocks and their economic impact and likewise allows for a critical questioning of the applied measurement techniques and models throughout the case of interest. Thus, this chapter concludes by deriving the research question predominantly from the methodological shortcomings in past research.

3.1 Trade Shocks

Trade shocks as such are not reviewed in depth in past trade literature. Shocks are mostly related to macroeconomic shocks like monetary policy-, fiscal- or technology shocks (Ramey, 2016). This work sticks to a simple and non-technical definition, as the definition is mainly applied to identify the trade shock as such and the point in time it occurred. This work follows the definition from the World Economic Vulnerability Monitor (WEVM) initiative of the United Nations' (UN) Department of Economic and Social Affairs (DESA). Trade shocks are defined as gains or losses from trade caused by changes in international prices and/or in the volume of goods and services that are traded internationally (Izurieta & Vos, 2009).[3] The signs of change in trade flow are either positive or negative, in terms of gains or losses.

As outlined in the previous chapter, the US-CHN trade shock occurred because of the bilaterally imposed import tariffs in 2018. It resulted in economic losses due to a decrease in bilateral trade flow, US-production and prices. Hence, the signs of this shock are negative.[4] Furthermore, unlike the definition by Izurieta and Vos (2009), the shifts in global markets in this work are not outside of the influence of individual countries but much more driven by the economic policy consequences of individual countries. Based on previous research, the following chapter analyses the economic impact of the bilateral trade shock on the overall US-CHN economy and on the bilateral soybean trade flow in an exemplary manner.

[3] The application of the definition in this work focuses on the change in trade flow of traded goods.
[4] When mentioning the term 'trade shock' in the context of the US-CHN trade shock in this work, a negative bilateral trade shock is associated.

3.2 The Economic Impact of Trade Shocks

Trade shocks have had a great impact on international trade. For example, China's World Trade Organization (WTO) accession in 2001 accounts for over one-third of the Chinese export growth to the US in the years 2000-2005 (Handley & Limão, 2017).[5] Due to the significant increase of export volume after this change in multilateral trade, it is referred to as a trade shock. Unlike this multilateral trade shock, which resulted in gains from trade, the economic impact of the bilateral US-CHN trade shock in 2018 on the economy is analysed hereafter.

Throughout the US-CHN trade conflict, the implementation of US import tariffs and the Chinese retaliatory tariffs have resulted in a reduction of bilateral trade and a redirection of goods traded internationally. Amiti, Redding, and Weinstein (2019) estimate a reduction in US real income of $8,2 billion during 2018, with an additional cost of $14 billion to domestic importers and consumers in the form of tariff revenues which are transformed to the government. US-tariffs are directly passed through into US domestic prices of imported goods.[6] Flaaen, Hortaçsu, and Tintelnot (2019) support this finding, as they estimate a high tariff pass-through to retail prices for washing machines, the first product charged with US import tariffs. Fajgelbaum, Goldberg, Kennedy, and Khandelwal (2020) apply a GE model which implies a small aggregate real income loss of $7,2 billion compared to their PE estimates that implies an annual loss for the US of $51 billion. Hence, a substantial redistribution from buyers of foreign goods to the government and US-producers is found.

Having regarded the measurement of the economic impact of the trade shock on the US-CHN trade, the focus is shifted from the macro-level to the micro-level in this work – the impact on the US-CHN soybean trade flow. This trade flow resembles the case of interest in this work, which is why the following section outlines the methods applied to measure the economic impact of the trade shock on this flow. Hence, shortcomings within the applied approaches are analysed and solutions for the proceeding in this work derived.

3.2.1 Measuring the Economic Impact

PE economic models have been the main tool to predict and measure the economic impact of the Chinese import stop on US soybeans in 2018. Forecasts and measurements of the impact of the trade shock likewise make use of PE models. PE models are frequently applied where the economic impact of economic or policy changes are estimated and offer a cost-effective and reasonable way to provide answers (Roningen, 1997). They focus on a very limited set of

[5] The accession also reduced the US threat of a trade conflict with China, see Handley and Limão (2017).
[6] This is consistent with the finding of Cavallo, Gopinath, Neiman, and Tang (2019) and Fajgelbaum, Goldberg, Kennedy, and Khandelwal (2020)

factors, e.g. few policy variables, and allow for a quick and transparent analysis of a wide range of economic impact or policy issues. Useful insights of the respective issues can be drawn under data and time constraints that preclude more complex forms of analysis, such as GE models. Yet, PE models do not take into account many of the factors emphasized in GE trade theory which represents the root of the practical limitations presented in the upcoming section (Francois & Hall, 1997).

Zheng et al. (2018) apply a PE trade model to predict the economic impact of China's possible retaliatory tariffs on US soybeans. Using the Global Simulation Model, they analyse the quantitative impact of a 25% tariff increase on exports, US domestic prices, welfare and production. The model was developed by Francois and Hall (2003) and represents a modelling strategy for PE analysis of global trade policy changes. It enables the simultaneous assessment of such changes at the industry, on a global, national, or regional level, which allows the analysis of importer and exporter effects. Zheng et al. (2018) populate the GSIM with various data sets – inter alia the UN's trade statistics for the top 24 US-trading partners – and select the year 2016 as a basis for their forecasts, in order to obtain compatible data across sources. Regarding the Chinese tariffs on US soybeans in mid-2018, they estimate that the US-value of soybean exports to China will decrease by approximately 34%. Furthermore, they predict that US domestic soybean prices will decrease by 3,9%; US-production by 1,6%.

Sabala and Devadoss (2019) develop a theoretical and empirical Spatial Equilibrium Model to analyse the effects of the Chinese tariffs after they were imposed. This spatial PE model is especially useful when examining how trade flows are reallocated due to trade policies. The authors aim to contribute to the literature by demonstrating the ability of the model to capture the reallocation of trade and the bilateral trade flows arising from the policy change. For their empirical analysis, they collect the required data for the years 2015-2018. They find that the US and China incur welfare losses through higher producer and consumer prices as a result of the tariffs. Due to less US soybean exports to China, US-producer and consumer prices both decline by approximately 12%, since more US soybeans are available for domestic sales. The decrease of US soybean prices is supported by the work from Adjemian et al. (2019), who estimate that the price will decrease by 9,9% compared to the average price per bushel in the US in 2017 (USDA, 2020). Sabala and Devadoss (2019) measure the drop in prices to cause a 3,96% decrease in production and a 3,1% increase in consumption. They find China's consumer prices to increase by approximately 6,77% and consequently the producer prices to increase by 4,7%. Thus, consumer prices decrease consumption by approximately 1,36% and producer prices expand production by 1,57%. In addition to its own soybean production increase, China raised its imports especially from the Americas, inter alia from Brazil, Argentina and Paraguay. The US conversely alleviated parts of its export losses by increased exports to e.g. the EU, Japan or Mexico – which, however, did not preserve the US from facing the most severe economic downturn. In contrast, Brazil was the greatest beneficiary of the tariffs, as it occupied most of the US-loss in China's soybean market (Sabala & Devadoss, 2019).

Regarding the results of the PE models, both, the estimates for the decrease of US soybean production and the decrease in US soybean prices, are higher in the research by Sabala and Devadoss (2019), published after the import tariffs were implemented. The only study that applies a GE model to predict the impact of the trade shock, is the study by Taheripour and Tyner (2018), situated in the Global Trade Analysis Project (GTAP). Their model was initially developed to study the economic implications of trade policies which trace production, consumption, and trade of all types of goods and services at the global level. In their work, they aggregate the world into six regions of major players in the soybean market, including Brazil, China, the EU and the US, and collect the needed data – inter alia from the Food and Agriculture Organisation FAO – to represent the global economy in 2016. They estimate the US soybean production to decrease by 16,9% in a 30% import tariff scenario. In this scenario they expect Chinese soybean imports from the US to decrease drastically by 71,2% and the total US soybean exports by 40,3%. Hence, their model forecasts a stronger decrease of US soybean exports to China compared to the estimations by Zheng et al. (2018).

3.2.2 Shortcomings in the Measurements

Despite PE models enabling a better understanding of a problem after the modelling exercise, the economic impact problem is not completely resolved (Roningen, 1997). They omit many important factors, which are emphasized in GE trade models, in order to enable a rapid and cost-effective approach that focusses on a limited set of factors (Francois & Hall, 1997).

Within their analysis of the trade shock on the US-CHN trade, Amiti et al. (2019) admit that the estimates in their PE model do not consider the fact that foreign countries have placed retaliatory tariffs on imports from the US and China – e.g. on approximately $121 billion US exports – after certain tariffs were not of a bilateral but multilateral nature.[7] These tariffs mainly targeted US-agricultural exports as well as exports of steel, consumer goods, and automobiles. Turning back to the analysis of the Chinese import stop on US soybeans, Sabala and Devadoss (2019) admit that their spatial PE model assumes that soybeans are a homogenous commodity from all suppliers. This assumption presumes that importing countries buy soybeans based solely on the lowest purchase price. Therefore, reallocations of soybean trade do not reflect real-world trade flows in their model. Non-economic factors which account for real-world trade decisions, such as political incentives – which are important for the trade

[7] They apply a PE model of import demand and export supply with a perfectly competitive market structure.

conflict at stake – are not taken into account. Zheng et al. (2018) face similar problems. Despite their PE model employing national product differentiation, various exogenous variables are omitted, which leads to distorted results. Such variables are included in GE models, as applied by Taheripour and Tyner (2018). However, besides forecasting the economic impact of the Chinese import stop on US soybeans falsely based on either a 10% or a 30% import tariff scenario, their methodological approach is hardly traceable and more complex than necessary. Furthermore, they cluster the world into six main regions, which does not enable the inclusion of bilateral trade flows and barriers when measuring the economic impact on trade. They lack explanation for reallocation of trade flows. Zheng et al. (2018) include the top 24 US trading partners, which is more plausible. The applied data in both the forecasts of Taheripour and Tyner (2018) and Zheng et al. (2018) represents the global economy in 2016 which is understandable given the publication dates, but clearly leaves space for an updated analysis as conducted in this work.

3.3 Summary and Research Question

In this chapter, the economic impact of a trade shock and the measurement of the impact were identified in an exemplary manner, focusing on the overall and specifically the US-CHN soybean trade. Previous research has outlined the economic impact of the shock in terms of change in bilateral soybean trade flow, production and prices for consumers and producers. These effects were predominantly forecasted and measured with PE models which arguably are insufficient to guarantee a comprehensive analysis of the effect. As outlined in the previous section, a comprehensive GE approach is needed to obtain results which mirror endogenous as well as exogenous factors that influence the economic impact of the trade shock. Measuring partial effects of the trade shock with PE models does not guarantee comprehensive results.

With regards to possible alternatives to PE models, Sabala and Devadoss (2019, p. 292) mention the Gravity Equation but argue that, “the nature of econometric estimation […] does not allow the researchers to quantify trade flow reallocations.” with this approach. Yet, this work aims to prove the opposite, by showing how to quantify counterfactual trade flows and multilateral trade reallocations within a GE framework.

Given the mixed results, multiple outcome variables and different models in previous research the derivation of precise assumptions on the percentual change in trade flow after the bilateral trade shock would be too arbitrary. The deduction of the expected effect in terms of hypotheses is unfeasible since the applied methodological approaches and PE models differ, just as the measured outcome variables trade flow, production and consumer and producer prices. However, the estimated economic impact clearly seems to be negative, in terms of the assumed decrease in US-CHN soybean trade flow, decreasing soybean prices and a decrease in US soybean production. As a consequence, I expect a decline in bilateral soybean trade flow from the US to China – the final outcome variable of this work – after the trade shock hit the bilateral soybean trade flow in terms of a Chinese import stop on US soybeans in 2018. This assumption is based on the expected increase in bilateral trade costs, inter alia due to the bilateral tariffs, when regarding the US-CHN soybean trade flow in 2018. Given the bilateral soybean trade concessions and first steps towards a US-CHN trade deal in 2019, the costs are expected to decrease in 2019.

The GE effect of this shock on the US-CHN soybean trade flow and hence, the economic impact in terms of counterfactual trade flow is estimated based on the novel methodological approach by Hinz et al. (2020). By keeping the application of the approach well-structured and transparent, the aim is to generalize and enable its application to similar cases in which the impact of economic or policy changes are estimated econometrically. The Gravity Model of Trade, outlined below, and the SCM are combined in a three-step approach in order to answer the research question, which is derived from the outlined shortcomings in the literature: "*What is the general equilibrium effect of the Chinese import stop on US soybeans in 2018 on the US-CHN soybean trade flow?*".

4. Theoretical Framework

This chapter presents the theoretical framework upon which the analysis is based. At first, the theoretical foundation of the Gravity Model of Trade – which shifted from being a neglected and criticised model to a popular workhorse in trade literature – is presented. Thereafter, the role and importance of trade costs in international trade and their relation to the Gravity Equation are outlined, trade costs are classified and a short introduction on the theoretical background and the difficulties of measuring trade costs is given. The applied structural gravity equation, the required trade cost estimates and the SCM are explained in the upcoming methodological chapter.

4.1 Gravity Model of Trade

The Gravity Model of Trade, first introduced by Tinbergen (1962), builds on the metaphor of Newton's Law of Universal Gravitation to describe the patterns of bilateral aggregate trade flows between two countries as proportional to the gross national products of those countries and inversely proportional to the distance between them (Chaney, 2013). As the name suggests, gravity equations are a model of bilateral interactions in which size and distance effects enter multiplicatively. The typical or “naive” Gravity Equation relates bilateral trade flows of two countries not only to size and distance but also to various other bilateral trade effects, like language differences or colonial relationship (Head & Mayer, 2014; Novy, 2013). It describes the bilateral trade flow of two countries as proportional to the gross national product and inversely proportional to distance. The more resistant to trade with all others a country is, the more it is pushed to trade with a given bilateral partner (Anderson & van Wincoop, 2003).

The Gravity Model of Trade has become known as the workhorse in trade literature and is one of the most popular, successful and intuitive frameworks in economics. The effect of various determinants in international trade has been studied with the gravity equation, which is one of the most approved models for analysing the determinants of bilateral trade flows (Head & Mayer, 2014). It is the perhaps most accepted method to econometrically estimate the impact of economic or policy changes. This is the case since the model is a structural model with a solid and widely accepted theoretical foundation, which is outlined in the upcoming section. This property makes the Gravity Model of Trade particularly appropriate for counterfactual analysis by, e.g. quantifying the effects of trade policies. The model structure guarantees a high analytical traceability and a highly realistic and comprehensive GE environment that simultaneously accommodates a plurality of countries, regions, sectors or even firms. Thus, the framework can inter alia be applied to capture the possibility that trade policy changes in one country may trigger ripple effects in another country. Finally, one of the strongest arguments of the Gravity Model of Trade is its remarkable predictive power. The empirical Gravity Equations deliver a fit between 60% and 90% in aggregate data (Larch & Yotov, 2016; Wanner, 2019; Yotov, Piermartini, Monteiro, & Larch, 2016). Despite these highly promising arguments, the model lacked a theoretical foundation for a long time up to 1995.

4.1.1 Theoretical Foundation of the Model

Since Tinbergen (1962), trade economists have estimated Gravity Equations on bilateral trade data. Yet, due to the criticism on a missing theoretical foundation, the work was outside of the mainstream of trade research until 1995 (Deardorff, 1984). Despite the model being probabilistic, Anderson (1979) set forth a conventional economic model of gravity, being the first to offer a theoretical economic foundation for the Gravity Equation. More than a decade later, Leamer and Levinsohn (1995) pointed out that gravity models produce one of the clearest and robust findings in economics, even though they did not influence international economics at that point in time. In the same year, McCallum's (1995) application of the Gravity Equation on interprovincial trade data aiming to refute that national borders had lost their economic relevance, showed the usefulness of the Gravity Equation. He demonstrated the need to include the mentioned ripple effects, the so-called multilateral resistance (MR) variables or multilateral trade barriers in the model, which demonstrate that not only bilateral trade barriers, but also multilateral trade barriers determine trade flows between two countries. In order to solve McCallum's (1995) puzzle, Anderson and van Wincoop (2003) were the first to adjust and include MR terms in the Equation. This decisive step for the theoretical backing of the Gravity Equation enabled the derivation of structural gravity equations, as presented below.

4.1.2 Theory on the Structural Gravity Equation

In two seminal papers, Eaton and Kortum (2002) and Anderson and van Wincoop (2003) finally dismissed the conventional wisdom that gravity equations lack theoretical micro-foundations. Most importantly, these papers pointed the way toward estimation methods that took the structure of the models into account (Head & Mayer, 2014). Eaton and Kortum (2002) derive gravity on the supply side as a Ricardian structure with intermediate goods and show that Ricardian models of trade are fully consistent with gravity. In their derivation, the trade cost elasticity corresponds to one of the coefficients of the Fréchet distribution. The productivity varies across products. On the demand-side derivation of the Gravity Equation, Anderson and van Wincoop (2003), popularized the Armington-CES (Constant Elasticity of Substitution) Model by Anderson (1979).[8] As in Armington (1969), each country is the unique source of each product. Anderson and van Wincoop's (2003) structural model emphasizes the importance of the GE effects of trade costs and includes both domestic and international trade costs. Despite the derived gravity Equation from Eaton and Kortum (2002) departing from the CES-based approach in almost every respect, the obtained results are very similar (Head & Mayer, 2014).

The “naive” Gravity Equation contains the important insight that bilateral trade should be roughly proportional to the product of country sizes. Yet, a range of theoretical underpinnings pointed to the need to revise the view of the appropriate way to think of country size. Following Head and Mayer (2013), a country’s total output needs to be discounted by the opportunities it has for exporting it and, similarly, a country’s total expenditure should be discounted by the opportunities it has to source from alternative suppliers. These adjustments are transposed through MR variables, “which are general equilibrium trade cost terms that capture the fact that a change in bilateral trade costs between any two partners […], will result in additional effects (in addition to the direct partial effects).” (Yotov et al., 2016, p. 72). This is the case since a change in bilateral trade costs might affect other countries in the world with possible feedback effects on the original partners, e.g. with regards to bilateral import tariffs. Thus, MR variables describe the size of trade barriers each country in a bilateral trade relation faces with all its trading partners, including domestic and internal trade (Anderson & van Wincoop, 2003).

[8] The Armington assumption is a standard assumption to facilitate simple trade models (Armington, 1969).

4.2 Trade Costs in International Trade

Trade costs include all costs that occur when delivering a good to the final user, other than the cost of producing the good itself. Such costs are e.g. transportation costs (freight and time costs), insurance costs, policy barriers (tariffs and non-tariff barriers) or legal and regulatory costs. These variables can be divided in direct policy instruments (e.g. tariffs or quotas) and indirect policy instruments (e.g. transport infrastructure investment, regulation or language) – whereas the latter are claimed to be more important (Anderson & van Wincoop, 2004). Trade costs are large, as in a representative industrialized country, the ad valorem tax equivalent equals about 170%. This number breaks down into 55% local distribution costs and 74% international trade costs (1,7 = 1,55 * 1,74 - 1). Including both, domestic and international trade costs is important, as it would be arbitrary to stop counting trade costs once goods cross a border. Generally, Trade costs have substantial welfare implications. For example, Anderson and van Wincoop (2001) find that policy related costs can be worth more than 10% of national income. Obstfeld and Rogoff (2000) argue that all the major puzzles of international macroeconomics hang on trade costs.

Early research on trade costs in the late nineteenth century has stressed the singular role played by developments in transportation and communication technologies. In the most influential contribution to the early literature of international trade costs, O'Rourke and Williamson (1999) state that the increase in commodity market integration in the late nineteenth century was a consequence of sharply declining transport costs. However, they omit other costs of trade besides transport could be responsible for the increase in global trade in this period. Jacks (2005) offers evidence from North Atlantic grain markets between 1800 and 1913 that freight costs can only explain a relatively modest fraction of trade costs. Furthermore, he finds that trade costs are influenced by the choice of monetary regime, commercial policy and the diplomatic environment in which trade took place. Further literature finds that monetary regime coordination, distance, tariffs as well as cultural and political factors played an important role in explaining global trade patterns and thus, international trade costs.[9] Despite this additional evidence, a substantial portion of trade costs remained unexplained.

4.2.1 Measuring Trade Costs

The accurate direct measurement of trade costs faces many difficulties, as good and complete data for direct measures of trade costs are remarkably sparse and inaccurate. A large portion of trade costs that cannot be measured directly lacks a theoretical foundation. Developments in the early 2000s have bridged the gap between practice and theory in the inference of trade

[9] For more information see Estevadeordal, Frantz, and Taylor (2003), Flaaen et al. (2019) and Meissner (2003).

costs from trade flows. Within their influential work “Trade Costs”, Anderson and van Wincoop (2004) clarify how trade costs – or trade barriers – can indirectly be inferred from the gravity model of trade, linking trade flows to observable variables and unobservable trade costs. Following their approach, “Gravity links the cross-country general equilibrium trade allocation to the cross-country trade barriers, all conditional on the observed consumption and production allocations” (Anderson & van Wincoop, 2004, p. 3). As a result, Novy (2013) derives a theoretically consistent micro-founded trade cost measure, based on the structural gravity equation by Anderson and van Wincoop (2003). He explains that “The crucial intuition is that a change in bilateral trade barriers does not only affect international trade but also intranational trade.” (Novy, 2013, p. 3).

Alternatively, Feenstra (2004) showed that importer and exporter fixed effects can be used to capture the MR terms that emerged in the different theoretical models. The combination of being consistent with the theory and easy to implement in practice lead to a rapid adoption in empirical work. Amongst others, Anderson, Larch, and Yotov (2015) recommend to estimate Gravity Equations with importer and exporter fixed effects by Feenstra (2004). Fally (2015) shows that estimated importer and exporter fixed effects in the Poisson Pseudo Maximum Likelihood (PPML) specification are consistent with the definition of multilateral resistance indexes and the equilibrium constraints that need to be satisfied. Hence, gravity regressions with fixed effects and PPML can be applied as a simple tool to estimate bilateral trade costs and thus, solve the estimation problem raised by Anderson and van Wincoop (2003).

5. Research Design and Methodology

This work conducts a comparative case study and follows the logic of causal case studies, which predominantly aim to identify the causal effect of one variable on another (Gerring, 2017). It analyses the causal economic effect of the bilateral trade shock on the US-CHN soybean trade flow by comparing the actual US-CHN soybean trade flow, given the trade shock in 2018, with a counterfactual ‘no shock’ situation. The comparison is conducted for the past decade, with a special focus on the two years after the shock occurred.

This chapter presents the two applied methodologies, the structural gravity equation and the SCM, to identify the causal effect of the trade shock on the respective trade flow. First, the structural gravity equation is introduced based on the work by Anderson and van Wincoop (2003). Thereafter, the bilateral trade costs required to generate the synthetic control case for the treated unit are estimated based on a similar approach as presented in Anderson et al. (2015). The SCM by Abadie and Gardeazabal (2003) and Abadie, Diamond, and Hainmueller

(2010) and its underlying computation is presented subsequently. This approach enables the estimation of the effect of the intervention on the outcome variable 'bilateral trade costs' and hence, the generation of a counterfactual situation. The implementation of subsequent placebo tests which were conducted to estimate the validity of the results, are explained in the following chapter as well. Having introduced both methods separately, the combined approach is outlined subsequently. This is followed by a more detailed explanation, of the methodological operationalization, the underlying data and the applied predictor variables.

5.1 Structural Gravity Equation

This work refers to the structural gravity equation as developed by Anderson and van Wincoop (2003) and further explained by Anderson et al. (2015) and Yotov et al. (2016). In their GE model on international trade, they include MR variables and incorporate bilateral trade costs. They assume a CES over all goods. Goods are differentiated by region or for the case of this work, by country of origin. Referring to the Armington assumption, it is assumed that each country is specialized in one good of which the supply is fixed, whereas prices of goods differ across countries due to trade costs. Following the derivation of the micro-founded Gravity Equation by Anderson and van Wincoop (2003)[10], the structural gravity system is resembled by the equations (1-3) where x_{ij} denotes trade flows from exporter i to destination j as

(1) $$x_{ij} = \frac{Y_i E_j}{Y} \left(\frac{t_{ij}}{\Pi_i P_j}\right)^{1-\sigma} .$$

Y_i is income of country i (sales to all destination) and Y is the world income which is defined as $Y = \sum_i Y_i$. E_i resembles the total expenditure at country j from all origins. t_{ij} (and vice versa t_{ji}) denote the bilateral trade costs and are assumed to be symmetric ($t_{ij} = t_{ji}$). $\sigma > 1$ is the elasticity of substitution and Π_i and P_j are price indices that resemble the mentioned MR variables. The equation relates all bilateral trade flows to the incomes of the countries i and j, to bilateral trade costs t_{ij} and to the MR terms Π_i and P_i. When bilateral trade costs rise, bilateral trade decreases (Novy, 2013).

P_j is the inward MR term (IMR), which aggregates the incidence of trade costs in each country and the CES price index of the demand system:

(2) $$\mathrm{P}_j^{1-\sigma} = \sum_i \left(\frac{t_{ij}}{\Pi_j}\right)^{1-\sigma} \frac{Y_i}{Y}.$$

[10] See the equations (1) to (9) in Anderson and van Wincoop (2003, p. 172-175) or the equations (1-1) to (1-7) in Yotov et al. (2016, p. 13-15) for a detailed derivation of the structural gravity system.

Π_i is the outward MR (OMR) which aggregates i's outward trade costs relative to the destination price indexes as

(3) $$\Pi_i^{1-\sigma} = \sum_j \left(\frac{t_{ij}}{P_j}\right)^{1-\sigma} \frac{E_j}{Y}.$$

Referring to equation (1), the theoretical Gravity Equation that determines bilateral trade flows can be decomposed into two separate terms: A trade cost term, $\left(t_{ij}/(\Pi_i P_j)\right)^{1-\sigma}$, and a size term, $Y_i E_j / Y$. Following Anderson and van Wincoop (2003) and Yotov et al. (2016), the trade cost term captures the total effects of trade costs which drive a wedge between realized and frictionless trade. Thus, one can derive a decomposition of the trade cost term into three components:

1) The bilateral trade costs, t_{ij}, between country i and country j, which are commonly approximated by trade policy and geographic variables such as distance or tariffs.
2) The strucutrual term P_j (IMR), which represents the importer j's ease of market access (or the resistance of i to trade).
3) The structural term Π_i (OMR), which measures the exporter i's ease of market access (or the resistance of j to trade).

5.1.1 Fixed Effects Trade Cost Estimate

Before presenting the fixed effects trade cost estimate, practical arguments are given, such as why this approach is chosen over the alternative by Novy (2013). Following Novy's (2013) approach, the solution for the MR variables in equation (2) and (3) can be exploited to derive a micro-founded measure of the bilateral trade costs τ_{ij}, expressed as

(4) $$\tau_{ij} = \left(\frac{x_{ii} x_{jj}}{x_{ij} x_{ji}}\right)^{\frac{1}{2(\sigma-1)}} - 1$$

where $x_{ij} x_{ji}$ are bilateral trade flows between the countries i and j and $x_{ii} x_{jj}$ are intranational trade flows. Following the equation, the intuition for bilateral trade costs is as follows: If bilateral trade flows $x_{ij} x_{ji}$ between i and j decrease but intranational trade flows $x_{ii} x_{jj}$ remain constant one can assume that it must have become harder for these countries to trade with each other. Based on this commonly applied measure in international trade research, bilateral trade costs can be directly computed from observable variables. Yet, in order to estimate the bilateral trade costs, it is noteworthy that bilateral exports and followingly imports are reciprocal. If the exports from i to j equal zero, the denominator in the first part of Novy 's (2013) equation equals zero. Furthermore, the resulting bilateral trade costs τ_{ij} equal zero if the respective exports are not reciprocal to some part – regardless of the remaining values. Given the frequent null values caused by one-directional soybean trade, Novy's (2013) bilateral trade cost estimation is not appropriate for the striven analysis in this work. This is the case since the world's soybean exports are concentrated on very few countries and there are more importers than exporters.

This work bases its trade cost estimation on the approach by Anderson et al. (2015), who fully exploit the combined properties of the structural gravity equation and the GE Poisson Pseudo-Maximum-Likelihood estimator to derive conditional and full GE responses. In this approach, the inward and outward MR's are inferred from origin and destination fixed effects in a standard gravity regression along with inference on the unobservable bilateral trade costs. The estimated fixed effects have shown to provide a strong data fit under the PPML structure. As mentioned previously, Fally (2015) shows that estimating gravity with estimated fixed effects in the PPML specification are consistent with the definition of the IMR and OMR indexes – and the equilibrium constraints they need to satisfy – by more structural approaches such as those of Anderson and van Wincoop (2003). Referring to Silva and Tenreyro (2006), PPML is consistent with the presence of zero bilateral trade flows, which are – as in the case of this work – highly prevalent in disaggregated data. Furthermore, they show that PPML consistently estimates the Gravity Equation for trade and is robust to measurement error and different patterns of heteroskedasticity. These properties make it preferable to alternative procedures, such as ordinary least squares, and argue in favour of the PPML estimator for gravity regressions. Unlike the approach by Dekle, Eaton, and Kortum (2008), Anderson et al. (2015) base their calculations on fitted (predicted) trade flows instead of observed trade flows, which is in line with the approach of this work.[11]

Taking these considerations into account, many studies – including Anderson et al. (2015) – estimate the theoretical structural gravity equation in equation (1) in terms of equation (5):

$$x_{ij} = \exp\left(T_{ij}\beta + \pi_i + P_j\right) + \epsilon_{ij}. \tag{5}$$

Referring to Anderson et al. (2015), T_{ij} is the vector of trade cost variables and β is a vector of coefficients. π_i is an exporter fixed effect that accounts for the OMR's and for outputs, and P_j is an importer fixed effect that accounts for expenditures and for the IMR's. ϵ_{ij} is the actual bilateral error term or residual which practically accounts for the change in bilateral trade costs, as required for the SCM analysis in this work. In addition, this equation is applied to estimate the synthetic ϵ_{ij} based on the present fixed effects data, which is then included into the theoretical structural gravity equation (1) as an estimate of t_{ij}. Hence, the synthetic

[11] See Anderson et al. (2015) for a more technical explanation of their GE PPML approach.

counterfactual trade flow for 2018 can be estimated by inter alia including the estimated synthetic trade cost term ϵ_{ij} into the equation.

5.2 Synthetic Control Method

In comparative case studies, researchers compare units affected by an intervention or event of interest to a group of unaffected units. They are only feasible when some units are exposed to the intervention and others are not (Abadie et al., 2010). The rationale behind this method is to use the outcome of the control group to approximate the outcome that would have been observed for the treated group in the absence of the treatment or the intervention. Traditional comparative case study methods leave the choice of control units to the analyst, prompting questions about the degree to which control units can credibly proxy counterfactual outcomes for treated units, the selection process and its arbitrariness. As a result, researchers often struggle to find suitable control units that are similar to the treated unit (Abadie, Diamond, & Hainmueller, 2011; Lijphart, 1971).

The Synthetic Control Method by Abadie and Gardeazabal (2003) and Abadie et al. (2010) addresses these shortcomings and provides a systematic data-driven control-group selection procedure to identify suitable comparison or control units that are most-similar to the unit of interest (Abadie et al., 2011). To produce this quantitative inference, the SCM constructs an untreated synthetic counterfactual of the unit of interest based upon a so called "donor pool" of possible control units and a set of variables that predict the outcome variable for the unit of interest. The constructed counterfactual is based on a weighted average of all potential comparison units, which best resemble the characteristics of the interested unit. A combination of unaffected units often provides a more appropriate comparison than any single unaffected unit alone. Thereafter, the development of the unit of interest in presence of the treatment is compared with the synthetic counterfactual of this unit of interest, in absence of the treatment (Abadie, Diamond, & Hainmueller, 2015). The approach of the SCM resembles a generalization of Mill's Method of Difference in its basic concept.[12] However, the SCM provides several advantages over the general difference-in-difference approach. It maximizes the observable similarity of control and treatment cases. Furthermore, the method is feasible even when no single untreated case is identified as an adequate comparison case to the treatment case. Moreover, the selection of controls units is formal and objective, and the often-obscure justification of ad hoc decisions is avoided.

[12] For more information on Mill's Method of Difference see Gerring (2017).

The aim of the SCM consists on estimating the effect of interventions that are implemented at an aggregate level affecting a small number of large units (such as a cities, regions, or countries), on some aggregate outcome of interest (Abadie, 2019). The SCM has frequently been applied to measure the effect of economic or policy interventions.[13] This work applies the method introduced by Abadie et al. (2010, 2015) to elaborate the underlying computation of the SCM. In the following, a simple model is presented that provides the rational for the use of the SCM in comparative case studies. The terms “intervention", “event” and “treatment" are used interchangeably. The terms “treated" and “untreated" will refer to units exposed and not exposed to the intervention or event of interest.

Suppose that we observe $J + 1$ units, that are identified as potential comparison units – including the treated unit – where $j = 1$ is the case of interest, or the “treated unit”, which is exposed to the event of intervention or “treatment”. The untreated units $j = 2$ and $j = J + 1$ constitute the potential comparison units which are jointly termed as the “donor pool”. This donor pool must be restricted to units with outcomes driven by the same structural process as the unit representing the case of interest.

All units in the longitudinal data set are observed at the same time periods, $t = 1, \dots, T$. The sample includes the pre-treatment periods T_0 as well as the post-treatment periods $T = 1$. Thus, $T = T_0 + T_1$, whereas no effect of the Chinese import stop on US soybeans is expected within the pre-intervention periods but during the post-intervention periods. The synthetic counterfactual is defined as a “synthetic control as a weighted average of the units in the donor pool” (Abadie et al., 2015: 497). Hence, it resembles a combination of available untreated units, in our case untreated country pairs, as a $(J\ x\ 1)$ vector of weights $W = (w_2, \dots, w_{J+1})'$, with $0 \leq w_j \leq 1$ for $j = 2, \dots J$ and $w_2 + \dots + w_{J+1} = 1$. The value of W is chosen, such that the characteristics of the treated unit are best reflected by the characteristics of the synthetic control, with the smallest possible deviation. Thus, the means squared predictor error (MSPE), which corresponds to the difference between the treated unit and the synthetic counterfactual, must be minimized. Let the values of the pre-treatment characteristics, the predictor variables, of the treated unit be a vector X_1, and the characteristics of the untreated units in the donor pool be a matrix $k\ x\ J$, described as X_0. This difference is given by the vector $X_1 - X_0$, for which the synthetic control, $W*$, is chosen to minimize the difference. Referring to Abadie et al. (2015, p. 497) this is operationalized by: ”For $m = 1, \dots, k$, let X_{1m} be the value of the m-th variable for the treated unit and let X_{0m} be a $1\ x\ J$ vector containing the values of the m-th variable for the units in the donor pool.” Hence, the value $W*$ of W is chosen in order to minimize

[13] For more information see the applications by Abadie et al. (2015) and Abadie and Gardeazabal (2003).

$$\sum_{m=1}^{k} V_m (X_{1m} - X_{0m} W)^2.$$

V_m is an additional weight that represents the relative importance and thus, the weights for the different predictor variables, similar to W, for the untreated units in the donor pool. Thus, when applying a data-driven procedure to choose V_m, it is chosen such that the MSPE of the outcome variable is minimized. The variables with the larger predictive power for the outcome of interest are consequently assigned larger V_m weights and vice versa.

Following the presented method and practical examples, this work examines the economic impact, in terms of the counterfactual bilateral trade flow, of the trade shock on the US-CHN soybean trade. Unlike most previous research applying the SCM, this work does not apply per-capita GDP nor similar economic output or activity measures as the outcome variable. This work applies bilateral 'trade costs' as the outcome variable to estimate the difference in bilateral trade costs after the treatment. It thereby equals the bilateral trade shock on the US-CHN soybean trade, caused by import tariffs related to the US-CHN trade conflict. Thus, the bilateral trade costs of the treated country pair, the US and China, are compared with the identified untreated synthetic unit composed of weighted bilateral trade costs of country pairs from the donor pool. The bilateral trade costs are estimated based on the approach by Anderson et al. (2015). A comprehensive explanation of how both methods are combined is given, after explaining the for the validity of the SCM-results required falsification tests.

5.2.1 Placebo Tests

To perform quantitative inference in comparative case studies and to assess the ability of the SCM to reproduce the evolution of a counterfactual unit without intervention, Abadie et al. (2010) introduce placebo studies. This mode of inference is based on permutation methods. When having a single treated unit at hand, a permutation distribution is obtained by iteratively reassigning the treatment to all units in the donor pool which enables the estimate of placebo effects in each iteration. The distribution is computed under random permutations of the sample units' assignments to all intervention and non-intervention groups (Abadie, 2019). Following Abadie et al. (2010) this allows the researcher to assess whether the effect estimated by the SCM for the country affected by the intervention is large relative to the effect estimated for a country chosen at random. Hence, this exercise produces exact inference regardless of the number of available comparison countries – in this work bilateral country pairs –, time periods, and the decision about using individual or aggregate data.

There are two types of placebo tests. The first test option introduced, the “in-time” placebo test, assigns the treatment to the actual unit of treatment, but a random point in time. If this exercise still indicates an effect of the treatment, the validity of the results would have to be discarded. In the second option, the “in-space” placebo test, the treatment is assigned to each control unit in the donor pool. For each unit a synthetic counterfactual is computed and the differences in the outcome variable ‘bilateral trade costs’ are compared. If the treated unit is the only unit for which a clear treatment effect is shown after the occurrence of the treatment, the researcher can assume the results to be robust (Abadie et al., 2010)

5.3 Combining the Structural Gravity Equation & the Synthetic Control Method

This work applies a combination of the Gravity Equation and the SCM. As outlined earlier, the solid theoretical foundations and the structural properties of the Gravity Model of Trade make the GE gravity framework particularly appropriate for the striven counterfactual analysis. Since the SCM constructs untreated synthetic counterfactuals for the respective unit of analysis, a systematic three-step approach is derived based on the combination of both methods. This combination of the respective methods allows for a comprehensive and likewise traceable quantification of the effects of trade policies. The methodological approach is applied to the case of interest and aims to estimate the GE effect of the shock in terms of bilateral trade flow. Hence, this relative new approach enables to estimate the economic impact of future trade shocks and similar economic or policy interventions, given the outlined benefits.

In a first step, the bilateral trade costs of world country pairs, including the treated country pair US-CHN, are estimated with an estimated structural gravity equation. These trade costs serve as the SCM’s economic output measure. The SCM analysis enables the measurement of the change in bilateral trade costs over time by generating the synthetic trade costs for the treated unit. In the following, the applied three-step approach is presented.

1) Identify the shock and estimate the bilateral trade costs with fixed effects – based on the approach by Anderson et al. (2015) – for all country pairs in the donor pool.
2) Generate the synthetic control case for the treated unit from the donor pool and with the predictor variables and derive the treatment effect for the outcome variable ‘bilateral trade costs’ with the SCM by Abadie et al. (2010) and Abadie and Gardeazabal (2003).
3) Plug the synthetic bilateral trade costs into the theoretical structural gravity equation by Anderson and van Wincoop (2003) to estimate counterfactual bilateral trade flows for the treated unit and thus, the GE effects of the shock.

The latter step additionally allows to extrapolate the GE effect for untreated units. Thus, besides estimating the GE effect of the trade shock on the US-CHN soybean trade flow, the additional GE effect on the US-EU soybean trade flow is analysed, as outlined before. Turning back to the US-CHN case, the following section presents the underlying theoretical and methodological background for the qualitative selection process of this case.

5.3.1 Case Selection

As presented in the previous part of this chapter, the comparative analysis follows a quantitative approach. In contrast, the initial case selection followed a qualitative approach. This is the case, since the range of interventions in terms of bilateral trade shocks of this dimension are sparse in past decades. Following the SCM, the effect of this intervention occurred at an aggregate level affecting a small – for our case single – number of large units (country pairs). Besides the strong media attention, the US-CHN soybean trade received especially in 2018 because of its economic importance for the bilateral US-CHN trade, there are more profound theoretical reasons for the selection of this case. As outlined by the influential work of King, Keohane, and Verba (1994) on causal inference in qualitative research, the case selection should be based on the independent variable and controls and not on the dependent variable. Only during the research process the values of the dependent variables are to be discovered which lead to initial causal inference. Furthermore, as Blatter and Haverland (2012) state, selecting on the dependent variable' would introduce selection bias. The present study followed these approved recommendations as the focus during the case selection was put on the impact of the trade shock – the independent variable – and not on the trade costs, which resemble the outcome variable of the SCM to estimate the dependent variable trade flow.[14]

Based on a set of three qualitative conditions this single case of analysis was chosen as suitable to estimate the GE effect of the bilateral trade shock on this specific trade flow and demonstrate the applicability of the methodological approach: 1) affectedness, 2) definability and 3) significance. First, the respective trade flow had to be directly affected by the tariffs of either country during the conflict. Second, the trade flow had to be clearly definable from other trade flows, especially from trade flows of products within the same sector, e.g. wheat. This mainly includes the product being definable from others in terms of production and trade data. Third, the trade flow had to be of great significance for the bilateral trade relationship and the bilateral economy of the US and China in terms of trade value.

First, the US-CHN soybean trade flow has been directly affected by the Chinese tariffs in July 2018 (USTR, 2018), as US soybean exports were covered with 25% import tariffs. Second,

[14] The dependent and independent variable as well as their operationalization are outlined in the section "Operationalization and Data".

the trade flow of the product "soybeans" can be clearly differentiated from the trade flow of similar crop types, as the required production and trade data for soybeans can be accessed separately. Third, the soybean trade flow represents a significant trade flow for both countries, as China purchased more than half of all US soybean exports between 2013 and 2018, equal to e.g. 62% of US soybean exports in 2016 and 57% in 2017 (USITC, 2019).

5.3.2 Temporal Domain

As the trade shock hit the US-CHN soybean trade flow in mid-2018, the post-treatment period is limited to the years 2018 and 2019.[15] Despite recurring tariff exemptions by the US and China especially in 2019 – including soybeans – I expect a lasting effect of the bilateral trade shock on the soybean trade flow throughout both post-treatment years due the intervention in 2018. As there is no specific ratio of pre-to post-treatment defined in the literature, this work, compared to the post-treatment period, applies a generous pre-treatment period of eight years. This seems more than sufficient, as the pre-treatment period in Abadie et al. (2015) is approximately three times the size of the post-treatment period. Unlike their work, this work does not cover a total time period of over 40 years. Given the actuality of the case, but also the rather recent increase of China's soybean imports from the US in the last two decades, the total period of analysis covers the years 2010-2019.

5.3.3 Operationalization and Data

To answer the research question and achieve valid results, the operationalisation of the SCM and the structural gravity equation is outlined in the following. Previous research has analysed the economic impact of the bilateral trade shock on the US-CHN soybean trade and has forecasted and measured the effects for different outcome variables. This work aims to identify the GE effect of the shock on the US-CHN soybean trade flow. The trade shock is determined as the independent variable. The GE effect of this trade shock in terms of bilateral trade flow represents the dependent variable. The initial effects of bilateral trade costs are thereby translated into trade flows, whereas this work operationalizes trade flows in terms of bilateral imports and exports. The structural gravity equation additionally captures the effect that trade policy changes in one country might not only trigger effects of a bilateral trade flow, but also enables the estimation of ripple effects on multilateral trade flows. In this context, MR's are the vehicles that translate the initial PE effects of trade policy at the bilateral level to country-specific GE effects at the multilateral level (Yotov et al., 2016).

[15] No reliable trade and production data were available for 2020 when writing this work.

In order to first estimate bilateral trade costs, annual data on the countries' soybean production (in tons) is derived from the crops section in the database of the FAO for the years 2010-2018. As the FAOs production data is not available for the year 2019, the 2019-data is complemented with data from the EU-Commissions "Oilseeds and protein crops statistics" for the EU member states, and with the respective Production, Supply and Distribution (PSD) data set from the United States Department for Agriculture (USDA) for all further countries (see EU Commission, 2020; USDA, 2020). The annual trade data on soybean exports and imports for all bilateral country pairs is derived from the UN COMTRADE database.

I employ annual over monthly production and trade data for several reasons. Soybean production data is not available on a monthly basis for the period of analysis. Disaggregating the annual production-data in monthly data would be connected to several risky assumptions, since the months in which soybeans are harvested differ significantly amongst countries due to hemispheric temperature differences. This problem also applies to a possible disaggregation of the trade data, since countries export and import soybeans given the respective harvesting months. This monthly variation can be exemplified by the monthly soybean exports of the US and Brazil. While the US supplies most soybeans from October to March, Brazil exports soybeans in the rest of the year (USITC, 2019).

To generate a synthetic control group which equals the treated group best, variables of the "CEPII Gravity Dataset" files are merged with the estimated bilateral trade costs.[16] The applied gravity datasets ("dist_cepii" and "gravdata") are bilateral, since they include variables valid for country pairs such as bilateral distance, contiguity, or colonial historical links. Such data is commonly used for the estimation of gravity equations by trade economists, to describe bilateral patterns of trade flows. However, these covariates, which are applied in this work, have also been used in other fields than international trade, e.g. the study of bilateral flows of foreign direct investments, but also by researchers interested in explaining international flows of tourists and traffic or migration patterns (Mayer & Zignago, 2011). Furthermore, the bilateral GTAP tariffs for soybeans are derived from the International Trade Centre's database "Market Access Map" for 2014. The statistical analysis itself, which follows the presented three-step approach, is conducted with the standard software package "R". For the SCM analysis, the "Synth" package in Abadie et al. (2011), which implements the SCM in R, is used.[17]

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[16] CEPII stands for "Centre d'Études Prospectives et d'Informations Internationales", a French research institute for international economics.
[17] For a more detailed explanation on the application of the R package "Synth" see Abadie et al. (2011).

5.3.4 Predictor Variables and Donor Pool

Unlike most SCM studies, this work applies static and not time-varying predictor variables, for which the average or mean over the analysed time period is calculated. The reason therefore is the static nature of the applied variables. As stated previously, most predictor variables are derived from the dyadic datasets by Mayer and Zignago (2011). It includes a set of different distance and common dummy variables used in gravity equations to identify particular links between countries, for which the predicted trade cost fit is very high.[18] The selection of predictor variables for this work is based on multiple factors. A first pre-selection is based on commonly applied variables in the gravity literature. To capture the pattern of bilateral trade flows best, the notion of distance is generalized and other aspects beyond being physically apart, that may also influence bilateral trade costs, are included as a representative form of bilateral trade policy, e.g. whether these countries have a colonial history, share a common language, or whether they are joint members of a regional trade agreement (RTA).[19] In doing so, one can infer the effect of these additional variables on bilateral trade costs. Furthermore, the potential similarity of variables – such as multiple distance variables – and the given variance and thus, the prediction power of the variables is analysed. Finally, the following eight bilateral variables – valid for country pairs – are included in the statistical analysis: “colonial relationship”, “common language”, “contiguity”, “common currency”, “common legal origins after transition”, “regional trade agreement”, “weighted distance” and “bilateral tariffs”.

Given the multiplicative nature of the gravity model the logarithm is calculated for the variable “weighted distance” which indicates the weighted bilateral distance (population-weighted, km) between two countries. The variable “bilateral tariffs” indicates the bilateral tariff on soybeans for the respective direction of soybean trade flow between two countries. The remaining variables are dummy gravity variables which are coded with ‘1’ or ‘0’ depending on whether a country pairs fulfils the condition of the respective variable. Despite the implications of the dummy variables being intuitive, it is to be noted that the dummy variable ‘colonial relationship’ indicates whether a country pair has ever been in a colonial relationship and the variable ‘common legal origins after transition’ indicates whether origin and destination share common legal origins after a possible transition (Mayer & Zignago, 2011).[20] The dummy variables and the variable “weighted distance” are likewise assigned all pre-treatment years. The “bilateral tariffs” of 2015 are assigned all pre-treatment years due to data availability and the for the SCM required time-invariant variable characteristic.

[18] The data is supplemented by various sources indicated in the codebook by Mayer and Zignago (2011).
[19] See Anderson & van Wincoop (2003), Head & Mayer (2014), Wanner (2019) and Yotov et al. (2016).
[20] The exact definitions of all dummy variables are noted in the codebook.

The donor pool applied to construct the synthetic bilateral US-CHN trade costs originally consisted of all world country pairs, for which the trade and gravity data is listed in the analysed time period 2010-2019. However, not all country pairs were eligible for the SCM analysis due to unavailable or inconsistent country pair data in either the gravity or the trade data sets.[21] Incomplete country pairs had to be removed beforehand. This resembles a limitation of the analysis as e.g. autocracies or developing states may be more prone to boast poor data supply. Hence, incomplete country pairs may not be missing at random and the donor pool may be biased. However, as the data for the most significant soybean exporters and importers – thus, the data for potential comparison units – is available this limitation can be neglected.

With regards to the synthetic US-EU trade flow, the US soybean exports to the EU-members Germany, Spain and the Netherlands are analysed. These countries representatively resemble all EU-member states, since they are the only members for which all necessary data is recorded with regards to the US-EU soybean trade flow. Despite this comparatively small sample size, these countries represent the EU comparatively well, as they have been the top three US soybean importers in the EU in the last three years. When regarding the utilised UN COMTRADE data, the Netherlands clearly represent the largest US soybean importer in the EU, followed by Germany and Spain.

5.3.5 Validity and Reliability

The crucial value of any research depends on its validity, whether it measures what it is supposed to measure (Mayring, 2002). Validity can be separated into internal and external validity. Internal validity describes the question of whether the causal facts that studies produce are reliable, i.e. the identification of the treatment effect in the studied case (Samii, 2016). External validity focuses on how realistic the context is and whether results to subjects other than those in the study can be generalized. As it is the case in this study, the main emphasis is put on identification of the impact of a particular intervention, the trade shock, which generates internal validity. As an in-depth comparative case study that applies a comprehensive methodological approach is conducted for this study, a high internal validity is expected. Both falsification exercises, the placebo studies presented in the previous chapter, are expected to generate insights on the internal validity and the causal inference of the results. However, the focus on a single case is at the cost of limited external validity in terms of immediate generalizability to other settings (Abadie et al., 2010). I expect to demonstrate the generalizability of the combined approach of the SCM and the structural gravity equation and

[21] This was especially the case for 2019, the most recent year of analysis.

hence, to enable the application of this methodological approach to similar cases that investigate the effect of certain economic or policy events.

In addition to validity, reliability, the precision and consistency of the measurement in repeated trials is of major importance (Mayring, 2002). This work seeks to maximize the reliability of its results in terms of precision by including a comprehensive set of variables with a possible impact on the estimation of the GE effects into the analysis.[22] With regards to the consistency and the feasibility of others to repeat the three-step approach, I am confident that a repetition by others would result in the same results. Both, the methodological but also the theoretical approach are traceable and transparent which is why this work should entail a rather high reliability. Yet, assertions on the statistical error of the estimate are to be made after the results are presented.

6. Results

As outlined in the previous chapter, the SCM is applied to a set of predictor variables that influence bilateral trade costs to assess whether a possible change in estimated trade costs occurred due to the Chinese import stop on US soybeans. To derive the economic impact in terms of the counterfactual bilateral trade flow, the synthetic trade costs are plugged back into structural gravity equation. As the import stop occurred in mid-2018 following the bilaterally imposed tariffs, I expected an increased treatment effect with regards to the outcome variable bilateral trade costs. Hence, the bilateral soybean trade flow is expected to decrease in 2018 – and to increase slightly in 2019 – whereas the counterfactual trade flow is assumed to remain on a similar level compared to previous years.

I computed the SCM model on the dependent variable trade costs and the remaining 134 control units (country pairs) in the donor pool. The required weighted synthetic counterfactual (‘w’ weights) in Table 1 (appendix) was computed based on the eight weighted predictor variables (‘v’ weights) in Table 2 (appendix). A comparison of the treated and the synthetic unit, the predictor balance of the model, can be found in Table 3 (appendix). The model compares the trend in bilateral trade costs for the actual and the synthetic US-CHN soybean trade. To ensure the validity of the results, the performed placebo tests, which function as robustness checks, are outlined for the US-CHN case.

Given the synthetic trade costs results, one can then draw a conclusion on the effect the import stop has had on the US-CHN soybean trade flow by plugging the derived synthetic trade costs

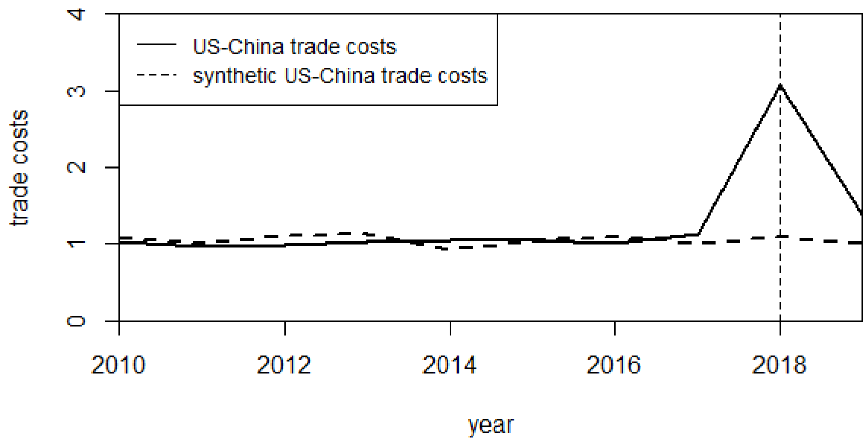
[22] This is especially noteworthy for the MR variables which are not included in PE models.

into the theoretical structural gravity equation in order to calculate the counterfactual US-CHN trade flow. Given the structure of the model, this step suffices to derive the counterfactual trade flow for the US-Germany, US-Spain and US-Netherlands case which represent the US-EU trade flow in this work. Given the GE effect of the Chinese import stop on US soybeans in 2018 on the US-CHN soybean trade flow, the research question is answered subsequently.

6.1 Counterfactual US-CHN Trade Costs

The computed model in Figure 2 shows the estimation of the evolvement of the actual and the synthetic US-CHN trade costs.[23] Table 1 shows, that the synthetic case is mainly computed based on the country pair Argentina-China (40%), but also Brazil-Japan (12%) and country pairs which smaller weights were assigned, as e.g. country pairs with US export flows. The model exhibits the previously outlined relative residual trade cost estimates on the y-axis and the timeline in years on the x-axis. It provides an almost perfect fit with the actual US-CHN trade costs up to the import stop in 2018.

Figure 2: Trends in soybean trade costs – US-CHN and synthetic US-CHN



This is proven when controlling for the MSPE in Figure 3 (appendix), as slight deviations are only recorded for the pre-treatment years 2015 and 2017.[24] The MSPE of the US and China equals about 0.01. With the imposition of the Chinese import tariffs in 2018 the US-CHN trade costs roughly tripled. Since the synthetic US-CHN trade costs lack this treatment effect, and remain on the previous constant level, a significant correlation between the independent variable 'trade shock' – the Chinese import stop of the US soybeans – and the dependent variable 'trade costs' can be presumed. If the conducted placebo tests in the upcoming section

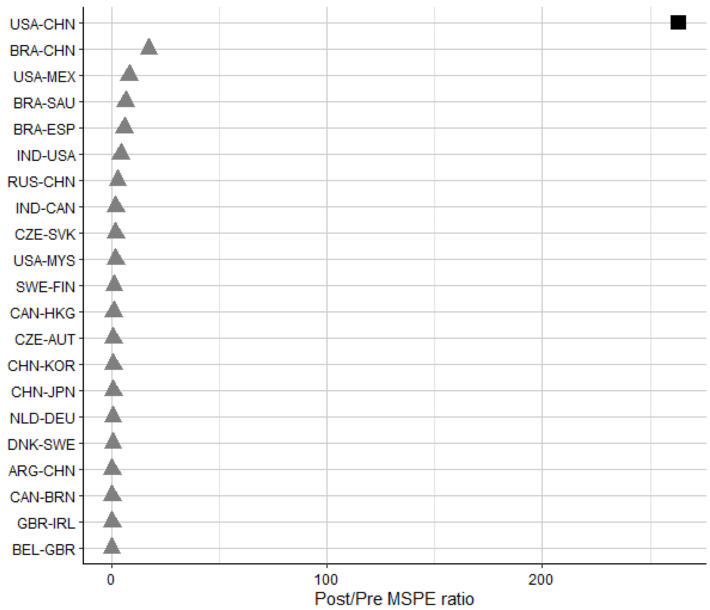
[23] The dashed line marks the last pre-treatment year.
[24] The MSPE is the average of the squared discrepancies between the trade cost residual measure of the US and China and its synthetic counterpart during the period 2010-2017.

are robust, one can confirm the causality of the correlation. To derive the economic impact of the shock and thus, the counterfactual US-CHN trade flow, these promising results are inserted into the structural gravity equation.

6.1.1 Placebo Tests

In this section the results of the falsification exercises are presented. They control for the internal validity and causal inference of the results and determine whether the estimated effects in the post-treatment period can be attributed to the imposition of the bilateral trade shock. Figure 4 (appendix) shows that the results of the in-time placebo test are robust to the assignment of the fictive treatment year 2014 – four years prior to the actual intervention – since the model does not predict a treatment effect. Hence, first inference on the validity of the results is gained. Second, to further prove the robustness of the rise of trade costs due to the bilateral import shock, the in-space placebo is applied. Figure 5 (appendix) outlines the development of the MSPE of the synthetic US-CHN trade costs in relation to the development of the MSPEs of the control units under false imposition of the shock. The grey lines represent the gaps that equal the difference in trade costs between each control unit country pair and its respective synthetic version. The superimposed black line denotes the estimated US-CHN gap. As the figure makes apparent, this estimated gap is unusually large relative to the distribution of the gaps for the country pairs in the donor pool. No other control unit exhibits a similarly strong treatment effect. This contrast is visualized clearly by the MSPE-ratio between pre- and post-treatment period in Figure 6 – country pairs with a pre-shock MSPE five times higher than US-CHN are discarded.

Figure 6: MSPE-ratio between pre- and post-treatment period



6.2 Counterfactual Trade Flows

As a last step in the introduced methodological three-step approach, the synthetic bilateral trade costs are plugged into the structural gravity equation, equation (5). The estimated synthetic counterfactual trade costs for the US-CHN soybean trade flow refer to ϵ_{ij}. The IMR of China and the OMR of the US refer to P_j and π_i and are captured by importer and exporter fixed effects. Having solved the equation one can estimate the counterfactual bilateral trade flows for the treated unit, the GE effect of the shock, and answer the research question.

Figure 7: Change in percent of US soybean export flows in 2018

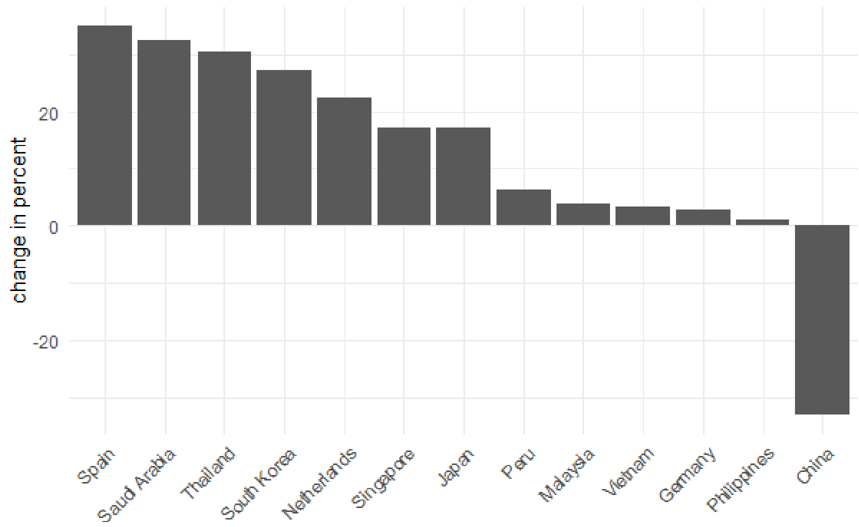


Figure 7 shows the GE effect of the Chinese import stop in 2018 in terms of change in US soybean exports, inter alia for the US-CHN trade flow.[25] Their bilateral soybean trade flow decreased by 33% in 2018 and hence, in the computed counterfactual 'no shock' situation the US would have exported 33% more soybeans to China, as visualized in Figure 8 (appendix).

Apart from this significant effect, Figure 7 also visualises further trade diversion effects. The economic impact of the bilateral trade shock on the US soybean exports to EU member states is clearly visible. Due to the shock, the US exported 35% more soybeans to Spain and 22% more soybeans to the Netherlands. The exports to Germany increased by 3%. This increase of US soybean exports to EU member states would have not occurred in a counterfactual 'no shock' situation. Furthermore, Saudi Arabia (32%) and especially South-East Asian states compensated the missing US soybean exports in 2018.

[25] Figure 7 does not visualize all US soybean export destinations but only those which show a substantial change in trade flow due to the import stop in 2018.

When regarding the change in trade flows for the second post-treatment year 2019, which can be derived from Figure 9 (appendix), a decreased economic impact in terms of change in trade flow is visualised. In the computed counterfactual situation, the US would have inter alia exported 4% more soybeans to China,15% less to Spain and 11% less to the Netherlands in 2019. The effect would likewise have been mitigated for further trade flows when comparing the years 2018 and 2019. Despite the more moderate effect, the trade shock indicates a lasting impact on the US-CHN soybean trade flow and further US soybean exports in 2019.

7. Discussion

The presented results underline the significant economic impact the US-CHN trade conflict and hence, the Chinese import stop of soybeans, has had on the US soybean exports to China. The protectionist trade measures entailed a decrease of bilateral soybean trade flow equal to one third of the estimated counterfactual trade flow in 2018 without the occurrence of the trade shock. This result resembles the bilateral trade flow predictions of the PE model by Zheng et al. (2018) very closely but contradict with those of the GE model by Taheripour and Tyner (2018), which expect the Chinese soybean imports from the US to decrease drastically by more than 70%. However, besides applying a different model they forecast the effect for a 30% Chinese import tariff scenario, leaving the actual 25% tariff scenario unsolved. Given, the almost identical results of the presented GE model and the PE model by Zheng et al. (2018) the question arises, whether the initially presumed need for a GE model is fully justified?

When regarding the underlying computations of the structural gravity equation and the overall methodological approach of this work on a theoretical level, the answer is yes. Unlike the applied comprehensive GE model, a PE model would have focused solely on the single US-CHN market and not included the impact of multilateral trade barriers and the reallocation or diversion of trade flows, which is why the estimated trade flows would have been distorted. This is underlined by the practical implications of this work. Besides exporting less soybeans to China, the US increased its exports not only to the EU but especially to South-East Asia. Given the impact of the Chinese import tariffs, exports to other trading partners have become significantly more favourable. This is illustrated by the drastic increase of bilateral trade costs between the US and China, the intermediate outcome variable in this work. Unlike any other country pair, the trade costs increased between these countries (see Figure 6). The need for including this impact in a GE framework is further visualized in Figure 10 and 11 (appendix). Figure 10 visualises the increase of the US-CHN trade costs (deviant values) as an outlier, whereas Figure 11 shows the effect this change in trade costs of the single treated country pair has had on the trade flow of multiple other world country pairs. Hence, it is necessary to include the effect but also the counter-effect one unit has on multiple other units. Despite the PE effect, measured in previous research, being very similar to the estimated GE effect, the results of this work are less prone to be biased or random. A missing impact of additional factors, such as the effect of multilateral trade barriers, which are included in the GE framework of this work, can be precluded when regarding the consequential effects the change in one unit has had on other units, referring to Figure 10 and 11.

The states Germany, the Netherlands and Spain resemble these effects perfectly, as the Chinese import stop on US soybeans led to the trade diversion of US soybeans to these EU member states. This significant increase of EU soybean imports, compared to previous years, is a consequence of Chinese imports of US soybeans being less favourable to China due to increased trade costs. However, the EU-shift in US soybean exports in 2018 seems to additionally confirm that this purchase contributed to the prevention of the threatened US-auto import tariffs from the EU. Hence, the increase in soybean trade flow was not only driven by economic but also – if not predominantly – political reasons. This brings us back to the PE model by Sabala and Devadoss (2019) in which they assume soybeans to be a homogenous commodity from all suppliers and importing countries to buy soybeans solely based on the lowest purchase price. Yet, despite the soybean prices and the change in prices after the trade shock not being discussed in this work, the supposed political motivation behind the US soybean trade flow diversion to EU member states needs to be captured in a GE framework in order to reflect real-world trade flows in the respective models. Despite there being valid reasons with regards to adverse and biased affectedness of the control units involving EU member states, this underlines the importance of regarding trade flows and barriers on a multilateral and not a bilateral level, which solely includes the market of interest. However, it seems noteworthy to investigate whether untreated control units in the donor pool seem to be affected by the treatment based on an alleged secondary link, which leads us to the predominantly methodological limitations of this work.

The selection of the donor pool does not only entail limitations with regards to the selection of the control units but also with regards to missing data. Various control units were ineligible for the SCM analysis due to unavailable or inconsistent data in the gravity or the trade data sets, especially for 2019, the most recent year of analysis. Furthermore, the analysis is based on annual and not monthly data since the required data is only available on an annual basis. Despite the effect of the US-CHN trade shock being clearly visible in 2018, monthly data would have been more suitable to conduct a more precise analysis, as the shock occurred in July and Chinese imports were down to zero in November. In addition, the effect on the rotational US- and Brazilian soybean exports to China would have been underlined. With regards to the generalizability of the results, the focus on a single case in this work is at the cost of limited external validity in terms of immediate generalizability to other settings – despite the internal validity being high referring to the placebo tests. The results certainly underline the effect such a protectionist trade policy or intervention can have, not only on the imposing and directly affected bilateral trade flow, but also on multilateral trade flows. Apart from the rather limited generalizability of the specific results, I conclude in the last chapter that the combination of the two methods and hence, the three-step methodological approach can be applied to econometrically estimate the effect of similar economic or policy changes.

8. Conclusion

The main goal of this work was to estimate the GE effect of the Chinese import stop on US soybeans in 2018 on the US-CHN soybean trade flow, as outlined in the research question. The GE effect of this trade shock was clearly identified in terms of a counterfactual trade flow as China would have imported 33% more US soybeans if the shock would have not occurred. Furthermore, I was interested in the economic impact of the trade shock on the US-EU soybean trade flow. Spain and the Netherlands – representing the EU – imported 35% and 22% more US soybeans compared to a counterfactual ‘no shock’ situation. Despite the increased imports of US soybeans by EU member states, the US could only partially compensate the missing counterfactual soybean trade flow to China. As trade tensions between the US and China remain, and the soybean trade flow seems to only recover gradually, the new EU Commission announced at the end of 2019 to reduce the scale of long-distance transport of agricultural products – including soybeans – from the Americas. This step complies with the new EU food policy, which is embedded in the European Green Deal, incentivising EU farmers to increase regional soybean production (EURACTIV, 2019). Moreover, the US is confronted with constant economic but also political pressure – multiple states significantly rely on soybean exports – despite the latest US-CHN trade deal initiating a drastic increase of US agricultural exports to China. Whether these expectations can be met seems questionable, given China’s sharply reduced demand for soybeans in 2019 due the swine fever outbreak, an increase in Chinese soybean production and a second, more reliable, soybean exporter in the Americas – Brazil (PIIE, 2019).

In summary, the methodological approach as developed by Hinz et al. (2020), has shown to be a perfect tool to econometrically estimate the GE effect of the trade shock in terms of trade flow. It allows the estimation of counterfactual trade flows for an unobservable scenario in the past. Although the case-specific results of this work cannot be generalized, the traceable approach can be applied as a tool to econometrically estimate the effect of economic or policy changes. Researchers, economists and political decision makers can quantify the impact of such interventions in a GE framework and apply the evaluation tool to a broad range of topics.

To conclude, future research should apply the methodological approach to similar scenarios in order to clarify to what extend the approach can be applied to evaluate different economic or policy changes. The entire spectrum of respective interventions such as economic free- and regional trade agreements (e.g. Mercosur) or European integration (e.g. EU enlargement) and disintegration (e.g. Brexit) policies should be analysed in order to reveal the advantages, the disadvantages and most importantly the generalizability of the approach.

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Appendix

Tables

Table 1: Synthetic control model – Country pair weights

	w.weights	unit.names	unit.numbers
1	0.000	ARG-BOL	1
2	0.000	ARG-CHL	2
3	0.402	ARG-CHN	3
4	0.000	ARG-PRY	4
5	0.000	ARG-URY	5
6	0.000	AUS-KOR	6
7	0.010	AUS-TWN	7
8	0.000	BEL-CZE	8
9	0.000	BEL-DEU	9
10	0.000	BEL-FRA	10
11	0.000	BEL-GAB	11
12	0.000	BEL-GBR	12
13	0.000	BEL-LTU	13
14	0.000	BEL-NLD	14
15	0.000	BEL-POL	15
16	0.008	BRA-CHN	16
17	0.001	BRA-ESP	17
18	0.001	BRA-FRA	18
19	0.012	BRA-GBR	19
20	0.001	BRA-IRN	20
21	0.001	BRA-ITA	21
22	0.124	BRA-JPN	22
23	0.000	BRA-KOR	23
24	0.001	BRA-NLD	24
25	0.003	BRA-NOR	25
26	0.000	BRA-PRT	26
27	0.000	BRA-PRY	27
28	0.013	BRA-SAU	28
29	0.001	BRA-THA	29
30	0.003	BRA-TWN	30
31	0.000	CAN-BEL	31
32	0.001	CAN-BRN	32
33	0.009	CAN-DEU	33
34	0.000	CAN-FRA	34
35	0.000	CAN-HKG	35
36	0.000	CAN-IRL	36
37	0.010	CAN-ITA	37
38	0.000	CAN-JAM	38
39	0.012	CAN-JPN	39
40	0.000	CAN-MUS	40
41	0.001	CAN-MYS	41
42	0.009	CAN-NLD	42
43	0.001	CAN-NOR	43
44	0.000	CAN-NZL	44
45	0.000	CAN-PHL	45
46	0.000	CAN-SGP	46
47	0.003	CAN-SUR	47
48	0.001	CAN-THA	48
49	0.000	CAN-TTO	49
50	0.013	CAN-TWN	50
51	0.011	CAN-UKR	51
52	0.000	CAN-USA	52
53	0.014	CAN-VNM	53
54	0.000	CHE-AUT	54
55	0.000	CHE-DEU	55
56	0.000	CHE-FRA	56
57	0.001	CHL-USA	57
58	0.011	CHN-AUS	58
59	0.000	CHN-HKG	59
60	0.000	CHN-JPN	60
61	0.000	CHN-KOR	61
62	0.000	CHN-MYS	62
63	0.000	CHN-SGP	63
64	0.000	CHN-TWN	64
65	0.000	CZE-AUT	65
66	0.000	CZE-SVK	66
67	0.000	CZE-UKR	67
68	0.000	DNK-SWE	68
69	0.000	GBR-CYP	69
70	0.000	GBR-IRL	70
71	0.000	GBR-MLT	71
72	0.000	HKG-CHN	72
73	0.000	IND-ARE	73
74	0.001	IND-BHR	74
75	0.000	IND-CAN	75
76	0.000	IND-KWT	76
77	0.087	IND-QAT	77
78	0.000	IND-USA	78
79	0.000	ITA-AUT	79
80	0.000	ITA-BEL	80
81	0.000	ITA-CHE	81
82	0.000	ITA-DEU	82
83	0.000	ITA-DNK	83
84	0.000	ITA-FRA	84
85	0.000	ITA-GRC	85
86	0.000	ITA-SWE	86
87	0.070	JPN-HKG	87
88	0.013	JPN-USA	88
89	0.001	KOR-USA	89
90	0.000	NLD-BEL	90
91	0.000	NLD-DEU	91
92	0.002	NZL-PYF	92
93	0.000	PRT-AGO	93
94	0.000	PRT-ESP	94
95	0.000	PRY-ARG	95
96	0.000	PRY-BRA	96
97	0.001	PRY-GRC	97
98	0.013	PRY-ISR	98
99	0.001	PRY-ITA	99
100	0.001	PRY-NLD	100
101	0.000	PRY-PER	101
102	0.001	PRY-PRT	102
103	0.001	PRY-RUS	103
104	0.000	RUS-CHN	104
105	0.000	SWE-FIN	105
106	0.026	URY-CHN	106
107	0.000	USA-BRB	107
108	0.000	USA-CAN	108
110	0.001	USA-COL	110
111	0.001	USA-CRI	111
112	0.001	USA-CUB	112
113	0.010	USA-DEU	113
114	0.013	USA-EGY	114
115	0.000	USA-ESP	115
116	0.001	USA-GTM	116
117	0.014	USA-IDN	117
118	0.013	USA-JPN	118
119	0.000	USA-KOR	119
120	0.000	USA-MEX	120
121	0.001	USA-MYS	121
122	0.010	USA-NLD	122
123	0.000	USA-PAN	123
124	0.001	USA-PER	124
125	0.000	USA-PHL	125
126	0.001	USA-SAU	126
127	0.000	USA-SGP	127
128	0.001	USA-THA	128
129	0.011	USA-TUN	129
130	0.002	USA-VEN	130
131	0.014	USA-VNM	131
132	0.000	ZAF-LSO	132
133	0.000	ZAF-MOZ	133
134	0.000	ZAF-NAM	134
135	0.000	ZAF-SWZ	135

Table 2: Synthetic control model – Predictor variable weights

	Predictor Variables	v.weights
1	contig	0.070
2	comlang_off	0.101
3	colony	0.129
4	log_distw	0.379
5	comcur	0.099
6	comleg_posttrans	0.004
7	fta_wto	0.002
8	tariff	0.215

Table 3: Synthetic control model – Predictor balance

	Treated	Synthetic	Sample Mean
contig	0	0.004	0.246
comlang_off	0	0.006	0.336
colony	0	0.001	0.082
log_distw	9.322	9.322	8.206
comcur	0	0.002	0.112
comleg_posttrans	0	0.019	0.47
fta_wto	0	0.015	0.433
tariff	0.015	0.015	0.165

Figures

Figure 3: Trade Costs Gap between US-CHN and synthetic US-CHN

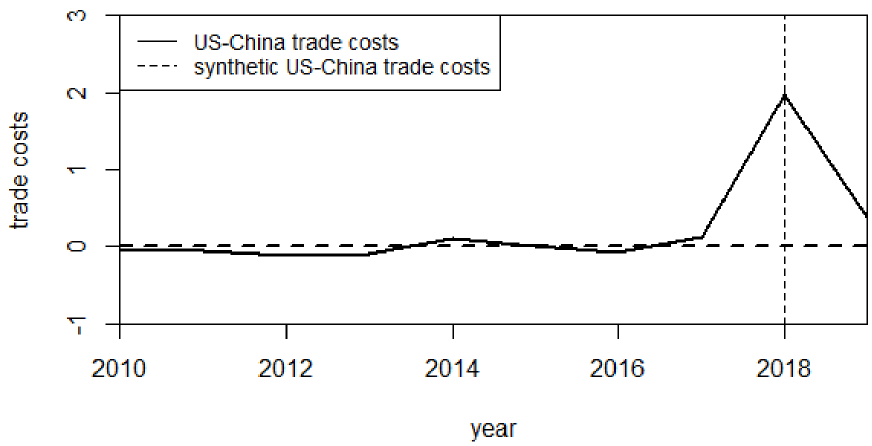

Figure 4: In time placebo plot – US-CHN and synthetic US-CHN, treatment in 2014

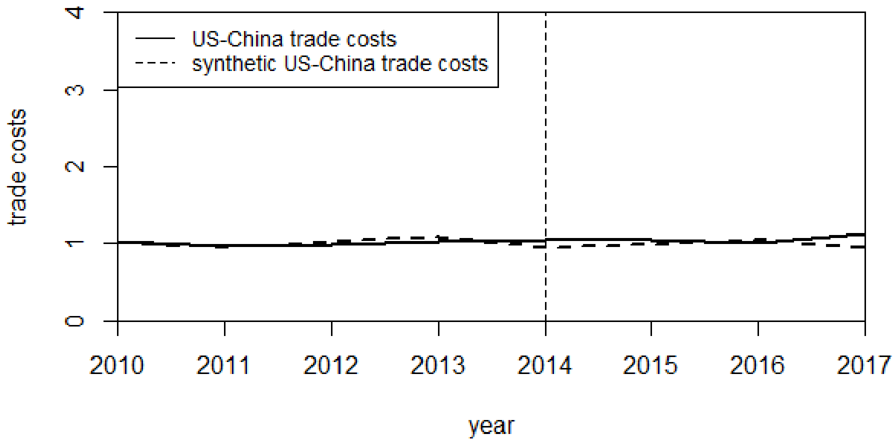

Figure 5: In-space placebo plot – US-CHN and synthetic US-CHN, all control units treated (discards country pairs with a pre-shock MSPE five times higher than US-CHN)

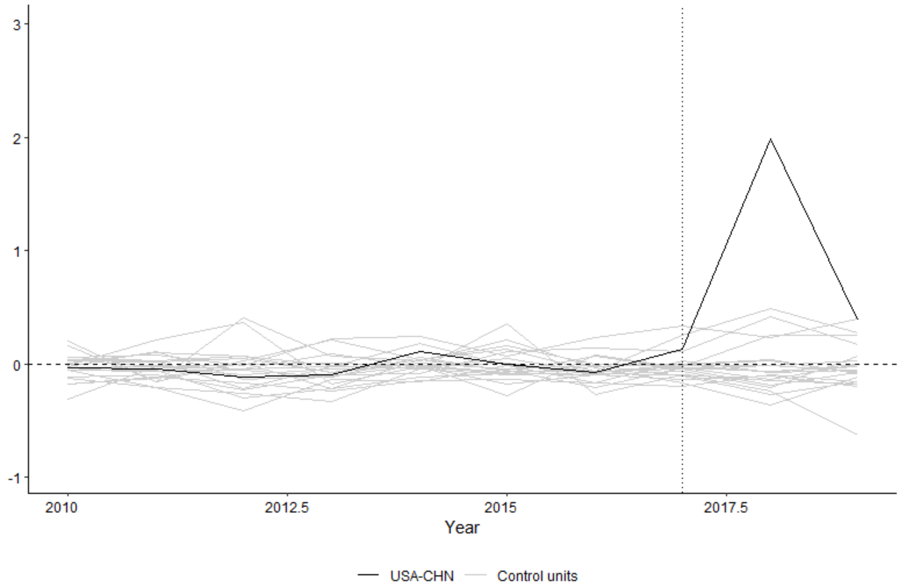

Figure 8: Change in percent of US soybean counterfactual export flows in 2018

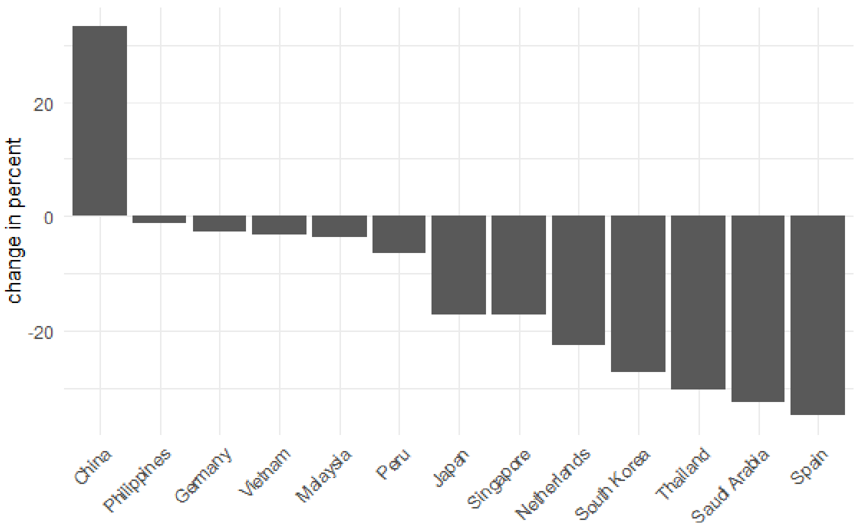

Figure 9: Change in percent of US soybean export flows in 2019

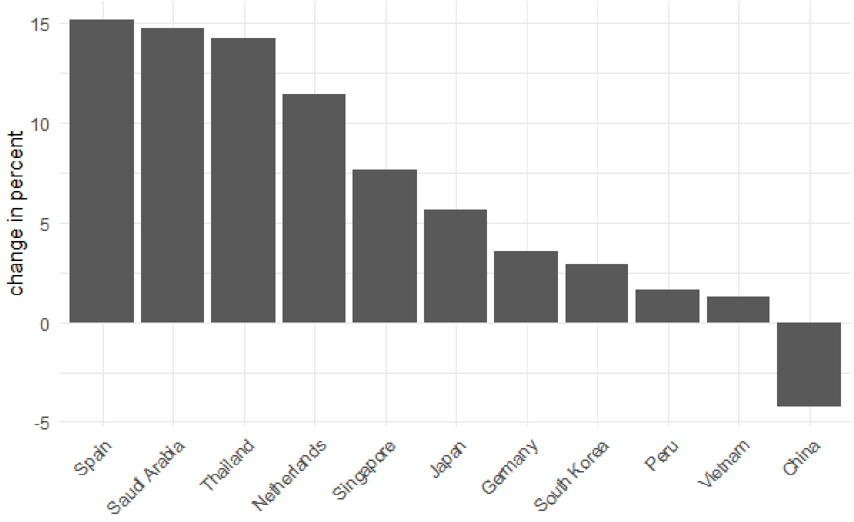

Figure 10: Scatter plot – Actual and synthetic trade costs (logarithmic scales - base 10)

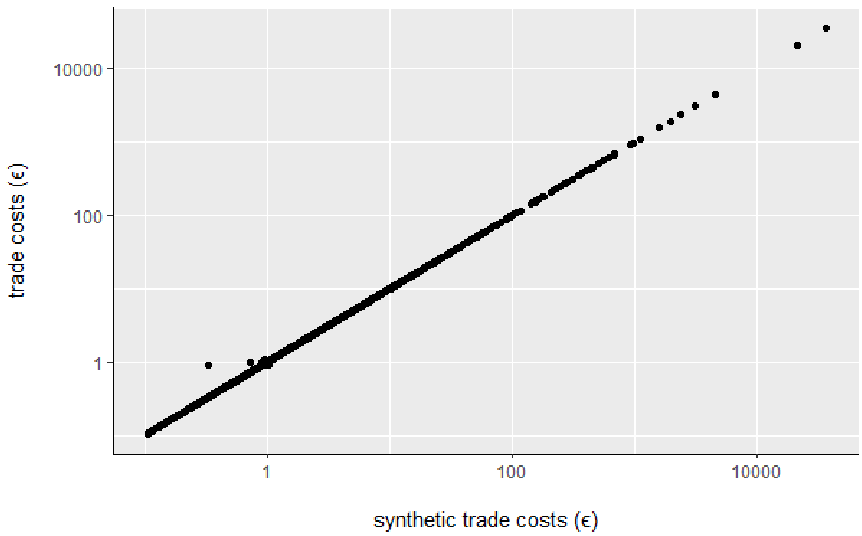

Figure 11: Scatter plot – Actual and synthetic trade flow (logarithmic scales - base 10)