Applications of Granular Macro-Network Models: US-China Trade War and Covid-19 Impact

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A thesis submitted for the degree of

Doctor of Philosophy in Economics

Department of Economics

University of Essex

Date of submission for examination March 2024

Dedicated to my mother, my father and my sister.

AUTHOR’S DECLARATION

I, Simin Nie, declare that this thesis submission represents my ideas in my own words, where others’ ideas or words have been included. I have adequately cited and referenced the original sources.

I also declare that I have adhered to all academic honesty and integrity principles in my submission. I understand that any violation of the above will cause disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been appropriately cited or from whom proper permission has not been taken when needed.

Signed by: Simin Nie
Date: 17th of December 2023

ABSTRACT

This thesis applies Granular Macro-Network Models to analyse the impacts of two major recent economic events – the US-China trade war and the COVID-19 pandemic – on sectoral and total GDP in the US and Chinese economies. Using the OECD Inter-country Input-Output (ICIO) database along with Leontief inverse coefficients and the Ghosh model, supply and demand shocks are introduced to estimate changes in economic output. A critical methodological contribution is developing the partial extraction method based on the hypothetical extraction method (HEM) to trace intermediate goods shock propagation (an advancement over traditional GDP models focused solely on final demand). The author also categorises tariff data and ICIO data by matching 6-digit Harmony System (HS) codes to input-output sectors and calculating sector-level weighted average tariffs.

In Chapter 1, the trade war analysis, import demand changes from tariffs and elasticities are modelled. Chapter 2 extends this by assessing three trade response strategies – foreign trade diversion, domestic import substitution, and a mixed approach of both. Chapter 3 applies similar Leontief and Ghosh models to estimate COVID-19 shutdowns, adding empirically derived lockdown constraints differentiated by severity, lockdown duration, and fiscal interventions. Across analyses, results highlight the significance of interconnected production structures in propagating sectoral shocks. The applied models estimate granular national and industry-level impacts by quantifying total and sectoral GDP changes. This demonstrates how supply/demand disruptions to one sector can widely transmit through integrated macro-network models, capturing intermediate interdependencies absent in traditional GDP frameworks. This novel approach provides robust analytic capabilities for crisis scenario modelling and policy analysis focused explicitly on the interconnected intermediate good trade network – an essential contrast from existing final demand-centric GDP impact analyses. The predictive capabilities exhibited by this model suggest its potential for application to additional economic crisis situations that may arise in the future.

ACKNOWLEDGEMENTS

First and foremost, I would like to express my deepest gratitude to my supervisor, Professor Sheri Markose, for her invaluable guidance, support, and advice throughout my PhD study. Her insights and direction were instrumental in completing my dissertation. I am deeply grateful for the time she dedicated to advising me and helping me develop my academic skills.

I also sincerely thank my PhD panel chair, Piero Gottardi, for his thoughtful suggestions and insights, which assisted me substantially in strengthening my work.

In addition, I wish to thank my PhD cohorts Hamid, Aitor, Mohsen, Zhexin and Camila. Their thoughtful feedback, inspiration, and encouragement helped me improve and complete my work. Their diverse perspectives pushed me to strengthen my own research.

I am also grateful to my friends Eva and Maria for their encouragement and reassurance when I needed motivation to persist. I appreciate their interest in my work and presence throughout this experience.

I would also like to thank my family - my parents and my sister - for their unconditional love and support. They gave me strength through this challenging endeavour. I could not have accomplished this without their support from the other side of the earth in China.

The contributions of my supervisor, colleagues, friends, and family have been vital in completing my work. I could not have accomplished this without their input and tireless support. I dedicate this thesis to my sister and wish her a bright future and to always be surrounded by love.

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Chapter 1 Introduction

Recent global macroeconomic shocks, including the US-China trade war beginning in 2018 and the COVID-19 pandemic in 2020, have disrupted international trade flows and rippled through globally interconnected supply chains. Quantifying these exogenous effects presents modelling challenges that require moving beyond the partial equilibrium methods predominant in traditional economic analyses.

The Input-output models provide vital tools for capturing the complexity of shock propagation and inter-sectoral spillovers. These approaches better capture how effects propagate through supply chains versus standard economic frameworks, such as Partial equilibrium analysis. Partial equilibrium analysis examines how shifts in supply and demand affect price and quantity in a single market, holding other factors constant (Varian, 2010). By contrast, Leontief's (1936) and Ghosh's (1958) input-output frameworks provide general equilibrium perspectives on intersectoral linkages. Rather than isolating effects to one market, they trace how economic shocks cascade across multiple interconnected sectors.

In recent decades, using computable general equilibrium (CGE) models or input-output models has been a constant debate. Some argue that CGE models incorporate more flexible prices and substitution while retaining input-output insights on propagation mechanisms (Shoven & Whalley, 1984). However, others argue that CGE models sacrifice valuable granularity of inter-sector linkages (Oosterhaven, 1988). He also argues that the empirical foundation of input-output analysis in actual observed inter-industry transactions makes it superior to the typical neoclassical theoretical assumptions in applied general equilibrium models. Input-output models thus better incorporate natural interconnectedness.

Dietzenbacher (1997) contends that input-output analysis should be viewed as a complement rather than a substitute for CGE analysis. While CGE has advantages in topics like trade or tax policies, input-output has strengths in tracing structural change over time through empirically grounded inter-industry linkages.

This thesis consists of three self-contained chapters that touch on important topics in understanding the uses of Input-Output Macro-Network modelling techniques to measure the economic impacts of the previous mentioned external shocks – the US-China trade war and the COVID-19 pandemic.

The chapter two examines the 2018-2020 US-China trade war's impact on regional and sectoral GDP. By tracking bilateral tariffs across industries and factoring trade responsiveness into a multi-country model, we aim to find the main targeted sectors in each country by processing the data on all Tariff changes from the US and China during the trade war period, the volume of products that are affected and the overall change in sectoral tariffs. Then, we apply these aggregated data and their corresponding import elasticity to find the potential impact on GDP when the changes directly occur to the final demands. Then, we compare the direct impact results with when we consider the interconnectedness of input-output data on the intermediate goods. The objective is to provide a view of the GDP affected in both countries and the primarily affected sectors, as well as how the results differ when we take into consideration of intermediate goods.

The third chapter builds on the foundation of the model established in chapter two. We explore response strategies from the US under the US-China Trade War circumstance, like domestic import substitution and foreign trade diversion, and a mixed response strategy where both are present. The model represents countries shifting imports under different scenarios. We aim to show results indicating the different potential outcomes for the US under different response strategies and each strategy's strengths, weaknesses and limitations. Therefore, we could find a preferable solution for the trade war shock responses. In this chapter, we also focus on China and the rest of the world and how they would be affected by the actions of the US.

Chapter four moves away from the US-China trade war and focuses on the COVID-19 pandemic lockdown shocks. The unique nature of the pandemic is that the crisis shock comes from both the demand and supply side as people are not able to produce (supply), and their consumption (demand) is also affected.

We use the partial extraction method (PEM) to implement the demand and supply shocks developed from the hypothetical extraction method (HEM) proposed by (Los et al. 2016) to estimate US GDP changes under different pandemic sectoral lockdowns and reopen assumptions. The model captures complex network effects beyond direct demand drops by incorporating sectoral linkages. We further extend the model by considering the stages of lockdowns and fiscal policies implemented.

Overall, the interconnected perspective proves vital for quantifying cascading economic disruptions (Oosterhaven, 1988). Compared to traditional equilibrium analyses, this approach represents multiplier effects across industries. Limitations include data generalisation, model assumptions, and capturing simultaneous demand-supply disturbances. These limitations also create potential future work to improve the accuracy of the analytic results, but the present analysis still provides credibility on post-crisis event predictions.

In summary, granular macro-network models provide critical insights into sectoral and economy-wide crisis impacts. As supply chain disruptions increase, input-output analyses will remain essential for understanding complex contagion and guiding resilient policies.

Quantifying mechanisms allows the targeting of relief efforts. Future work should incorporate updated information and advance the current models.

Chapter 2 Granular macro-network model: Application to the US-China Trade War

2.1 Introduction

"China is neither an ally nor a friend — they want to beat us and own our country."[1] So tweeted Trump long before running for president. It shows Trump's opinion of China and hints at the rise of the trade war. However, the tension between the US and China is way more profound, and the seed of rivalry goes back to two decades ago.

In 2001, China joined the WTO, became a vital part of globalisation, and benefited from the low tariff rate. China's low-cost competitive strategy led to a 10 per cent GDP growth per year. Meanwhile, China also becomes the second-largest debt holder of the US, with more than one trillion dollars[2].

In 2018, after the US threat to revert to Smoot-Hawley tariffs[3] (starting the trade war), the most significant change can be the rise of trade policy uncertainty between China and the US. The most robust fuel that gave China the most power to expand its economy and international trade was the accession to the World Trade Organization. As we can see from Figure 1 below by Handley (2017), becoming a member of WTO in 2001 gave China a platform to maximise the benefit of China's large labour force and abundant resources, to export more and gain more

1 China is neither an ally nor a friend–they want to beat us and own our country. — Donald J. Trump (@realDonaldTrump) September 21, 2011 http://didtrumptweetit.com/116575636583227392-2/

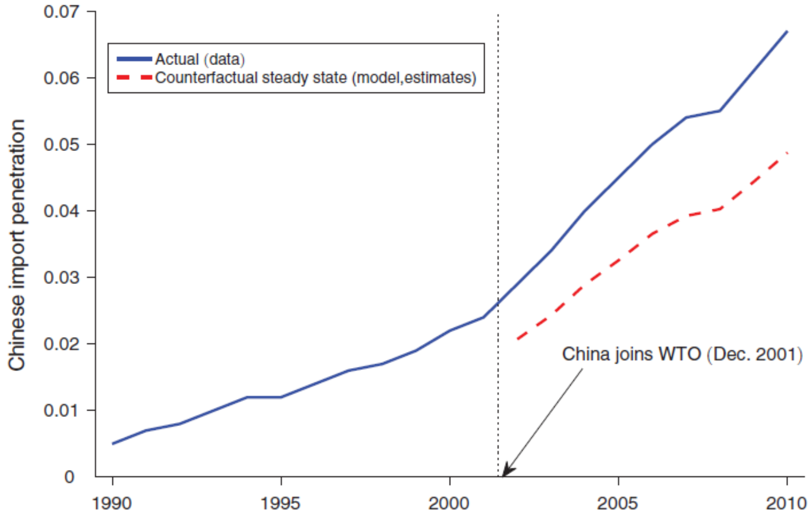
2. US Department of the Treasury. "Debt to the Penny." https://fiscaldata.treasury.gov/datasets/debt-to-the-penny/debt-to-the-penny accessed August 2021

3 Smoot-Hawley Tariff Act https://corporatefinanceinstitute.com/resources/knowledge/economics/smoot-hawley-tariff-act/

international trading power, especially in the case with the United States. Boden G. (2012) mentioned that the first decade of China's WTO accession gave China better market access to its 152 WTO trade partners. As a part of the agreement to be in WTO, all members must follow the most favoured nation (MFN) policy. For instance, Handley et al. (2017) mentioned that the US MFN tariff was 4 per cent in 2000, but if China lost its MFN status, then the average tariff from the US could quickly increase to 31 per cent, which would create massive damage to China's GDP from export. In the first five years (2002-2007), after accessing those countries, net exports as a share of GDP in China increased from 2.6% to 7.7% (Chen, 2009). 2010, China's current account balance was $305 billion (IMF). China relied heavily on inexpensive labour to produce and export labour-intensive manufactured goods. This phenomenon shifted workers away from the primary sector towards the secondary sector (Marti, 2011).

Figure 2.1 : Chinese Import Penetration in the United States: Actual (Blue line) versus Counterfactual under Policy Uncertainty (Red line) in Percentage, before and after joining WTO.[4]

[4] Import penetration ratio is defined as manufacturing imports from China as a share of total US expenditure on manufacturing (total shipments − net exports). The counterfactual line adjusts Chinese imports as if uncertainty was reintroduced in any year after 2001.



Source: Handley et al. (2017)

After almost two decades of the Chinese entry into WTO, the trade imbalance between the US and China began to put severe pressure on the US economy. This led to growing tension between the two countries. Kapustina et al. (2020) mentioned that the consistently growing bilateral trade imbalance has threatened the dominance of the US in the global economy with China An imbalance in bilateral trade between the US and China has jeopardised US economic dominance. China is engaging in unfair trade practices, using trade liberalisation and WTO membership to its benefit while protecting its domestic market from foreign rivals through export-friendly policies like currency devaluation and subsidies. (Miteva-Kacarski, et al., 2021)

China has significantly expanded the high-tech industry in the past decade. The Belt Road Initiative and other projects have dramatically increased China's investments abroad. Not to mention the low-cost manufacturing advantage that contributed to most of the annual exports from China, it slowly turned the world into "Made in China" and made China the world's largest exporter. (Lawrence et al., 2020)

Therefore, after years of problems with China and the treatment from WTO, the US decided to stop the accumulation of trade deficit, started violating international law and agreements, dropped out from a few organisations, and decided to put "America first" as the primary purpose. Therefore, the US-China trade war inevitably took place in 2018.

Researchers also started questioning the mechanism of the WTO to settle trade disputes. Adekola (2019) states that the US-China Trade War shows that the WTO is on the verge of becoming dysfunctional, as members such as the US resort to “self-help” without recourse to the rules and procedures of the organisation for dispute settlement. On top of the initial tension, since China joined WTO, the US has been unpleasant even more after the WTO granted China the status of a market economy in 2017 because it has become more challenging for the US to apply protectionism against Chinese companies.

In this paper, we aim to analyse the impact of the US-China Trade War on the US and China with detailed sectoral studies using an input-output data framework.

In the section 2 literature review, we will dive deep into the whole period of the US-China Trade War from July 2018, when the first wave of the tariff was implemented from the US to China, until the phase one trade agreement was made in January 2020 with tariff timeline and overviews. Break down the focused industries of this paper, such as Soybean and R&D, and compare our method with some other models that are analysing the trade war from different angles, such as the Caliendo-Parro (2019) model used by the Bank of Canada,

Section 3 introduces the cross-border granular macro-network model in the methodology with the Leontief model, Ghosh model, and partial extraction method extension.

Section 4 demonstrates all the data we used for the model, including cross-border input-output trade flow, Pre-Trade War sectoral tariff rate and value, Post-Trade War sectoral tariff rate, and sectoral trade elasticity. In addition, the data sorting progress with greater detail is demonstrated in the appendix.

Section 5 shows an overview of the results, sectoral breakdowns and different scenarios to show how the trade war affects the countries and the sectors. We aim to capture the unique findings and contribution using the granular macro-net model for the Trade War Impact.

Section six, as well as the last section, is the conclusion. It wraps up the paper by addressing the critical findings from the analysis.

2.2 Literature Review

In this section, we will explain the timeline of the US-China trade war with a brief tariff data overview, discussions on the tension between the US and China that led to the Trade War, the prior focus during the Trade War and general predictions about the Trade War outcome, followed by some updates on the Phase One Trade Deal and how it could affect the direction of US-China trading. Then, a few analytic models will be briefly mentioned, and the method and the analysis result will be compared with the Granular Macro-Net Model, with some materials explaining the uniqueness of this model and its suitability for this study.

2.2.1 US-China Trade War: Timeline and Tariff Overview

According to the timeline information collected and generated by China-Briefing.com[5], on the 6th of July 2018, the US officially implemented the first China-specific 25 per cent tariffs affecting products with a value of US $34 billion. On the 10th of July 2018, after the second list of 10 per cent tariffs on over 6,000 commodities, then on the 2nd of August, the US changed

[5] Trade War Timeline https://www.china-briefing.com/news/the-us-china-trade-war-a-timeline/

all the 10 per cent tariffs to 25 per cent on products with a total worth of US$200 billion on imports.

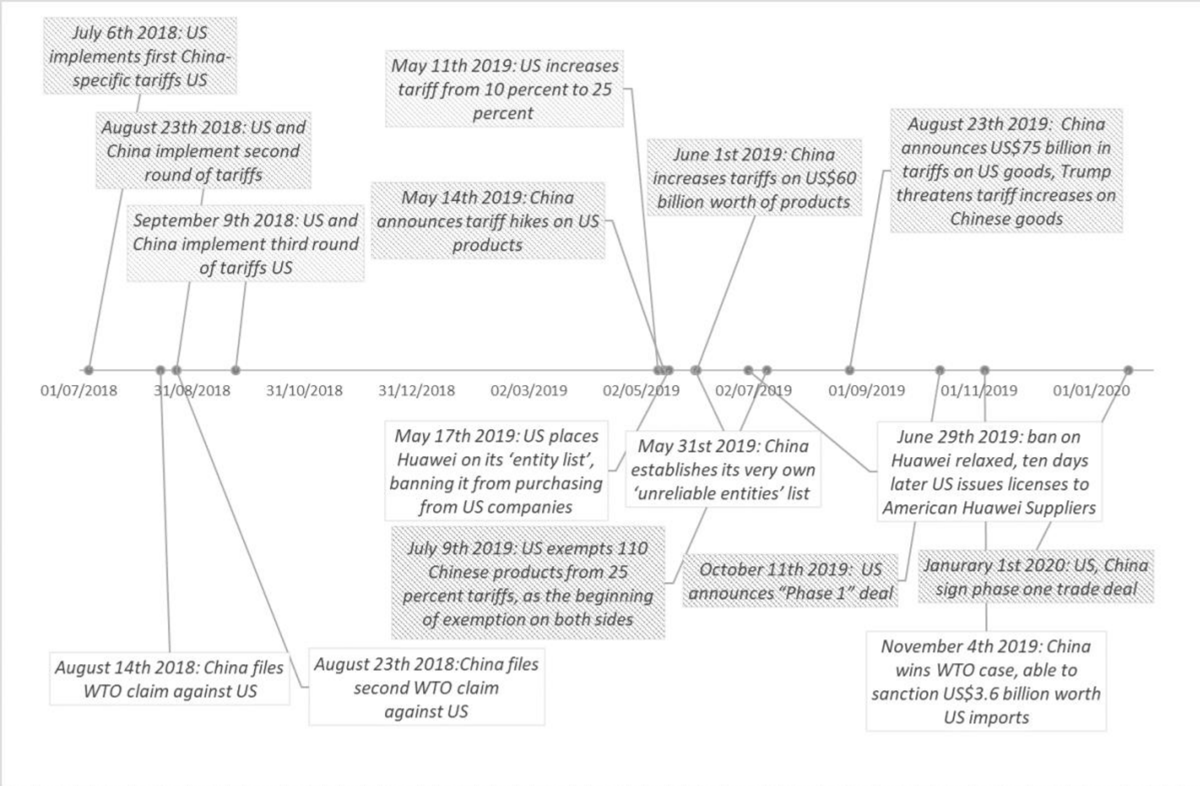
On the 3rd of August, in response to the announcement from the US, China gave a range of additional tariffs on 5,207 products originating from the US (worth US$60 billion), and thus the Trade War officially started.

In 2019, China filed a WTO Claim against the US regarding tariffs and new waves of tariffs were added on both sides. A few negotiations took place, while others were cancelled.

Also, it is worth mentioning that on the 19th of November 2018, the US released a list of proposed export controls on emerging technologies of China, including the biggest tech company in China – HUAWEI. On the 16th of May 2019, the US placed Huawei on its 'entity list', banning it from purchasing from US companies.

Until the 28th of August, the ban on Huawei was relaxed, some new tariffs were eased, and some additional tariffs were added. The attitudes from both sides are still shifting and ambiguous. To date, the total US tariffs applied exclusively to Chinese goods valued at US$550 billion, US$185 billion from China to the US. On the 15th of January 2020, the US and China found a temporary truce on the tariff battle when both countries signed a phase one trade deal.

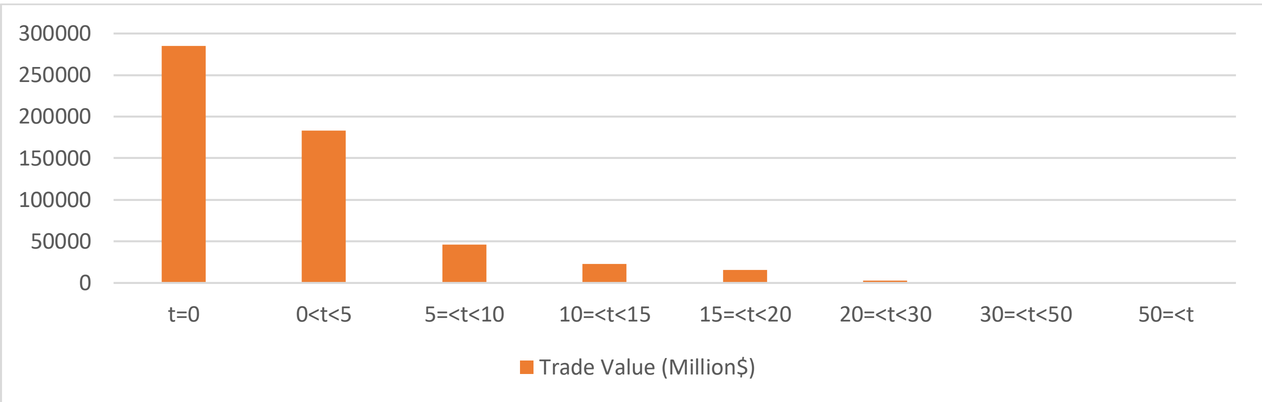
Figure 2.2: Visualised US-China Trade War Timeline



Source: from China-Briefing.com and constructed by author

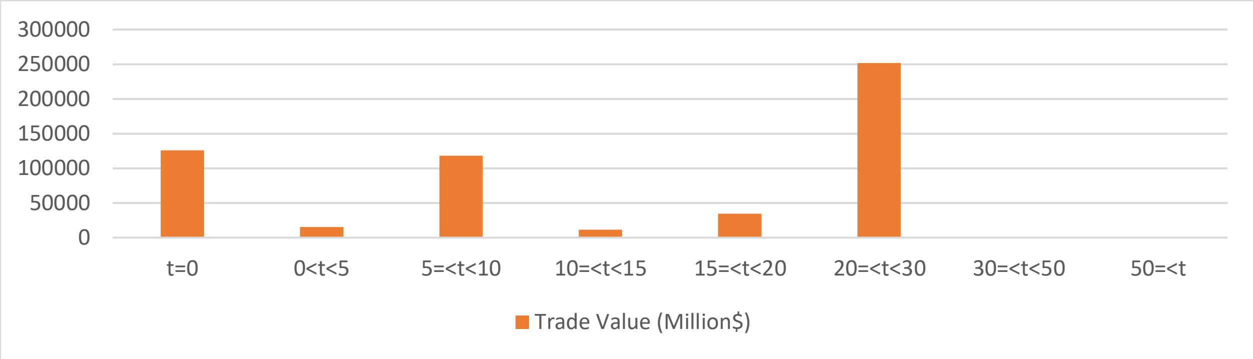
2.2.1.1 *US Tariff Overview*

Figure 2.3: Pre-Trade War (2017) value of US imports from China under different tariffs (in $Mn)



Source: Assembled by the author from US and China official policy announcements.
Note: t stands for tariff rate.

Figure 2.4: Post Trade War (2020) value of US imports from China under different tariffs (in $Mn)



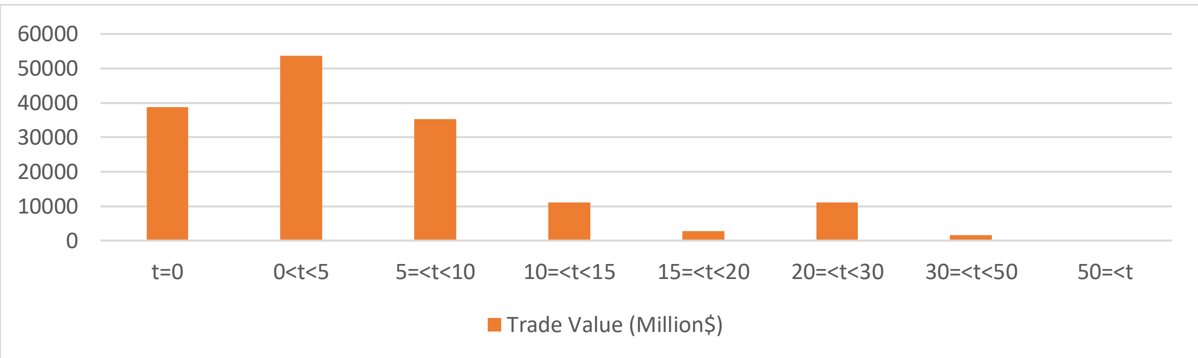
Source: Assembled by the author from US and China official policy announcements.
Note: t stands for tariff rate.

In the overview of US imports from China, most pre-trade war tariffs in the sub-sectors are less than 5 per cent, in both trade value and numbers of sub-sectors. Moreover, in the post-trade war stage, most sub-sectors have shifted to 10 or 25 per cent tariff.

The overview graphs of the pre-trade war differential tariffs for the US and China show how China have zero to low tariff access to US markets while US exporters are impeded by relatively high tariffs for the bulk of US exports to China.

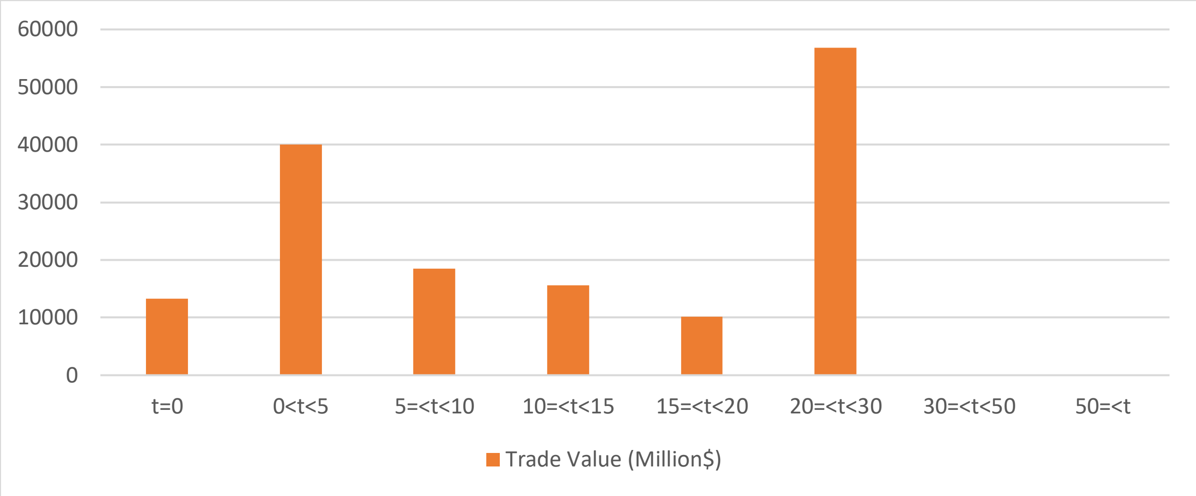
2.2.1.2 *China Tariff Overview*

Figure 2.5: Pre-Trade War (2017) value of Chinese imports from the US under different tariffs (in $Mn)



Source: Assembled by the author from US and China official policy announcements.
Note: t stands for tariff rate.

Figure 2.6: Post-Trade War (2020) value of Chinese imports from the US under different tariffs (in $Mn)



Source: Assembled by the author from US and China official policy announcements.
Note: t stands for tariff rate.

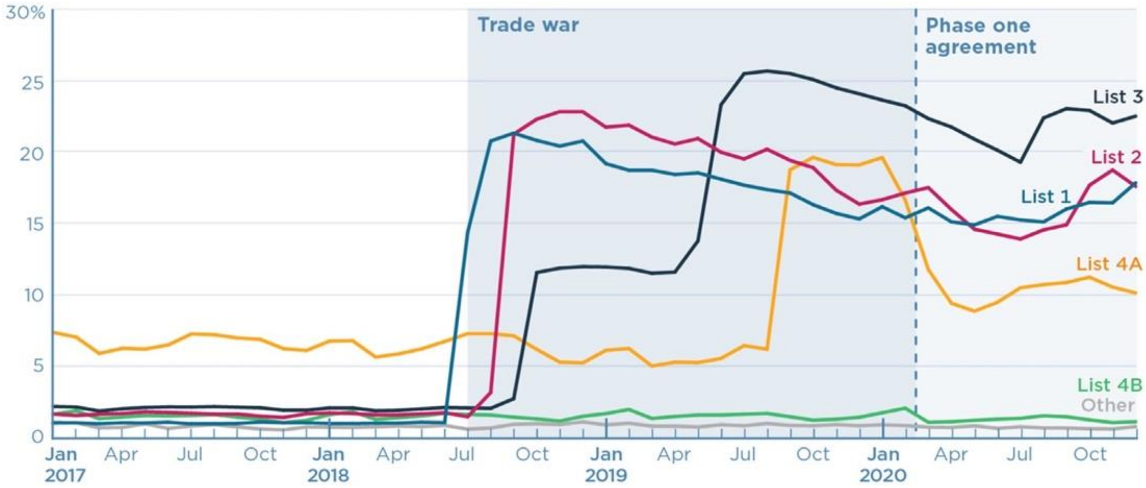
For China's imports from the US, there is a decrease in both sub-sectors and trade values with low tariff rates from 0 to 15 per cent. A slight increase occurred in sub-sectors with a 15 to 20 per cent tariff rate, and the number and trade values of sub-sectors with 20 to 30 per cent tariff rates witnessed a significant increase.

2.2.2 Phase One Agreement

The Phase One agreement between the United States and China entered into force on the 14th of February 2020. Elms (2021) considered the agreement less a negotiation towards a mutual compromise and more a series of commitments by China on issues of concern to the United States. The agreement included provisions on intellectual property rights, non-tariff barriers for agricultural goods, market opening for financial services in China, etc.

Muhammad et al. (2021) believe that the Phase One Trade Agreement sets the stage for a decrease in tensions and the eventual removal of tariffs. In the agreement, China has agreed to increase manufacturing imports by about 45% each year for the next two years (2020 and 2021). However, Muhammad states that there is no evidence suggesting that China will satisfy its commitments by increasing all imports proportionally. Like the chess game the US and China played during the trade war period, the negotiation will likely continue in the trade deals.

Figure 2.7: Average US tariffs on China for different Section 301 product lists, including exclusions, January 2017–December 2020.



Source: Bown (2021) calculations based on products listed in USTR announcements and US import data from the US Census.

Bown's (2021) paper shows that the trade war led with a clear jump in List 1 and 2, followed by List 3 and the second wave of the significant increase in List 3 that took place in mid-2019. Finally, the lists 4A and 4B were never implemented. According to the trend post-phase one agreement, we can see that despite a steady decrease in tariffs around the period, they bounced back after a quarter of a year. It suggested that the post-Trade War era would last for a while as an alternative measure from the Trade War with less tension between the two countries.

According to the White House, China had made purchasing commitments of US$200 billion for a range of goods across a two-year timeframe. According to Trump's administration's agenda, the agreement aims to address the enormous trade deficits. The purchases are mainly soybeans, energy products, manufactured goods, and services. They are expected to play a significant role in reversing the US trade deficit with China. However, as Elms (2021) mentioned whether the purchase targets from Phase One are realistic is still an unclear question. The overall levels exceeded the highest Chinese exports to the United States. The COVID-19 pandemic and the election of Joe Biden can also affect the level of purchase, the potential Phase Two Deal, and the future direction of US and Chinese trade relations.

2.2.3 During Trade War: Trade War focuses (sector, priority)

The US-China Trade War has multiple battlegrounds: manufacturing, agriculture, R&D, machinery, etc.

2.2.3.1 *Soybean*

Although the US is the largest importer of Chinese goods, which means the US holds more power in the Trade War, China still has few weapons against the US. Soybean is one of the critical products; with the increase in import tariff of soybean from the US to China, He et al. (2019) argue that the direct effect will be a short-term soybean surplus in the US, the cost of agricultural production increase globally in the short term. In the long term, China will try to be self-sufficient in soybean production, and the US will try to decrease soybean production and find alternative importers.

2.2.3.2 *Battle in R&D and technology*

Chen et al. (2020) interprets the Trade War as a war over technological dominance; they suggest that technological advances will lead to other advantages, from economic prosperity to military superiority. The intention of the US to start this technology cold war is not limited to separating Chinese and US tech sectors but also the potential to divide the world, as indicated by the boycott against Chinese 5G equipment, etc. One significant action taken was that Australia, Japan, and New Zealand joined the US in banning Chinese telecommunications equipment from their 5G networks.

Barkin (2018) states that Washington has been building a coalition with Five Eyes and other nations such as Germany, France and Japan to counter China's foreign operations and investments in sensitive technology. At the same time as the trade war took place, the US was building alliances to fight against Chinese technology and tech companies. Another example is that under intense US Pressure, Australia, Japan and New Zealand have joined the US in banning Chinese telecommunications equipment from their 5G networks. Canada, France, Italy and the UK may follow suit. The US-China trade war is a war over technological dominance. (Chen et al., 2020)

2.2.3.3 *The US ally against China's Belt Road Initiative and more*

The U.S.-Mexico-Canada Agreement was signed on the 30th of November 2018. This provision effectively prevents Canada and Mexico from signing free trade agreements with China, and the United States may also duplicate the provision in other trade deals. (Chen et al., 2020)

To counter China's 'Belt and Road Initiative', Trump signed into law the Better Utilization of Investments Leading to Development (BUILD), which seeks to facilitate the participation of private sectors in economic development projects in emerging countries to complement the US assistance and foreign policy (Schindler, et al., 2023).

2.2.4 Post-Trade War Predictions

Many researchers have analysed or predicted the outcome/impact of the Trade War; some bring attractive models, while others show unique points of view.

He et al. (2019) suggests that a change in international soybean trade would lead to growing global environmental costs in the short term due to the soybean surplus in the USA and the increased food transportation mileage.

Vlados (2020) highlighted the impact of the current Global Restructuring, which he called "new globalisation" from the US-China Trade War. Specifically, from the economic perspective, by increasing trade tariffs and setting up entity lists, trade protectionism from the US and China can reduce production and inhibit societal progress. (Cheong & Tongzon, 2018; Georgiadis & Gräb, 2016)

Even though the US and China are rivals, they are closer than they seem. The trade imbalance shows that China has always been the biggest exporter of the United States. the East-West Bank CEO Dominic Ng (USCBC, 2017) states that the trade imbalance should be dealt with from both sides. For China, it is necessary to increase intellectual property enforcement and reduce the overcapacity of specific manufacturing sectors. As for the United States, they should remove outdated barriers that hinder US companies from exporting products to China.

The US-China Trade war forces a scale-up in prices of foreign goods in the home country, trade diversion, and distortions in global value chains. (Iqbal et al. 2019) It is repositioning the role of Europe; the EU needs to work with its Asia-Pacific partners and the USA to revise the trade rules, reduce border impediments, and lay the ground for a more prosperous global marketplace for the twenty-first century (Plummer, 2019).

2.2.5 Quantitate methods used for analysis

In this section, we will briefly show a few research studies that use different models to analyse the trade war issues. We will investigate and compare the methods and results with our research method.

2.2.5.1 *Single Market Partial Equilibrium Simulation Tool (SMART) model*

Similar to our objective in our study, Tu et al. (2020) focus on replicating the trade creation/loss impacts, trade diversion effects, and welfare consequences of the US-China tariff conflict. Implementing the United Nations' trade database, COMTRADE, to address the Trade War issue is another commonality. Unlike the Macro-Net Model, which keeps the granular level of trade movements throughout the process, the SMART model is based on a partial equilibrium framework, uses minimal data, and analyses the effects on categorised product lines.

The main findings of Tu’s paper are that US imports from China and Chinese imports from the US could be reduced by an estimated $91,459 million and $36,706 million, respectively, and the most affected industries in the US could be machinery and electrical products. The most affected industries in China could be soybeans, automobiles, machinery and electrical products.

2.2.5.2 *The computable general equilibrium (CGE) model*

Itakura (2020) applies a recursively dynamic computable general equilibrium global trade model to quantify the economic impacts of the US-China trade war. The paper simulates three scenarios examining how the trade war could affect the United States, China, and other countries. In the short run, the trade war reduced the US trade deficit and increased China's trade surplus. However, up to 2035, these trade balance changes taper off and eventually become detrimental - worsening the US deficit and reducing China's surplus. The simulations indicate the trade war does not economically benefit either country, even for industries protected by import tariffs, as output gains disappear due to impacts on investment and productivity. However, the analysis focuses narrowly on import tariffs, investment and productivity. Broader political dynamics and technology regulations shaping the rivalry extend beyond this study's scope.

2.2.5.3 *The Caliendo-Parro model*

Charbonneau et al. (2018) uses a Ricardian trade model developed by Caliendo and Parro (2015) to analyse recent and proposed US tariff changes including steel/aluminium tariffs and US-China tensions. They prioritize on finding the trade war impact on Canada. By incorporating updated trade data and elasticity estimates, they quantify trade and output impacts. Results indicate considerable trade flow and sectoral output reallocations from recent and proposed tariffs, with significant short-run price effects. However, aggregate economic impacts appear relatively modest over the long run. Model adaptations like trade balance endogenization only marginally alter conclusions. Across scenarios, US-China clashes negatively ripple through integrated supply chains tying Canada, Mexico and Asia. The analysis reveals vulnerabilities from potential sector capacity constraints as production shifts outpace labour and capital mobility. While not estimating economy-wide losses, the study highlights risks of tariff escalation including concentrated industrial declines and global propagation. Findings reinforce that apparently localized trade protections can still destabilize interconnected partners. With intricate supply chain couplings, perturbation dampening requires coordination across economies.

Tu et al. and Itakura’s paper shows unique contributions of SMART model and CGE model but doesn’t observe the clear and dynamic interconnection of sectors, Charbonneau applied the input-output data but focus is primarily on the trade war impact on Canda. Our paper provides an interconnective perspective on US-China trade war and focus on the sectoral impact on US and China.

2.3 Methodology

The paper is based on the foundation of the Cross-border Granular Macro-Network Model, which focuses on the point-to-point trade flow and the impact of its interconnectivity to the macroeconomics aspect. To show that, we implement the Leontief Technology Coefficient and Ghosh Model to show the indirect impacts from intermediate production on top of the direct impact from the traditional look on final demand. The partial extraction method will be used for the cases of US-China Trade War Tariff change and strategies. Carvalho and Gabaix (2013) Introduced that the granular macro-net model views the economy as an interconnected system. It portrays Macroeconomics not by using standard equations and aggregate-level shocks but by approaching input-output from the networked perspective. The tariff changes can be implemented on the granular macro-net model to analyse the trade war's impact on GDP and final demand.

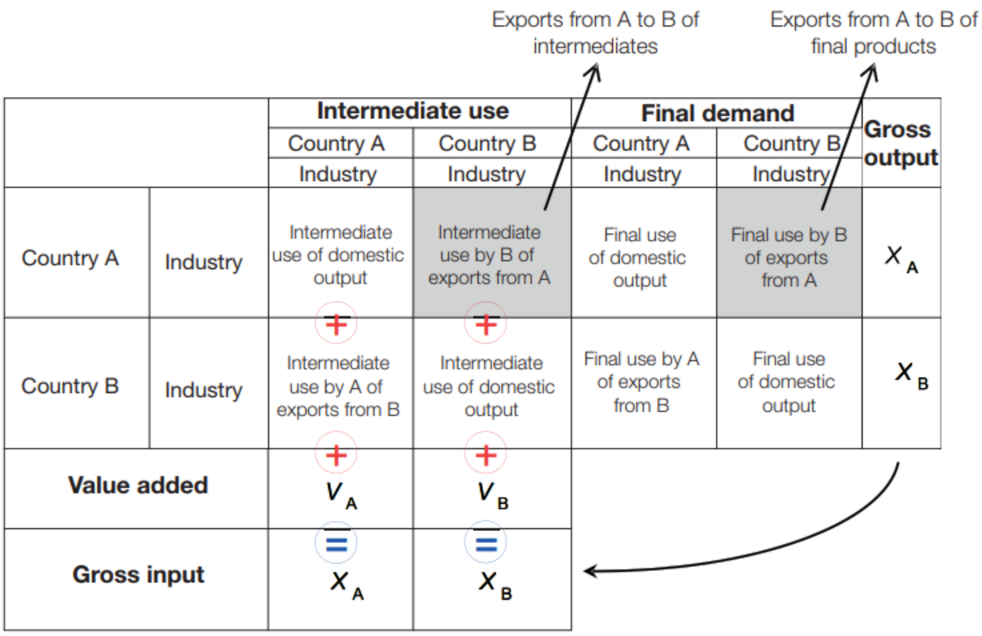
2.3.1 Baseline Granular Macro-Network Model framework

This section is a basic introduction to the Input-Output (ICIO) database, the granular macroeconomics approach and the baseline network model.

ICIO data structure follows the illustration in the paper of Wixted et al. (2006); it can be seen from the figure below which shows how an economy's (country/region) trade flows across the economy and to other economies by sectors.

We assume a two-country model, because this paper will study the case of two countries' trade relation revolution. Asiam et al. (2017) showcased a clear view of the framework. This framework is an example of an ICIO table for two economies. There are two types of goods: intermediate goods and final-demand goods. Goods have two ways to go: domestically or exporting to another country.

Figure 2.8: The two country's input-output trade framework



Source: *Asiam et al. (2017)*

This is an intention of the baseline framework where two countries trade with each other rather than one country trade domestically. It can expand to N*N form with N countries if adequate data supports the model.

The domestic intermediate matrix (also called the X matrix in this paper) details how an economy's sectors buy and sell raw materials, industrial components, and services to other sectors. The imported intermediate products are summarise in the rest of the world section for all the intermediate foreign transactions.

The value-added section includes taxes, salaries, gross operating surplus, etc. The column of domestic intermediate goods plus value-added is the gross input of an economy. The final demand section plus the row of domestic intermediate goods makes up the output of an economy. The whole data follows the nature of the gross output equals gross input.

2.3.2 Leontief model

Leontief model highlights the contribution of sectors to others and shows the level of input from one sector contributes to the output of other sectors. It also focuses on the role of final demands.

In this model, an economy has N sectors for different products, such as goods and services of various industries. For instance, sector j produces a total output of xj, and the outputs will be used as intermediate products to the other sectors to be used as their input or become a part of other sectors' final demand and consumed as final goods. The sector j plays both the buyer and the seller roles, it is the demander of some trades and supplier in other trades. To produce one unit of sound, sector j will have demand of aij units input from sector i, xij is the total intermediate goods that sector i sends to sector j, then we can get $\mathrm{a_{ij}} = \frac{\mathrm{x_{ij}}}{\mathrm{x_j}}$. Apart from intermediate goods, final demands also need to be considered, and we use dj as the final demand of sector j.

Figure 2.1 shows that all gross output produced in either country is used as an intermediate or final good, domestically or abroad. Therefore, country i's gross output, x_i, is given by:

$$x_i = a_{ii}x_j + a_{ij}x_i + y_{ii} + y_{ij} \qquad i,j = 1,2 \qquad 2.1$$

Where y_{pq} is the quantity of country p's output consumed as a final good in country q and $a_{ij}$is the units of intermediate goods produced in country i needed to produce one unit of the good in country j. These are called IO coefficients or technology coefficients. These can be found by dividing the total intermediate use in country j of country i's product, int_{ij}, given in the intermediate section in the IO table, by the gross output of country i, $a_{ij} = {int_{ij}}/{x_i}$. Equation 2.1 can then be written in matrix form as:

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} y_{11} + y_{12} \\ y_{21} + y_{22} \end{bmatrix}$$

Which can be summarised as:

$$X = AX - Yi \qquad 2.2$$

Where $Y = \begin{bmatrix} y_{11} & y_{12} \\ y_{21} & y_{22} \end{bmatrix}$ and i is column vector in which all elements are 1, which, when multiplied by Y sums each of the rows in Y, as shown in the last component of equation 2.2. Rearranging equation 2.2 to make the X vector the subject, we have:

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} I - a_{11} & -a_{12} \\ -a_{21} & I - a_{22} \end{bmatrix}^{-1} \begin{bmatrix} y_{11} + y_{12} \\ y_{21} + y_{22} \end{bmatrix} = \begin{bmatrix} l_{11} & l_{12} \\ l_{21} & l_{22} \end{bmatrix} \begin{bmatrix} y_{11} + y_{12} \\ y_{21} + y_{22} \end{bmatrix} \qquad 2.3$$

Or, more simply:

$$X = (I - A)^{-1} Yi = LYi \qquad 2.4$$

Where L is known as the Leontief inverse matrix. Each element of L, l_{ij}, is a Leontief coefficient and gives the amount of country i's output required to produce one more unit of the final good in country j.

2.3.3 Partial Extraction

Leontief and Ghosh's Model shows how the intermediate good, final demand and value-added can affect each other and eventually change the gross output of an economy, not just in a direct way but also in a deeper layer of interconnectivity. The next question is, how do we project the trade war impact onto this model?

In the paper of Los et al. (2016), the Hypothetical Extraction Method (HEM) is illustrated. The basic idea of this method is to create a hypothetical world; in this world, country A and country B do not import or export to each other, while the rest of the economic status stays the same.

The new coefficient matrix is $\boldsymbol{A}^{\#}$ in the new structure, and the new final demand is Y#. Therefore the new GDP under the hypothetical condition is calculated as:

$$GDP^{\#} = \boldsymbol{V}(\boldsymbol{I} - \boldsymbol{A}^{\#})^{-1}\boldsymbol{Y}^{\#}\boldsymbol{i} \qquad 2.5$$

The effect of the partial extraction is simply the original GDP minus the new GDP:

$$DVA^{\#} = GDP_{O} - GDP^{\#} \qquad 2.6$$

This result represents the change in Value Added because of the reduction of exports between the two countries.

However, changing the exports to zero might be a very extreme case. In the reality of the Trade War, we adapt the HEM to a partial extraction method (PEM) where the demand changes according to the change of tariff and other factors. As presented in the formula below:

$$M_i = \left(\frac{eP_{Fi}}{P_i}\right)^{\varepsilon_{Di}} Y_D \eta_{Di} \qquad 2.7$$

Table 2.1: The notations in equation 2.7.

M_i	**domestic import demand for commodity *i***
e	**exchange rate**
P_{Fi}	**foreign price for commodity *i***
P_i	**domestic price of commodity *i***
ε_{Di}	**domestic relative price elasticity of commodity** *i* (<0)
Y_D	**domestic income**
η_{Di}	**income elasticity of demand for imports of commodity *i*** (>0)

This formula made it very clear that the volume of import demand of commodity i is a combination of the factors listed above.

To find the change in demand over time, the equation differentiates with respect to time:

$$\dot{M_i} = \varepsilon_{Di}(\dot{e} + \dot{P_{Fi}} - \dot{P_i}) + \eta_{Di}\dot{Y_D} \qquad 2.8$$

Where $\dot{x} = \frac{\partial lnx}{\partial t}$. Assuming that e,P_i and Y_D are fixed, import demand is given only by the relative price elasticity, $\varepsilon_{Di}$and the foreign price for commodity i, P_{Fi}:

$$\dot{M}_{\iota} = \varepsilon_{Di}\dot{P_{F\iota}} \quad 2.9$$

We already assumed that P_i is fixed. Now we also assume that the only channel by which the foreign price of commodity i can change is by introducing new tariffs that China and the United States have announced during the past year. Therefore, the change in import demand between the US and China is given by:

$$\dot{M}_{\iota} = \varepsilon_{Di}\tau_i \quad 2.10$$

Where τ_i are the Trade War tariffs change on sector$i$ and $\varepsilon_{Di}$is the import elasticity of sector i in the domestic country.

As we know, elasticities are always less than zero; any increase in tariffs can reduce import demand.

The elements of the matrices that are altered are any elements that involve interaction between the US and China. To aid understanding, consider a three-country, one-sector ICIO model, the three countries/regions being China (C), the US (U), and ROW (R). The$A$ and Y matrices for this model will be given as:

$$A = \begin{bmatrix} a_{CC} & a_{CU} & a_{CR} \\ a_{UC} & a_{UU} & a_{UR} \\ a_{RC} & a_{RU} & a_{RR} \end{bmatrix} Y = \begin{bmatrix} y_{CC} & y_{CU} & y_{CR} \\ y_{UC} & y_{UU} & y_{UR} \\ y_{RC} & y_{RU} & y_{RR} \end{bmatrix} \quad 2.11$$

Where a_{pq} gives the units of intermediate goods produced in-country p needed to produce one unit of the good in country q. Similarly, $y_{pq}$is the same for the final products. The elements that involve interaction between the US and China will be affected by the new tariffs, ε_{Di} multiplied by the new sectoral tariffs in each country τ_i, given by M_i in equation (18). Since there is only one sector in each country, the modified A and Y matrices are then:

$$A = \begin{bmatrix} a_{CC} & \boldsymbol{a_{CU*}} & a_{CR} \\ \boldsymbol{a_{UC*}} & a_{UU} & a_{UR} \\ a_{RC} & a_{RU} & a_{RR} \end{bmatrix} Y = \begin{bmatrix} y_{CC} & \boldsymbol{y_{CU*}} & y_{CR} \\ \boldsymbol{y_{UC*}} & y_{UU} & y_{UR} \\ y_{RC} & y_{RU} & y_{RR} \end{bmatrix} \quad 2.12$$

Where$\boldsymbol{a_{pq}}^* = a_{pq} + \dot{M}_p$ and$\boldsymbol{y_{pq}}^* = y_{pq} + \dot{M}_p$.

This matrix can be extended to the $NK \times NK$ coefficient matrix A and $NK \times N$ final demand matrix Y, the data we used. The new GDP under a Trade War can be calculated for each sector in each country and is given by:

$$GDP^* = \boldsymbol{V}'(\boldsymbol{I} - \boldsymbol{A}^*)^{-\mathbf{1}}\boldsymbol{Y}^*\boldsymbol{i} \tag{2.13}$$

Using the original GDP, the change in value-added as a result of the Trade War can be calculated as:

$$DVA^* = GDP_O - GDP^* \tag{2.14}$$

DVA is the $NK \times 1$ vector with each element showing the change in VA due to the Trade War in all K sectors in all N countries.

2.4 Data source, sorting and demonstrations

There are two main types of crucial data for the analysis: Trade Value and Trade Tariff. How much the US and China were trading with each other and what is the difference in trade tariffs for both countries before and after the trade war? Those are the two questions that need data support. After obtaining these two sets of data, the question of what impact the trade war had on both countries can be answered.

In this section, we will break down all the data that are required for the analysis: the source of data, the supporting data and the procedure to increase the data accuracy, with some sample demonstrations.

In addition, in this paper, we assume that the data tariff change only happens to the US and China; there are no tariff changes in the rest of the world.

2.4.1 Data on US-China Pre-Trade War and Post-Trade War Cross-border Trade and Tariff: Source and format

We use the Most Favoured Nation (MFN) Tariff Data from the World Trade Organisation (WTO) to access the pre-trade war tariff data. [6] After China joined WTO in 2001, both the US and China were included in MFN.

Since the trade war started in July 2018, we use 2017 MFN tariff data, the latest pre-trade war data. This database uses Harmonized Commodity Description and Coding Systems (HS)[7] classification on a 6-digit level.[8]

The UN trade statistics website defined the HS system: "The Harmonized System is an international nomenclature for classifying products. It allows participating countries to classify traded goods on a common basis for customs purposes. At the international level, the Harmonized System (HS) for classifying goods is a six-digit code system."

To access the post-trade war tariff data, we follow the recorded data from the US and China government authorised files during the trade war period:

The US data is published by the Office of the US Trade Representative (USTR). [9] China data is published by the Ministry of Finance of China.[10] Both datasets are under the HS classification, the same as the MFN dataset.

2.4.2 Trade Value Data

In this paper, we used two trade value databases that provide different aspects of trade value data. Therefore, we use them for different purposes of analysis. The two databases are shown below:

6 MFN tariff data from WTO: http://tariffdata.wto.org/Default.aspx?culture=en-US

7 HS website: https://unstats.un.org/unsd/tradekb/Knowledgebase/50018/Harmonized-Commodity-Description-and-Coding-Systems-HS

8 The HS comprises approximately 5,300 article/product descriptions that appear as headings and subheadings, arranged in 99 chapters, grouped in 21 sections. The six digits can be broken down into three parts. The first two digits (HS-2) identify the chapter the goods are classified in, e.g. 09 = Coffee, Tea, Maté and Spices. The following two digits (HS-4) identify groupings within that chapter, e.g. 09.02 = Tea, whether or not flavoured. The following two digits (HS-6) are even more specific, e.g. 09.02.10 Green tea (not fermented)... Up to the HS-6 digit level, all countries classify products similarly (a few exceptions exist where some countries apply old versions of the HS).

9 USTR tariff list website: https://ustr.gov/issue-areas/enforcement/section-301-investigations/tariff-actions

10 Ministry of Finance of China : http://www.mof.gov.cn/

We use Organisation for Economic Co-operation and Development (OECD) Inter-Country Input-Output (ICIO) data to get Cross-Nation Input-output Data.[11] from the year 2018, the classification for this database follows International Standard Industrial Classification (ISIC) revision 4.[12]

United Nations Statistical Division (UNSD) Commodity Trade (COMTRADE) data[13] is used to calculate the weighted average tariff, which will be explained later. The data that has been used is the latest data available, which is the year 2017, the classification for this database is also Harmonized Commodity Description and Coding Systems (HS).

2.4.3 Comparison of two trade value data sets: OECD-ICIO and UNSD COMTRADE

Both OECD ICIO data and UNSD Commodity Trade (COMTRADE) data start with 98 categories of industries of an economy following the HS07 classification. The classification is listed in the Appendix. In this paper, we call all 2-digit categories "industries", all 6-digit categories "sub-industries", and the aggregated 36 categories "sectors". A whole economy has a certain number of industries, 98 industries to be exact in most countries. Each industry includes many sub-industries that contain more specific products. The 96 industries will be aggregated into 36 sectors for analysis. The data classification system matching is shown in the Appendix, where we show examples of each type and level of data.

Table 2.2: Comparing OECD ICIO data and COMTRADE data

11 OECD-ICIO data: https://www.oecd.org/sti/ind/inter-country-input-output-tables.htm

12 ISIC Rec.4 website: https://unstats.un.org/unsd/classifications/Family/Detail/27

13 COMTRADE data website: https://comtrade.un.org/Data/

	OECD ICIO DATA	UNSD COMTRADE DATA
Classification System	International Standard Industrial Classification (ISIC) revision 4	Several systems including Harmony System 2017
Classification Level	2 Digits	**6 Digits**
Matching with MFN Tariff Classification	Needs a 2-step conversion process	**Directly matching**
Information Include	Intermediate good and Final demand Input-Output Trade Flow, **Value Added, Total Output**	Trade Volume, Trade Value
Data Completion	**Higher**	Lower
Comparison	Higher completion, better option for the final trade analysis after trade tariff change under 2-digit level.	More detailed sub-section and matching system, better option for the calculation of weighted tariff, but not ideal for the final trade analysis
Purpose of use	Pre and Post trade war **trade flow changes**	**Weighted Tariff** calculation

OECD data has 36 categories of sectors (generated from 98 industries from ISIC Rev.4 data classification.) The strength of this data set is that it covers all the OECD countries with completed input-output data for both intermediate goods and final demand goods, as well as value-added. It has the data we need to do cross-country network trade analysis. However, it is not ideal for calculating the tariff multiplier as it cannot identify sub-industry trade value. In order to get the weighted tariff for every sector, we need to get the tariff rate and corresponding trade value in a 6-digit sub-industry level, and COMTRADE data provides a 6-digit trade value. Therefore, we introduce the COMTRADE data, which allows us access to most sub-industries from all 98 industries.

2.4.4 Simple average tariff and weighted average tariff: Why do we use weighted Average tariff

The reason for us aiming to get weighted tariffs instead of simple average tariffs is that with weighted average tariffs, we can get more accurate results and show a greater variety of tariff changes in different industries. The overall view of the difference in tariffs in industries by using these two methods is shown in the resulting graph and analysis section, as well as a numeral example.[14]

We can write the equation for the weighted average tariff rate as:

$$WTR_S^{2D} = \frac{\sum_n^i TR_{Si}^{6D} TV_{Si}^{6D}}{\sum_n^i TV_{Si}^{6D}} \qquad 2.15$$

Where WT is the weighted average tariff rate, TR is the tariff rate, TV is Trade value, 2D stands for the 2-digit level, 6D stands for the 6-digit level, S stands for sector S, and i stands for the sub-industries in sector S.

The COMTRADE data is commonly used for trade-related research. For instance, In the paper from the Bank of Canada written by Charbonneau et al. (2018), The trade War in Numbers, they created a representative European Union by combining COMTRADE data for each of the 28 member states, as well as the rest of the world by taking the combined trade value between a country and all its partners in our sample and subtracting it from the trade value between this country and the entire world. Minghao Li et al also briefly mentioned using COMTRADE data on The US–China trade war: Tariff data and general equilibrium analysis.

We added all the tariff rates for a simple average tariff and divided the sum by the total number of sub-industries.

14 Variable and Notation List:
WTR: Weighted Average Tariff Rate
STR: Simple Average Tariff Rate
TR: Tariff Rate
TV: Trade Value
2D: 2-digit category level
6D: 6-digit category level
S: Sector S
i: Sub-Industry i

$$STR_S^{2D} = \frac{\sum_n^i \{TR_{Si}^{6D}\}}{n} \qquad 2.16$$

Where STR is the simple average tariff rate, TR is the tariff rate, 2D stands for the 2-digit level, 6D stands for the 6-digit level, S means the sector S, i stands for the sub-industries in sector S. n is the total number of *i*s.

In the following numeral example, we take the mining sector of the US to see how the result can be so different using a simple average and using a weighted average.

In the mining sector, the post-trade war tariff has three types, 7.5%, 25%, and 0 %, which stayed unchanged. If we calculate a simple average tariff, we only investigate the tariff rate and Number of sub-industries, and we can see the largest group of sub-industries has a 25 per cent tariff. Therefore, the simple average tariff after the calculation is 17.64%, which is mainly close to 25%. Using the weighted average method, we investigate the trade values; we can see that most of the trade value does not have any tariff, which means the weighted average tariff rate is low by a calculation of 6.5 %. This case shows that the weighted average tariff represents more accurate results.

Table 2.3: Mining sector sub-industries tariffs and corresponding trade values of US imports from China in 2017

Tariff rate (%)	Number of sub-sectors	Trade Value ($Million)
7.5	6	49.15
25	49	131.97
0	17	386.11

2.4.5 US Import Tariff Rates from China Pre and Post-Trade War Level (Weighted Average and Simple Average)

Figure 2.9: Pre and Post Trade War US import weighted average tariff from China (%)

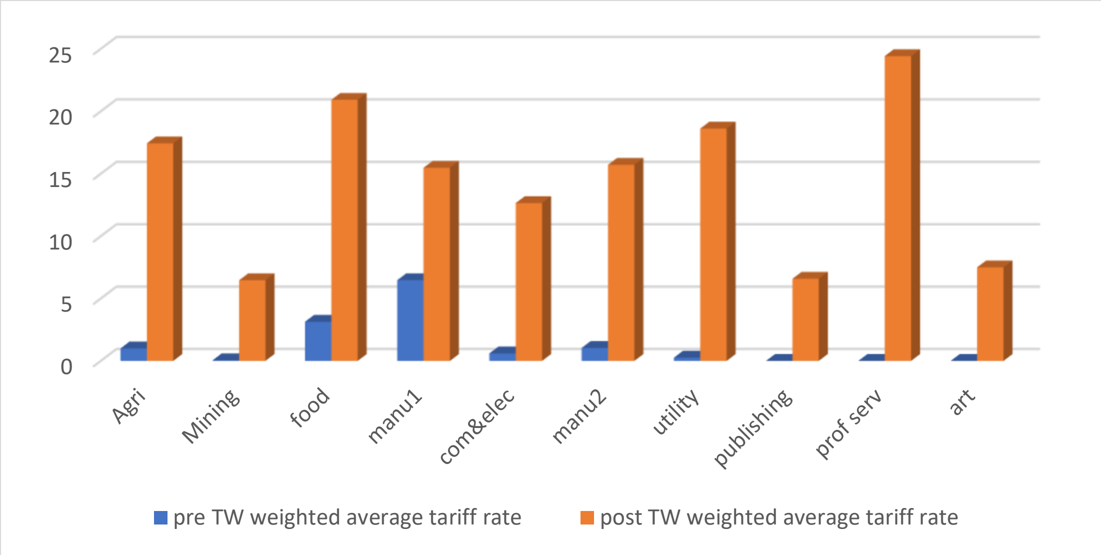
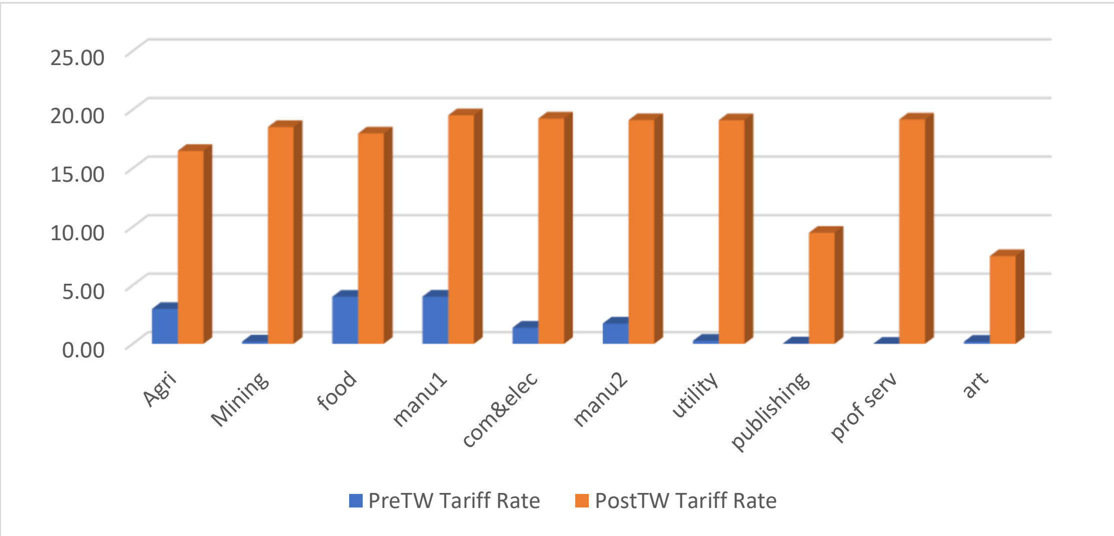


Figure 2.10: Pre and Post Trade War US import from China simple average tariff (%)



For the US, we can see that the pre-trade war tariffs in both methods are similar, but there is a massive difference in post-trade war tariffs.

On a simple average, the tariffs in most sectors are all around 15-20 per cent; the reasons that most tariffs the US implemented are 10 per cent and 25 per cent, and when we take a simple average, the number will fall into 15-20. However, in the weighted average, we see in mining, it is only around 5 per cent, while in the professional service sector it almost reached 25 per cent. In mining, many sub-sectors with significant trade value are unaffected, while in the professional services sector, only one sub-sector stays unchanged.

2.4.6 China Import Tariff Rates from the US Pre and Post-Trade War Level (Weighted Average and Simple Average)

Figure 2.11: Pre and Post Trade War China import from US weighted average tariff(%)

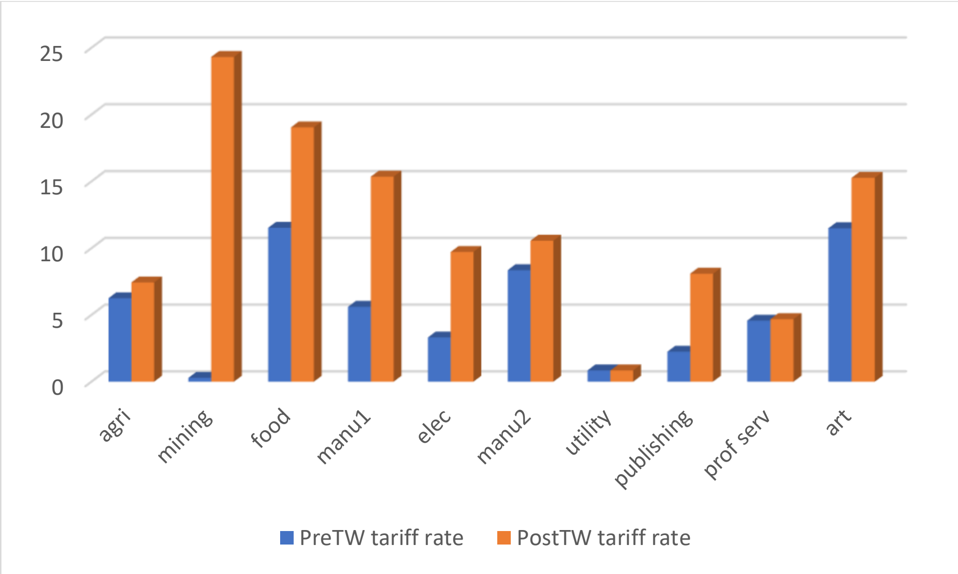
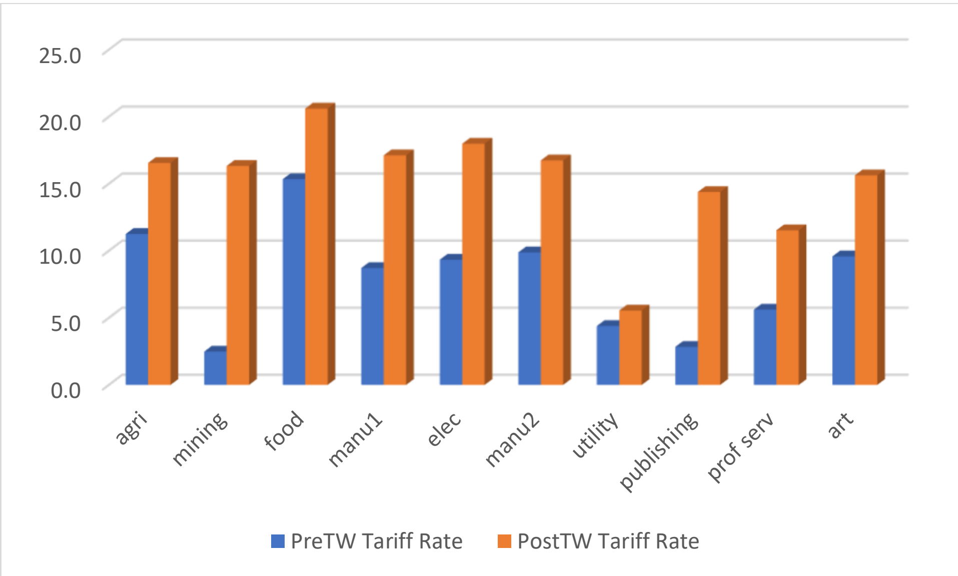


Figure 2.12: Pre and Post Trade War China import from US simple average tariff (%)



The same reason can be applied to tariff change; we can see a big difference in the mining sector again, but in the opposite way, where the weighted average shows a more significant tariff rate increase.

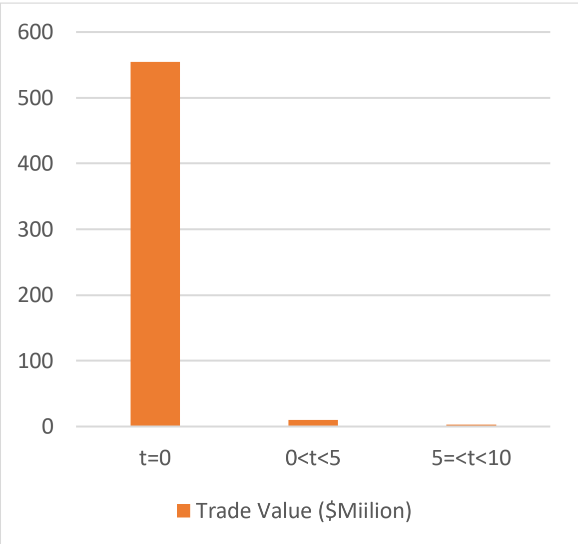
Overall, the weighted average represents more accurate tariff changes in each sector.

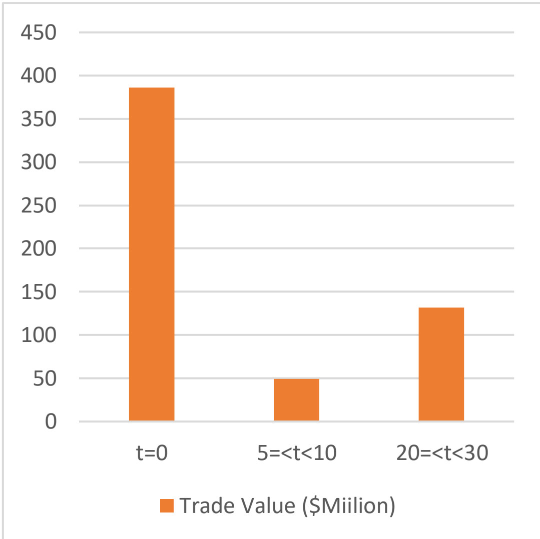
2.4.7 Sub-Sector role and contribution in Overall Sectors

We use the mining sector as an example to observe the impact of sub-sectors tariff and trade value distribution.

Figure 2.13: US import in Mining from China Pre Trade War: Numbers of sub-sectors and Trade Value ($Million) (Left)

Figure 2.14: US import in Mining from China Post Trade War: Numbers of sub-sectors and Trade Value ($Million) (Right)

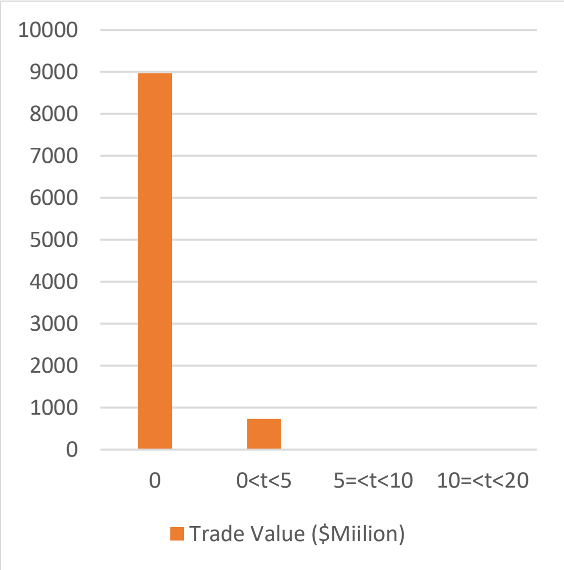


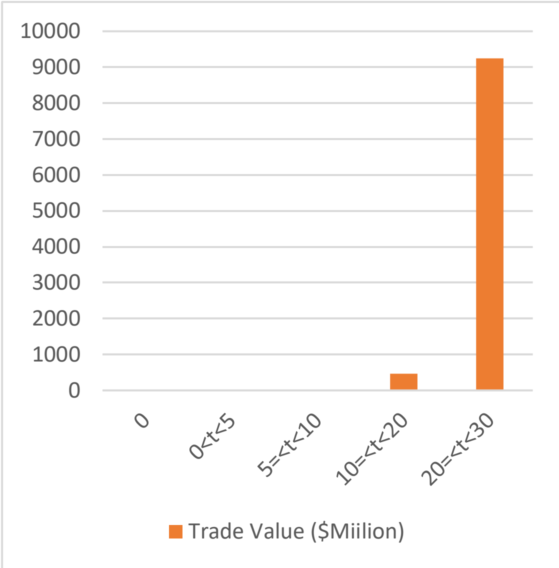


In the US Pre-Trade War and Post-Trade War Tariff Change figures, in terms of the number of sub-sectors that increased their tariff, we see a significant shift from zero tariffs to 20 to 30 per cent tariff. However, when we look at the trade value, the shift is not as significant as the shift of numbers.

Figure 2.15: China import in Mining from US Pre Trade War: Numbers of sub-sectors and Trade Value ($Million) (Left)

Figure 2.16: China import in Mining from US Post Trade War: Numbers of sub-sectors and Trade Value ($Million) (Right)





In the China import Pre- and Post-trade war tariff change, we see all the sub-sectors with less than 5 per cent tariff have changes to a higher tariff, in both numbers and trade values aspect. By looking into the sub-sectors in the mining sector, it can be explained why the simple average tariff of US imports is higher than the weighted average, while in China, it shows a similar outcome.

Table 2.4: Tariff rate and the trade value of Mining sub-sectors

Mining Sector	Stage	Tariff rate	Number of sub-sectors	Trade Value ($Million)
US imports from China	Pre-Trade War	t=0	62	554.55
		0<t<5	8	9.83
		5=<t<10	2	2.86
	Post-Trade War	t=0	17	386.11
		5=<t<10	6	49.15
		20=<t<30	49	131.97
	Pre-Trade War	0	19	8968.58

China imports from the US		0<t<5	49	735.91
		5=<t<10	14	20.30
		10=<t<20	3	2.52
	Post-Trade War	0	2	8.18
		0<t<5	5	6.09
		5=<t<10	2	0.04
		10=<t<20	21	473.47
		20=<t<30	55	9239.53

2.4.8 Trade Tariff Value change before and after trade war using the weighted average method.

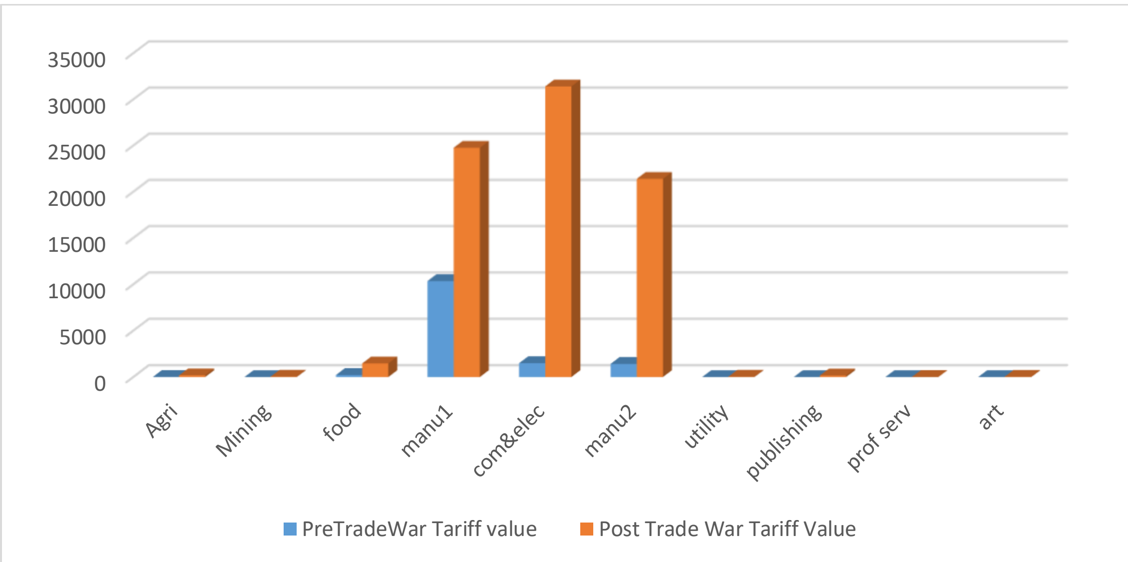
In order to calculate the Sectoral Trade Tariff Value, the calculation is shown below:

$$TAR_S = WTR_S TV_S \qquad 2.17$$

Where TAR is Tariff Value, WTR is weighted tariff rate; TV is Trade value, S means sector S.

2.4.8.1 *US Trade Tariff Value change*

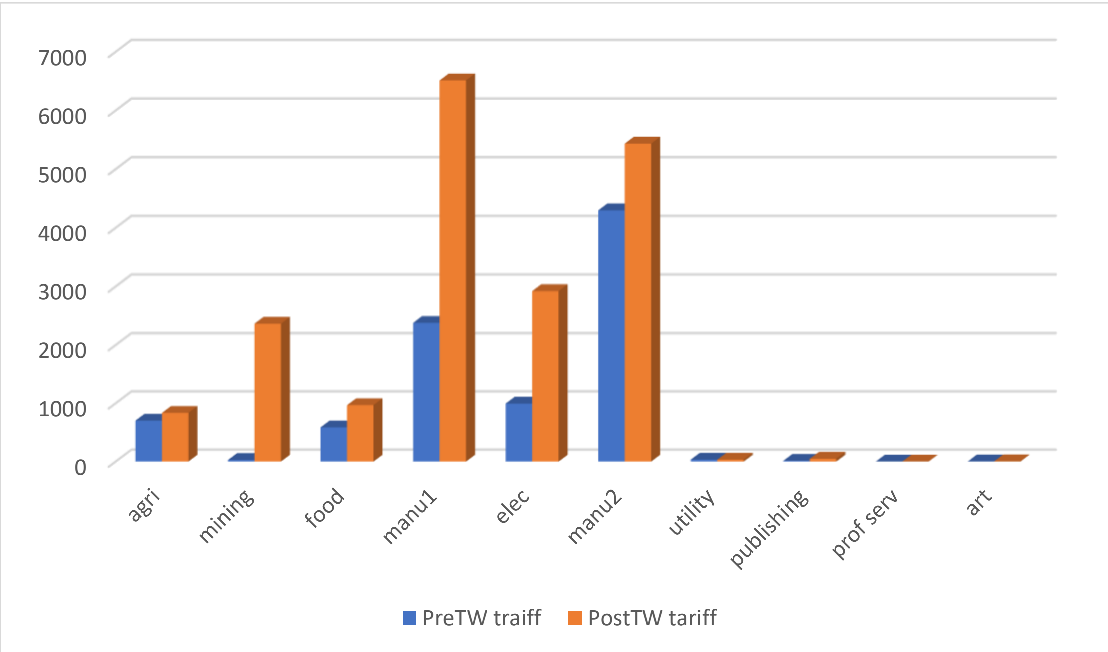
Figure 2.17: Pre and Post Trade War US import from China Trade Tariff Value (US$ in million)



In the US, we can see that the Tariff Value changes occur mainly in three sectors. For trade value, the three sectors have the most significant number; at the same time, these three sectors witnessed a big tariff raise. Therefore, the outcome is significant. This is a clear sign that the US initiated the trade war to reduce China's profit from exporting to the US.

2.4.8.2 *China Trade Tariff Value change*

Figure 2.18: Pre and Post Trade War China import from US Trade Tariff Value (US$ in million)



Meanwhile, we can see for imports to China from the US, the highest difference is only around 5 billion in manufacturing 1, while for the US, the biggest one is nearly 30 billion in Computer &Electronic. Manufacturing also has a just below 15 billion increase in Tariff Value.

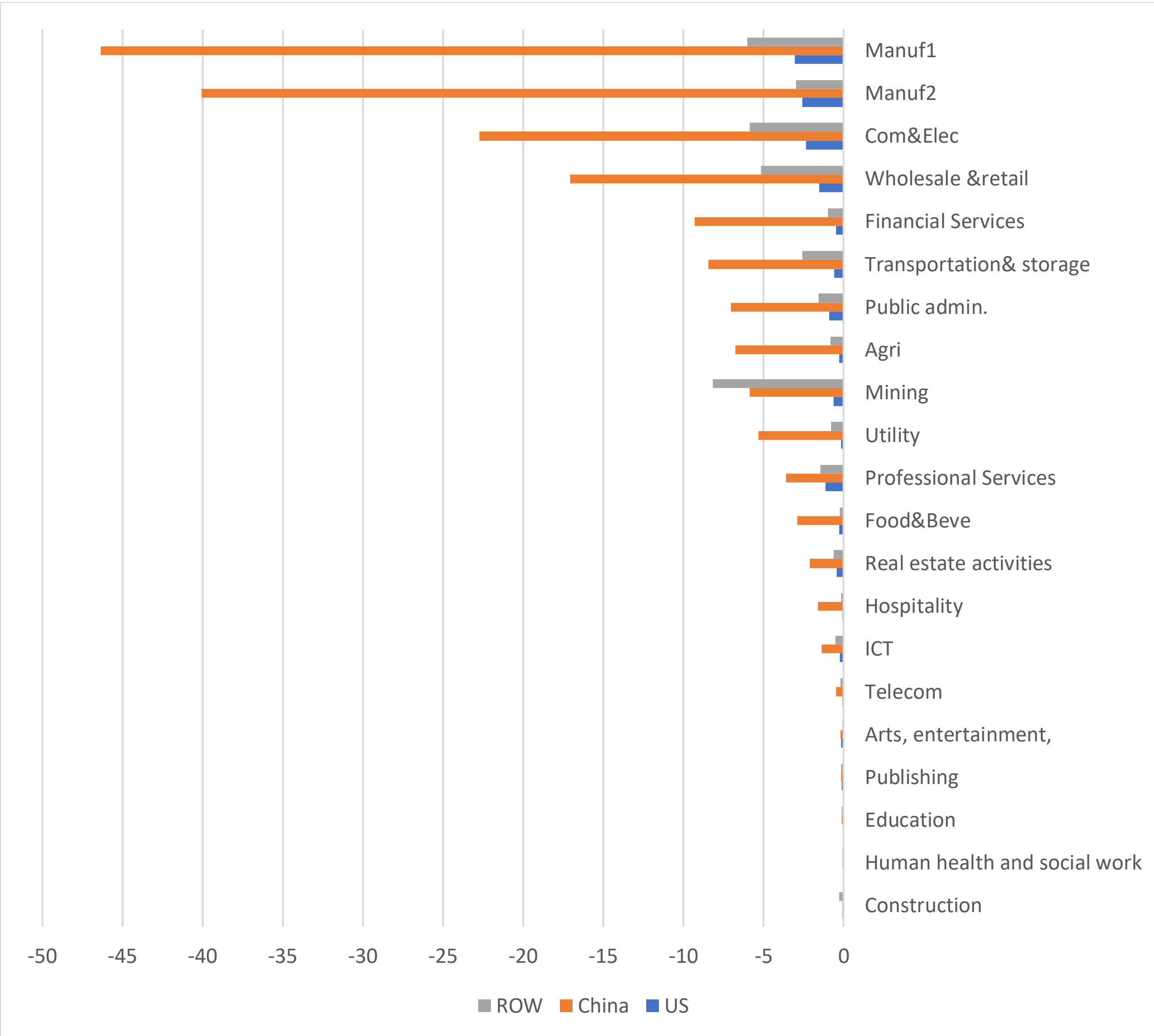
2.5 Analysis Results

2.5.1 Overview

In this part, we show the prediction for the impact of the Trade War Tariff Change (Annually) when neither the US nor China takes any action to divert exports to other alternative receivers. However, in order to show the importance of the role intermediate good transactions played in the Trade War, we separated the results into three parts: the direct loss when the output is only affected by the final demand changes, the indirect losses when the output is affected by the loss in intermediate good demand/supply, the mixed case where the whole picture is shown.

2.5.2 Direct Impact from Final Demand

Figure 2.19: Impact on VA from Final Demand Changes in Trade War (In $Bn)



Tariff change has a great impact on final demand for both countries. However, the reduction of final demand will significantly impact value-added goods (GDP) in China than in the US.

As China has been highly dependent on exporting manufacturing goods to the whole world, including the US as the biggest importer, we can see from the graph above that China's light manufacturing and heavy manufacturing sectors have the most considerable losses of approximately $46 billion and $40 billion.

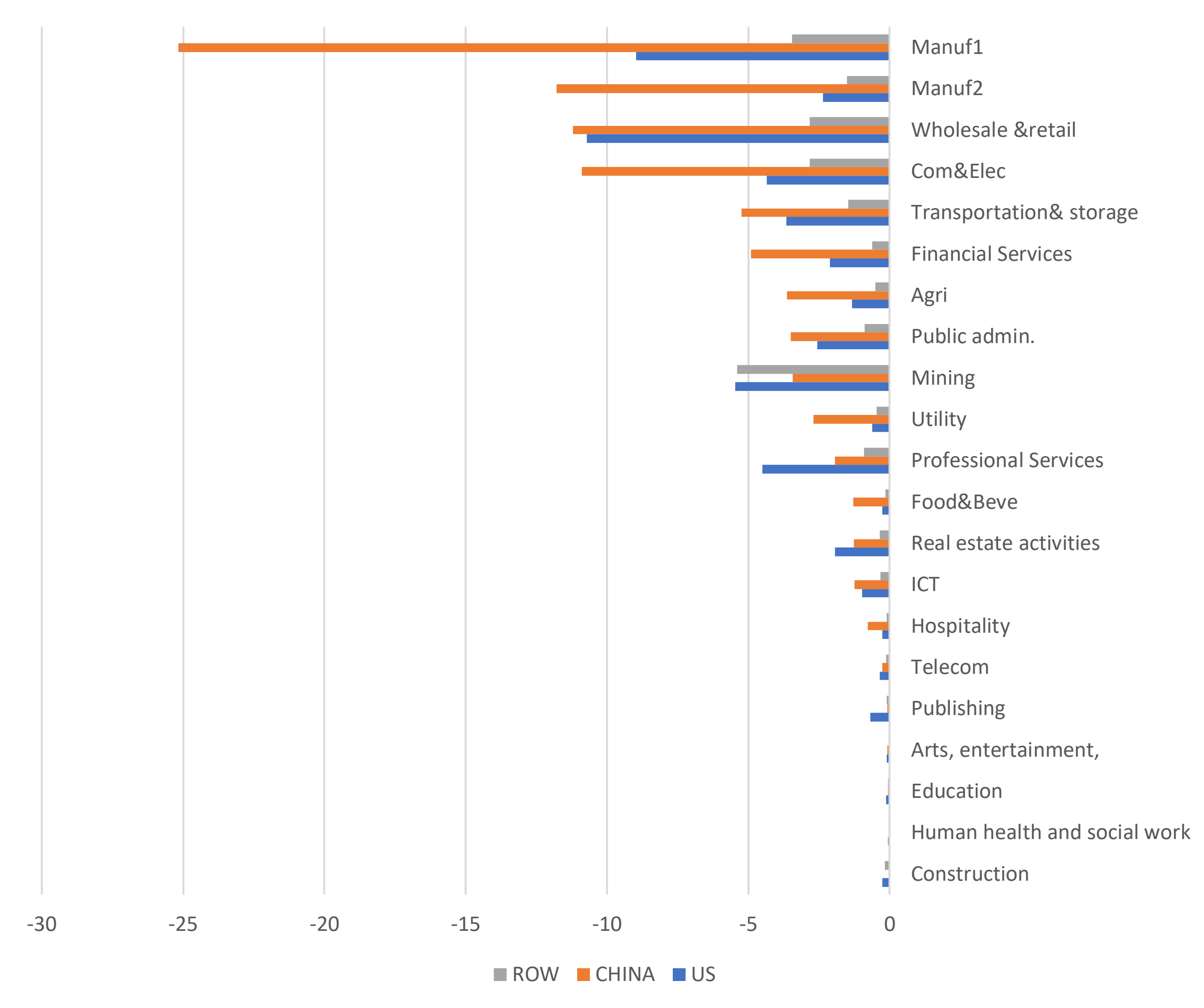
The other three sectors that are witnessing significant losses are the computer and electronic sector, this sector of China has arisen into the competition as the Electronic technology companies in China have taken a more robust position worldwide in recent years and have been threatening the US traditional strong technology dominance; The wholesale &Retail sector of China is also a rising and interconnecting sector in China as Chinese companies have been expanding oversea retail towards foreign Chinese/Asian demographic and more; The financial sector is an example of the impact of interconnectedness, even though this sector itself has not faced tariff changes, because of the significant investments into other sectors, it still suffers from a big hit.

As less of an exporter of final products to China than China is to the US, the US is likely to be less affected by the tariff change in the final demand aspect. The top three most negatively affected sectors of the US are Manufacturing-one, two and the Computer& Electronic sector, with less than $ 5 billion in losses.

A unique sector in both countries is the construction sector, as it did not face any tariff change nor is it interconnected with other sectors.

2.5.3 The indirect impact of intermediate goods imports changes

Figure 2.20: Direct Impact on VA from Intermediate Good Changes in Trade War (In $Bn)



The impact on value-added goods from intermediate good changes due to tariff increases shows the same trend as the final demand impact, where China loses more GDP than the US. However, the gap between them is smaller than in the case of final demand. The Manufacturing sector of China lost almost $46 billion in GDP from final demand but only around $ 25 billion in the intermediate goods section, meanwhile, the loss of the US Manufacturing sector doubled from less than $4 billion to more than $8 billion. This pattern also appears in some other sectors. The US often export intermediate good to China and import them back as final goods, this is part of the negative impact that much research failed to investigate.

2.5.4 The mixed impact of intermediate goods imports and final demand changes

Figure 2.21: Mixed Impact on VA from Intermediate Good and Final Demand Changes in Trade War (In $Bn)

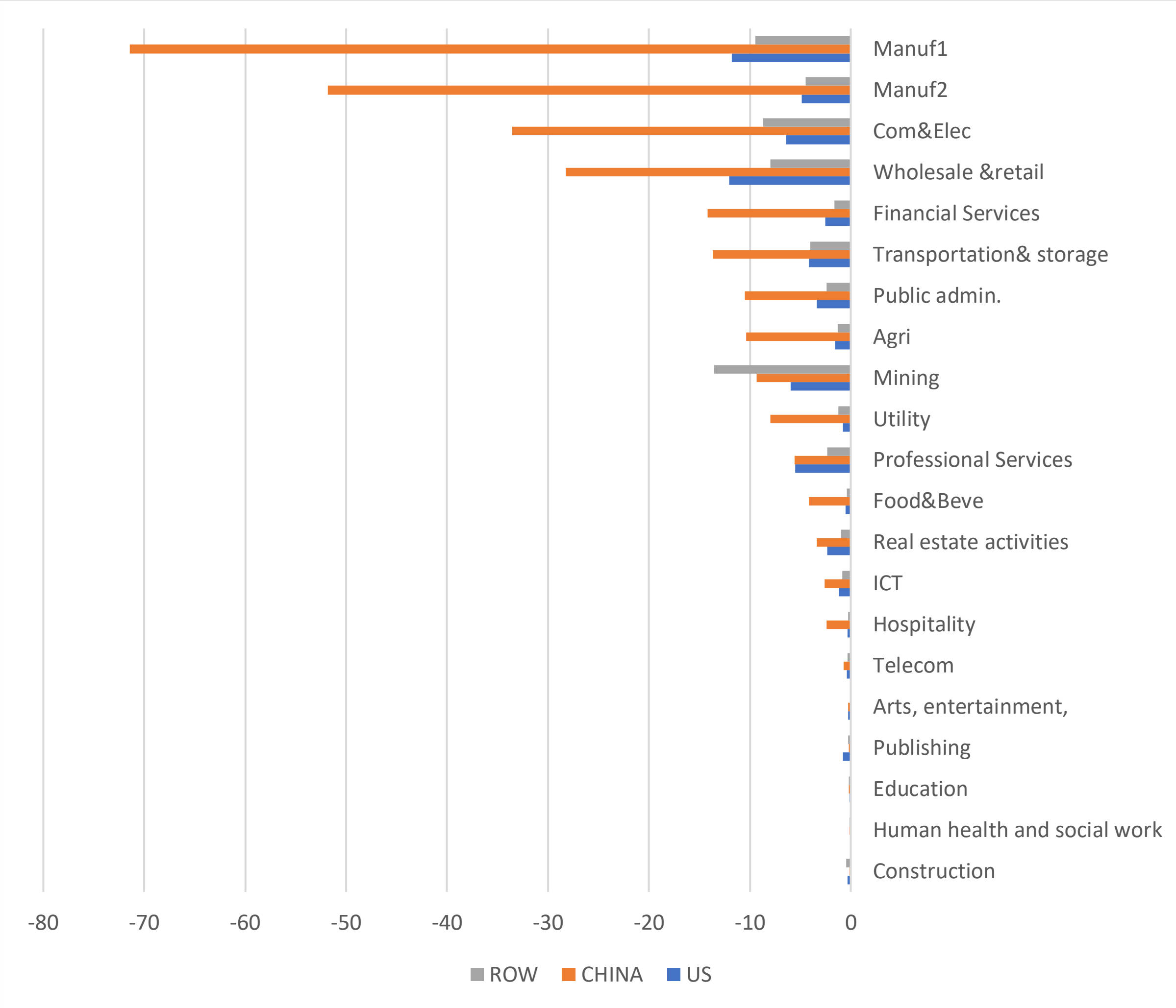


Figure 2.22: Total GDP losses after Trade War Tariff Changes, Final Demand Impact VS. Full Impact ($Bn)

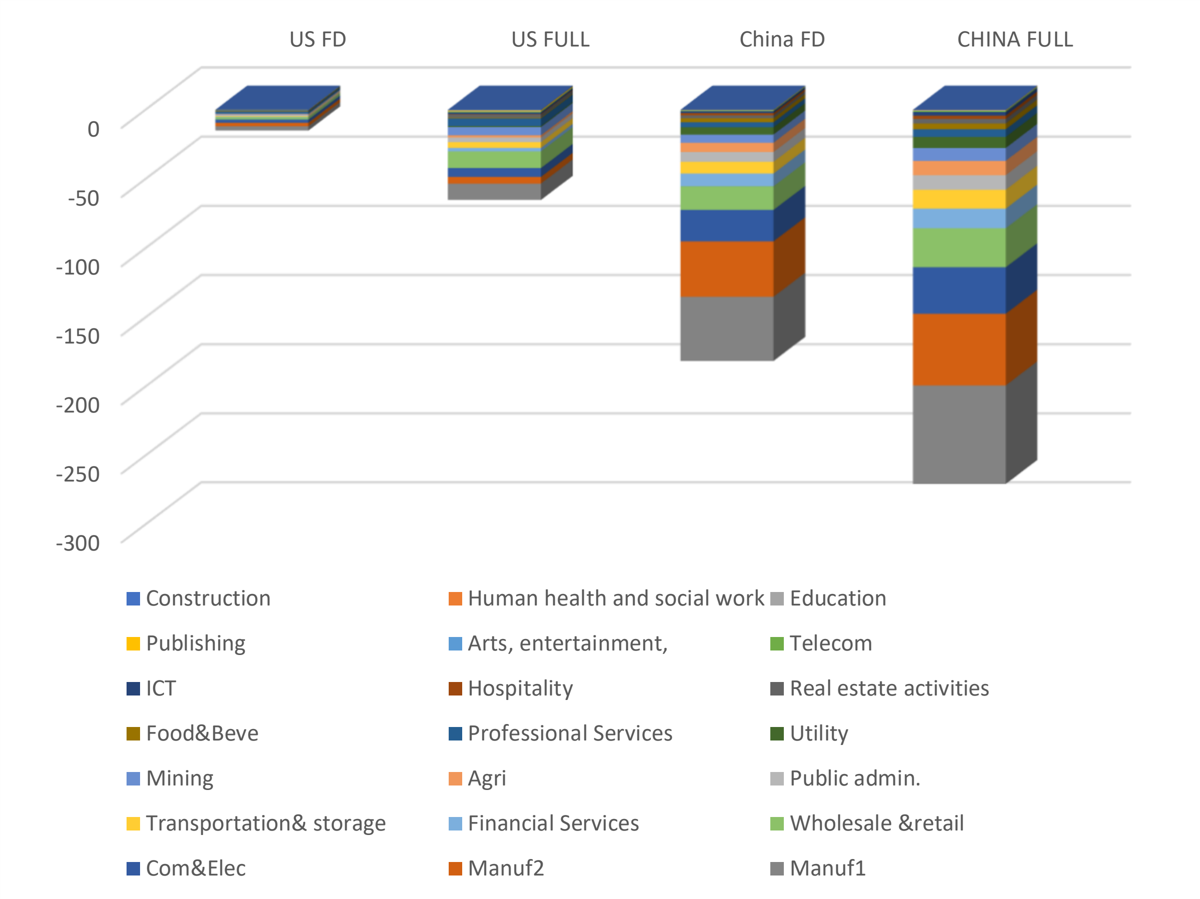


Table 2.5: Total GDP losses (with 2018 data) after Trade War Tariff Change in percentage by sector

	US	China	RoW
Computer &Electronic	**-0.021**	**-0.103**	**-0.013**
Manuf2	-0.007	**-0.054**	-0.002
Manuf1	**-0.010**	**-0.032**	-0.002
Mining	**-0.018**	**-0.028**	-0.006
Wholesale &retail	-0.006	**-0.022**	-0.001
Transportation& storage	-0.006	**-0.022**	-0.002
Utility	-0.002	-0.019	-0.001
Professional Services	-0.003	-0.019	-0.001
Financial Services	-0.002	-0.014	-0.001
Agri	**-0.008**	-0.011	-0.001
ICT	-0.002	-0.010	-0.001
Food&Beve	-0.002	-0.010	0.000
Hospitality	-0.001	-0.010	0.000
Public admin.	-0.001	-0.008	0.000
Telecom	-0.001	-0.006	0.000
Publishing	-0.002	-0.005	-0.001
Real estate activities	-0.001	-0.004	0.000

Arts, entertainment,	-0.001	-0.003	0.000
Human health and social work	0.000	0.000	0.000
Education	0.000	0.000	0.000
Construction	0.000	0.000	0.000

Table 2.6: Total GDP losses after Trade War Tariff Change in percentage by sector with 2018 and 2015 data

	2018			2015		
	US	China	ROW	US	China	ROW
Com & Elec	**-0.021**	**-0.103**	**-0.013**	-0.016	-0.041	-0.005
Manuf2	-0.007	**-0.054**	**-0.002**	-0.01	-0.019	-0.001
Manuf1	-0.010	**-0.032**	-0.002	-0.011	-0.017	-0.003
Mining	**-0.018**	**-0.028**	**-0.006**	-0.005	-0.016	-0.001
Wholesale &retail	-0.006	**-0.022**	-0.001	-0.006	-0.014	-0.001
Transportation& storage	-0.006	**-0.022**	**-0.002**	-0.006	-0.014	-0.001

Results show several essential points: The common main targets of the trade war are the Computer & Electronic sector and the Manufacturing sector, both tariff level increases and the trade value involved lead to massive loss in GDP produced. The Com & Elec sector, with a 10% loss, shows the firm intention of the US to stop the evolution of Chinese tech companies such as ZTE and Huawei. The mining sector might not have the most significant decrease in terms of absolute value, but the dramatic increase of tariff from zero to 25 per cent from the US side and under 5 per cent to 15 per cent on the China side has forced a 2.8 per cent and 1.8 per cent of losses for China and the US. The losses in services sectors such as professional services and Wholesale & retail, despite no tariff change in those sectors, show that the tariff change in one sector can affect other highly interconnected sectors. The impact of tariff change will result in a multiplier effect, especially in the intermediate goods section. This leads to the most significant contribution of this paper: how the tariff affects intermediate goods and creates a much more significant impact than on final demand. Considering all the granular interactions from sector to sector in the intermediate good section, we witness around double the losses in China than just considering final demand and around four times more losses in the US than just considering final demand. Overall, China suffers more GDP losses than the US, but the US take more damage from the intermediate good section than the final demand section is a unique finding and needs more focus.

Figure 2.23: World Bank data on the US and China's annual GDP in $ trillion[15]

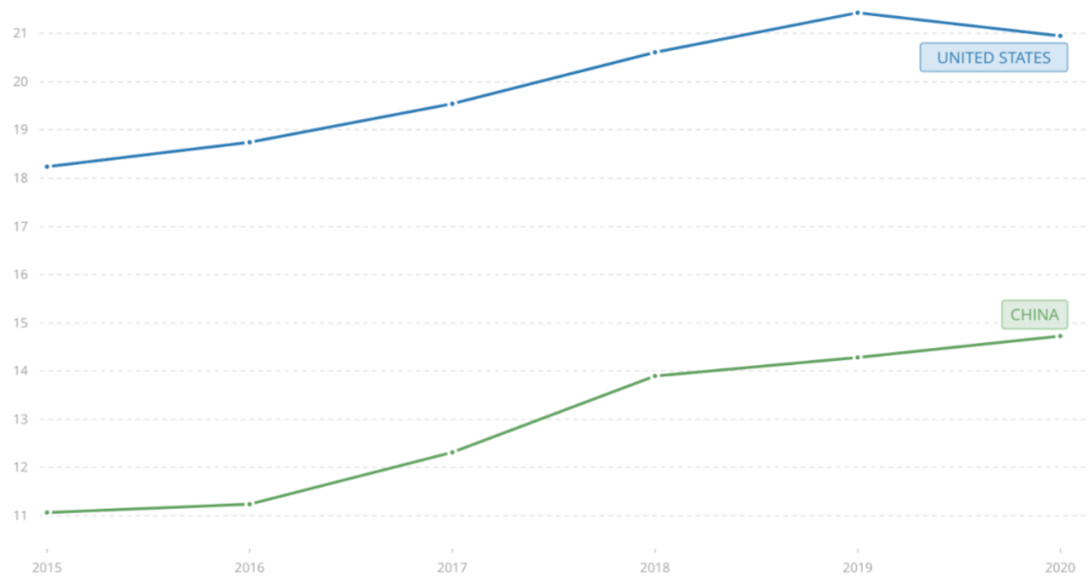
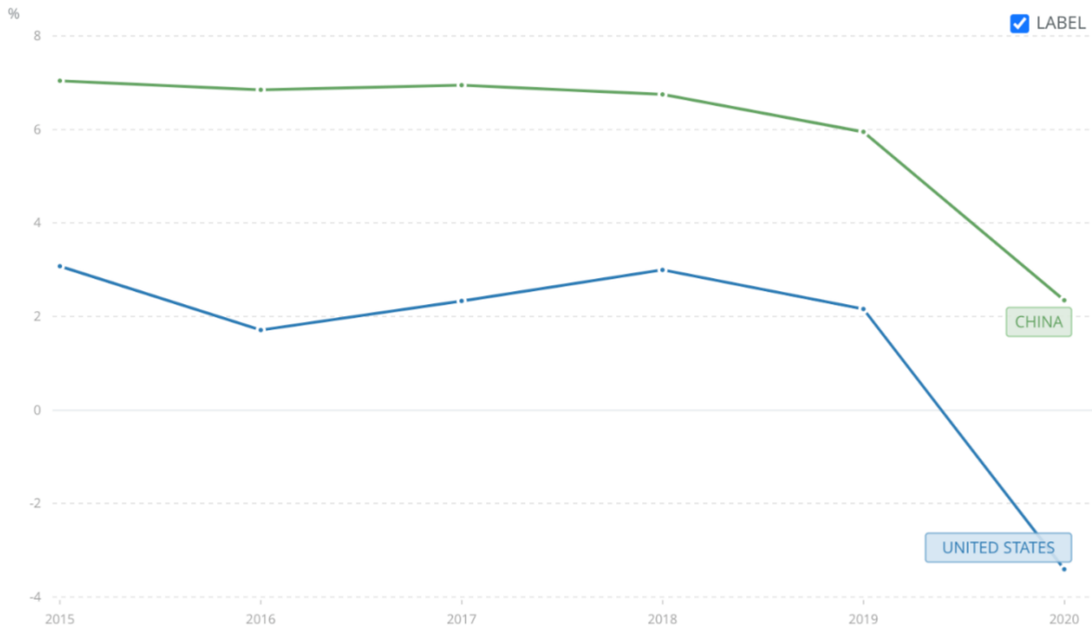


Figure 2.24: World Bank data on the US and China annual GDP growth %

15 Worldbank data on US and China annual GDP in $ trillion and annual GDP growth %https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?end=2020&locations=US-CN&start=2017



Comparing our analysis result and the real-world GDP data, we can see a strong semblance between the data from the World Bank and our results. Between 2018 and 2019, the amount of GDP of the US is still increasing but compared with from 2017 to 2018 it has gone flatter. However, you can see an apparent slowdown in the GDP increase for China. It shows that the trade war has affected China much more than the US. If we move on to the second graph, which is the percentage change of GDP growth, you can see both countries have less GDP growth from 2018 to 2019, those are the effects of the trade war. Both countries have suffered a negative impact, with a 0.8 drop in GDP growth in China and the US. In further research of Chapter 3, we will further examine the potential response strategy from US and China to the trade war.

2.5.5 Network interconnectedness Analysis

In this section, we visualize the interconnectivity among sectors and focus on the eigenvalues.

In the following figures in this section, the red nodes stand for net payer sectors, while the blue nodes mean net receiver sectors.

Figure 2.25: Connectivity network of US and China sectors in original 2018 ICIO data

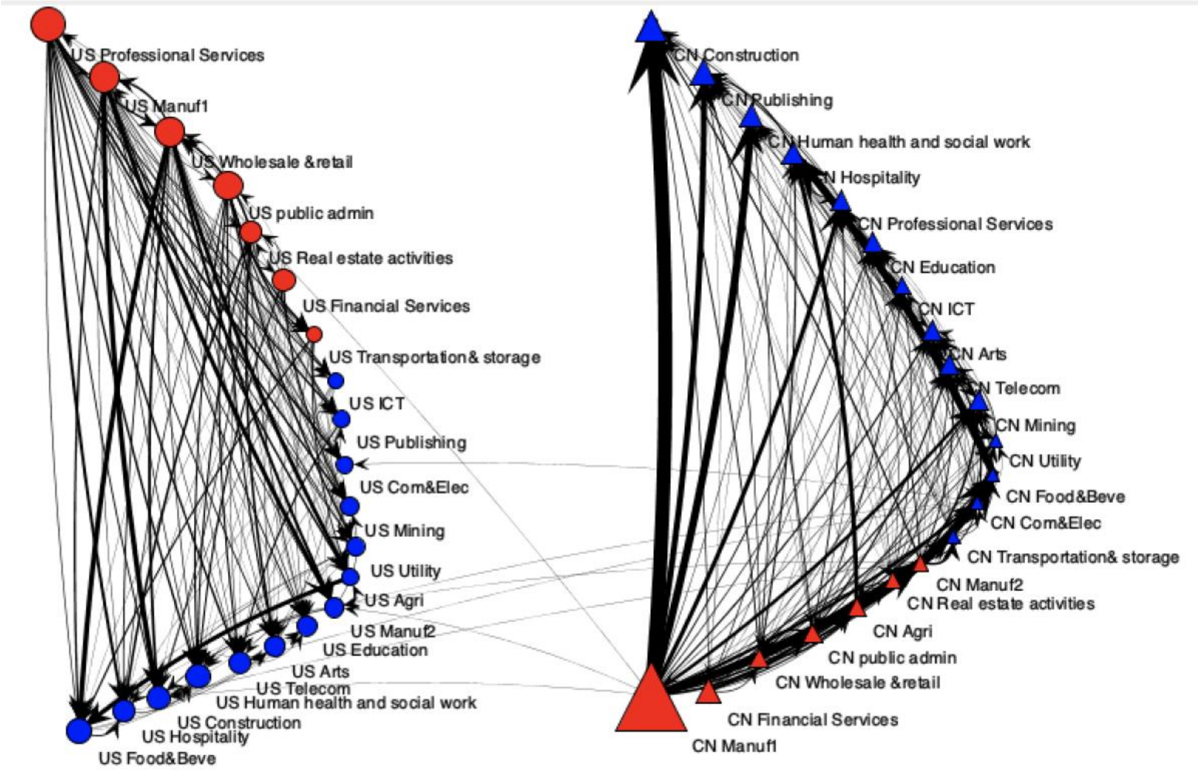


Figure 2.26: The connectivity network of US and China sectors in mixed tariff impacted 2018 ICIO data

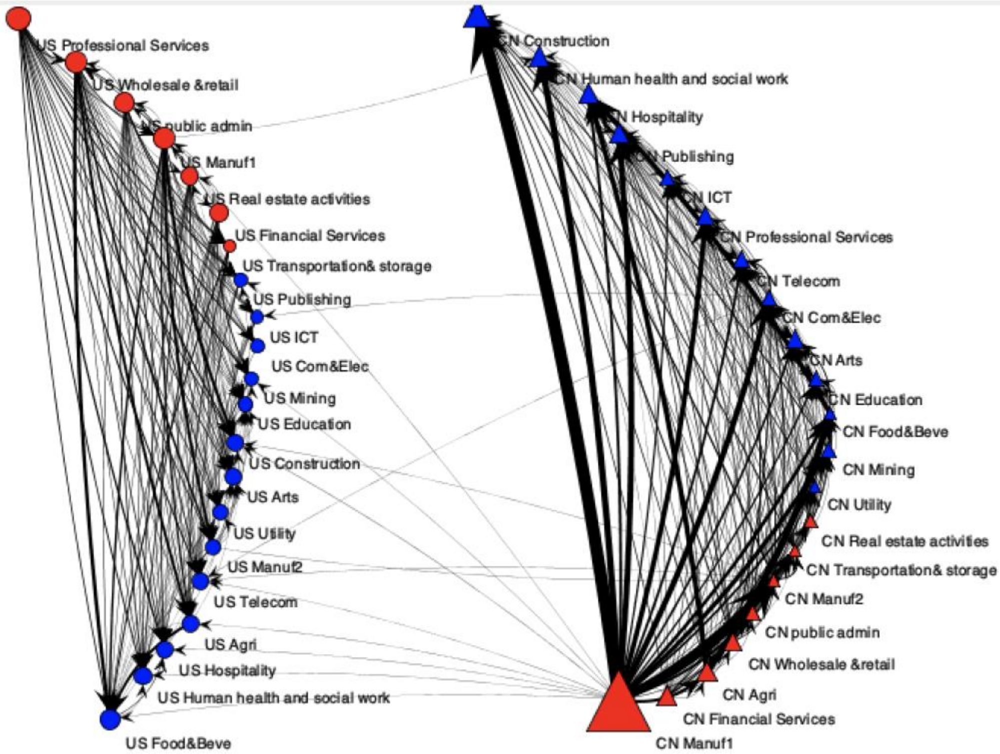


Figure 2.27: Cross-border connectivity network of US and China sectors in 2018 ICIO data

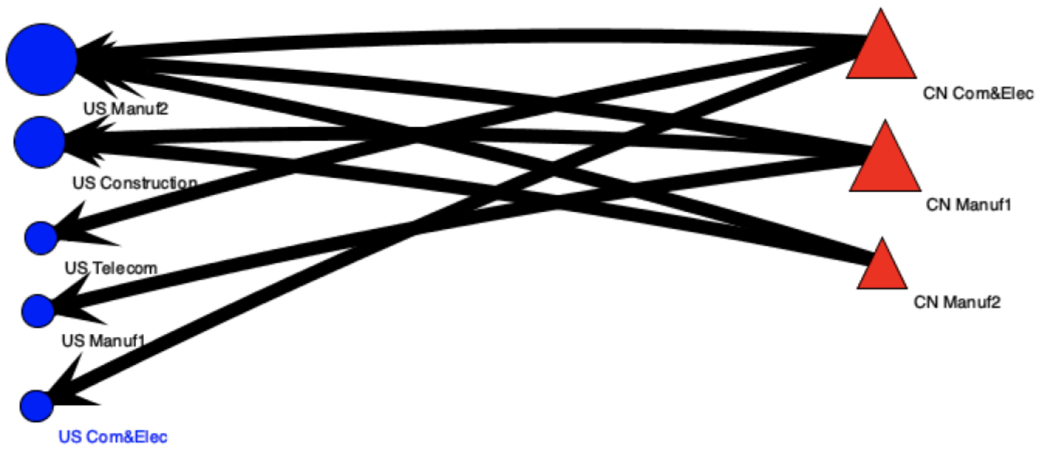


Figure 2.28: Cross-border connectivity network of US and China sectors in mixed tariff impacted 2018 ICIO data

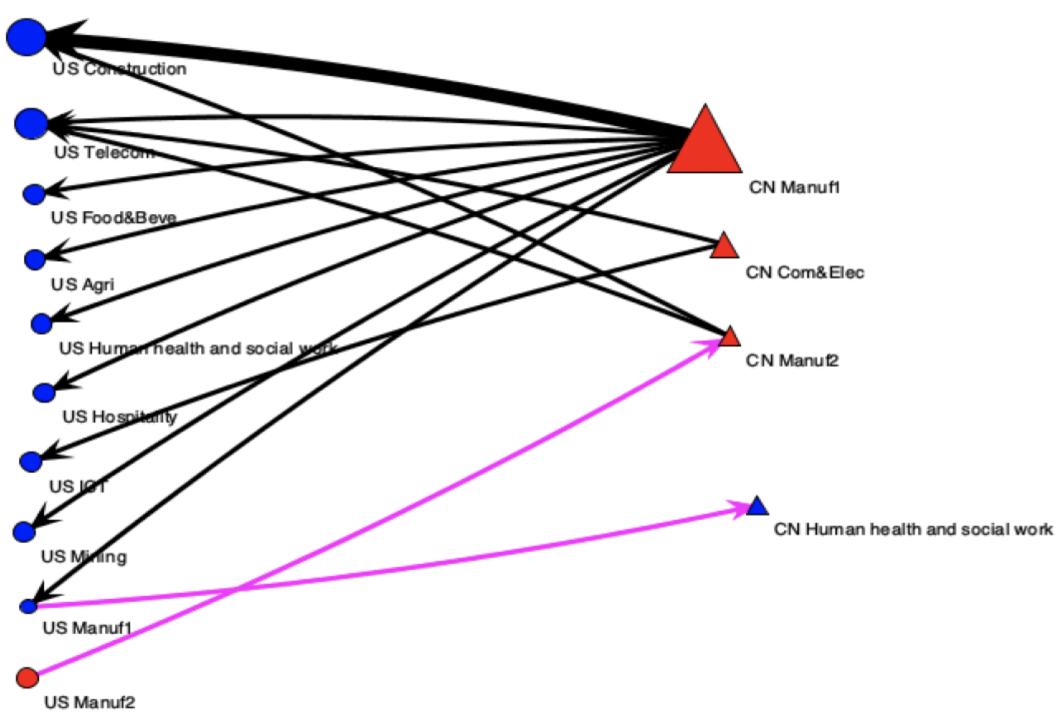


Figure 2.25 and Figure 2.26 show that in the Original data, the US is the cross-border net receiver in 5 sectors, including all the major ones, such as manufacturing and Computer &Electronic. In contrast, those sectors of China are the major net payers. That means China has been providing inputs from their manufacturing and Computer &Electronic sectors to the corresponding sectors in the US.

Our simulation shows that after the US targeted the tariffs of those significant sectors in China, the net imports from China dramatically shrank, and some other sectors took over some of the imports. However, the overall trade imbalance decreased and was split more evenly among the sectors.

Figure 2.29: Domestic connectivity network of US and China sectors in 2018 ICIO data

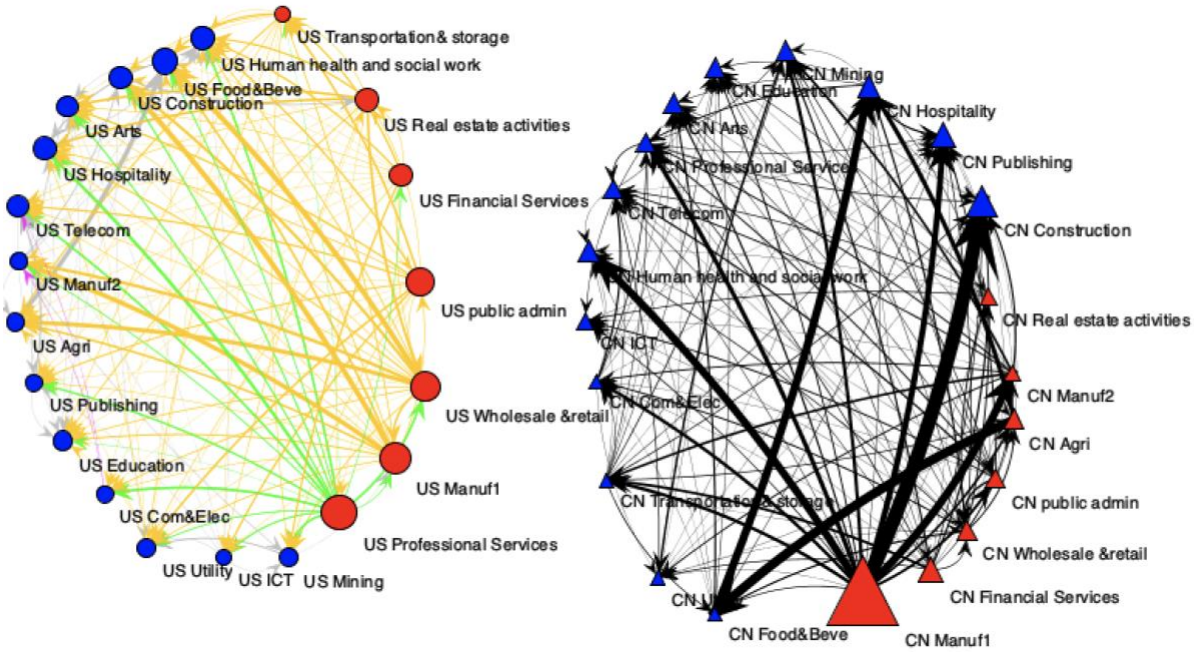
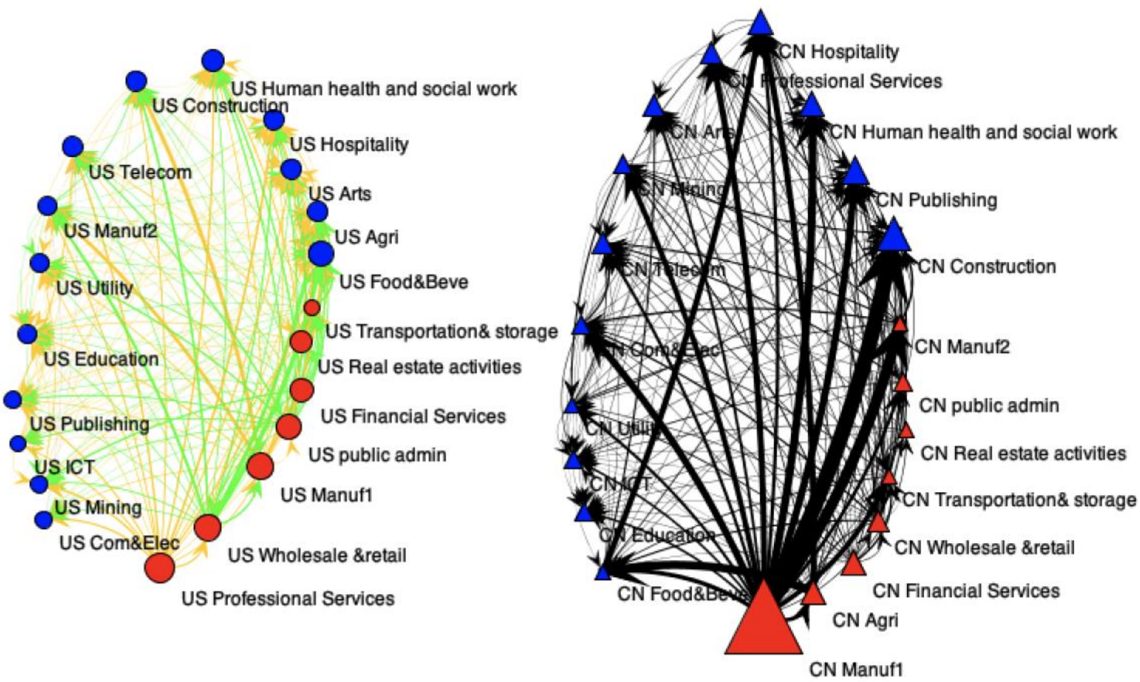


Figure 2.30: Domestic connectivity network of US and China sectors in mixed tariff impacted 2018 ICIO data



Domestically, neither the US nor China's input-output relation among sectors has witnessed significant changes. After the trade war hit the main trading sectors, the other sectors started to provide more and take more prominent roles in supplying inputs. However, sectors like US professional services and Chinese manufacturing-one still play the leading role in supplying domestic sectors.

These comparisons show that the trade war results in many shifts of cross-border trading, making some sectors lose interconnectedness, but it only rearranges the sector's domestic production role a little.

2.6 Conclusion

Two years of the US-China Trade War we witnessed battles in several fields, such as Agriculture, Manufacturing and Electronics. It reached a temporary truce with the Phase One trade deal, but the Trade War's impact has already occurred. In the paper, we applied the granular macro-net model to this issue. We used the Leontief production coefficient to demonstrate the importance of sectors in both countries, bringing the aspect of intermediate goods and how its interconnectedness plays a vital role in the Trade War picture. The trade war is essentially a battle of tariffs; with the US and China increasing the import tariffs on certain products, those products became less competitive in the market, inevitably impacting both supply and demand. Therefore, the first important step is to identify the changes that happened, and the granular macro network model tracks the changes down to each product. In contrast, many other models fail to consider that.

The results show a similar trend as some other research mentioned in the literature review, but the differences are significant, too. On the one hand, by bringing intermediate goods into perspective, this paper shows that the US has more of a disadvantage in this area than it shows in the final demand area; on the other hand, this paper applies tariff impact to the sectoral level and shows precisely how the sectors gain and lose connectivity with other sectors and which sectors witnesses decreases in input and output. These are the two significant contributions of the granular macro-network model to the topic of the impact of the US-China trade war.

The results have shown that the US started the Trade War to weaken China’s import volume, and they succeeded by targeting multiple sectors, especially Manufacturing and Computer and Electronic devices, with a 10% drop in GDP in Computer &Electronic. However, China's retaliation also damaged several US sectors, mainly Come& Elec and Mining.

Agriculture was also the primary target. Those are the direct impacts of the tariff changes; however, from the network interconnective model, we see that some other services sectors suffered from massive losses in gross output, such as wholesale & retail and the financial sector. Both sectors rely heavily on the production of goods sectors. This is an example of the chain effect of Tariff impacts.

Chapter 3 Respond strategy for demand/supply side shock on input-output data and constraints on Granular Network Model.

3.1 Introduction

As global supply chains grow increasingly complex and interconnected, localised economic disruptions frequently flow across borders. Recent crises like the US-China trade war and the COVID-19 pandemic demonstrated such dynamics, with impacts propagating across multiple industries and geographies (Bekkers & Rojas-Romagosa, 2021; McKibbin & Fernando, 2020). However, traditional partial equilibrium analyses overlook crucial production network spillovers along input-output linkages connecting sectors (Oosterhaven, 1988).

While the previous chapter centres on the 2018-2020 US-China trade conflict, this event's legacy continues to reshape global trade patterns. Recent signs show the emergence of gradual decoupling between the two superpowers with limited reversal of tariffs and import substitution, signalling more enduring relocations (Boz et al., 2022). New regional partnerships like the Comprehensive and Progressive Agreement for Trans-Pacific Partnership (CPTPP) and Regional Comprehensive Economic Partnership (RCEP) aim to solidify Asia-centred trade alliances. The latter agreement covering 15 Indo-Pacific nations took effect in 2022, and early modelling suggests increases in inter-regional trade and welfare over the next decade while potentially diverting trade away from non-members (Corong, 2022). Meanwhile, accelerating climate change brings shifting comparative advantages with new shipping pathways like the Arctic Northern Sea Route viable as the ice melts open access and countries race to capitalise on opportunities for cost and time savings (Bekkers et al., 2021). Understanding these evolving structural forces can aid strategic policy for countries.

This chapter explores strategic resilience policies to mitigate the losses of the US and China in different scenarios. Building on the granular network approaches developed earlier quantifying trade war impacts, scenarios incorporating trade diversion and import substitution are evaluated. Navigating crises requires such mapping of vulnerabilities intertwined across supply relationships with trading partners and domestic producers.

In this chapter, we adapt the trade diversion and demand substitution; we focus on the main sectors affected by the trade war and what strategy most reduces the impact on the sectors.

There are two strategies purposed: the first strategy is Demand Substitution, to increase domestic demand for the products affected by export demand decrease due to trade war tariff shock. The US has been actively adapting to this strategy, as the country initiated the trade war to “bring the job back to the states” (Trump’s 2016 election campaign) by cutting down imports from several major industries in China, e.g., electronics companies.

The second strategy is trade diversion:

Trade diversion means seeking alternative trading partners. With the geographical closeness with Mexico and Canada, the United States has expanded imports from these two neighbouring countries.

Some research shows that response strategies connect to established concepts like comparative advantage. Countries benefit by specialising where they are relatively more efficient and procuring other inputs from trade partners with reverse relative costs. However, temporary strategic interventions can prove prudent when comparable prices shift abruptly with large exogenous shocks (De Soyres et al., 2022). Accounting for the temporal lags and costs of realigning complex production relationships also influences critically adjusting optimal reactions (McKibbin & Fernando, 2021).

This chapter aim to contribute uniquely by integrating empirically detailed networks capturing sectoral interdependence with the consideration of several constraints. The capacity to represent granular levels of economic heterogeneity holds particular value for targeting resilience investments and policies. The integrated perspective developed here seeks insight into navigating increasingly inevitable disruptions.

The structure of Chapter 3 is the following:

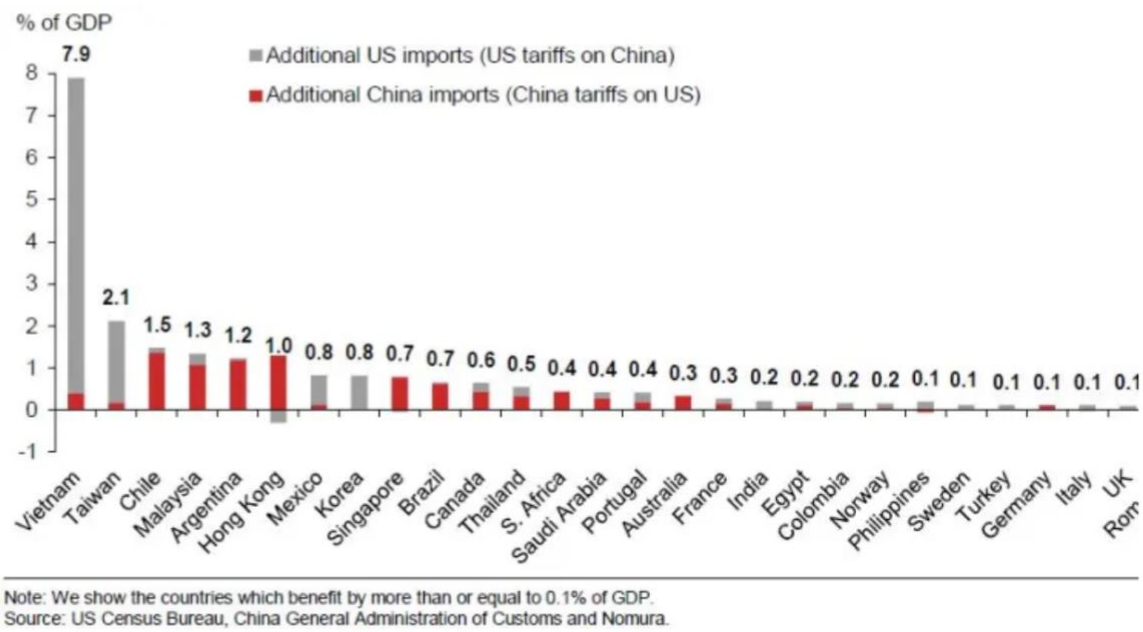
Section 2 is the Literature review of the response strategies of the US and China facing the Trade War, the role of the rest of the world and some predictions and analysis from other authors on this issue; section 3 shows the Methodology of the extension on the tariff shock model from chapter 1. We introduce three trade war response strategies: import substitution, trade diversion, and mixed strategy. Section 4 focuses on empirical results on the benefits and limitations of each strategy, the sectors that are affected the most by the different strategies, the impact on GDP under each scenario, followed by section 5, which concludes the paper.

3.2 Literature review

After two years of the trade war aftermath, several recent papers have analysed the economic impacts of the 2018-2020 US-China trade war using detailed trade data.

Onto fractural data analysis, the central focus has been quantifying the declines in bilateral trade flows between the US and China resulting from successive waves of retaliatory tariffs. Bown (2022) finds that Chinese exports dropped sharply for products facing 25% US tariffs but were largely unaffected for those with lower or no new tariffs imposed. However, overall, US imports from China remain substantially depressed in the post-trade-war years. Similarly, Huang et al. (2020) calculate a $36 billion annual reduction in US imports from China and a $17.5 billion decrease in Chinese imports from the US. The scale of observed declines varies considerably depending on product-level rates levied (Fajgelbaum et al. 2020). Moreover, depressed volumes persist through post-tension periods, exhibiting no sharp recovery as conflict declines (Bown 2022). Estimates indicate these shifts cumulatively lowered US real incomes to 0.5% while tripling China's GDP losses (Fajgelbaum et al., 2021). Consumer welfare plunged due to higher prices amid limited domestic firm gains (Cavallo et al., 2022). Much literature also documents trade war impacts across economic sectors and third countries other than. For instance, Totty (2023) describes the most benefited countries from the dispute, like Vietnam, which increased exports of products such as phones, furniture, and vacuum cleaners as US importers substituted away from more expensive Chinese goods. Specific countries benefited from diversion in distinct industries - Argentina and Chile exported more soybeans and copper to China, while Canada and Mexico sold more manufactured inputs to US firms. However, China experienced large revenue and output declines in exporting manufacturing sectors, as noted by Cigna et al. (2021).

Figure 3.1: The increased exports from Mexico and Vietnam to the US and China.



Source: (Lee, 2019).

Some exporters in the US and China may be willing to absorb part of the additional tariff costs in their profit margins, and some multinationals could opt to re-shore production, but the trade literature shows that, over time, the most enormous response is likely to be trade diversion,

A key issue explored in several papers is the extent to which the importing countries diverted trade towards third countries unaffected by the elevated bilateral tariffs. However, findings generally show limited trade diversion in the initial period of the dispute, with substitution effects building slowly over time. Charbonneau et al. (2018) argue that the significant negative direct impacts of the tariff hikes contrasted with modest trade diversion likely due to lags in importers shifting to new suppliers. Similarly, Cigna et al. (2021) find no surge of US imports from the rest of the world in the first year; diversion appears more prevalent as the bilateral tensions persist. The industry also matters - Flaaen and Pierce (2019) note that more sophisticated intermediate goods are harder to substitute and divert imports for than finished consumer goods.

The factor analyses broader ripple effects beyond directly impacted flows. Analyses underscore intermediate input distortions could multiply negative externalities by hampering third countries integrated with affected supply chains (De Soyres et al., 2022; Li et al., 2021). Empirical examination reveals tariff-triggered Chinese component losses vibrated across myriad US sectors unable to rapidly substitute such niche inputs (Cigna et al. 2021). However, initial forecasts of swift import diversion have not yet emerged, with evidence that substitution has gradually been built (Charbonneau et al. 2018; Totty 2023). Capturing complex dynamics behind such global propagation remains an ongoing challenge.

Some papers have also investigated uneven cost distribution across groups. Major exporting industries and consumer-facing retailers witnessed severe losses (Fajgelbaum et al. 2020), contrasting with insulated domestic manufacturers (Flaaen & Pierce 2019). Furthermore, significant within-sector firm heterogeneity predicated individual exposures and strategic responses based on pricing power, substitute access, scale, and structural flexibility/adaptivity

(Flaaen et al., 2020). Quantifying and merging such differential impacts across levels remains vital.

Moreover, empirical analyses highlight temporal evolutions. Overall responses imply modest initial diversion despite later acceleration (Cigna et al., 2021; Totty, 2023). Incorporating such complex dynamics - with lags between economic shocks and observable multi-sector trade adjustments – constitutes an ongoing but crucial frontier.

3.3 Methodology

In chapters 1 & 2, we introduced the Leontief inverse and Ghosh inverse to analyse the contribution of each sector in an economy. Then, we applied the partial extraction method on the direct impact of demand-side shock on final demand and supply-side shock on Value Added. Eventually, we found the effect of the shocks on GDP.

However, there were limitations to the method, as it did not consider the responses of the economies after applying the shocks. As mentioned in the literature review section, the US made clear response policies before and during the US-China Trader War.

In this section, we take into consideration the possible response strategies of the US and apply them to our original granular macro-network from chapters 1 and 2. Therefore, we further introduce the Trade Diversion and Domestic Substitution strategies after direct shocks.

As the US announced the tariff policies and China responded to it and told the counter policy, there can be four different scenarios: i: remain in the same trading relationship with each other under the new tariffs; ii: diverting the sectoral import demand from the counter country to alternative countries with fewer import tariffs; iii: substituting the sectoral import demand from the counter country for domestic demand; iv: combing all the options above to find the best strategy.

3.3.1 Trading Elasticity

This chapter has two determining factors for a response strategy: the targeted product/sector and the alternative trading country. Therefore, we need to have the trading volume of the sector and the corresponding country's trade elasticity.

The Imbs and Mejean (IM, 2017) paper illustrated that trade elasticities could be very different across countries and sectors. Therefore, it is essential to include heterogenous elasticities in the analysis. In addition, we used the database on elasticities from IM.

3.3.2 Trade Diversion

After the Trade War officially started, the US and China searched for alternative ways to meet commodity demands. Substituting imports from where they are relatively expensive to where they are cheaper will be a great way to handle it. Because China and the US are both in WTO, they mostly follow MFN tariff regulations. However, some tariffs will be much higher than MFN with the new tariffs. Therefore, they need to find other countries as a substitution. This involves altering the A and D matrices to consider this.

We are using the same three-country example equation 14 as before, from the element $\boldsymbol{a_{CU}}^* = a_{CU} + \dot{M}_C$, it is clear that $\dot{M}_C$ represents the change in import demand in China for US products. Now, suppose that China's import demand for products from the ROW changes by the same amount, so that China still imports the same amount; however, currently, it imports from the ROW instead of the EU. The modified A and D matrices now become:

$$A^{im} = \begin{bmatrix} a_{CC} & \boldsymbol{a_{CU*}} & a_{CR} \\ \boldsymbol{a_{UC*}} & a_{UU} & a_{UR} \\ \boldsymbol{a_{RC}^{TD}} & \boldsymbol{a_{RU}^{TD}} & a_{RR} \end{bmatrix} \quad D^{im} = \begin{bmatrix} d_{CC} & \boldsymbol{d_{CU*}} & d_{CR} \\ \boldsymbol{d_{UC*}} & d_{UU} & d_{UR} \\ \boldsymbol{d_{RC}^{TD}} & \boldsymbol{d_{RU}^{TD}} & d_{RR} \end{bmatrix} \qquad 3.1$$

Where $\boldsymbol{a_{RC}}^{\boldsymbol{TD}} = a_{RC} - \dot{M}_C$ and $\boldsymbol{D_{RC}}^{\boldsymbol{TD}} = D_{RC} - \dot{M}_C$, which shows the increased demand for imports from the ROW. Using these new matrices, it is then possible to calculate the new GDP as a result of this import substitution, given by:

$$GDP^{TD} = \boldsymbol{V}'(\boldsymbol{I} - \boldsymbol{A^{TD}})^{-1}\boldsymbol{D^{TD}}\boldsymbol{i} \tag{3.2}$$

This can then be used to find the change in VA as a result of post-Brexit import substitution with the ROW as given by:

$$DVA^{TD} = GDP_O - GDP^{TD} \tag{3.3}$$

3.3.3 Import Substitution

$$A^{im} = \begin{bmatrix} \boldsymbol{a_{CC}^{IM}} & \boldsymbol{a_{CU*}} & a_{CR} \\ \boldsymbol{a_{UC*}} & \boldsymbol{a_{UU}^{IM}} & a_{UR} \\ a_{RC} & a_{RU} & a_{RR} \end{bmatrix} \qquad D^{im} = \begin{bmatrix} \boldsymbol{d_{CC}^{IM}} & \boldsymbol{d_{CU*}} & d_{CR} \\ \boldsymbol{d_{UC*}} & \boldsymbol{d_{UU}^{IM}} & d_{UR} \\ d_{RC} & d_{RU} & d_{RR} \end{bmatrix} \tag{3.4}$$

Where$\boldsymbol{a_{CC}}^{\boldsymbol{IM}} = a_{CC} - \dot{M}_C$ and $\boldsymbol{d_{CC}}^{\boldsymbol{IM}} = d_{CC} - \dot{M}_C$, which shows the increased demand for imports from the ROW. Using these new matrices, it is then possible to calculate the new GDP as a result of this import substitution, given by:

$$GDP^{IM} = \boldsymbol{V}'(\boldsymbol{I} - \boldsymbol{A^{IM}})^{-1}\boldsymbol{D^{IM}}\boldsymbol{i} \tag{3.5}$$

This can then be used to find the change in VA as a result of post-Brexit import substitution with the ROW as given by:

$$DVA^{IM} = GDP_O - GDP^{IM} \tag{3.6}$$

3.3.4 Mixed respond strategy

In the mixed respond strategy, we consider both domestic and oversea supply/demand substitution. The technical coefficient adjustment is decided by the original level.

$$A^{MX} = \begin{bmatrix} \boldsymbol{a_{CC}^{IM}} & \boldsymbol{a_{CU*}} & a_{CR} \\ \boldsymbol{a_{UC*}} & \boldsymbol{a_{UU}^{IM}} & a_{UR} \\ \boldsymbol{a_{RC}^{TD}} & \boldsymbol{a_{RU}^{TD}} & a_{RR} \end{bmatrix} \qquad D^{MX} = \begin{bmatrix} \boldsymbol{d_{CC}^{IM}} & \boldsymbol{d_{CU*}} & d_{CR} \\ \boldsymbol{d_{UC*}} & \boldsymbol{d_{UU}^{IM}} & d_{UR} \\ \boldsymbol{d_{Rc}^{TD}} & \boldsymbol{d_{RU}^{TD}} & d_{RR} \end{bmatrix} \tag{3.7}$$

Where $\boldsymbol{a_{CC}^{IM}}= a_{CC} - \frac{\dot{M}_C * a_{CC}}{a_{CC} + a_{RC}}$ and $\boldsymbol{a_{RC}^{TD}}= a_{RC} - \frac{\dot{M}_C * a_{RC}}{a_{CC} + a_{RC}}$,the change in $\boldsymbol{a_{UC}}$ is redistributed to both domestic demand and rest of the world demand proportionately, again same method applies to the final demand changes as well.

3.4 Analysis results

We aim to study the total impact of trade diversion, import substitution, and mixed strategy If these strategies are applied to all the sectors affected by trade wall tariffs.

Without considering the intermediate goods section, the impact on sector final demand can be rather simple under the four different scenarios. China witness decreases in or scenarios as it is not able to recover from the dramatic cut down of export to the US, the US gains final demand when they decide to substitute input domestically or choose the mixed strategy. The rest of the world would gain final demand on the scenarios involving trade diversion. Overall, the net decrease in final demand for China with benefit the US and the rest of the world since the decrease amount will be distributed.

Figure 3.2: The US-China Trade War impact on sectoral final demand of US, China and Rest of the world under 4 different respond strategies

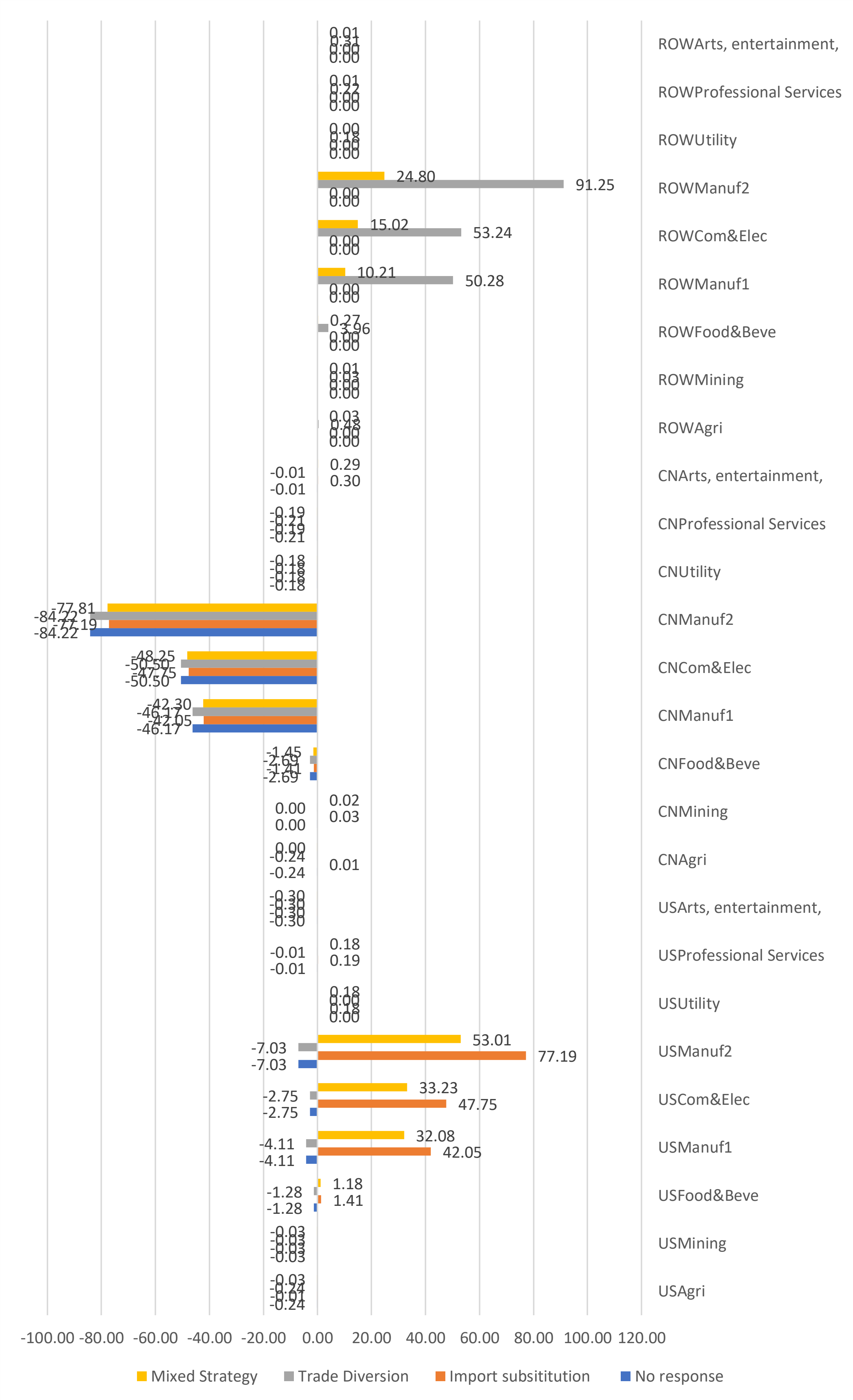
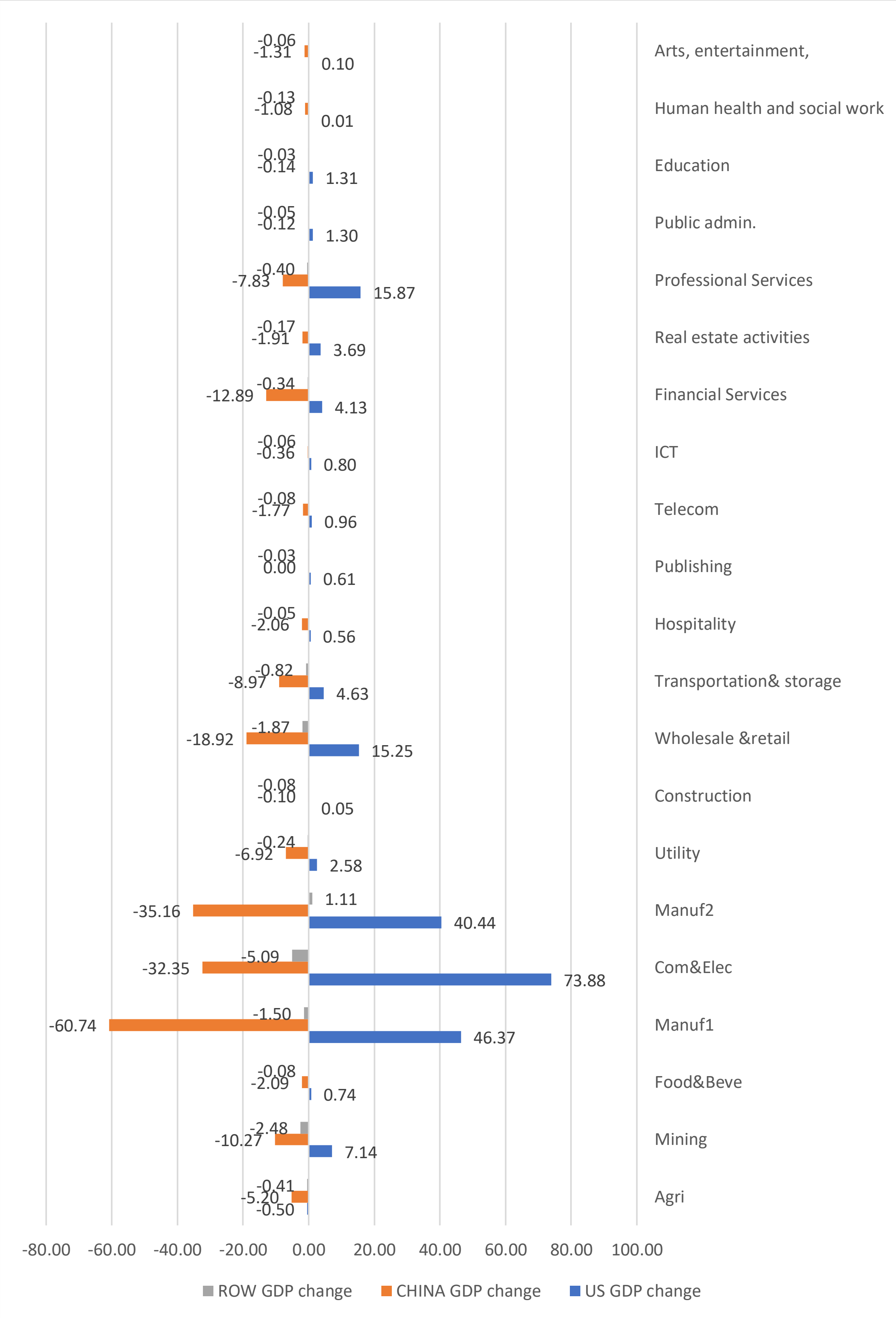

ROWArts, entertainment,
ROWProfessional Services
ROWUtility
ROWManuf2
ROWCom&Elec
ROWManuf1
ROWFood&Beve
ROWMining
ROWAgri
CNArts, entertainment,
CNProfessional Services
CNUtility
CNManuf2
CNCom&Elec
CNManuf1
CNFood&Beve
CNMining
CNAgri
USArts, entertainment,
USProfessional Services
USUtility
USManuf2
USCom&Elec
USManuf1
USFood&Beve
USMining
USAgri
24.80
91.25
15.02
53.24
10.21
50.28
-77.81
-84.22
-77.19
-84.22
-48.25
-50.50
-47.75
-50.50
-42.30
-46.17
-42.05
-46.17
53.01
77.19
-7.03
-7.03
33.23
47.75
-2.75
-2.75
32.08
42.05
-4.11
-4.11
1.18
1.41
-1.28
-1.28
-100.00 -80.00 -60.00 -40.00 -20.00 0.00 20.00 40.00 60.00 80.00 100.00 120.00
Mixed Strategy
Trade Diversion
Import subsititution
No response

Figure 3.3: Trade War total impact on GDP in US China and ROW under import substitution ($Bn)

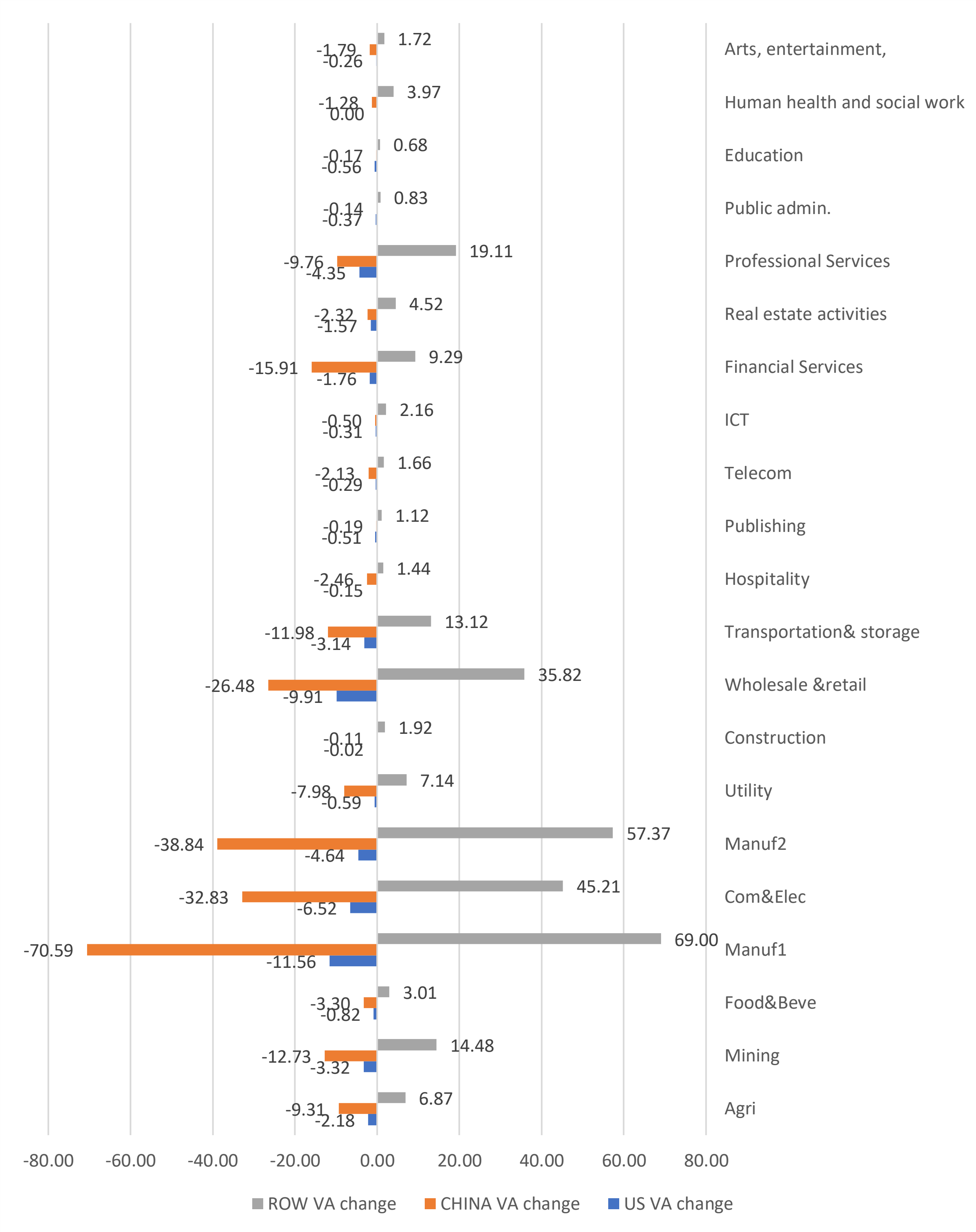


In the import substitution scenario, we see a negative overall impact on China's GDP but a positive increase in the US. Despite witnessing no tariff adjustments and not being the substitute trading partner, the rest of the world is still affected in specific sectors. In this scenario, we can see that in a perfect domestic substitution scenario, China would have a large negative change in sectors such as manufacturing and computer and electronics. Whereas the US GDP increases correspondingly.

This perfect scenario assumes that all of the import from China to US are replaced by US domestic production, which, in reality would not be the case. With a big difference between Chinese export to US and US export to China, we can see in the world, the US would indeed "bring the jobs home".

Rather than a reflection of what a realistic, domestic substitution will look like, this scenario portraits the bigger role of exporter China is.

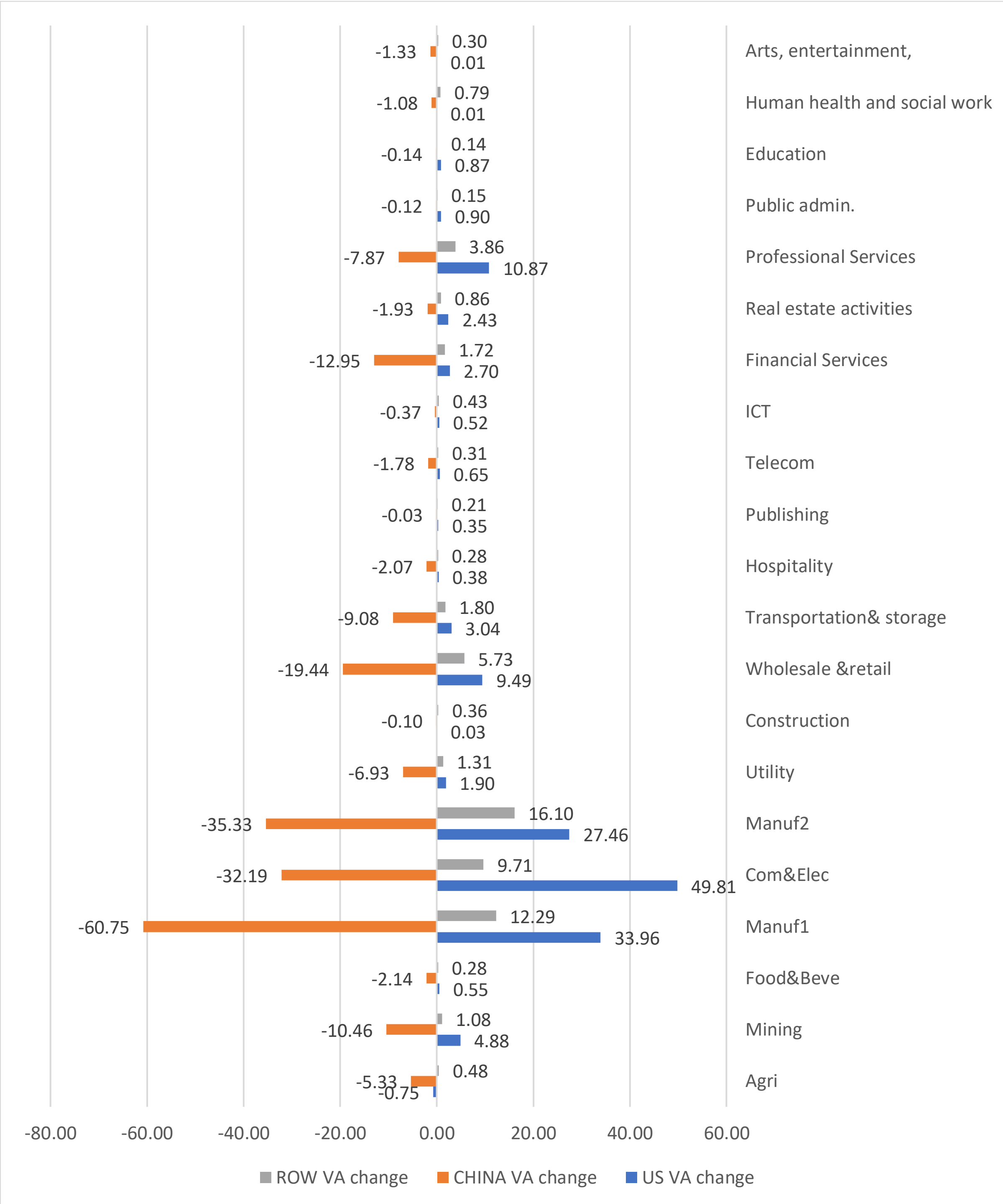
Figure 3.4: Trade War total impact on GDP in US China and ROW under Trade Diversion ($Bn)



In this scenario of trade diversion, we see the total opposite of the previous scenario.

In this scenario, we assume all the difference in export will be perfectly substituted by a alternative trading partners in the rest of world for both countries. The main changes still occur for the manufacturing computer and electronic sectors since they are affected by the most significant change in tariff. But instead of the US benefiting from the trade diversion, it also witnesses a decrease like China, but on a smaller scale. While the rest of the world, especially the countries that provide products from manufacturing computer and electronic sectors.

Figure 3.5: Trade War total impact on GDP in US China and ROW under Mixed Strategy scenario ($Bn)



In the mixed strategies scenario, the results are closer to reality as the cutdown from both countries is proportionally distributed to domestic production and imports from the rest of the world. While this scenario still has limitations, such as the constraint of domestic supply and demand, the rest of the world is assumed to be unified and share the same sectoral and national import elasticity.

Now, we focus on the sectoral changes in all parties. China's three most significant sectors together witness nearly 130 billion dollars of decrease in GDP, which are redistributed to the rest of the world and the US; that's the result of the major cutdown from the biggest importer, the US. China's wholesale retail, mining and agriculture sectors are also witnessing different levels of decrease. All these physical production sectors are directly affected by the change in tariff. In contrast, some of the service sectors are affected indirectly, such as the financial service sector and the professional service sector. These are shown because their intermediate goods section has extensive connectivity to other sectors, making them the most important and the most vulnerable.

3.5 Conclusion

This paper has analysed potential strategic responses by the US and China to mitigate economic losses resulting from the 2018-2020 bilateral trade war. By extending the granular trade network model developed in earlier sections, three scenarios were evaluated: trade diversion to alternative import partners, domestic import substitution, and a mixed approach combining both strategies.

Results indicate substantial variation across scenarios and sectors. For China's major exporting industries like manufacturing and computers/electronics, deteriorating US export demand exacted large GDP costs absent effective substitutes. However, the US also witnessed negative ripple effects once intermediate input distortions were incorporated. Pursuing import substitution proved beneficial for the US but infeasible to replace lost Chinese inputs fully. Meanwhile trade diversion shifted losses onto third countries.

These outcomes showcase the complexity of strategic trade responses given economic interdependence. They underscore the value of data-driven modelling to map vulnerability and assist resilience policies. Yet assumptions around elasticities and aggregations constitute simplifications. Future work should integrate updated data and parameters while representing granular firm behaviours. A deeper analysis of phase-in constraints and time lags would also prove valuable.

Overall, the integrated perspective developed here lends insight into the multi-faceted repercussions propagating across sectors and borders as the trade war played out. Quantifying mechanisms and knock-on effects aid targeted support and recovery efforts when crisis events disrupt interconnected global supply chains.

Chapter 4 Granular Macro-Net Model Application to US Economy under Covid-19 Impact

4.1 Introduction

4.1.1 Post-COVID-19 Global Supply Chain Model

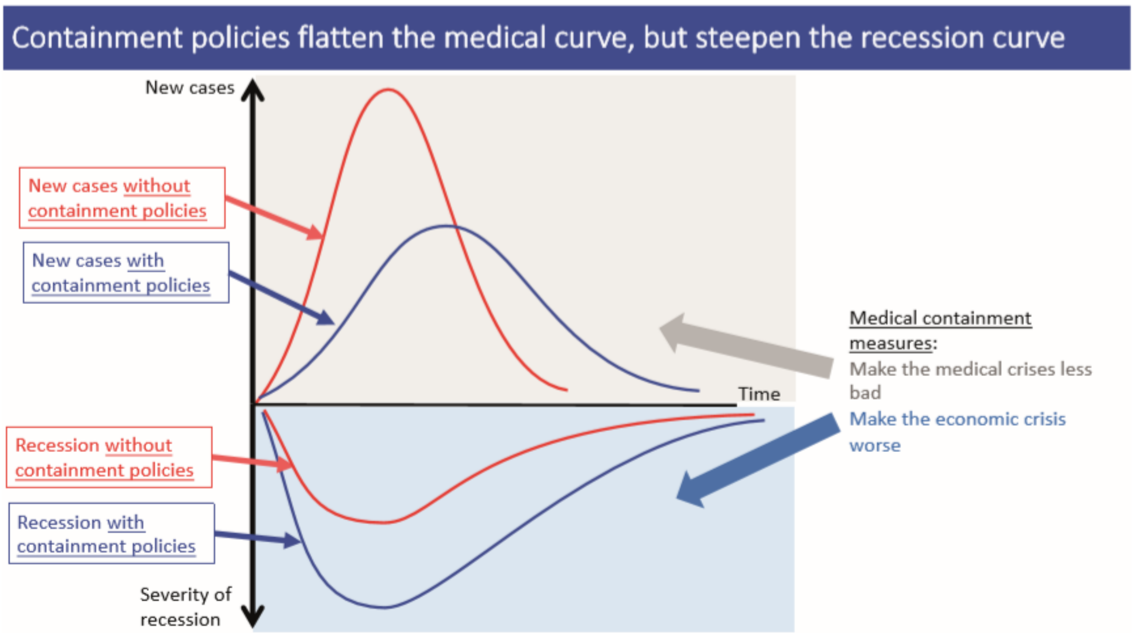
In chapter one, we analysed the impact of the US-China Trade War on the US and China using the granular macro-network model. This has now taken a back seat while the world grapples with COVID-19, a major macroeconomic problem related to the US-China trade war and its resolution.

Starting from January 2020, COVID-19 initially was a national crisis in China, followed by Italy. Still, due to the highly contagious nature of this virus, it became a worldwide pandemic by the end of March 2020. It not only puts millions of lives and well-being in danger but also puts economies at risk. In May 2023, more than three years into the pandemic, the WHO Emergency Committee on COVID-19 recommended that the global emergency COVID-19 has caused is over. Hence, the global pandemic came to an end, but the economic impact it has had on many countries is still present.

Since the first COVID lockdown in Wuhan, China, in March 2020, most countries and regions, including the United States, have followed similar procedures. The purpose of a lockdown is to "flatten the epidemic curve" by reducing physical contact and, hence, the spread of the virus. This implies a trade-off and an economic cost. The simulations provided by Ferguson et al. (2020) show how, in the case of the UK, the number of patients in critical condition will exceed the surge critical care bed capacity if lockdowns are not in force. Moreover, the lack of bed capacity will increase the death rate. On the other hand, isolation and quarantine measures can flatten the epidemic curve.

However, when the medical curve is flattened, the recession curve will get steeper and deeper without policy rescue packages. As discussed by Gourinchas (2020), the challenge for economic modellers is to see what macroeconomic costs follow due to containment with the lockdown of sectors when viewed with and without policy rescue packages, as shown. Baldwin et al. (2020) made simulations of these curves inspired by the illustrations of Gourinchas (2020), which show that the epidemic and recession curves are anti-correlated. The stricter the containment policy is, the slower the number of new cases arises. However, this "flatten the curve" strategy will directly cause a deeper recession and make the economic crisis even harder to address.

Figure 4.1: Epidemic and recession curves: With and without Containment Policies – flattening and steepening.



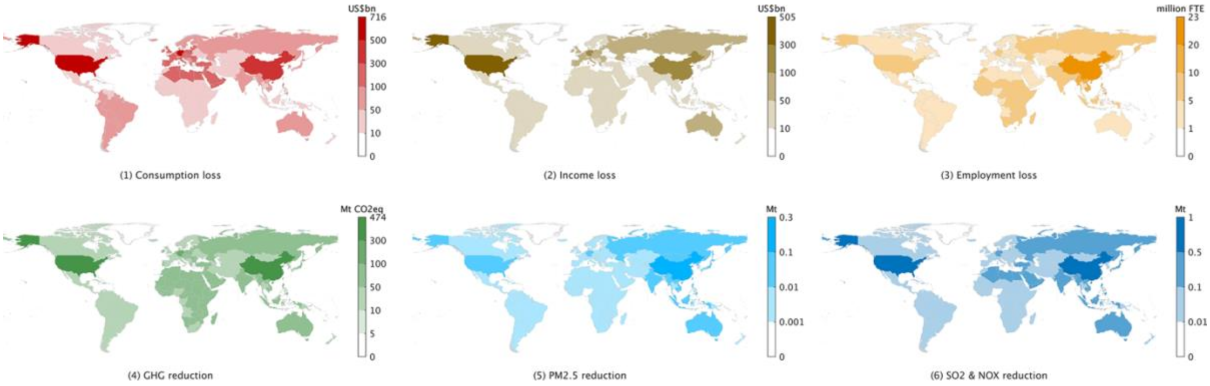
Source: Elaboration from Baldwin et al. (2020), inspired by illustrations of Gourinchas (2020).
Note that containment here means isolation and lockdowns.

Gourinchas (2020) also pointed out that economic shock comes with different layers: medical shocks, such as workers not producing GDP, the economic impacts of containment measures, and expectation shocks. Specifically, Gourinchas mentioned in his paper: “A modern economy is a complex web of interconnected parties: employees, firms, suppliers, consumers, banks, and financial intermediaries. Everyone is someone else’s employee, customer, lender, etc.” In our model, the same idea is implied: a modern world economy is a more extensive and complex web, which is why the granular macro-net model is an excellent tool for analysing the impact of COVID-19.

Gourinchas's sombre analysis cautions that even if the direct health crisis of the pandemic recedes, the "virus" could essentially mutate into an economic recession. He uses ominous language, warning of this "mutation" inflicting continued damage by infecting the very economic system we rely upon. Though not as deadly as the raw viral outbreak, this economic mutation could nonetheless cause substantial harm. Just as public health officials have focused on "flattening the epidemiological curve," Gourinchas argues economic policymakers must flatten the recession curve. Rather than offering optimistic predictions or reassurance, his paper sounds the alarm about the virus' lingering impacts, which could metastasize into macroeconomic calamities even after initial health containment.

Gourinchas's paper did not bring up optimistic predictions. Instead, it spotted some issues we will be facing, "a real danger is that the virus mutates and infects our economic system even as we manage to root it out of our bodies. Its economic form is not as deadly but can nonetheless do real damage." That is why "flattening the curve" is also necessary for macroeconomic recession.

Figure 4.2: Global impacts from the COVID-19 pandemic broken down by world region.



Source: Lenzen et al. (2020)

Lenzen et al. (2020) disaggregate the pandemic's impacts across multiple dimensions. Countries with widespread viral transmission and stringent lockdowns, like China, the United States, and Italy, suffer the largest consumption and income declines. OPEC members face income losses as transport reductions, especially in aviation, suppress oil extraction and refining. Job losses concentrate in lower-wage nations like China and India. Greenhouse gas emissions fall globally but most sharply in emissions-intensive China and North America compared to Europe. Fine particulate matter pollution (PM2.5) reductions center on China and India, while transport and energy-linked SO2 and NOx emissions also drop across Asia and the Americas. The multidimensional breakdown provides nuanced profiles of varied viral impacts among countries and economic sectors.

In this paper, we focus on the economic impact of the COVID-19 pandemic, precisely, the impact of the sectoral lockdowns in the US. We try to explain how the sector gets affected by different lengths and strengths of lockdown and how government intervention takes the role of economic recovery; after taking into consideration that intermediate goods transactions also get affected besides the final demand, how much GDP loss would occur in the US, and more in which sectors.

The structure of Chapter 4 is the following:

Section 2 is a Literature review and technical details for COVID-19 including research on COVID lockdown from different perspectives; section 3 shows the Methodology of the Global Granular Macro-Net model, Hypothetical Extraction Method (HEM) for supply and demand shocks from sectoral COVID-19 lockdown; COVID-19 lockdown ratio, lockdown phases, and government intervention; section 4 describes the database we are working with some general insights and characteristics. Section 5 focuses on empirical results on COVID-19 sectoral lockdown impact on the US under several scenarios varying from differences in Shock direction, direct and indirect effects, lockdown duration and government interventions, followed by section 6, which concludes the paper.

4.2 Literature and Technical Review

4.2.1 Technical Details of the COVID-19 Pandemic

4.2.1.1 *Lockdown periods and the trade-off between economy state and public health*

Many researchers have discussed COVID-19's impact on the global economy since the beginning of the pandemic, and many papers have their unique research directions and areas. Compared with our paper, some other papers have similar approaches that can be referenced, while others have analysis results on the same topic under different methods that we can observe.

Since the COVID-19 lockdown took place in March/April 2020, much research has been analysing the impact of lockdown measures, such as which measures are more effective, the consequences of lockdowns, etc.

The paper of the European Network for Economic and Fiscal Policy Research (Dorn F et al. 2020) on the Economic Costs of the COVID Shutdown in Germany set six scenarios on the impact of shutdowns and predicted an economic shrink by 4.3 to 20.6 percentage points in

Germany. The variation depends on the level of macroeconomic value-added decline and the duration of the post-shutdown phase. They also mentioned the effect on the labour market; specifically, a shutdown of one-month results in a loss of 160,000 to 340,000 jobs subject to social insurance contributions. If the shutdown lasts three months, the losses increase to 780,000 to 1.8 million employment relationships subject to social insurance contributions. In the worst-case scenario, almost 5 per cent of the labour market will lose their job based on the record of total employment on the *Statista* website.

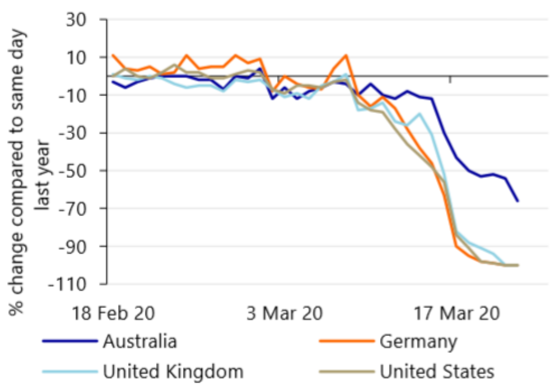
The circumstance of Germany is not unique or isolated; some papers acknowledge COVID-19 as a human-transmitted disease and have a strong network contagious nature, which makes network analysis a more suitable method. Chen et al. (2021) consider this factor and combine epidemiological and economic models using the same ICIO I-O dataset as our paper. They analysed three government interventions with different lockdown durations to find the best trade-off between infection/death rates and GDP losses. The optimal scenario was 90% compliance and a 45-day lockdown, resulting in a $3.4 trillion economic loss but saving 110,000 lives and preventing 115 million infections. This model mainly analyses trade-offs at the sectoral level and highlights the importance of simulation-based analysis for guiding public health policy decisions. At the same time, our paper focuses on the recovery strategy after fixed lockdown periods, considering government interventions as stress relief for workers and their impact on demands.

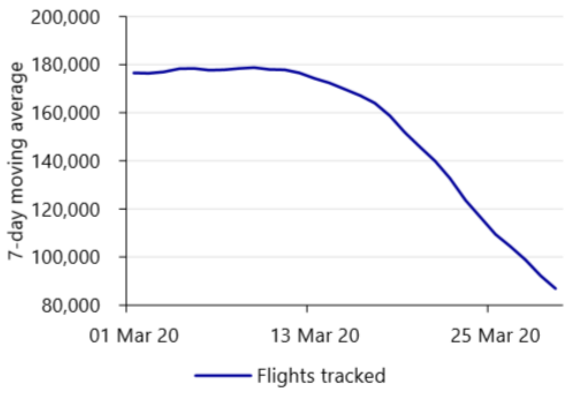
4.2.1.2 *Industries Affected*

Erken et al. (2020) from Rabobank illustrated that some sectors are taking bigger hits in the US than others. On auto sales, the number of global flights taken, and restaurant bookings all sketch a grim picture. It says:” In many respects, this is almost the perfect economic storm of collapsing demand and supply feeding on each.”

Figure 4.3: Restaurant bookings have collapsed.(Left)

Figure 4.4: Flights have been cancelled.(Right)





Source: OpenBook

Source: Flightradar24

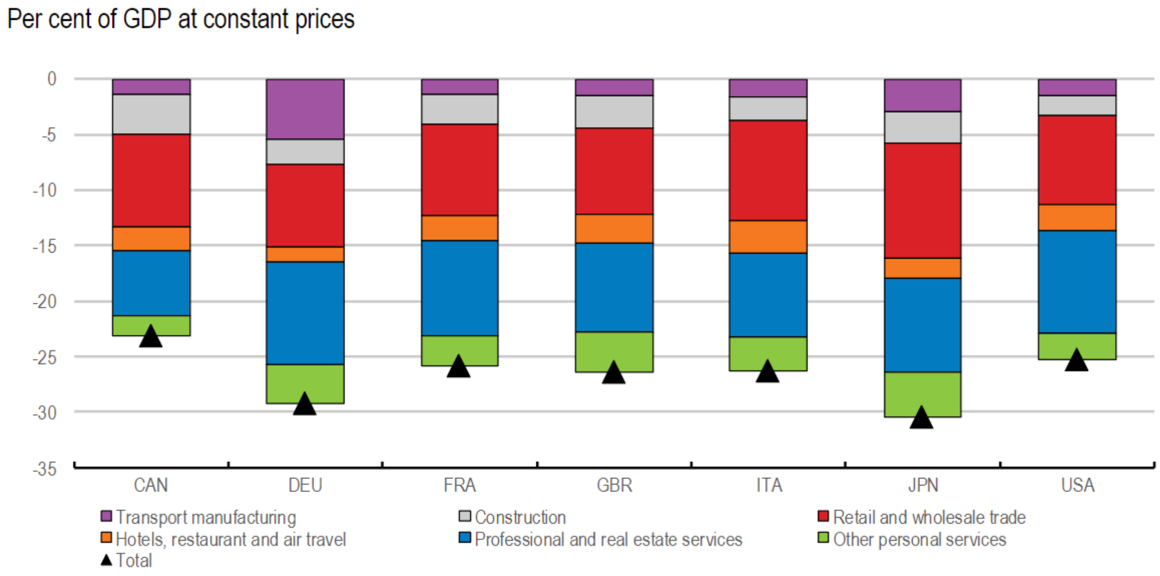
Hospitality and Air transport are hit instantly and significantly by the COVID-19 lockdowns. Still, the need for more productivity affects more sectors, such as retail and other professional/personal services.

OECD has predicted the initial impact of sectoral shutdowns; apart from the sectors mentioned above as the most affected sectors, non-service sectors like transport manufacturing and construction are also affected:

Figure 4.5: The potential initial impact of partial or complete shutdowns on activity in the G7 economies[16]

[16] Note: The sectoral data are on an ISIC rev. 4 basis in all countries. The sectors included are manufacturing of transport equipment (ISIC V29-30), construction (VF), wholesale and retail trade (VG), air transport (V51), accommodation and food services (VI), real estate services excluding imputed rent (VL-V68A), professional service activities (VM), arts, entertainment, and recreation (VR), and other service activities (VS). The latter two are grouped as other personal services in the figure. Real estate services, excluding imputed rent, are assumed to be 40% of total real estate services in countries where separate data are unavailable. Complete shutdowns are assumed in transport manufacturing and other personal services; declines of one-half are assumed for output in construction and professional service activities; and declines of three-quarters are assumed in all the other output categories directly affected by shutdowns. The calculations are based on an assumption of an economy-wide shutdown rather than a shutdown confined to particular regions only.

Source: OECD Annual National Accounts; and OECD calculations.



4.2.1.3 *Government intervention and stimulus package*

On the 25th of March, the US Senate passed the historical Covid-19 stimulus package. The initial size of the package was $2.2 trillion, but it quickly grew to $3.6 trillion (on the 15th of June). In addition, The Federal Reserve initiated several actions, such as asset purchases and emergency lending, which could total as much as $ 5.9 trillion (*COVID Money Tracker: Policies Enacted to Date*, 2020).

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https://www.oecd-ilibrary.org/sites/fe40a82a-en/index.html?itemId=/content/component/fe40a82a-en#:~:text=The%20sectors%20in%20which%20shutdowns%20were%20assumed%20to,impact%20on%20GDP%20in%20the%20national%20shutdown%20estimates

Table 4.1: The United States Covid-19 stimulus package

Response	Allowed	Disbursed/ Committed
Legislative Actions	**$3.6 trillion**	**$1.8 trillion**
Coronavirus Preparedness & Response Supplemental Appropriations Act	$8 billion	~$3 billion
Families First Coronavirus Response Act	$192 billion	~$52 billion
CARES Act	$2.7 trillion	$1.4 trillion
Paycheck Protection Program and Health Care Enhancement Act	$733 billion	$287 billion
Paycheck Protection Program Flexibility Act	Unknown	Unknown
Administrative Actions	**~$380 billion**	**~$307 billion**
Declare national emergency	~$50 billion	Unknown
Delay tax filing deadline to July 15	~$300 billion	~$300 billion
Other executive actions	~$30 billion	$7 billion
Federal Reserve Actions	**>$5.9 trillion**	**$2.4 trillion**
Interest rate changes	N/A	N/A
Asset purchases	$1.9 trillion**	$1.8 trillion
Liquidity measures	>$1.9 trillion	$470 billion
Emergency lending programs and facilities	>$2.1 trillion	$188 billion

Source: (COVID Money Tracker: Policies Enacted To Date, 2020)

The centrepiece of the US pandemic stimulus is the $2.7 trillion Coronavirus Aid, Relief and Economic Security (CARES) Act. The relief targets individuals and families through measures like expanded unemployment benefits, student loan suspensions, tax deductions, and medical aid. Direct payments provided up to $1,200 for adults earning under $99,000 annually and $500 per child. The CARES Act also incentivizes business retention of employees via 50 percent credit on up to $10,000 of wages paid between March 13 and December 31. Additionally, the Act allocated $600 weekly pandemic unemployment payments for COVID-related job losses. Though substantial, the relief remains temporary and narrowly targeted, with calls for enhanced aid such as expanded eligibility, larger direct payments, and state and local government assistance.

The most significant part of the stimulus package to date is the Coronavirus Aid, Relief and Economic Security Act (CARES Act), which allowed $2.7 trillion to be spent on emergency assistance and health care response for individuals, families, and businesses affected by the COVID-19 pandemic (*COVID Money Tracker: Policies Enacted To Date*, 2020). The relief is given to individuals who incorporate unemployment benefits, student loans, tax deductions, retirement plans and medical services. The Cares Act assists workers and their families by providing up to $1200 per adult earning less than $99,000/year and $500 per child under 17 years of age. Moreover, to incentivise businesses to keep employees on the payroll, it offers them a 50 per cent credit on up to $10,000 of wages paid or incurred between the 13th of March and the 31st of December. The cherry on the cake was what has been referred to as pandemic unemployment insurance, which gave a weekly payment of $600 to anyone unemployed because of COVID-19 (Smith, 2020).

Consequently, despite the extreme spike in unemployment, the pandemic unemployment insurance payment has caused the number of U.S. citizens living in poverty to drop (Han, Meyer, and Sullivan, 2020).

To break the relief packages down into sectors, we collected the data from the Committee for a Responsible Federal Budget as below:

Table 4.2: COVID Stimulus package by sector

in $mn	**Stimulus package amount**
Agri	54200
Mining	4656
Food&Beve	0
Manuf1	0
Computer &Electronic	0
Utility	1936
Warehousing and support activities for transportation	0
Postal and courier activities	0
Publishing, audiovisual and broadcasting activities	0
Telecommunications	9860
IT and other information services	1588
Financial and insurance activities	2044100
Administrative and support services	51600
Public administration and defence; compulsory social security	2750
Human health and social work activities	495200
Real estate activities	16798
Manuf2	53790

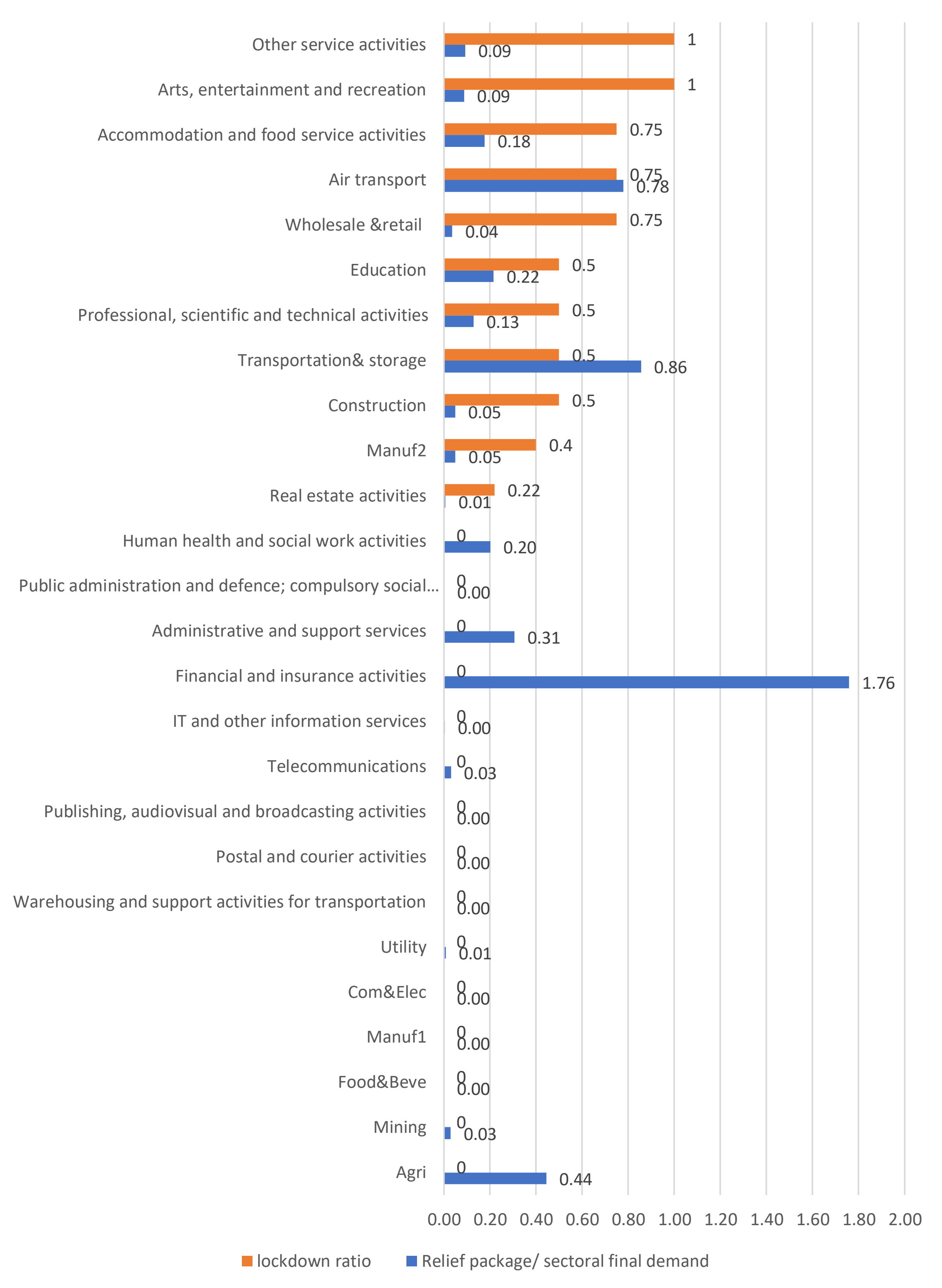
Construction	65000
Transportation& storage	222630
Professional, scientific and technical activities	67000
Education	300000
Wholesale &retail	68844
Air transport	95410
Accommodation and food service activities	142400
Arts, entertainment and recreation	23000
Other service activities	41830

The author collected data from The Committee for a Responsible Federal Budget.
Source: https://www.covidmoneytracker.org/

Comparing the COVID relief package and the lockdown ratio, we can see from the graph below that most sectors that are getting benefits are the sectors that are affected by sectoral lockdowns and are mainly services sections.

With the exceptions of health, admin, financial sector, and agriculture, the health admin and agriculture sectors play vital roles in dealing with the pandemic and, therefore, require substantial support, while the financial sector received funding for the multi-purpose of economic stability and recovery.

Figure 4.6: Comparing the relief package percentage in terms of the sectoral final demand and the sectoral lockdown ratio



The author collected data from The Committee for a Responsible Federal Budget.
Source: https://www.covidmoneytracker.org/

4.2.1.4 *Supply-side shock*

Another key point of the discussion is the uniqueness of the COVID-19 lockdown, which is a demand- and supply-side spontaneous shock.

Some papers heavily focus on supply/production, while others work on methods of spontaneous impacts.

del Rio-Chanona (2020) 's paper focuses on the ways that COVID-19 affects the labour supply by examining various categories of working/production ability, such as individuals unable to go to work, unable to work from home, and those who have lost their jobs entirely. The study provides valuable insights into the industries most affected by COVID-19. The paper aims to clarify the supply-side reductions caused by the closure of non-essential industries and the inability of workers to perform their activities remotely. It also considers demand-side changes resulting from people's responses to the pandemic, such as reduced demand for goods and services that pose a risk of infection, like tourism.

While some research's direction is estimating the supply shock from labour supply (Dingel and Neiman, 2020; Koren and Peto, 2020), this paper introduces a methodology to estimate work that can be done from home based on work activities. Additionally, it identifies industries where working from home is irrelevant due to their essential nature. The study compares the estimated supply shocks to the demand shock, often a more significant constraint on output in many industries.

Sayan, S. and Alkan, A.'s 2021 paper highlights the significant economic costs associated with the COVID-19 pandemic, including a decline in final demand and a contraction in supply, resulting in substantial output and employment losses across various sectors.

The challenge for policymakers is to strike a balance between public health concerns and the adverse economic and social outcomes of measures taken to control the spread of the virus.

Finding the right combination of measures that consider both public health and employment and income considerations is crucial.

Building on a previous study by Sayan and Demir (1998), this paper introduces a novel methodology to measure the economic costs of sectoral shutdowns implemented to contain the spread of COVID-19. By employing a supply-driven input-output model, the study measures the losses in sectoral outputs and the overall contraction of GDP. This systematic approach to measuring output and job losses resulting from sectoral shutdowns provides essential insights for informed decision-making, assisting policymakers in striking the appropriate balance between public health and the economic costs of the pandemic.

Additionally, Deger (2020) examines the spillover effects of COVID-19-induced decreases in demand for specific service sectors, utilizing credit card purchase data to analyse the impact.

4.2.1.5 *Other relevant literature on the methodology*

Recent research has built on the hypothetical extraction approach to model economic shocks, but also addressed it's limitations. Cano's (2021) article adopts the approach of Klimek et al. (2019) to capture a more dynamic response by modelling the reaction to demand shocks using a first-order ordinary differential equation (ODE).

However, as input-output linkages evolve, static forecasts shows the short-term approximations before adjustments reshape interconnections. Faturay (2020) has a similar approach towards these topics as this paper, as we both applied the Hypothetical extractions method in the analysis.

They advances techniques by adding supply-side event matrices directly representing disasters reducing production capacity. Thus, input-output analyses effectively quantify immediate cascading impacts but struggle to capture complex economic evolution.

Dietzenbacher (2019) and his co-authors have been exploring the application of input-output data in estimating and simulating the impact on supply chains from real-life events. Dietzenbacher summaries integrating hypothetical extractions with trade substitution to replace domestic supply losses. Still, continual shifts in technology and behaviour necessitate greater dynamism.

Based on the method mentioned above, Faturay (2020), in their paper on disaster analysis of Taiwan, implemented the Production-layer decomposition analysis. They take supply shocks as our starting point. Instead of building a supply-driven model (Ghosh, 1958) or using nonlinear programming techniques (Oosterhaven and Bouwmeester, 2016), they use a linear programming model in connection with the so-called event matrix as proposed by Steenge and Bočkarjova (2007) where A disaster or disruption leads to damages and a reduction in production capacity.

4.3 Methodology

In the Methodology section, we introduce the baseline model for this paper, the Input-Output network, followed by two models applied to demand shock and supply shock, the Leontief Model and the Ghosh Model.

The second part explains the partial extraction method used for sectoral shocks.

The third part focuses on several scenarios under different assumptions, including direct impacts, mixed impacts on the demand side and supply side, and finally, Government interventions.

The last part of the Methodology section defines three different stages of the Covid-19 lockdown based on the policies announced by the US government.

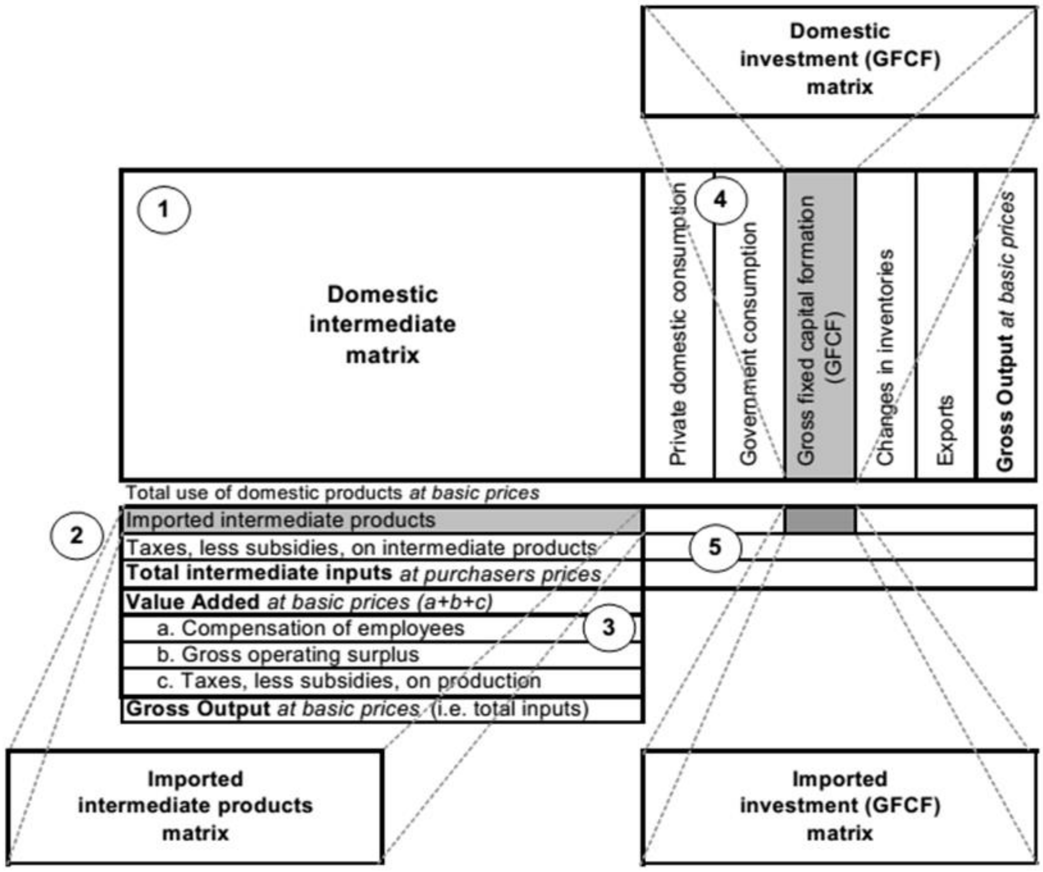
Overall, this section demonstrates the whole process of implementing an I-O data network in the analysis of the COVID-19 lockdown impact on the GDP of the United States, taking into consideration sectoral impacts, government interventions and lockdown stages.

4.3.1 Input-Output data, Leontief Model and Ghosh model

4.3.1.1 *Input-Output Data Framework*

In analysing the impact of the COVID-19 sectoral lockdown of the United States on GDP, we based it on the OECD Inter-Country Input-Output (ICIO) database (Latest year 2018 data).

Figure 4.7: The basic structure of input-output data (Source: Wixted et al., 2006)



The input-output dataset has three main sections: domestic intermediate matrix, value-added, and final demand.

The intermediate use matrix (also called the X matrix in this paper) details how all the sectors of an economy buy and sell raw materials, industrial components, and services to other sectors. In this paper, we combine 45 sectors (in the original OECD ICIO data) into 26 more general sections (in the analysis of the COVID-19 lockdown). (It has few more sectors than the Trade War analysis in chapter one, which has 21 sectors, and that is since COVID-19 lockdowns affect both goods production and services sectors; therefore, we have more detailed breakdowns of services)

The imported intermediate products can also be called the rest of the world (ROW) section to summarise all the foreign intermediate transactions.

The value-added section, as its name describes, illustrates the values that need to be considered in the gross input of the economy. Breaking down the Value-Added section, we have several parts: taxes, salaries, gross operating surplus, etc. The column of domestic intermediate goods plus value-added is the gross input of an economy.

The final demand section covers five types of final demand: private domestic consumption, government consumption, gross fixed capital formation, changes in inventories, and exports. The row of domestic intermediate goods plus final demand is the output of an economy.

The I-O database follows a natural rule: the gross output equals gross input because an economy's gross input and output should always be the same.

4.3.1.2 *Convert Value Added to GDP*

This chapter focuses on the domestic change in GDP facing COVID-19 lockdown shocks in the United States. In our model, we aim to simulate the impacts of sectoral shocks on GDP, which can't be directly obtained from the raw data. In the OECD ICIO data, there are the Gross Value Added and the "TAXSUB" which is the Taxes less subsidies on intermediate and final products, $\boldsymbol{TP} - \boldsymbol{SP}$, where $\boldsymbol{TP}$ is taxes on products, and $\boldsymbol{SP}$ are subsidies on products.

As the total aggregates of taxes on products and subsidies on products are only available at the whole economy level, Gross value added is used for measuring gross regional domestic product and other measures of the output of entities more minor than a whole economy.

Based on the standard method of converting GVA to GDP, the relationship between GVA and GDP is defined as:

$$\mathbf{GVA} = \mathbf{GDP} + \mathbf{subsidies\ on\ products} - \mathbf{taxes\ on\ products} \qquad 4.1$$

It can also be written as

$$GDP = GVA + TP - SP \qquad 4.2$$

Therefore, in the ICIO data,

$$GDP = GVA + TAXSUB \qquad 4.3$$

From here, we directly consider $\boldsymbol{GDP}$ in the model instead of $\boldsymbol{GVA}$.

4.3.1.3 *Leontief Model*

This OECD ICIO data provides activity on both the demand and supply sides with the input-output structure; we can use two models to analyse the connectedness for both the demand and supply aspects. The demand-driven model is called the Leontief model, while the supply-driven one is called the Ghosh model.

The Leontief Technology Coefficient is the foundation for showing the connectedness of all sectors. The data includes data for intermediate goods inputs, Value-Added (and GDP after modification, formula seen below equation 1, final demand and total gross output.

The implementation of Leontief model is different for COVID-19 impact than the US-China trade war as we are focusing on the US domestic input-output data instead of inter-country dat. Therefore, the intermediate good section only contains the US sectors and the final demand section is an array of final demand in domestic sectors instead of matrices.

Based on OECD ICIO data, all gross output produced in a country is used as an input for intermediate goods or final goods, domestically or abroad. Therefore, in a country, sector i's gross output, x_i, is given by:

$$\boldsymbol{x_i = a_{i1}x_1 + a_{i2}x_2 + \cdots + a_{ij}x_j + \cdots + a_{in}x_n + x_{iROW} + d_i} \quad 4.4$$

Where $\boldsymbol{d_i}$ is the quantity of sector i's output consumed as a final good in all sectors domestically and internationally and $\boldsymbol{a_{ij}}$is the units of intermediate goods produced in sector $\boldsymbol{i}$ that are needed to produce one unit of the good in sector $\boldsymbol{j}$, these are called IO coefficients or technology coefficients. These can be found by dividing the total intermediate use in sector $\boldsymbol{i}$ of sector j's product, $\boldsymbol{x_{ij}}$**,** given in the intermediate section in the IO table, by the gross output of country $\boldsymbol{i}$, that is $\boldsymbol{a_{ij}} = {}^{\boldsymbol{x_{ij}}}/_{\boldsymbol{x_j}}$**.** Equation (1) can then be written in matrix form as:

$$\begin{bmatrix} x_1 \\ x_2 \\ . \\ . \\ x_n \end{bmatrix} = \begin{bmatrix} a_{1,1} & \cdots & a_{1,n} \\ \vdots & \ddots & \vdots \\ a_{n,1} & \cdots & a_{n,n} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ . \\ . \\ x_n \end{bmatrix} + \begin{bmatrix} d_1 \\ d_2 \\ d_3 \\ . \\ d_{13} \end{bmatrix} \quad 4.5$$

$$\Uparrow \qquad\qquad \Uparrow \qquad\qquad \Uparrow \qquad \Uparrow$$

Total Output Technology Matrix Total Output Final Demand

Which can be summarised as:

$$\boldsymbol{X = AX - D} \quad 4.6$$

$\boldsymbol{X}$ is the vector of Total outputs, $\boldsymbol{A}$ is the matrix of technology, $\boldsymbol{and\ D}$ is the vector of Total Demand.

Equation 3 can be re-written as:

$$(\boldsymbol{I}-\boldsymbol{A})\boldsymbol{X}=\boldsymbol{D} \tag{4.7}$$

Where $\boldsymbol{I}$ stands for the identity matrix, the identity matrix has all diagonal elements as one and the rest of the elements as 0. If the matrix $(\boldsymbol{I}-\boldsymbol{A})$is invertible, it means the linear system of equations has a unique solution:

$$\boldsymbol{X}=(\boldsymbol{I}-\boldsymbol{A})^{-\mathbf{1}}\boldsymbol{D} \tag{4.8}$$

Where $(\boldsymbol{I}-\boldsymbol{A})^{-\mathbf{1}}$is also called the global Leontief inverse matrix. Each element of $(\boldsymbol{I}-\boldsymbol{A})^{-\mathbf{1}}$ is a Leontief coefficient and gives the amount of the sector $\boldsymbol{j}$'s output required to produce one more unit of the final good in sector $\boldsymbol{i}$, etc.

4.3.1.4 *Ghosh Model*

Ghosh's model is an extension of the original Leontief model. Following a similar idea to the Leontief model, where we take a closer look at intermediate good input contribution to output, the Ghosh Model, instead of aiming to find out how many units of input are needed to produce one unit of output, fixes the allocation proportion of input from one sector for every sector. Therefore, the calculation is from the horizontal direction instead of the vertical, which will be explained in the following section.

Using $\boldsymbol{b_{ij}}$ to represent the output coefficients and $\boldsymbol{b_{ij}}=\frac{x_{ij}}{x_i}$. The formula can be written as:

$$\boldsymbol{x_i}=\boldsymbol{b_{1i}x_1}+\boldsymbol{b_{2i}x_2}+\cdots+\boldsymbol{b_{ji}x_j}+\cdots+\boldsymbol{b_{ni}x_n}+\boldsymbol{x_{ROWi}}+\boldsymbol{v_i} \tag{4.9}$$

$\boldsymbol{x_{ROWi}}$ is the amount of goods that sector $\boldsymbol{i}$ imported from the rest of the world, and $\boldsymbol{v_i}$ is the total value-added of sector $\boldsymbol{i}$.

By simplifying equation (4), it can be written as:

$$\boldsymbol{X}'=\boldsymbol{X}'\boldsymbol{B}+\boldsymbol{V}' \tag{4.10}$$

And by rewriting it, the Ghosh model can be presented as:

$$\boldsymbol{X}'(\boldsymbol{I}-\boldsymbol{B}) = \boldsymbol{V}' \quad 4.11$$

Therefore, $\boldsymbol{X}'$ can be represented by $\boldsymbol{B}$ and $\boldsymbol{V}'$, which is

$$\boldsymbol{X}' = \boldsymbol{V}'(\boldsymbol{I}-\boldsymbol{B})^{-\mathbf{1}} \quad 4.12$$

Thus $\boldsymbol{X}'$ corresponds to the variable Value Added, and $(\boldsymbol{I}-\boldsymbol{B})^{-\mathbf{1}}$ is called the output inverse matrix.

By comparing equations 1 to 5 with 6 to 9, we can see the similarity where the output in the Leontief Model depends on the final demand and Leontief Inverse function and in the Ghosh Model, the output depends on Ghosh Inverse and Value Added. Both Leontief and Ghosh models are being used to show the impact on GDP if specific sectors change the volume of intermediate supply, the share of final demand or even wage, etc.

4.3.2 Partial Extraction

We apply the method introduced in chapter two, the partial extraction method (PEM), in a domestic environment, sector A and sector B only partially supply to or demand from each other while the rest of the economic status stays the same. Under the PEM method, the new coefficient matrix is $\boldsymbol{A}^{\#}$, and the new final demand is named $\boldsymbol{FD}^{\#}$,; the new GDP under the hypothetical condition is calculated as:

$$\boldsymbol{GDP}^{\#} = \boldsymbol{VA} * \boldsymbol{I} * (\boldsymbol{I}-\boldsymbol{A}^{\#})^{-\mathbf{1}}\boldsymbol{FD}^{\#} \quad 4.13$$

Note that $\boldsymbol{VA} * \boldsymbol{I}$ here stands for the **Value-Added Coefficient,** where the matrix has the Value Added/Output($\boldsymbol{V}/\boldsymbol{X}$) for each sector on the diagonal while everywhere else is zero. ($\boldsymbol{V}$ is the K x 1 vector of the list of Value Added from each sector.)

The effect of the partial extraction is simply the original GDP minus the new GDP:

$$\boldsymbol{DVA}^{\#} = \boldsymbol{GDP}^{\#} - \boldsymbol{GDP}_{\boldsymbol{O}} \quad 4.14$$

This result represents the change in Value Added because of the reduction of production.

4.3.2.1 *Covid-19 Sectoral Lockdown ratio and remaining ratio*

For the domestic lockdown impact on total output/GDP, we first obtained the lockdown ratio given by OECD,

It applies across whether on gross output, value-added and final demand, and intermediate goods.

For Value Added and Final Demand, the ratio is directly implemented onto the original value.

$$\boldsymbol{R = 1 - L} \tag{4.15}$$

Where L is the Lockdown Ratio on production, R is the remaining ratio of the sector that is still producing.

The remaining ratio R will be applied as the direct impact on Final Demand under a demand shock and on Value Added under a supply shock.

In the scenario of Lockdown shock on Final Demand, the new Final Demand $\boldsymbol{FD^{\#}}$ will be calculated following the equation below:

$$\boldsymbol{FD^{\#} = FD * R} \tag{4.16}$$

For instance, the Transportation sector has a sectoral lockdown of 40%, which means the new Final Demand for the Transportation sector will be:

$$\boldsymbol{FD^{\#}_{Tran} = FD_{Tran} * R_{Tran}} = (1 - 0.4) * \boldsymbol{FD_{Tran}} \tag{4.17}$$

For the intermediate good section, Eduardo A. et al (2020) introduced a method for inter-industry demand where:

$\forall \boldsymbol{aij¿} = \mathbf{1,\ldots}$, we compute a corresponding restricted flow, such that:

$$\boldsymbol{a^{\#}_{ij}} = \begin{cases} \boldsymbol{R_i a_{ij}, if\ \ R_i < R_j} \\ \boldsymbol{R_j a_{ij}, if\ \ R_i > R_j} \end{cases} \tag{4.18}$$

We simplify it to:

$$\boldsymbol{a}_{ij}^{\#} = \min(\boldsymbol{R}_{i,}\boldsymbol{R}_{j}) * \boldsymbol{a}_{ij} \tag{4.19}$$

where $\boldsymbol{a}_{ij}$ represents the total inter-industry production capacity of sector $\boldsymbol{i}$ to all sectors $\boldsymbol{j}$, and $\boldsymbol{R}_{\boldsymbol{n}}$ defines the share of non-restricted workers in each group in each sector. In the COVID-19 impact scenario, it defines the remaining share of the sector's productivity.

A successful production needs both adequate input and the corresponding demand for output. If for instance, the agriculture sector has a complete lockdown (R = 0) while the Mining sector has a 50% lockdown, this means even though the Mining sector still has 50 per cent production remaining (R = 0.5) after the lockdown, without any inputs from Agriculture the $\boldsymbol{a}_{AgriMin}$ will be zero.

In further improvement of the methodology, we consider a more complex and realistic formula to adjust the Leontief Technology Coefficient.

Instead of directly applying the remaining percentage onto the a_{ij}, we consider the lockdown directly on the inputs and outputs. Therefore, for instance, in cases where both the input and output sectors have the same remaining percentage, they still have the same relation in the Leontief Technology Coefficient.

The formulas below break down the new approach and simplify it.

Where Leontief Technology Coefficient $\boldsymbol{a}_{ij}^{\#}$ is calculated by:

$$\boldsymbol{a}_{ij}^{\#} = \frac{\mathbf{min}(\boldsymbol{R}_{i,}\boldsymbol{R}_{j})\boldsymbol{X}_{ij}}{\boldsymbol{R}_{j} * \boldsymbol{X}_{j}} \tag{4.20}$$

That means in the case of $\boldsymbol{a}_{ii}^{\#}$

$$\boldsymbol{a}_{ii}^{\#} = \frac{\mathbf{min}(\boldsymbol{R}_{i,}\boldsymbol{R}_{i})\boldsymbol{X}_{ii}}{\boldsymbol{R}_{i} * \boldsymbol{X}_{i}} = \frac{\boldsymbol{R}_{i} * \boldsymbol{X}_{ii}}{\boldsymbol{R}_{i} * \boldsymbol{X}_{i}} = \boldsymbol{X}_{ii}/\boldsymbol{X}_{i} = \boldsymbol{a}_{ii} \tag{4.21}$$

For when $\boldsymbol{R}_{i} \geq \boldsymbol{R}_{j}$,

$$\boldsymbol{a}_{ij}^{\#} = \frac{\mathbf{min}(\boldsymbol{R}_{i,}\boldsymbol{R}_{j})\boldsymbol{X}_{ij}}{\boldsymbol{R}_{j} * \boldsymbol{X}_{j}} = \frac{\boldsymbol{R}_{j} * \boldsymbol{X}_{ij}}{\boldsymbol{R}_{j} * \boldsymbol{X}_{j}} = \boldsymbol{X}_{ij}/\boldsymbol{X}_{j} = \boldsymbol{a}_{ij} \tag{4.22}$$

For when $\boldsymbol{R}_{i} < \boldsymbol{R}_{j}$,

$$\boldsymbol{a^{\#}_{ij}} = \frac{\min(\boldsymbol{R_{i,}R_j})\boldsymbol{X_{ij}}}{\boldsymbol{R_j * X_j}} = \frac{\boldsymbol{R_i * X_{ij}}}{\boldsymbol{R_j * X_j}} \qquad 4.23$$

Therefore, the only situation in the Leontief Coefficient $\boldsymbol{a^{\#3}_{ij}}$is different from the original $\boldsymbol{a_{ij}}$is when the input sector I has a lower R ratio than the demand sector j.

Therefore, we get:

$$\boldsymbol{a^{\#}_{ij}} = \begin{cases} \dfrac{\boldsymbol{R_i * X_{ij}}}{\boldsymbol{R_j * X_j}}, & \boldsymbol{if\ \ R_i < R_j} \\ \boldsymbol{a_{ij}}, & \boldsymbol{if\ \ R_i \geq R_j} \end{cases} \qquad 4.24$$

And

$$\boldsymbol{FD^{\#}_i = FD_i * R_i} \qquad 4.25$$

The new GDP under the COVID-19 lockdown can be calculated for each sector and is given by:

$$\boldsymbol{GDP^{\#} = VA * I * (I - A^{\#})^{-1} FD^{\#}} \qquad 4.26$$

Using the original GDP, the change in value-added as a result of the Covid-19 lockdown can be calculated as:

$$\boldsymbol{DVA^{\#} = GDP_O - GDP^{\#}} \qquad 4.27$$

Where DVA is the $K \times 1$ vector, with each element showing the change in VA as a result of the covid-19 lockdown in all K sectors.

Similarly, we implemented the idea onto the Ghosh Inverse $\boldsymbol{b_{ij}}$**,**

The method to define $\boldsymbol{b^{\#}_{ij}}$ follows a procedure similar to the Leontief model $\boldsymbol{a^{\#}_{ij}}$**.**

$$\boldsymbol{b^{\#}_{ij}} = \frac{\min(\boldsymbol{R_{i,}R_j})\boldsymbol{X_{ij}}}{\boldsymbol{R_i * X_i}} \qquad 4.28$$

That means in the case of $\boldsymbol{b^{\#}_{ii}}$

$$\boldsymbol{b^{\#}_{ii}} = \frac{\min(\boldsymbol{R_{i,}R_i})\boldsymbol{X_{ii}}}{\boldsymbol{R_i * X_i}} = \frac{\boldsymbol{R_i * X_{ii}}}{\boldsymbol{R_i * X_i}} = \boldsymbol{X_{ii}/X_i = b_{ii}} \qquad 4.29$$

For when $\boldsymbol{R_i \leq R_j}$**,**

$$\boldsymbol{b}_{ij}^{\#} = \frac{\mathbf{min}(\boldsymbol{R}_{i,}\boldsymbol{R}_{j})\boldsymbol{X}_{ij}}{\boldsymbol{R}_i * \boldsymbol{X}_i} = \frac{\boldsymbol{R}_i * \boldsymbol{X}_{ij}}{\boldsymbol{R}_i * \boldsymbol{X}_i} = \boldsymbol{X}_{ij}/\boldsymbol{X}_i = \boldsymbol{b}_{ij} \tag{4.30}$$

For when $\boldsymbol{R}_i > \boldsymbol{R}_j$,

$$\boldsymbol{b}_{ij}^{\#} = \frac{\mathbf{min}(\boldsymbol{R}_{i,}\boldsymbol{R}_{j})\boldsymbol{X}_{ij}}{\boldsymbol{R}_i * \boldsymbol{X}_i} = \frac{\boldsymbol{R}_j * \boldsymbol{X}_{ij}}{\boldsymbol{R}_i * \boldsymbol{X}_i} \tag{4.31}$$

Therefore, we get:

$$\boldsymbol{b}_{ij}^{\#} = \begin{cases} \dfrac{\boldsymbol{R}_i * \boldsymbol{X}_{ij}}{\boldsymbol{R}_j * \boldsymbol{X}_i}, & \boldsymbol{if} \;\; \boldsymbol{R}_i > \boldsymbol{R}_j \\ \boldsymbol{b}_{ij}, & \boldsymbol{if} \;\; \boldsymbol{R}_i \leq \boldsymbol{R}_j \end{cases} \tag{4.32}$$

4.3.2.2 *Partial Extraction Matrices*

The elements of the matrices that are altered are any elements that involve interaction between different sectors within the United States. To aid understanding, consider a three-sector input-output model with sectors 1, 2, and 3. The A and FD matrices for this model will be given as:

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \quad FD = \begin{bmatrix} FD_1 \\ FD_2 \\ FD_3 \end{bmatrix} \tag{4.33}$$

Where a_{pq} gives the units of intermediate goods produced in sector p needed to produce one unit of the good in sector q, FD_prepresents the demand for the final products in sector p. The elements that involve interaction between sectors will be affected by the lockdown impact on production, following the formulas (24,25) for the lockdown production remaining percentage. After considering the sectoral lockdown impacts, the modified A and FD matrices are then:

$$A = \begin{bmatrix} a_{11} & \boldsymbol{a}_{\mathbf{12}}^{\#} & a_{13} \\ \boldsymbol{a}_{\mathbf{21}}^{\#} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \quad FD = \begin{bmatrix} FD_1 \\ \boldsymbol{FD}_{\mathbf{2}}^{\#} \\ FD_3 \end{bmatrix} \tag{4.34}$$

4.3.3 Analysis Scenarios

In this paper, we gradually consider more complex shocks from COVID-19 lockdowns step by step with five different scenarios.

4.3.3.1 *Scenario one: Direct demand shock on Final Demand*

In Scenario one: Direct demand shock on Final Demand, we start with the simple final demand shock without considering the impact of the lockdown on the intermediate goods section.

To be specific, only the Final Demand Section of each lockdown sector is affected. It is the first wave's direct impact on the demand side. The shrinking of the excellent demand size affects Value Added therefore GDP:

The New GDP post-Final Demand Shock is defined as:

$$\boldsymbol{GDP^{\#}} = \boldsymbol{VA} * \boldsymbol{I} * (\boldsymbol{I} - \boldsymbol{A})^{-1}\boldsymbol{FD^{\#}} \tag{4.35}$$

Note that $\boldsymbol{VA} * \boldsymbol{I} *$ here stands for the **Value-Added Coefficient** where the matrix has the Value Added/Output($\boldsymbol{V}/\boldsymbol{X}$) for each sector on the diagonal while everywhere else is zero. ($\boldsymbol{V}$ is the K x 1 vector of the list of Value Added from each sector.)

Therefore, $\boldsymbol{GDP^{\#}}$ is a vector of sectoral GDP after the Final Demand Shock.

4.3.3.2 *Scenario two: Mixed demand shock on Final Demand and intermediate good*

In Scenario two: Mixed demand shock on Final Demand and intermediate good, we extend Scenario 1 by including the intermediate good section, by doing so, we have a new Leontief Technology coefficient, $\boldsymbol{A^{\#}}$.

$\boldsymbol{A^{\#}}$ follows the rule of equation 13, which that means in this scenario, we have all the impact on demand from final demand as well as intermediate goods production. But in this case, not only the demand side (output side) is affected, but the supply side (input side) also is affected by the sectoral lockdowns.

The formula for this scenario is as follows:

$$\boldsymbol{GDP}^{\#} = \boldsymbol{VA} * \boldsymbol{I} * (\boldsymbol{I} - \boldsymbol{A}^{\#})^{-\mathbf{1}} \boldsymbol{FD}^{\#} \tag{4.36}$$

In the real-world input-output data, we focus heavily on the overlooked intermediate good section in scenario 2 specifically, we analyse the full impact and compare it to scenario 1 to show the effects on the intermediate good.

4.3.3.3 *Scenario three: Direct Supply Shock on Value Added*

In Scenario three: Direct Supply Shock on Value Added, we switch the focus onto the supply side, the role of Value-Added and its impact since the Covid-19 lockdown is not only a demand but also a supply shock. Therefore, we apply the Ghosh Inverse Model instead of Leontief Inverse Model. We can recall equation 9 from the above methodology section:

$$\boldsymbol{X}' = \boldsymbol{V}^{\#\prime} (\boldsymbol{I} - \boldsymbol{B})^{-\mathbf{1}} \tag{4.37}$$

The Value-Added is the only section that's directly affected by sectoral lockdowns in this scenario. Therefore, only V changed to $\boldsymbol{V}^{\#}$ as a direct impact.

4.3.3.4 *Scenario four: Mixed Supply shock on Value Added and Intermediate good.*

In Scenario four: Mixed Supply shock on Value Added and Intermediate good., we extend scenario 3 with the addition of impact from the intermediate good section, but unlike scenario 1&2, the intermediate good coefficients are the Ghosh Matrix $\boldsymbol{B}$, where $\boldsymbol{b_{ij}} = \frac{x_{ij}}{x_i}$.

The impact on Output is calculated as:

$$\boldsymbol{FD}^{\#} = \boldsymbol{V}^{\#\prime} (\boldsymbol{I} - \boldsymbol{B}^{\#})^{-\mathbf{1}} \boldsymbol{FDc}' * I \tag{4.38}$$

Note that $\boldsymbol{FDc} * \boldsymbol{I}$ here stands for the **Final demand Coefficient,** where the matrix has the Final Demand/Output($\boldsymbol{FD}/\boldsymbol{X}$) for each sector on the diagonal while everywhere else is zero. ($\boldsymbol{FD}$ is the 1x K vector of the list of Value Added from each sector.)

Then apply the new $\boldsymbol{FD}^{\#}$ onto the demand side shock. And follow the steps for scenario two.

4.3.3.5 *Scenario five: Mixed Supply shock on Value Added and Intermediate good with Government intervention on VA and FD*

In Scenario five: Mixed Supply shock on Value Added and Intermediate good with Government intervention on VA , we introduce the government interventions, which are presented in many ways of fiscal policy such as wage compensation, giving citizens free money, etc. The initial one is a shock within Value-Added (Wage sector in further breakdowns), and the latter is a shock on Final Demand.

We implement those shocks based on the policies from the United States government in 2020-2022. (COVID policy money implementation timeline in appendix)

We can recall table 2, the government intervention that is used in the calculations of the Leontief inverse with hypothetical extraction is done by increasing the final demand for the following sectors:

Table 4.3: COVID Stimulus package by sector

in $mn	**Stimulus package amount**
Agri	54200
Mining	4656
Food&Beve	0
Manuf1	0
Computer &Electronic	0
Utility	1936
Warehousing and support activities for transportation	0
Postal and courier activities	0
Publishing, audiovisual and broadcasting activities	0
Telecommunications	9860
IT and other information services	1588

Financial and insurance activities	2044100
Administrative and support services	51600
Public administration and defence; compulsory social security	2750
Human health and social work activities	495200
Real estate activities	16798
Manuf2	53790
Construction	65000
Transportation& storage	222630
Professional, scientific and technical activities	67000
Education	300000
Wholesale &retail	68844
Air transport	95410
Accommodation and food service activities	142400
Arts, entertainment and recreation	23000
Other service activities	41830

Data was collected from the Committee for a Responsible Federal Budget by the author.
Source: https://www.covidmoneytracker.org/

The sectoral impact in response to government intervention is based on the US policy rescue packages and the expected increased spending in respons to the CARES ACT. The cost of the government intervention for these 13 months of lockdown totals at $5.37 trillion which, compared to the estimates of *COVID Money Tracker: Policies Enacted To Date* (2020), is a conservative estimate. According to their calculations, the total cost could come close to $7 trillion.

4.3.3.6 *Scenario Six (with Lockdown Phases): Mixed Supply shock on Value Added and Intermediate good with Government intervention on VA and FD with Lockdown Phases*

In addition, in Scenario six: Mixed Supply shock on Value Added and Intermediate goods with Government intervention on VA and FD and the three lockdown phases., we also investigate the recovery from COVID Lockdowns, which means starting from the strictest hard lockdown policies, the US has eased Lockdowns as time goes by, and therefore the productions also gradually recovered.

The three main phases in the US are complete lockdown, social distance/mask mandate/limited public gathering, and mask mandate in indoor places.

In this model, we implement three vital points of change of policies to the three phases: phase one, the initial Hard Lockdown; phase two, The medium soft lockdown; and phase three, the restrictions-only phase. The two core elements for designing the phases are the length of lockdown periods and the sectoral lockdown percentage in each period. The preview of the lockdown phases design is shown below:

Table 4.4: Overview of Lockdown Operation percentage in three phases

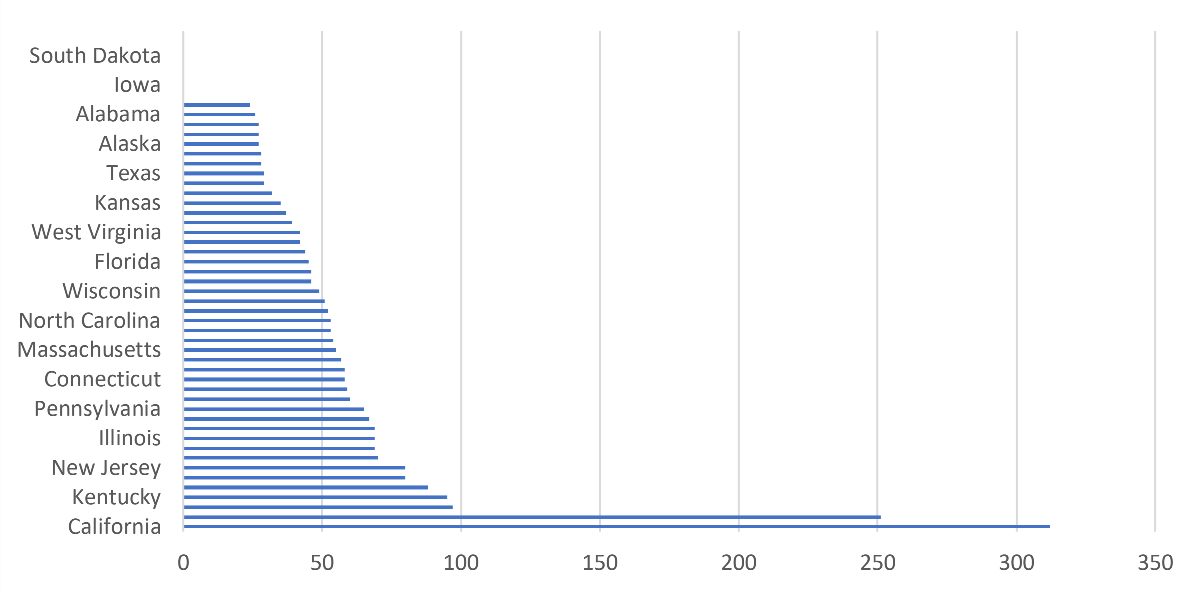
Operating percentage	Phase 1	Phase 2	Phase 3
Real estate services	79%	79%	79%
Manufacturing 2	60%	79%	100%
Educational services	50%	50%	79%
Professional services	50%	60%	79%
Other transportation	50%	60%	79%
Construction	50%	50%	79%
hospitality	25%	50%	79%
Travel arrangement and reservation services	25%	50%	60%
Air transportation	25%	25%	50%
Wholesale and retail	25%	25%	60%
Entertainment, Publishing, Culture and Sport	0%	25%	25%
Other personal services	0%	25%	60%

Source: Bureau of Economic Analysis, calculations done by author

Based on the BEA data, we see the first stage is the same as the previous sections; in phase 2, many sectors have raised their operation percentage, including most non-service sectors, while close contact sectors still remain a relatively small operation percentage. In phase 3, all sectors have raised the operation percentage to above 50% apart from entertainment sector.

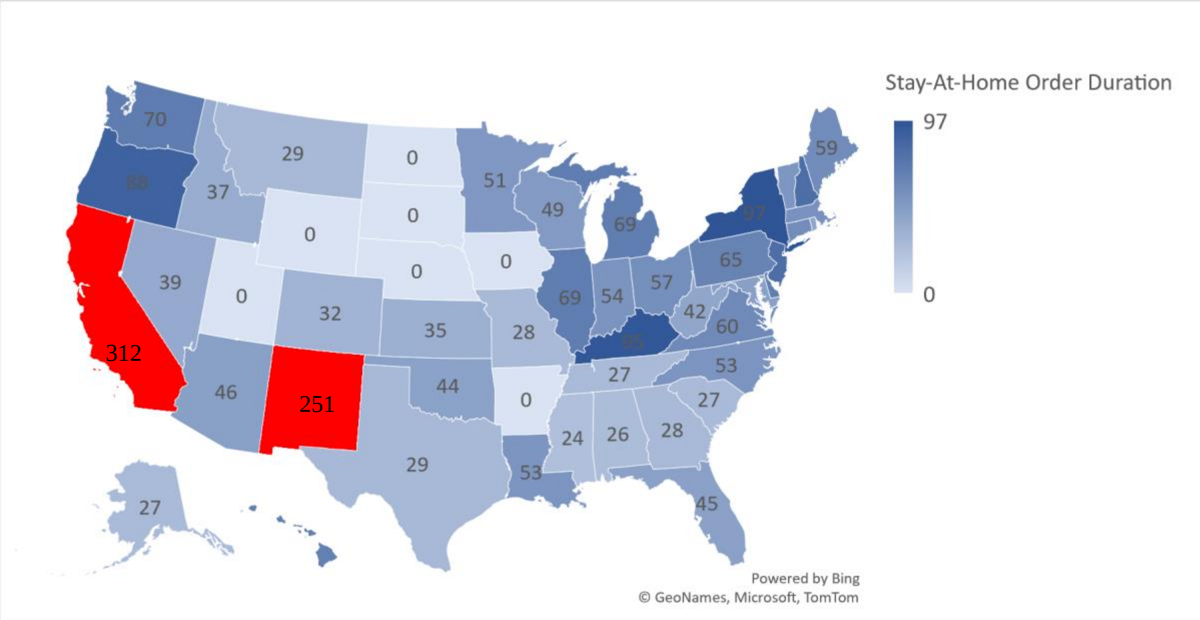
In the following section, we will show the process of deciding the lockdown phases based on state policies and government mandates.

Figure 4.8: The US Stay-At-Home Order Duration in March 2020



Source: https://statepolicies.com/data/library/ Illustrated by author

Figure 4.9: Stay-At-Home Order Duration By States in US around March 2020 (Averge 53days)



Source: https://statepolicies.com/data/library/ Illustrated by author

In phase one, Based on the stay-at-home order state by state, we get a clear timeline for each state for the first lockdown. Overall, the mean length of lockdown is around 1-2 months across the nation except for New Mexico and California. Hence, we assume the first hard lockdown lasted for 2 months.

Phase two is the period after the complete lockdown but still has social distancing, and the restaurants and other hospitality services are restricted. (4 months) In phase three, the mask mandate remains, but the majority of the restrictions on business have been lifted. (6 months) After phase 3, there are no longer any sectoral lockdowns.

Table 4.5: Employment by industry, April 2020 compared with historical levels and changes (Numbers in thousands)

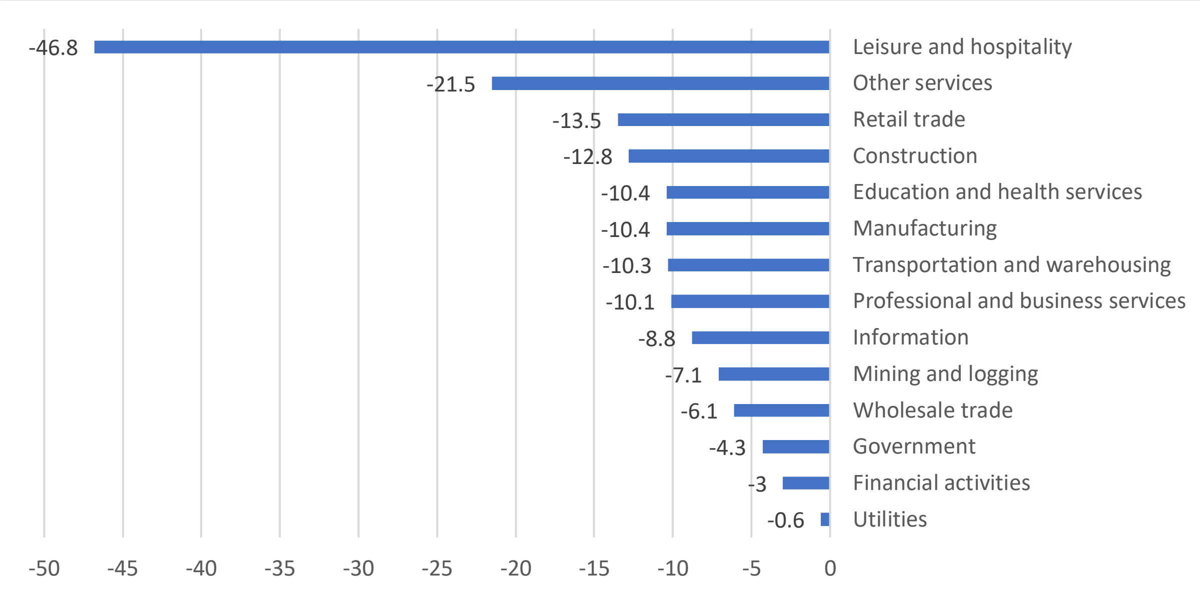
Industry	April 2020			Last time employment level was lower		Last time monthly loss was larger (or next largest loss)		Last time monthly percent loss was larger (or next largest loss)	
	Employ-ment level	Monthly change	Monthly percent change	Date	Employ-ment level	Date	Monthly change	Date	Monthly percent change
Total nonfarm	131,045 (c)	-20,537 (c)	-13.5	Jan 2011 (c)	130,841 (c)	Sep 1945	-1,959	Sep 1945	-4.8
Total private	109,308 (c)	-19,557 (c)	-15.2 (c)	Mar 2011	109,096	Sep 1945	-1,766	Sep 1945	-5.1
Mining and logging	657	-50	-7.1	Feb 2017	655	Apr 1981	-134	Apr 1981	-11.6
Construction	6,631	-975	-12.8	Jan 2016	6,620	Mar 1960	-172	Jul 1943	-7.5
Manufacturing	11,488	-1,330	-10.4	Mar 2010	11,453	Sep 1945	-1,715	Sep 1945	-12.1
Wholesale trade	5,569	-363	-6.1	Feb 2012	5,562	Feb 2009	-48	Jun 1942	-1.3
Retail trade	13,520	-2,107	-13.5	Jul 1994	13,516	Apr 1951	-123	Apr 1951	-2.6
Transportation and warehousing	5,087	-584	-10.3	Jan 2017	5,078	Aug 1997	-148	Aug 1997	-3.7
Utilities	543	-3	-0.6	Aug 1971	542	Jul 2018	-4	Jul 2012	-1.3
Information	2,636	-254	-8.8	Aug 2011	2,634	Aug 1983	-586	Aug 1983	-25.4
Financial activities	8,580	-262	-3.0	May 2018	8,567	Apr 2009	-57	Jan 1947	-1.2
Professional and business services	19,305 (c)	-2,165 (c)	-10.1 (c)	Oct 2014	19,285	Feb 2009	-196	Sep 1945	-2.4
Education and health services	21,941	-2,544	-10.4	Apr 2015	21,906	Nov 2008	-101	Jan 1949	-0.8
Leisure and hospitality	8,715	-7,653	-46.8	Aug 1988	8,663	Mar 2020	-499	Mar 2020	-3.0
Other services	4,636	-1,267	-21.5	Jan 1996	4,625	Nov 2008	-40	Nov 2008	-0.7
Government	21,737	-980	-4.3	Jan 2005	21,735	Jun 2000	-260	Sep 1945	-3.1

(c) Corrected May 11, 2020

Source: Bureau of Economic Analysis

By organizing the sectoral Employment loss ratio, we get the bar graph below:

Figure 4.10: US Employment March-April 2020 Change in percentage (%)



Based on the employment data, we can see that the hospitality sector has witnessed the largest layoff of employees, followed by other services. Most of the services sectors have suffered from a certain degree of loss in employment rate. Outside of the Services sectors, the Construction sector, Manufacturing and Transportation also had huge layoff ratios.

4.4 Data

In the analysis of the sectoral lockdown impact on GDP during Covid-19, we apply the lockdown percentage from the prediction of the initial impact of sectoral shutdowns from OECD in Figure 4.5:

Based on the prediction of the OECD, we set the lockdown percentages as below:

Table 4.6: Sectoral Lockdown and Remaining Productivity Percentage applied for this paper.

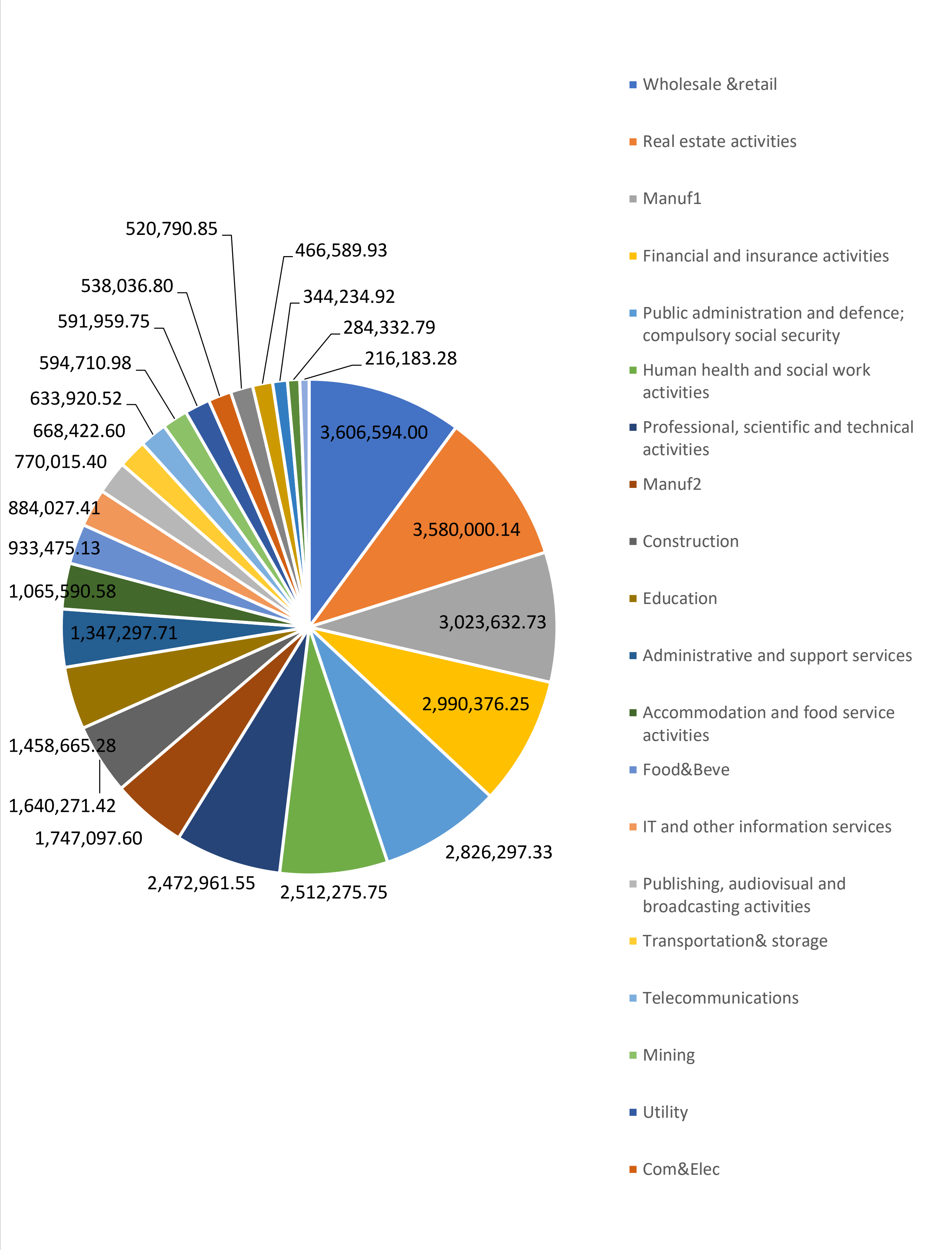
	Other sectors	Real estate	Manuf2	Construction	Transport	Professional activities	Education	Wholesale &retail	Air transport	Accom and food service	Arts, entertainment	Other service
Lockdown	0	0.21	0.4	0.5	0.5	0.5	0.5	0.75	0.75	0.75	1	1
Remaining	1	0.78	0.6	0.5	0.5	0.5	0.5	0.25	0.25	0.25	0	0

The entertainment & publishing sector and other personal services sectors fully shut down.

Wholesale & Retail, Air transport services, Hospitality and Travel agency are under 75% lockdown.

Constructions, Other Transport (excluding Air Transport), Professional Services, and Education services are under 50% lockdown and Manufacturing 2 suffers from 40% lockdown. In addition, a particular case in the Real estate services sector is that it is under 75% lockdown excluding rental, which means in total it has 21% shutdown.

Figure 4.11: The US sectoral Gross Output in 2018 (£Mn)



Pre-Covid Sectoral Gross Output Shares 2018 (Ranked from largest)

Wholesale & retail, real estate manufacturing, one and financial services are the top four sectors in the US, and based on Table 4.6 we can see that all these sectors are witnessing different level of Covid lockdown impact which demonstrates how severe the Covid lockdown is to economy of United States

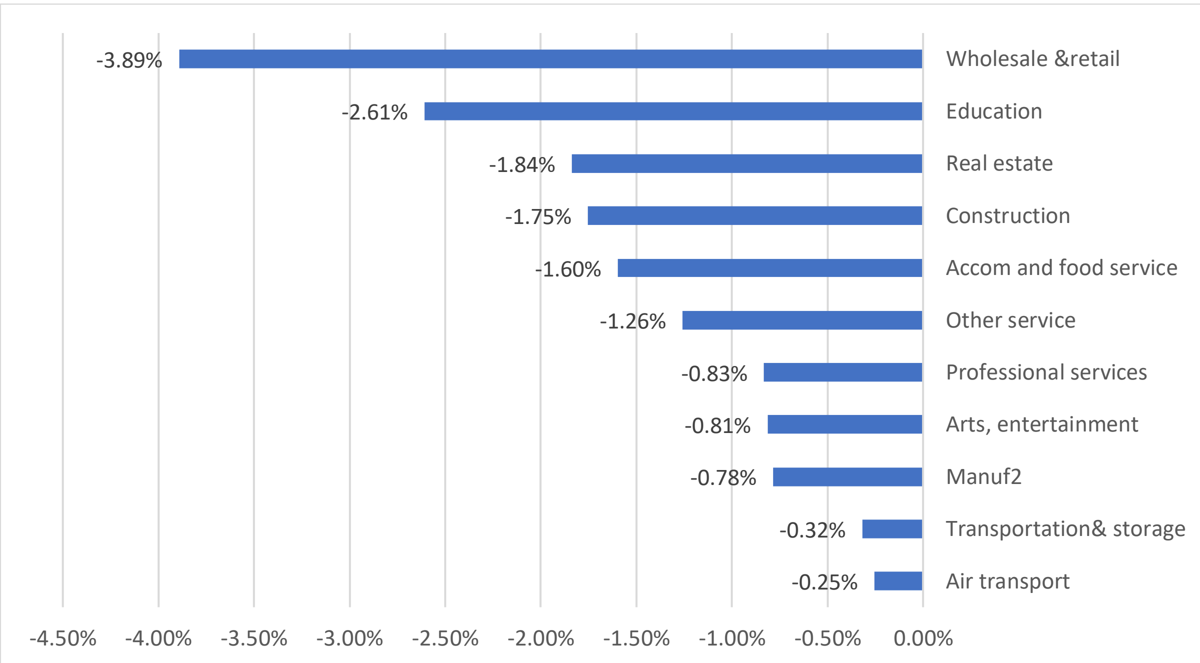
4.5 Analysis Results

In the results we demonstrate the impact of Covid-19 sectoral lockdowns in different scenarios. In Scenario 1-4, we apply the hard sectoral lockdown impact on the annual OECD ICIO data, therefore all the results show the impact after 12 months of hard sectoral lockdowns. In reality, the lockdown has different stages with different durations, which are applied in further scenarios 5 and 6.

In Scenario 1&2, we focus on the demand side shock, which means we assume the demand for goods decreases due to the restrictions during the COVID-19 lockdown.

4.5.1 Scenario one: Direct demand shock on Final Demand

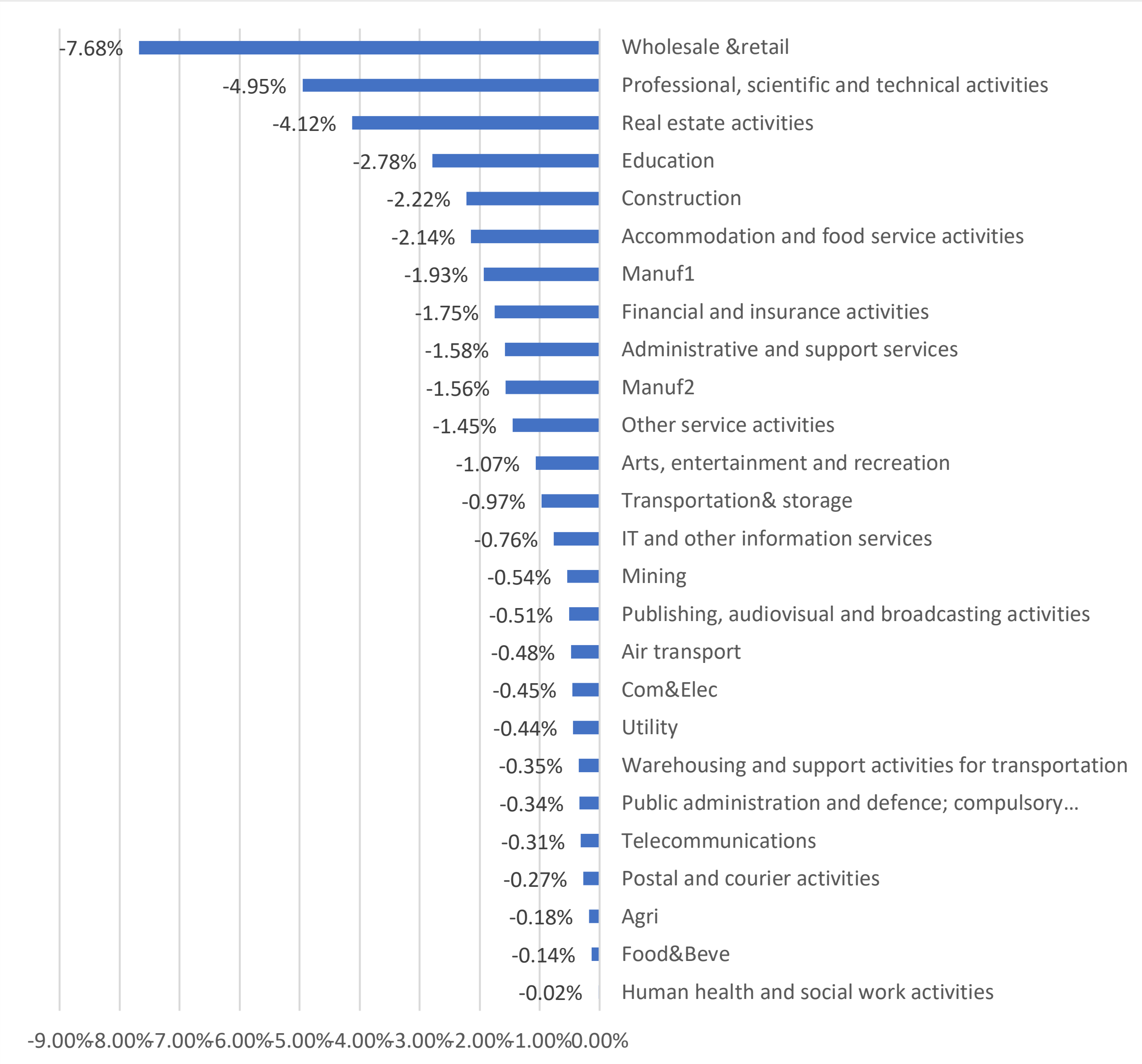
Figure 4.12: GDP losses percentage by sector with 12 months lockdown: under the impact of direct shock on Final Demand (Total: $3.2Tn, 15.95% of Total GDP)



With direct sectoral lockdown impact on final demand but the intermediate good section unaffected, the effects are only showing in the lockdown sectors. Reduction in final demand shrinks the GDP for corresponding sectors, wholesale and retail witness the most significant decrease with 3.89% of total GDP since it is the largest sector with a 75% lockdown percentage.

4.5.2 Scenario two: Mixed demand shock on Final Demand and intermediate good

Figure 4.13: GDP losses percentage by sector under 12 months lockdown: the direct demand side shock on Final Demand and intermediate goods (Total:$7.8tn, 39% of Total GDP)

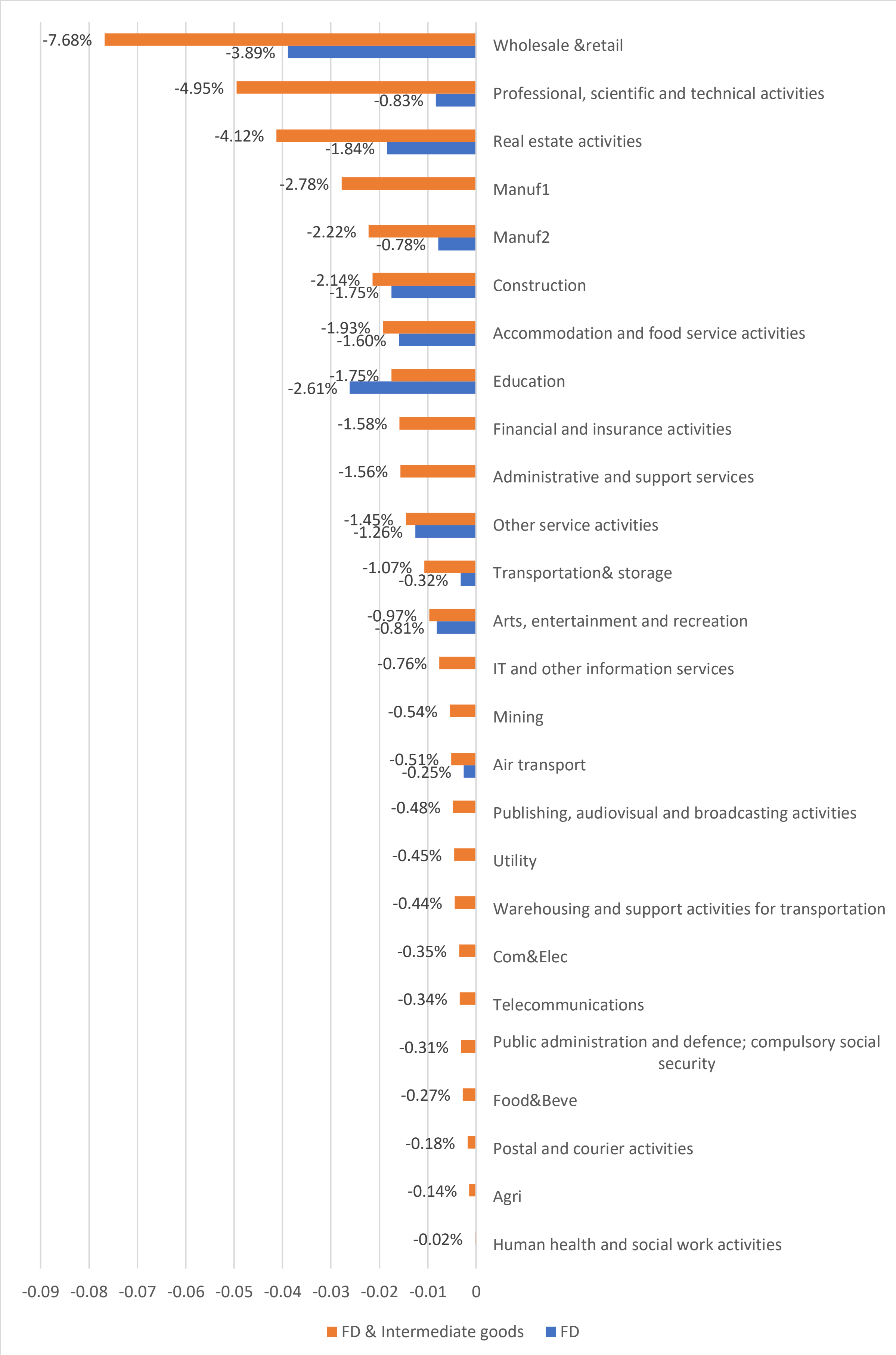


In scenario two, we take into consideration of intermediate products, and the most visible change in the GDP is that not only the sectors that have lockdown are affected, but so are all other sectors.

Reduced demand for intermediate goods causes the decrease of all input to a sector, therefore there are indirect negative shocks in all sectors which results in a decrease in sectoral GDP.

In scenario 2, the wholesale & retail sector doubles their losses by decreasing 7.6% of total GDP. Human Health and social work sector decreased the least because they share the least connectivity with other sectors.

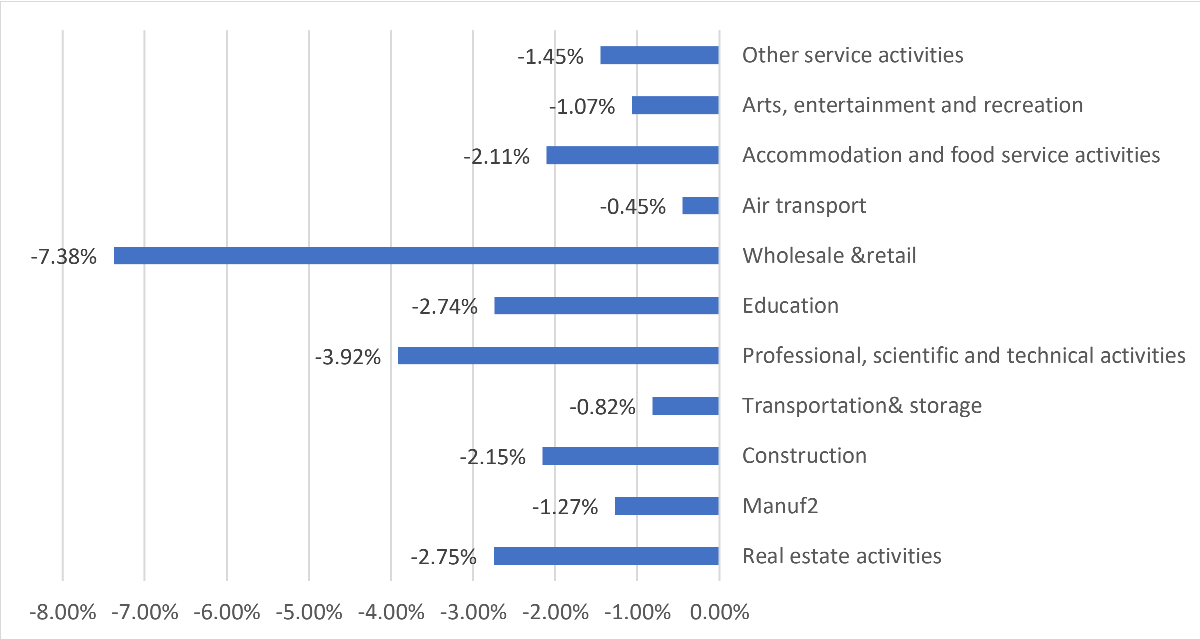
Figure 4.14: The direct demand side shock on Final Demand VS Mixed Impact on FD and Intermediate goods under 12 months lockdown


Wholesale &retail
-7.68%
-3.89%
Professional, scientific and technical activities
-4.95%
-0.83%
Real estate activities
-4.12%
-1.84%
Manuf1
-2.78%
Manuf2
-2.22%
-0.78%
Construction
-2.14%
-1.75%
Accommodation and food service activities
-1.93%
-1.60%
Education
-1.75%
-2.61%
Financial and insurance activities
-1.58%
Administrative and support services
-1.56%
Other service activities
-1.45%
-1.26%
Transportation& storage
-1.07%
-0.32%
Arts, entertainment and recreation
-0.97%
-0.81%
IT and other information services
-0.76%
Mining
-0.54%
Air transport
-0.51%
-0.25%
Publishing, audiovisual and broadcasting activities
-0.48%
Utility
-0.45%
Warehousing and support activities for transportation
-0.44%
Com&Elec
-0.35%
Telecommunications
-0.34%
Public administration and defence; compulsory social security
-0.31%
Food&Beve
-0.27%
Postal and courier activities
-0.18%
Agri
-0.14%
Human health and social work activities
-0.02%
-0.09 -0.08 -0.07 -0.06 -0.05 -0.04 -0.03 -0.02 -0.01 0
FD & Intermediate goods
FD

When taking consideration of the intermediate goods and the interconnection of sectors, we can see the losses of each sector not only get more severe, the losses from other sectors that are not shutdown also emerges. Manufacturing two and Financial services despite not being locked down, still contribute to around 2.7% and 1.6% decrease in total GDP.

4.5.3 Scenario three: Direct Supply Shock on Value Added

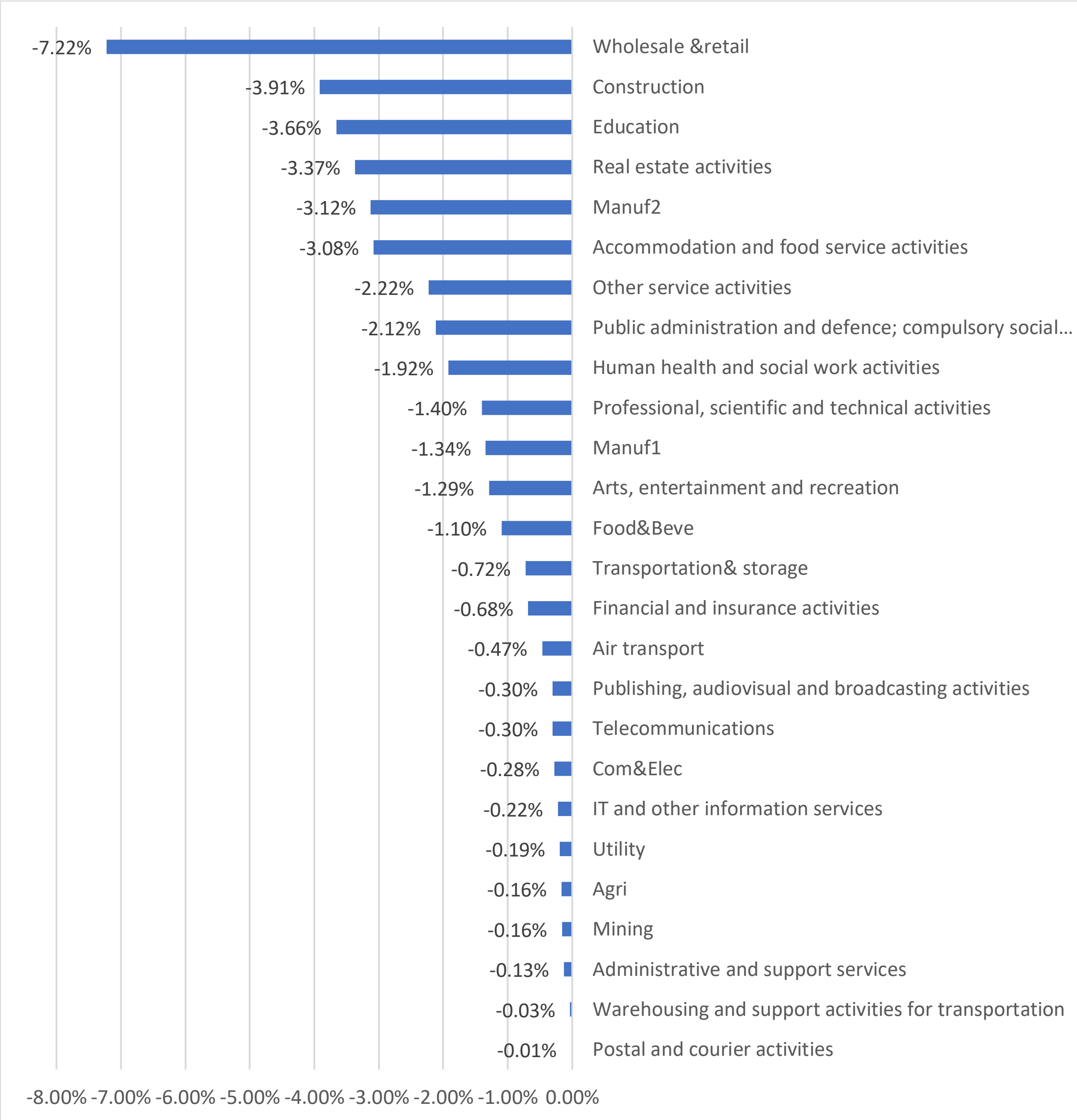
Figure 4.15: Direct Supply Shock on Value Added, GDP Losses Ratio Under Direct Supply Side Shock under 12 months lockdown (Total: $5.2Tn, 26% of Total GDP)



In the supply side shock scenario, we implement the lockdown onto value added instead of final demand, and it shows that the decrease in GDP would be more severe. Wholesale and retail GDP suffers from lockdown the most in both scenario, but the second largest decrease is from professional service when value added is affected instead of real estate in the case for final demand. It shows that even with simple direct shock, demand side and supply side would have some level of difference in reaction.

4.5.4 Scenario four: Mixed Supply shock on Value Added and Intermediate good

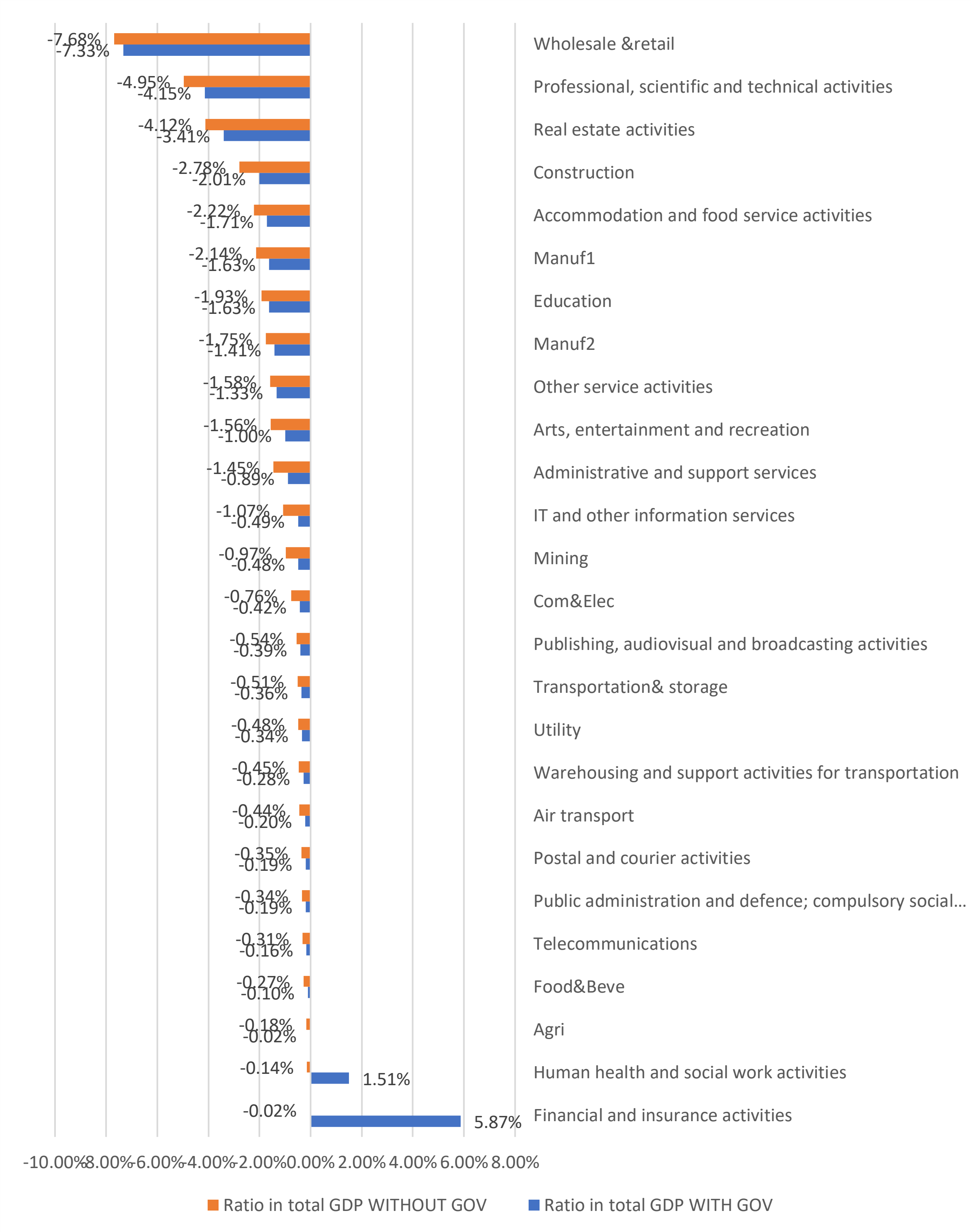
Figure 4.16: Mixed Supply shock on Value Added and Intermediate good under 12 months lockdown (Total: $8 Tn, 40% of Total GDP)



Despite the differences in direct shocks from demand and supply side, the overall interconnected shock, including direct and indirect presents very similar outcome. As when the demand shock is implemented, the total lost of GDP is $7.8 trillion, and the number is $8 trillion when the shock is on supply side. We expect a similar result when both shocks happens spontaneously, however, further advance of the methodology on spontaneous shock might present otherwise. Therefore it is necessary to explore further in future works.

4.5.5 Scenario five: Mixed Supply shock on Value Added and Intermediate good with Government intervention on VA

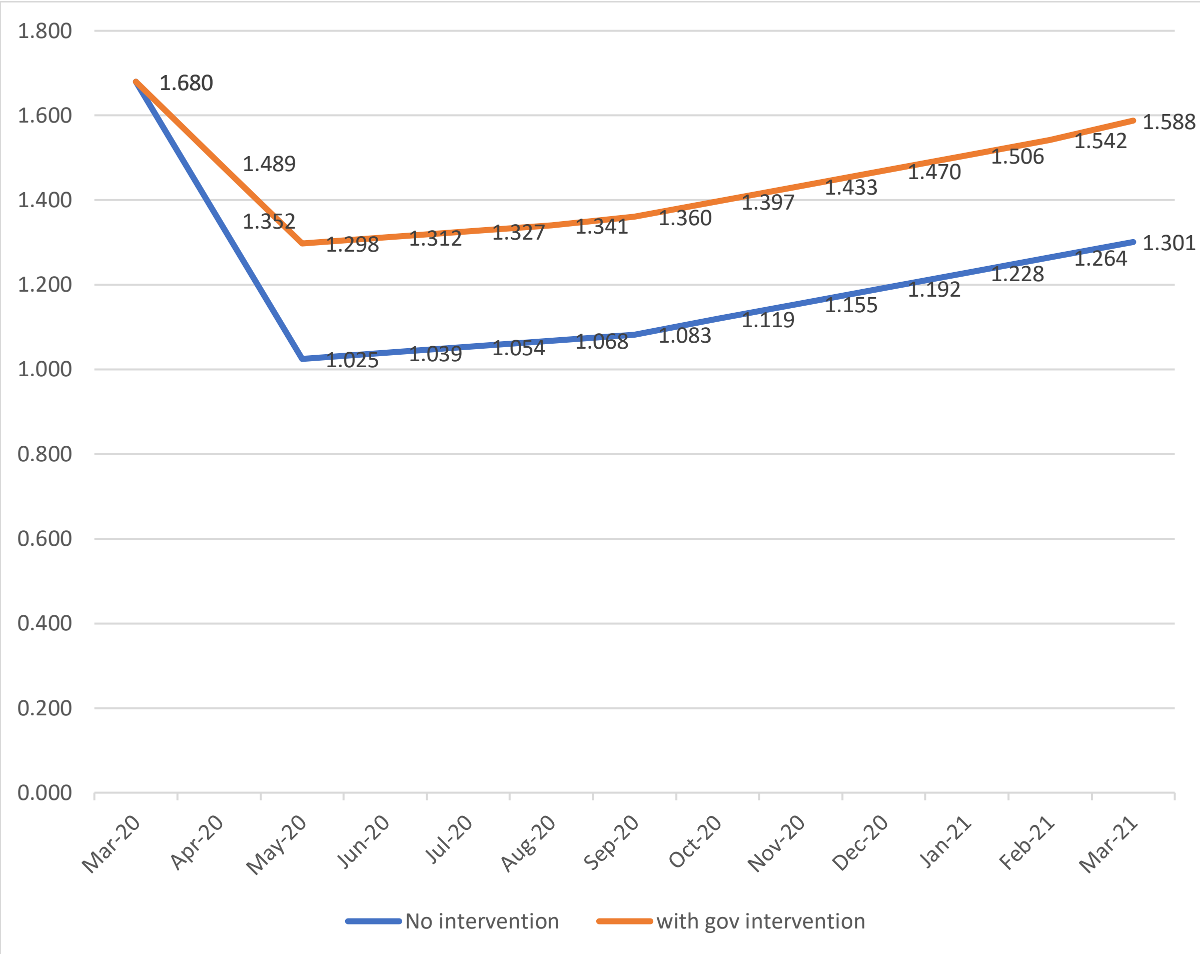
Figure 4.17: Mixed Supply shock on Value Added and Intermediate good with Government intervention on VA



In scenario five, we implemented the government fiscal policy interventions, which, primarily targeting human health sector and financial sector. Specifically, the value added is increased according to the rescue package data. Overall, all sectors has witness certain degree of recovery, by health and financial sector are getting increase in GDP due to the high spending during Covid-19 period.

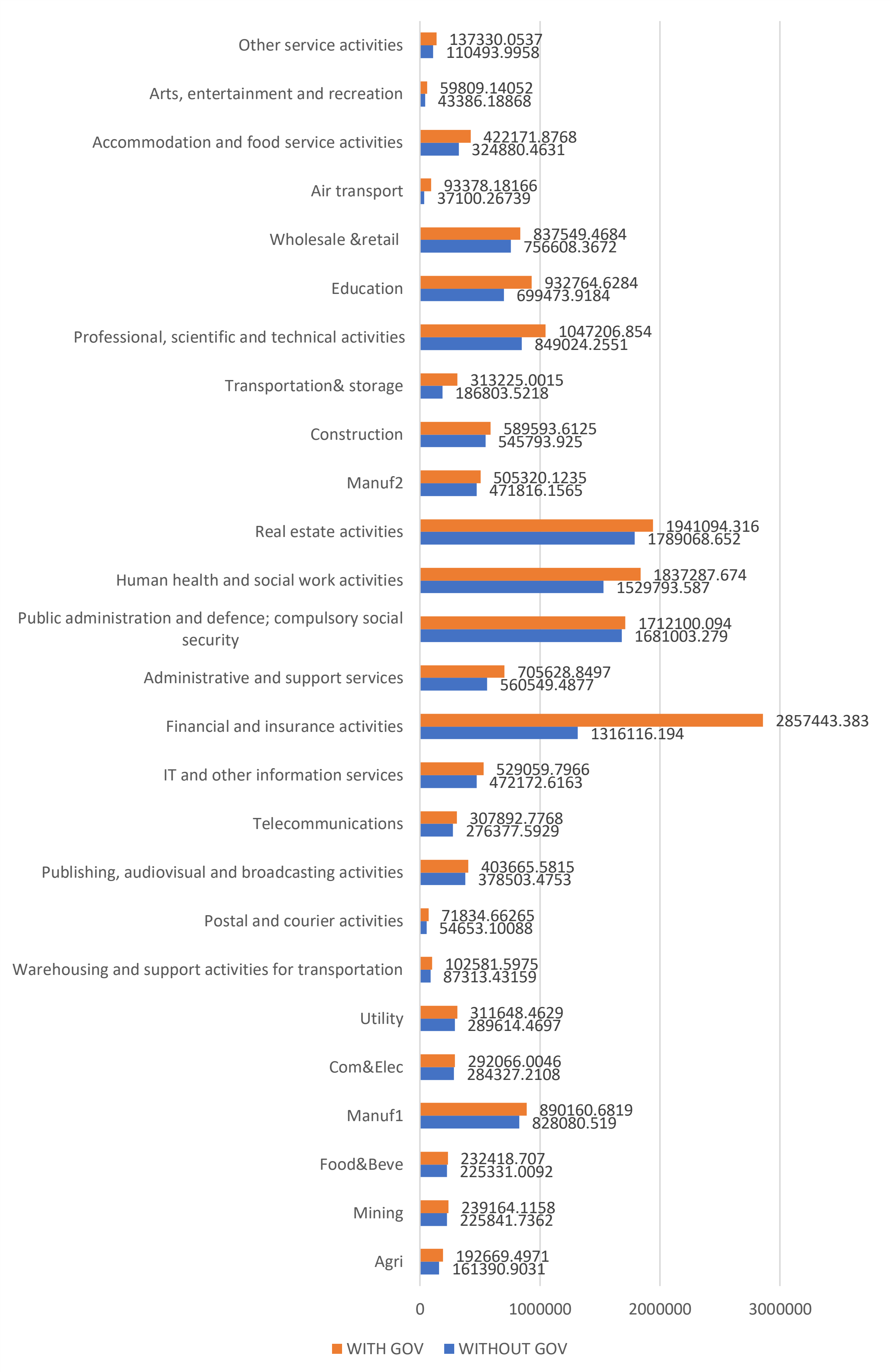
4.5.6 Scenario six: Mixed Supply shock on Value Added and Intermediate goods with Government intervention on VA and FD and the three lockdown phases.

Figure 4.18: Comparison of the US GDP under 3 lockdown phases with and without government intervention. ($Tn) (Phase one: March 2020- May 2020, Phase two: May 2020 – Sep 2020, phase 3: Sep 2020 – March 2021



Finally, in scenario six, we combine our conditions including intermediate good impact, government intervention, and three phases of lockdown, we find this comparison of the monthly GDP trend. In this graph, we assume the recovery during each lockdown phase is steady. Therefore, we can see this trend of a steep decrease in monthly GDP initially, slowly recover to almost reaching the original level when government intervention is present. Without government intervention, it shows a flatter recovery trend, and by the end of the 12 month period, GDP fails to restore to original level.

Figure 4.19: Comparison of the US sectoral GDP under 3 lockdown phases with and without government intervention. ($Mn)


Other service activities
137330.0537
110493.9958
Arts, entertainment and recreation
59809.14052
43386.18868
Accommodation and food service activities
422171.8768
324880.4631
Air transport
93378.18166
37100.26739
Wholesale &retail
837549.4684
756608.3672
Education
932764.6284
699473.9184
Professional, scientific and technical activities
1047206.854
849024.2551
Transportation& storage
313225.0015
186803.5218
Construction
589593.6125
545793.925
Manuf2
505320.1235
471816.1565
Real estate activities
1941094.316
1789068.652
Human health and social work activities
1837287.674
1529793.587
Public administration and defence; compulsory social security
1712100.094
1681003.279
Administrative and support services
705628.8497
560549.4877
Financial and insurance activities
2857443.383
1316116.194
IT and other information services
529059.7966
472172.6163
Telecommunications
307892.7768
276377.5929
Publishing, audiovisual and broadcasting activities
403665.5815
378503.4753
Postal and courier activities
71834.66265
54653.10088
Warehousing and support activities for transportation
102581.5975
87313.43159
Utility
311648.4629
289614.4697
Com&Elec
292066.0046
284327.2108
Manuf1
890160.6819
828080.519
Food&Beve
232418.707
225331.0092
Mining
239164.1158
225841.7362
Agri
192669.4971
161390.9031
0
1000000
2000000
3000000
WITH GOV
WITHOUT GOV

We can also look into the sectoral changes, similar to previous results, Financial sector is the sector with the most dramatic difference when the government intervention is implemented, all sectors benefited from the government rescue package. Overall, comparing with the pre-COVID GDP level, without government intervention, there are $5.9 trillion GDP loss (29.63%), And with government intervention, there are only a $2.6 trillion GDP loss (12.86%). The shock of COVID-19 lockdown is evitable, but with government rescue package, the GDP loss can be halved.

4.6 Conclusion

This chapter continues to build on the basic input-output network framework from Chapter 1 but applies it to analyse the complex economic impacts of COVID-19 sectoral lockdowns in the United States. The COVID-19 crisis represents a unique simultaneous shock to both supply and demand across interconnected sectors.

The paper develops a granular macro-network model incorporating multiple scenarios of demand-side reductions in final demand, supply-side constraints on value-added, and government fiscal interventions. By utilizing the OECD ICIO database and adapting input-output techniques like hypothetical extraction, the model provides valuable insights into sectoral propagation effects and quantified losses at the sectoral level.

Key findings demonstrate the significance of intermediate input linkages in propagating shocks across the economy, as well as the importance of fiscal relief in mitigating GDP declines. The sectoral analysis illustrates which industries suffered the most severe impacts based on their position in the production network.

While this paper marks an essential step in modelling COVID-19's sectoral economic effects, some limitations remain to be addressed. The slow updating of input-output data reduces the accuracy of the results for the 2020 pandemic crisis. The partial extraction assumptions could be expanded by incorporating potential coping strategies like trade substitutions. Additionally, further work is needed to capture the evolving, dynamic adaptation of input-output relationships over time.

Nonetheless, the granular network approach provides a valuable foundation for understanding how lockdowns affected interconnected US sectors. Extending the model with more recent data and additional mechanisms would further strengthen the analysis. Ultimately, these insights can inform policy aimed at resilient economic recovery from sectoral shocks. The integrated input-output methodology demonstrates a promising way to model complex crises like COVID-19.

Chapter 5 Limitations and extensions

While the granular network approaches developed in this thesis offer valuable insights, several modelling limitations persist alongside rich avenues for future research. The core limitations and extensions are as followed:

5.1 Limitations

The chapter three only applied a broad application across all sectors and the rest of the world is generalised, it provides a comprehensive analysis of responsive strategy outcomes, but the sectoral trade war shocks to highly affected sectors and to specific diverted trading partners would improve the analysis on primary targeted products and the impact of trading strategies on them.

In Chapter four, the model does not fully simulate the dynamic impacts of combined demand and supply-side shocks that often occur during disaster events. The improved partial extraction method in Chapter four adapts to spontaneous shocks but needs further development to capture two-sided shock dynamics.

In general, there are some database limitations. The OECD ICIO data used updates slowly with a multi-year delay (e.g. latest available data is 2018 as this paper is written in 2023). This affects result accuracy for analysing events like COVID-19. Also, import elasticities are generalized across countries and sectors due to data complexity, rather than using specific values. Import elasticities data accuracy can be improved with additional data collection and calculations.

5.2 Future Work

The future work and extension are as followed:

Enhance the methodology to measure demand and supply-side shocks simultaneously to better represent real-world conditions during disasters; Apply the model and analysis to specific products to evaluate the system-wide impacts of responsive strategies to negative shocks to the key products.; Incorporate employment rate changes and worker welfare impacts relevant to the shocks studied, extend the analysis focus on the supply-side value-added components; Seek more recent and higher frequency input-output databases for improved timeliness. Gather disaggregated elasticity data by country and sector if feasible to increase accuracy.

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Appendix A. Chapter Two

A.1. Sectoral Tariff implemented During US-China Trade War

Table 0.1: Pre and Post Trade War China import from US numbers of sub-sector under different tariffs and corresponding trade values (in million$)

China Import from the US	Pre-Trade War		Post Trade War	
Tariff Rate (%)	Numbers of sub-sectors	Trade Value	Numbers of sub-sectors	Trade Value
t=0	264	38829.07	38	13229.15
0<t<5	425	53727.02	75	40026.20
5=<t<10	1571	35294.98	460	18501.29
10=<t<15	1167	10973.90	724	15552.96
15=<t<20	400	2699.04	278	10101.75
20=<t<30	274	11079.43	2590	56848.76
30=<t<50	63	1642.15	11	62.62
50=<t	15	190.06	4	112.92

Source: Author gathered from US and China official announcements and WTO websites.

Table 0.2: Pre and Post-Trade War US import from China numbers of sub-sector under different tariffs and corresponding trade values (in million$)

US Import from China	Pre-Trade War		Post-Trade War	
Tariff Rate	Numbers of sub-sectors	Trade Value ($Mn)	Numbers of sub-sectors	Trade Value ($Mn)
t=0	1820	285396.50	185	125427.40
0<t<5	1530	183424.50	81	14961.05
5=<t<10	647	46003.29	1038	118088.10
10=<t<15	288	22944.62	36	11403.55
15=<t<20	57	15219.42	44	34497.01

20=<t<30	24	2756.71	2985	251393.30
30=<t<50	1	14.18	0	0
50=<t	2	11.20	0	0

Source: Author gathered from US and China official announcements and WTO website.

A.2. Model Sample for full calculation process for the changes in GDP and Gross Output

In the sample model of the cross-border input-output data analysis on the US-China Trade War, we set the United States, China and the rest of the world with only three sectors: Agriculture, Mining and Food & Beverage.

The ultimate purpose is to find the direct impact of tariff change on intermediate goods to Value added, the direct impact of tariff change on final demand to Value Added, and eventually, the mixed effect from both changes.

A.2.1. Data and variables

First, we have the input-output data:

Table 0.3: Original ICIO Data

	In $Mn	US INTERMEDIATE			CHINA INTERMEDIATE			ROW INTERMEDIATE						
	Original ICIO	Agri	Mining	Food&Beve	Agri	Mining	Food&Beve	Agri	Mining	Food&Beve	USAFD	CHNFD	ROWFD	TOTAL OUTPU
US INTERMEDIATE	Agri	61629.95	129.29	202786.76	3598.18	81.49	4933.17	3700.57	10.52	13982.82	102241.52	5142.39	14006.07	455757.42
	Mining	5635.16	84388.67	17412.29	19.18	129.06	1.68	558.88	3979.22	186.64	31512.20	33.55	2846.57	446346.55
	Food&Beve	30267.36	67.94	100584.12	632.95	13.40	913.88	3478.59	59.46	8673.20	560846.05	4252.50	36614.26	935808.35
CHINA INTERMEDIATE	Agri	249.95	0.41	845.49	371601.33	7764.62	534375.01	1594.95	7.60	5702.05	426.74	541493.67	6096.25	1742206.34
	Mining	2.65	17.51	3.96	6618.66	72705.20	1192.89	33.59	325.79	23.29	3.57	10873.96	887.90	806895.29
	Food&Beve	298.15	0.10	936.79	147879.79	373.26	193668.80	2859.40	3.92	7402.19	4478.53	749152.03	21779.22	1387735.54
ROW INTERMEDIATE	Agri	5132.74	11.15	17712.63	12079.98	306.99	15433.76	577791.59	5067.15	1092736.21	10914.89	16224.37	1680660.77	3835314.76
	Mining	195.21	4109.61	1480.20	661.10	9920.13	373.86	71211.35	748201.42	23491.82	1716.35	4501.24	232457.75	3485109.97
	Food&Beve	2333.26	13.81	7684.82	6226.63	42.44	6886.43	251297.86	1484.63	643420.77	51782.31	28580.27	2419253.63	4144944.13
	VA	195383.54	319552.96	256486.10	892689.79	352953.07	406258.13	2157744.32	2063410.68	1164103.84	489686.54	568375.09	1919008.69	74677481.00
	TOTAL	455757.42	446346.55	935808.35	1742206.34	806895.29	1387735.54	3835314.76	3485109.97	4144944.13	1253608.70	1928629.06	6333611.11	

It contains the 9*9 intermediate good input-output matrix, final demand matrix, Value Added and total output.

Now we get the Leontief Coefficient to show how much percentage of goods each sector imports/exports to/from other sectors. For instance, in the table below, the agriculture sector of the rest of the world exported intermediate goods to the agriculture sector of China, which makes up 1% of the total output of the China mining sector.

Table 0.4: Leontief Coefficient Matrix (A Matrix)

Leontief Coefficient Matrix (A Matrix)		US INTERMEDIATE Agri	US INTERMEDIATE Mining	US INTERMEDIATE Food&Beve	CHINA INTERMEDIATE Agri	CHINA INTERMEDIATE Mining	CHINA INTERMEDIATE Food&Beve	ROW INTERMEDIATE Agri	ROW INTERMEDIATE Mining	ROW INTERMEDIATE Food&Beve
US INTERMEDIATE	Agri	0.14	0.00	0.22	0.00	0.00	0.00	0.00	0.00	0.00
	Mining	0.01	0.19	0.02	0.00	0.00	0.00	0.00	0.00	0.00
	Food&Beve	0.07	0.00	0.11	0.00	0.00	0.00	0.00	0.00	0.00
CHINA INTERMEDIATE	Agri	0.00	0.00	0.00	0.21	0.01	0.39	0.00	0.00	0.00
	Mining	0.00	0.00	0.00	0.00	0.09	0.00	0.00	0.00	0.00
	Food&Beve	0.00	0.00	0.00	0.08	0.00	0.14	0.00	0.00	0.00
ROW INTERMEDIATE	Agri	0.01	0.00	0.02	0.01	0.00	0.01	0.15	0.00	0.26
	Mining	0.00	0.01	0.00	0.00	0.01	0.00	0.02	0.21	0.01
	Food&Beve	0.01	0.00	0.01	0.00	0.00	0.00	0.07	0.00	0.16

To implement the tariff change into the IO matrix, we use the equation for the change in import demand:

$$\dot{M_\iota} = \varepsilon_{Di}\tau_i \qquad 0.1$$

Where τ_i are the Trade War tariffs change on sector i and $\varepsilon_{Di}$is the import elasticity of sector i in the domestic country.

This equation requires two sets of data, tariff change and import elasticity.

Table 0.5: Tariff change and import elasticity

Sectoral Tariff Change τ (%)		Agri	Mining	Food&Beve
US Tariffs	MFN	0.9984461	0.05337664	3.13562259
	Post Trade War	17.431959	6.46636315	20.9202359
	Change	16.43	6.41	17.78
CHN tariff	MFN	6.25247713	0.28473026	11.534512
	Post Trade War	7.43597513	24.3133518	19.0437149
	Change	1.18	24.03	7.51

We use the Post Trade War weighted tariff minus the pre-trade war MFN tariff to get the tariff change τ .

Table 0.6: Sectoral and Country Elasticity

Sectoral Elasticity	Agriculture	Mining	Food&Bev
	-4	-4	-4
Country Elasticity	China	US	ROW AVER
	-7	-5.9	-7.9
Country Relative	China	US	ROW AVER
	1	0.84285714	1.13846154

As for the ε_D, we use the Average Sectoral Elasticity data from Imbs, J. et al. (2017), with the country's relative elasticities as the scale level. However, due to the lack of information, for the sectors that we don't have the Average Sectoral Elasticity data, we use -4 following Vandenbussche et al. (2017), which is a lower-end estimate of the trade elasticity.

By multiplying all three factors, we get the change in the import demand matrix on both intermediate goods and final demand in percentage.

Table 0.7: Import Elasticity Multipliers

ε_D * τ		US INTERMEDIATE			CHINA INTERMEDIATE			ROW INTERMEDIATE		
		Agri	Mining	Food&Beve	Agri	Mining	Food&Beve	Agri	Mining	Food&Beve
US INTERMEDIATE	Agri	0	0	0	-4	-4	-4	-2.96139	-2.96139	-2.96139
	Mining	0	0	0	-4	-4	-4	-2.96139	-2.96139	-2.96139
	Food&Beve	0	0	0	-4	-4	-4	-2.96139	-2.96139	-2.96139
CHINA INTERMEDIATE	Agri	-3.3714286	-3.3714286	-3.3714286	0	0	0	-2.96139	-2.96139	-2.96139
	Mining	-3.3714286	-3.3714286	-3.3714286	0	0	0	-2.96139	-2.96139	-2.96139
	Food&Beve	-3.3714286	-3.3714286	-3.3714286	0	0	0	-2.96139	-2.96139	-2.96139
ROW INTERMEDIATE	Agri	-3.3714286	-3.3714286	-3.3714286	-4	-4	-4	0	0	0
	Mining	-3.3714286	-3.3714286	-3.3714286	-4	-4	-4	0	0	0
	Food&Beve	-3.3714286	-3.3714286	-3.3714286	-4	-4	-4	0	0	0

In the baseline model analysis, we assume both countries take no reactions in terms of coping with the Trade War, and there is no import constraint.

The analysis has three steps, the first step we calculate the direct losses of final demand in both countries and the indirect impact on Value Added,

In the second step, we calculate the direct changes in intermediate good input-output flow and its impact on Value Added.

In the last step, we mix both intermediate good and final demand changes to view the change in Value added as a whole.

A.2.1.1. Direct change in Final Demand: Tariff Change Impact on Value Added

In step one: we have the original final demand,

Table 0.8: Original final demand

In $Mn	Original Final Demand	US	CHN	ROW
US	Agri	102241.52	5142.39	14006.07
	Mining	31512.20	33.55	2846.57
	Food&Beve	560846.05	4252.50	36614.26
CHINA	Agri	426.74	541493.67	6096.25
	Mining	3.57	10873.96	887.90
	Food&Beve	4478.53	749152.03	21779.22
ROW	Agri	10914.89	16224.37	1680660.77
	Mining	1716.35	4501.24	232457.75
	Food&Beve	51782.31	28580.27	2419253.63

We calculate the change in final demand by multiplying total elasticity, tariff change and final demand.

Table 0.9: Final demand import elasticity

In $Mn	Final Demand *ε_D * τ	US	CHN	ROW
US	Agri	0	-243.44015	0
	Mining	0	-32.247711	0
	Food&Beve	0	-1277.316	0
CHINA	Agri	-236.4327	0	0
	Mining	-0.7710202	0	0
	Food&Beve	-2685.3088	0	0
ROW	Agri	0	0	0
	Mining	0	0	0
	Food&Beve	0	0	0

By using the original FD plus FD changes, we get a new FD sum:

Table 0.10: New Total Final Demand

In $Mn	New Final Demand	US	CHN	ROW
US	Agri	102241.52	4898.9461	14006.0737
	Mining	31512.199	1.30364251	2846.57192
	Food&Beve	560846.05	2975.18583	36614.2645
CHINA	Agri	190.307115	541493.671	6096.25334
	Mining	2.79506311	10873.9582	887.89714
	Food&Beve	1793.22492	749152.025	21779.2215
ROW	Agri	10914.8914	16224.3657	1680660.77
	Mining	1716.35191	4501.24322	232457.752
	Food&Beve	51782.3084	28580.2693	2419253.63

With a new final demand, the imported intermediated goods needed for the sectors will be changing, as well as the value-added.

To calculate that, we need the Value-added coefficient in Matrix form.

Table 0.11: Value-added coefficient

VA/X	In $Mn	US INTERMEDIATE			CHINA INTERMEDIATE			ROW INTERMEDIATE		
		Agri	Mining	Food&Beve	Agri	Mining	Food&Beve	Agri	Mining	Food&Beve
US INTERMEDIATE	Agri	0.42870073	0	0	0	0	0	0	0	0
	Mining	0	0.71593017	0	0	0	0	0	0	0
	Food&Beve	0	0	0.27407973	0	0	0	0	0	0
CHINA INTERMEDIATE	Agri	0	0	0	0.51239039	0	0	0	0	0
	Mining	0	0	0	0	0.43742116	0	0	0	0
	Food&Beve	0	0	0	0	0	0.29274895	0	0	0
ROW INTERMEDIATE	Agri	0	0	0	0	0	0	0.56259902	0	0
	Mining	0	0	0	0	0	0	0	0.59206473	0
	Food&Beve	0	0	0	0	0	0	0	0	0.2808491

We find the new VA by calculating VA coefficient*Leontief Inverse*FDsum based on the Leontief Inverse function $x = (I - A)^{-1}d$, and output inverse function $x'(I - B) = V'$ where the change in final demand and intermediate goods are responding to each other and output, therefore indirectly affecting VA. The equations are explained in the methodology.

the result is as shown:

Table 0.12: Value Added Changes

VACoe*A*NewFdsum	Sectors	New VA ($Mn)	Original VA ($Mn)	Absolute Difference ($Mn)	Relative Difference
US	Agri	194989.372	195383.538	-394.16585	-0.20%
	Mining	318773.22	319552.962	-779.74207	-0.24%
	Food&Beve	256032.726	256486.097	-453.37144	-0.18%
CHINA	Agri	887100.97	892689.794	-5588.8236	-0.63%
	Mining	345260.822	352953.071	-7692.2494	-2.18%
	Food&Beve	404079.632	406258.127	-2178.4952	-0.54%
ROW	Agri	2157092.83	2157744.32	-651.48516	-0.03%
	Mining	2056674.06	2063410.68	-6736.6281	-0.33%
	Food&Beve	1163916.67	1164103.84	-187.1686	-0.02%

Despite that the change in final demand is only taking place in the US and China, due to the interconnectivity of input-output trade flow, the rest of the world also witnesses losses in Value Added.

A.2.1.2. Intermediate Good Tariff Change Impact on Value Added

The second analysis is instead of changing Final Demand and keeping intermediate goods unchanged, we focus only on intermediate goods.

First, we have the Leontief Coefficient matrix and import demand change matrix from the previous section:

Table 0.13: Leontief Coefficient

	In $Mn	US INTERMEDIATE			CHINA INTERMEDIATE			ROW INTERMEDIATE		
	Original ICIO	Agri	Mining	Food&Beve	Agri	Mining	Food&Beve	Agri	Mining	Food&Beve
US INTERMEDIATE	Agri	61629.95	129.29	202786.76	3598.18	81.49	4933.17	3700.57	10.52	13982.82
	Mining	5635.16	84388.67	17412.29	19.18	129.06	1.68	558.88	3979.22	186.64
	Food&Beve	30267.36	67.94	100584.12	632.95	13.40	913.88	3478.59	59.46	8673.20
CHINA INTERMEDIATE	Agri	249.95	0.41	845.49	371601.33	7764.62	534375.01	1594.95	7.60	5702.05
	Mining	2.65	17.51	3.96	6618.66	72705.20	1192.89	33.59	325.79	23.29
	Food&Beve	298.15	0.10	936.79	147879.79	373.26	193668.80	2859.40	3.92	7402.19
ROW INTERMEDIATE	Agri	5132.74	11.15	17712.63	12079.98	306.99	15433.76	577791.59	5067.15	1092736.21
	Mining	195.21	4109.61	1480.20	661.10	9920.13	373.86	71211.35	748201.42	23491.82
	Food&Beve	2333.26	13.81	7684.82	6226.63	42.44	6886.43	251297.86	1484.63	643420.77

In the case of no reaction from either country, the losses in each sector fully and directly take effect on itself, and the rest of the world is not witnessing any direct changes.

Therefore, the new Leontief Coefficient is A + $\dot{M}_{\imath} * A$, the original Leontief Coefficient plus the import demand changes (which will be negative).

Table 0.14: Import Elasticity In Leontief Coefficient

M*A		US INTERMEDIATE			CHINA INTERMEDIATE			ROW INTERMEDIATE		
		Agri	Mining	Food&Beve	Agri	Mining	Food&Beve	Agri	Mining	Food&Beve
US INTERMEDIATE	Agri	0.0000	0.0000	0.0000	-0.0001	-0.0001	-0.0011	0.0000	0.0000	0.0000
	Mining	0.0000	0.0000	0.0000	0.0000	-0.0002	0.0000	0.0000	0.0000	0.0000
	Food&Beve	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0002	0.0000	0.0000	0.0000
CHINA INTERMEDIATE	Agri	-0.0003	0.0000	-0.0005	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Mining	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Food&Beve	-0.0004	0.0000	-0.0006	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ROW INTERMEDIATE	Agri	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Mining	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Food&Beve	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

First, we get the change in import demand M*A, then we add the changes to the original Leontief Coefficient.

Table 0.15: New Leontief Coefficient

A + M*A		US INTERMEDIATE			CHINA INTERMEDIATE			ROW INTERMEDIATE		
		Agri	Mining	Food&Beve	Agri	Mining	Food&Beve	Agri	Mining	Food&Beve
US INTERMEDIATE	Agri	0.1352	0.0003	0.2167	0.0020	0.0000	0.0025	0.0010	0.0000	0.0034
	Mining	0.0124	0.1891	0.0186	0.0000	0.0000	0.0000	0.0001	0.0011	0.0000
	Food&Beve	0.0664	0.0002	0.1075	0.0003	0.0000	0.0005	0.0009	0.0000	0.0021
CHINA INTERMEDIATE	Agri	0.0002	0.0000	0.0004	0.2133	0.0096	0.3851	0.0004	0.0000	0.0014
	Mining	0.0000	0.0000	0.0000	0.0038	0.0901	0.0009	0.0000	0.0001	0.0000
	Food&Beve	0.0003	0.0000	0.0004	0.0849	0.0005	0.1396	0.0007	0.0000	0.0018
ROW INTERMEDIATE	Agri	0.0113	0.0000	0.0189	0.0069	0.0004	0.0111	0.1507	0.0015	0.2636
	Mining	0.0004	0.0092	0.0016	0.0004	0.0123	0.0003	0.0186	0.2147	0.0057
	Food&Beve	0.0051	0.0000	0.0082	0.0036	0.0001	0.0050	0.0655	0.0004	0.1552

The final step is the same as the final demand impact case, we find the new VA by calculating VA coefficient*Leontief Inverse*FDsum, however, in this case, the change happens in the Leontief Inverse part instead of FD sum.

Table 0.16: Changes of Value Added from import shock on intermediate goods

VACoe*(A + M*A)*Fdsum	Sectors	New VA ($Mn)	Original VA ($Mn)	Absolute Difference ($Mn)	Relative Difference
US	Agri	193469.725	195383.538	-1913.8134	-0.98%
	Mining	316134.33	319552.962	-3418.6321	-1.07%
	Food&Beve	256042.026	256486.097	-444.07129	-0.17%
CHINA	Agri	888366.937	892689.794	-4322.8568	-0.48%
	Mining	346954.974	352953.071	-5998.0975	-1.70%
	Food&Beve	404962.662	406258.127	-1295.465	-0.32%
ROW	Agri	2157180.63	2157744.32	-563.69031	-0.03%
	Mining	2057222.69	2063410.68	-6187.9918	-0.30%
	Food&Beve	1163936.5	1164103.84	-167.33247	-0.01%

A.2.1.3. Intermediate good and final demand tariff change impact on value-added

In the final case of mixed impact, both the Leontief Inverse and the sum of FD are changing, so we use the new Leontief Inverse in the second case and the sum of new FD in the first case, we get the final result.

Table 0.17: Changes of Value Added from import shock on both final demand and intermediate goods

VACoe*(A + M*A)*NewFdsum	Sectors	New VA ($Mn)	Original VA ($Mn)	Absolute Difference ($Mn)	Relative Difference
US	Agri	193105.791	195383.538	-2277.7476	-1.17%
	Mining	315442.294	319552.962	-4110.6683	-1.29%
	Food&Beve	255596.977	256486.097	-889.11966	-0.35%
CHINA	Agri	882796.058	892689.794	-9893.7358	-1.11%
	Mining	339290.216	352953.071	-13662.856	-3.87%
	Food&Beve	402789.267	406258.127	-3468.8602	-0.85%
ROW	Agri	2156533.86	2157744.32	-1210.4587	-0.06%
	Mining	2050545.65	2063410.68	-12865.032	-0.62%
	Food&Beve	1163750.85	1164103.84	-352.98616	-0.03%

A.3. Data classification system matching

We have three types of data: MFN Tariff Data, COMTRADE data and OECD ICIO data, where MFN and COMTRADE use the same code system, which is HS07, and OECD ICIO data uses ISIC Rev. 4. Therefore, we follow a 5-step process to get the final form of data we needed for the analysis.

A.3.1.1. Get 6-digit Harmony System 2017 classification in COMTRADE data

Table 0.18: COMTRADE DATA classification with corresponding Trade Value in dollars (China's import from The United Stated 2018)

Commodity Code	Commodity	Trade Value (US$)($TR^{6D}$)
010190	Live horses/asses/mules/hinnies other than pure-bred breeding animals	258000
010611	Live primates	45805088
010619	Live mammals, n.e.s.	200002
010620	Live reptiles, incl. snakes & turtles	35963
…	…	…

A.3.1.2. Switch from HS2017 to ISIC REV.4

According to the statistic division website of United Nation, we convert data from HS07 to Central Product Classification (CPC) Ver. 2 first, then we convert CPC2 to ISIC4[17]. Therefore, all data are under ISIC4 categorisation.

A.3.1.3. Get weighted average tariff of 2-digit industries

Recall equation 1

$$\mathrm{WTR}_{\mathrm{S}}^{2\mathrm{D}} = \frac{\sum_{\mathrm{n}}^{\mathrm{i}} \mathrm{TR}_{\mathrm{Si}}^{6\mathrm{D}} \mathrm{TV}_{\mathrm{Si}}^{6\mathrm{D}}}{\sum_{\mathrm{n}}^{\mathrm{i}} \mathrm{TV}_{\mathrm{Si}}^{6\mathrm{D}}} \qquad 0.2$$

We get the weighted average tariff of the sectors which follows the ISIC Rev.4 classification

Table 0.19: International Standard Industrial Classification of All Economic Activities (ISIC) Revision 4 list of Industries

Code	Description
1	Crop and animal production, hunting and related service activities
2	Forestry and logging
3	Fishing and aquaculture

17 Reference for conversion process: https://unstats.un.org/unsd/classifications/Econ

5	Mining of coal and lignite
6	Extraction of crude petroleum and natural gas
…	…

(Full list in International Standard Industrial Classification of All Economic Activities (ISIC) Revision 4)

A.3.1.4. Match ISIC with OECD ICIO Classification

We match the classification with the OECD ICIO data, which is condensed from 98 industries to 36 sectors. For instance, sectors 1 to 3 are merged into Agriculture, forestry and fishing.

Table 0.20: the classification of the OECD ICIO data

Code	**Sector**
D01T03	Agriculture, forestry and fishing
D05T06	Mining and extraction of energy-producing products
D07T08	Mining and quarrying of non-energy producing products
D09	Mining support service activities
…	…

(Full list in OECD, Inter-Country Input-Output (ICIO) Tables industry code, 2018 edition)

A.3.1.5. 36 sectors condensed to 10 condensed sectors

In the final step, in order to show more significant results, we further merged some sectors, for instance, sectors 5 to 9, into one, which is mining. In addition, some services sectors don't have trade value, therefore, eventually, we get 10 sectors in our final analysis data.

Table 0.21: Final aggregated sectors list

Sector	**Short**
Agriculture, forestry and fishing	Agri
Mining	Mining
Food products, beverages and tobacco	Food

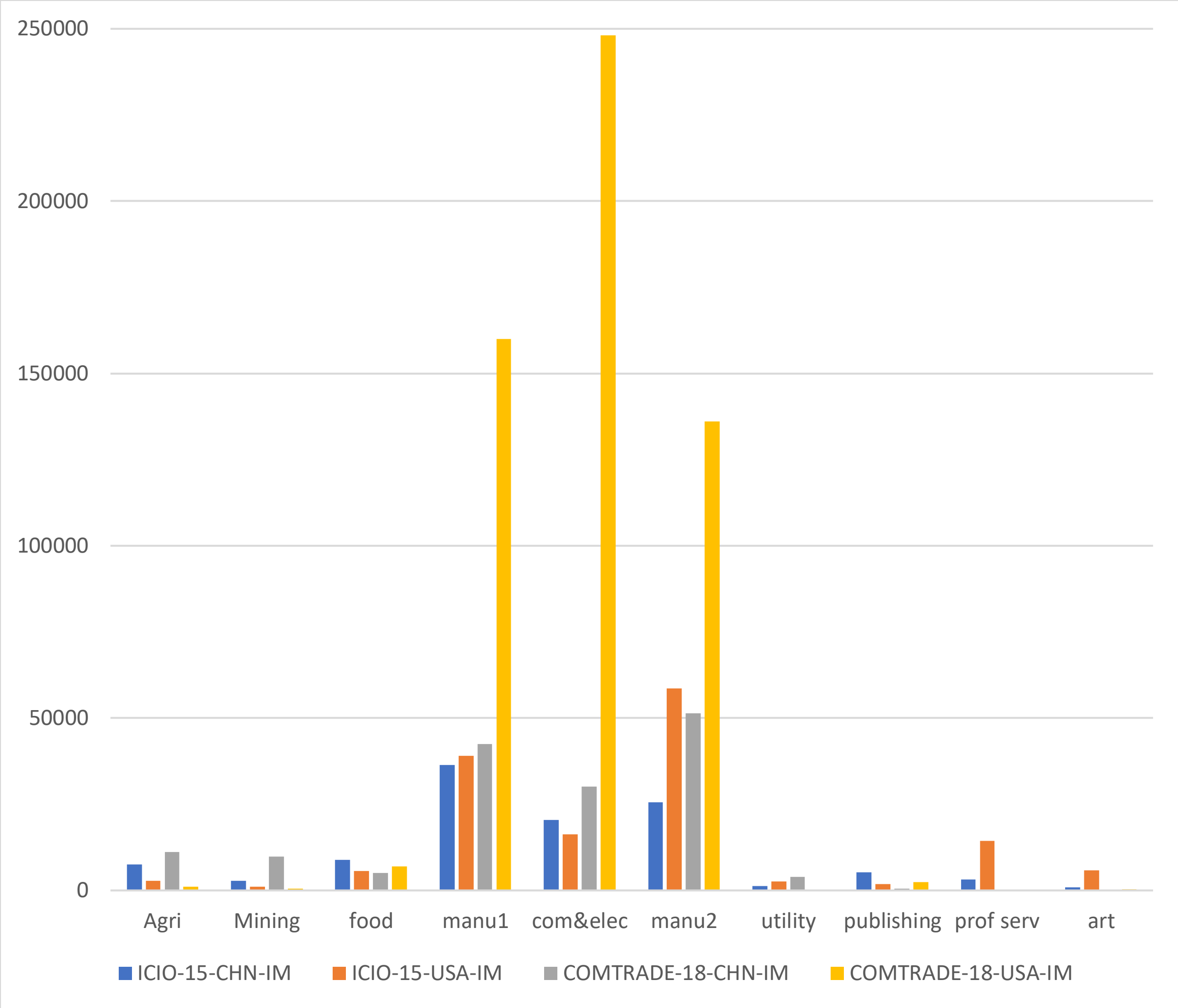
Manufacturing 1	Manuf1
Electrical equipment and Computer	Elec&Com
Manufacturing 2	Manuf2
Electricity, gas, water supply, sewerage, waste and remediation services	Utility
Publishing, audiovisual and broadcasting activities	Publishing
Professional services	Prof Serv
Arts, entertainment, recreation and other service activities	Art

Overall:

HS07 6-digit categories → ISIC REV.4 categories → Calculate Weighted average tariff rate → 36 ICIO sectors → 10 sectors for the final result.

A.3.1.6. ICIO OECD 2015 VS COMTRADE 2018: similarity and differences

Figure 0.1: US and China import from each other: ICIO 2015 intermediate good trade value VS. COMTRADE2018 trade value (million$)



We can see that throughout the years, both countries have increased the volume of trade, but US import from China has a rather dramatic rise. In general, the key trade sectors are consistently the three sectors: manufacturing 1 &2 and Computer/Electronic devices, especially for computer &Electronic, China imported more than the US in 2015 but three years later US imported around ten times more from China than China imported from the US. It can be a supporting reason for the US released a ban on Chinese tech companies in 2018 such as HUAWEI. Secondly, the US is highly relying on foreign manufacturing in recent years and China is one of the main suppliers. In manufacturing, the sectors that are attracting focuses are Steel and Aluminium. In May 2019, the US implemented a tariff raise on Steel and Aluminium for several countries such as China, Canada and Mexico. According to the tariff change, government file from the US, the import tariff rate for China in most Steel and Aluminium sectors is increased from 6-8 per cent to 20-25 per cent.

A.4. International Standard Industrial Classification of All Economic Activities (ISIC) Revision 4[18]

Code	Description
1	Crop and animal production, hunting and related service activities
2	Forestry and logging
3	Fishing and aquaculture
5	Mining of coal and lignite
6	Extraction of crude petroleum and natural gas
7	Mining of metal ores
8	Other mining and quarrying
9	Mining support service activities
10	Manufacture of food products
11	Manufacture of beverages
12	Manufacture of tobacco products
13	Manufacture of textiles
14	Manufacture of wearing apparel
15	Manufacture of leather and related products
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw
17	Manufacture of paper and paper products
18	Printing and reproduction of recorded media
19	Manufacture of coke and refined petroleum products
20	Manufacture of chemicals and chemical products
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
22	Manufacture of rubber and plastics products
23	Manufacture of other non-metallic mineral products
24	Manufacture of basic metals
25	Manufacture of fabricated metal products, except machinery and equipment
26	Manufacture of computer, electronic and optical products
27	Manufacture of electrical equipment
28	Manufacture of machinery and equipment n.e.c.
29	Manufacture of motor vehicles, trailers and semi-trailers
30	Manufacture of other transport equipment
31	Manufacture of furniture
32	Other manufacturing
33	Repair and installation of machinery and equipment
35	Electricity, gas, steam and air conditioning supply
36	Water collection, treatment and supply
37	Sewerage

[18] https://unstats.un.org/unsd/classifications/Family/Detail/27

38	Waste collection, treatment and disposal activities; materials recovery
39	Remediation activities and other waste management services
41	Construction of buildings
42	Civil engineering
43	Specialized construction activities
45	Wholesale and retail trade and repair of motor vehicles and motorcycles
46	Wholesale trade, except of motor vehicles and motorcycles
47	Retail trade, except of motor vehicles and motorcycles
49	Land transport and transport via pipelines
50	Water transport
51	Air transport
52	Warehousing and support activities for transportation
53	Postal and courier activities
55	Accommodation
56	Food and beverage service activities
58	Publishing activities
59	Motion picture, video and television programme production, sound recording and music publishing activities
60	Programming and broadcasting activities
61	Telecommunications
62	Computer programming, consultancy and related activities
63	Information service activities
64	Financial service activities, except insurance and pension funding
65	Insurance, reinsurance and pension funding, except compulsory social security
66	Activities auxiliary to financial service and insurance activities
68	Real estate activities
69	Legal and accounting activities
70	Activities of head offices; management consultancy activities
71	Architectural and engineering activities; technical testing and analysis
72	Scientific research and development
73	Advertising and market research
74	Other professional, scientific and technical activities
75	Veterinary activities
77	Rental and leasing activities
78	Employment activities
79	Travel agency, tour operator, reservation service and related activities
80	Security and investigation activities
81	Services to buildings and landscape activities
82	Office administrative, office support and other business support activities
84	Public administration and defence; compulsory social security
85	Education
86	Human health activities
87	Residential care activities
88	Social work activities without accommodation
90	Creative, arts and entertainment activities
91	Libraries, archives, museums and other cultural activities
92	Gambling and betting activities
93	Sports activities and amusement and recreation activities
94	Activities of membership organizations
95	Repair of computers and personal and household goods
96	Other personal service activities
97	Activities of households as employers of domestic personnel

98	Undifferentiated goods- and services-producing activities of private households for own use
99	Activities of extraterritorial organizations and bodies

A.5. OECD, Inter-Country Input-Output (ICIO) Tables industry code, 2018 edition[19]

Code	Industry	ISIC Rev.4
D01T03	Agriculture, forestry and fishing	01, 02, 03
D05T06	Mining and extraction of energy producing products	05, 06
D07T08	Mining and quarrying of non-energy producing products	07, 08
D09	Mining support service activities	09
D10T12	Food products, beverages and tobacco	10, 11, 12
D13T15	Textiles, wearing apparel, leather and related products	13, 14, 15
D16	Wood and products of wood and cork	16
D17T18	Paper products and printing	17, 18
D19	Coke and refined petroleum products	19
D20T21	Chemicals and pharmaceutical products	20, 21
D22	Rubber and plastic products	22
D23	Other non-metallic mineral products	23
D24	Basic metals	24
D25	Fabricated metal products	25
D26	Computer, electronic and optical products	26
D27	Electrical equipment	27
D28	Machinery and equipment, nec	28
D29	Motor vehicles, trailers and semi-trailers	29
D30	Other transport equipment	30
D31T33	Other manufacturing; repair and installation of machinery and equipment	31, 32, 33
D35T39	Electricity, gas, water supply, sewerage, waste and remediation services	35,36, 37, 38, 39
D41T43	Construction	41, 42, 43
D45T47	Wholesale and retail trade; repair of motor vehicles	45, 46, 47
D49T53	Transportation and storage	49, 50, 51, 52, 53
D55T56	Accomodation and food services	55, 56
D58T60	Publishing, audiovisual and broadcasting activities	58, 59, 60
D61	Telecommunications	61
D62T63	IT and other information services	62, 63
D64T66	Financial and insurance activities	64, 65, 66
D68	Real estate activities	68
D69T82	Other business sector services	69, 70, 71, 72, 73, 74, 75, 77, 78, 79, 80, 81, 82
D84	Public admin. and defence; compulsory social security	84
D85	Education	85
D86T88	Human health and social work	86, 87, 88
D90T96	Arts, entertainment, recreation and other service activities	90, 91, 92, 93,94,95, 96
D97T98	Private households with employed persons	97, 98

19 https://www.oecd.org/sti/ind/inter-country-input-output-tables.htm

Appendix B. Chapter Four

B.1. Selecting the correct methodology for applying lockdown restrictions on input-output tables of an economy.

B.1.1. Method 1: We apply the lockdown R ratios directly of the Leontief coefficients and Final Demand.

Leontief Technology Coefficient:

$$\boldsymbol{a_{ij}} = {}^{\boldsymbol{x_{ij}}}/_{\boldsymbol{x_j}} \tag{0.3}$$

New Leontief Technology Coefficient:

$$\boldsymbol{a_{ij}^{\#1}} = \min(\boldsymbol{R_i}, \boldsymbol{R_j}) * \boldsymbol{a_{ij}} \tag{0.4}$$

New Final Demand:

$$\boldsymbol{FD_i^{\#1}} = \boldsymbol{FD_i} * \boldsymbol{R_i} \tag{0.5}$$

We set the example ICIO data as below:

Table 0.22: Example ICIO data pre-lockdown

ICIO data	**Construction**	**Manufacturing**	**Final Demand**	**Gross Output**
Construction	500	300	200	1000
Manufacturing	400	100	300	800
Value Added	100	400		
Gross input	1000	800		

This example is a two-sector ICIO data framework where the Gross Inputs are equal to the Gross Outputs and are the sum of their respective Columns/Row.

Therefore, the Leontief coefficient (A Matrix) is:

Table 0.23**:** Example A Matrix pre-lockdown (in percentage)

A Matrix (%)	**Construction**	**Manufacturing**	**Final Demand**
Construction	*0.5*	*0.375*	0.2

Manufacturing	*0.4*	*0.125*	0.375
Value Added	0.1	0.5	
Gross Output	1	1	

Lockdown R ratios applied on the Leontief coefficients & FD:

Table 0.24: Example Lockdown R Ratios

	Construction	Manufacturing
Lockdown Percentage	0.5	0.4
Remaining Percentage	0.5	0.6

Based on formulas 24 & 25, we can get the new A matrix $A^{\#1}$ that includes the components:

$\min(\boldsymbol{R_{i,}R_j}) * \boldsymbol{a_{ij}}$; $\boldsymbol{R_{i,}} * \boldsymbol{a_{ii}}$; $\boldsymbol{R_{i,}} * \boldsymbol{FD_i}$

Table 0.25: Example New $A^{\#1}$ matrix after lockdown (in percentage) & $FD^{\#1}$

A#1 Matrix (%)	Construction	Manufacturing	FD (£)
Construction	0.25	0.1875	100
Manufacturing	0.2	0.075	180

The new gross output $\boldsymbol{GO^{\#1}} = \boldsymbol{X^{\#1}} = (\boldsymbol{I} - \boldsymbol{A^{\#1}})^{-1} * \boldsymbol{FD^{\#1}}$

$$\boldsymbol{X^{\#1}} = \begin{bmatrix} \mathbf{192.38} \\ \mathbf{236.19} \end{bmatrix}$$

The post-lockdown Value Added is assumed to be:

$$\boldsymbol{VA^{\#1}} = (\boldsymbol{VA/X} * \boldsymbol{I}) * \boldsymbol{X^{\#1}} = \begin{bmatrix} \mathbf{0.1} & \mathbf{0} \\ \mathbf{0} & \mathbf{0.5} \end{bmatrix} \begin{bmatrix} \mathbf{192.38} \\ \mathbf{236.19} \end{bmatrix} = \begin{bmatrix} \mathbf{19.23} \\ \mathbf{118.09} \end{bmatrix}$$

Hence, post lockdown

$$\boldsymbol{GDP^{\#1}} = \boldsymbol{VA^{\#1T}} * \boldsymbol{I} = \mathbf{137.3}$$

This compares to pre-Covid GDP of 500.

B.1.2. Method 2: Scaling Down the Gross Output both for sectoral gross flows and the Final Demand as a linear transformation of the Lockdown R_i ratios.

$$X_{ij}^{\#2} = X_{ij} * R_i \tag{0.6}$$

= (Scaled down sector gross flow from i to j by i’s R ratio).

$$FD_i^{\#2} = FD_i * R_i \tag{0.7}$$

So though scaling down of final demand remains same in method 1 & 2, the Leontief Coefficients in Method 2 are different as follow:

$\boldsymbol{a_{ij}^{\#2} = X_{ij} * R_i / X_j * R_j}$ (Input).

This implies that sector Leontief coefficient remains unchanged from pre-covid, but the aij coefficients change as follows. The sectoral gross flow from ij is scaled down by sector i's R Ratio, but the denominator is scaled down by j's R ratio.

Using same pre-covid matrix as above and with $R_1 = 0.5$ and $R_j = 0.6$, we have the Table 2.1

Table 0.26: scaled down post Covid X – matrix and FD.

	Construction	Manufacturing	Final Demand	Lockdown Gross Output
Construction	250	150	100	500
Manufacturing	240	60	180	480
Value Added	10	270		
Gross Output	500	480		

In this framework, Leontief coefficients remain unchanged. But FD is scaled down using the R ratios of the sectors, however, VA takes a hit as the input and output should be the same for any sectors.

The problem with this method is that we assume the Construction sector is demanding R=0.5 production level while Manufacturing supplies 0.6 of original input, which results in Construction taking more inputs than demanded and the Value Added in this case is taking the hit.

Table 0.27: Leontief $A^{\#2}$ Matrix

	Construction	Manufacturing
Construction	0.5	0.3125
Manufacturing	0.48	0.125
Value Added	0.02	0.56

In this case, Leontief Matrix is not being used.

Note this can be directly obtained as a linear scale-down of pre-Covid Gross outputs.

$$X^{\#2} = \begin{bmatrix} 500 \\ 480 \end{bmatrix}$$

$$X^{\#\#2} = (I - A^{\#2})^{-1}\, FD^{\#2} = \begin{bmatrix} 500 \\ 480 \end{bmatrix}$$

Post Covid VA#2:

$$VA^{\#2} = \begin{bmatrix} 0.1 & 0 \\ 0 & 0.5 \end{bmatrix} \begin{bmatrix} 500 \\ 480 \end{bmatrix} = \begin{bmatrix} 50 \\ 240 \end{bmatrix}$$

$$\mathrm{GDP}^{\#2} = \begin{bmatrix} 0.02 & 0 \\ 0 & 0.56 \end{bmatrix} \begin{bmatrix} 500 \\ 480 \end{bmatrix} = \begin{bmatrix} 10 \\ 270 \end{bmatrix}$$

This method discarded the limitation of demand and intersectoral interconnectedness.

B.1.3. Method 3

In Method 3 most parts are the same as in Method 1, however, we take the consideration of when the input of one sector changes, the output will also scale down correspondingly, for the case of a sector providing to itself, the initial Leontief Coefficient aii should remain the same.

We apply the lockdown R ratios directly to the Leontief coefficients and Final Demand.

Leontief Technology Coefficient:

$$\boldsymbol{a_{ij}} = {}^{\boldsymbol{X_{ij}}}\!\big/_{\boldsymbol{X_j}} \tag{0.8}$$

New Leontief Technology Coefficient $\boldsymbol{a_{ij}^{\#}}$ **is calculated by**:

$$\boldsymbol{a_{ij}^{\#3}} = \frac{\mathbf{min}(\boldsymbol{R_{i,}R_j})\boldsymbol{X_{ij}}}{\boldsymbol{R_j * X_j}} \tag{0.9}$$

That means in the case of $\boldsymbol{a_{ii}^{\#}}$

$$\boldsymbol{a_{ii}^{\#3}} = \frac{\mathbf{min}(\boldsymbol{R_{i,}R_i})\boldsymbol{X_{ii}}}{\boldsymbol{R_i * X_i}} = \frac{\boldsymbol{R_i * X_{ii}}}{\boldsymbol{R_i * X_i}} = \boldsymbol{X_{ii}/X_i = a_{ii}} \tag{0.10}$$

For when $\boldsymbol{R_i \geq R_j}$,

$$\boldsymbol{a_{ij}^{\#3}} = \frac{\mathbf{min}(\boldsymbol{R_{i,}R_j})\boldsymbol{X_{ij}}}{\boldsymbol{R_j * X_j}} = \frac{\boldsymbol{R_j * X_{ij}}}{\boldsymbol{R_j * X_j}} = \boldsymbol{X_{ij}/X_j = a_{ij}} \tag{0.11}$$

For when $\boldsymbol{R_i < R_j}$,

$$\boldsymbol{a_{ij}^{\#3}} = \frac{\mathbf{min}(\boldsymbol{R_{i,}R_j})\boldsymbol{X_{ij}}}{\boldsymbol{R_j * X_j}} = \frac{\boldsymbol{R_i * X_{ij}}}{\boldsymbol{R_j * X_j}} \tag{0.12}$$

Therefore, the only situation the Leontief Coefficient $\boldsymbol{a_{ij}^{\#3}}$is different from the original $\boldsymbol{a_{ij}}$is when the input sector I has a lower R ratio than the demand sector j.

New Final Demand is the same as Method 1:

$$\boldsymbol{FD_i^{\#3}} = \boldsymbol{FD_i} * \boldsymbol{R_i} \tag{0.13}$$

With the same Example ICIO data pre-lockdown we see in table A1.1, we get the new Leontief coefficient Matrix $A^{\#3}$ & $\boldsymbol{FD_i^{\#3}}$**:**

Table 0.28: A Matrix#

A#3 Matrix (%)	**Construction**	**Manufacturing**	**FD (£)**
Construction	0.5	0.3125	100
Manufacturing	0.4	0.125	180

The only difference between A and $A^{\#3}$ is Construction to Manufacturing, which shrank from 0.375 to 0.3125 because construction had a smaller R ratio than Manufacturing.

Note that Method $A^{\#3}$ matrix is identical to pre-Covid except for a_{12} because we are imposing the restriction.

Demand-side constraint is imposed, meaning the sector that suffers more in terms of output now reduces its inputs from another sector by the same amount.

With immediate capacity shocks, the equilibrium gross output

$$\boldsymbol{GO^{\#3}} = \boldsymbol{X^{\#3}} = (\boldsymbol{I} - \boldsymbol{A^{\#3}})^{-\boldsymbol{1}} * \boldsymbol{FD^{\#3}}$$

$$\boldsymbol{X^{\#3}} = \begin{bmatrix} 460 \\ 416 \end{bmatrix}$$

$$\boldsymbol{VA^{\#3}} = (\boldsymbol{VA/X} * \boldsymbol{I}) * \boldsymbol{X^{\#3}} = \begin{bmatrix} \boldsymbol{0.1} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{0.5} \end{bmatrix} \begin{bmatrix} \boldsymbol{460} \\ \boldsymbol{416} \end{bmatrix} = \begin{bmatrix} \boldsymbol{46} \\ \boldsymbol{208} \end{bmatrix}$$

We use the same VA/X ratio as method 1 which is the pre-covid Value Added coefficient because the shock in this case does not have a direct impact on Value-added (supply side).

$$\boldsymbol{GDP^{\#3}} = \boldsymbol{VA^{\#3T}} * \boldsymbol{I} = \boldsymbol{254}$$

For the supply side direct shock, we have the Ghosh Inverse and direct shock on VA, following the similar approach from the demand side shock, we get:

Ghosh Coefficient:

$$\boldsymbol{b_{ij}} = {}^{\boldsymbol{X_{ij}}}\!\big/_{\boldsymbol{X_i}} \qquad 0.14$$

Table 0.29: B Matrix

B	**Construction**	**Manufacturing**
Construction	0.5	0.3
Manufacturing	0.5	0.125

New Ghosh Coefficient:

$$\boldsymbol{b_{ij}^{\#3}} = \frac{\mathbf{min}(\boldsymbol{R_{i,}R_j})\boldsymbol{X_{ij}}}{\boldsymbol{R_i * X_i}} \qquad 0.15$$

That means in the case of $\boldsymbol{b_{ii}^{\#3}}$

$$\boldsymbol{b_{ii}^{\#3}} = \frac{\mathbf{min}(\boldsymbol{R_{i,}R_i})\boldsymbol{X_{ii}}}{\boldsymbol{R_i * X_i}} = \frac{\boldsymbol{R_i * X_{ii}}}{\boldsymbol{R_i * X_i}} = \boldsymbol{X_{ii}/X_i = b_{ii}} \qquad 0.16$$

For when $\boldsymbol{R_i \leq R_j}$,

$$\boldsymbol{b_{ij}^{\#3}} = \frac{\mathbf{min}(\boldsymbol{R_{i,}R_j})\boldsymbol{X_{ij}}}{\boldsymbol{R_i * X_i}} = \frac{\boldsymbol{R_i * X_{ij}}}{\boldsymbol{R_i * X_i}} = \boldsymbol{X_{ij}/X_i = b_{ij}} \qquad 0.17$$

For when $\boldsymbol{R_i > R_j}$,

$$\boldsymbol{b_{ij}^{\#3}} = \frac{\mathbf{min}(\boldsymbol{R_{i,}R_j})\boldsymbol{X_{ij}}}{\boldsymbol{R_i * X_i}} = \frac{\boldsymbol{R_j * X_{ij}}}{\boldsymbol{R_i * X_i}} \qquad 0.18$$

Table 0.30: B# Matrix

B#	**Construction**	**Manufacturing**
Construction	0.5	0.3

Manufacturing	0.41666667	0.125

Therefore, the only situation the Leontief Coefficient $\boldsymbol{b_{ij}^{\#3}}$ is different from the original $\boldsymbol{b_{ij}}$ **is** when the input sector I has a higher R ratio than the demand sector j.

$$\boldsymbol{X^{\#3\prime}} = \boldsymbol{VA^{\#\prime}}(\boldsymbol{I} - \boldsymbol{B^{\#}})^{-1} \tag{0.19}$$

Table 0.31: New Output X#

Sector	X#
Construction	664
Manufacturing	773.333333

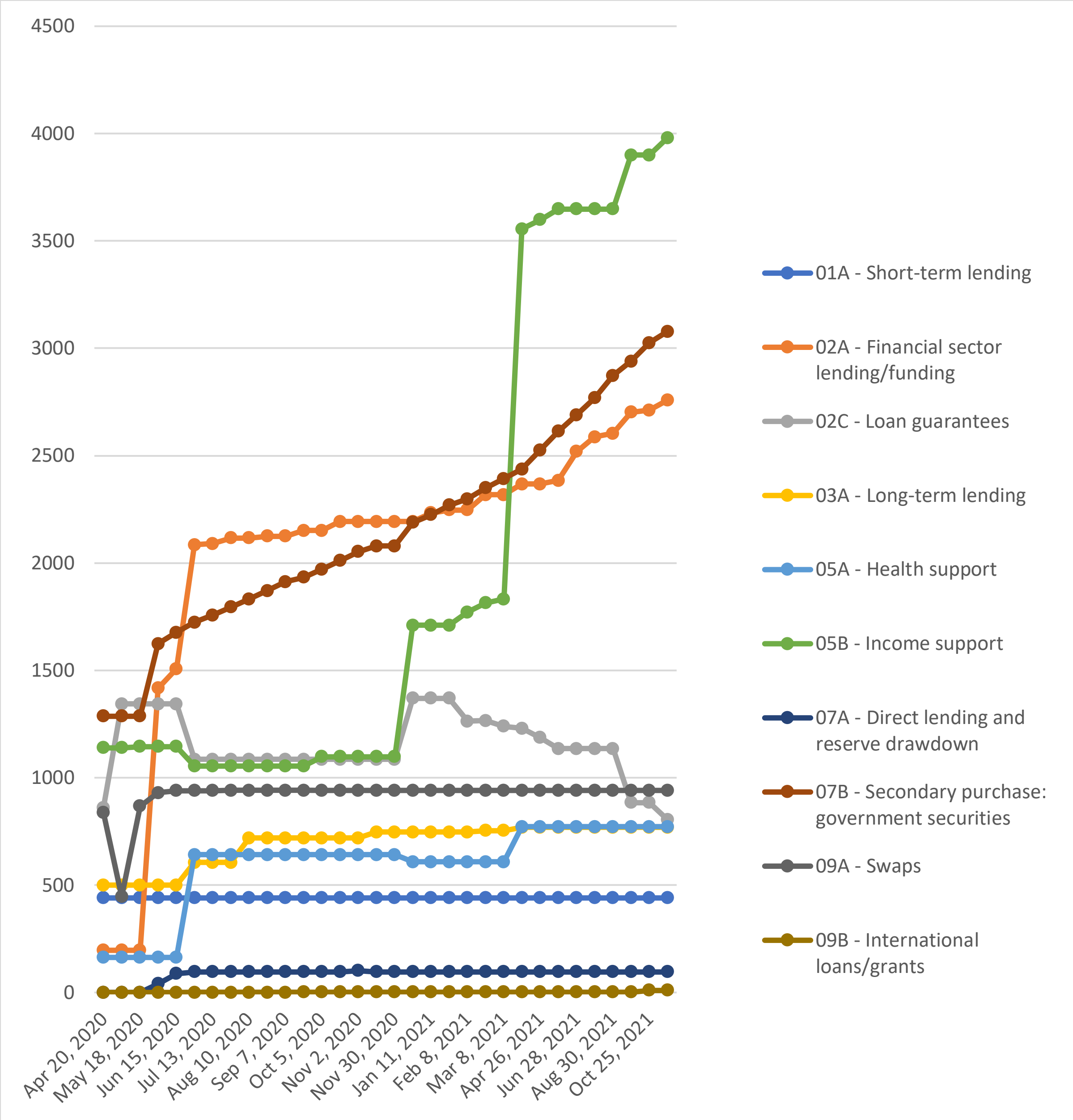
$$\boldsymbol{FD^{\#3\prime}} = (\boldsymbol{FD^{\#\prime}}/\boldsymbol{X} * \boldsymbol{I}) * \boldsymbol{X^{\#3\prime}} \tag{0.20}$$

Table 0.32: New Final Demand FD#

Sector	FD#
Construction	132.8
Manufacturing	290

B.2. COVID policy money implementation timeline

Figure 0.2: The United States Government Covid-19 policy measures (in $Bn)



Organized from source: *ADB COVID-19 Policy Database* https://covid19policy.adb.org/

In the guide for the policies *ADB COVID-19 Policy Database: A Guide* by Felipe and Fullwiler (2020) there are definitions for each category:

"We note that Measures 01–04 mostly correspond to monetary policy, while Measure 05 corresponds to fiscal policy. Three additional measures are effectively double counting from an accounting perspective but are nonetheless important measures. We label them Measures 06–08. These three measures are sources of funds, while Measures 01–05 are uses of funds.

Measure 09 is the mirror image of Measure 08. We add Measure 010 to take into account those actions for which the current information is unclear about the particular measure they should be added to."

Therefore, we only use measures 01-05 for our model with the monetary policy and fiscal policy.

Figure 0.3: The United States Government Covid-19 monetary policy (in $Bn)

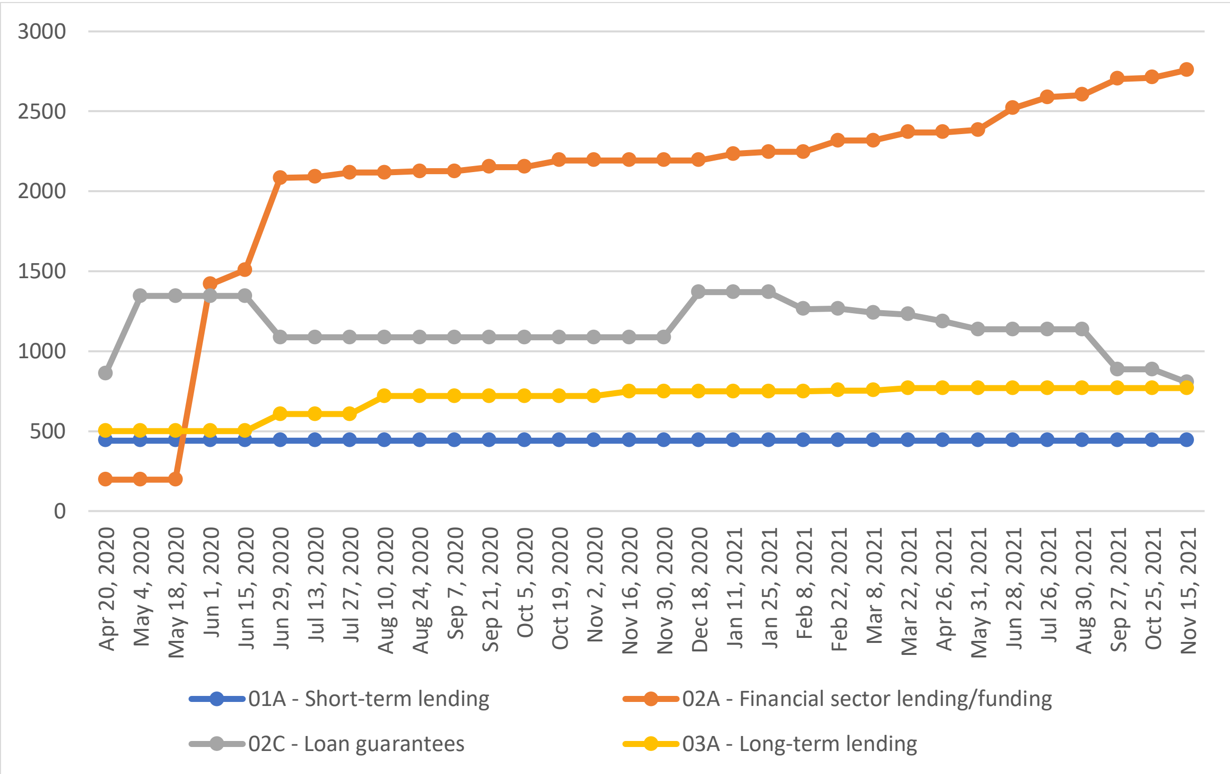
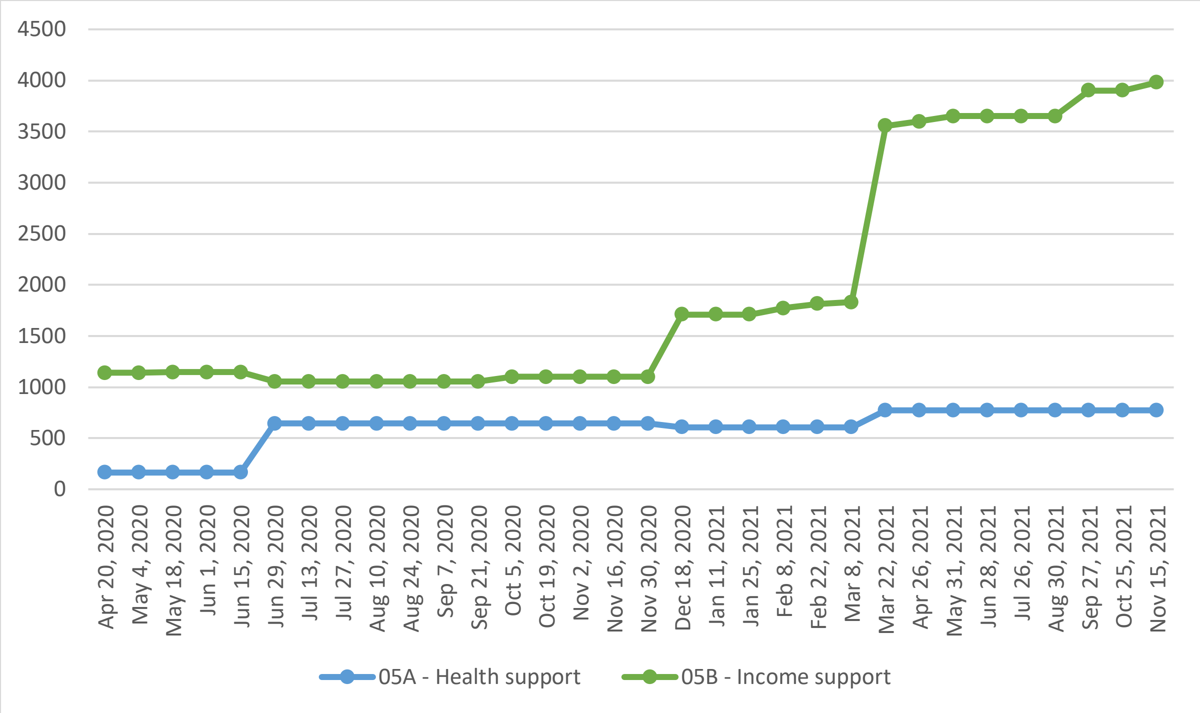


Figure 0.4: The United States Government Covid-19 fiscal policies (in $Bn)



In the Figure 0.4, we focus on the fiscal policies, and we can see stable support for the public health sector, with a slight jump in June 2020 and March 2021, the other periods stayed stable and consistent, while for the income support (a large proportion of income compensation) we can see a slight increase in December 2021 and a dramatic increase On March 2021.