COVID-19'S EFFECT ON INTERNATIONAL TRADE AND PRODUCTIVITY

by
Alexandra "Sasha" Rafaela Samperio

A Thesis submitted to the Department of Economics,
College of Liberal Arts and Social Sciences
in partial fulfillment of the requirements for the degree of

Bachelor of Science
in Economics

Chair of Committee: Dr. Kei-Mu Yi
Co-Chair of Committee: Dr. German Cubas
Committee Member: Dr. Olivia Miljanic

University of Houston
May 2023

Table of Contents

1 Abstract

In this paper, I aim to analyze the long-term effects from the Coronavirus epidemic in 2019, 2020 and 2021. Through the mechanism of international trade, my research aims to bridge the gap between the data we know and our expectations for the future. Within this research paper I begin with an augmented gravity trade regression using aggregated and sectorized data. I employ a case study to assess relative changes in the degree of Covid stringency. Relying on Arkolakis et. al (2012) and preliminary assumptions, I translate Covid's effect on trade into an effect on welfare and ultimately productivity. I conclude my research with a Solow model simulation and predict the components of growth for the next 50 years. Based on my research, I conclude that long term growth experiences a close to instantaneous drop in the level of inputs and outputs of growth.

2 Acknowledgements

I would like to take the time to acknowledge the effort that a multitude of people contributed to the completion of my thesis program and research. Dr. Bettinger of the University of Houston's Honors College is the Senior Thesis advisor. Her advice and help with the administrative end of the program made the process run smoother than I could have imagined. I am grateful she approved my thesis topic and allowed me such an advantageous opportunity to explore one of my academic passions: Economic research.

Such an experience would not have been possible without the guidance, mentoring and effort from my three thesis advisors. It would have especially not been possible without the guidance and mentoring of Dr. Kei-Mu Yi, my primary thesis advisor, who was always willing to offer advice and take time out of his schedule to foster and mold my economic knowledge. As much as Dr. Yi taught me the rationale behind economic theory, he challenged me to apply economic topics to my work and finetune my economic critical thinking skills. I would also like to take the time to express my gratitude to my secondary thesis advisor, Dr. German Cubas. Taking his Advanced Macroeconomics course, the semester before I began my thesis program allowed for a wider competence of macro-level economics especially with respect to the Solow Growth model and long run growth portion of my research. I would also like to express my appreciation to my honors reader, Dr. Olivia Miljanic, who although does not specialize in Economics research was able to provide a fresh perspective on my research through a public policy lens. Her insights cannot go unacknowledged as she tested my ability to relate to a periphery field of academic research and explore the applicability of my research to fields outside of economics.

Without the guidance, advising and contributions of these individuals above, I am unsure where my research pursuits would have gone, but I am thankful, in the end, that I was able to complete something as ambitious as a Senior thesis research project.

3 Introduction

Following the worldwide outbreak of Coronavirus in 2020, global economic activity suffered a sharp decline. According to the International Monetary Fund (IMF), global trade declined by 8.8 percent and global GDP declined by 3.3 percent. While the world economy rebounded in 2021, it seems likely that there could be long-run effects from Covid. The Coronavirus impacts are believed, by some, to be solely incurred in the short run, however, the effects to each economy's productivity level can potentially cause problems for the state of our future world economy. This paper aims to answer: What are the long run effects of growth from Covid through the mechanism of trade?

With my research I created four 47-country datasets across 6 years; including various trade characteristics — the first 3 are sector-based trade and the last focused on aggregate trade data. These datasets included bilateral import trade statistics, GDP, distance between countries, and the

Oxford University Covid-19 Government Response Policy Index. I then ran a series of gravity trade regressions on the four data sets to gain a fuller image of the effects Covid had on a micro and macro level. By estimating a coefficient for the Covid effect on trade, independent of other factors, I was able to separate this effect from the more influential factors such as GDP, distance, etc. I conducted further research by performing a brief case study. This case study envisioned how the different stringency levels affect the state of the economy if they are held at the highest level and for the longest period. I conducted a transformative process with the Arkolakis et al. (2012) to equate the Covid effect on trade to an effect on a country's total factor productivity. I then concluded my research with an in-depth Solow Model analyses of a permanent negative productivity shock in the economy. I forecast the Solow mechanics of the model 50 years into the future and analyzed the economic implications to the transitional growth dynamics and equilibrium levels, specifically directing my attention to the US economy.

From this research, I found that the agricultural sector was largely unaffected by the pandemic and to some degree experienced positive spillovers. Manufacturing and services sector trade performed similarly with a negative effect in 2020 and a slight recovery in 2021. What was striking was the impact Covid had on the aggregate level; where due to the mechanics of the gravity trade regressions, I generated positive fixed effects for the 2020 year. This theoretical meant that, in disregarding other extenuating factors even the Covid variable itself, 2020 was a good year for trade. Although this felt counterintuitive, the model explained the crowding out influence of the Covid variable. The regression result could have generated an overstated Covid effect because the pandemic forced the economy to find more efficient techniques to produce goods. In the Solow model, I deduced that the negative shock to the economy from productivity had long-term effects to the steady-state levels and growth track. The steady state performed at a lower level instantaneously and tended toward a lower equilibrium for all future periods because of this decrease in efficiency. I created a more encompassing image of what "efficiency" can mean and how these effects can further affect the long-term state of the economy.

Literature Review

The "gravity" equation has been widely used since the early 1960s, beginning with Tinbergen (1962). Head and Meyer's chapter: *Gravity Equations: Workbook, Toolkit, and Cookbook* provides much of the empirical and conceptual knowledge behind such an equation. The equation was originally met with skepticism due to the "lingering perception that gravity trade equations were more physics analogies than economic analysis," (Head 8). However, the gravity equation became widely used due to its potential to address the concept of missing trade (see Trefler (1995)), applicability to any country and industry (see Eaton and Kortum (2002)) and ability to generate clear and robust results (see Leamer and Levinsohn (1995)).

Arkolakis et al. (2012) explores the scope of welfare effects in an international context using what is known as the substitution effect. This theoretical paper analyzes the scope of welfare, through the impacts a shock has towards its domestic expenditure share. While this is a complex connection to undertake — connecting welfare and consumption from trade effect to pure productivity – with the proper baseline assumptions set, we can equate this type of effect to a Total Factor Productivity phenomenon.

The Solow model is the concluding model that this paper relies on (Solow (1956)). This model establishes a linkage between Total Factor Productivity and GDP, and subsequent GDP growth factors. This model is heavily used in macroeconomic theory and has a long-standing history in its adequate estimate of an economy's growth track. The unique quality of this model is its relatively simplistic setup coupled with its effectiveness at gauging long-run growth implications for major inputs and outputs of an economy's growth (such as capital, labor, GDP, etc.). Exploring the transitional dynamics of an economy allows us to assess the recovery trajectory of an economy. Additionally, the ability to analyze an economy's reaction to a multitude of shocks and forces made the Solow model applicable to my long-term growth research.

4 Empirical Section

a. Methodology

The primary purpose of the Empirical Section of this research is to estimate Covid's effect on International Trade, independent of natural forces such as GDP. Below, I begin with a baseline gravity trade regression with yearly fixed effects to examine the behavior of trade, without the influence of a Covid variable. Then, I run an augmented gravity trade regression, including Covid variables, to generate a coefficient for Covid's effect on import trade.

The first step of this empirical section involves running a baseline gravity trade regression. Analogous to Newton's gravity equation, this model draws a generalized relationship between bilateral trade of two countries, both the countries' GDPs and the distance between both countries. This model provides a solid foundation to begin my research as it has been widely used in International Economics research[1] and has a founded theory behind it.[2] The baseline equation in a log-log structure is:

$$\ln\left(\mathit{Bilateral\ Trade}_{ij}\right) = \beta_0 + \beta_1\left(\ln\left(GDP_i\right)\right) + \beta_2\left(\ln\left(GDP_j\right)\right) - \beta_3\left(\ln\left(\mathit{distance}_{ij}\right)\right) + \varepsilon_{ij}$$

[1] Bussière, Matthieu, and Bernd Schnatz. "Evaluating China's Integration in World Trade with a Gravity Model Based Benchmark." European Central Bank. European Central Bank, 2006. http://www.ecb.int.

[2] Keith Head, Thierry Mayer, Chapter 3 - Gravity Equations: Workhorse,Toolkit, and Cookbook, Editor(s): Gita Gopinath, Elhanan Helpman, Kenneth Rogoff, Handbook of International Economics, Elsevier, Volume 4,2014, Pages 131-195, ISSN 1573-4404, ISBN 9780444543141, https://doi.org/10.1016/B978-0-444-54314-1.00003-3. (https://www.sciencedirect.com/science/article/pii/B9780444543141000033)

where Bilateral Trade$_{ij}$ denotes the amount of import trade (in USD) from country j to country i, GDP$_i$ is the GDP of country i (in USD), GDP$_j$ is the GDP of country j (in USD), distance$_{ij}$ is the distance between country i and country j's capitals (in kilometers), and ε_{ij} is the error term on country i and country j's data. It is worth noting that both GDP variables have a positive correlation on Bilateral Trade whereas distance has a negative correlation. Conceptually, this makes sense because the bigger both trading countries' GDP's (or economies) are, the more likely they are to trade with one another. When an importing countries' GDP is higher, it also translated more demand in general, and by consequence, more demand for imports. With simple supply-demand economics, more supply, or output in these terms, will decrease the price of goods and spur trade. Conversely, the further away countries are from one another geographically, the less likely they are to trade with one another due to higher transportation and transaction costs.

Including yearly fixed effects allows me to gauge trade discrepancies across time. The year fixed effects are structured as a series of dummy variables that serve to control for variations over time. The regression with time fixed effects included is as follows:

$$\ln\left(BilateralTrade_{ijt}\right) = \beta_0 + \beta_1\left(\ln\left(GDP_{it}\right)\right) + \beta_2\left(\ln\left(GDP_{jt}\right)\right) - \beta_3\left(\ln\left(distance_{ij}\right)\right)$$
$$+ \gamma_{2017}\left(Y_{2017}\right) + \gamma_{2018}\left(Y_{2018}\right) + \gamma_{2019}\left(Y_{2019}\right) + \gamma_{2020}\left(Y_{2020}\right) + \gamma_{2021}\left(Y_{2021}\right) + \varepsilon_{ijt}$$

Regressions that follow this structure are (1) in Table 5 and regressions (1) and (2) in Table 6. Regression (3) in Table 6 slightly departs from this structure as Services sector data omits 2021 data. See data section for more information. Because of this, regression (3) in Table 6 takes the form of:

$$\ln\left(BilateralTrade_{ijt}\right) = \beta_0 + \beta_1\left(\ln\left(GDP_{it}\right)\right) + \beta_2\left(\ln\left(GDP_{jt}\right)\right) - \beta_3\left(\ln\left(distance_{ij}\right)\right)$$
$$+ \gamma_{2017}\left(Y_{2017}\right) + \gamma_{2018}\left(Y_{2018}\right) + \gamma_{2019}\left(Y_{2019}\right) + \gamma_{2020}\left(Y_{2020}\right) + \varepsilon_{ijt}$$

Recall that the purpose of this section is to generate a coefficient for Covid's effect on trade, independent of other factors such as distance and GDP effects. To ascertain such an effect, I rely on an augmented gravity trade model that includes Covid variables for country i and country j. The Covid data chiefly relies on the University of Oxford's Government Response Tracker, denoting a specific number for the degree of Covid in a specific country. See data section for more information. A Covid-augmented gravity trade equation takes the form of:

$$\ln(BilateralTrade_{ij}) = \beta_0 + \beta_1(\ln(GDP_i)) + \beta_2(\ln(GDP_j)) - \beta_3(\ln(distance_{ij})) - \beta_4(\ln(Covid_i)) - \beta_5(\ln(Covid_j)) + \varepsilon_{ij}$$

where the $Covid_i$ and $Covid_j$ variables represent the Covid index in country i and country j, respectively. Both Covid variables have a negative correlation because it is estimated that as the degree of Covid in a country is higher, the trade within that country is expected to decrease. As Coronavirus began at the end of 2019 and the Covid index begins at the start of 2020, the data spans from 2020 to 2021. However, for the aggregate covid regression (Regression (2) in Table 5) we assume that the covid variable index to is "0" for all pre-covid data years. With the aspect of time and time fixed effects, the structure becomes:

$$\begin{aligned}
&\ln(BilateralTrade_{ijt}) = \beta_0 + \beta_1(\ln(GDP_{it})) + \beta_2(\ln(GDP_{jt})) \\
&- \beta_3(\ln(distance_{ijt})) - \beta_4(\ln(Covid_{it})) - \beta_5(\ln(Covid_{jt})) \\
&+ \gamma_{2017}(Y_{2017}) + \gamma_{2018}(Y_{2018}) + \gamma_{2019}(Y_{2019}) + \gamma_{2020}(Y_{2020}) \\
&+ \gamma_{2021}(Y_{2021}) + \varepsilon_{ijt}
\end{aligned}$$

Regression (1) and (2) from Table 7 follow a similar structure but the span of data is shorter (from 2020 to 2021). The form is:

$$\begin{aligned}
\ln(BilateralTrade_{ijt}) = \beta_0 + \beta_1(\ln(GDP_{it})) + \beta_2(\ln(GDP_{jt})) - \beta_3(\ln(distance_{ijt})) \\
- \beta_4(\ln(Covid_{it})) - \beta_5(\ln(Covid_{jt})) + \gamma_{2021}(Y_{2021}) + \varepsilon_{ijt}
\end{aligned}$$

However, regression (3) from Table 7 omits 2021 data, so the structure does not include a time aspect. Because of this, regression (3) from Table 7 takes the form of:

$$\ln\left(BilateralTrade_{ij}\right) = \beta_0 + \beta_1\left(\ln\left(GDP_i\right)\right) + \beta_2\left(\ln\left(GDP_j\right)\right) - \beta_3\left(\ln\left(distance_{ij}\right)\right) - \beta_4\left(\ln\left(Covid_i\right)\right) - \beta_5\left(\ln\left(Covid_j\right)\right) + \varepsilon_{ij}$$

b. Data

For the empirical section, each regression uses the same data sources for GDP, Distance and the Covid policy index respectively. I pulled all yearly GDP from the World Bank Database. For distance between countries, I used the Geodist CEPII research and expertise on World Economy. The Covid policy index data is from the University of Oxford's Covid-19 Government Response Tracker which denotes a specific number for the degree of Covid in a country, starting in January 2020. This data particularly measures the degree of Covid policies implemented in a specific country at a specific time.

For the aggregate, agricultural and manufacturing trade regressions, I pulled all import trade data from the UN Comtrade database for 47 countries from 2016-2021. Aggregate trade data is annual total import trade. Agricultural trade data is annual import trade data disaggregated by Standard International Trade Classification (SITC) codes. Specifically, agricultural import trade data is made up of SITC codes 0, 1, 2, 3, 4, and 5. Similarly, Manufacturing trade data is also annual import trade data disaggregated by SITC codes 6, 7 and 8.

Service sector trade data is pulled from the World Trade Organization using the Balance of Payments (BOP6): Services imports database for 44 countries (not including Nigeria, Pakistan, and Thailand) from 2016-2020 due to the lack of data for the year 2021.

Below are summary statistic tables for each set of regressions. The first three tables (Table 1, 2 and 3) focus on sector-specific regressions: Agricultural trade, Manufacturing trade and Service sector trade respectively. The final summary statistic table (Table 4) displays summary statistics for aggregate trade data. Manufacturing trade has the largest standard deviation, largest mean and encompasses more observations than services and agriculture. This shows the importance of manufacturing trade when looking into the effects of shocks such as covid in terms of sector-specific trade. Note for sector-specific Reporter Covid and Partner Covid summary statistics, the span of data is solely from Covid years (2020-2021). For aggregate data, this data spans from 2016-2021. Note all variables are in logged terms.

Table 1: Agricultural Trade Summary Statistics

VARIABLES	Obs.	Mean	Std. Dev.	Min	Max
Agriculture Trade	12,055	19.148	2.437	5.737	26.006
Distance	12,055	8.347	1.079	4.088	9.892
Reporter GDP	12,055	26.962	1.493	23.758	30.767
Partner GDP	12,055	26.990	1.475	23.758	30.767
Reporter Covid	3,565	3.968	0.160	3.555	4.358
Partner Covid	3,565	3.972	0.163	3.555	4.358

Table 2: Manufacturing Trade Summary Statistics

VARIABLES	Obs.	Mean	Std. Dev.	Min	Max
Manufacturing Trade	12,086	19.420	2.688	4.585	26.983
Distance	12,086	8.344	1.081	4.088	9.892
Reporter GDP	12,086	26.976	1.487	23.758	30.767
Partner GDP	12,086	26.992	1.473	23.758	30.767
Reporter Covid	3,446	3.964	0.157	3.555	4.358
Partner Covid	3,446	3.967	0.162	3.555	4.358

Table 3: Service-sector Trade Summary Statistics

VARIABLES	Obs.	Mean	Std. Dev.	Min	Max
Services Trade	6,549	5.409	2.406	0.000	11.714
Distance	6,549	8.041	1.145	4.088	9.883
Reporter GDP	6,549	26.696	1.626	23.758	30.696
Partner GDP	6,549	27.061	1.462	23.758	30.696
Reporter Covid	1,237	3.871	0.118	3.555	4.107
Partner Covid	1,237	3.891	0.130	3.555	4.129

Table 4: Aggregate Trade Summary Statistics

VARIABLES	Obs.	Mean	Std. Dev.	Min	Max
Total Trade	12,806	20.328	2.298	7.896	27.057
Distance	12,806	8.354	1.080	4.088	9.892
Reporter GDP	12,806	26.995	1.478	23.758	30.767
Partner GDP	12,806	27.001	1.471	23.758	30.767
Reporter Covid	12,806	1.293	1.870	0	4.358
Partner Covid	12,806	1.293	1.871	0	4.358

c. Aggregate Regressions

Table 5 below showcases the aggregate trade regressions with Yearly Fixed Effects. The first regression (1) does not include the Covid policy index for reporter and partner country. The second regression (2) includes the Covid policy index variables for reporter and partner country. Both regressions have the same time span from 2016-2021.

Table 5: Aggregate Trade Regressions

	(1)	(2)
VARIABLES	Aggregate	Aggregate
Ln (Reporter GDP)	0.974***	0.978***
	(0.007)	(0.007)
Ln (Partner GDP)	0.970***	0.968***
	(0.006)	(0.006)
Ln (Distance)	-1.025***	-1.025***
	(0.009)	(0.009)

Ln (Covid - Reporter)	-	-0.355***
		(0.136)
Ln (Covid - Partner)	-	0.240
		(0.149)
FE: 2017	-0.029	-0.029
	(0.033)	(0.033)
FE: 2018	-0.047	-0.047
	(0.033)	(0.033)
FE: 2019	-0.075**	-0.075**
	(0.033)	(0.033)
FE: 2020	-0.062*	0.387
	(0.034)	(0.813)
FE: 2021	-0.106***	0.368
	(0.034)	(0.860)
Constant	-23.539***	-23.570***
	(0.266)	(0.266)
Observations	12,806	12,806
R-squared	0.779	0.779

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

From these results, we can deduce that Reporter GDP, Partner GDP, and Distance are statistically significant at the 1% level. All baseline gravity equation variables show expected values that line up with previous literature and economic theory. Both coefficients for the GDP variables are approximately positive 1, whereas the distance coefficient is approximately -1.

Regression (1) shows that the yearly fixed effect coefficients for 2019, 2020 and 2021 are negative and statistically significant to some degree. This suggests that across all countries for the years 2019-2021, there was a significant negative effect on trade beyond the effect of the independent variables in the regression. In including covid-specific variables, Regression (2) shows some interest in that the reporting Covid variable is negative, and the partner Covid variable generates a positive coefficient. Yet what is most intriguing is that the years of interest (2020 and 2021) display positive fixed effects. This theoretically states that once you control for GDP and Covid, trade in 2020 was a good year. This could allude to a positive externality from Covid: countries were forced to be more efficient. What this could also mean is that the covid variable is too strong: meaning that the negative effect on trade is overstated and must be offset by the positive fixed effect variable. Yet, the Reporting Covid variable is statistically significant at the 5% level. This provides sufficient evidence to seek further exploration into the non-linear relationship of trade to Covid. With these conclusions, further exploration at the service-sector level creates a more fleshed out image of how Covid affects trade.

d. Sector-specific Regressions

Table 6 includes Sector-specific Trade regressions for Agriculture, Manufacturing and Services. This table does not include regressions with Covid variables. Note Services data only spans from 2016-2020.

Table 6: Sector-specific Trade Regressions

	(1)	(2)	(3)
VARIABLES	Agriculture	Manufacturing	Services
Ln (Reporter GDP)	0.999***	0.995***	0.967***
	(0.009)	(0.010)	(0.009)
Ln (Partner GDP)	0.950***	1.061***	0.818***
	(0.008)	(0.008)	(0.010)
Ln (Distance)	-1.026***	-1.239***	-1.213***
	(0.011)	(0.013)	(0.013)
FE: 2017	-0.015	-0.062	-0.014
	(0.040)	(0.047)	(0.043)
FE: 2018	-0.025	-0.091*	-0.035
	(0.041)	(0.047)	(0.043)
FE: 2019	-0.058	-0.109**	0.005

	(0.040)	(0.047)	(0.044)
FE: 2020	0.009	-0.122***	-0.151***
	(0.041)	(0.047)	(0.044)
FE: 2021	-0.195***	-0.197***	-
	(0.048)	(0.055)	
Constant	-24.816***	-25.609***	-32.738***
	(0.331)	(0.363)	(0.343)
Observations	12,055	12,086	6,549
R-squared	0.702	0.672	0.784

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7 below shows the Sector-specific regressions with the Covid variables included. Note the Services regression only includes data from 2020, so therefore does not include any time fixed effects.

Table 7: Sector-Specific Trade Regressions with Covid

VARIABLES	(1) Agriculture	(2) Manufacturing	(3) Services
Ln (Reporter GDP)	1.013***	1.009***	0.983***
	(0.016)	(0.019)	(0.023)
Ln (Partner GDP)	0.930***	1.054***	0.833***
	(0.017)	(0.017)	(0.024)
Ln (Distance)	-1.029***	-1.238***	-1.244***
	(0.022)	(0.025)	(0.030)
Ln (Reporter Covid)	0.235	-0.512**	-0.573*
	(0.190)	(0.222)	(0.300)
Ln (Partner Covid)	0.304	-0.198	0.145
	(0.196)	(0.250)	(0.252)
FE: 2021	-0.308***	0.066	-
	(0.077)	(0.094)	
Constant	-26.706***	-23.171***	-31.852***
	(1.133)	(1.303)	(1.423)

Observations	3,565	3,446	1,237
R-squared	0.694	0.672	0.791

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Both Table 6 and Table 7 show that all baseline gravity-trade regression variables are statistically significant to the highest degree and like the aggregate trade regression results, the coefficients align with the previous literature and economic theory.

The agricultural trade regressions from both tables appear somewhat unaffected by the influence of Covid. From Table 6, we can see that all yearly fixed effects are statistically insignificant except for the year 2021 which is slightly negative. From Table 7, we can see that both Covid variables are statistically insignificant and surprisingly positive, meaning that the higher the degree of Covid, the more positive effect it had on agricultural imports. Although, the coefficient for yearly fixed effects was negative and statistically significant to the highest degree. From these results, we can deduce that agricultural trade was largely unaffected by the influence of Covid.

The manufacturing trade regression from Table 6 show a negative coefficient on all yearly time fixed effects. Most notably, as time increases, the coefficients become higher in magnitude and higher in degree of significance. This suggests that as time passed a notable decline in manufacturing trade occurred, especially for the years of 2020 and 2021. Table 7 expands on this effect with both Covid variables being negative; reporting Covid being the higher-in-magnitude of the two. Although only the reporting covid variable is statistically significant. The time fixed effect for the year 2021 is positive and statistically significant. From both regression tables, we can conclude that manufacturing trade had been declining even before Covid hit in 2020. However, once Covid hit, there was a statistically significant negative effect on trade more so than implied by GDP's recessionary effects. Assumably these effects were due to the global supply chain issues in 2020 and 2021. However, because the 2021 fixed effect is slightly positive in Table 7 it suggests that there was a rebound in supply chain issues as well as a slight recovery.

The service sector regressions appear like that of the manufacturing regressions. Both sectors experienced a negative 2020 fixed effect in Table 6 and are statistically significant at the 1% level. Also, in Table 7, the services regression has a statistically significantly negative reporting Covid coefficient and is slightly higher in magnitude than that of manufacturing. This indicates that, like manufacturing, the services sector also experienced a negative effect from Covid beyond that of GDP recessionary effects. Such an effect can likely be attributed to the decline in travel and tourism during the year 2020 because of Covid.

In comparing all sector-specific regressions, we can conclude that manufacturing and services were more affected than agriculture which saw a slight increase in covid-specific years. Manufacturing and services appeared to respond in a similar manner when Covid hit at the beginning of 2020, likely because of the global supply chain problems and lack of travel and tourism. When comparing the sector-specific regression results to aggregate trade's results, for both Manufacturing and Services, the Reporter Covid coefficient is higher in magnitude than that of aggregate trade. This suggests that the negative effect from Covid was felt to a higher degree in manufacturing and services than that of total trade. A similar conclusion can also be found in both sectors' higher coefficients in 2020's fixed effects than that of aggregate trade. For manufacturing, services, and aggregate trade we can conclude that covid had adverse effects on trade beyond that of GDP and its recessionary effects.

5 Theoretical Section

a. Case Study

This section addresses the unexpected results from the Aggregate covid-included regression through the lens of a Case Study processes. When we look deeper into the relationship between Covid and trade, there are some inconsistencies with the regression results that needed addressing. Firstly, when I attempted to calculate the overall covid effect on US trade, my results were heavily overstated; stating that the independent Covid effect causes 40% of the fall in trade — which is simply too high of a number. Additionally, when we look at the yearly fixed effects from both 2020 and 2021 analogous of the effect from Covid, both yearly fixed effects are positive. This means that once controlled for GDP and Covid, bilateral trade in covid-specific years was positive. In this context, countries came up with many ways to be more efficient in international trade. Because fixed effects are positive, this indicates that the Covid variable is too strong, and the positive year fixed effect partially offset the exaggerated effect from Covid. For these reasons stated above, it is likely that there is a nonlinear relationship between trade and Covid.

Due to multiple inconsistencies with the original regression coefficient, we thought it more advantageous to explore relative changes in the degree of Covid of different countries in the same year. In this section, I explore two hypothetical case studies that alter the covid stringency levels between bilateral pairings. These case studies focus specifically on Covid data from 2020-2021 with USA as the reporter crossed against 7 major partner economies (Canada, China, Germany, United Kingdom, Japan, South Korea, and Mexico). The first case postulates the relative percent change if US and the partner country had the same Covid level, and the second case explores the relative percentage change if the US had the least Covid stringency from that year. The aim of these case studies is to compare the real effect of covid to hypothetical cases where the stringency of the reporter, partner or both has been altered. This step was integral to my research because it allowed for a connection from a change in trade to a change in utility. Later, this will allow for a more succinct transition from Covid's effect on trade to its effect on total factor productivity. Both real and hypothetical total covid effects were calculated in the same manner:

$$\ln\left(Total\ Covid\ Effect_{ijt}\right) = \beta_{Covid_i} \cdot \ln\left(Covid_{it}\right) + \beta_{Covid_j} \cdot \ln\left(Covid_{jt}\right)$$

where the left-hand side of the equation is the total covid effect on trade independent of extenuating variables (such as GDP, distance, etc.) between reporting country i and partner country j in year t, β_{Covidi} is the coefficient for Covid for the reporter country, β_{Covidj} is the coefficient for Covid for the partner country and $Covid_{it}$ and $Covid_{jt}$ are the degree of Covid in country i and country j during time t, respectively. Note that both coefficients were generated previously in the regression analysis section and this case study focuses mainly on changing both reporting and partner country's degree of Covid.

The relative difference was calculated as a percentage change which was easy to calculate because the original regression is in log levels:

$$\%\ change = \left(\ln\left(TotalEffect_{real}\right) - \ln\left(TotalEffect_{hypoth.}\right)\right) \cdot 100$$

The first case study explores a difference in relative terms on how the real covid effect compares to the hypothetical situation where both reporter and partner country had the same degree of Covid as the reporter country. Amongst the seven bilateral pairings, the average percentage change in 2020 was approximately -1.46%, meaning that if the US and partner country had the same degree of Covid restrictions as the US for 2020 trade levels, the total effect from Covid on average would decrease by 1.46%. However, the average percentage change for 2021 was approximately 1.44%. Theoretically, this means that if the US and partner country had the same degree of Covid restrictions as the US for 2020 trade levels, the total effect from Covid on average would increase by 1.46%. However, when the percentage change is compared across 2020 and 2021, the positive change indicates that there is a certain level of recovery between years. The real data compared to if the hypothetical situation of US trading with a country with the same level of Covid stringency would have a slight positive increase in trade as time persists. Also, because the percentage change on average approximates zero, it indicates that the US is not entirely independent to the real covid stringency levels of its partners in both years.

The second case study explores a difference in relative terms on how the real covid effect compares to the hypothetical situation where both the reporter country level is the min level for that year and the partner remains its' real covid level. The average percentage change in 2020 is -14.62% and the average percentage change in 2021 is -9.44%. The decrease in the magnitude of the percentage change as time persists indicates that the difference between the minimum level of covid stringency and the real US covid level is slightly less impactful across time. Like the first case, this shows a degree of recovery in all countries compared to the least covid stringency. The average percentage change for both years together is -12.03%. This means that if the reporting country (the US) was least affected by Covid, Covid's total effect on trade would go down by approximately 12.03%. Because the magnitude of the percentage change is bigger than the first hypothetical case, this shows that if the disparity between the level of Covid stringency between bilateral partners is exaggerated, then the impact on the total effect of Covid on trade is bigger. When transitioning a Covid effect into a TFP and welfare shock, this section helped provide a better understanding of the interrelationship of Covid and TFP.

b. Transitioning Covid into a TFP Shock

This portion of my research focuses on taking the international, independent shock from Covid and translating it into that of a growth economic phenomenon — Total Factor Productivity (used interchangeably with the term "Productivity"). Within this section there is a strong economic literature tie to Arkolakis et. al (2012). In this paper, the significance of welfare on trade phenomenon is explored through the aspect of domestic share and substitution effect — in basic terms, this states that if the price of a good decreases, consumers will substitute away from goods that are relatively expensive and towards more of inferior or less expensive goods. The substitution effect primarily concerns consumption behavior which Arkolakis et al. (2012) bridges to a welfare effect.

In attempting to transition a trade effect into a TFP effect, I focus primarily on the U.S. imports between the 46 partners. This section is comprised of a set of assumptions and equations from Arkolakis et al. (2012) The first assumption is that the level of U.S. GDP remained consistent between 2019 and 2020. This assumption was made for simplification purposes: if we standardize GDP across the years in question, we can focus in on the independent trade effect. I compared 2019 and 2020 US trade levels. For 2019 I used real data, but for 2020 I relied on the Covid coefficient generated from Section (IV). I estimated the predicted trade effect in 2020 due to Covid using the formula below:

$$Real\ Covid\ Effect_{US_{2020}} = \left[\hat{\beta}_4\left(Covid_{US_{2020}}\right) + \hat{\beta}_5\left(Covid_{j_{2020}}\right)\right]$$

where $\hat{\beta}_4$ is the estimated coefficient on the covid variable for the reporting country and $\hat{\beta}_5$ is the estimated coefficient on the covid variable for the partner country. Both values were taken from the Empirical Section 4.c. in Table 5 column (2).

Once I had calculated the independent effect Covid had on aggregate trade, I thought it best, given the bias within my covid coefficients to assess the relative effect based on a counter theory. What is the predicted difference between our estimated covid effect on trade and the hypothetical case of the US and its partner displaying the maximum level of the covid index for 2020? The hypothetical real effect equation was calculated with:

$$Hyp.\ Covid\ Effect_{US_{2020}} = \left[\hat{\beta}_4\left(Covid_{Max_{2020}}\right) + \hat{\beta}_5\left(Covid_{Max_{2020}}\right)\right]$$

The subsequence difference between both effects was calculated as a trade-weighted difference. Meaning that once the difference between hypothetical and real effect was calculated, I would then multiply that number by the ratio of the individual partner's exports to the total number of US imports. This would provide a more accurate description of the "World" effect Covid had on the US. The equation of the difference between both effects can be seen below:

$$Diff_{j_{wt.}} = \frac{Trade_{USj_{2020}}}{\sum_{k=1}^{k=46} Trade_{USj_{2020}}} \cdot (Hyp.\ Effect - Real\ Effect)$$

The next step was to transform that differenced value into a percentage world covid effect on the US. This involved summing up all the differenced effects from each of the 46 partners and taking the exponential value (because the estimated betas are in logged form). The equation is below:

$$\%\ World\ Covid\ Effect = 1 - e^{\left[\sum_{k=1}^{k=46} Diff_{j_{wt}}\right]}$$

Now that I had calculated the percentage change Covid had on the US, put into world economy terms, I would move on to the Arkolakis et al. (2012) portion of this section. This began with calculating the change in domestic shares. This is calculated by comparing the ratio of trade to overall GDP from 2019 to 2020 levels. Note that the "Domestic Share Pre-Covid" was calculated by multiplying the "% World Covid Effect" above times the 2019 US import trade level. The equations are displayed below:

$$\widehat{\lambda_{jj}} = \frac{DomesticShareCovid}{DomesticSharePreCovid} \qquad DomesticShare_{jt} = \left(\frac{GDP_{jt} - Trade_{jt}}{GDP_{jt}}\right)$$

Once we have those variables calculated, the next equation is strictly from the Arkolakis et al. (2012) paper. $\hat{W_j}$ is the change in welfare from consumption terms. This stage of this section is bridged together by a string of assumptions. However the baseline equation is:

$$\hat{W}_j = \widehat{\lambda}_{jj}^{\frac{1}{(1-\sigma)}}$$

This equation breaks down the welfare effect in terms of the substitution effect of domestic expenditure pre and post Covid. We assume σ to equal 4 based on previous economic literature.

But in order, to equate this welfare effect into a TFP effect, we assume a direct change in consumption is equal to the welfare change. This is applied with the rationale that the substitution effect encapsulates the consumer behavior of the economy. As previously stated, the consumer will look to buy inferior goods if the outlook of the economy is expected to worsen. This direct transition to consumption assumes $\hat{W_j}$ to be a consumption effect. To transition to an output and growth phenomena, we apply another assumption: the idea that capital and labor, factors of production, are stable between years. We can then equate that change in output to a change in TFP because TFP is a factor of output through the Solow model. See Section 6 for more detail.

In assessing the full weight of this assumption, we must discuss the dimensions behind the labor market and employment factors. Labor went strikingly down with Covid as many people lost their job and the economy experienced a tighter labor market. Stating that the labor market had no play in the economy's productivity is strikingly false, however the focus of our research is the specific effect trade had on productivity from the Covid shock. To include employment as a factor on TFP, we would have to calculate the decline in employment due to international trade from Covid, which would require several complex regressions. Intuitively, if labor did decline from Covid through the lens of trade, the TFP shock we calculated would decrease in magnitude. We have previously calculated the fall in output due to international trade form Covid. If we aim to include employment as an additional factor to output, it will lessen the weight of our TFP shock because the effects on output will be split between labor and TFP.

For our research and applied methodology, the calculated welfare impact from Covid through international trade is a 0.02% decrease in TFP. This calculation is then applied to our next section where we discuss the long run growth implications of an assumed permanent shock to TFP.

6 Long Run Growth Implications

The focus for this section of research is to utilize the calculated TFP shock from Covid found in the previous section and perform a Solow model simulation to gauge the long-term effects to the U.S. economy. This section begins by discussing the content and mechanisms behind the Solow growth, moves on to explain the methodology used, expands on the real data necessary for this section, and concludes with the analysis and findings from this research (section 6.d.).

a. Model

We start this section with some general context behind the mechanisms and equations of this model and what rationale we justify this model's use within my research (see Solow (1956)). The Solow model has been widely used throughout economic literature to evaluate effects on long term economic growth. This model is an amalgamation of various mathematical equations to evaluate how an effect on one variable, such as productivity[3] will impact GDP growth and the overall growth track of the economy. Since its creation, it has been able to serve as an adequate model to predict and gauge how the economy will react to certain shocks. This model is appealing to use in my research primarily because it can gauge how a phenomenon such as Covid; an event that specifically affects TFP will react to the economy in the future.

[3] Known economically as Total Factor Productivity or TFP, represented as "A" in any mathematical equations

Focusing in on the general mechanisms of the Solow Model and inputs that determine such a model: the chief equation of this model is comprised of GDP, or in Solow terms: "output", as a factor of TFP, capital, and labor and constants. The equation is:

$$Y = AK^{\alpha}L^{(1-\alpha)}$$

where Y is GDP or output, A is total factor productivity, K is capital, L is labor and α represent the share of capital relative to labor. Typically, α is assumed to equal 0.33 based on previous data and economic literature. The most elusive variable of this baseline equation is productivity ("A") for its difficulty to quantify. There is no accurate data measure to gauge the productivity of an economy although there have been many attempts at postulating the determinants of TFP. (See Comin et.al (2020)). They have fallen short in defining what fully encompasses productivity. However, despite that specific caveat, it's important to view TFP as a comparison of the total outputs of the economy (GDP) relative to its total inputs (mainly capital and labor).

Another driving force of the Solow model is an equation known as the capital accumulation equation. Below is a general formula (without population growth):

$$K_{t+1} = I_t + (1 - \delta) K_t$$

where K_{t+1} represents capital in the next period, I_t represents investment, δ represents the depreciation rate and K_t represents capital in the current period. Theoretically, this equation states that capital in the next period is determined by the saved capital from the previous period (I_t) and the capital that has depreciated has been lost from previous periods [(1- δ) K_t]. A useful derivation is the equation's per capita counterpart: model is an equation known as the capital accumulation equation.

$$k_{t+1} = i_t - (\delta + n) k_t$$

which brings in population growth. i_t represents per capita investment which we can replace to equal via the equation $i_t = s*y_t$:

$$k_{t+1} = s \cdot y_t - (\delta + n)\, k_t$$

where s is the savings rate and y_t is output per capita. From the per capita equation we can calculate what is known as the steady state. This equation is viewed as the "driver" of the model because it allows for what is known as "steady-state" calculations — the key factor of the Solow model. The Solow model operates under the assumption that an increase in growth cannot last forever, and the economy will reach a natural leveling-off point known as the "steady-state". This is known as a natural equilibrium that the growth track of an economy. Mathematically, this is where K_{t+1} equals K_t which means that all depreciation of capital from the previous period will equal that of total investment. Theoretically, we interpret this to mean all investment is being used to repair up to the amount of capital that is created: no new capital is being created. Thus, this model has the capabilities to calculate what that eventual steady state will be based on a derivation that sets k_{t+1} to k_t. To find the steady-state level for each variable, we begin with finding k*:

$$k^* = \left(\frac{sA}{n + \delta}\right)^{\frac{1}{1-\alpha}}$$

Then from that equation, we can find steady state levels: y*, c*:

$$y^* = Ak^{*\,\alpha} \qquad\qquad c^* = (1 - s) \cdot Ak^{*\,\alpha}$$

b. Data

I began this section of theoretical analyses with downloading data from the Penn World Tables database. This data is from the University of Groningen typically provides data on the relative levels of income, output, input, and productivity broken down by country in yearly time periods. My data span focused on the USA form 2000-2019. This collection focused primarily on capital stock, employment (labor force), population, Real GDP, and average depreciation rate of the capital stock from the span of 2000 to 2019. I relied on investment data from National Income and Product Accounts from the St. Louis Fed's: Federal Reserve Economic Database. The specific data that I used was the Gross Private Domestic Investment with an annual frequency.

c. Methodology

Once the necessary real data has been collected, we can start conducting calculations to set up the Solow model scope the long run implications of a TFP shock caused by Covid. This first portion of this process uses US real data as a starting point. The goal of this step was threefold: 1.) calculate necessary constants, 2.) calculate the "A" level based on 2019 levels, and 3.) calculate the steady state k* based on 2019 levels. The second portion focuses on calculating the new "A" based on the approximate percentage change (seen in Section 5.b) and assessing the effects a decrease in "A" has on the growth path and steady-state dynamics of the US for the future 50 periods. Below outlines the process taken to perform the Solow model analysis.

In calculating constants, I needed to generate values for population growth, savings rate, and the deprecation rate. These constants were calculated using the equations below:

$$n = \frac{1}{18}\sum_{2001}^{2019}\left(N_t - N_{t-1}\right) \qquad \delta = \frac{1}{19}\sum_{2000}^{2019}\delta_t \qquad s = \frac{1}{19}\sum_{2000}^{2019}\left(\frac{I_t}{Y_t}\right)$$

where population growth, depreciation and savings rate are represented by n, δ, and s respectively. Note N_t represents population of the US in period t. Additionally, we assumed alpha to be approximately 0.33 based on previous economic literature.

To calculate the original, pre-covid "A" level, I reworked the main Solow equation and plugged in 2019 period data. The formula for the original "A" is below.

$$A_{2019} = \frac{Y_{2019}}{K_{2019}{}^{\alpha} \cdot L_{2019}{}^{1-\alpha}}$$

Then, I used the k* equation to calculate the steady state for capital based on 2019's data. Making this calculation is integral, because for the next portion of this section, we assume 2019 to be at its ideal steady state level. In 2020, the shock "hits" and the analysis of the shock on the economy can be conducted.

The next half of this research focuses on the theoretical component of the Solow model analysis. The first step is to calculate the shock to A which entails multiplying the original shock to A times the assumed decrease in A from Covid (calculated in the previous period). The basic formula is as follows.

$$A_{new} = A_{org} \cdot (\, 1 - (\, \%\ \Delta\ shock)\,)$$

In our case, the percentage change to A was found to be -0.02 approximately. Then we can begin computing the transitional dynamics for the next 50 periods: Yt, Ct, Kt, It, and its per capita counterparts. The central equation for this section is the capital accumulation equation in per capita terms, reworked to include population growth:

$$k_{t+1} = \frac{1}{(1+n)} \cdot \left[sA_t k_t{}^{\alpha} + (1-\delta) \cdot k_t \right]$$

See appendix for the derivation. Once k_t was found for all future periods, calculating the growth track of other variables in the Solow model relies on general Solow model equations. These formulas are displayed below:

$$Y_t = C_t + I_t \qquad C_t = (1 - s) \cdot Y_t \qquad K_t = k_t \cdot L_t \qquad I_t = s \cdot Y_t$$

In the next section, I discuss the implications found from this process.

d. Analysis

Once the constants have been calculated and the steady state from 2019 data had been calculated, I operated that the Covid shock occurred in 2020 and therefore would have a different steady state than pre-covid years. From section (IV), we concluded productivity decreased by approximately 0.2% due to Covid, independent from other factors. Thus, the new A level for post-covid periods was then approximately 99.8% of the originally calculated A level.

With the transitional dynamics and calculating the new steady state, I can see how the US economy would behave and ultimately recover in the next 50 years. In calculating future Y_t, C_t, K_t and its per capita level counterparts, the recovery was seen the most in the per capita levels. Whilst y_t, c_t, and k_t all had almost instantaneous dips in their tracks due to the decrease in A. This shows that the economy was affected initially by the decrease in productivity, but soon after there appears to be a trend towards the new lower steady state (see figures from Appendix 6.d.2, 6.d.1, 6.3 respectively).

Although it's worth noting in the future 50 periods, the steady state is never reached even as we assume that the shock to TFP exists forever. Mainly the drop in TFP created an immediate dip in the levels of all factors, meaning the economy performed at a less productive level than its pre-Covid years. In economic terms, this means that at every level of capital per worker, workers produced less output.

Given a permanent lower value of A creates a similar reaction in Y_t, C_t, K_t where there is an immediate and steep drop in their levels, however they begin to increase and slowly recover in the future 50 periods. Yet, it is worthy to note that despite their recovery, these variables never reach the new A's steady state (see Appendix 6.d.4). This primarily due to the assumption that the population grows forever. The driving force of this trend becomes the constantly increasing population and not necessarily productivity phenomena — although there is some interrelationship between the two. These variables don't appear to be reaching a distinct steady state as they all continue to increase without any leveling off in their growth rates. This is typically because a contributing factor to Kt is the labor growth rate n.

But when we look at the per capita levels of capital, consumption and output, there is a degree of approaching their new steady state levels. Like the non-per-capita levels, they decrease almost immediately in 2020, although c_t and y_t were already decreasing even before such a shock. k_t is interesting to focus in on because it experiences the biggest hit in the magnitude of its growth rate. But slowly it levels off to its new steady state by the end of the 50-year period. c_t and y_t, although they do not take as big of a hit as capital, reach approximately their steady state levels within approximately 100,000 of their mark which is relatively close for growth terms.

7 Conclusion

Through my research I was able to conduct an analysis into the long-term effect of Covid through the lens of trade. By disaggregating trade by sector, I discovered the overall agricultural gains Covid spurred despite the heavy hits taken to Manufacturing and Services trade. The counterintuitive nature of the Covid variable formed a more complex image of what "efficiency" stands to mean. Do we define Covid as an inefficient time because of all the supply chain issues or perhaps did the work-from-home orders and re-evaluation and subsequent disregard of unnecessary work practices make our society that much more efficient? In any case, the efficiency concept became much denser from the research I conducted — placing more merit on the exploration of the pandemic's long-term effects. I found that although the productivity shock created by Covid incited an almost immediate drop in all facets of growth, the recovery towards the approaching of the new, albeit lower, steady-state level happened relatively quickly. Out of this research, its best to note that despite the gradual approaching of the new steady-state level, it never fully reaches the ideal steady-state level. This means that there are still more improvements needed to reach the ideal steady-state level based on the lower level of TFP.

There are many takeaways that this research offers. In particular, the difficulty in estimating the proper level of Covid in a country at a specific time illuminates the need for a more accurate Covid data source. Although stringency and governmental policy initiatives are integral, the problem is the lack of a full-encompassing dataset for Covid. Nevertheless, the long run implications from Covid indicate that despite the lessening of the Covid disease, the economy's still face a shock that will go on to affect the next 50 years. There is comfort in that the influence of Covid does not affect the transitional dynamics trends of the Solow model. It will continue to approach its steady-state levels, even if the productivity shock creates a lower steady-state level.

Despite the insightful conclusions of my research, I believe there are many points where I would hope to expand on in the future. The biggest difficulty was the less-than-ideal covid coefficient, which inhibited my research into the ideal EK/DFS model. Including this model in my paper would have furthered the strength of my analyses regarding the theoretical section of this paper. I believe this issue was caused by the non-linear relationship between Covid and trade along with the data source I used for my Covid variable. There is an indication to the non-linear mechanics of the Covid variable with the results of the fixed effect coefficients. The data issue can be explained by multiple factors however I believe the biggest issue to be the choice of the government response index. This data focuses primarily on containment/health policies such as vaccination and lockdown orders, stringency policies with closure policies and economic support index which accounts for income support and debt relief. The issue with this data is that it fails to consider the number of deaths and infected peoples in the country at a specific time. I also see the issue of imperfect multicollinearity. This is one of the most common issues in linear regression analysis because of the complexity it requires to address it. The multicollinearity between the GDP regressors and Covid regressors can be seen with the higher the degree of Covid affecting the GDP output during that period. Typically, this issue can only be solved with an instrumental variable regression — however the difficulty lies with finding an optimal instrument that correlates with trade, but not with the other independent variables.

Another potential drawback from the physical structure of the Gravity trade equation is the omittance of supply-chain-specific issues. There is no supply chain variable within my augmented model: how good is a gravity trade model without the consideration of supply chain issues? This goes into the scope of the Covid variable which affected any trade-specific interactions with lockdown orders, travel orders, etc. Supply chain issues are directly related to trade-specific interactions, meaning any supply chain effect will be embedded into the overall covid effect. If a supply chain issue occurred in 2020, it was related to the lockdown procedures aimed at lessening the virus and not outside of that effect. Also, thinking about the GDP effect on trade: supply chain issues also go into the performance of a country's economy. If countries are unable to produce to their normal levels because of the scarcity of intermediary goods, that aspect will also be seen in the GDP variable which is a key factor in the original model.

In terms of long run growth, I would like to explore a non-permanent shock to productivity. In this paper, I assume the effect to TFP remained at a lower state forever, but this is not representative of the real world. I think in exploring the temporary shock to TFP, I would be able to analyze a world more like our own — one where innovation and advancement is not stagnant but ever-changing.

8 References

Arkolakis, Costas, et al. “New Trade Models, Same Old Gains?” American Economic Review, 2009, https://doi.org/10.3386/w15628.

“Analysing the Trade in Services Data .” *UNstats*, Sept. 2006, https://doi.org/https://unstats.un.org/unsd/tradeserv/TFSITS/Meetings/2007-01/TFSITS0701-21.pdf.

“Balance of Payments (BOP6) : Services Imports.” *OECD.stat*, https://stats.oecd.org/index.aspx?queryid=67117#. Accessed 18 Apr. 2023.

Chaney, Thomas. “The Gravity Trade Equation In International Trade: An Explanation.” NBER Working Paper Series. National Bureau of Economic Research, August 2013. https://www.nber.org/system/files/working_papers/w19285/w19285.pdf.

Comin, Diego, et al. “A New Measure of Utilization-Adjusted TFP Growth for Europe and the United States.” 2020, https://doi.org/10.3386/w28008.

Eaton, J., Kortum, S., 2002. Technology, Geography, and Trade. Econometrica 70 (5), 1741–1779.

“Groningen Growth and Development Centre.” *Penn World Table Version 10.01*, 1 Jan. 2020, https://www.rug.nl/ggdc/productivity/pwt/?lang=en. Accessed 17 Apr. 2023.

Kimura, Fukunari, and Hyun-Hoon Lee. “The Gravity Equation in International Trade in Services.” *Review of World Economics*, vol. 142, no. 1, 2006, pp. 92–121., https://doi.org/10.1007/s10290-006-0058-8.

Keith Head, Thierry Mayer, Chapter 3 - Gravity Equations: Workhorse,Toolkit, and Cookbook, Editor(s): Gita Gopinath, Elhanan Helpman, Kenneth Rogoff, Handbook of International Economics, Elsevier, Volume 4,2014, Pages 131-195, ISSN 1573-4404, ISBN 9780444543141, https://doi.org/10.1016/B978-0-444-54314-1.00003-3. (https://www.sciencedirect.com/science/article/pii/B9780444543141000033)

Leamer, E., Levinsohn, J., 1995. International trade theory: the evidence. In: Handbook of international economics. Vol. 3. Elsevier, pp. 1339–1394.

Mayer, Thierry. “CEPII Research and Expertise on World Economy,” 2011. http://www.cepii.fr/CEPII/en/bdd_modele/presentation.asp?id=6.

“NIPA: Gross Private Domestic Investment (GPDIA).” *Gross Private Domestic Investment (GPDIA)*, 1 Jan. 2022, https://fred.stlouisfed.org/series/GPDIA. Accessed 17 Apr. 2023.

“OECD Statistics on International Trade in Services.” *OECD*, 2019, https://www.oecd-ilibrary.org/trade/oecd-statistics-on-international-trade-in-services_22258000. Accessed 18 Apr. 2023.

Prescott, Edward C. “Robert M. Solow’s Neoclassical Growth Model: An Influential Contribution to Economics.” The Scandinavian Journal of Economics 90, no. 1 (1988): 7–12. https://doi.org/10.2307/3440145.

Solow, Robert M. “A Contribution to the Theory of Economic Growth.” *The Quarterly Journal of Economics* 70, no. 1 (1956): 65–94. https://doi.org/10.2307/1884513.

Tinbergen, J., 1962. Shaping the World Economy: Suggestions for an International Economic Policy. Twentieth Century Fund, New-York.

Trefler, D., December 1995. The case of the missing trade and other mysteries. The American Economic Review 85 (5), 1029–1046

Unctad. “Classifications.” UNCTADstat, https://unctadstat.unctad.org/EN/Classifications.html.

“United Nations Comtrade Database,” August 2020. https://comtrade.un.org/data/.

“University of Oxford's Overall Government Response Index.” University of Oxford: University of Oxford, 2020.

“World Bank Database,” 2021. https://data.worldbank.org/indicator/NY.GDP.MKTP.CD.

9 Appendix

I began my research project by constructing a balanced panel dataset of 47 countries pulled over a period of 2016-2021. This was necessary because it would be the basis for the gravity trade regression analysis which would ultimately generate an unbiased coefficient for Covid’s effect on trade, independent of outside factors such as GDP. These 47 countries represent a simplified world economy and were chosen based on previous International economic literature. They encompass developed and middle or “developing” economies. In total, the 47 countries are: Argentina, Australia, Austria, Belgium, Brazil, Canada, Switzerland, Chile, China, Colombia, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, Great Britain, Greece, Hungary, Indonesia, India, Ireland, Iceland, Israel, Italy, Japan, South Korea, Lithuania, Luxembourg, Latvia, Mexico, Nigeria, Netherlands, Norway, New Zealand, Pakistan, Poland, Portugal, Russia, Slovakia, Slovenia, Sweden, Thailand, Turkey, United States, and South Africa. The basis for the determining a developed economy is Organization for Economic Co-operation and Development (OECD) encompasses majority of the developed economies in the world, most of my data encapsulates OECD countries. The economies from non-OECD countries are Argentina, Brazil, Chile, China, India, Indonesia, Nigeria, Russia, South Africa, Thailand, and Turkey. These additional countries data were included based on previous literature.

I began the downloading and cleaning process of the data by collecting import trade data from all 47 countries. Using the United Nations International Statistics Database (UN Comtrade database) was integral to this step because it broke down a countries' import data via their exporting partner country and allowed for the implementation of SITC-specific trade date. Because I wanted to assess the sector-specific versus aggregate trade behavior and impacts, I aimed to construct 4 separate datasets for gravity trade regression analysis. The 3 sector-specific groups were Agriculture, Manufacturing, and Services sector. Agriculture and Manufacturing import trade data was separated via Standard International Trade Classification codes (SITC) where SITC codes (0, 1, 2, 3, 4, 5) are agriculturally focused (Food and live animals, Beverages and tobacco, Crude materials, inedible, except fuels, Mineral fuels, lubricants and related materials, Animal vegetable oils, fats and waxes, Chemicals and related products and SITC codes (6, 7, 8) are manufacturing focused (Manufacturing goods, Machinery and transport equipment, and Miscellaneous manufactured articles). SITC code classification descriptions are based on the United Nations Conference on Trade and Development. UN Comtrade data accounted for trade data for aggregate, agriculture sector and manufacturing sector datasets, but Services data was much more elusive. From research into different data sources, Services are typically underreported and therefore underrepresented in data internationally because it is such a transactional phenomenon and non-goods-based sector (See UN stats source in references). In assessing the lack of data, I had to condense the span of data for the services sector dataset. Thus, Service sector trade data is pulled from the World Trade Organization using the Balance of Payments (BOP6): Services imports database for 44 countries (not including Nigeria, Pakistan, and Thailand) from 2016-2020 due to the lack of data for the year 2021.

Once I had downloaded all the trade data for these 4 groups, I began to download other variables necessary for the construction of the Gravity trade regression. This includes GDP, distance and Covid data which would remain uniform throughout all datasets. Aggregate yearly GDP data was pulled from the World Bank database for all 47 countries from 2016-2021. Distance data between each country's capitals was pulled from Geodist CEPII research and expertise on World Economy. The Covid policy index data is from the University of Oxford's Covid-19 Government Response Tracker which denotes a specific number for the degree of Covid in a country, starting in January 2020. This data has a daily frequency, so I took the average for each year based on the 365 datapoints to create an annualized Covid data. From years 2016-2019 I made the covid variable "0" because Covid did not officially become a phenomenon until the start of 2020. Therefore, for the Covid variable, 2020 and 2021 datapoints for the 47 countries are the only non-zero Covid observations.

Once I had collected all the data necessary for the gravity trade equation, I began to construct the datasets in the long format. This means each observation or line of data would have all the variables pertaining to the import trade data from the reporting country i and partner country j in time t including their respective GDPs, distance between one another and individual covid index data. This section relied on the STATA coding language to reshape, format, and organize each dataset.

Once the format was uniform amongst all variables for each of the 4 types of trade data, I began my analysis for this section. I began with a surface level analysis which was comprised of summary statistics for each variable (min, max, mean, number of observations, etc.) and general correlation between each independent variable on trade itself. This allowed me to verify the data aligned up with previous research and encompassed the full scope of countries and years I was using for my analysis.

After the superficial, perfunctory analysis, I began running gravity trade regression analysis on the datasets. I took the logged value of each of the variables and generated regression results in STATA for a log-log regression structure of the gravity equation. There are 2 separate regressions that I ran on my four datasets. The first is a baseline gravity trade equation omitting the covid variable. Below is a generalized regression equation to show the general structure of the first regression:

$$BilateralTrade_{ijt} = \beta_0 + \beta_1\left(\ln\left(GDP_{it}\right)\right) + \beta_2\left(\ln\left(GDP_{jt}\right)\right) - \beta_3\left(\ln\left(distance_{ij}\right)\right) + \varepsilon_{ijt}$$

This regression shows logged bilateral trade (import trade data) from country j to country i as a function of logged GDP of country i and logged GDP of country j with logged distance between country i and j and an error term composed of country i, country j and time effects. Below is the generalized regression with time fixed effects:

$$\ln\left(BilateralTrade_{ijt}\right) = \beta_0 + \beta_1\left(\ln\left(GDP_{it}\right)\right) + \beta_2\left(\ln\left(GDP_{jt}\right)\right) - \beta_3\left(\ln\left(distance_{ijt}\right)\right)$$
$$+ \gamma_{2017}\left(Y_{2017}\right) + \gamma_{2018}\left(Y_{2018}\right) + \gamma_{2019}\left(Y_{2019}\right) + \gamma_{2020}\left(Y_{2020}\right) + \gamma_{2021}\left(Y_{2021}\right) + \varepsilon_{ijt}$$

It is the same model presented above but with the addition of dummy variables to account for time-specific variation in the model. With the span of time being 2016-2021, the dummy variable for 2016 is dropped to prevent perfect multicollinearity.

It's best to envision the above formula as a sort of "control" to compare to the augmented gravity trade equation that encompasses a covid variable for both reporting and partner country. The covid-specific regression, with time fixed effects, is as follows:

$$\ln\left(BilateralTrade_{ijt}\right) = \beta_0 + \beta_1\left(\ln\left(GDP_{it}\right)\right) + \beta_2\left(\ln\left(GDP_{jt}\right)\right) - \beta_3\left(\ln\left(distance_{ijt}\right)\right) - \beta_4\left(\ln\left(Covid_{it}\right)\right)$$
$$- \beta_5\left(\ln\left(Covid_{jt}\right)\right) + \gamma_{2017}\left(Y_{2017}\right) + \gamma_{2018}\left(Y_{2018}\right) + \gamma_{2019}\left(Y_{2019}\right) + \gamma_{2020}\left(Y_{2020}\right) + \gamma_{2021}\left(Y_{2021}\right) + \varepsilon_{ijt}$$

Below are the set of Solow generalized equations, used in section VI of the paper:

$$Y_t = AF\left(K_t, L_t\right)$$
$$Y_t = C_t + I_t$$
$$K_{t+1} = I_t + (1-\delta)K_t$$
$$I_t = sY_t$$

In the next section of the Appendix, I show the mathematical workings behind the Solow model's steady-state calculations for k*

We begin with the capital accumulation:

$$K_{t+1} = I_t + (1-\delta)K_t$$

To get the equation into per capita terms, we must divide by Nt on both sides.

$$\frac{K_{t+1}}{N_t} = \frac{I_t}{N_t} + (1-\delta)\frac{K_t}{N_t}$$

Simplifying where we can, the issue is the LHS of the equation.

This means that we must multiply the LHS by N_{t+1} / N_{t+1}

$$\frac{K_{t+1}}{N_t} \cdot \frac{N_{t+1}}{N_{t+1}} = i_t + (1-\delta)k_t$$

Rewritten we get:

$$\frac{K_{t+1}}{N_{t+1}} \cdot \frac{N_{t+1}}{N_t} = i_t + (1-\delta)\,k_t$$

K_{t+1}/N_{t+1} will simplify to k_{t+1}

Nt+1/Nt will simplify to (1+n) because it represents the change in the population.

$$k_{t+1} \cdot (1+n) = i_t + (1-\delta)\,k_t$$

The capital accumulation equation, in per capita terms, becomes:

$$k_{t+1} = \frac{1}{(1+n)}\left[i_t + (1-\delta)\,k_t\right]$$

Once we have generated the capital accumulation equation in per capita terms we can aim to solve for k*.

The requirement is to set $k_{t+1} = k_t = k^*$. We can also substitute it for sy_t based on a general Solow formula. sy_t can be replaced via $y_t = Ak_t^{\alpha}$. With simple algebra,

$$k^* = \frac{1}{(1+n)}\left[sAk^{*\,\alpha} + (1-\delta)\,k^*\right]$$

$$k^*(1+n) = sAk^{*\,\alpha} + (1-\delta)\,k^*$$

$$k^*(1+n) - (1-\delta)\,k^* = sAk^{*\,\alpha}$$

$$k^*(1+n-1+\delta) = sAk^{*\,\alpha}$$

$$k^*(n+\delta) = sAk^{*\,\alpha}$$

$$\frac{k^*}{k^{*\,\alpha}} = \frac{sA}{(n+\delta)}$$

$$(k^*)^{1-\alpha} = \frac{sA}{(n+\delta)}$$

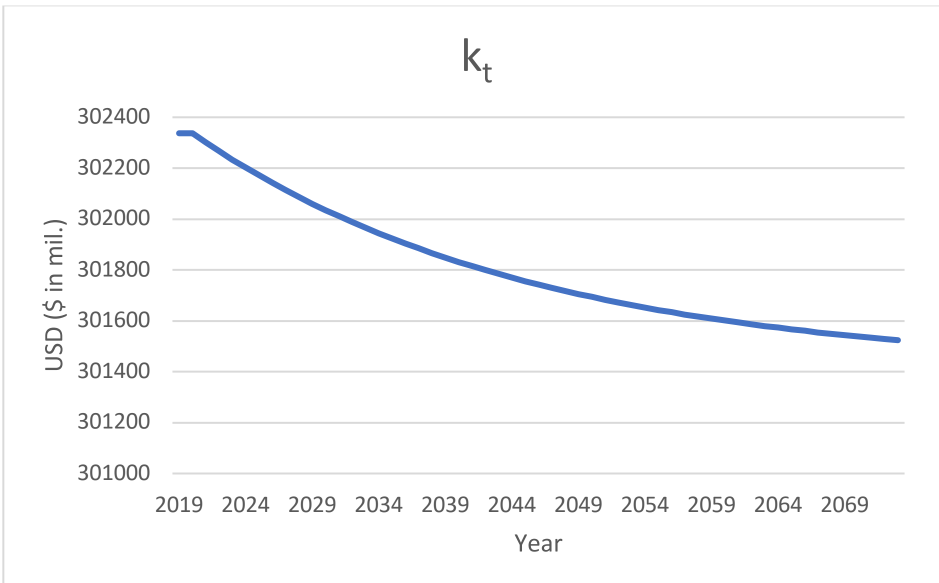
The resulting equation becomes:

$$k^* = \left(\frac{sA}{n+\delta}\right)^{\frac{1}{1-\alpha}}$$

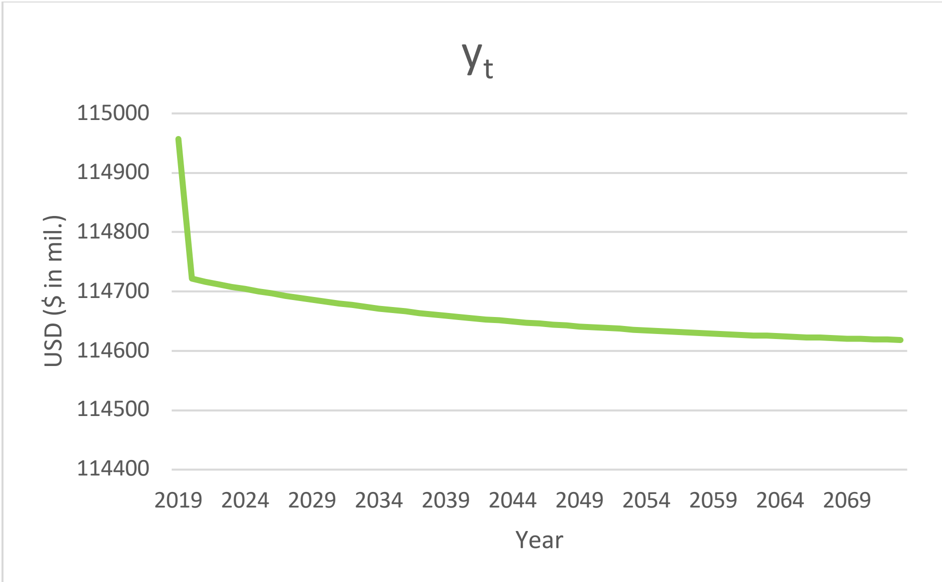
This equation represents the steady state k* with population growth and out of it, we can generate the y* and c* to form all steady states of the Solow model.

In the final section of the Appendix, I include related figures to Section (VI) of the paper. Particularly, these figures display Solow model growth paths of various inputs/outputs:

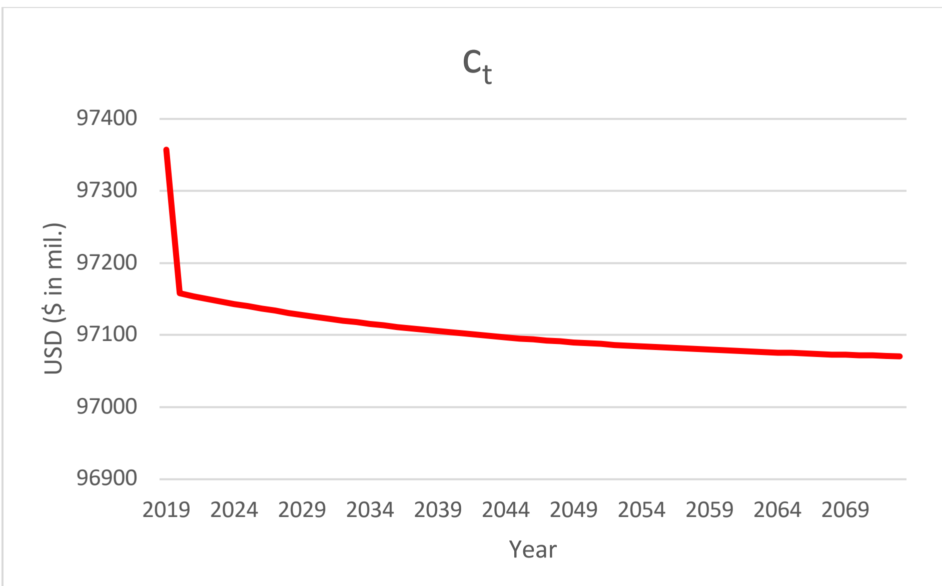
Appendix 6.d.1



Appendix 6.d.2



Appendix 6.d.3



Appendix 6.d.4