The Economic Benefit of the Freedom of the Seas

by

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Abstract

Maritime travel has existed for thousands of years. Today, much of international trade occurs by sea. Such trade would be limited without the international policy of freedom of the seas. The purpose of this study is to estimate the economic benefit of the freedom of the seas, in so far as it facilitates international trade. I generate initial and counterfactual least-cost routes between countries, and use the distances of these routes to solve a conventional model of international trade estimating the potential welfare effects of violating the freedom of the seas principle in various counterfactual scenarios. I estimate that the average gains from maritime trade range from 5.7% to 34.8%. In counterfactual scenarios, I find heterogeneous and economically significant welfare effects. I also show that, for countries in Southeast Asia, the magnitude of welfare losses is directly correlated with military spending as a proportion of GDP. This result suggests that these countries are responding to incentives around the possibility of a closure of the South China Sea. Overall, this study suggests that there is a large, sustained, and geopolitically important economic benefit to the policy of the "freedom of the seas."

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"The programme of the world's peace, therefore, is our programme; and that programme, the only possible programme, as we see it, is this... Absolute freedom of navigation upon the seas, outside territorial waters, alike in peace and in war, except as the seas may be closed in whole or in part by international action for the enforcement of international covenants."

\- Woodrow Wilson, 1918

Contents

1 Introduction

The purpose of this study is to add to the broader understanding of how the oceans contribute to total human welfare. My primary question of interest is: what is the economic benefit of the freedom of the seas? In other words, how would trade flows and incomeschange if the policy of freedom of the seas did not exist? The specific question to study is: what would be the effect of closing critical chokepoints in maritime routes on bilateral trade between affected countries?[1] My basic methodological approach is to simulate initial and counterfactual trade routes using GIS software, and then calculate distances along these routes. I then use these distances to solve a general equilibrium trade model estimating the welfare effects of moving from initial to counterfactual states. Closing a critical sea route is comparable to making it costlier to travel through that area, which effectively increases the distance between countries. Thus, the basic idea is to see how trade would change if some countries were "farther apart."

I simulate six counterfactual scenarios in particular. First, a closure of the Panama Canal. Second, a closure of the Suez Canal. Third, a blockade of the Oresund Strait. Fourth, conflict over the Pacific Ocean. Fifth, a dispute over the South China Sea and a blockade of the Malacca Strait. Sixth, and lastly, I simulate the welfare gains from all maritime trade using a counterfactual in which trade is prohibitively costly for all country pairs except countries that are land-connected. These counterfactual scenarios were chosen due to grounding in historical contexts or current geopolitical tensions. For example, the Suez Canal was closed from 1967 to 1975 due to the Six Day War between Egypt and Israel. Control of the Panama Canal has changed hands over the transition between American and Panamanian ownership. Denmark levied a tax on all goods passing through the Oresund Strait for over 400 years. World War II was, in part, a war for control of the Pacific, and greatly disrupted shipping through that area. Lastly, there has been a recent increase in Chinese military and naval presence in the South China Sea. Given the vast amount of goods flowing through that region, the strategic advantages of controlling passages such as the Malacca Strait are quite clear.

I estimate that the average gains from maritime trade range from 5.7% to 34.8%. In counterfactual

[1] With "affected" meaning a country pair whose least cost maritime trade route crosses the closed areas.

scenarios in which certain regions of the sea are "closed," I show that there are heterogeneous and economically significant welfare effects, including both gains and losses. For a counterfactual involving the closure of the South China Sea, I show that all countries would experience a welfare loss. I also show that, for countries in Southeast Asia, the magnitude of these welfare losses is directly correlated with military spending as a proportion of GDP. This result suggests that these countries are responding to incentives around the possibility of a closure occurring. I also conduct sensitivity analyses to show what changes in parameters affect the estimated welfare effects. The welfare effects are robust to most parameter changes. Overall, this study suggests that there is a large, sustained, and geopolitically important economic benefit to the policy of the "freedom of the seas."

The rest of this paper proceeds as follows: Section 2 provides a review of the relevant literature and background. Section 3 discusses the conceptual and theoretical framework. Section 4 describes available data sources and the details of the data used. Section 5 describes the methodological approach from generating distances to simulating results. Section 6 discusses the results of each counterfactual scenario. Section 7 provides sensitivity analysis, robustness checks, and a few extensions. Section 8 gives some overall discussion, and Section 9 concludes.

2 Background

2.1 Freedom of the Seas

The oceans can only be used to transport goods if it is free and safe to do so. Thus, the long-held maritime policy of "freedom of the seas" is crucial to deriving any value from the seas with regard to trade.[2] The concept of freedom of the seas is rooted in a treatise by Dutch philosopher Hugo Grotius titled *Mare Liberum* published in 1609.[3] Grotius' immediate goal was to argue in favor of Dutch access to the growing East Indian trade market, but his work has had far reaching effects (Armitage, 2012). In 1918, Woodrow Wilson argued for the freedom of the seas as one of his

[2] In this context, I assume "freedom of the seas" to mean a generally-held international policy that ships are able to sail through international waters without excessive risk, and that the vast majority of the ocean consists of such international waters.

[3] Literally: The Free Sea.

Fourteen Points for peace negotiations after World War I (Wilson, 1918).

At present, the freedom of the seas is most directly supported by policy from the United Nations. The United Nations Convention on the Law of the Seas (UNCLOS) establishes guidelines for resource extraction, trade, and sovereignty over the oceans (UNCLOS, 1982).[4] Importantly, the UNCLOS establishes "Exclusive Economic Zones" (EEZs) along each coastline extending 200 nautical miles offshore.[5] EEZs give a nation claim to the natural resources in that zone. However, EEZs are not the same as territorial waters. Nations only have territorial claim to the waters extending 12 nautical miles offshore. Anything beyond 12 nautical miles is considered international water, and ships are free to travel through. Essentially, my study is interested in counterfactuals extending territorial waters, thus potentially restricting commercial traffic.

2.2 The Gravity Model

One of the key drivers of bilateral trade is distance between the two countries. There is a well-developed literature on how distance affects the gains from trade. It is simply costlier for one country to trade with another country that is farther away. There may also be institutional or cultural barriers that hinder trade as well. The so-called "gravity model," which studies bilateral trade flows between two countries as a function of distance and incomes, has led to many studies of the "puzzling persistence" of the distance effect on trade (Disdier and Head, 2008).[6]

The gravity model has long been used to study the effects of distance on trade and national income. Elmslie (2018) argues that Adam Smith laid out the key elements for a theoretical gravity model of trade. Isard and Peck (1954) are typically credited with being the first to empirically link distance and trade flows. Tinbergen (1962) was the first to develop a full gravity model of trade. Anderson (1979) developed the first theoretical foundation for the gravity model.[7]

[4] The international agreement was signed 1982 and most recently amended in 1994. Of note, the United States is a non-party, primarily due to a desire for more control over rights to oil fields (Malone, 1983).

[5] 1 nautical mile is equal to approximately 1.15 miles.

[6] Puzzling in the sense that distance effects do not seem to be driven entirely by transportation costs. That is, countries that are farther from each other trade less, and much less than would be expected simply due to transportation costs increasing with distance. Distance effects also hold up to a wide range of methodologies, and do not seem to be declining over time. Blum and Goldfarb (2006) find that distance effects persist even in the case of digital goods traded over the Internet for which there are no trading costs.

[7] In a later paper, Anderson (2011) called the gravity model an "intellectual orphan" until only recently, as the theory backing the model has just come in to line with broader economic theory.

The typical gravity equation specifies bilateral trade between two countries as a function of the incomes of both countries, the populations of both countries, the distance between the two, and a few other bilateral characteristics, such as shared languages, common borders, or trade agreements. The methodology, discussed further in Section 5, follows a gravity model developed by Anderson and van Wincoop (2003). In the counterfactual scenarios I study, closures or blockades increase effective and relative distance between country pairs. Distance is increased when the optimal maritime route is longer, or when the optimal route involves costlier overland travel. Thus, when relative distance increases, the gravity effect implies that trade is costlier. Note that recently air shipping is becoming a more and more practical alternative to maritime shipping. However, it is well known that air transportation is still far costlier than sea transportation, and that air transport is primarily used for low-weight and high-value goods.[8]

2.3 Insecurity and Trade

For some key chokepoints along maritime trade routes, such as the Suez and Panama Canals, complete closure is physically possible. For other important straits, such as the Strait of Gibraltar and the Strait of Hormuz, practical closure could be achieved through mines or blockades.[9] The vast expanse of the open ocean could not feasibly be blocked off; however, international insecurity or war could make it impractical or extremely risky to pass through large regions of the ocean. Thus, this study is also closely related to literature studying the effects of insecurity and risk on trade. Anderson and Marcouiller (2002) develop a model of import demand in an insecure world, and find that poor institutions restrict trade on a level comparable to tariffs. Feyrer (2009) studies the closing of the Suez Canal to examine the effects of distance on trade and estimates a distance elasticity of 0.2 - 0.5, about half the size of other studies. Besley, Fetzer, and Mueller (2015) estimate that Somali piracy attacks increased shipping costs by 8% to 12% due to the added costs of protection, insurance, and ransoms.

[8] See, for instance, industry resources from Freightos on making a decision between air and ocean freight: `https://www.freightos.com/freight-resources/air-freight-vs-ocean-freight-making-the-decision/`.

[9] See Talmadge (2008) for a discussion of a hypothetical closure of the Strait of Hormuz.

2.4 Counterfactual Analysis

The proposed sort of counterfactual analysis follows much previous research. Donaldson and Hornbeck (2016) examine the historical impact of U.S. railroads. Allen and Arkolakis (2014) estimate the welfare gains of the interstate highway system. Donaldson (2018) applies a counterfactual to estimate the benefits of railroad infrastructure in India. Alder (2017) analyzes the effect of using a Chinese road system in India instead of recent highway projects. Costinot and Rordiguez Claire (2014) estimate the gains from trade through a counterfactual move to autarky for all countries. Head and Mayer (2013) estimate counterfactual welfare effects of removing all trade agreements.

However, there are far fewer studies involving counterfactual analyses focused on the oceans. Hugot and Umana Dajud (2016) study openings and closings of the Suez and Panama Canals to estimate distance elasticities and characterize changes in elasticities over time. They conduct a counterfactual exercise of closing the Panama Canal in 2012 and estimate welfare effects of such a closing. Hugot and Umana Dajud (2017) study the potential effects of the opening of Arctic routes on shipping distances. They conduct counterfactual simulations of trade and find that these routes would increase trade between China, Japan, and Korea with Western Europe.[10] Thus, one contribution of this study is add to the literature focused on maritime trade.[11]

2.5 Importance of Industry Variation

Industry variation is crucial to accurately estimating the gains from trade, because aggregating data too much can hide the importance of certain industries.[12] Ossa (2015) shows that accounting for cross-industry variation in trade elasticities triples the estimated gains from trade. The main point is simple: imports for a given country in certain industries are critical to the functioning of other industries. Aggregating too much masks the importance of these key industries. For example,

[10] Hugot and Umana Dajud (2017) is really similar to what I aimed to do in terms of counterfactual analysis. In fact, I hoped to do a counterfactual involving the Arctic passages before running in to software limitations. Unfortunately, I found this paper much later in my research, otherwise I would have based my methodology around this study.

[11] See Noer and Gregory (1996) for a non-economic analysis of maritime economic concerns in Southeast Asia. Noer and Gregory consider a number of hypothetical scenarios involving the closing of key chokepoints, in a similar vein as the proposed counterfactual analysis. However, this study is primarily from a national-security perspective, and has limited empirical analyses.

[12] As in, aggregating all industries in a country to the country level.

Ossa calculates the demand elasticity of iron ore to be 1.99 (which is relatively inelastic compared to other goods), whereas the elasticity of "office and stationary supplies" is 5.79 (highly elastic). For a country such as Japan, which has minimal iron ore reserves, one expects the gains from trade to be more substantial due to these key industries. Ossa (2015) shows that gains from trade for Japan are 3.3 times higher when accounting for cross-industry variation. Broda and Weinstein (2006) refine a method developed by Feenstra (1994) to estimate these industry level trade elasticities. These estimated trade elasticities can be used in counterfactual simulations to look at the effects on different industries of closing trade routes.

In this paper, I focus solely on a single-variety model. I attempt to estimate the importance of multiple industries by simulating trade with multiple values of the substitution elasticity, with lower values representing the important complementarity between industries. With more time, I would have liked to incorporate a multi-industry model in to the counterfactual analysis. See Section 8 for a discussion on ways such a model could be used in future research.

2.6 Economic Value of Oceans

The purpose of this study is to add to the broader understanding of how the oceans contribute to total human welfare. In general, there are three ways that the oceans contribute to human welfare: environmental benefits, natural resources, and trade. The oceans are a hugely valuable carbon sink and vital to many other environmental processes. Humans gather oil, food, and other valuable resources from the oceans. The oceans are also an important means of transportation for international trade.

The motivation for studying such a question is that it is important to have empirical evidence to drive policy discussions. Kildow and McIlgorm (2010) argue for the importance of understanding the economic impact of the seas, particularly in light of the volatile changes facing ocean and coastal economies, such as rising sea levels and unpredictable fuel costs. Costanza et al. (1997) estimate the economic value that ecological systems and natural capital stocks contribute directly and indirectly to human welfare, and conclude that the coastal and open oceans contribute 21 trillion per year (in 1997 dollars) to human welfare.

Although the added surplus of the oceans due to facilitating international trade is not comparable to the ecological impact, it would certainly be an important piece of maritime policy cost-benefit analysis. Obtaining additional economic justification to safeguard the seas could drive conservation and protection efforts. Such study is useful for understanding how trade might change due to rising sea levels. Importantly, increasing geopolitical tensions in the South China Sea and Arctic Ocean have real potential to shut down maritime routes. These tensions suggest the importance of understanding how such regions contribute to trade.

3 Conceptual Framework

The theoretical methods used in this study draw primarily from Anderson and van Wincoop (2003).[13] In turn, Anderson and van Wincoop draw primarily from Anderson (1979), who created a theoretical foundation for the gravity model starting from constant elasticity of substitution (CES) preferences and the assumption that goods are differentiated by region of origin. This assumption is based on the "Armington model" first described in Armington (1969). The reason to use such a model is that it greatly simplifies estimation. Importantly, it has been shown that the Armington model is isomorphic to more complex trade models.[14]

Assume that there are I countries, that each country specializes in the production of only one good, and that goods are differentiated by place of origin. Assume that consumers in each country have identical, homothetic preferences generated by a CES utility function with elasticity of substitution $\sigma > 1$.[15] Denote consumption by country j consumers of the good from country i as c_{ij}. Thus, the utility function (u_j) for a representative consumer in country j, who is consuming

[13] Anderson and van Wincoop show that the widely used gravity equations did not have a theoretical foundation and suffer from omitted variables bias. They then develop a method that incorporates "multilateral resistance" terms to correct for this bias and allow for comparative statics exercises. Anderson and van Wincoop show that the U.S. - Canada border effect calculated using "naïve" gravity equations is exaggerated due to the omitted variable bias, and find more moderate border effects of 20 - 50 percent. McCallum (1995) estimated that the U.S. - Canada border reduced trade between those countries by a factor of 22.

[14] Arkolakis, Costinot, and Rodríguez-clare (2012) show that the Ricardian model developed by Eaton and Kortum (2002) predicts the same gains from trade as the models developed by Melitz (2003) and others, and that these models are isomorphic to the much simpler Armington model.

[15] The point of assuming identical, homothetic preferences is that each individual consumer's indirect utility function is of the Gorman form, which makes it possible to calculate aggregate demand from a single representative consumer.

goods from all I countries, is given by:

$$u(c_{1j}, ..., c_{Ij}) = \left(c_{1j}^{\frac{\sigma}{\sigma-1}} + ... + c_{Ij}^{\frac{\sigma}{\sigma-1}}\right)^{\frac{\sigma-1}{\sigma}} \tag{1}$$

Further, assume that the supply of each good is fixed. Denote the price of country i goods in country j as p_{ij}. Importantly, prices differ between countries due to varying trade costs.[16] The central focus of this study is to simulate counterfactual trade costs under different scenarios, where trade costs are a function of distance. Then, consumers in aggregate in country j maximize equation (2) subject to the budget constraint given in equation (3):

$$\max_{c_{1j}...c_{Ij}} \quad u(c_{ij}, ..., c_{iJ}) \tag{2}$$

$$s.t. \quad \sum_{i}^{I} p_{ij}c_{ij} = y_j \tag{3}$$

Maximizing equation (2) subject to constraint (3) yields the following demand function, where P_j is a price index described by equation (5):

$$c_{ij} = \left(\frac{p_{ij}}{P_j}\right)^{-\sigma} \frac{y_j}{P_j} \tag{4}$$

$$P_j = \left(\sum_{i}^{I} p_{ij}^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \tag{5}$$

Now, assume that the price of good i in country j is a function of the price to the exporter and trade costs. Denote the price to the exporters of good i in country i as p_i, and trade costs from country i to country j as t_{ij}. Then, write p_{ij} as follows:

$$p_{ij} = p_i t_{ij} \tag{6}$$

Next, assume that for each unit of good i shipped to country j, the exporter incurs costs equal to $(t_{ij} - 1)$. Assume further that the exporter passes these costs entirely on to the importer. Then

[16] i.e., $p_{ij} \neq p_{ij'}$, the same good originating in country i is not necessarily priced the same in countries j and j'.

represent the nominal expenditure by country j on the good i from country i, denoted x_{ij}, as the sum of the value of the production at the origin $(p_i c_{ij})$ and the trade cost passed on to country j, which is $(t_{ij}-1)p_i c_{ij}$. The resulting equation is:

$$x_{ij} = p_j c_{ij} + (t_{ij}-1)p_i c_{ij} = t_{ij} p_i c_{ij} = p_{ij} c_{ij} \tag{7}$$

Rewrite x_{ij} by substituting equation (4) in to (7) as:

$$x_{ij} = p_{ij} \left(\frac{p_{ij}}{P_j}\right)^{-\sigma} \frac{y_j}{P_j} = \left(\frac{p_i t_{ij}}{P_j}\right)^{1-\sigma} y_j \tag{8}$$

In order to solve this system of I equations, it is necessary to make some assumption to close the model. Assume that the market clears. In other words, total income in country i is the sum of exports to all other countries, including itself. This amounts to writing income in country i, denoted y_i, as:

$$y_i = \sum_j x_{ij} = \sum_j \left(\frac{p_i t_{ij}}{P_j}\right)^{1-\sigma} y_j = p_i^{1-\sigma} \left(\sum_j \left(\frac{t_{ij}}{P_j}\right)^{1-\sigma} y_j\right) \tag{9}$$

Solve equation (9) for $p_i^{1-\sigma}$ in order to substitute that expression in to equation (8):

$$p_i^{1-\sigma} = \frac{y_i}{\left(\sum_j \left(\frac{t_{ij}}{P_j}\right)^{1-\sigma} y_j\right)} \tag{10}$$

$$x_{ij} = \frac{\left(\frac{t_{ij}}{P_j}\right)^{1-\sigma}}{\left(\sum_j \left(\frac{t_{ij}}{P_j}\right)^{1-\sigma} y_j\right)} y_j y_i \tag{11}$$

Define the nominal income of the world (y_w) to be $y_w = \sum_i y_i$ and country i's income share θ_i to be $\theta_i = \frac{y_i}{y_w}$. Substituting these expressions in to equation (11) gives the following expression for exports from country i to country j, where Π_i and P_j are defined as follows:

$$x_{ij} = \left(\frac{t_{ij}}{\Pi_i P_j}\right)^{1-\sigma} \frac{y_i y_j}{y_w} \tag{12}$$

$$\Pi_i = \left(\sum_j \left(\frac{t_{ij}}{P_j} \right)^{1-\sigma} \theta_j \right)^{\frac{1}{1-\sigma}} \tag{13}$$

$$P_j = \left(\sum_i \left(\frac{t_{ij}}{\Pi_i} \right)^{1-\sigma} \theta_i \right)^{\frac{1}{1-\sigma}} \tag{14}$$

Note that equations (13) and (14) are a non-linear system of $2I$ equations and $2I$ unknowns, and that if one flips the i and j in the expression for P_j, one gets back the expression for Π_i. This system of equations may be solved for all Π_i and P_j terms of income shares, trade costs, and the elasticity of substitution (θ_i, t_{ij}, and σ). However, a useful simplification is to assume that trade costs are symmetric, so $t_{ij} = t_{ji}$.[17] Imposing symmetry yields $\Pi_i = P_i$. We may then solve for an expression of $P_j^{1-\sigma}$ to substitute in to the expression for x_{ij} in equation (12). The basic gravity model constructed by Anderson and van Wincoop is equation (16) subject to equation (15):

$$P_j^{1-\sigma} = \sum_i P_i^{\sigma-1} \theta_i t_{ij}^{1-\sigma} \tag{15}$$

$$x_{ij} = \left(\frac{t_{ij}}{P_i P_j} \right)^{1-\sigma} \frac{y_i y_j}{y_w} = \frac{y_i y_j}{y_w} \frac{P_i^{\sigma-1} P_j^{\sigma-1}}{t_{ij}^{\sigma-1}} \tag{16}$$

Anderson and van Wincoop refer to the price indices (P_j) as "multilateral resistance" variables. These terms capture the general equilibrium forces in effect. The important innovation is that each P_j depends on all trade costs (t_{ij}), including those not involving country j at all. Notice that equations (15) and (16) imply that, as long as one includes trade costs within a region (t_{ii}), bilateral trade is homogenous of degree zero in trade costs.[18] The key point is that trade between countries depends on relative trade barriers. That is to say, trade between country i and country j depends on trade costs between i and j relative to the average trade costs country i and country j face with all other countries. Intuitively, this is because both countries are able to substitute to

[17] This assumption is quite reasonable in my context, because trade costs will be a function of distance, and the distance by sea between country i and country j is the same as the distance between country j and country i. Notice that this symmetry assumption would not hold under a more involved cost structure involving factors such as tariffs or ocean currents.

[18] In other words, a uniform increase or decrease in trade costs will not change bilateral trade flows. Thus, a counterfactual supposing that travel over every part of the ocean is more expensive would not reveal anything. This result does not, of course, hold if overland trade between neighboring countries is allowed, though that is a limitation of the methodology I propose, not the model developed by Anderson and van Wincoop.

other goods based on relative prices.

The last step is to specify the form of the trade costs between each pair of countries (t_{ij}). I specify trade costs as follows, where d_{ij} is the distance between countries i and j, ρ is the distance elasticity, α_{ij} is equal to 1 if country i and country j share a land border, δ_{ij} is equal to 1 if country i and country j share a common language, and γ_{ij} is equal to 1 if country i and country j are the same, and zero otherwise (i.e., $\gamma_{ii} = 1$ and $\gamma_{ij} = 0$ for $i \neq i$), . Note that it is possible to include other controls here, such as shared colonial links or trade agreements.

$$t_{ij} = d_{ij}^{\rho} b_1^{\alpha ij} b_2^{\delta ij} b_3^{\gamma ij} \tag{17}$$

I then substitute equation (17) in to equation (16) and take logs to arrive the following stochastic estimating equation, where k is a constant and ϵ_{ij} is an error term.

$$\begin{aligned} \ln(x_{ij}) \;=\; & k \;+\; (1-\sigma)\rho\ln(d_{ij}) \;+\; (1-\sigma)(\alpha_{ij})\ln(b_1) \;+\; (1-\sigma)(\delta_{ij})\ln(b_2) \\ & +\; (1-\sigma)(\gamma_{ij})\ln(b_3) \;+\; (\sigma-1)\ln(P_i) \\ & +\; (\sigma-1)\ln(P_j) \;+\; \ln(y_i) \;+\; \ln(y_j) + \;\epsilon_{ij} \end{aligned} \tag{18}$$

There are now two possible approaches to estimating this model. The first is to estimate equation (18) using non-linear least squares, minimizing the sum of squared errors and implicitly solving for the price indices. The parameters which are estimated as a result are k, $\beta_1 = (1-\sigma)\rho$, and $\beta_{n+1} = (1-\sigma)\ln(b_n)$ for $n = 1, 2, 3$. My coefficient of interest is β_1. Note that the elasticity of substitution (σ) cannot be estimated separately from the other parameters (ρ, $\ln(b_n)$, and β_m). However, one may make reasonable assumptions on σ in order to find explicit values for ρ and $\ln(b_n)$.

An alternative approach is to replace the multilateral resistance terms (P_i) with country specific dummies (i.e., fixed effects). This approach is sufficient if the purpose is to get consistent estimates for ρ and b_n. In this case an OLS specification is adequate.[19] My chosen methodology, described further in Section 5, is to estimate equation (18) using OLS and PPML regressions to obtain estimates for β_1 through β_4, and then fix a value of σ to calculate explicit values of ρ and b_1 to b_3.

[19] Anderson and van Wincoop suggest Hummels (1999) as an example.

Then, I use counterfactual distances along with the estimates of parameters to solve the system of equations described by equation (16) for counterfactual trade flows and incomes.

4 Data

4.1 Overview

This study requires unifying a number of disparate data sources. Primarily, I need geographic data on country borders, port locations, and bilateral distances as well as trade data on bilateral import and export flows. Further, I use other data sources for additional bilateral information, to generate internal expenditure flows, and to conduct additional analysis and robustness checks. With a few exceptions, almost all of the data used come from 2015, as this was the most recent year for which all the various datasets are available. Not all of our data come from outside sources; an original contribution of this paper is the generation of new bilateral distance data for maritime trade routes, both initially and under the various counterfactual scenarios.

4.2 Geographic Data

In order to generate bilateral maritime distances between ports, I need the geographic data on the location of all ports in the analysis and some means of distinguishing land from sea. More advanced counterfactual analysis could incorporate further types of geographic data, but my analysis is limited to the distinction between land and sea. I obtain all geographic data from Natural Earth, which has freely available shapefiles of the oceans, coastlines, land, country borders, ice caps, ports, and other resources (Patterson and Kelso, 2018).[20] Specifically, I use the 1:10m large scale Countries and Ports shapefiles.[21] Figure 1 shows the geographic data on ports and country borders that were used.

As further described in Section 5, I generate all cost rasters from the Countries shapefile by

[20] A shapefile is a file format used by GIS programs. Natural Earth has shapefiles at the 1:10m, 1:50m, and 1:110m (million) scales.

[21] Available for download at `https://www.naturalearthdata.com/downloads/10m-cultural-vectors/`. I would like to acknowledge that there are numerous sensitivities and controversies concerning some national borders. I defer to the borders utilized by this dataset, and hope to take no political position therein.

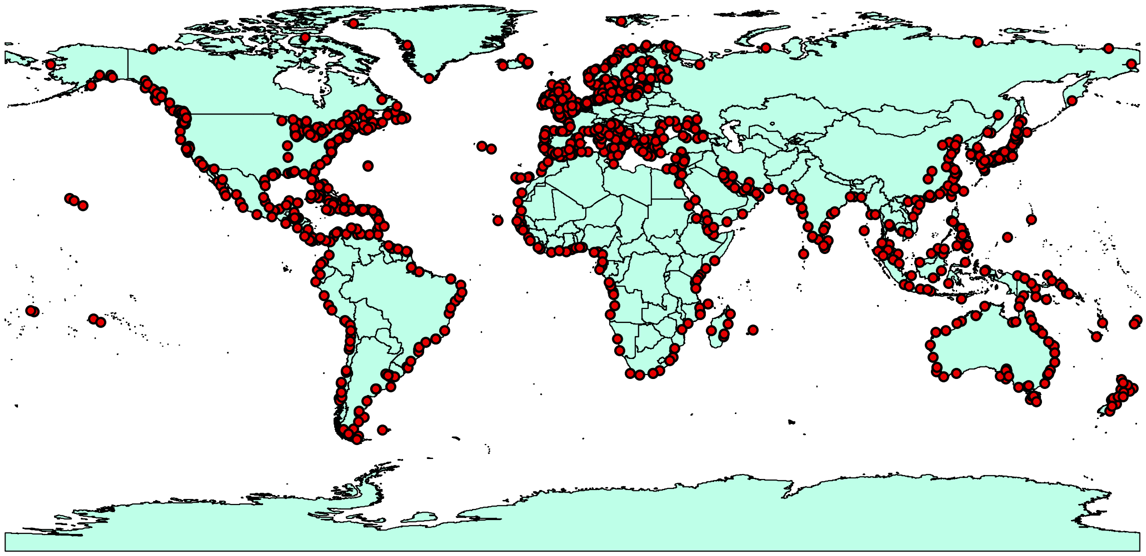

Figure 1: Country and Port Shapefiles

converting country polygons into a raster layer, then filling in the remaining empty pixels as the sea. Because of time constraints imposed by limitations of the algorithm used to generate bilateral distances, I focus on a small subset of 57 ports. I utilize data on GDP from the World Bank's World Development Indicators (WDI) to choose the 50 largest economies in the world.[22] The WDI include 1,600 time-series indicators for over 220 economies, going back as far as 50 years (The World Bank, 2018). I then use data from the World Port Rankings 2015, a dataset produced by the American Association of Port Authorities, to choose the largest port by value for each country, where available.[23]

Another piece of geographic data necessary for this study is the matrix of bilateral distances between all countries included in the analysis. Most other work on the gravity model in international trade uses distances between countries based on straight line distances between capitals, or straight-line

[22]Available for download at `https://datacatalog.worldbank.org/dataset/world-development-indicators`.

[23]Available for download at `https://www.aapa-ports.org/unifying/content.aspx?ItemNumber=21048`. The World Port Rankings list the top 100 largest ports by total cargo volume and by container traffic (AAPA, 2015).

distances between weighted population centers. For example, CEPII's GeoDist database includes such bilateral variables for 225 countries and is cited by many studies (Mayer and Zignago, 2011).[24] However, distances calculated this way are only a rough approximation of how far maritime trade actually travels. Such straight-line distances may over- or under-state the real-world distances traveled by ships. Additionally, distances based on largest cities or population weighting would not change under counterfactual scenarios involving closure of sea lanes. Thus, I generate my own bilateral distance data between countries using ArcGIS. See Section 5 for further description of this process.

4.3 Trade Data

The second major piece of data necessary for the analysis is the matrix of bilateral trade. Following the conceptual framework outlined in Section 3, I need expenditures by consumers in country i on goods from country j for all pairs ij, including such that $i = j$. There are a number of potential sources for bilateral trade flows. The World Bank provides the World Integrated Trade Solution (WITS) database for free (WITS, 2018). The data here are quite detailed and include industry variation. The Center for International Data (CID) provides the World Trade Flows (WTF) database, which consists of country-level bilateral trade flows for all available countries from 1984 to 2016 (Feenstra, 2016). These files are easily accessible and prepared for use with Stata, but do not include industry variation. The Global Trade Analysis Project (GTAP) outputs the GTAP-9 database, which contains bilateral trade data for 140 countries and 57 industries (Center for Global Trade Analysis, 2018).[25] Ossa (2015) supplements the GTAP-8 database with NBER-UN data, which is another potential source of trade data. The GTAP-9 database contains aggregate trade flows for many years and industry-specific trade flows for 2004, 2007 and 2011.

I use the WTF bilateral trade data published by Feenstra for the year 2015.[26] This dataset was chosen because it covers all 47 countries in our sample and all but a handful of bilateral pairs.

[24] Available for download from `http://www.cepii.fr/cepii/en/bdd_modele/bdd.asp`.

[25] The GTAP-9 database is available for a nominal fee for one-license users. Notably, GTAP releases previous versions of the database for free. GTAP-8 will become free when GTAP-10 is released. GTAP-10 was scheduled for release in early-2019, but that has since been pushed back to mid-2019. Hence, it was not possible to use those data in this study, though I had hoped to do so.

[26] Available for download from `https://www.robertfeenstra.info/datav2/`.

Table 1: Summary of 2015 WTF Trade Data

	Count	Mean	Standard Deviation	Minimum	Maximum
Total trade in \$1000s	31,646	591,327.6	6,446,455	.001	504,000,000

I suggest the GTAP database as a source of industry variation for any extended analysis. Table 1 summarizes the bilateral trade flows both outside and inside our sample.

It is worth nothing here the difficulty of calculating internal expenditure flows from trade data. Hypothetically, one is able to infer trade with self from production and export data. However, this is difficult because reported GDP includes many service sectors that are rarely traded. Some researchers have relied on production from manufacturing industries, such as Head and Mayer (2014). As the data set I use does not have internal expenditure flows for all countries, I use a few different sources to estimate internal trade flows following a process outlined further in Section 5. I use data from Costinot and Rodriguez-Clare (2014) to obtain internal expenditure shares for most countries and then predict internal expenditure shares for the remaining countries not in sample.[27] I then use Services as a percentage of production from the World Bank's WDI data, as well as GDP data, to back out the internal flow of expenditures on tradeable goods.[28]

4.4 Additional Data

In addition to the geographic and trade data described above, I also need data on a number of other bilateral characteristics. CEPII publishes a gravity dataset for all world pairs of countries from 1948-2015, including shared borders, languages, colonial links, trade agreements and so on (Head, Mayer, and Ries, 2010).[29] I use a small subset of this dataset for 2015 to obtain bilateral information on shared borders and languages for the primary analysis. Secondary robustness checks use other variables from this dataset. As described in Section 5.7, I estimate certain parameters using only countries that are not land-connected to try to isolate the effect of distance specifically on maritime trade. For that regression, I use a bilateral variable on land-connectedness that is

[27] Available for download from `https://eml.berkeley.edu/~arodeml/`.

[28] Available for download at `https://datacatalog.worldbank.org/dataset/world-development-indicators`.

[29] Available for download from `http://www.cepii.fr/cepii/en/bdd_modele/presentation.asp?id=8`.

drawn from the "Dynamic Gravity Dataset," published by Gurevich and Herman (2018) at the U.S. International Trade Commission.[30] Lastly, I draw on a few other data sources for additional sensitivity analysis and robustness checks. I use data from Head and Mayer (2014) for year 2000 trade data.[31] I also use data on military expenditures from the Stockholm International Peace Research Institute (SIPRI, 2019).[32]

5 Methodology

5.1 Overview

My primary methodological approach may be summarized as follows. First, generate initial and counterfactual distances using GIS software. Second, combine the distance information with other bilateral data and trade data. Then, use these data to estimate important parameters for the model described in Section 3, primarily the distance elasticity. Lastly, solve the model to generate equilibrium welfare effects under the various counterfactual scenarios. In practice, the methodology requires a few assumptions and adjustments along the way for the sake of feasibility. The end results are sets of equilibrium welfare changes under various parameters. In this section, I describe the general methodological approach. A more detailed description is offered for the ArcGIS work, as the counterfactual distance generation is one of the more original contributions of this paper.

5.2 Assumptions

I made a number of assumptions for feasibility. First, I limit my analysis to the 50 largest economies in the world due to computational and data constraits. Large changes in trade costs have negligible welfare effects if the trade flows are small, thus limiting my sample to the largest economies still captures the largest welfare changes. Additionally, I remove landlocked countries from the analysis. Of the top 50 economies, I remove Switzerland, Austria, and the Czech Republic, leaving 47 countries in the sample. The top 50 economies output 94% of world GDP, and the 47

[30] Available for download from `https://www.usitc.gov/data/gravity/dataset.html`.
[31] Available for download from `https://sites.google.com/site/hiegravity/`.
[32] Available for download from `https://sipri.org/databases/milex`.

economies in my sample output 92% of world GDP.[33]

The next major assumption I make is to consider all trade observed in the data as maritime trade. This assumption is necessary because I do not observe whether trade is by air, land, or sea. Such data are available for a few countries, such as the U.S., but not for many. However, this assumption is reasonable because the vast majority of world trade by weight is still by sea (Hummels, 2007).[34]

Next, I assume that all trade for a country originates from and is received at a single port. Again, this assumption is for simplicity and computational feasibility. Small changes in distance arising from having multiple ports would have a minimal impact on the results. However, I do not assign a single port to countries with two major coasts. For those countries, I assign two ports. Countries with two ports in the analysis are: Australia, Canada, Colombia, France, India, Israel, Mexico, Russia, Saudi Arabia, and the United States.[35]

5.3 Ports

Thus, the sample consists of 47 countries and 57 ports. Table 2 shows the list of country and port pairs. Ports were chosen based on shipping ranking and data availability. The most recent edition of the World Port Rankings (2016) lists the 100 largest ports in the world by shipping tonnage. This list was used to choose the largest port in each country if available.[36] For countries which did not have a port listed here, a port was chosen with discretion using Google Maps and other sources. Lastly, the choice of a few ports was determined based on what data were available in the Natural Earth ports data. For a few cities, the port in this file was simply listed by a different name than the nearby major city. Additionally, a small number of port locations were adjusted by hand, and a few ports not available in the data were generated by hand.[37] Importantly, for

[33]My calculation, using World Bank WDI data for 2015.

[34]As described in Section 5.7, I attempt to isolate the distance elasticity of maritime trade by capturing land trade through border and regional connection effects.

[35]Note that Russia's secondary port is on the Black Sea, not the Sea of Japan or the Sea of Okhotsk, as there is limited overland transportation across Siberia.

[36]Since the World Port Rankings lists the 100 largest ports, many of the smaller countries in my sample did not have a port listed here.

[37]Of the ports that ended up in the final sample, only Trieste, Italy, and Elat, Israel were adjusted by hand.

Table 2: List of Ports by GDP (billions of 2017 USD)

Country	ISO3	Port	GDP	Country	ISO3	Port	GDP
United States	USA	Newark	19,391	Belgium	BEL	Antwerpen	493
United States	USA	Los Angeles	19,391	Thailand	THA	Laem Chabang	455
China	CHN	Shanghai	12,238	Iran, Islamic Rep.	IRN	Bandar Abbas	440
Japan	JPN	Nagasaki	4,872	Norway	NOR	Oslo	399
Germany	DEU	Hamburg	3,677	United Arab Emirates	ARE	Dubai	383
United Kingdom	GBR	London	2,622	Nigeria	NGA	Tin Can Island	376
India	IND	Ratnagiri	2,598	Israel	ISR	Tel Aviv Yafo	351
India	IND	Visakhapatnam	2,598	Israel	ISR	Elat	351
France	FRA	Marseille	2,583	South Africa	ZAF	Richards Bay	349
France	FRA	Le Havre	2,583	Hong Kong SAR	HKG	Hong Kong	341
Brazil	BRA	Santos	2,056	Ireland	ISL	Dublin	334
Italy	ITA	Trieste	1,935	Denmark	DNK	Helsingor	325
Canada	CAN	Montreal	1,653	Singapore	SGP	Singapore	324
Canada	CAN	Vancouver	1,653	Malaysia	MYS	Port Dickson	315
Russia	RUS	Novorossiysk	1,578	Philippines	PHL	Manila	314
Russia	RUS	Saint Petersburg	1,578	Colombia	COL	Cartagena	309
Korea, Rep.	KOR	Ulsan	1,531	Colombia	COL	Buenaventura	309
Australia	AUS	Newcastle	1,323	Pakistan	PAK	Karachi	305
Australia	AUS	Port Hedland	1,323	Chile	CHL	San Antonio	277
Spain	ESP	Algeciras	1,311	Finland	FIN	Helsinki	252
Mexico	MEX	Progreso	1,150	Bangladesh	BGD	Chittagong	250
Mexico	MEX	Manzanillo	1,150	Egypt, Arab Rep.	EGY	Alexandria	235
Indonesia	IDN	Tanjung Priok	1,016	Vietnam	VNM	Ho Chi Minh City	224
Turkey	TUR	Mersin	851	Portugal	PRT	Sines	218
Netherlands	NLD	Rotterdam	826	Romania	ROU	Tulcea	212
Saudi Arabia	SAU	Jubail	684	Peru	PER	Callao	211
Saudi Arabia	SAU	Jeddah	684	New Zealand	NZL	Wellington	206
Argentina	ARG	Buenos Aires	638				
Sweden	SWE	Goteborg	538				
Poland	POL	Gdansk	525				

most countries, the exact location of the chosen port is not consequential, because small changes in distance have a negligible effect on welfare. My study is concerned with large and heterogeneous changes in distance.

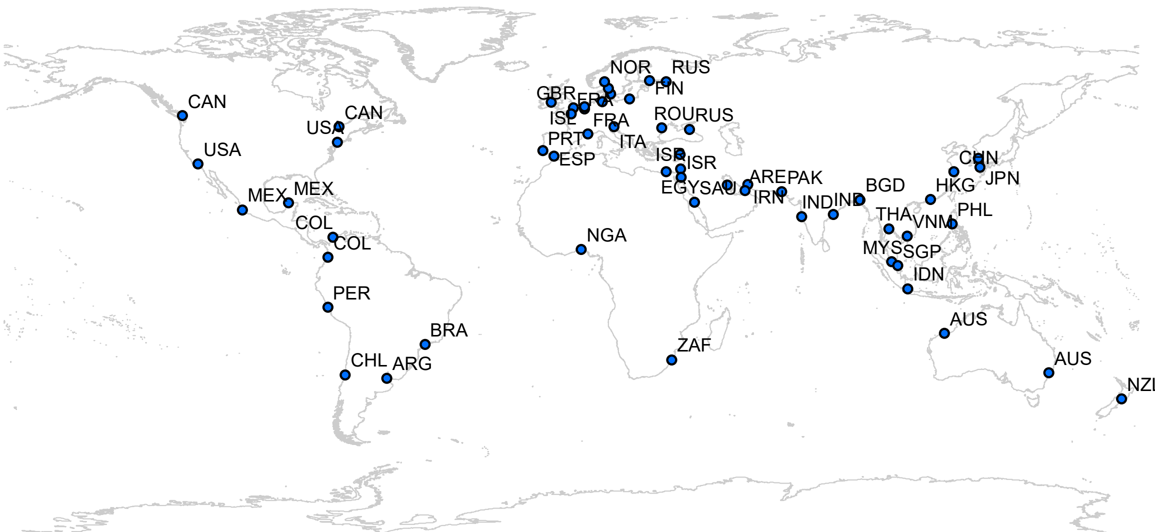

Figure 2: Locations of the Fifty Seven Ports in Sample

At this point, I have the locations of 57 ports corresponding to 47 countries as geospatial data in ArcGIS. Figure 2 displays the chosen ports on a map in the chosen World Equidistant Cylindrical projection.

5.4 Initial and Counterfactual Distances

The next step is to generate bilateral distances between all of these ports, both initially and under counterfactual scenarios. As generating these distances is one of the more original contributions of this project, I aim to describe this step of the methodology in greater detail. The goal is to generate a matrix of bilateral distances. [38] In order to do that, one method is to create these conditional routes as polylines, and store the data in an ArcGIS Catalogue. ArcGIS

[38] As there are 57 ports, the final matrix consists of N*(N-1)/2 = 57*56/2 = 1,596 distances.

automatically calculates the planar lengths of lines and planar area of shapes for data that is stored in a Geodatabase located in a Catalogue.[39]

Although another way of calculating distances, such as converting straight lines to geodesic, would be closer to the "real-world" sea distance, software limitations make this method the most feasible given time constraints. Additionally, because all distances are generated the same way, any systematic and small biases in distance calculation should have little to no effect on welfare changes. Finally, distance is only an approximation of shipping costs regardless. I am unable to account for other factors, such as weather, currents, and wind patterns. The distances generated this way are still better approximations of shipping costs than the straight lines between weighted population centers typically used in such analyses. I conduct sensitivity analysis of the distance data in Section 7.

Thus, my goal is to obtain these conditional routes as polylines. ArcGIS then automatically outputs the length of those lines. I choose the World Equirectangular Projection (also known as Plate Carée or World Equidistant Cylindrical) as a compromise between distance and area distortions. This projection was chosen because the scale of distances is correct along the meridians and the standard parallels, and area and direction distortions are less along the central latitudes where much of world trade occurs.[40]

I generate route polylines using the Cost Connectivity tool in ArcGIS. This tool takes as inputs a list of points and a cost raster, and outputs the least accumulated cost route network between those points. Least cost routes are calculated using Kruskal's algorithm.[41] Thus, if the input list of points consists of just two points, the output is the least cost route over the cost raster between those two points. I use a Python script to loop through all 57 ports to generate the 1,596 unique distance pairs.[42] A quirk of using this tool was that the Cost Connectivity tool would not generate

[39] See ArcGIS Help Resource Center for more detail on how ArcGIS calculates these distances: `http://resources.arcgis.com/en/help/main/10.1/index.html#//0017000000tv000000`.

[40] See ArcGIS documentation for more detail: `http://desktop.arcgis.com/en/arcmap/10.3/guide-books/map-projections/equirectangular.htm`. The North Pole Azimuthal Equidistant projection was discussed as an alternative. In the end, this projection was not used because the distances ArcGIS automatically calculates would have been wildly inaccurate. It would have been necessary to find another way to go from polylines to distances.

[41] See https://community.esri.com/thread/189141-which-minimum-spanning-tree-algorithm for official answer from Esri staff regrading the question of which algorithm the Cost Connectivity tool is based on. Kruskal's algorithm determines the least cost route between any two vertices in a graph.

[42] I would like to acknowledge and thank Drew Macqueen for this script. Finishing this project would not

routes north or south of the northernmost and southernmost ports in the sample. This issue was worked around by manually adding a 'north extent' and 'south extent' port. The routes to and from these ports were not used in any analysis and thus have no effect on the welfare results.

Another limitation is that raster layers in ArcGIS are two dimensional. A raster is a grid of squares, with each square being assigned a numerical value. Thus, the Cost Connectivity algorithm does not wrap routes around the globe; rather, it determines the least cost route on a flat, rectangular surface. My solution to this problem was to use two separate projects and generate all the routes twice. The first project is centered on the Atlantic Ocean, at the Prime Meridian (0.0 degrees). The second project is centered on the Pacific Ocean, at the 160.0-degree meridian.[43] The optimal routes are generated for both projects, but the distance actually used in the analysis is the minimum of the Atlantic/Pacific routes. Figures 3 and 4 illustrate the difference between the Atlantic and Pacific projections.

Before running the shortest-route algorithm, it was necessary to generate the cost rasters that were used as inputs. The rasters were generated from the Natural Earth shapefile of country borders using the Polygon to Raster tool. Then, all other cells are treated as water and filled in using the Reclassify tool. The cell-size used is 10,000, because this size is sufficient to open most major straits and to give relatively precise locations of ports relative to nearby land features.[44] Additionally, a greater number of cells increases the computational time of the generating the shortest routes; thus, a larger size for each cell was chosen for computational efficiency. The Panama and Suez Canals were added manually to create the initial rasters, again by designating pixels where the canals would be as sea instead of land.

The land pixels were then assigned a very high cost and the sea pixels were then assigned a low unit value.[45] The high value ensures that the algorithm does not take any "shortcuts" overland that

have been possible without his assistance.

[43]Note that one cannot just solve this issue by re-projecting a raster layer, as changing the projection does not change where the edges of the raster are. It is possible to re-project a polygon shapefile, and then generate a new raster from that projection, which is what I did.

[44]A cell-size of 10,000 implies that the width of a single cell corresponds to approximately 6.2 miles or 10.0 kilometers at the equator (24,901 miles / 4,008 pixels, where 24,901 miles is the circumference of the Earth at the equator). In practice, it was necessary to "widen" the Strait of Gibraltar by reassigning some land pixels near the Strait to be "ocean" pixels. This modification was necessary because the algorithm takes a weighted average when moving diagonally between pixels, and the Strait of Gibraltar was narrow enough that none of the routes would pass through without this change.

[45]Specifically, the high value was 1,000,000 and the low value was 1. In practice, sometimes the values

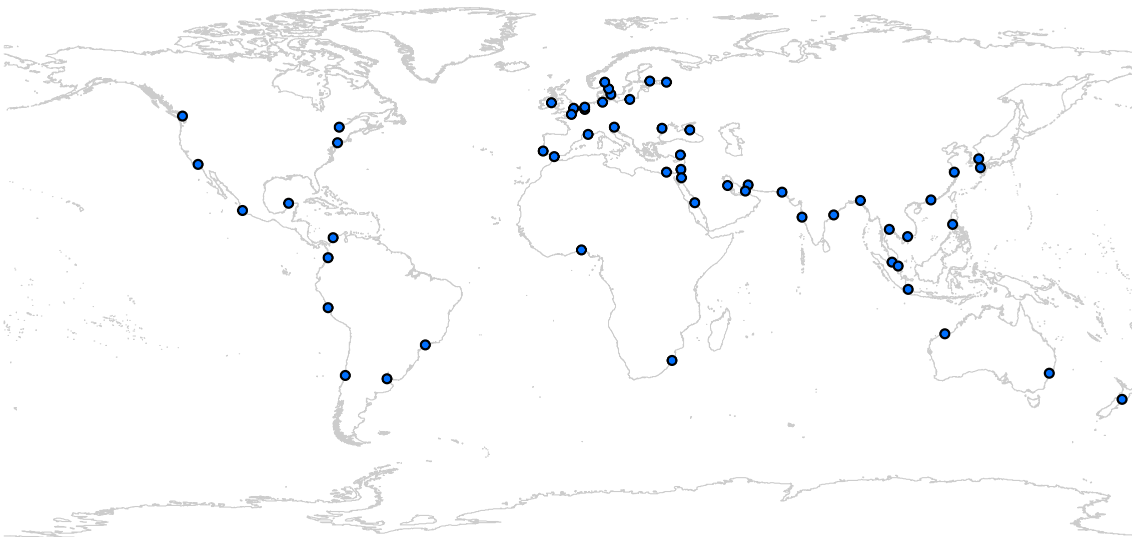

Figure 3: Atlantic Projection

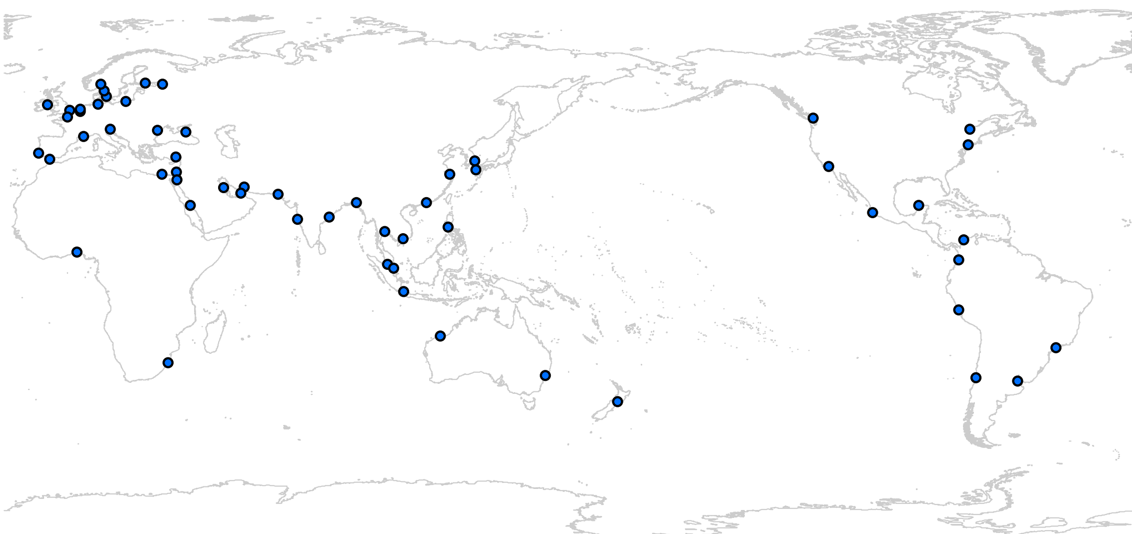

Figure 4: Pacific Projection

could be cost-effective with a lower value. Hypothetically, it would be possible to assign differential costs by longitude based on currents and the curvature of the Earth, but these additions were outside the scope and timeframe of this project. Counterfactual rasters were then generated by creating polygon shapes over the areas that are to be "closed," i.e., inaccessible to maritime trade. The Mosaic tools in ArcGIS are then used to create a new raster by merging the initial raster with the raster representing the area to be closed. Figure 5 is an example image of the initial raster, and Figure 6 is an example of the raster used for the South China Sea counterfactual. I then generate counterfactual rasters for six different scenarios. See the Appendix for exact boundaries.

At this step I have 14 rasters, including the initial scenario, six counterfactuals, and twice each for the Atlantic/Pacific pairs, as well as one set of 59 ports, consisting of the list of 57 plus the North and South extent. The Cost Connectivity script was run taking the 59 ports and each of the 14 rasters as inputs. This step of the process was the most time constraining, as it took approximately 12 hours to run the script each time. For this reason, it was necessary to limit the analysis to 50 countries, as this step of the process would have taken exponentially longer. The script then outputs a layer of routes representing the matrix of least cost routes between each unique pair of ports. The output is labeled with ID numbers for the pair of ports used to generate the route, allowing for merging with other bilateral data next. By saving this layer of polylines in a Catalogue, ArcGIS automatically calculates the planar distance in meters.

At this stage the data consists of 14 sets of 1,711 distances. Here I performed some ad-hoc checking of the reasonableness of the distances generated using a few maritime shipping websites. My generated distances were typically at most plus or minus 25% from these other sources, and there was considerable variation across sources. Thus, the distances generated seem to be reasonable approximations to the real-world shipping distance between these ports. See Appendix for a figure showing the initial network of maritime trade routes.

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were slightly different for certain cells, such as 1, 2, 3, or 4 for certain ocean values or 1,000,000 to 1,000,004 for certain land values. These differences were for simplicity in distinguishing values and shapes to ensure that the rasters were generated correctly, but have no effect on the network of routes in practicality.

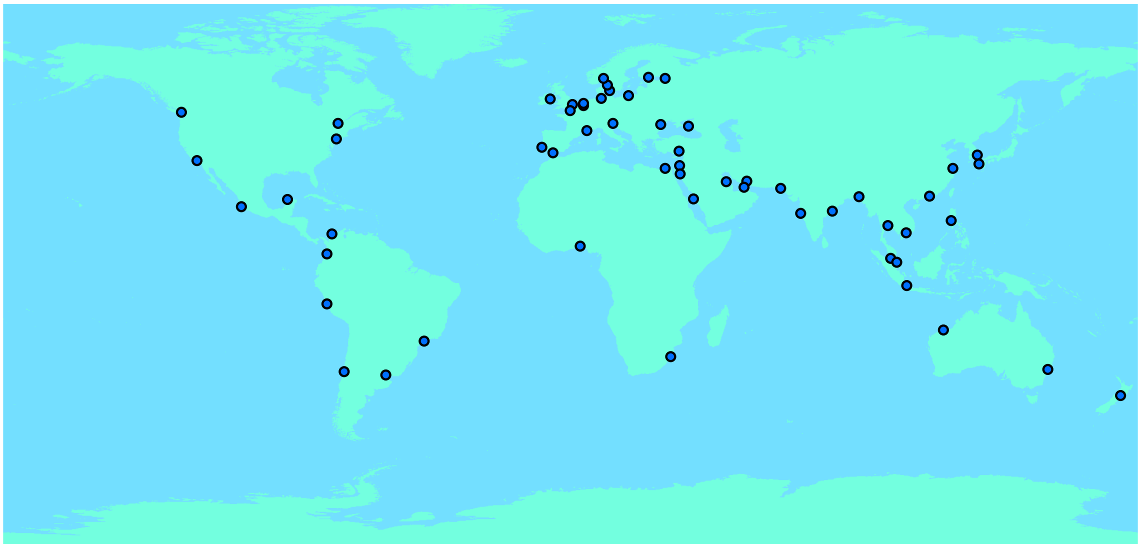


Figure 5: Initial Cost Raster

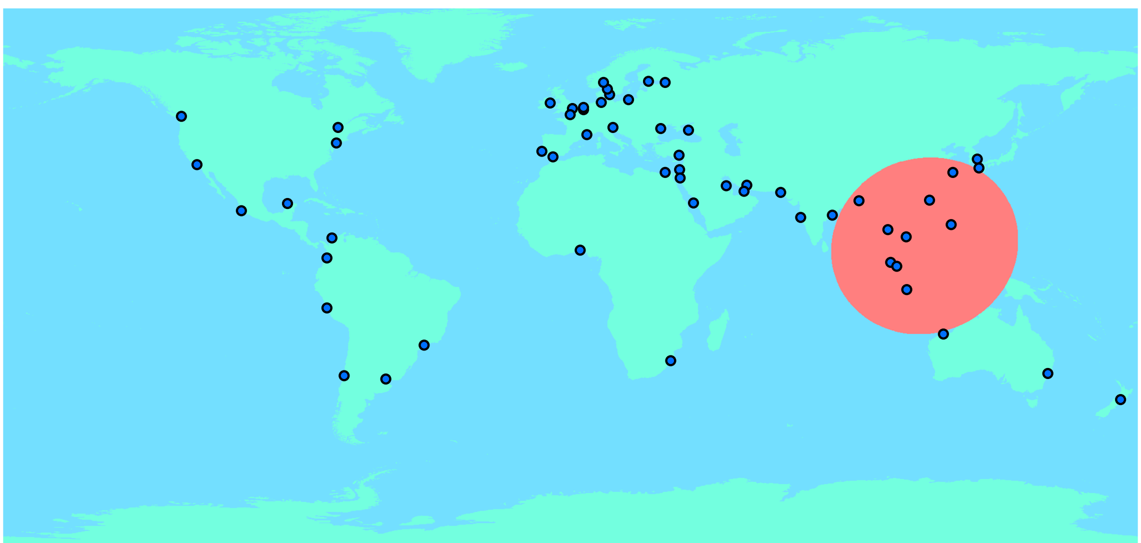


Figure 6: Raster for South China Sea Counterfactual

Note: These figures show raster layers used in the analysis. The green cells represent land cells, the blue cells represent ocean cells, and the red cells represent the area that is "closed," i.e., prohibitively costly, in the counterfactual scenario.

5.5 Data Processing and Merging

I processed and cleaned the data using Python. Here it was necessary to choose the shortest route for each pair of ports. For example, the U.S. and Russia were both assigned two ports: Newark (East Coast), and Los Angeles (West Coast) for the U.S. and Saint Petersburg (Baltic Sea) and Novorossiysk (Black Sea) for Russia. Thus, 8 bilateral distances between the U.S. and Russia were generated, but only the shortest of these distances should be assigned to the bilateral trade flow. For a few countries in certain counterfactual scenarios (specifically, the Oresund Strait and South China Sea counterfactuals), a country's only port was entirely surrounded by a "closed" area of the sea.[46] Here I assume that such countries are forced nearly to autarky. This assumption is modeled by increasing all distances involving that country up to an extremely high number.[47]

In addition to choosing the shortest route for each pair of countries, I also append other bilateral info from CEPII and other sources, such as whether the countries share a common language, share a border, are land connected, and so on. At this stage the dataset consists of 2,209 bilateral pairs, including same-country pairs (i.e., USA to USA), with bilateral information and bilateral distances. I then merge this dataset with the WTF trade data for 2015. The year 2015 was chosen because all of the necessary data were available for this year.[48] Only a few bilateral flows that are not internal are missing from these data. For these ten pairs, I assume that there is actually zero trade between these countries. These pairs are assigned the smallest value of trade in the dataset, although these pairs are left out of the regressions used to estimate parameters for the model.[49]

Importantly, I am missing most of the internal expenditure flows, i.e., trade with self x_{ii}. These internal expenditure flows are critical because, as discussed later in this section, welfare changes are calculated using changes in internal expenditure shares (i.e., the proportion of expenditures which are on goods produced in that country). Unfortunately, it is not possibly to simply take the GDP of a given country and subtract all the other trade flows. This difficulty is because GDP

[46]For example, Singapore in the South China Sea counterfactual.

[47]1,000,000 km was chosen as the impossibly high distance, which is over two and a half times the distance from Earth to the moon. Note that the model still allows for trade between countries separated by even this far a distance. However, such trade flows are quite small because the cost is so high.

[48]A small list of datapoints were still missing for this year. For example, Services as a % of GDP was available for Canada for 2014, but not 2015.

[49]For example, there is no reported trade between Israel and Iran. The smallest non-zero value in the data is $41,007.99.

includes many service sectors that are rarely traded internationally, let alone by sea. Most other papers have relied on generating the value of production from manufacturing industries, such as using WIOD or CEPII production databases. Head and Mayer (2014) do this process with CEPII data for the year 2000. Costinot and Rodriguez-Clare (2014) do this process with WIOD data for the year 2008. In order to get an approximation of more recent trade, I estimate internal trade shares and then use service shares of GDP to implicitly calculate internal expenditure flows. In Section 7, I test the sensitivity of these estimates. Although it would technically be possible to calculate internal expenditure shares from WIOD data for 2015, that would have been outside the scope of this project. Additionally, the WIOD data would still not include all of the countries I aim to include in the analysis.

5.6 Calculation of Internal Expenditure Flows

I calculate internal expenditure flows (x_{ii}) as follows. First, I use the internal expenditure shares ($\lambda_{ii} = \frac{x_{ii}}{\sum x_{ni}}$) calculated by Costinot and Rodriguez-Clare (2014) for all the countries that are in both samples.[50] Then, I use the internal expenditure shares generated by Costinot and Rodriguez-Clare to predict internal expenditure shares for the countries that are in this sample but not in their sample. I predict these shares using an OLS regression of internal expenditure share on GDP and GDP per capita.

$$\lambda_{ii} = \alpha_0 + \alpha_1 GDP_i + \alpha_2 GDPpc_i \tag{19}$$

Table 3 reports the results of this regression. Since domestic goods are a normal good, I expect that larger economies with the same population will consume more of their good, all else equal. Hence, the sign of the coefficient on GDP is expected to be positive. However, I also expect that as countries get richer per person, people will increase their consumption of foreign goods, since foreign goods are also normal. Hence, the sign of the coefficient on GDP per capita is expected to be negative. The coefficients on GDP and on GDP per capita were in the expected direction.

[50] 26 countries are in both samples, including the United States, China, Japan, Germany, and the United Kingdom. 18 of the top 20 countries by GDP are included in both samples.

Then, I use the fitted values for the internal expenditure shares that were not in the 2008 data.[51] Although there may be some bias in these fitted values, it is necessary to estimate the internal expenditure flows by some means. Additionally, I only use the fitted values for 21 out-of-sample countries.

Table 3: Predicting Internal Expenditure Shares

	λ_{ii}
GDP	.016***
(billions, USD)	(.0044)
GDP per capita	-0.014*
(ten thousands, USD)	(0.001)
Constant	0.821***
	(0.022)
Observations	33
Adjusted R^2	0.310

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

Next, I back out the internal flow of expenditures on traded goods. I do this using service shares as a percentage of GDP from the World Bank (The World Bank, 2018) and assume the following hold:

$$S_i = x_{ii}^{NT}/(x_{ii}^{T} + x_{ii}^{NT}) \tag{20}$$

$$\lambda_{ii} = (x_{ii}^{T} + x_{ii}^{NT})/GDP_i \tag{21}$$

Where x_{ii}^{T} is expenditures on tradeable goods and x_{ii}^{T} is expenditures on non-tradeable goods. I want to calculate x_{ii}^{T}. I now have S_i, λ_{ii}, and GDP_i, so it is possible to solve these two equations together to get:

$$x_{ii}^{T} = \lambda_{ii} * GDP_i * (1 - S_i) \tag{22}$$

See Section 7 for robustness checks of the accuracy of these values. Additionally, I also run the

[51]The reason to not use solely the fitted values is primarily that, for a few countries such as the United States, the predicted internal expenditure share is a high outlier at 99.9%.

full analysis with the year 2000 data from Head and Mayer (2014), of which 40 countries are in both samples. Those internal expenditure flows are calculated based on production values rather than predicted on an ad-hoc basis. Section 7 shows that the direction and magnitudes of the welfare changes are comparable, particularly given the changes in production that would have occurred from 2000 to 2015.

5.7 Estimation of Model Parameters

At this point I now have the complete square dataset of 2,209 entries (47 * 47) and all necessary distance and trade data. The next step in the process is to generate parameters for the model, in particularly the elasticity of trade with respect to distance. It would be possible to simply pull median values of this parameter from the literature; however, I choose to estimate the values that fit these data. In Section 7.3 I test the sensitivity of the welfare results to other values of the distance elasticity.

I run two OLS regressions and two PPML regressions that are based on equation (18), which was derived from the model described in Section 3. PPML refers to Poisson pseudo maximum likelihood estimators, which Silva and Tenreyo (2006) show perform better than OLS estimators for many log-linearized models, such as the gravity model for trade, due to bias resulting from heteroskedasticity. The first OLS and first PPML regressions include all of the bilateral trade flows. The following equation represents the base specification for the first OLS regression, where k is a constant, η_i and η_j are country fixed effects, d_{ij} is the bilateral distance, α_{ij} is a dummy variable for whether the countries share a border, δ_{ij} is a dummy variable for whether the countries share a language, and γ_{ij} is a dummy variable for when the two countries are the same:

$$\ln(x_{ij}) = k + \eta_i + \eta_j + \beta_1 \ln(d_{ij}) + \beta_2\alpha_{ij} + \beta_3\delta_{ij} + \beta_4\gamma_{ij} \tag{23}$$

Note that this equation is consistent with equation (18) and the parameters β_1 through β_4 are the same as those described in Section 3. The first PPML specification is the same, except that I use x_{ij} rather than $\ln(x_{ij})$. The second specifications leave out countries that are land-connected in the same region, and thus for which I would expect there to be substantial overland trade. The reason for these second specifications is to generate a distance elasticity that is more specific to maritime trade. Although I cannot limit the later analysis to only such country pairs as it is necessary to have square data, I attempt to better represent the responsiveness of maritime trade to distance here. Table 4 reports the results of each of these four regressions.

Table 4: Parameters

	(1) Log Trade	(2) Log Trade	(3) Trade	(4) Trade
Log Distance	-0.815***	-0.964***	-0.512***	-0.687***
	(0.0288)	(0.0429)	(0.0325)	(0.0407)
Shared Border	0.332**		0.836***	
	(0.125)		(0.127)	
Shared Language	0.407***	0.289***	0.480***	0.0828
	(0.0749)	(0.0798)	(0.105)	(0.0679)
Same Country	1.162***		0.996***	
	(0.205)		(0.140)	
Specification	OLS	OLS	PPML	PPML
Sea-Only		X		X
Observations	2198	1851	2209	1856
Adjusted R^2	0.819	0.808		

Standard errors in parentheses

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

First, note that the coefficients on log of distance estimated using PPML are much less (in absolute value) than the coefficients estimated using OLS. This result is consistent with the literature and the design of PPML. Second, note that these estimated distance coefficients are all less than the median value in the literature. Head and Mayer (2014) survey the gravity literature and report a median distance coefficient of -.89 for all gravity and -1.14 for structural gravity. They choose to use the median value for structural gravity in their analysis. So, the coefficients I estimate here are less than the median in the literature. However, the standard deviations for the surveyed distance coefficients are .4 for all gravity and .41 for structural gravity. In other words, my estimates are only at most one standard deviation below the mean. Thus, I choose to use my parameter estimates rather than values from the literature.

There may be a compelling reason why my estimates are smaller in absolute value. I have generated distances that better reflect the actual routes taken by ships than the straight line distances typically used in the literature. If real-world trade routes are longer than the straight line distances, then I would expect gravity estimates using straight line distances to over-estimate the effect of distance on trade. In Section 7, I discuss the sensitivity of our results to changing the distance elasticity. In Section 6, I report results using the parameters from regression (3), the PPML regression with all countries, as my preferred specification. Importantly, because my chosen value for the distance elasticity is below average (in absolute value) when compared to other estimates in the literature, my results may in some ways be thought of as a lower bound on welfare effects.

Note that the estimated distance coefficients are not estimates of the distance elasticity. Rather, β_1 is equal to $\rho(1-\sigma)$, where ρ is the distance elasticity and σ is the substitution elasticity. By assuming a value for σ, I back out $\hat{\rho}$ given an estimated value for $\hat{\beta}_1$. I then use $\hat{\rho}$ and the chosen value for σ to calculate counterfactual trade costs t_{ij} under changes in effective distances.

5.8 Welfare Analysis

Now, I have generated the full dataset and also estimated the parameters to be used in the model. Note that it is not possible to simply calculate counterfactual changes in trade directly from the counterfactual distances and the distance elasticity. Recall that the reason for this is that changes in trade costs between two countries will also affect trade with third countries. I follow Head and Mayer (2014) in generating these General Equilibrium Trade Impacts (GETI). Head and Mayer specify the general equilibrium trade effects as follows, where $\hat{x}_{ij} = \frac{x'_{ij}}{x_{ij}}$ represents the counterfactual to initial value ratio for any variable:

$$GETI_{ij} = \hat{x}_{ij} = \frac{x'_{ij}}{x_{ij}} = \frac{\hat{y}_j \hat{x}_i}{\hat{P}_j \hat{\Pi}_i} * \hat{\phi}_{ij} \tag{24}$$

$$\phi_{ij} = t_{ij}^{\varepsilon} \tag{25}$$

Where P_i and Π_i are the price indices described in Section 3, $\phi_i j$ is a measure of bilateral accessibility, and ε is the elasticity of trade with respect to trade costs. Thus, ϕ_{ij} is between 0 and

1. Arkolakis et al. (2012) show that $\varepsilon = 1 - \sigma$, where σ is the constant elasticity of substitution between all varieties of goods.[52] I follow Head and Mayer in assuming symmetric trade costs, as none of my trade cost determinants are directional. Note that equation (24) is entirely consistent with the conceptual framework described in Section 3 and estimated above, as Head and Mayer use the same Armington model based on Anderson and van Wincoop (2003). Additionally, Arkolakis et al. (2012) show that a large class of trade models, including this one, have a common measure of welfare changes.

Next, I assume that each country's labor endowment is fixed. Thus, $y_i = w_i L_i$. Since L_i is fixed, then proportional changes in production are determined solely by proportional changes in wages, i.e., $\hat{y}_i = \hat{w}_i$. In other words, changes in GDP are pinned down by changes in wages. The market clearing conditions imply that:

$$\hat{y}_i = \frac{y_i^{'}}{y_i} = \frac{1}{y_i} \sum_j \lambda_{ij}^{'} x_j^{'} \tag{26}$$

Where $\lambda_{ij} = \frac{x_{ij}}{x_j}$ is the share of country j's expenditure on goods from country i and $x_j = \sum_i x_{ij}$ is the total expenditures of country j. Additionally, Dekle et al. (2007) show that:

$$\hat{\lambda}_{ij} = \frac{(\hat{y}_i \hat{t}_{ij})^{\varepsilon}}{\sum_n \lambda_{nj} (\hat{y}_n \hat{t}_{nj})^{\varepsilon}} \tag{27}$$

Plugging this equation in to the market clearing condition gives:

$$\hat{y}_i = \frac{1}{y_i} \sum_n \hat{\lambda}_{ni} \lambda_{ni} \hat{y}_n x_n = \frac{1}{y_i} \sum_n \frac{\lambda_{ni} \hat{y}_i^{\varepsilon} \hat{\phi}_{ni}}{\sum_\ell \lambda_{n\ell} \hat{y}_\ell^{\varepsilon} \hat{\phi}_{n\ell}} \hat{y}_n x_n \tag{28}$$

Given initial GDP and initial trade shares λ_{ij}, as well as estimated changes in ϕ, equation (28) defines a system of equations that determine $\hat{y}_i$ for each country. It is necessary to take a certain value of ε as given. With ε, changes in ϕ, and changes in y, I then substitute in to equation (27) to obtain the matrix of changes in expenditure shares, i.e., the matrix of all changes in bilateral trade. I follow the methodology of Head and Mayer, which solves this system of equations in Stata

[52] To see this, define ε as the partial elasticity of relative imports with respect to trade costs: $\varepsilon = \frac{\partial ln(x_{ij}/x_{jj})}{\partial ln(t_{ij})}$. Since $x_{ij} = \left(\frac{w_i t_{ij}}{P_j}\right)^{1-\sigma} y_j$, one has $ln(x_{ij}/x_{jj}) = ln\left(\left(\frac{w_i t_{ij}}{w_j t_{jj}}\right)^{1-\sigma}\right)$ and thus $\frac{\partial ln(x_{ij}/x_{jj})}{\partial ln(t_{ij})} = 1 - \sigma$.

using a dampening factor until the λ matrix stops changing. As shown by Arkolakis et al. (2012), welfare changes for each country are then given by:

$$\hat{W}_i = \frac{W_i'}{W_i} = \left(\frac{\lambda_{ii}'}{\lambda_{ii}}\right)^{\frac{1}{\varepsilon}} = \left(\hat{\lambda}_i\right)^{\frac{1}{\varepsilon}} \tag{29}$$

Where W_i is welfare in country i. Before solving the system of equations defined by (28), I must determine proportional changes in ϕ. Since only distance changes in the counterfactual scenarios, all other factors affecting trade costs will drop out. I define the proportional change in bilateral accessibility as:

$$\hat{\phi}_{ij} = \hat{t}_{ij}^{\frac{1}{\varepsilon}} = \left(\frac{d_{ij}'}{d_{ij}}\right)^{\rho\varepsilon} = \left(\frac{d_{ij}'}{d_{ij}}\right)^{\beta_1} \tag{30}$$

Note that $\hat{\phi_{ij}}$ clearly equals one if there is no change in distance. I use Stata code made available by Head and Mayer (2014) which solves the system of equations described by (28). Lastly, I calculate GETI and welfare changes by:

$$GETI_{ij} = \hat{\lambda}_{ij}\hat{y}_j \tag{31}$$

$$\hat{W}_i = \hat{\lambda}_{ii}^{\frac{1}{\varepsilon}} \tag{32}$$

In Section 6, I focus on welfare changes, although I also examine the general equilibrium trade effects for certain scenarios.

Note that choosing a value for σ pins down ε. I report results in Section 6 for values of σ equal to 2, 4, and 6. Head and Mayer choose a median value of ε from the literature of -5.03, which corresponds to an elasticity of substitution of 6. I use $\sigma = 6$ as a lower bound and smaller values of σ to represent the importance of certain industries. In Section 7 I report sensitivity analyses of various values of σ. A smaller value of σ tends to lead to greater welfare effects.

6 Results

6.1 Overview

In this section I review the results for each counterfactual. The primary results that I focus on are percentage changes in welfare under the counterfactual scenario compared to the initial equilibrium. In my case, welfare refers to real per capita GDP, up to a normalization. As discussed in Section 3, I am implicitly calculating differential price levels across nations, and take a labor endowment as fixed. Thus, welfare could be thought of as real per capita GDP. Since I normalize all of the wage vectors such that initial wages are equal to one in a chosen country, I do not report level values of real per capita GDP, but only percentage changes in welfare.[53] Of course, one could compare the estimated percentage changes with reported values of real per capita GDP to calculate level changes in welfare. Recall that the ratio of counterfactual to initial welfare is calculated from the following equation:

$$\hat{W}_i = \hat{\lambda}_{ii}^{\frac{1}{\varepsilon}} \tag{33}$$

Where $\lambda_{ii} = \frac{x_{ii}}{x_i}$ is the share of country i's total expenditures spent on goods from country i, i.e., the share of expenditures spent on domestic goods, and ε is the elasticity of trade with respect to trade costs. Arkolakis et al. (2012) show that these statistics are sufficient to determine changes in income levels up to normalization. I then calculate the percentage change in welfare as follows:

$$\%\Delta W_i = (1 - \hat{W}_i) * 100 = (1 - \hat{\lambda}_{ii}^{\frac{1}{\varepsilon}}) * 100 \tag{34}$$

I begin the discussion of each counterfactual scenario by reporting percentage changes in welfare for the five countries with the largest welfare losses and the five countries with the largest welfare gains. See the Appendix section for full tables of welfare changes for each scenario.[54] Note that all welfare changes reported in this section use the parameters calculated from the PPML regression of all bilateral flows reported in Table 4 Column (3). As discussed in Section 5, this is my preferred

[53] I follow Head and Mayer (2014) in setting Japan as the normalizing country.

[54] Since the analysis covers 47 countries, it would be unreasonable and distracting to report welfare changes for so many countries here. Additionally, for most counterfactual scenarios, many countries see a negligible change in welfare. Thus, it is primarily the outliers that I am interested in.

specification. The value of the coefficient on log distance from this specification is $\hat{\beta}_1 = -.512$. Recall that this value is lower than the median value in the literature. Thus, the welfare changes reported here are lower bounds for what would be estimated if I used a larger distance elasticity. See Section 7.3 for discussion of the sensitivity of these welfare results to the distance elasticity.

I report a range of welfare changes for each country, corresponding to different values of σ, the elasticity of substitution. I report results for values of σ equal to 2, 4, and 6. Much of the literature uses a value of ε equal to -5, where ε is the elasticity of trade with respect to trade costs. Since σ equal to 6 corresponds to a trade elasticity ε equal to -5, this represents my baseline welfare effect. However, having a constant elasticity of substitution underestimates the gains from trade because it does not account for the importance of industry variation. As discussed in Ossa (2015), Costinot and Rodriguez-Clare (2014), and others, the welfare gains from trade are larger when accounting for cross-industry variation. Thus, I also report welfare results for smaller values of σ, corresponding to less substitutability of goods from different countries. I consider σ equal to 6 as a lower bound, and σ equal to 2 as an upper bound on welfare effects. See Section 7.4 for discussion of the sensitivity of these results to changes in σ and ε. In the rest of this section, I examine the results of each of the five counterfactual scenarios in turn. I discuss which countries are the biggest gainers and losers, and consider the implications in historic and current policy environments.

6.2 Panama Canal

Table 5 reports the countries with the largest gains and losses from a counterfactual closing of the Panama Canal. Perhaps not surprisingly, the countries experiencing the largest simulated welfare changes from a counterfactual closing of the Panama Canal are South American countries. Specifically, South American countries on the western side of the continent have the largest welfare losses, and South American countries on the eastern side of the continent have the largest welfare gains. The largest loss in our sample is attributed to Peru, which sees a welfare loss of -.308% to -1.444%. Chile experiences the second largest welfare loss of -.172% to -.824%. Interestingly, the next largest losses are for European countries, specifically Spain, the Netherlands, and Finland, though these effects are quite small.

The country seeing the largest welfare gain is Colombia, but at an economically insignificant

Table 5: Percentage Changes in Welfare - Panama Canal

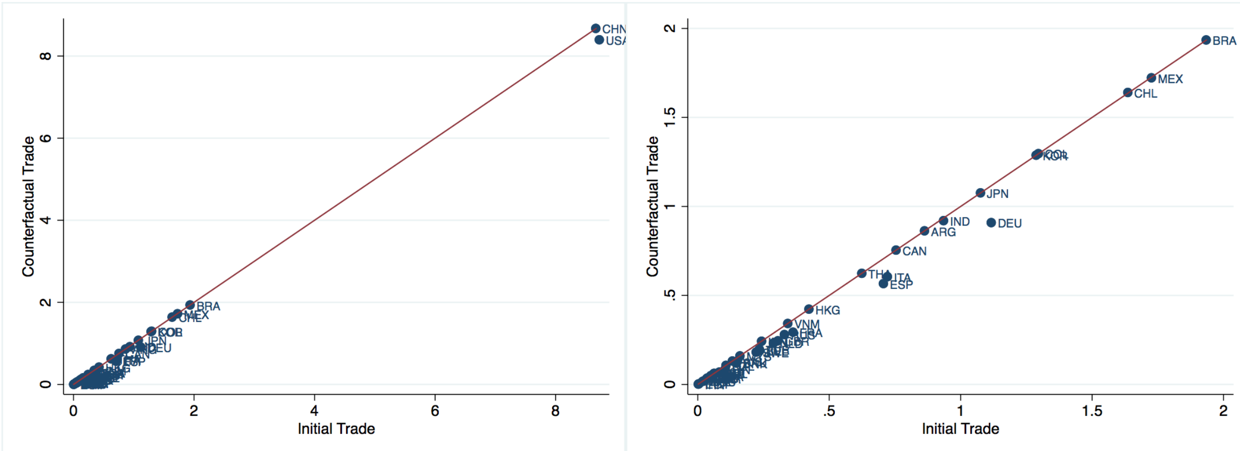
	Country	(1) $\sigma = 2$	(2) $\sigma = 4$	(3) $\sigma = 6$
1	Peru	-1.444	-0.507	-0.308
2	Chile	-0.824	-0.284	-0.172
3	Spain	-0.057	-0.019	-0.011
4	Netherlands	-0.039	-0.013	-0.007
5	Finland	-0.032	-0.011	-0.006
5	South Korea	0.002	0.001	0.001
4	Argentina	0.003	0.001	0.001
3	Brazil	0.003	0.001	0.001
2	Canada	0.003	0.001	0.001
1	Colombia	0.006	0.003	0.002

See Appendix for full tables of welfare effects.

range of .002% to .006%. The other countries with the largest welfare gains are Canada, Brazil, Argentina, and South Korea. Surprisingly, the list of countries that experienced welfare gains - countries on the east coast of South America - is economically interesting even though the magnitudes of the gains are marginal. This result may imply that, although on average trade is diverted from the west coast of South America to the east coast, the amount of trade is not significant enough to be a boon to the larger countries on the east coast, even though that same amount of trade is a significant loss to countries on the west coast.

Since my analysis was limited to the top fifty countries, I do not observe welfare changes for other South and Central American countries for which I might expect the largest welfare changes, such as Ecuador or Guatemala. I would expect to see larger gains for Uruguay or Venezuela. Importantly, these results illustrate the large advantage of having access to two coasts. Although Colombia is primarily on the western side of South America, because it has ports on either side of Central America I do not observe a welfare loss.

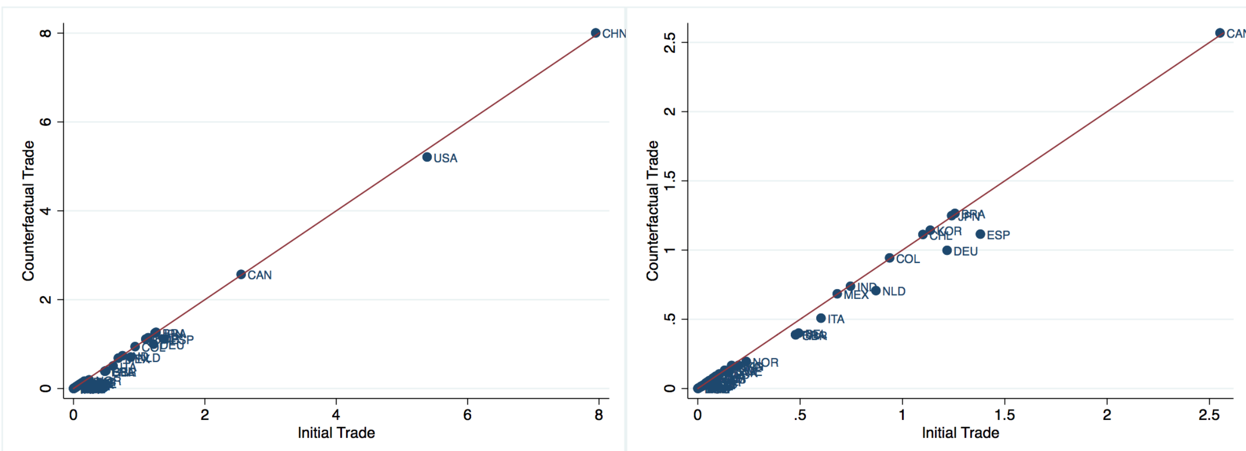
To better understand what drives the welfare losses and gains, I examine how individual trade flows change for some of these countries. Figure 7 shows initial versus counterfactual imports and Figure 8 shows initial versus counterfactual exports for Peru. First, I find that Peru imports substantially less from the United States than before. Imports also decrease from European



(a) All trade flows

(b) Trade flows less than $3 billion

Figure 7: Initial and Counterfactual Imports to Peru



(a) All trade flows

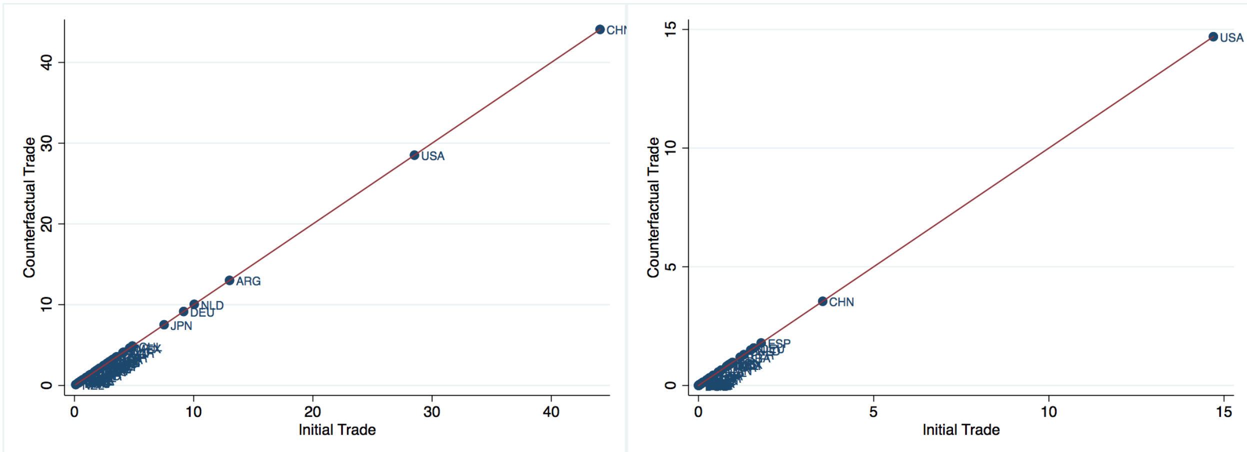
(b) Trade flows less than $3 billion

Figure 8: Initial and Counterfactual Exports from Peru

countries such as Germany, Italy, and Spain. Peruvian exports to these same countries decrease substantially as well. I find similar results for Chile.

Figure 9(a) shows initial versus counterfactual exports from Brazil, and Figure 9(b) shows initial versus counterfactual exports from Colombia. Although these countries saw marginal welfare gains from the closing of the Panama Canal, I find that these small gains are not driven by large changes in any specific trade flows.

Interestingly, my results do not suggest that the U.S. gains much economically from the Panama Canal. The simulated welfare changes for the U.S. for our preferred specification range from -.002% to -.010%. In terms of rank, this is the fourteenth largest loss among the 47 countries. These results



(a) Exports from Brazil

(b) Exports from Columbia

Figure 9: Initial and Counterfactual Exports from Brazil and Columbia

seem at odds considering the significant financial and political stake the U.S. has had in the Panama Canal historically.[55] One explanation may be that my welfare estimates are low because I ignore overland costs. My model treats imports arriving at Newark the same as imports arriving at Los Angeles, and ignores the cost of moving those goods across the U.S. Were the Panama Canal to be closed, goods that typically travel from the Pacific through the Panama Canal to the east coast of the U.S. would likely be diverted to the west coast, but there would be substantial costs to transporting those overland. However, in the long-run one might expect consumers and firms to move closer to the coasts to reduce such transportation costs. My results are more representative of a long-run equilibrium. Perhaps in the short-run, the U.S. would experience economically significant welfare losses, but not in the long-run.

Hugot and Umana Dajud (2016) estimate the general equilibrium welfare effects of the opening of the Panama and Suez Canals in 1929 and 1879, respectively, and also conduct a similar counterfactual exercise of the effect of closing the Panama and Suez Canals in 2012 on overall trade flows. My results are not exactly comparable to theirs, as they do not estimate welfare effects for the closings in 2012. However, they employ the same methodology from Head and Mayer (2014). For the general equilibrium welfare effects of the opening of the Panama Canal, Hugot and Umana Dajud report the following results.[56] Peru experiences a .65% to 1.21% gain. Chile experiences a .19% to .35%

[55] Of course, the U.S. had other important military interests in the construction of the Canal, such as the ability to move naval ships between coasts much faster.

[56] The values of ε, the elasticity of trade with respect to trade costs, used by Hugot and Umana Dajud are

gain. Argentina, Brazil, and the United States see 0.00% changes in welfare. Two countries not in my sample but included in theirs are El Salvador and Ecuador, which see a .77% to 1.41% gain and a .69% to 1.31% gain, respectively. Thus, my results are of similar magnitude and direction to those found by Hugot and Umana Dajud.

6.3 Suez Canal

Table 6: Percentage Changes in Welfare - Suez Canal

	Country	(1) $\sigma = 2$	(2) $\sigma = 4$	(3) $\sigma = 6$
1	Saudi Arabia	-7.06	-2.40	-1.44
2	United Arab Emirates	-5.17	-1.66	-0.98
3	Turkey	-4.08	-1.30	-0.77
4	Egypt	-3.94	-1.23	-0.73
5	Russia	-2.71	-0.93	-0.57
5	Argentina	0.07	0.03	0.02
4	Mexico	0.08	0.03	0.02
3	Nigeria	0.09	0.04	0.03
2	Chile	0.10	0.05	0.03
1	Israel	0.15	0.07	0.05

See Appendix for full tables of welfare effects.

Table 6 reports the countries with the largest gains and losses from a counterfactual closing of the Suez Canal. The results are of the direction, and perhaps magnitude, that one might expect. Countries on the Arabian Peninsula, specifically Saudi Arabia and the United Arab Emirates, experience the largest welfare losses. Welfare losses for Saudi Arabia range from -1.44% to -7.06%. For the United Arab Emirates, losses are -.98% to -5.17%. Other countries experiencing large welfare losses are Turkey, Egypt, and Russia, with upper bounds from our preferred specification, of -4.08%, -3.94%, and -2.71%, respectively.

Once again, the countries that gained from a closing of the Suez Canal are interesting, but the magnitudes of the effects are economically small. The countries with the largest welfare gains are, in order from largest to smallest, Israel, Chile, Nigeria, Mexico, and Argentina, but the largest

-3.95, -3.78, and -2.08. For comparison, I use values of ε of -1, -3, and -5.

welfare gain is merely .15%. It is important to note that, in my list of ports, Israel has a port on both the Mediterranean Sea (Tel Aviv) and on the Red Sea (Elat). Thus, in my simulation, I would expect to see Israel gain some of the trade that would otherwise have passed through the Suez Canal. Additionally, although Egypt does have a coastline along the Red Sea, I did not assign Egypt a port there because the major population centers are along the Mediterranean coast. The Egyptian port used in the analysis is solely Alexandria. Thus, my results again underscore the importance of access to multiple coasts. It is likely that if I re-ran the analysis with a Red Sea port for Egypt, the welfare effect would no longer be a loss. The result that far away countries such as Chile, Mexico, and Argentina experience slight welfare gains from a closing of the Suez Canal underscore the importance of estimating general equilibrium effects, where changes in trade costs with countries near the Suez Canal also effects trade flows of third countries.

The simulated welfare loss for Saudi Arabia is by far the largest in this counterfactual scenario. A reason that one expect Saudi Arabia to experience such a large loss is that Saudi Arabia exports enormous quantities of oil through the Suez Canal. Interestingly, since my analysis does not account for the differential cost of shipping different goods by weight, I would expect the welfare loss of 7% to be lower than if I accounted for the weight of goods. Oil is heavy and therefore expensive to ship. Thus, it would be even more costly for Saudi exporters to move oil all the way around the Cape of Good Hope on the way to Europe or North America.

The result that Egypt and Israel would see opposite and significant welfare losses and gains, respectively, is interesting in a historic context. The 1967-1975 closure of the Suez Canal was a result of the Six Day War, which was a conflict primarily between Israel and Egypt. The canal was closed by Egypt at the beginning of the Six Day War on June 5th, 1967, and remained closed until after the end of the later Yom Kippur War. Additionally, the importance of Israel's Red Sea port is emphasized in a historical context. Egypt also closed the Straits of Tiran in 1967, which effectively blockade Elat (Oren, 2017).

Hugot and Umana Dajud (2016) also estimate general equilibrium welfare effects for the opening of the Suez Canal. However, they estimate these effects using data from 1879, not present day, and so there are only a limited number of countries in their sample. Still, I compare my results to theirs to get an understanding of the general magnitude of such effects. They estimate a welfare gain due to the opening of the Suez Canal for Great Britain to be in the range of .45% to .83%, and for the Netherlands to be from .07% to .14%. My results for the closing of the Suez Canal in 2015 for Great Britain range from welfare changes of -.29% to -1.45%, and for the Netherlands from -.42% to -2.27%.[57] Our welfare effects are much greater in magnitude, but of the same direction.

Lastly, it is worth noting that this counterfactual scenario would be especially interesting to examine in the context of industry variation. Since there is so much oil that is traded through the Suez Canal, one might expect there to be much greater welfare effects, especially for countries not near the Suez Canal, if I accounted for the importance of oil in many different industries. Unfortunately, I must leave that extension to future research.

6.4 Oresund Strait

Table 7: Percentage Changes in Welfare - Oresund Strait

	Country	(1) $\sigma = 2$	(2) $\sigma = 4$	(3) $\sigma = 6$
1	Poland	-46.84	-18.89	-11.79
2	Finland	-42.09	-16.70	-10.39
3	Russia	-4.76	-1.74	-1.07
4	Netherlands	-3.84	-1.30	-0.78
5	Germany	-3.81	-1.34	-0.81
5	China	-0.07	-0.02	-0.013
4	Malaysia	-0.07	-0.02	-0.01
3	Iran	-0.03	0.0	0.0
2	Nigeria	-0.01	0.01	0.01
1	Denmark	8.84	3.13	1.91

See Appendix for full tables of welfare effects.

Table 7 reports the largest gains and losses from a counterfactual scenario closing the Oresund Strait. These results are also not surprising, though the magnitude may be greater than expected. I find that Poland and Finland see the largest losses, with ranges of -11.79% to -46.84% and -10.39% to -42.09%, respectively. However, recall that I effectively send countries that cannot be reached in the counterfactual scenario close to autarky. Thus, it is not surprising to see large welfare losses

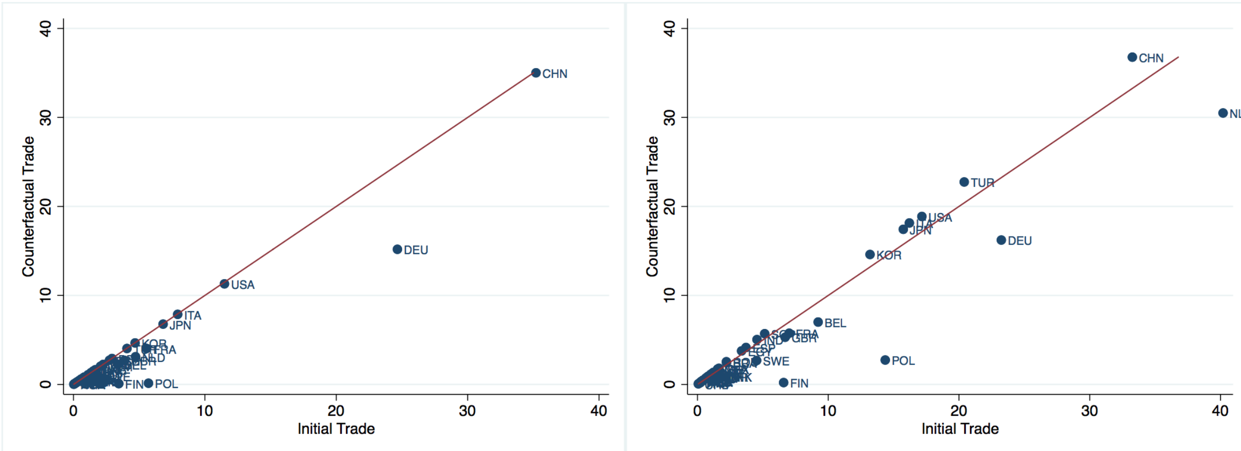
[57]See Appendix for the full table of welfare effects in the Suez Canal counterfactual.

for Poland and Finland as these countries have almost no international trade in this counterfactual scenario.

Perhaps more interesting are the other countries that see large welfare losses. I find that Russia sees a -1.07% to -4.76% change in welfare. The Netherlands and Germany see welfare changes of -.78% to -3.84% and -.81% to -3.81%, respectively. Note that the Netherlands and Germany both have coasts that are west of the Oresund Strait and thus not affected by this counterfactual scenario. Even so, these countries still see significant welfare losses, perhaps due to a loss of trade with neighboring countries such as Poland, Russia, and Finland. Of course, I do not account for overland trade between these neighboring countries, such as Poland and Germany, as I do not observe modes of transportation in the data, thus a real-world welfare loss may be smaller than these simulated changes.

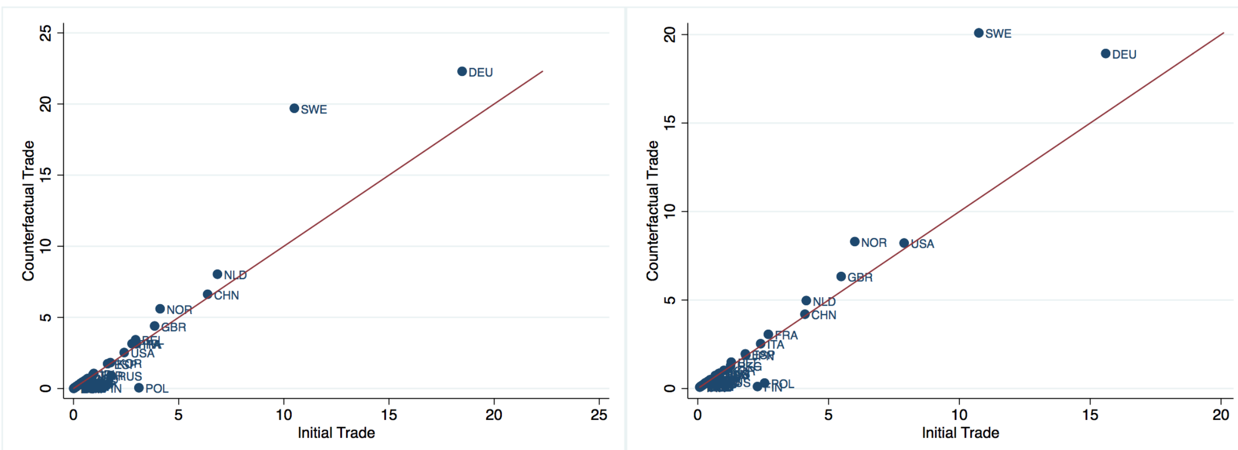
For Russia, these results emphasize the importance of having access to a Black Sea port (Novorossiysk). Without a port here, Russia would have been moved to autarky by this scenario. And even with the Black Sea port, Russia still experiences large welfare losses of nearly 5%. In light of the huge importance of such a port to Russian imports and exports, it is perhaps less surprising to see Russia exert military and political control in the Crimean Peninsula. Crimea was annexed by Russia in 2014 in the middle of larger political and social unrest across the Ukraine. Figure 10 shows initial versus counterfactual imports to and exports from Russia. Although Russian imports from a few countries, such as Germany, decrease substantially, Russian exports to many countries decrease even more. For example, Russian exports to the Netherlands, Germany, Belgium, Poland, and Finland all decrease substantially. These results seem to suggest that the welfare loss for Russia in this counterfactual scenario is driven by a decrease in exports, rather than a decrease an imports.

The country seeing the largest gain from a closing of the Oresund Strait is, unsurprisingly, Denmark, with simulated welfare increases of 1.91% to 8.84%. Figure 11 shows initial versus counterfactual imports to and exports from Denmark. I find that the welfare gains for Denmark must be driven by substantial increases in trade with nearby countries including Sweden, Germany, the Netherlands, and Norway. However, it is interesting that Denmark sees such large welfare gains, particularly in light of the marginal to zero positive effects I have seen in the other counterfactual scenarios so far. Denmark is not physically closer to any countries than before. In fact, the way the



(a) Imports (b) Exports

Figure 10: Initial and Counterfactual Trade to and from Russia



(a) Imports (b) Exports

Figure 11: Initial and Counterfactual Trade to and from Denmark

boundaries were drawn on the raster, none of the bilateral distances involving Denmark change. However, in this counterfactual scenario Denmark is, in fact, relatively "closer" to other countries compared to the initial state, because Finland, Poland, and Russia are now less accessible. It seems that, in my model, Denmark received much of the trade that would have gone to these other three countries.

These results are especially interesting when put in a historical context. For over 400 years, from 1429 to 1857, Denmark levied the Sound Toll on all foreign ships passing through the Oresund Strait (Degn, 2018). Ships were required to pay this toll whether they were trading in Denmark or not, under threat of cannon fire from the mainland. Beginning in 1497, Danish customs officers kept meticulously detailed records of the cargo of all ships that stopped at the port of Elsinore to pay the Sound Dues. Over those 360 years, nearly two million ships passed through and paid the toll. The tax was based on self-reported cargo values by ship captains; however, the Danish ingeniously prevented much cheating by reserving the right to purchase any cargo at the stated price. The Sound Toll was finally abolished in 1857 with the ratification of the Copenhagen Convention, in part a result of American and British gunboat diplomacy at the time (Degn, 2018). The Sound Toll could be thought of as a partial 'closing' of the Oresund Strait, as it makes it more expensive for goods to be transported through the strait. Thus, the revenue generated by this tax would be analogous to the welfare gain for Denmark associated with the closing of the Oresund Strait today. In fact, in 1857 the toll accounted for approximately one eight (12.5%) of Danish state income (Degn, 2018), which is surprisingly comparable to my estimate of an 8.8% welfare gain for Denmark from closing the Strait. Were it geopolitically feasible for Denmark to levy a tax on the Oresund Strait today, there would be a strong incentive to do so.

6.5 Pacific Ocean

Table 8: Percentage Changes in Welfare - Pacific Ocean

	Country	(1) $\sigma = 2$	(2) $\sigma = 4$	(3) $\sigma = 6$
1	United States	-3.42	-1.09	-0.64
2	Chile	-3.06	-1.10	-0.67
3	New Zealand	-2.76	-0.96	-0.58
4	Mexico	-2.62	-0.73	-0.42
5	Peru	-2.49	-0.83	-0.50
5	Pakistan	0.24	0.10	0.06
4	Netherlands	0.27	0.12	0.08
3	Ireland	0.33	0.15	0.10
2	Bangladesh	0.38	0.16	0.10
1	Israel	0.48	0.21	0.13

See Appendix for full tables of welfare effects.

Table 8 reports the countries with the largest gains and losses from a counterfactual scenario involving a closing of the Pacific Ocean. Note that, in this scenario, the cost raster was created in such a way that the north-south extent of the Pacific Ocean was closed, but only for a narrow piece of the ocean in the east-west direction.[58] In other words, this counterfactual scenario does not simulate complete inaccessibility to the entire Pacific, but rather an end of trans-Pacific trade. Figure 12 shows the differences between intial and counterfactual routes for two pairs of ports.

I find that the U.S. sees the largest welfare loss in this scenario, ranging from -.64% to -3.42%. Chile, New Zealand, Mexico, and Peru are the other countries rounding out the top five largest losses, ranging from -.67% to -3.06% for Chile to -.50% to -2.49% for Peru. The countries with the largest gains are Israel, Bangladesh, Ireland, the Netherlands, and Pakistan. Gains are small but not economically insignificant. I find the largest gains for Israel, ranging from .13% to .48%. Gains for Pakistan are small, ranging from .06% to .24%, but the upper bound of nearly a quarter percent is still economically significant. It seems reasonable that the U.S. would have the most to lose, since the U.S. trades so much with countries such as China, Japan, and Korea. However, it may be surprising that China does not a greater welfare loss. I find that China would see a welfare decrease of -.29% to -1.29%, which is economically significant but not as large as might be expected considering how much China trades across the Pacific. One reason for this result may be that Chinese exporters would simply trade with closer countries, or increase trade with Europe, if there were no trans-Pacific trade. Interestingly, the countries that gain in this scenario are primarily smaller countries farther away from the Pacific, such as Israel, Ireland, or the Netherlands. This result may simply be because these countries already ship few goods across the Pacific Ocean.

Notably, there is nearly an even split between countries than gain and countries that lose in this scenario. I find that 21 countries would see a welfare loss, while 26 would see a welfare gain. Interestingly, the magnitudes of these effects are relatively small. One might think that cutting off trans-Pacific trade would large huge welfare effects, because it results in huge changes in relative distances. However, though there would be many changes in relative distances, large changes in trade costs do not necessarily imply large welfare effects. Importantly, a uniform increase in trade costs would not change bilateral trade flows. Thus, since this counterfactual scenario raises trade costs for almost all countries, it is not surprising that the welfare effects are small.

[58] Meaning that these pixels were all assigned a cost value of 1,000,000.

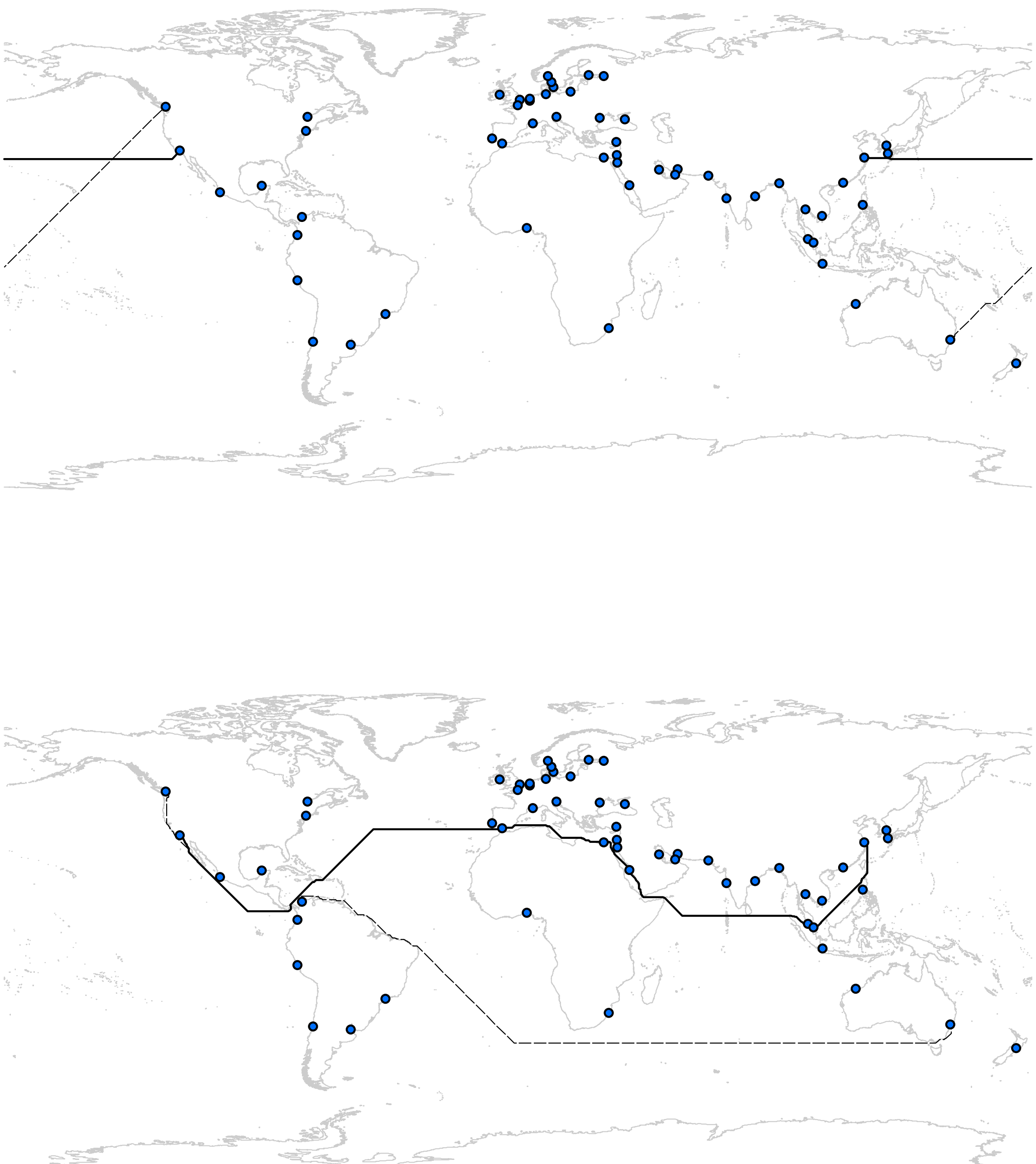
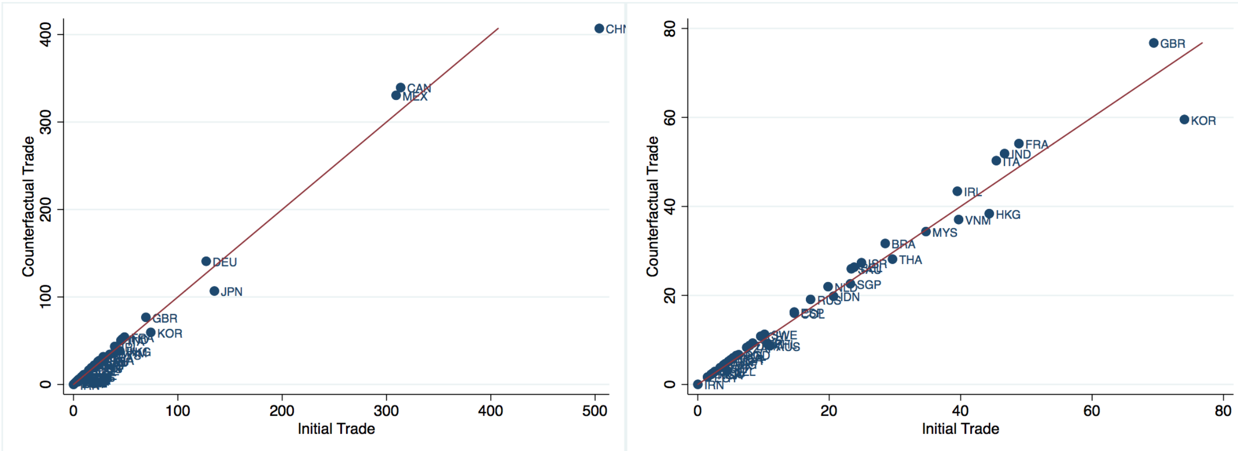
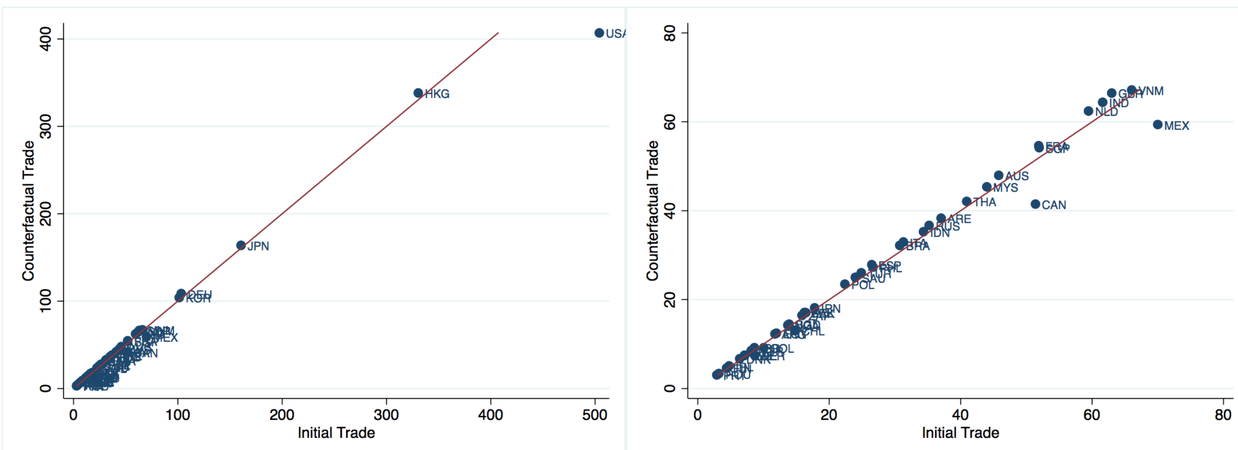


Figure 12: Initial Routes (above) vs. Counterfactual Routes (below) With Pacific Ocean Closed, for Los Angeles to Shanghai and Vancouver to Brisbane



(a) All trade flows (b) Trade flows less than \$100 billion

Figure 13: Initial and Counterfactual Imports to the U.S.



(a) All trade flows (b) Trade flows less than \$100 billion

Figure 14: Initial and Counterfactual Exports from China

However, even though there are smaller welfare effects, that does not imply that trade remains the same. In fact, it is likely that trade flows have changed substantially. Who is trading with who is likely shuffling around a great amount in this scenario. Thus, I find it valuable to examine the individual bilateral trade flows in this scenario. I focus on the U.S. and China, as these two large economies are some of the most affected by this counterfactual scenario. Figure 13 shows initial and counterfactual imports to the U.S., while Figure 14 shows initial and counterfactual exports from China.

I find that, unsurprisingly, the U.S. imports far less from China, Japan, South Korea, and other East Asian countries. Additionally, the U.S. imports much more from Canada, Mexico, and European Countries such as Germany, the United Kingdom, France, and Italy. Interestingly, U.S. imports from India, Brazil, and Russia also increase substantially. However, this may be less surprising considering that imports are a normal good. The U.S. initially consumes so much of the goods from China that in the counterfactual scenario one would expect that spending to be spread out among many countries that are now relatively closer.

For China, I find that Chinese exports to the U.S., Canada, and Mexico decline substantially. However, recall that I did not find a relatively large welfare loss for China in this scenario. It appears that this small loss is driven by an increase in exports to just about every other country. Although exports to North America fall, I find that Chinese exports to East Asia, Europe, Australia, and even South America increase under this counterfactual scenario.

For the preceding counterfactual scenarios, it would be practically feasible for a country to close the area analyzed. I have already discussed real-world examples involving the closure of the Panama and Suez Canals or taxation on the Oresund Strait. Of course, that is not the case for the Pacific Ocean. It is difficult to imagine a situation in which a single country could blockade trans-Pacific trade. However, this counterfactual scenario is still worth considering because there are many other ways in which trans-Pacific travel could become dangerous or risky. For instance, large-scale global conflicts could significantly increase the risk, and thus expected cost, of trade over the Pacific. World War II is a historical example in which passage over the entire Pacific Ocean was contested and dangerous.

6.6 South China Sea

Table 9 reports the five countries with the largest losses and the five countries with the largest gains for a counterfactual scenario involving a closure of the South China Sea. Figure 15 shows the differences between initial and counterfactual routes for two pairs of ports. Importantly, none of the countries in my sample saw a positive change in welfare in this simulation. Rather, all countries see a welfare loss. Thus, Table 9 is really reporting the countries that lost the most and the countries that lost the least. For this counterfactual scenario, I drew a large area around the South China Sea, Java Sea, and Gulf of Thailand. There were eight countries for which the port

Table 9: Percentage Changes in Welfare - South China Sea

		(1)	(2)	(3)
	Country	$\sigma = 2$	$\sigma = 4$	$\sigma = 6$
1	Hong Kong	-93.29	-60.29	-42.73
2	Singapore	-76.94	-39.11	-25.82
3	Vietnam	-62.16	-27.74	-17.72
4	Malaysia	-59.39	-26.23	-16.74
5	Thailand	-53.17	-22.52	-14.22
5	Chile	-1.15	-0.25	-0.12
4	Romania	-1.14	-0.31	-0.17
3	Peru	-0.95	-0.20	-0.10
2	Canada	-0.72	-0.15	-0.07
1	Colombia	-0.58	-0.10	-0.05

See Appendix for full tables of welfare effects.

or ports were entirely within the "closed" boundary. See Appendix for a precise representation of the closed zone. As with the Oresund Strait counterfactual, these countries were assumed to move nearly to autarky.[59] The eight countries are Indonesia, Malaysia, Hong Kong, Singapore, Vietnam, the Philippines, Thailand, and Bangladesh.

Since these countries were moved almost to autarky, it is not surprising that they make up the top eight largest losses. However, I find that many other countries also see a welfare loss in this scenario. I find that Hong Kong sees the largest welfare loss, with a range of -42.73% to -93.29%. Of the eight countries moved to autarky, I find that Indonesia had the smallest welfare loss, ranging from -5.55% to -24.73%. These differential losses suggest that some of these countries, such as Indonesia, must have had greater internal trade to begin with, as otherwise the welfare losses would have been more substantial.

I find that Colombia, Canada, Peru, Romania, and Chile are the countries experiencing the smallest welfare losses in this scenario. However, these welfare losses are still economically significant on the upper end. Colombia, which as the smallest welfare loss in this simulation, still sees losses in the range of -.05% to -.58%, the upper bound of which is economically interesting.

Remarkably, every single country in my sample sees a welfare loss in this simulation. This

[59]In practice, I increased the distances for bilateral pairs involving any of these countries to 1,000,000km.

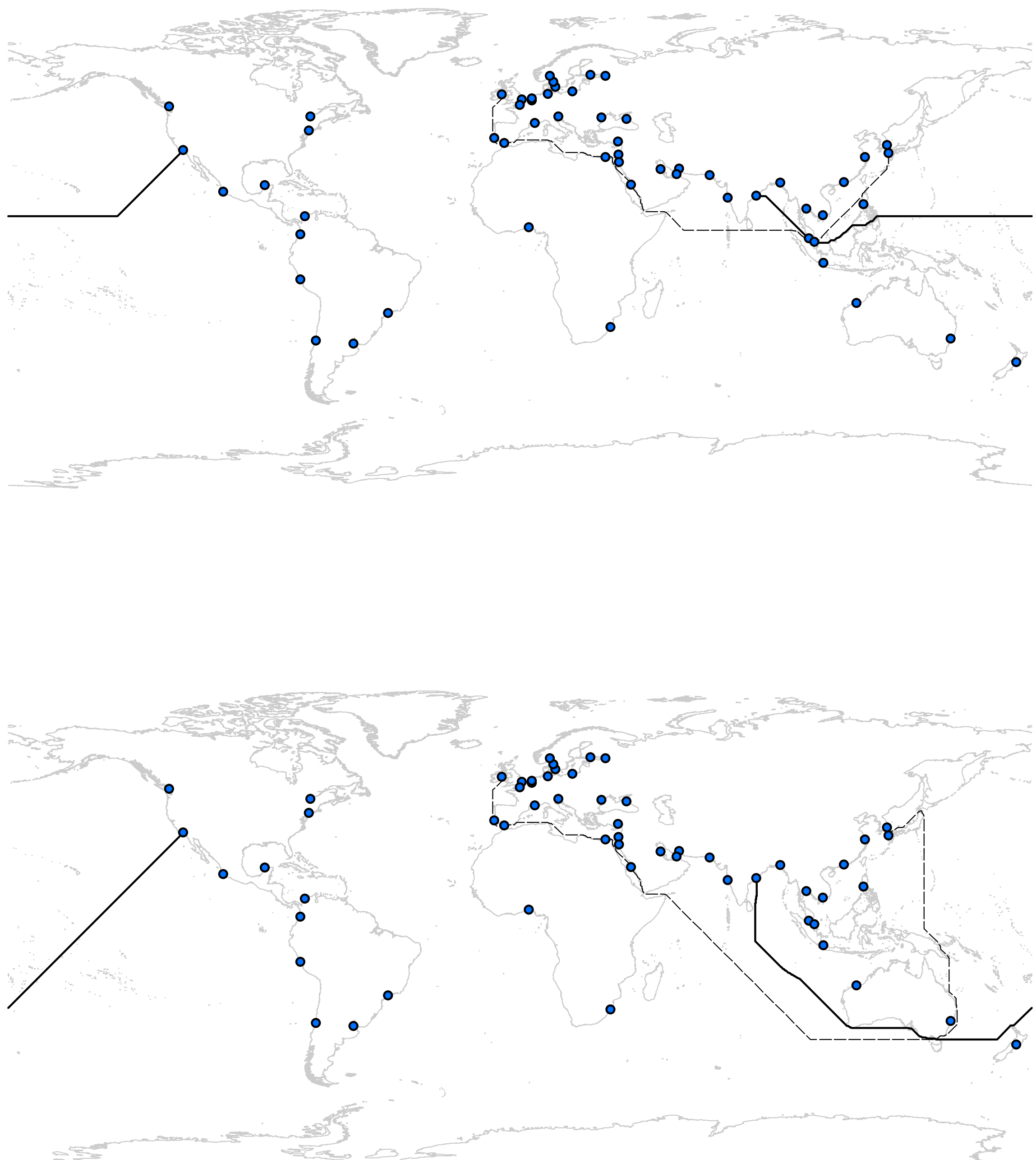


Figure 15: Initial Routes (above) vs. Counterfactual Routes (below) With South China Sea Closed, for Los Angeles to Visakhapatnam and London to Nagasaki

result suggests that not only are the countries that went to autarky contributing substantially to global trade, but that a vast amount of trade must pass through the South China Sea. The Strait of Malacca, which connects the Pacific Ocean and the Indian Ocean, is closed in our simulation. According to the United Nations Conference on Trade and Development, almost half of global maritime trade by tonnage annually passes through the Strait of Malacca (UNCTAD, 2009). A study by the Center for Naval Analysis concluded that a blockage in the South China Sea of this size would lead to nearly $8 billion (in 1993 dollars) of additional detour costs (Noer and Gregory, 1996). Given my results, that should not be surprising. Additionally, not only does every country experience a welfare loss, but almost all the losses are economically significant as well. Looking at the upper bound, 44 of 47 countries in our sample would see a welfare loss greater than one percent. 20 countries would see a welfare loss of greater than five percent, and 13 countries see a welfare loss greater than ten percent.[60]

These results are remarkable, especially given the marginal effects that I found thus far in other simulations. Even though this simulation covers a large area, the corresponding distance changes are likely not as large for affected country pairs as the closing of the Suez or Panama Canals, which can add thousands of miles to a route. Yet, I still find remarkably large welfare effects. This result again emphasizes that it is not only the magnitude of the distance changes that matter, but also the amount of trade involved.

Considering the wide-reaching and substantial welfare effects that I find in a counterfactual closing of the South China Sea, it is not surprising that large countries in the region, such as China, may exert a greater political or military presence there. Since the mid-1990s, China has been consolidating claims in the South China Sea and especially increasing jurisdiction over maritime rights. Since the mid-2000s, the pace of that consolidation has increased (Fravel, 2001). My results do not suggest an incentive for China to close the Malacca Straits or other parts of the South China Sea; I find that China would see a welfare loss in the range of -2.17% to -10.34%. However, my results do emphasize the value of a country maintaining control over that region, whether to increase stability or to levy taxes.

Given the high welfare losses attributed with a closure of the South China Sea, one might

[60] See Appendix for a full list of welfare effects in this counterfactual.

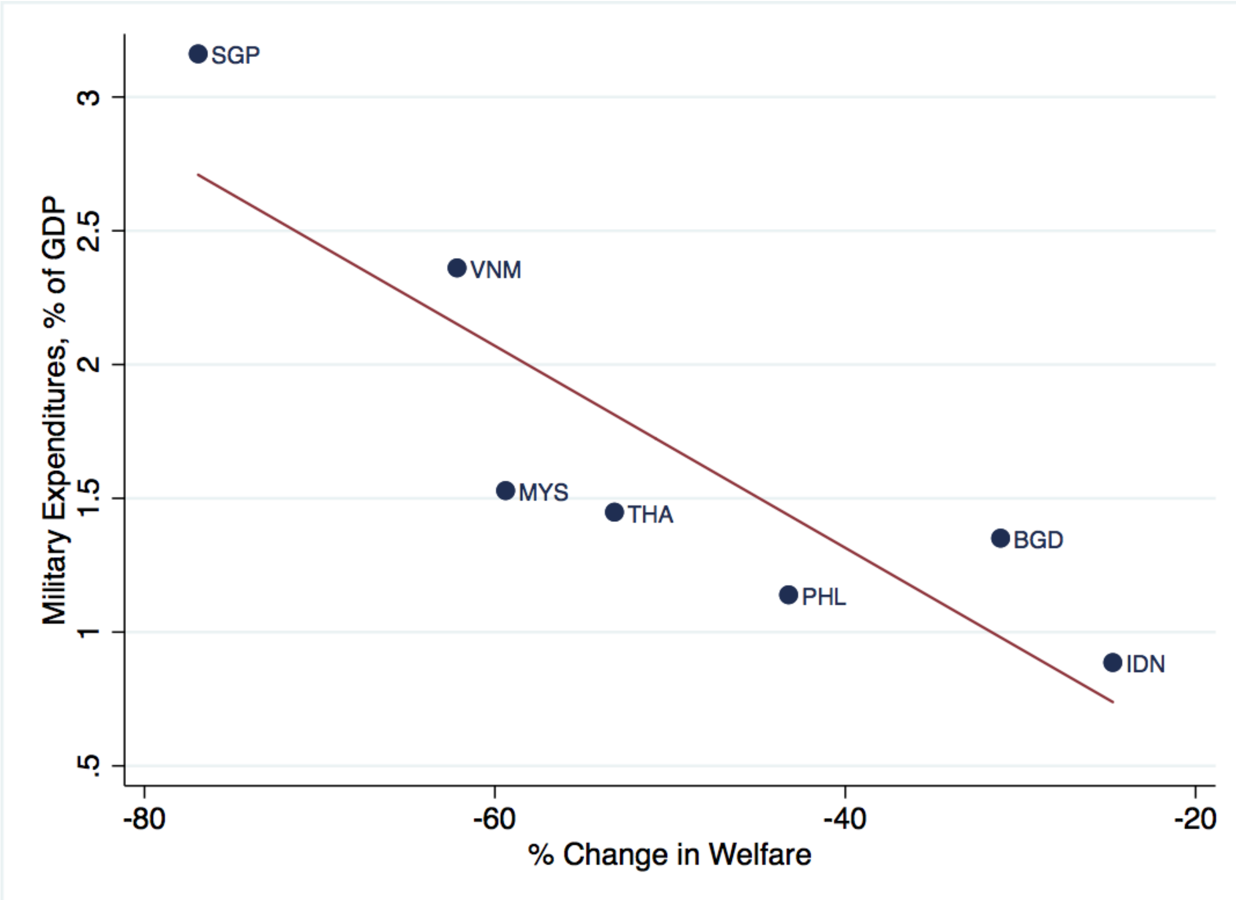


Figure 16: Correlation Between Welfare Losses and Military Spending, 2015

expect to see a correlation between military and naval expenditures by countries in that region and the expected welfare loss. In other words, I would expect Southeast Asian countries with higher predicted welfare losses to spend more on military expenditures in an effort to deter such a scenario. Using the SIPRI Military Expenditure Database, I look for a correlation between 2015 expenditures as a percentage of GDP and simulated welfare loss.

Figure 16 shows the relationship between predicted welfare losses and military expenditures as a percentage of GDP, as well as the fitted regression line between the two variables. I find that there is a remarkably direct relationship between the welfare loss and military expenditures. The country with the highest simulated welfare loss, Singapore, is also the country with the largest proportion of GDP spent on military expenditures. Likewise, the country in this region and my sample with the smallest welfare loss, Indonesia, is also the country in this group with the smallest percentage of GDP spent on military expenditures.

Table 10: Military Expenditure Regressions

	(1)	(2)	(3)	(4)	(5)
% Welfare Change	-0.0377*	-0.0374*	-0.0264	-0.0669*	-0.0199
	(0.00944)	(0.0124)	(0.0122)	(0.0206)	(0.0170)
GDP (billions)		-0.0000518			-0.000594
		(0.000984)			(0.000975)
GDP per capita (thousands)			0.0000161		0.0000196
			(0.0000120)		(0.0000143)
Population (millions)				0.00686	
				(0.00443)	
Constant	-0.195	-0.159	0.197	-2.354	0.696
	(0.500)	(0.883)	(0.549)	(1.464)	(1.014)
Observations	7	7	7	7	7
Adjusted R^2	0.714	0.643	0.753	0.776	0.707

Standard errors in parentheses

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

The correlation between these two variables is -0.873, which is remarkably high (in absolute value) considering how unrelated these data may at first seem. One might be concerned that, given the small sample size, this correlation is driven by outliers. For example, it could be that wealthier countries, which tend to see greater welfare losses, spend a greater proportion of GDP on military; Singapore is the third largest economy of these seven countries but the richest per capita. Alternatively, it could be that countries with more people, which tend to see smaller welfare losses all else equal, spend a smaller proportion of GDP on military; Indonesia is the largest country in this sample but has the smallest percentage expenditure on military spending.

In an effort to separate these various possible effects, I regress military expenditures as a share of GDP on the simulated welfare loss, and control for GDP, GDP per capita, GDP and GDP per capita, and population. Table 10 shows the results of these regressions. In every regression, I find a negative relationship between weflare change and military expenditures (i.e., a smaller welfare loss is associated with less military expenditures). When controlling for GDP or population separately, this relationship is statistically significant at the 5% level.

Given that my sample size is only 7 countries, I do not have the data to rigorously show a causal relationship. Still, these results support the conclusion that my simulated welfare losses have a direct correlation with military expenditures in the affected countries.

Overall, I find large welfare losses in a simulation of the closure of the South China Sea to international trade. Given these losses, combined with the volume of trade that flows through this region, the historically tense geopolitical situation, and the current political climate, I would predict that disputes over this region will continue in the future, and have economic and political importance. My results illustrate the importance of maritime trade through the South China Sea, and the strong economic incentives behind political and military movements.

6.7 All Maritime Trade

As a last scenario, I estimate the gains from all maritime trade by simulating the closure of all oceans. I do this by generating counterfactual distances based on whether or not countries are land-connected. This scenario is similar to other research, such as Costinot and Rodriguez Claire (2014) and Ossa (2015) which estimate the gains from international trade. However, in this scenario, I continue to allow overland trade. This estimation does not require any additional GIS work, although I do use the same initial distances as in the other scenarios.

In this simulation, the counterfactual bilateral distances are based on whether or not the two countries are in the same region. The regions that I use are based on data from the USITC gravity dataset (Gurevich and Herman, 2018).[61] If a pair of countries are in the same region, then I set the bilateral distance to be the same initial distance. If a pair of countries are not in the same, then I set the bilateral distance to be 1,000,000 km, which is the same value used in the other counterfactuals when a port is "closed" or inaccessible in the counterfactual scenario. Note that this designation does not eliminate all maritime trade. For example, for countries in the Southeast Asia region, many are separated by water but would still be considered regionally-connected in my scenario. Also note that, as in previous counterfactuals, setting the bilateral distance to 1,000,000 km is not the same as moving to autarky. It is prohibitively costly to trade with countries that far away, but the model still allows it and I expect to see a small, non-zero amount of trade between

[61] The regions are: Africa, Caribbean, Central America, Central Asia, East Asia, Eurasia, Europe, Middle East, North America, Pacific, South America, South Asia, South East Asia, and Southern Pole.

Table 11: Gains from Maritime Trade

	$\sigma = 2$	$\sigma = 4$	$\sigma = 6$
SGP	142.4 %	35.0 %	19.8 %
VNM	107.5 %	27.8 %	15.9 %
ARE	101.9 %	25.0 %	14.1 %
ISR	71.8 %	19.7 %	11.4 %
THA	68.7 %	19.1 %	11.1 %
MYS	62.5 %	17.9 %	10.4 %
ZAF	60.1 %	17.4 %	10.2 %
PHL	51.8 %	14.6 %	8.5 %
CHL	50.0 %	14.5 %	8.5 %
SAU	49.7 %	14.3 %	8.4 %
HKG	49.7 %	15.4 %	9.2 %
NZL	45.1 %	13.2 %	7.7 %
AUS	43.0 %	12.6 %	7.4 %
BGD	42.8 %	12.1 %	7.0 %
NLD	42.3 %	11.4 %	6.5 %
TUR	37.0 %	10.3 %	5.9 %
PER	33.6 %	9.8 %	5.7 %
COL	33.5 %	9.4 %	5.4 %
KOR	31.5 %	9.6 %	5.7 %
BEL	30.5 %	8.9 %	5.2 %
RUS	26.3 %	8.2 %	4.9 %
IND	25.6 %	7.3 %	4.2 %
USA	24.5 %	6.8 %	3.9 %
IRN	23.9 %	7.0 %	4.1 %
JPN	23.3 %	7.1 %	4.2 %
PAK	23.2 %	6.3 %	3.6 %
DEU	20.7 %	6.6 %	3.9 %
BRA	20.3 %	6.4 %	3.8 %
NGA	20.1 %	6.3 %	3.7 %
GBR	19.3 %	5.9 %	3.4 %
IRL	19.3 %	6.6 %	4.0 %
EGY	18.8 %	5.1 %	2.9 %
IDN	18.7 %	5.7 %	3.3 %
MEX	16.6 %	4.1 %	2.2 %
FIN	15.8 %	5.0 %	3.0 %
ITA	15.5 %	5.0 %	2.9 %
ESP	15.5 %	4.5 %	2.6 %
FRA	15.5 %	4.7 %	2.8 %
POL	15.4 %	4.2 %	2.3 %
CHN	15.4 %	5.0 %	3.0 %
ARG	15.3 %	4.7 %	2.7 %
CAN	13.7 %	3.7 %	2.1 %
DNK	13.6 %	4.3 %	2.5 %
NOR	12.6 %	3.5 %	2.0 %
SWE	10.7 %	3.4 %	2.0 %
ROU	10.3 %	3.1 %	1.8 %
PRT	8.9 %	2.6 %	1.5 %
Avg	34.8 %	9.8 %	5.7 %

countries that are that far apart. Thus, this counterfactual is aiming to estimate the gains from trade of all long-distance maritime trade.

I solve the same model as in the other counterfactual scenarios. Table 11 displays the resulting gains from maritime trade for all 47 countries in our sample. Note that I illustrate this scenario differently, showing the gains from maritime trade rather than the losses from a closure of all oceans. However, these results could be interpreted in that way as well. I report gains from trade for the three different values of σ used throughout the analysis. The country in my sample seeing the largest gains from maritime trade is Singapore, ranging from 19.8% to 142.4%. The country seeing the smallest gains from maritime trade is Portugal, ranging from 1.5% to 8.9%. The average gains from trade are in the range of 5.7% to 34.8%, for values of σ equal to 6 and 2, respectively.

These results are comparable to the previous literature. Costinot and Rodriguez-Claire (2014) estimate the gains from all trade using various models. For a one sector model, most comparable to my value of $\sigma = 6$, they estimate average gains from trade at 4.4%. For a multiple sector model without intermediates, the average gains from trade are 15.3%. For a multiple sector model of monopolistic competition with intermediate goods, the average gains from trade are 40.0%. Ossa (2015) estimates gains from trade in a model with cross-industry variation, which I attempt to approximate by lowering the value of σ to 2, decreasing the substitutability of each goods. Ossa reports median gains from trade of 48.6% to 55.9%. Thus, my results ranging from 5.7% to 34.8% for the gains from only maritime trade seem to be reasonably situated in the existing literature.

7 Sensitivity Analysis

7.1 Overview

In this section I conduct a number of sensitivity analyses, primarily focused on how changing parameters affects the simulated welfare gains and losses. These analyses are distinct from robustness checks in that I do not have a single coefficient that I want to show will stand up to various controls or changes. Rather, I aim to show how my results do or do not change when changing various parameters, i.e., how sensitive my results are to the parameters used. I focus on five different changes: sensitivity to distances, sensitivity to the distance elasticity ρ, sensitivity to the substitution elasticity σ, sensitivity to the estimation of internal expenditure shares λ_{ii}, and sensitivity to the geographic region analyzed.

7.2 Distances

Most of the gravity literature uses distances that are only an approximation to the real-world distance between countries. A commonly used dataset is the CEPII GeoDist database, which provides four different kinds of bilateral distances (Mayer and Zignago, 2011). First, a simple geodesic distance between areas determined to be the "most important" cities in each country. Second, the simple geodesic distance between the two capitals. Third and fourth, weighted distances calculated using city-level data on the geographic distribution of population using two different parameter values.[62] An important feature of this method is that it is a consistent way to calculate internal and external distances (i.e., both within and between country distances).

Although these weighted population distances are well-designed approximations, the distances do not necessarily reflect the real-world distances traveled by traded goods between countries, especially for maritime trade. In particular, because these distances are straight geodesic lines, these distances do not account for the paths ships would take travelling over the ocean around continents. One original contribution of this paper is generating a different set of distances based on the least-cost path between ports. The purpose of this section is to examine how my port-to-port distances compare with the straight-line weighted population center distances most often used in the literature. Note that I make all comparisons to the fourth specification, which corresponds to the "distwces" variable. I also use that variable for internal distances in my dataset. For all other bilateral distances, I use my original bilateral distances calculated from the GIS data.

Figure 17 shows the overall differences between my port-to-port distances and weighted distances from Mayer and Zignago by graphing each bilateral pair according to both distances. Overall, unsurprisingly, my port-to-port distances are on average substantially longer than the weighted

[62] The formula used for the weighted distances is $d_{ij} = \left(\sum_{k\in i}(pop_k/pop_i)\sum_{\ell\in j}(pop_\ell/pop_j)d_{k\ell}^{\theta}\right)^{\frac{1}{\theta}}$ where k and ℓ are population agglomerations in country i or j respectively. θ is the sensitivity of trade flows to distance. The third weighted distance corresponds to $\theta = 1$ and the fourth to $\theta = -1$. Since $\theta = -1$ is closer to my distance elasticity, I use this fourth category of distances as the comparison group.

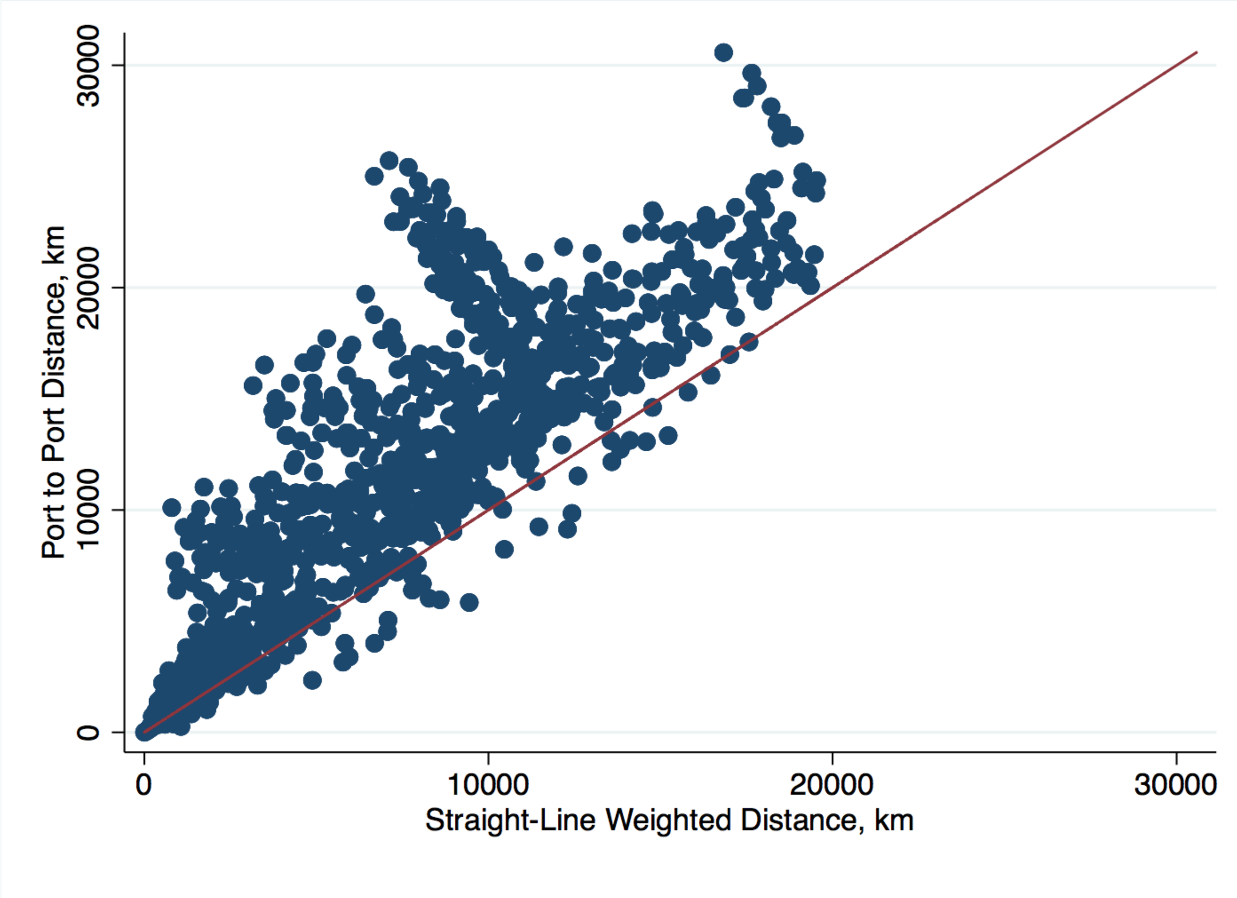


Figure 17: Port-to-Port versus Weighted Population Distances

population distances. However, there are a number of country pairs for which the port-to-port distance is less than the weighted distance. Importantly, the reason these differences actually have an effect on the analysis is that it is not a uniform increase. If my port-to-port distances were a uniform amount greater than the original weighted distance, then that would have no effect the analysis. Instead, I see that there are some "spikes" in the differences, where there are clearly certain country pairs and regions that are much farther apart based on the port-to-port distances than the weighted population distances.

To determine whether these differences in the distances actually affect the parameters estimated, I run the same regressions I used to estimate parameters for the general equilibrium trade model. Table 12 displays the results of these regressions. Unsurprisingly, I find that the coefficients on distance are larger in absolute value for all four regressions when I use the weighted distances rather than the port-to-port distances. For example, my preferred specification, corresponding to

Table 12: Sensitivity to Distances

	Port-to-Port Distances				Straight-Line Population Weighted Distances			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log Trade	Log Trade	Trade	Trade	Log Trade	Log Trade	Trade	Trade
Log Distance	-0.815***	-0.964***	-0.512***	-0.687***	-0.946***	-1.080***	-0.603***	-0.807***
	(0.0288)	(0.0429)	(0.0325)	(0.0407)	(0.0330)	(0.0523)	(0.0408)	(0.0546)
Shared Border	0.332**		0.836***		0.0714		0.523***	
	(0.125)		(0.127)		(0.128)		(0.138)	
Shared Language	0.407***	0.289***	0.480***	0.0828	0.356***	0.291***	0.574***	0.0332
	(0.0749)	(0.0798)	(0.105)	(0.0679)	(0.0749)	(0.0812)	(0.105)	(0.0729)
Same Country	1.162***		0.996***		1.198***		1.163***	
	(0.205)		(0.140)		(0.203)		(0.134)	
Specification	OLS	OLS	PPML	PPML	OLS	OLS	PPML	PPML
Sea-Only		X		X		X		X
Observations	2198	1851	2209	1856	2198	1851	2209	1856
Adjusted R^2	0.819	0.808			0.820	0.801		

Standard errors in parentheses

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

columns (3) and (7), is the PPML regression involving all country pairs. Using the port-to-port distances, the coefficient on distance in this specification is -0.512. Using the weighted population distances, the coefficient on distance is -.603. These results seem to explain why the coefficients estimated using my distances are lower than the median values in the literature.

Thus, I would expect gravity regressions that estimate the elasticity of trade with respect to distance to be biased downwards (or upwards in absolute value), because most estimates use these weighted distances. If my port-to-port distances are better approximations of the real-world distance traveled by goods, then these results are evidence that much of the gravity over-estimates the effect of distance on trade.

There are, of course, a number of weaknesses in my distance calculations. These port-to-port distances only correspond to one or two ports for each country. For most country pairs, there are likely pairs of ports that are somewhat closer together. Additionally, these distances only consider sea distance and ignore transportation over land. There are also the limitations in how distance was calculated from the least-cost routes, as discussed in Section 5.

Still, if it is the case that these port-to-port distances are better approximations of transportation costs due to distance than weighted population distances, then that would imply that gravity regressions using weighted distances would overstate the effect of distance on trade. I would assert that these port-to-port distances are more accurate, despite the limitations, and suggest that future research explore novel methods of estimating more accurate bilateral distances between countries.

7.3 Distance Elasticity

In the gravity regression I estimate as specified by equation (23), the resulting coefficient on distance, which includes the elasticity of trade with respect to distance (ρ) and trade costs (ε), is below the median value in the literature. As discussed above, this is most likely because I am using a better approximation to the real-world distances between countries. However, because these parameters are different from others estimated in the literature, in this section I test the sensitivity of the simulated welfare effects to changes in these parameters.

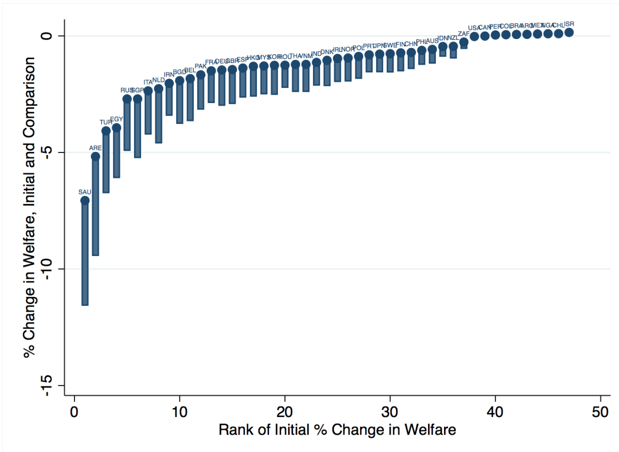
To test the sensitivity of the welfare effects to changes in parameters, I redo the entire welfare analysis for each counterfactual using one set of parameters described in Table 12, Column (3) as a baseline and different values as a comparison. I use my preferred set of coefficients as a baseline. For log of distance, the parameter is -.512. For common language, .480. For contiguity, .836. For the home country effect, .996. For the comparison set of coefficients, I use median values from the literature as described by Head and Mayer (2014).[63] Head and Mayer review estimates from 159 papers and report median and mean coefficients for both all gravity models and structural gravity models only. I use the median values from the literature for structural gravity models as my comparison group of coefficients, which are as follows: For log of distance, -1.14. For common language, .33. For contiguity, .52. For the home country effect, 1.55. Note that, for both the baseline and comparison analysis, I use $\sigma = 2$ as the substitution elasticity. I then compare the welfare changes estimated using this comparison group of parameters to those estimated using the baseline group of parameters.

Figure 18 shows both initial welfare changes, using the baseline parameters, and comparison welfare changes, using the comparison group of parameters, for four counterfactuals.[64] I am interested in seeing how two different factors change. First, does the magnitude of welfare effects change with these different parameters? Second, does the ordering of countries by welfare effects change with these different parameters?

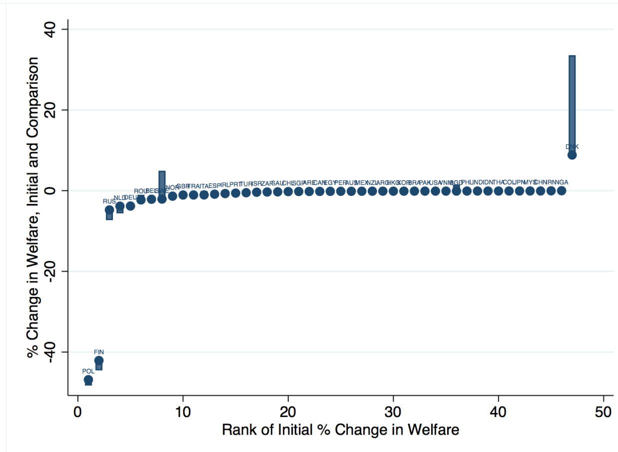
Overall, I find that if I moved my parameter values to the median values in the literature, almost all of the welfare changes would be greater in absolute value. In other words, the welfare losses get larger and the welfare gains get larger too. For the Suez Canal counterfactual, most countries see a substantially greater welfare loss, with countries such as Saudi Arabia and the United Arab Emirates seeing nearly a 5-percentage-point larger welfare loss. The ordering of countries by welfare loss remains mostly unchanged. For the Oresund Strait counterfactual, the welfare losses to Poland, Finland, and Russia are marginally greater, but the welfare gain to Denmark much greater, nearly 20 percentage-points higher. For the Pacific Ocean counterfactual, nearly all gains and losses are exaggerated. The welfare loss for the U.S. increases by about 3 percentage-points, while the welfare gain for Israel increases to almost 1%. Importantly, for the South China Sea counterfactual, there

[63] See Table 4 - Estimates of typical gravity variables.

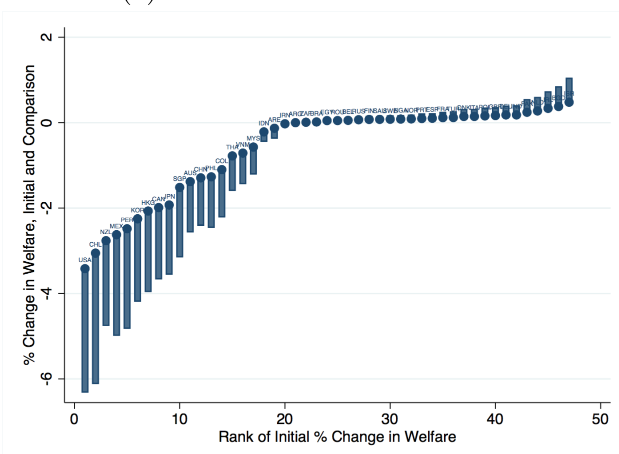
[64] I omit the figure for the Panama Canal counterfactual as there is little difference. Basically, the welfare losses for Peru and Chile increase by about one percentage point, but the welfare changes for the other countries stay the same.



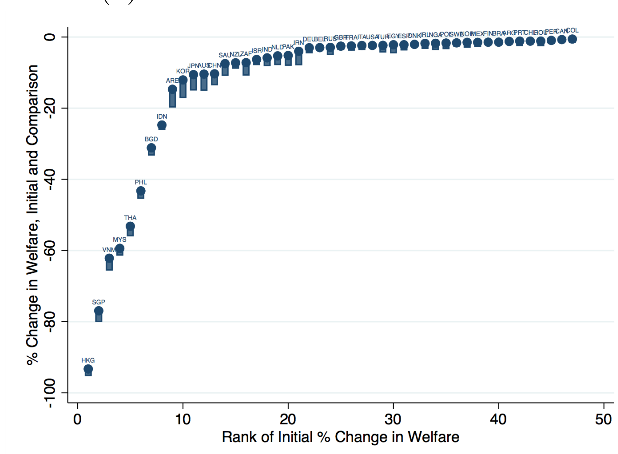
(a) Suez Canal Counterfactual



(b) Oresund Strait Counterfactual



(c) Pacific Counterfactual



(d) South China Sea Counterfactual

Figure 18: Sensitivity of Welfare Effects to Changes in ρ

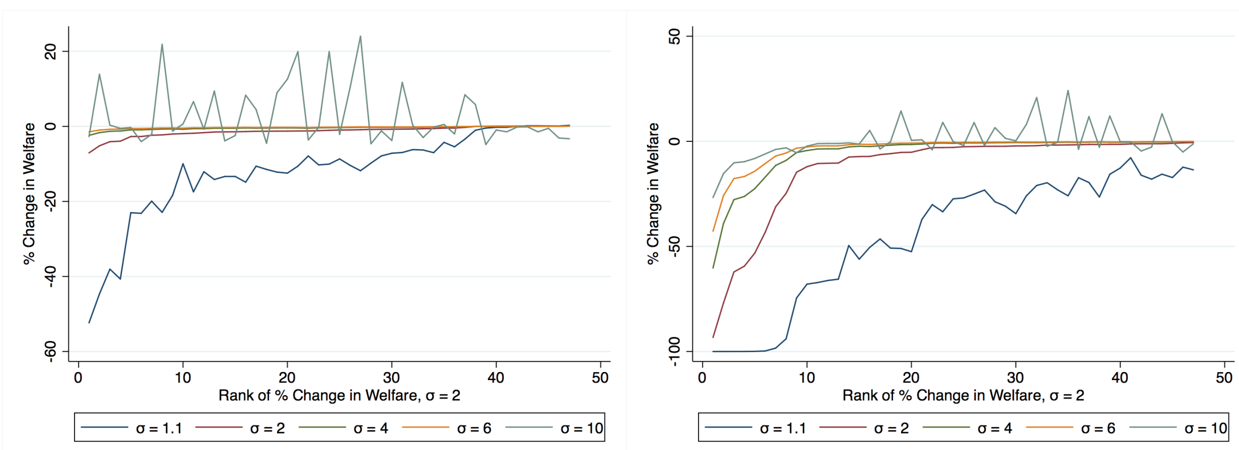
is not much of a difference between initial and comparison welfare effects; however, this result may be because the welfare effects in this scenario were large to begin with.

Additionally, I find that these differences seem to increase with effect size. Countries which saw a large welfare loss initially see an even bigger welfare loss with the comparison group of parameters when compared to a country that had a small welfare loss initially. Importantly, the ordering of the welfare effects only changes marginally. Overall, this evidence suggest that my results should actually be considered lower bounds on welfare effects. If I were to use median coefficient parameters from the literature, the simulated welfare effects would increase.

7.4 Substitution Elasticity

Recall that σ is the elasticity of substitution between varieties of goods originating from different countries, and is a parameter in the model due to designating CES preferences for consumers. Arkolakis, Costinot, and Rodriguez-Claire (2012) show that the elasticity of relative imports with respect to trade costs, ε, is equal to $(1-\sigma)$. Therefore, choosing a value for σ or for ε pins the other down as well. The median value in the literature most often chosen for ε is -5, which corresponds to a value of σ equal to 6. I report results for three values of σ equal to 2, 4, and 6. The reason for this is that I want to approximate industry variation, and absent industry-level data the simplest way to do this is to decrease the substitutability of goods.

Because σ and ε enter the model both as parameters and in the formula to calculate welfare changes, I would expect the welfare effects to be sensitive to changing σ (or, of course, ε). In this section, I aim to examine to what extent the welfare effects are sensitive to changes in σ. To do so, I re-run the welfare analysis for various values of σ. For all values of σ, I use the same set of other parameters, specifically the preferred set of initial parameters described above in Section 5.



(a) Suez Canal Counterfactual

(b) South China Sea Counterfactual

Figure 19: Sensitivity of Welfare Effects to Changes in σ

Figure 19 shows the result of this analysis for the Suez Canal and South China Sea counterfactuals, by graphing the distribution of welfare effects ordered by rank of initial percentage change in welfare corresponding to a value of σ equal to 2. See Appendix for similar figures for the other counterfactuals. I omit the remaining counterfactuals here because the results are similar. I run the welfare analysis for five values of σ: 1.1, 2, 4, 6, and 10.[65] Not surprisingly, as σ approaches one, welfare effects get much larger. This increase is because the country varieties of the single good are becoming less and less substitutable as σ approaches 1. I also find that there is not a substantial difference in the welfare effects for values of σ equal to 2, 4, or 6. In particular, the ordering of the countries by magnitude of welfare effect changes little.

However, if I increase σ up to a value of 10, i.e., the goods are much more substitutable, welfare effects are somewhat erratic. The spikes in the charts imply that the rank order of countries by welfare effects is changing substantially. Additionally, with σ equal to 10, many more countries see a welfare gain than before, rather than a welfare loss. For the Suez Canal counterfactual especially, there are a surprising number of countries seeing a welfare gain. For the South China Sea counterfactual, more countries see a gain than before, but many countries still see a welfare loss. These results seem reasonable given that the internal good would be a much better substitute for trade, thereby substantially decreasing the gains from trade. Overall, my results are sensitive to what value of σ is chosen. However, my results are relatively stable in the range of values for σ and ε typically used in the literature.

7.5 Internal Expenditures

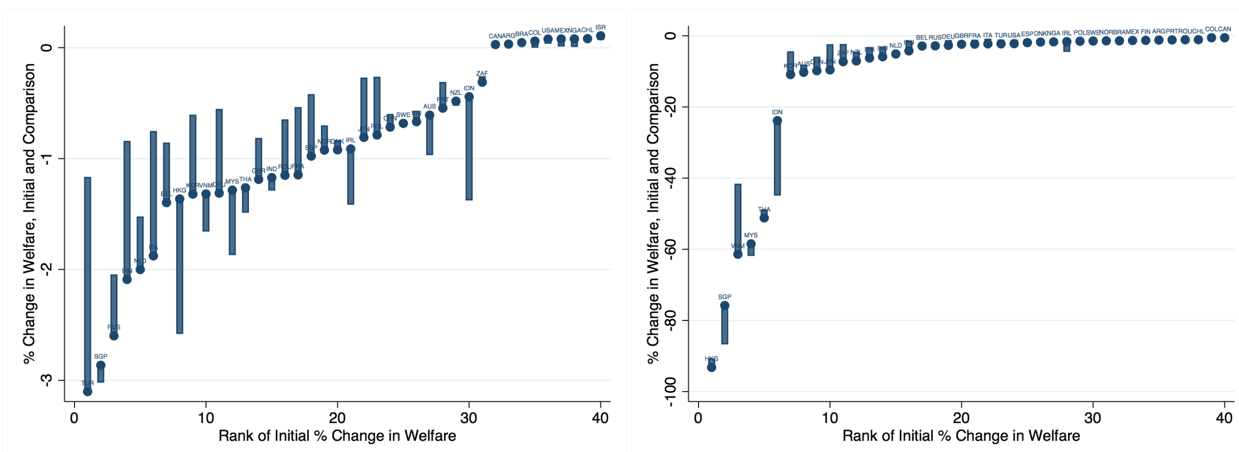
As discussed in Section 5, internal expenditure shares λ_{ii}, and thus internal expenditure flows x_{ii}, are critical pieces of data for my model. Unfortunately, these data are also difficult to find and estimate. Some may take issue with my ad-hoc method of estimating the internal expenditure flows. In an attempt to address that, in this section I re-run the welfare analysis using data from Head and Mayer (2014), which provide a complete square dataset built up from production data, including internal expenditure flows. I then compare these welfare results to baseline welfare effects from my preferred specification.

Importantly, there are a number of differences between the trade data I primarily use and the data from Head and Mayer. First, this second dataset is for the year 2000, whereas mine is for 2015. This dataset is built up from production data, whereas mine is based on overall trade data. The other main difference is that this second dataset has internal expenditure flows directly in the data,

[65]Note that I cannot use a value of σ equal to 1, since then the elasticity of trade, ε, would be zero.

whereas my internal expenditure flows are calculated to be internally consistent from predicted internal expenditure shares. One might argue that the internal expenditure flows in Head and Mayer are thus more accurate; in this section I aim to test the sensitivity of the welfare effects to having more accurate internal expenditure flows.

The dataset from Head and Mayer contains bilateral trade for 84 countries. There are 40 countries in both my sample and theirs.[66] I re-run the welfare analysis for all five counterfactuals using just this 40-country intersection, using parameters from the preferred specification, which corresponds to $\sigma = 2$ and coefficients from the PPML regression with all countries. Note that I generate new parameter values using just the 40-country sample, rather than use the coefficients in Table 12. This change does not make a large difference in the intial welfare results, but is necessary so that I am comparing the same 40 countries. Then, I also run the welfare analysis with the year 2000 data. I use $\sigma = 2$ and the coefficients from the same PPML regression, but using these trade data. However, note that I use the same bilateral distances in both analyses.



(a) Suez Canal Counterfactual (b) South China Sea Counterfactual

Figure 20: Sensitivity of Welfare Effects to Internal Expenditure Flows

Then, I compare the differences in welfare effects for each counterfactual in order to measure, at least in part, how sensitive my results are to the estimated expenditure flows. Figure 20 shows results for the Suez Canal and South China Sea counterfactuals. These scenarios were chosen because the results were mixed. For some counterfactuals, there is little change in the welfare

[66] The seven countries that are dropped from my previous analysis are the United Arab Emirates, Bangladesh, Egypt, Pakistan, Peru, the Philippines, and Saudi Arabia.

effects. For others, there is a larger change in welfare effects. These two counterfactuals illustrate both. See Appendix for similar graphs for all counterfactuals. I am again interested in two factors: whether the magnitude of welfare effects changed, and whether the rank ordering of countries by welfare effects changed.

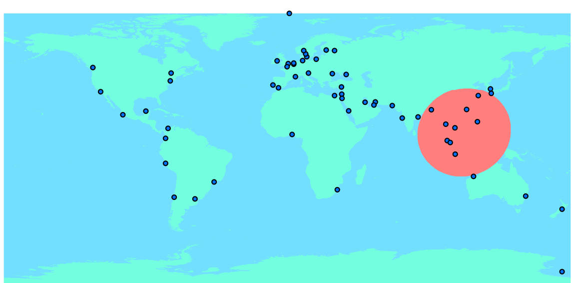
For the Suez Canal counterfactual, some of the welfare effects changed substantially. For example, the welfare loss for Turkey decreases by almost 2 percentage-points, but the welfare loss for Indonesia increased by nearly 1 percentage-point. Importantly, not only did some of the magnitudes change, but the rank ordering of welfare effects changed substantially as well. However, though these changes are large in a relative sense, none of these changes in welfare effects are large in a level sense. All changes are less than 2 percentage-points. Additionally, only the rank ordering of countries seeing large losses changes much. The countries that saw marginal gains or basically a zero change see little to no difference in the comparison sample.

In contrast, for the South China Sea counterfactual there are few changes in welfare effects. Some of these changes are large. For example, the welfare loss for Indonesia increased by nearly 20 percentage-points. However, most of the welfare effects did not change substantially. Only for three countries (Indonesia, Singapore, and Vietnam) did the welfare effect change by more than 5 percentage-points. Importantly, the rank ordering of countries by welfare effect changes quite little in this comparison.

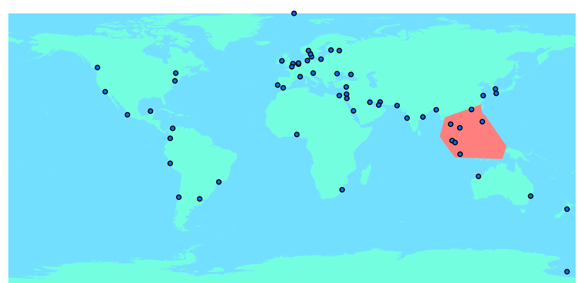
There are a number of different effects that could be driving these differences, or lack thereof. First, it could be changes in trade over time. Unfortunately, because of data and time constraints, it was not possible to compare data for the same year. Second, it could be differences in production versus overall trade data. Third, these differences could be driven by method used to calculate the internal expenditure flows. It seems that the first reason effect is the most likely explanation, especially considering that the biggest differences were for countries such as Indonesia, Singapore, and Vietnam, which have grown substantially from 2000 to 2015. For the Suez Canal counterfactual, although the rank order does change somewhat, the largest change in a welfare effect is less than 2 percentage points. Therefore, I would conclude that the overall welfare results are not sensitive to my method of calculating internal expenditure shares.

7.6 Geographic Region

Lastly, I look to examine whether the welfare results are sensitive to changes in the specific geography regions that are "closed." For the Panama Canal, Suez Canal, and Oresund Strait counterfactuals, it seems reasonable that such differences would be only marginal because the area designated as "closed" is quite small. However, for the Pacific and South China Sea counterfactuals, my results may be sensitive to the actual geographic area that is "closed." Unfortunately, it is not possible to make many adjustments to the geographic areas because running the ArcGIS analysis was so time consuming. However, I did generate routes for two different sized geographic regions over the South China Sea. One could be called a "medium" closure and the other a "large" closure.



(a) Large Region

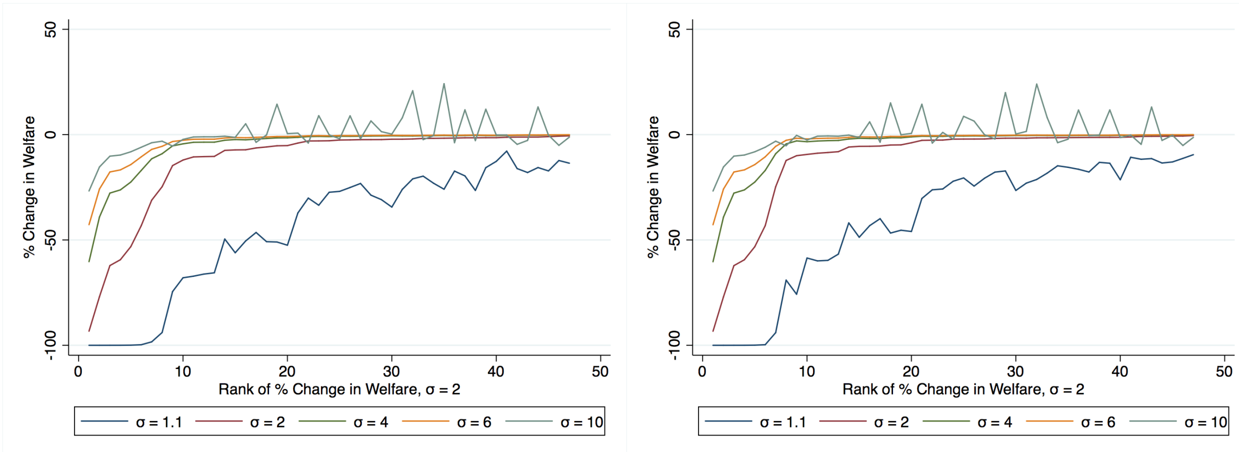


(b) Medium Region

Figure 21: Different Geographic Regions for South China Sea Counterfactual

Figure 21 compares the two regions side by side. Note that the results reported thus far for the South China Sea counterfactual have all been for the large region. I am interested in determining whether or not the welfare results are highly sensitive to the specific geographic area combined. For these two areas, I attempted to close the same major straits. However, the large region does "close" a bigger area and send more routes farther around. Additionally, the port for Bangladesh, Chittagong, is not "closed" in the medium size region, but is "closed" in the large size region. Rather than compare results for a single set of parameters, I run the welfare analysis for the various values of σ described earlier in this section. This also allows me to see whether any differences in geographic region are sensitive to changes in various parameters.

Figure 22 shows the distribution of welfare effects for various values of σ for both the "large"



(a) Large Region

(b) Medium Region

Figure 22: Sensitivity of Welfare Effects to Changes in Geographic Region

South China Sea region and the "medium" South China Sea region. Overall, there is not much of a distinguishable difference between the two results. Importantly, the lower end of the distribution of welfare changes, as in, the countries that see the largest welfare losses, looks look nearly identical for both regions. There is a small range of effects, around the 10th to 15th smallest effects, which shifts a small amount.

Overall, because there is no distinguishable difference between these two sets of welfare effects, I conclude that my results are not sensitive to the precise geographic area defined in the counterfactual.

8 Discussion

In this section, I aim to discuss the contributions, applications, and limitations of this paper, as well as suggest directions for future research. There are a number of original contributions of this paper. First, I generate an original set of bilateral distances between countries based on the shortest sea-routes between ports. These routes are generated using GIS software by solving for the least-cost route over a constrained cost surface. These distances are likely better approximations of the real-world distances traveled by tradeable goods between countries than the typical straight-line distances used in the gravity literature.

Second, I show that my constrained distances are, on average, greater than most straight-line weighted differences. Importantly, the port-to-port distances are not uniformly greater than the weighted-population distances, implying that these differences are not comparable to a uniform cost increase. The gravity coefficients estimated using these port-to-port distances are substantially smaller than the median coefficients in the literature, suggesting that the typical gravity equation using straight-line distances likely over-estimates the effect of distance on trade.

Additionally, I generate multiple sets of counterfactual bilateral distances representing different scenarios in which certain key maritime passages or straits are inaccessible to ships transporting tradeable goods. I then use these distances to solve a general equilibrium model estimating the welfare effects of moving from the initial to the counterfactual states. I find that there are economically significant and heterogeneous welfare effects of closures to these various regions. For some scenarios, certain countries see welfare gains while others see welfare losses. For other scenarios, such as a closure of the South China Sea, every country in my sample sees a welfare loss. I also estimate the gains from all maritime trade to each country, and find substantial gains ranging from 5.7% to 34.8% on average. These gains from trade are in line with other estimates in the literature.

Another original contribution of this paper is linking military expenditures and simulated welfare losses. For the South China Sea counterfactual, I show that military expenditures as a percentage of GDP are highly directly correlated with simulated welfare losses for countries in this region. In other words, for Southeast Asian countries in my sample, I show that countries with a greater simulated welfare loss spend a greater percentage of GDP on national defense. This result suggests that these countries may view the closure of the South China Sea as a legitimate possibility and threat, and may also suggest that these countries have responded to the incentive of an increased threat by increasing military spending.

My results emphasize the importance of access to the sea and maritime trade for economic growth. The results also emphasize the importance of having multiple ports, especially of having access to multiple coasts. For example, Russia's access to the Black Sea is especially critical to mitigating welfare losses in the event that the Baltic Sea is impassable. I also attempt to situate the discussion of these results in a historic and geopolitical context. For instance, in my simulated welfare results Denmark benefits enormously from a closure of the Oresund Strait. In fact, Denmark historically leveed a toll on all maritime trade passing through that Strait. My results emphasize that, were it geopolitically feasible for Denmark to close the Strait again today, there would be a large incentive to do so. In the present, my results emphasize the huge importance of maritime trade passing through the South China Sea. Given these large welfare effects, the recent geopolitical tensions in that area are perhaps not surprising. I predict that, for better or for worse, such tensions and threats regarding the Malacca Straits and the South China Sea will persist as long as these large trade flows remain.

There are, naturally, a number of limitations to this project. First, there are many ways that my initial and counterfactual port-to-port distances are not necessarily reflective of the true, real-world distance that tradeable goods are transported. For instance, I am only able to calculate distances for one or two ports per country. There are limitations in the GIS tools used to calculate the distances of these routes; these distances are planar distances calculated over a projection of the globe that includes distance distortions. Additionally, I am unable to account for currents, weather, or other spatial differences in transportation costs that may vary directionally or with distance.

Other than the limitations on my distance calculations, another limitation is that I do not actually observe the proportions of trade by sea, by land, or by air. If there are heterogeneous differences in transportation methods across countries, that would impact the results. Finally, it is crucial to the model to include internal expenditure flows, i.e., expenditures by a country on goods produced domestically. These data are difficult to measure, and it was necessary to estimate these internal flows in somewhat ad-hoc way.

Despite these limitations, I would assert that my results show that there are large and economically important gains from maritime trade, and that geopolitical events that increase insecurity in certain maritime regions could have substantial and heterogeneous welfare effects.

One important avenue for future research would be conducting such counterfactual studies using a multi-industry model, to account for the importance of critical industries in the gains from trade. A method for incorporating cross-industry variation would be to estimate industry-specific trade flows separately, solving for different values of the distance elasticity (i.e., ρ_k is the distance elasticity of good k). Intuitively, some goods are more expensive to ship than others over the same distance. However, this approach would fail to account for the interdependence of different industries. Ossa (2015) develops a multi-industry Armington trade model, using similar assumptions (such as CES preferences) to the model described in Section 3. The resulting gravity equation is:

$$X_{ijs} = p_{ijs}^{1-\sigma_s} P_{js}^{\sigma_s - 1} E_{js} \tag{35}$$

Where X_{ijs} is the trade flow from country i to country j of industry s, p_{ijs} is the price in country j of the industry s from country i, P_{js} is a price index of all industry s varieties available in country j, and E_{js} is the total expenditure in country j on industry s. Further extensions of this project could involve incorporating cross-industry variation, in which case it would be possible to use the industry-specific elasticities estimated by Ossa (2015) and this model to simulate counterfactual trade flows across industries.

Future research could also focus on better estimates of distances or transportation costs, as well as other counterfactual scenarios. I would also emphasize the importance of further research outside of the economics field on the political possibilities of the sort of scenarios discussed here. Because there are potentially large welfare effects associated with important canals and straits, and these regions could, in practicality, be closed or blockaded, it is important for governments to understand and prepare geopolitical instability that could lead to such insecure circumstances.

9 Conclusion

The purpose of this study is to estimate the gains from maritime trade, and to study how the gains from maritime trade would change under various counterfactual scenarios in which certain key sea lanes are impassable. I simulate these counterfactual scenarios by generating an original dataset of initial and counterfactual bilateral distances through GIS software. I then use these distances to solve a general equilibrium trade model to estimate the welfare effects of moving from initial to counterfactual states. I estimate that the average gains from maritime trade range from 5.7% to 34.8% on average. In counterfactual scenarios in which certain regions of the sea are "closed," I show that there are heterogeneous and economically significant welfare effects, including both gains and losses. For a counterfactual involving the closure of the South China Sea, I show that all countries would experience a welfare loss. I also show that, for countries in Southeast Asia, the magnitude of these welfare losses is directly correlated with military spending as a proportion of GDP. This result suggests that these countries are responding to incentives around the possibility of a closure occurring. I also conduct a number of sensitivity analyses to show what changes in parameters cause changes in the estimated welfare effects. The welfare effects are robust to most parameter changes. Overall, this study suggests that there is a large, sustained, and geopolitically important benefit to the policy of the "freedom of the seas."

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Appendix

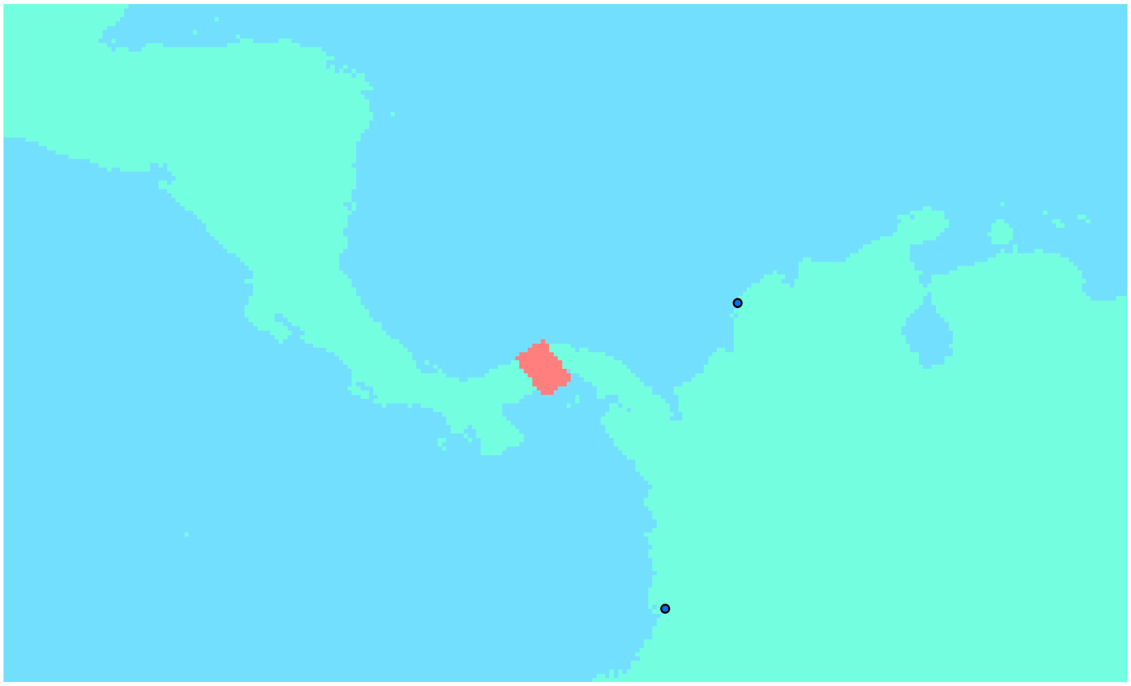

Figure A1: Raster for Panama Canal Counterfactual

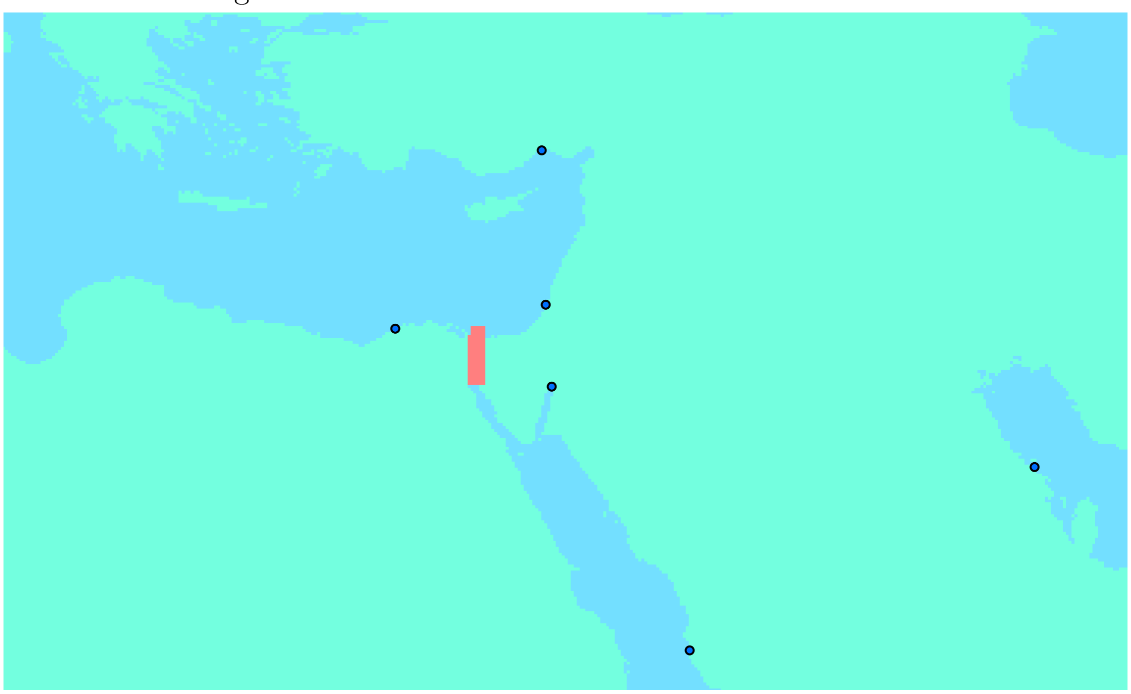

Figure A2: Raster for Suez Canal Counterfactual

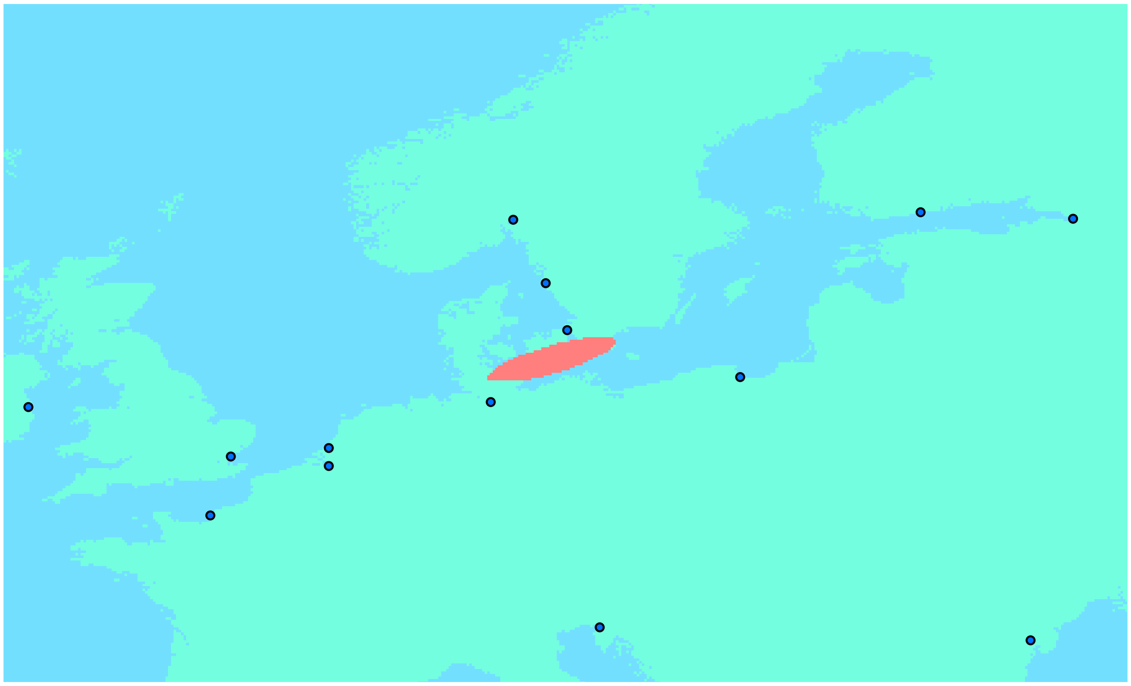

Figure A3: Raster for Oresund Strait Counterfactual

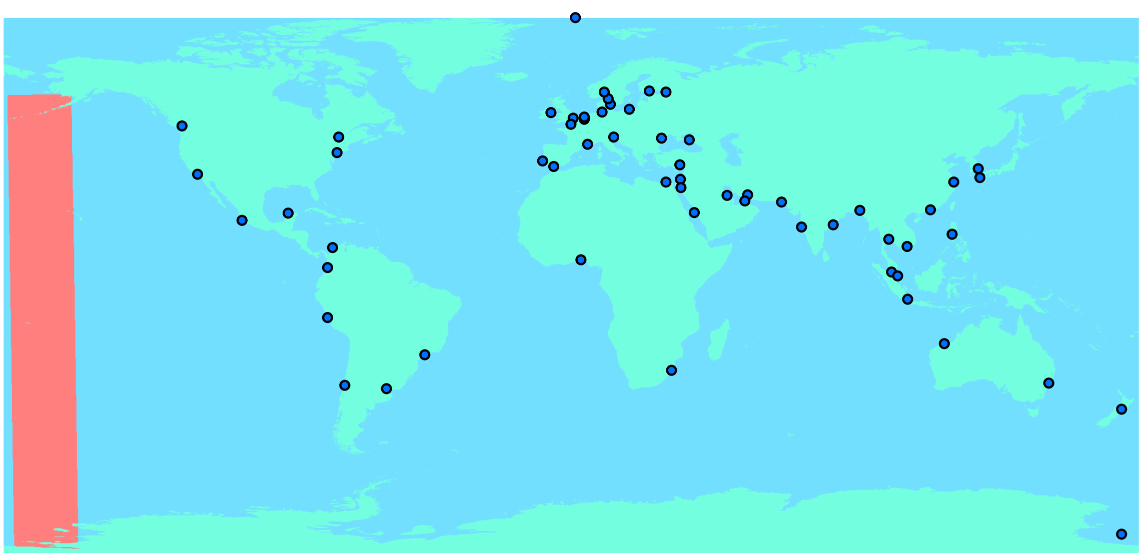

Figure A4: Raster for Pacific Ocean Counterfactual

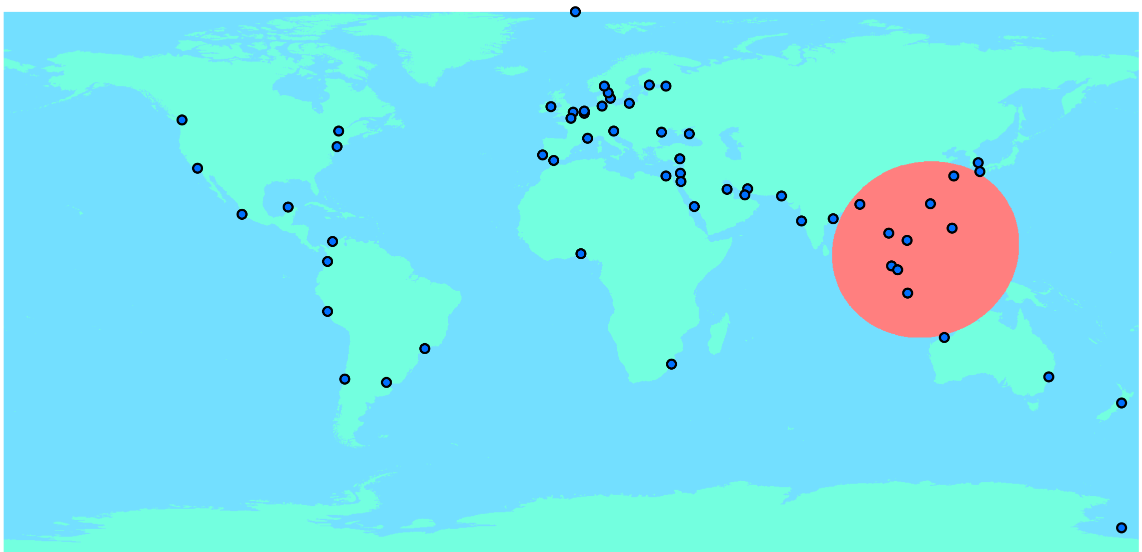

Figure A5: Raster for Large South China Sea Counterfactual

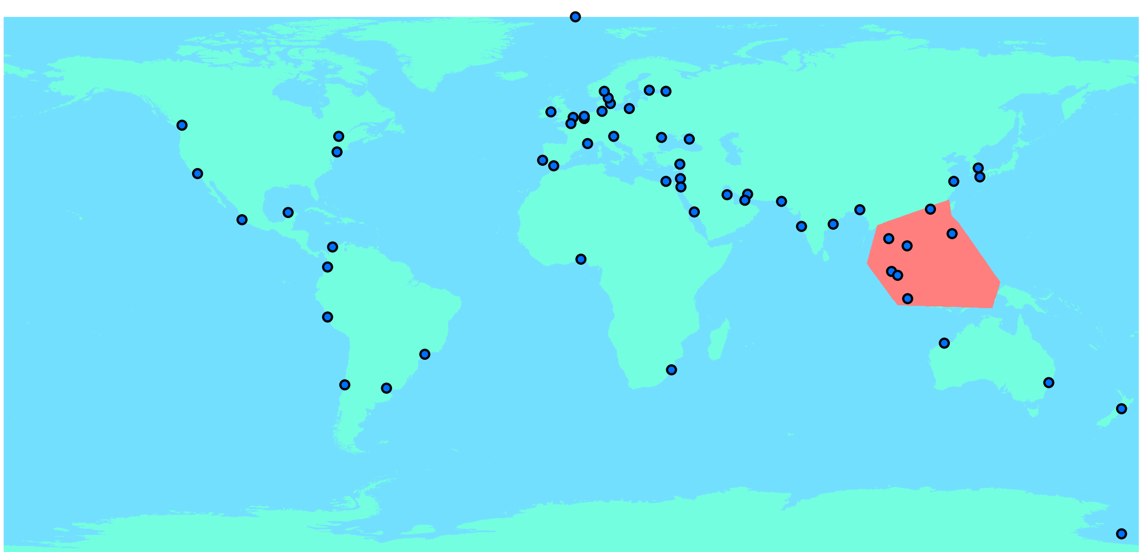

Figure A6: Raster for Medium South China Sea Counterfactual

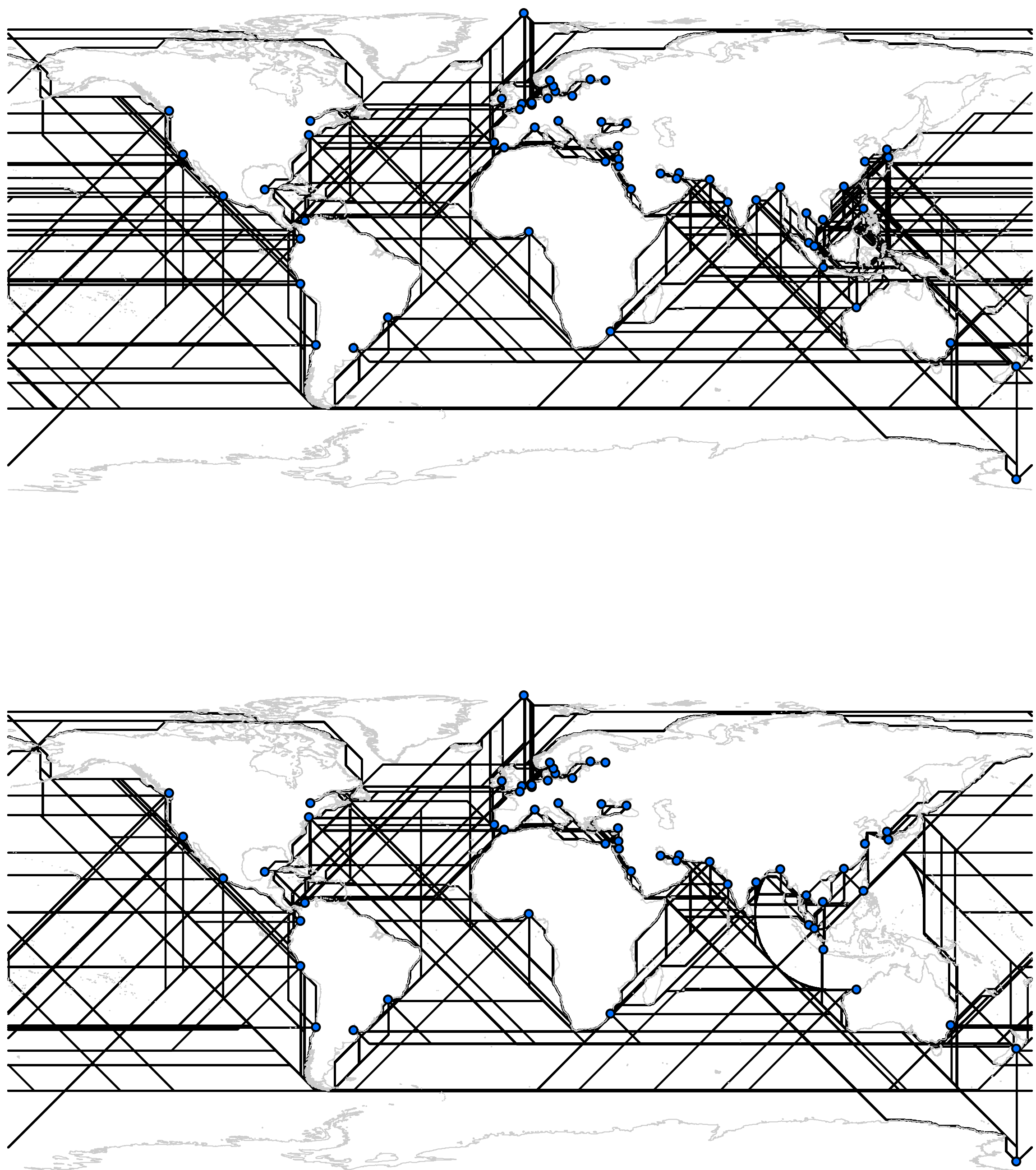

Figure A7: Initial Routes (above) vs. Counterfactual Routes (below) With South China Sea Closed

Table A1: All Percentage Changes in Welfare: Panama Canal

	$\hat{\beta}_{ln(dist)} = -.815$			$\hat{\beta}_{ln(dist)} = -.512$		
	$\sigma = 2$	$\sigma = 4$	$\sigma = 6$	$\sigma = 2$	$\sigma = 4$	$\sigma = 6$
ARE	0 %	0 %	0 %	0 %	0 %	0 %
ARG	0 %	0 %	0 %	0 %	0 %	0 %
AUS	0 %	0 %	0 %	0 %	0 %	0 %
BEL	-0.05 %	-0.02 %	-0.01 %	-0.03 %	-0.01 %	-0.01 %
BGD	0 %	0 %	0 %	0 %	0 %	0 %
BRA	0 %	0 %	0 %	0 %	0 %	0 %
CAN	0.01 %	0 %	0 %	0 %	0 %	0 %
CHL	-1.29 %	-0.45 %	-0.27 %	-0.82 %	-0.28 %	-0.17 %
CHN	0 %	0 %	0 %	0 %	0 %	0 %
COL	0.01 %	0 %	0 %	0.01 %	0 %	0 %
DEU	-0.03 %	-0.01 %	-0.01 %	-0.02 %	-0.01 %	0 %
DNK	-0.04 %	-0.01 %	-0.01 %	-0.02 %	-0.01 %	-0.01 %
EGY	0 %	0 %	0 %	0 %	0 %	0 %
ESP	-0.09 %	-0.03 %	-0.02 %	-0.06 %	-0.02 %	-0.01 %
FIN	-0.05 %	-0.02 %	-0.01 %	-0.03 %	-0.01 %	-0.01 %
FRA	-0.02 %	-0.01 %	0 %	-0.01 %	0 %	0 %
GBR	-0.02 %	-0.01 %	0 %	-0.01 %	0 %	0 %
HKG	0 %	0 %	0 %	0 %	0 %	0 %
IDN	0 %	0 %	0 %	0 %	0 %	0 %
IND	0 %	0 %	0 %	0 %	0 %	0 %
IRL	-0.01 %	0 %	0 %	-0.01 %	0 %	0 %
IRN	0 %	0 %	0 %	0 %	0 %	0 %
ISR	-0.01 %	0 %	0 %	-0.01 %	0 %	0 %
ITA	-0.03 %	-0.01 %	-0.01 %	-0.02 %	-0.01 %	0 %
JPN	0 %	0 %	0 %	0 %	0 %	0 %
KOR	0 %	0 %	0 %	0 %	0 %	0 %
MEX	0 %	0 %	0 %	0 %	0 %	0 %
MYS	0 %	0 %	0 %	0 %	0 %	0 %
NGA	0 %	0 %	0 %	0 %	0 %	0 %
NLD	-0.06 %	-0.02 %	-0.01 %	-0.04 %	-0.01 %	-0.01 %
NOR	-0.03 %	-0.01 %	-0.01 %	-0.02 %	-0.01 %	0 %
NZL	0 %	0 %	0 %	0 %	0 %	0 %
PAK	0 %	0 %	0 %	0 %	0 %	0 %
PER	-2.19 %	-0.77 %	-0.47 %	-1.44 %	-0.51 %	-0.31 %
PHL	0 %	0 %	0 %	0 %	0 %	0 %
POL	0 %	0 %	0 %	0 %	0 %	0 %
PRT	-0.01 %	0 %	0 %	-0.01 %	0 %	0 %
ROU	0 %	0 %	0 %	0 %	0 %	0 %
RUS	-0.01 %	0 %	0 %	-0.01 %	0 %	0 %
SAU	-0.01 %	0 %	0 %	0 %	0 %	0 %
SGP	0 %	0 %	0 %	0 %	0 %	0 %
SWE	-0.03 %	-0.01 %	-0.01 %	-0.02 %	-0.01 %	0 %
THA	0 %	0 %	0 %	0 %	0 %	0 %
TUR	-0.01 %	0 %	0 %	-0.01 %	0 %	0 %
USA	-0.02 %	-0.01 %	0 %	-0.01 %	0 %	0 %
VNM	0 %	0 %	0 %	0 %	0 %	0 %
ZAF	0 %	0 %	0 %	0 %	0 %	0 %

Table A2: All Percentage Changes in Welfare: Suez Canal

	$\hat{\beta}_{ln(dist)} = -.815$			$\hat{\beta}_{ln(dist)} = -.512$		
	$\sigma = 2$	$\sigma = 4$	$\sigma = 6$	$\sigma = 2$	$\sigma = 4$	$\sigma = 6$
ARE	-7.45 %	-2.4 %	-1.42 %	-5.17 %	-1.66 %	-0.98 %
ARG	0.1 %	0.05 %	0.03 %	0.07 %	0.03 %	0.02 %
AUS	-0.89 %	-0.26 %	-0.15 %	-0.58 %	-0.17 %	-0.1 %
BEL	-2.77 %	-0.92 %	-0.55 %	-1.83 %	-0.61 %	-0.36 %
BGD	-2.87 %	-1.15 %	-0.72 %	-1.92 %	-0.77 %	-0.48 %
BRA	0.09 %	0.04 %	0.03 %	0.06 %	0.03 %	0.02 %
CAN	-0.01 %	0.01 %	0 %	-0.01 %	0 %	0 %
CHL	0.14 %	0.07 %	0.05 %	0.1 %	0.05 %	0.03 %
CHN	-1.07 %	-0.38 %	-0.23 %	-0.71 %	-0.25 %	-0.15 %
COL	0.08 %	0.04 %	0.03 %	0.05 %	0.03 %	0.02 %
DEU	-2.24 %	-0.76 %	-0.46 %	-1.46 %	-0.5 %	-0.3 %
DNK	-1.61 %	-0.54 %	-0.32 %	-1.05 %	-0.35 %	-0.21 %
EGY	-5.2 %	-1.62 %	-0.96 %	-3.94 %	-1.23 %	-0.73 %
ESP	-2.04 %	-0.64 %	-0.38 %	-1.38 %	-0.43 %	-0.25 %
FIN	-1.12 %	-0.38 %	-0.23 %	-0.73 %	-0.24 %	-0.15 %
FRA	-2.22 %	-0.74 %	-0.44 %	-1.5 %	-0.5 %	-0.3 %
GBR	-2.2 %	-0.74 %	-0.45 %	-1.45 %	-0.49 %	-0.29 %
HKG	-1.97 %	-0.71 %	-0.44 %	-1.3 %	-0.47 %	-0.29 %
IDN	-0.68 %	-0.23 %	-0.14 %	-0.46 %	-0.15 %	-0.09 %
IND	-1.66 %	-0.57 %	-0.34 %	-1.14 %	-0.39 %	-0.23 %
IRL	-1.48 %	-0.51 %	-0.31 %	-0.97 %	-0.34 %	-0.2 %
IRN	-2.82 %	-0.94 %	-0.57 %	-2.04 %	-0.68 %	-0.41 %
ISR	0.22 %	0.11 %	0.07 %	0.15 %	0.07 %	0.05 %
ITA	-3.37 %	-1.17 %	-0.71 %	-2.36 %	-0.82 %	-0.5 %
JPN	-1.18 %	-0.39 %	-0.23 %	-0.78 %	-0.25 %	-0.15 %
KOR	-1.91 %	-0.63 %	-0.38 %	-1.26 %	-0.42 %	-0.25 %
MEX	0.12 %	0.05 %	0.03 %	0.08 %	0.03 %	0.02 %
MYS	-1.92 %	-0.66 %	-0.4 %	-1.29 %	-0.45 %	-0.27 %
NGA	0.14 %	0.07 %	0.04 %	0.09 %	0.04 %	0.03 %
NLD	-3.45 %	-1.09 %	-0.64 %	-2.27 %	-0.71 %	-0.42 %
NOR	-1.45 %	-0.45 %	-0.27 %	-0.95 %	-0.29 %	-0.17 %
NZL	-0.7 %	-0.21 %	-0.12 %	-0.45 %	-0.13 %	-0.08 %
PAK	-2.45 %	-0.88 %	-0.54 %	-1.67 %	-0.6 %	-0.37 %
PER	0.06 %	0.04 %	0.02 %	0.04 %	0.02 %	0.02 %
PHL	-0.94 %	-0.31 %	-0.18 %	-0.62 %	-0.2 %	-0.12 %
POL	-1.36 %	-0.37 %	-0.21 %	-0.88 %	-0.24 %	-0.13 %
PRT	-1.2 %	-0.36 %	-0.21 %	-0.81 %	-0.24 %	-0.14 %
ROU	-1.79 %	-0.58 %	-0.35 %	-1.26 %	-0.41 %	-0.25 %
RUS	-3.9 %	-1.35 %	-0.82 %	-2.7 %	-0.93 %	-0.57 %
SAU	-9.61 %	-3.28 %	-1.97 %	-7.06 %	-2.4 %	-1.44 %
SGP	-4.02 %	-1.37 %	-0.83 %	-2.7 %	-0.92 %	-0.55 %
SWE	-1.17 %	-0.4 %	-0.24 %	-0.76 %	-0.26 %	-0.16 %
THA	-1.83 %	-0.64 %	-0.39 %	-1.23 %	-0.43 %	-0.26 %
TUR	-5.58 %	-1.79 %	-1.06 %	-4.08 %	-1.3 %	-0.77 %
USA	-0.04 %	0 %	0 %	-0.03 %	0 %	0 %
VNM	-1.83 %	-0.73 %	-0.46 %	-1.22 %	-0.48 %	-0.3 %
ZAF	-0.41 %	-0.11 %	-0.06 %	-0.27 %	-0.07 %	-0.04 %

Table A3: All Percentage Changes in Welfare: Oresund Strait

	$\hat{\beta}_{ln(dist)} = -.815$			$\hat{\beta}_{ln(dist)} = -.512$		
	$\sigma = 2$	$\sigma = 4$	$\sigma = 6$	$\sigma = 2$	$\sigma = 4$	$\sigma = 6$
ARE	-0.39 %	-0.06 %	-0.03 %	-0.2 %	-0.04 %	-0.02 %
ARG	-0.14 %	-0.04 %	-0.02 %	-0.12 %	-0.04 %	-0.02 %
AUS	-0.26 %	-0.05 %	-0.03 %	-0.15 %	-0.04 %	-0.02 %
BEL	-2.4 %	-0.84 %	-0.51 %	-2.12 %	-0.73 %	-0.44 %
BGD	0.28 %	-0.03 %	-0.03 %	-0.1 %	-0.05 %	-0.03 %
BRA	-0.18 %	-0.04 %	-0.02 %	-0.11 %	-0.03 %	-0.02 %
CAN	-0.34 %	-0.06 %	-0.03 %	-0.18 %	-0.05 %	-0.03 %
CHL	-0.31 %	-0.08 %	-0.05 %	-0.22 %	-0.07 %	-0.04 %
CHN	0 %	-0.01 %	-0.01 %	-0.07 %	-0.02 %	-0.01 %
COL	-0.2 %	-0.03 %	-0.01 %	-0.08 %	-0.02 %	-0.01 %
DEU	-4 %	-1.44 %	-0.88 %	-3.8 %	-1.34 %	-0.81 %
DNK	18.93 %	6.51 %	3.96 %	8.84 %	3.12 %	1.91 %
EGY	-0.36 %	-0.04 %	-0.02 %	-0.16 %	-0.03 %	-0.01 %
ESP	-0.87 %	-0.3 %	-0.18 %	-0.87 %	-0.28 %	-0.17 %
FIN	-44.09 %	-17.63 %	-10.99 %	-42.09 %	-16.7 %	-10.39 %
FRA	-1.25 %	-0.38 %	-0.22 %	-1.07 %	-0.34 %	-0.2 %
GBR	-1.29 %	-0.36 %	-0.21 %	-1.07 %	-0.32 %	-0.19 %
HKG	-0.11 %	-0.04 %	-0.02 %	-0.12 %	-0.04 %	-0.02 %
IDN	-0.17 %	-0.03 %	-0.02 %	-0.09 %	-0.02 %	-0.01 %
IND	-0.17 %	-0.03 %	-0.01 %	-0.09 %	-0.02 %	-0.01 %
IRL	-0.78 %	-0.26 %	-0.15 %	-0.71 %	-0.24 %	-0.14 %
IRN	-0.18 %	-0.01 %	0 %	-0.03 %	0 %	0 %
ISR	-0.5 %	-0.11 %	-0.06 %	-0.38 %	-0.1 %	-0.06 %
ITA	-0.83 %	-0.34 %	-0.21 %	-1.05 %	-0.35 %	-0.21 %
JPN	-0.11 %	-0.01 %	-0.01 %	-0.07 %	-0.01 %	-0.01 %
KOR	0.01 %	-0.02 %	-0.01 %	-0.11 %	-0.03 %	-0.02 %
MEX	-0.31 %	-0.04 %	-0.02 %	-0.13 %	-0.03 %	-0.02 %
MYS	-0.08 %	-0.02 %	-0.01 %	-0.07 %	-0.02 %	-0.01 %
NGA	-0.15 %	0 %	0 %	-0.01 %	0.01 %	0.01 %
NLD	-4.64 %	-1.59 %	-0.96 %	-3.84 %	-1.3 %	-0.78 %
NOR	-1.07 %	-0.34 %	-0.21 %	-1.36 %	-0.44 %	-0.26 %
NZL	-0.25 %	-0.04 %	-0.02 %	-0.13 %	-0.03 %	-0.01 %
PAK	-0.17 %	-0.04 %	-0.02 %	-0.11 %	-0.03 %	-0.02 %
PER	-0.29 %	-0.06 %	-0.03 %	-0.15 %	-0.04 %	-0.02 %
PHL	-0.14 %	-0.03 %	-0.01 %	-0.09 %	-0.02 %	-0.01 %
POL	-47.66 %	-19.3 %	-12.06 %	-46.84 %	-18.89 %	-11.78 %
PRT	-0.7 %	-0.2 %	-0.11 %	-0.61 %	-0.18 %	-0.11 %
ROU	-2.05 %	-0.72 %	-0.43 %	-2.29 %	-0.72 %	-0.42 %
RUS	-6.08 %	-2.23 %	-1.37 %	-4.76 %	-1.74 %	-1.07 %
SAU	-0.43 %	-0.09 %	-0.05 %	-0.29 %	-0.08 %	-0.04 %
SGP	-0.12 %	-0.04 %	-0.02 %	-0.2 %	-0.05 %	-0.03 %
SWE	0.65 %	0.18 %	0.1 %	-2.08 %	-0.75 %	-0.46 %
THA	-0.11 %	-0.02 %	-0.01 %	-0.09 %	-0.02 %	-0.01 %
TUR	-0.37 %	-0.13 %	-0.08 %	-0.51 %	-0.15 %	-0.09 %
USA	-0.26 %	-0.03 %	-0.02 %	-0.11 %	-0.02 %	-0.01 %
VNM	0.07 %	-0.02 %	-0.02 %	-0.1 %	-0.04 %	-0.02 %
ZAF	-0.42 %	-0.1 %	-0.06 %	-0.33 %	-0.09 %	-0.05 %

Table A4: All Percentage Changes in Welfare: Pacific Ocean

	$\hat{\beta}_{ln(dist)} = -.815$			$\hat{\beta}_{ln(dist)} = -.512$		
	$\sigma = 2$	$\sigma = 4$	$\sigma = 6$	$\sigma = 2$	$\sigma = 4$	$\sigma = 6$
ARE	-0.24 %	-0.05 %	-0.02 %	-0.13 %	-0.02 %	-0.01 %
ARG	0 %	0.02 %	0.01 %	0 %	0.01 %	0.01 %
AUS	-2.01 %	-0.63 %	-0.37 %	-1.38 %	-0.43 %	-0.25 %
BEL	0.08 %	0.05 %	0.03 %	0.05 %	0.03 %	0.02 %
BGD	0.61 %	0.25 %	0.15 %	0.38 %	0.15 %	0.1 %
BRA	0.02 %	0.03 %	0.02 %	0.02 %	0.02 %	0.01 %
CAN	-2.89 %	-0.89 %	-0.52 %	-1.99 %	-0.61 %	-0.36 %
CHL	-4.62 %	-1.67 %	-1.02 %	-3.05 %	-1.1 %	-0.67 %
CHN	-1.89 %	-0.7 %	-0.43 %	-1.29 %	-0.48 %	-0.29 %
COL	-1.67 %	-0.49 %	-0.28 %	-1.1 %	-0.32 %	-0.18 %
DEU	0.29 %	0.13 %	0.09 %	0.18 %	0.08 %	0.06 %
DNK	0.23 %	0.11 %	0.07 %	0.14 %	0.07 %	0.04 %
EGY	0.08 %	0.05 %	0.03 %	0.05 %	0.03 %	0.02 %
ESP	0.16 %	0.08 %	0.05 %	0.1 %	0.05 %	0.03 %
FIN	0.12 %	0.06 %	0.04 %	0.07 %	0.04 %	0.03 %
FRA	0.18 %	0.09 %	0.06 %	0.12 %	0.06 %	0.04 %
GBR	0.26 %	0.12 %	0.08 %	0.17 %	0.08 %	0.05 %
HKG	-3.06 %	-1.12 %	-0.69 %	-2.07 %	-0.75 %	-0.46 %
IDN	-0.33 %	-0.1 %	-0.06 %	-0.22 %	-0.06 %	-0.04 %
IND	0.29 %	0.13 %	0.08 %	0.18 %	0.08 %	0.05 %
IRL	0.53 %	0.24 %	0.15 %	0.33 %	0.15 %	0.1 %
IRN	-0.05 %	0 %	0.01 %	-0.03 %	0 %	0.01 %
ISR	0.76 %	0.33 %	0.21 %	0.48 %	0.21 %	0.13 %
ITA	0.23 %	0.11 %	0.07 %	0.15 %	0.07 %	0.04 %
JPN	-2.8 %	-1 %	-0.61 %	-1.93 %	-0.69 %	-0.42 %
KOR	-3.28 %	-1.18 %	-0.72 %	-2.25 %	-0.81 %	-0.49 %
MEX	-3.86 %	-1.08 %	-0.61 %	-2.62 %	-0.73 %	-0.41 %
MYS	-0.89 %	-0.3 %	-0.18 %	-0.57 %	-0.19 %	-0.11 %
NGA	0.13 %	0.07 %	0.04 %	0.08 %	0.04 %	0.03 %
NLD	0.43 %	0.2 %	0.13 %	0.27 %	0.12 %	0.08 %
NOR	0.14 %	0.07 %	0.04 %	0.09 %	0.04 %	0.03 %
NZL	-3.87 %	-1.34 %	-0.81 %	-2.76 %	-0.96 %	-0.58 %
PAK	0.39 %	0.16 %	0.1 %	0.24 %	0.1 %	0.06 %
PER	-3.7 %	-1.24 %	-0.75 %	-2.48 %	-0.83 %	-0.5 %
PHL	-1.89 %	-0.65 %	-0.39 %	-1.27 %	-0.44 %	-0.26 %
POL	0.25 %	0.11 %	0.07 %	0.16 %	0.07 %	0.04 %
PRT	0.15 %	0.07 %	0.05 %	0.1 %	0.05 %	0.03 %
ROU	0.08 %	0.04 %	0.03 %	0.05 %	0.03 %	0.02 %
RUS	0.1 %	0.06 %	0.04 %	0.07 %	0.04 %	0.03 %
SAU	0.11 %	0.07 %	0.05 %	0.08 %	0.05 %	0.03 %
SGP	-2.34 %	-0.77 %	-0.45 %	-1.52 %	-0.49 %	-0.29 %
SWE	0.12 %	0.06 %	0.04 %	0.08 %	0.04 %	0.03 %
THA	-1.19 %	-0.41 %	-0.25 %	-0.78 %	-0.27 %	-0.16 %
TUR	0.19 %	0.09 %	0.06 %	0.12 %	0.06 %	0.04 %
USA	-4.97 %	-1.58 %	-0.94 %	-3.42 %	-1.08 %	-0.64 %
VNM	-1.08 %	-0.44 %	-0.28 %	-0.71 %	-0.29 %	-0.18 %
ZAF	0.01 %	0.03 %	0.02 %	0.01 %	0.02 %	0.02 %

Table A5: All Percentage Changes in Welfare: South China Sea

	$\hat{\beta}_{ln(dist)} = -.815$			$\hat{\beta}_{ln(dist)} = -.512$		
	$\sigma = 2$	$\sigma = 4$	$\sigma = 6$	$\sigma = 2$	$\sigma = 4$	$\sigma = 6$
ARE	-17.95 %	-6.69 %	-4.11 %	-14.68 %	-5.34 %	-3.27 %
ARG	-1.3 %	-0.5 %	-0.3 %	-1.24 %	-0.41 %	-0.25 %
AUS	-12.97 %	-4.56 %	-2.76 %	-10.43 %	-3.58 %	-2.16 %
BEL	-3.8 %	-1.08 %	-0.61 %	-2.98 %	-0.82 %	-0.46 %
BGD	-32.11 %	-11.93 %	-7.31 %	-31.13 %	-11.47 %	-7.01 %
BRA	-1.82 %	-0.61 %	-0.36 %	-1.44 %	-0.46 %	-0.27 %
CAN	-0.83 %	-0.17 %	-0.08 %	-0.72 %	-0.15 %	-0.07 %
CHL	-1.62 %	-0.37 %	-0.19 %	-1.15 %	-0.25 %	-0.12 %
CHN	-12.25 %	-4.33 %	-2.63 %	-10.34 %	-3.59 %	-2.17 %
COL	-0.95 %	-0.16 %	-0.07 %	-0.58 %	-0.1 %	-0.05 %
DEU	-3.97 %	-1.25 %	-0.73 %	-3.01 %	-0.93 %	-0.54 %
DNK	-2.68 %	-0.84 %	-0.49 %	-2.07 %	-0.63 %	-0.36 %
EGY	-3.12 %	-0.77 %	-0.42 %	-2.17 %	-0.55 %	-0.31 %
ESP	-2.95 %	-0.84 %	-0.48 %	-2.17 %	-0.62 %	-0.35 %
FIN	-1.92 %	-0.6 %	-0.35 %	-1.44 %	-0.44 %	-0.26 %
FRA	-3.29 %	-1.04 %	-0.61 %	-2.5 %	-0.78 %	-0.46 %
GBR	-3.4 %	-1.03 %	-0.6 %	-2.56 %	-0.76 %	-0.44 %
HKG	-95.03 %	-63.27 %	-45.17 %	-93.29 %	-60.29 %	-42.73 %
IDN	-25.96 %	-9.57 %	-5.86 %	-24.73 %	-9.07 %	-5.55 %
IND	-7.13 %	-2.23 %	-1.31 %	-5.85 %	-1.83 %	-1.07 %
IRL	-2.53 %	-0.79 %	-0.47 %	-1.79 %	-0.56 %	-0.33 %
IRN	-5.89 %	-1.91 %	-1.13 %	-4.01 %	-1.3 %	-0.77 %
ISR	-7.92 %	-2.78 %	-1.69 %	-6.31 %	-2.15 %	-1.29 %
ITA	-3.15 %	-1.01 %	-0.59 %	-2.38 %	-0.75 %	-0.44 %
JPN	-12.99 %	-4.52 %	-2.74 %	-10.58 %	-3.64 %	-2.2 %
KOR	-14.94 %	-5.5 %	-3.38 %	-12.06 %	-4.37 %	-2.67 %
MEX	-2.04 %	-0.42 %	-0.21 %	-1.49 %	-0.32 %	-0.16 %
MYS	-61.2 %	-27.16 %	-17.33 %	-59.39 %	-26.23 %	-16.74 %
NGA	-2.6 %	-0.7 %	-0.39 %	-1.76 %	-0.48 %	-0.27 %
NLD	-6.92 %	-2.05 %	-1.18 %	-5.3 %	-1.55 %	-0.89 %
NOR	-2.19 %	-0.6 %	-0.34 %	-1.49 %	-0.42 %	-0.24 %
NZL	-8.58 %	-2.84 %	-1.68 %	-7.25 %	-2.32 %	-1.37 %
PAK	-6.71 %	-1.97 %	-1.13 %	-5.2 %	-1.51 %	-0.87 %
PER	-1.39 %	-0.29 %	-0.14 %	-0.95 %	-0.2 %	-0.1 %
PHL	-44.46 %	-17.62 %	-10.95 %	-43.23 %	-17 %	-10.54 %
POL	-2.47 %	-0.59 %	-0.31 %	-1.7 %	-0.41 %	-0.22 %
PRT	-1.74 %	-0.46 %	-0.26 %	-1.16 %	-0.31 %	-0.18 %
ROU	-1.73 %	-0.46 %	-0.26 %	-1.14 %	-0.31 %	-0.17 %
RUS	-4.03 %	-1.32 %	-0.78 %	-2.91 %	-0.94 %	-0.56 %
SAU	-9.44 %	-3.41 %	-2.08 %	-7.48 %	-2.66 %	-1.62 %
SGP	-79.59 %	-41.39 %	-27.46 %	-76.93 %	-39.11 %	-25.82 %
SWE	-2.19 %	-0.68 %	-0.4 %	-1.64 %	-0.5 %	-0.3 %
THA	-55.59 %	-23.81 %	-15.07 %	-53.17 %	-22.52 %	-14.22 %
TUR	-3.28 %	-0.87 %	-0.48 %	-2.35 %	-0.63 %	-0.35 %
USA	-2.87 %	-0.81 %	-0.46 %	-2.36 %	-0.66 %	-0.37 %
VNM	-65.03 %	-29.56 %	-18.96 %	-62.16 %	-27.74 %	-17.72 %
ZAF	-9.51 %	-3.36 %	-2.04 %	-7.19 %	-2.46 %	-1.48 %