Naval Forces: Truly Indispensable to Global Trade Flows?

Harrison J. Hawkins

The U.S. Navy considers itself a protector of the global commons, indispensable to a global commercial system in which the majority of trade travels by sea. But as Congress debates where to allocate American defense funds, it is important to consider what drives the utility of naval forces. This paper investigates the extent to which global trade flows actually depend on naval force presence. Using a standard regression model based on the naval power of maritime countries over time, I find that force presence may actually be detrimental to trade flows, throwing doubt on the widespread notion of the importance of naval presence in securing trade routes. The presented analysis supports the theory that global trade is highly robust, and that reductions in naval presence may not end up negatively impacting the continued flow of commerce. Because of this seemingly counterintuitive result, the paper then proceeds with robustness checks of the initial findings and concludes with a discussion of important attendant policy considerations for the American taxpayer.

I. Introduction and Literature Review

Delve into any *Foreign Affairs* issue these days and it is likely you will read some commentary on what the rise of increasingly belligerent states like China could mean for global relations. Included in this discussion is how hostile action might affect global trade flows. Specifically, and in consideration of deteriorating relations between China and Taiwan, many analysts fear the outbreak of war across the Taiwan Straits could have devastating effects on trade in East Asia. Given President Biden's commitment (in line with past presidents) to defend Taiwan in the event of a Chinese invasion, the United States has a direct stake in this conflict beyond just how war may affect trade. Furthermore, because of the geography of East Asia, naval forces will likely play a prominent role. However, from the halls of Congress to the academic fields of military analysis, the utility of naval forces continues to be a hot-button issue. As other geopolitical threats emerge to strain the resources of the United States military, it will be important to consider what role the U.S. Navy will have in this rapidly changing environment.

This paper will investigate one traditional role of naval forces, protecting sea lanes. Alan Beatie at the *Financial Times* points out that "even in calmer geopolitical times, the US's military contribution to civilian trade is easy to overlook," and that "the most obvious example is the American navy's decades-old role patrolling sea lanes used by commercial shipping" (Beattie 2023). Although this quote is U.S.-centric, it requires no great stretch of the imagination to see that every navy has a vested interest in defending its country's civilian trade.

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able to a global commercial system in which 90 percent of global trade travels by sea. But to what extent do trade flows actually depend on naval force presence? For a topic of such importance to the world of policy, and as Congress debates where to allocate American defense funds, it is surprising that the economics research on the linkages between naval force presence and trade flows is so thin. Most of the academic discussion on trade and force is sprinkled within commentary pieces in newspapers like the *Financial Times* (Beattie 2022) or in think tank reports from the Center for Strategic and International Studies (CSIS) (Friedman 2022). Articles from the former tout the perils to trade posed by an increasingly belligerent China, while Benjamin Friedman, a policy director at CSIS, assures his readers that the robustness of global supply chains and the fuzzy logic of naval deterrence means assuming global trade depends on the navy is a "bad idea."

To date, no economist has attempted to examine the issue, although some previous papers have sought to determine the relationships between some closely related phenomenon. Anderson and Wincoop, in their broad-spanning paper on trade costs, break down the constituent pieces of trade prices into transportation and distribution, but leave out any kind of military dimension when thinking about the costs of trade flows (Anderson and Wincoop 2004). Additionally, Morabito and Sergi use a gravity model based on the trade flows of southeast Asian countries to estimate the impact of piracy on trade volumes, but again there is no mention of the potential roles of the regional navies (Morabito and Sergi 2018, 255-265). Danzell et al. (2021, 179-200) get closest to the topic by using a binomial regression model to determine if naval force presence, instrumented by regional naval bases, can decrease the likelihood of piracy, but lacks any dimension related explicitly to trade.

As such, the time is ripe to precisely seek an accurate representation of the relationship between naval force presence and trade flows over time. This paper attempts to do just that, using a standard regression model based on the naval power of maritime countries over time to quantify the impact of naval patrols on global trade flows in the post-war period.

This paper makes three primary contributions. First, this analysis presents the initial explicit econometric investigation into the relationship between trade and naval force presence, ideally paving the way for future research in the field. Second, the analysis offers the seemingly counterintuitive result that force presence may actually be detrimental to trade flows, throwing doubt on the widespread notion of the utility of perpetual naval presence in securing trade routes. Third, because of the attendant considerations of the results, this analysis will contribute to important policy debates about the future of navies in general, and the United States Navy in particular.

Section II discusses my data sources and provides some summary statistics. Section III follows with the economic theory and empirical methodology underpinning my regressions, while Section IV presents these results. Section V speaks to the robustness of my findings, and Section VI concludes.

II. DATA

This paper is based on compiling two separate original datasets. The first is an index of naval power compiled by Brian Crisher and Mark Souva at Florida State University, presenting 147 years of naval data on all the world's navies between 1865 and 2011 (Crisher and Souva 2014). Compiled in 2014 explicitly for use in further research, the data is organized by country-year and details the total aggregate tonnage of naval 'capital' ships for that country-year pair. In this sense, Crisher and Souva define a 'capital' ship as a ship "capable of using kinetic force to inflict damage on other structures or peoples" (ibid.). To sum the total tonnage, the data also necessarily includes the quantities of capital war ships for a given country-year pair, such as number of submarines, battleships, aircraft carriers, and so forth. The entries of interest for my research are the approximately 5,000 observations of total naval tonnage for a given country-year pair.

The second dataset is the CEPII Gravity database, the highly useful repository of all information necessary to estimate gravity equations between any given pair of countries from 1948 to 2020 (Conte, Cotterlaz, and Mayer 2022). For my purposes, I specifically used CEPII's approximately 1 million observations on trade flows compiled by the IMF, as reported by destination country. Reconciling these two datasets will take up the bulk of Section III.

III. Empirical Methodology

To quantify the impact of naval patrols on global trade flows, there must exist a reasonable source of variation within some measurement of naval forces. Through the Crisher and Souva dataset, I was able produce a constructed right-hand-side variable, referred to in this text as Neighbors' Navy (NN), which uses the total tonnage of all countries to create a sum of naval power allocated to a given trade route between two countries, with this sum weighted by distance of a 'third' country to the trade route in question. Within this part of the paper, the first subsection will walk the reader through the construction of this independent NN variable, and the second subsection will introduce the basic regressions of trade on the NN variable.

Constructing the Independent Variable
The overarching theme of constructing the NN variable was reconciling the Crisher/Souva naval data with the CEPII gravity database, then using this new database to calculate the weighted distances that would compose the gravity-style NN variable. As such, the first step in this construction was cleaning the naval dataset. This consisted of removing all observations prior to 1948 (and thus not covered by the trade data), replacing country IDs to match the identifications used by CEPII, and finally merging the CEPII country codes with the Chrisher/Souva naval data.

Second, using the CEPII country codes, I generated a 'triad' dataset. The triad refers to origin country, destination country, and a third 'neighbor' country, with the latter referring to all other countries of the world. This triad dataset consisted of approximately 4.5 million observations, reflecting every possible triad combination among all the countries in which CEPII provided data. More importantly, because

this dataset was constructed from the information already available in CEPII, it already consisted of the next variable of interest: the distances between each of these three countries (that is, distance between origin and destination, origin and third country, and destination and third country). To make future calculations with these distances computationally less difficult, I then dropped all country triad entries in which distances between countries were either zero or missing.

With the dataset constructed, I then went about calculating the weighted distances for the NN variable. This calculation can be thought of broadly in two parts. First, finding the actual distance of any third 'neighbor' country to a given trade route. Second, comparing these distances across every neighbor to generate a weight based on those distances, with larger weights assigned to neighbors closer to the trade route.

To calculate actual distance to the trade route, I treated the entire country triad relationship as simply one large triangle, with the distance between origin and destination (in other words, the distance of the trade route) as the base of this triangle. The distances between origin and neighbor country, and destination and neighbor, thus comprised the other two sides of the triangle. Therefore, the distance between the third neighbor country and the trade route can be thought of as simply the height, or altitude, of the triangular representation. Figure 1 depicts this relationship graphically. One way to calculate triangular altitude is simply dividing two times the area of the triangle by the base, as shown in Equation 1.

Equation 1:
$$h_b = 2\frac{A}{b}$$

As evident by the equation, a necessary input is the area of the triangle. Calculating area based on side distances is depicted by Equation 3, which uses 's,' a necessary input reflecting the total side length of the triangle, as shown by Equation 2.

Equation 2:
$$s = a + b + c$$

Equation 3:
$$A = \sqrt{s * (s - a)(s - b)(s - c)}$$

With these equations in place, it was simply a matter of plugging in the distance data available in the dataset to calculate the areas and altitudes of every country triad.

Next was using the altitude (the distance of the neighbor to a given country pair's trade route) to create a system of weights. Each triad was assigned a weight by dividing one by the respective altitude entry. This computation assigned to each neighbor country a list of weights based on the distances of that third country to each trade route. So, if these weights were summed across all trade routes for a given third country, the sum would be close to one, with higher weights assigned to closer trade routes. With about 3.5 million observations, the triad dataset was complete,

and so I next merged the naval data onto the triad data using a many to one merge, with the third (neighbor) country as the key.

Finally, with all necessary inputs generated, the NN variable could be calculated. Organized by an origin/destination trading pair, the NN variable is essentially a double summation; across all years present in the trade and naval data (1948-2011), and across all available countries, the previously calculated weights are first divided by the sum of all weights for that trade route that year to create a 'true weight', which is then multiplied by the total naval tonnage present across all neighbor countries. This calculation is depicted by Equation 4.

Equation 4:
$$NN_{ijt} = constructed \ neighbors' \ navy \ variable$$
$$= for \ years \ (1948 - 2011): \sum_{i=country}^{All \ countries} x_i = \frac{NN_{weights}}{\Sigma NN_{weights}} * totton$$

Looking from right to left, the multiplication of the true weight by total naval tonnage reveals what raw magnitude of a given neighbor country's navy is used to protect and patrol that particular trade route that particular year. This tonnage is then summed up for all 'third' neighbor countries, resulting in the final NN value for that year and that route. Then, this process is repeated for all years between 1948 and 2011, providing a raw NN number for all years and trade routes in the data.

The final step in this construction was then merging the CEPII gravity data with the NN (triad) dataset, achieved by sorting the entire CEPII gravity database by origin, destination, and year, then merging many to one with the triad dataset using those same variables as keys. This last step provided the final dataset, consisting of all needed gravity data and constructed NN variables for a given country pair (trade route) for every year. This set forms the basis for the regressions described in the next subsection.

Figure 2 graphically depicts the relationship between the constructed NN variable and trade flows, by plotting the average of the NN variable between 1948 and 2011 with the average trade flow across all routes for the same period. Perhaps counterintuitively, but as evident in the figure, total naval tonnage has declined even as trade flows have increased since 1948. Figure 3 more closely examines how the NN variable has changed over time. Panel A depicts the density of observations of the variable in the year 1950, while Panel B depicts the same observation density for the year 2000. As shown, since the end of World War II, the navies of the world have gotten smaller and lighter, with fewer countries boasting large quantities of naval tonnage.

Regressions

My primary analysis regresses trade flows (lnX_{ijt}) on the constructed neighbors' navy variable (NN_{ijt}), using standard ordinary-least-squares (OLS) with many levels of fixed effects. As shown above, NNijt is an independent variable reflecting the sum of total naval tonnage of all other countries, weighted by proximity to the trade flow.

This regression is shown by Equation 5.

Equation 5: $\ln \ln X_{ijt} = \beta lnNN_{ijt} + \delta_{it} + \delta_{jt} + \delta_{ij} + \varepsilon_{ijt}$

The unit of observation for this regression is trade flows, constructed from a weighted sum of origin and destination trade flows as reported by the IMF, in thousands of current USD. Beyond the two independent and dependent variables, the gammas in the above equations refer to fixed effect coefficients. Listed in order, these gammas refer to an origin fixed effect over time, a destination fixed effect over time, and an origin-destination fixed effect. The primary coefficient of interest is the beta ß, which captures the effect of the neighbors' navy RHV on trade flows, or more specifically, the estimated elasticity of trade flows with respect to naval force presence. At first glance, and if one believes the existing literature from the navy pundits out there, this coefficient should be positive; increased naval presence should contribute to safer sea lanes and increased trade flows.

To briefly discuss the plausible exogeneity of my constructed NN variable, the variable can be reasonably expected to be uncorrelated with any omitted factors present in the residual which could be influencing trade flows. Because the variable takes into account the naval tonnage of all counties from which there is data, it is unlikely to be prohibitively influenced by regional outbreaks of conflicts or other events which could affect trade flows. Further, simply looking at the naval presence of say, the origin country, would be problematic, because the origin country could (and probably is) making trade and military decisions simultaneously, with obvious trade-offs (no pun intended) between the two. Another example of a potential RHV with obvious correlation with the residual would be some kind of construction reflecting the presence of threats to trade, such as Somali pirates. More pirates likely means both more naval ships in the area and less overall trade. For more on the identification assumption of my RHV, see Section V.

As such, the NN variable, constructed from the Chrisher/Souva dataset provides a strong jumping-off point for investigating the relationship between navies and trade. The results of the basic regression depicted by Equation 5 and related regressions across varying time periods are presented and discussed in detail in the following section.

IV. Results

As Table 1 depicts the results from the first three regressions of the experiment. Column 1 corresponds to the basic regression for the interaction between NN and trade across the entire dataset period. The result is a highly significant (-1.953). Because the regressions contain logs on either side of the equal sign, this coefficient means a one percent increase in naval presence, represented by NN, is associated with about 1.9 percent decrease in trade flows. Columns 2 and 3 refer to similar regressions. The former depicts the basic regression when just including the recent past,

meaning the 2000-2011 time period. When looking at this period, the coefficient becomes a more negative (-4.227); a 1% increase in NN is associated with a 4.2% decline in trade flows. Column 3 depicts the regression when looking at the pre-2000 period, and results in a (-0.484) coefficient. All results are highly statistically significant. Table 1 shows that when looking at any post-war time period, the relationship between trade and naval power is solidly negative but has become increasingly negative since 2000.

This change in the regression coefficient over time becomes even more apparent when breaking down the basic regression over the 1948-2011 time period, as depicted by Figure 4. The trade/navy relationship remained consistent between 1948 and 1980 but became rapidly negative during the late eighties and early nineties. This period not only corresponds roughly to the collapse of Soviet Russia and the end of the Cold War, but also a time characterized by rapid globalization and an increasingly integrated global economy. The decline of naval tonnage in this period as depicted in Figure 2, combined with the trade-flow increases from nineties-era globalization, meant fewer ships and more trade, and thus explains the rapid fall in the trade elasticity coefficient for this period shown in Figure 4.

It is worth noting that the way in which the regressions were organized (taking into account origin, destination, and combined time fixed effects which might have location-specific trade impacts) speaks well to the robustness of the regressions. If the results remain consistent even when produced under fixed effects which have imposed additional constraints, the results are expected to be reasonable and accurate depictions of the relationship between the variables of interest.

V. Robustness

As clear in the previous section, the presented results do not support the seemingly intuitive hypothesis that trade should respond positively to increased naval presence, because that naval presence presumedly keeps the sea lanes protected and safe.

One obvious issue that could complicate the results of the model is conflict, which can impact trade flows by effectively shutting down certain parts of the world and limiting the continued and consistent flow of goods. One way to investigate the potential effects of the presence of conflict is by imposing conditions on the basic regression. Figure 5 provides a graphical depiction of this robustness check, revealing how the trade coefficient changes in response to shock conditions represented by imposing conditional leads and lags on the model. The figure specifically incorporates leads two years after the present and lags two years prior to the present. When these time conditions are imposed, the coefficient at year 0 (the present) flips signs and becomes positive, and all results become noisier with larger standard deviations (although no result returns a p-value larger than 0.42). Interpreting these results, this graph suggests that when incorporating leads and lags into the model, trade actually benefits from increased naval presence. Further, a high naval presence in prior years is good for trade today (because the coefficient in the lags is positive), while a high

naval presence in the immediate future is very bad for trade today. These results make intuitive sense. A high naval presence two years ago could suggest the existence of conflict two years ago and a resulting decline in trade in that period and shortly after. Two years later, if the conflict has simmered down, trade can be expected to "rebound" and recover. On the flip side, a high naval presence two years from the present could suggest that international relations are deteriorating today, and trade is expected to decline in the future. Taken together, these results suggest the model is highly conditional to time considerations and reflects the ability of conflict to influence trade flows. Therefore, an important consideration to the entire policy debate that influenced this research is the ability of naval forces to manage conflict. In light of an increasingly assertive Chinese Navy within the economically important waterways of East Asia, if U.S.-led naval forces are able enough to deter aggression on commerce and ensure the continued free flow of goods, that would be enough to justify their continued existence, even considering the analysis above that looks exclusively at the historical relationship between trade and force presence. For example, any outbreak of war will probably lower the trade flows of the involved parties, but it is not unreasonable to assume that these values would decline by even more without the presence of naval forces. The important question is by how much?

The model can be further tweaked to estimate the impact navies have on protecting the trade of their global trading partners. Specifically, by dropping the trade flows of the world's largest navies from the dataset and re-running the regressions, the results will describe how the smaller countries of the world benefit from the presence of large navies around the globe. This gets at the question of how America's trading partners, which lack their own formidable navies, benefit from the presence of U.S. warships near their trade routes. Do non-global players benefit from the presence of global navies?

Table 2 depicts what happens when the regressions are run after any entries that include the United States, the Soviet Union/Russia, or China as either the origin or destination country are dropped by the dataset. As evident by the table, the basic results from Table 1 do not change any remarkable amount but remain highly statically significant. Across the entire time period and the 1948-2000 period the results get even more negative and become only slightly less negative in the post-2000 period. In the entire period, a 1% increase in naval presence is now associated with a 2.2% decline in trade flows. If the year-by-year coefficients were plotted like in Figure 4, the trends would appear exactly the same as the earlier basic regression inclusive of all navies, but with values shifted slightly further down the y-axis. So, even when global players are omitted from the regression, trade continues to respond negatively to force presence.

VI. Conclusions

The results of the analysis suggest that when put to the econometric test, there exists a negative relationship between trade flows and naval force presence. As the first explicit

investigation into this relationship, these results offer important considerations for a consequential but understudied topic. However, as discussed previously, the presented results are highly conditional to time considerations and are possibly affected by conflict. One area for future research would be testing how the trade flows respond when using both the NN variable and a new weighted instrument considering if a country in a given country pair is at war. Unfortunately, a dataset like this that stretches back to the period identified in the IMF trade data does not yet exist. If the regressions from this data suggest a negative relationship between trade and conflict, then an important aspect of the policy conversation would be how effectively naval forces can manage conflict. A further area for future investigation is assessing if the general results can be interpreted across particular geographies. Specifically, do the results change if looking at trade between countries within certain continents, regions, or oceans? Answers to these questions could help temper the general conclusions to the results presented by this initial analysis.

But if even after further research the general results presented here hold, this analysis offers important policy considerations. As pointed out by Friedman (2022), "the notion that naval presence is vital to global trade is very expensive." Further, according to the Congressional Budget Office, one-sixth of federal spending goes to national defense (Congressional Budget Office 2022). To continue to maintain readiness and cost-effectiveness, all the while dealing with an ever-increasing national debt, a rethinking of U.S. Navy missions and force composition will become increasingly important in policy debates. The presented analysis supports the theory that global trade is more robust than it gets credit for; reductions in naval presence may not end up negatively impacting the continued flow of global commerce. Although these results may present a bitter pill for the Navy to swallow, this transformation in thinking is already underway (Work 2021). If the U.S. Navy can accept that continual presence may no longer be needed, the service may be able to refocus its priority on core military missions (such as enforcing sanctions, antiproliferation, and gaining control of sea lanes), combat its readiness problems, and reduce its burden on the American taxpayer.

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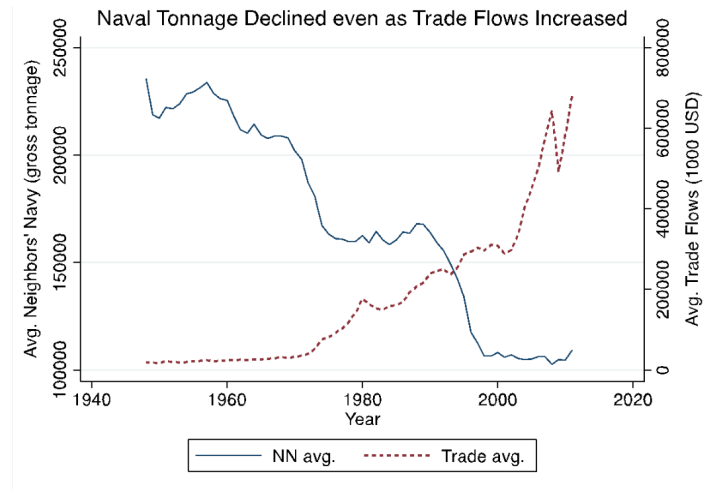
TABLES AND FIGURES

Figure 1:

Distance (h_b) from third country (t) to the trade route (distance b)
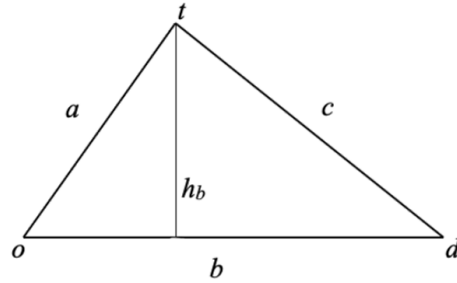
$$h_b = 2\frac{A}{b}$$

$h_b = height\ from\ intersection\ of\ ac\ to\ b$

$A = Area$

$b = distance\ between\ origin\ (o)\ and\ destination\ (d);(base)$

Figure 2:

Notes: Plots the average of the constructed neighbors' navy variable (sum of all other countries naval tonnage, weighted by distance to origin's trade route) across countries per year (left-side) and the average trade flows, in 1000 USD, across all countries for the same time period (right-side). Trade flows come from the IMF, reported by destination country.
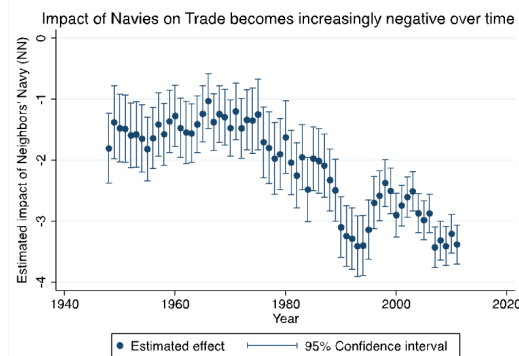
Figure 3:

Naval Power Index (NN) in 1950
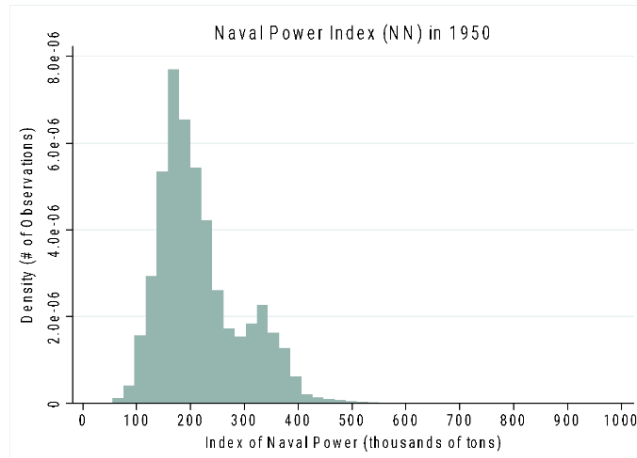
Notes: Density of observations from constructed NN index in the year 1950.


Naval Power Index (NN) in 2000
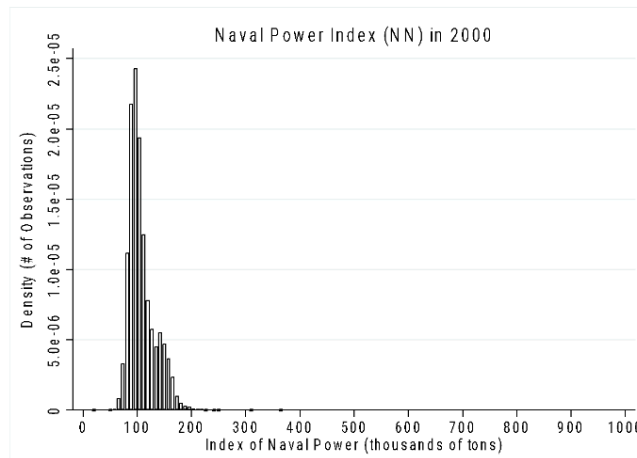
Notes: Density of observations reported from constructed NN index in the year 2000. Since 1950, the navies of the world have gotten smaller and lighter.

Figure 4:

Impact of Navies on Trade becomes increasingly negative over time

Notes: Regression coefficients of the NN variable on trade, produced from OLS regression with many fixed effects, plotted over the 1948-2011 period. All results are negative and highly significant (P> |t| = 0.00).

Figure 5:

Trade Flows are highly conditional on naval shocks
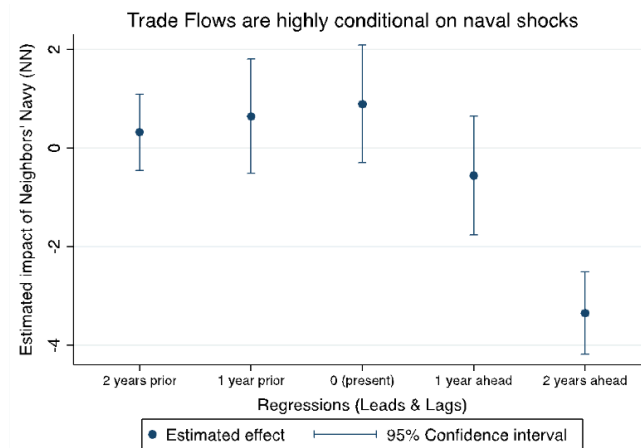
Notes: Plots regression coefficients of the NN variable on trade, produced from OLS regression with many fixed effects, but conditional on leads and lags. Specifically, plots the effects of constructed NN on trade flows conditional on two years before the present, one year before present, the present effect, one year after the present, and two years after the present. Conditional on leads and lags, the sign of the baseline regression at year 0 becomes positive, and the results become noisier, but no result boasts a p-value larger than 0.42.

Table 1:

Table 1 – Trade Flows declines as Naval Presence increases

Dependent Variable: (log) Trade Flows	(1)	(2)	(3)
(log) Neighbor Navy (1948-2011)	-1.953*** (0.0842)		
(log) Neighbor Navy (2000-2011)		-4.227*** (0.848)	
(log) Neighbor Navy (1948-1999)			-0.484*** (0.0957)
Observations	491,153	177,872	294,471
R-squared	0.890	0.932	0.892
Standard errors in parentheses	*** p<0.01, ** p<0.05, * p<0.1		

Notes: Describes the output from regressing trade flows on the constructed NN variable. Column (1) reports the output over the entire timeframe (1948-2011), Column (2) depicts the relationship in the years 2000-2011, and Column (3) displays regression results when just looking at the pre-2000 period. The regressions come from OLS regression using many fixed effects (origin-year, destination-year, and origin-destination-year). The second regression produces a larger standard error of 0.85, but all results are highly statically significant.

Table 2:

Table 2 - Trade / NN Interaction with Largest Navies Omitted

Dependent Variable: (log) Trade Flows	(1)	(2)	(3)
(log) Neighbor Navy (1948-2011)	-2.168*** (0.0905)		
(log) Neighbor Navy (2000-2011)		-4.208*** -0.888	
(log) Neighbor Navy (1948-1999)			-0.593*** (0.105)
Observations	463,800	169,271	278,499
R-squared	0.883	0.928	0.886
Standard errors in parentheses	*** p<0.01, ** p<0.05, * p<0.1		

Notes: Describes the output from regressing trade flows on the constructed NN variable, but after omitting the world's largest navies from the data, which refers to the United States, Russia/USSR, and China. Like Table 1, Column (1) reports the output over the entire timeframe (1948-2011), Column (2) depicts the relationship in the years 2000-2011, and Column (3) displays regression results when just looking at the pre-2000 period. The regressions come from OLS regression using many fixed effects (origin-year, destination-year, and origin-destination-year). The second regression produces a larger standard error of 0.85, but all results are highly statically significant.